Opportunity Commission (EEOC) and the Department of Labor (DOL) also receive complaints about unlawful employment practices, including retaliation against employees who report or object to discriminatory behavior, wage theft, and other violations. The EEOC and DOL should actively seek information about NDAs and related practices in the course of their investigations and should make pursuit of retaliation claims a top priority.

In addition to redoubling enforcement efforts in their respective spheres of jurisdiction, the aforementioned agencies should collaboratively develop and implement strategies for amplifying their collective oversight impacts.

Prohibit the Most Pernicious Uses of NDAs

New federal laws should be enacted to ban employer-imposed secrecy regarding key categories of essential information, including firm diversity, harassment and discrimination, compensation practices, and workplace health and safety. The recently proposed Ending the Monopoly of Power Over Workplace Harassment through Education and Reporting Act (EMPOWER Act) would make it illegal for an employer to require or enforce an NDA or nondisparagement clause related to workplace harassment based on a range of protected characteristics, including sex, race, national origin, disability, age, or religion. The proposed law, which enjoys bipartisan support, would also establish a confidential tip line for reporting systematic workplace harassment.

The EMPOWER Act is a step in the right direction, but federal legislation should go even further. New laws are needed to protect a wider range of disclosures and to ensure that employees know their rights. A section of California's Silenced No More Act provides one example. It prohibits companies from using NDAs to silence employees not only about harassment, but also about discrimination and other illegal conduct. To ensure that employees know their rights, the act requires employers who use NDAs for lawful purposes to include in these contracts language clarifying that "[n]othing in this agreement prevents you from discussing or disclosing information about unlawful acts in the workplace, such as harassment or discrimination or any other conduct that you have reason to believe is unlawful."

The federal Defend Trade Secrets Act (DTSA) provides another example of a provision that could be incorporated into new legislation aimed at reining in NDAs.[39] Signed into law by President Obama in 2016, the DTSA requires employers to include language in all employment contracts notifying employees that they are immune from liability when blowing the whistle on unlawful employer behavior, even if doing so involves revealing trade secrets. This notice requirement could be expanded to cover any discussions about workplace conditions. It could also clarify that the NDAs may cover only technical information that is truly secret and not general skills, know-how, and job-related experience.

[39] Lobel, O. (2017). The DTSA and the New Secrecy Ecology. *Business, Entrepreneurship & Tax Law Review*, 1(2): 369–382.

Ensuring that the widest possible swath of employers is bound by the provisions proposed herein requires Congressional action. However, President Biden could immediately enact such provisions with respect to federal contractors. The president has the power to issue an executive order restricting or prohibiting the federal government from entering into contracts with companies that fail to adhere to certain rules. President Biden could issue an executive order requiring that federal contractors adhere to new rules prohibiting use of NDAs to conceal essential information, including information on firm diversity, harassment and discrimination, compensation practices, workplace health and safety, and other areas of regulatory compliance. In addition to the benefits discussed above, such rules could help prevent concealment of fraud by government contractors.

Collect Data and Require Disclosure

Research tells us that NDAs are common in American workplaces. Recent events have shown that some employers use NDAs to cover up unlawful behavior. Yet information on the prevalence and content of NDAs is still relatively scarce. Employers are not currently required to disclose their NDAs to any outside party or government regulator. Employers are also free to prohibit employees who sign NDAs from even revealing that the agreement exists. Without adequate information on the scope and nature of the NDA problem, it is difficult for lawmakers to craft well-tailored policy solutions that account for a variety of stakeholder concerns. Any law limiting NDAs must balance the damages that concealing information from the public impose against the value of NDAs for employers when used appropriately. Legislation must also consider the personal interests of victims of misconduct who may prefer to keep their experiences secret.

Policymakers should therefore require organizations to disclose their NDAs and related clauses in employment agreements. The FTC should use its investigative authority under Section 6(b) of the FTC Act[40] to gather and study these documents. The SEC should also consider requiring disclosure of companies' use of NDAs as part of its broader response to investor demand for credible information about human-capital management[41,42] and environmental, social, and governance performance.[43]

In addition, the various agencies that investigate violations of employment laws should collaborate to conduct more research on the scope and effects of NDAs (as well as other corporate-secrecy practices) across states and industries. For instance, the EEOC already receives annual reports from employers about worker demographics, salary breakdown by gender and race, and other employment information. A coordinated agency effort could provide insight into how NDAs affect diversity and equity in employment. Developing these types of data will help

[40] 15 U.S.C. § 46(b).
[41] Intelligize. (2021). *Human Capital Disclosure Report: Learning On the Job.* May.
[42] Just Capital. (2021). As the SEC Finally Takes on Climate Disclosure Standards, It Must Also Consider ESG Standards Affecting Workers.
[43] Lee, A.H. (2021). A Climate for Change: Meeting Investor Demand for Climate and ESG Information at the SEC. March 15.

lawmakers assess the anti-competitive effects of corporate secrecy, balance competing policy interests, and draft effective legislation.

DAY ONE PROJECT

About the Authors

Rachel Arnow-Richman is the inaugural Gerald A. Rosenthal Chair in Labor & Employment Law at the University of Florida Law School. Prior, Professor Arnow-Richman was the Chauncy Wilson Memorial Research Professor and Director of the Workplace Law Program at the University of Denver, Sturm College of Law. She has also held faculty appointments at the University of Colorado Law School, Fordham Law School, Temple University School of Law, and Texas A& M Law School (formerly Texas Wesleyan). Before entering law teaching, she served as a judicial clerk to the New Jersey Supreme Court and practiced employment and commercial law at Drinker, Biddle and Reath LLP in Philadelphia.

Gretchen Carlson is a fierce, fearless and internationally recognized advocate for women's rights, whose bold actions against Fox News Chairman Roger Ailes helped pave the way for the global #MeToo movement. A former CBS News and Fox News journalist, author, TED talk alum, and champion for workplace equality, Carlson was named one of Time Magazine's "100 Most Influential People in the World". She's a PEOPLE TV special contributor and host of the new daily news podcast "Get The News With Gretchen Carlson" on Quake Media. Carlson is the author of the New York Times bestseller "Be Fierce" and "Getting Real," and recently co-founded the non-profit Lift Our Voices to end the silencing of harassment victims through forced arbitration and non-disclosure agreements. Carlson's story of harassment and retaliation at Fox News has garnered international attention, including the Showtime mini-series "The Loudest Voice" and movie "Bombshell."

Orly Lobel is the Warren Distinguished Professor of Law at the University of San Diego and the award-winning author several books and numerous articles. She is a prolific speaker, commentators and scholar who travels the world with an impact on policy and industry. A graduate of Tel-Aviv University and Harvard Law School, Lobel clerked on the Israeli Supreme Court and is a member of the American Law Institute. She has recently been named as one of the most cited legal scholars in the country. Her books You Don't Own Me: How Mattel v. MGA Entertainment Exposed Barbie's Dark Side (Norton 2018) and Talent Wants to Be Free: Why We Should Learn to Love Leaks, Raids and Free Riding (Yale University Press 2013), are the winners of several prestigious awards, and she has received several grants for her research. In 2016 Lobel was invited to Washington DC to present Talent Wants to be Free at the White House, a meeting which resulted in a presidential call for action. In 2020 she was the keynote speaker and advisor to the Federal Trade Commission on labor market competition policy. Her new book The Equality Machine: Harnessing Tomorrow's Technologies for a Brighter, More Inclusive Future is coming out in the Fall 2022 with PublicAffairs

Political activist and advocate **Julie Roginsky** has long been an outspoken champion of women's rights and issues. A nationally recognized political consultant, Roginsky began her career working at a prominent organization dedicated to electing more women to political office. Throughout her career, she has focused her efforts on mentoring and empowering women who seek to become engaged in the political process. Roginsky is a former contributor at CNBC and the Fox News Channel, where she was a frequent co-host of "Outnumbered" and "The Five". In 2017, she became one of the first women to file a sexual harassment and retaliation lawsuit against the Fox News Channel and its chairman. Since then, she has fought relentlessly against non-disclosure agreements and other tools that organizations use to silence women from publicly disclosing their experiences with toxic work environments. She serves as an advisor to major corporations, start-ups, non-profits, labor unions, and dozens of elected officials, including governors, senators, members of the House of Representatives, and state legislators.

Jodi L. Short is the Associate Dean for Research and the Honorable Roger J. Traynor Professor of Law at UC Hastings Law. Her research investigates business compliance with public and private forms of regulation, including environmental laws and labor standards in global supply chains. She is particularly interested in the secrecy tactics companies use to hide wrongdoing and evade compliance with legal obligations and normative expectations.

Dr. Evan Starr is an Associate Professor of Management & Organization at the Robert H. Smith School of Business, University of Maryland. His research examines issues at the intersection of employee mobility, human capital, entrepreneurship, and technology. He is particularly interested in the impacts of postemployment restrictions on workers and firms. Dr. Starr has authored more than a dozen articles in leading journals in economics and management and testified in front of the US Senate and the US House of Representatives. His research has been covered in major news outlets including The New York Times, The Wall Street Journal, The Economist, NPR, Financial Times, and The Washington Post. Formerly a professor at the University of Illinois, Dr. Starr received his PhD in Economics from the University of Michigan and received a BA from Denison University.

About the Day One Project

The Federation of American Scientists' Day One Project is dedicated to democratizing the policymaking process by working with new and expert voices across the science and technology community, helping to develop actionable policies that can improve the lives of all Americans. For more about the Day One Project, visit **dayoneproject.org.**

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U.S. DEPARTMENT OF THE TREASURY

THE STATE OF LABOR MARKET COMPETITION

March 7, 2022

U.S. DEPARTMENT OF THE TREASURY

THE STATE OF LABOR MARKET COMPETITION

EXECUTIVE SUMMARY

On July 9, 2021, President Biden signed an historic executive order on Promoting Competition in the American Economy. That order underscored the importance of competition in the labor market, stating that "a competitive marketplace creates more high-quality jobs and the economic freedom to switch jobs or negotiate a higher wage." The order tasked the Treasury Department, in consultation with the Department of Justice, the Department of Labor, and the Federal Trade Commission to investigate the effects of a lack of labor market competition on the United States labor market.

The purpose of the report is to summarize the prevalence and impact of uncompetitive firm behavior in labor markets. In particular, the report catalogues the ways in which insufficient labor market competition hurts workers, documents the proliferation of barriers to job mobility, and illustrates how a lack of labor market competition can hold back the broader macroeconomy, while also providing an assessment of the degree to which lack of competition lowers wages. **This analysis is followed by a description of Biden Administration actions to improve competition, including a commitment by the Department of Justice and Federal Trade Commission to vigorously enforce antitrust laws in labor markets**.

In discussing the market characteristics that enable monopsony power, this report describes how monopsony power emerges when a single firm can restrain its hiring to lower wages and boost profits. While most labor markets do not literally feature a single employer, a market with a small set of employers may mimic a monopsony by each engaging in practices that give them market power over workers. Concentration in particular industries and locations can lead to workers receiving less pay, fewer benefits, and worse conditions than what they would under conditions of greater competition.

There is also increasing recognition that market power may be *inherent* in the firm-worker relationship. Much of the theory of labor markets and wage setting is premised on the idea that individual workers and firms search for one another, seek and find matches that maximize productivity and wages, and bargain over employment terms. Workers often find themselves at an *informational* disadvantage relative to firms, not knowing what other, similarly placed workers earn, the competitive wages for their labor, or the existence of workplace problems like discriminatory conduct or unsafe working conditions. Workers also may have a limited or no ability to switch locations and occupations quickly and may lack the financial resources to support themselves while they search for jobs that pay more and better match their skills and abilities. These conditions can enable firms to exert market power, and consequently offer lower wages and worse working conditions, even in labor markets that are not highly concentrated.

The report details the range of practices that firms use to restrain competition for workers, most clearly to lower wages and benefits, but also potentially to negatively impact job characteristics beyond just compensation. Firms can engage in tacit collusion by sharing wage information for different occupations, conspiring to fix wages, adopting no-poach agreements where firms agree not to hire other firms' workers, or forcing workers to sign non-compete agreements that limit their ability to switch jobs. Non-disclosure agreements can be so broad as to effectively operate as non-compete agreements. Mandatory arbitration agreements prevent workers from legal recourse to rectify violations of labor laws, antitrust laws, or employment terms. Lack of pay transparency, from firms' use of salary history, pay secrecy, and punitive practices against workers sharing pay information, also restrains competition.

A growing literature in economics seeks to measure the labor market power exerted by firms over workers. As David Card, the most recent recipient of the Nobel Prize in Economics, stated in his presidential address to the American Economic Association, "I will try to make the case that the time has come to recognize that many—or even most—firms have some wage-setting power."

Measuring the extent of labor market power can be challenging, as it requires extensive insight into the relationship between firms and workers that goes beyond standard measures collected. **As this report highlights, a careful review of credible academic studies places the decrease in wages at roughly 20 percent relative to the level in a fully competitive market.** In some industries and occupations, like manufacturing, estimates of wage losses are even higher.

Wage-setting power is also evident in the large number of workers who are subject to rules and agreements that limit their ability to switch jobs and occupations and, hence, their bargaining power. For example, a recent paper estimates that one-in-five workers is currently subject to non-compete agreements and double that number report having been bound by a non-compete agreement in the past. As the report discusses, many workers are also subject to excessive occupational licensing requirements that impede their ability to switch jobs across states or their ability to enter a new occupation.

The report also highlights the ways in which employers alter the structure of their own work relationships to lower their labor costs and undercut competition at the expense of workers. The labor market has become "fissured," a wide variety of roles ranging from cafeteria workers and janitors to lawyers that were once "in-house" are now contracted out. This domestic outsourcing is estimated to reduce wages from 4 percent to 24 percent in some industries and occupations. Moreover, when firms misclassify workers, they offload labor costs and risks onto workers—for example, by avoiding unemployment insurance taxes and workers' compensation premiums—and make it difficult for workers to organize or join a union and bargain collectively for better wages and conditions.

The decline in union density rates further weakens workers' bargaining power, leaving them with less ability to counterbalance firms' wage setting power.

The impacts of insufficient labor market competition often fall hardest on women and workers of color, who make up a larger share of workers in lower-paid occupations. These workers often have diminished bargaining power because they lack the resources to easily switch jobs or occupations, to reject or negotiate against signing restrictive employment agreements, or to seek legal recourse for violations of labor and employment law.

The report also highlights the ways in which a lack of labor market competition can impact the broader economy. Lack of labor market competition contributes to high levels of income inequality, diminishes incentives for firms to invest, inhibits the creation and expansion of new firms, and reduces productivity growth through lower reallocation of labor across firms and industries.

The Biden Administration is committed to promoting robust competition in labor markets and has directed a government-wide effort to support labor market competition. The Department of Justice and Federal Trade Commission are committing to the vigorous enforcement of antitrust laws in labor markets, to combat anticompetitive agreements, conduct, or mergers. The Administration has called on Congress to raise the minimum wage and support increased worker power through increased organizing and collective bargaining facilitated by the Protecting the Right to Organize Act and other legislation.

The President's Task Force on Worker Organizing and Empowerment recommended 70 actions that executive branch agencies and departments will implement to facilitate greater union organizing and collective bargaining. As part of his Executive Order on competition, the President encouraged the Federal Trade Commission to consider banning or limiting the use of non-compete agreements. The President's Executive Order increasing the minimum wage for federal employees and contractors raised wages for more than 300,000 private-sector employees and 70,000 federal employees.

Finally, in addition to education, compliance assistance, and enforcement of workplace laws, the Department of Labor's administrative actions include addressing worker misclassification, supporting worker organizing, and working to improve job quality, including access to jobs with higher wages and better working conditions.

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INTRODUCTION

On July 9, 2021, President Biden signed a historic Executive Order on Promoting Competition in the American Economy. The Order affirms the importance of competition for workers, stating that "a competitive marketplace creates more high-quality jobs and the economic freedom to switch jobs or negotiate a higher wage." Yet, as the Order explains, empirical evidence suggests that anti-competitive forces and practices have weakened workers' bargaining positions and, consequently, worsened outcomes for workers. The Order outlined a whole-of-government approach to addressing the excessive concentration of labor markets in the United States. As part of this comprehensive approach, the Order directed the Secretary of the Treasury, in consultation with the Attorney General, the Secretary of Labor, and the Chair of the FTC, to produce a report on the effects of lack of competition on labor markets.

This report reaffirms the urgent need to promote competition in labor markets and increase workers' bargaining power. A central finding is that the American labor market is characterized by high levels of employer power. Sources of this market power include natural labor market frictions, employer concentration, and anti-competitive labor market practices. Employers exploit this market power by holding wages and certain non-wage benefits beneath their competitive level. Simultaneously, the decline in unionization reduced worker bargaining power.[1] As a result, workers are forced to accept lower wages and worse benefits than in a competitive market. These impacts are often disproportionately felt by socioeconomically vulnerable people, such as low-income workers, workers of color, women, and immigrants. Problems stemming from lack of competition harm more than just the well-being of workers and their families; it also holds back our entire economy, contributing to income inequality, inhibiting innovation, and curbing economic growth.

Employer market power can manifest in forms beyond reductions in workers' earnings that are challenging to measure. Many of today's jobs impose unpredictable just-in-time schedules, detailed on-the-job monitoring coupled with demanding speed requirements and punitively short breaks, inadequate safety systems, and no opportunity for advancement. While these determinants of job quality are harder to measure than wages, and therefore less well studied, they also suggest that labor markets are not perfectly competitive.

First, this report begins by exploring some of the theoretical underpinnings of firm labor market power. We then survey the empirical literature on many of the primary developments that have contributed to persistently low labor market competition and worker bargaining power in recent decades. Topics surveyed include shifting firm boundaries (fissuring of the workplace), restrictive employment agreements (e.g., non-compete agreements), mandatory arbitration clauses, and occupational licensing. We also document the decline in worker mobility and bargaining power and note the literature on the divergence between labor productivity and labor income, labor's share of overall income, and declining enforcement actions, among other things. We highlight how these developments have impacted specific industries and sectors of the economy, including hospitals and nursing, agricultural inputs and food processing, and minor league baseball.

Empirical studies of labor market power have proliferated recently, as academic interest in the topic enjoys a renaissance. As papers address the empirical problem using a variety of methods, economists can increasingly paint a nuanced picture of labor market power as it exists today. Considerable debate over details—big and small—persist, but recent literature agrees on the broader picture: many employers exert market power when hiring workers, and those workers are compensated less as a result.

We conclude the analysis portion of the paper by highlighting the implications of diminished labor market competition on the broader economy. This includes growing income inequality, declining business investment and

1 Farber, Henry S., Daniel Herbst, Ilyana Kuziemko, and Suresh Naidu. 2021. "Unions and Inequality over the Twentieth Century: New Evidence from Survey Data." *The Quarterly Journal of Economics* 136 (3): 1325–1385.

productivity growth, declining worker mobility and productivity growth through less reallocation, and lower levels of firm formation and innovation.

The extent to which this area has gained traction was demonstrated by an address by economist David Card, the most recent recipient of the Nobel Prize in Economics, at the annual meeting of the American Economic Association. In his address, Card calls on the field of economics to study the role of imperfect competition in labor markets, while observing that widespread lack of competition has become the consensus view in economics. Card concludes his address by noting:

> One of the most exciting developments in the field today is the evidence of labor economists taking questions about wage setting seriously. This effort began with Manning's (2003) landmark book: I hope that the growing body of work since then finds its way into the classroom and into the textbooks soon. I also expect this work to lead to some re-thinking on policies such as minimum wages, the regulation of trade unions, and anti-trust (see Longella and Manning 2021, and Naidu and Posner 2022). Perhaps we may even see a re-evaluation of the widespread belief that excessive wages are the root cause of many economic problems. After all, if your employer set your wage, it's hard to believe that it's too high.[2]

With a similar spirit, the Biden Administration has prioritized policies to restore labor market competition and increase the relative bargaining power of workers. The report concludes with the Administration's policies to counteract the decline in labor market competition, including a policy favoring full enforcement of the antitrust laws in labor markets, expanding opportunities for collective bargaining, raising the minimum wage, and extending health insurance coverage to reduce job lock and boost mobility.

2 Card, David. 2022. "Who Set Your Wage?" *National Bureau of Economic Research* Working Paper 29583.

THEORIES OF LABOR MARKET POWER

Defined simply, the labor market matches workers and firms, creating jobs. Jobseekers offer their skills and time to firms, which in turn offer pay and benefits. Simplicity, however, insufficiently describes the labor market. It misses the pervasive variety: on one side of the market, each worker brings a unique set of skills, dispositions, and circumstances to an employer. On the other side, there is an enormous variety of jobs in the United States.[3] In this sense, labor markets are very different than some product markets, like commodity markets, where the product is relatively homogenous, and buyers are usually indifferent to who is selling and vice-versa. In the labor market, both buyers (firms) and sellers (workers) take great interest in their counterpart's characteristics.

In a strong and expanding economy, a well-functioning labor market typically delivers wage growth, low unemployment rates, regular job switching, and improved job quality. This dynamic benefits society: when workers and firms can easily match and separate, it increases the average productivity of each job. Over their careers, workers find jobs that increasingly suit them, and employers find workers who best fit their needs. However, "well-functioning" is not the default state of labor markets. The job search is beset by frictions, among them time, information, diverse worker preferences, and geography. Alongside other factors, these frictions can frequently generate market power for employers of all sizes, decreasing the market's efficiency and reducing the gains that would otherwise accrue to society.

We define "labor market power" (herein, "monopsony" or "market power") as a firm's power to reduce the compensation it pays to its workers, paying less than an equivalent job would, in a hypothetical perfectly competitive market. Market power allows a firm to decrease its compensation without losing its entire workforce, where compensation refers to not just wages, but also benefits, job quality and working conditions.[4] Likewise, the firm can expand its workforce by raising compensation.[5] Lower pay is the effective outcome of a labor market characterized by "monopsony"—the situation when an individual firm has some control over the market and thus can affect compensation. Still, monopsony does not imply a complete absence of market forces. So long as workers have *any* alternatives, markets help dictate the extent of a monopsonist's power.

Monopsony's counterpart is perfect competition, an economic model in which both workers and firms take wages as given—meaning they cannot raise or lower the prevailing wage. Under perfect competition, the residual labor supply curve (or firm-specific labor supply curve) is flat, meaning each firm can hire whatever amount of labor it wants but only at the market wage. Therein lies the key technical distinction between monopsony and competition: an upward sloping versus flat residual labor supply curve. Note that in both contexts, the aggregate (market-level) labor supply curve is typically upward-sloping.

To illustrate the contrast between competition and market power, consider this question: if an employer cut their wages by 5 percent, what fraction of their workers would quit? In a perfectly competitive market, all workers would leave. Yet, we know that this is not true in practice—indicating that many employers have some degree of market power.

A labor market monopsonist leverages their position to pay their workers less than the competitive rate for a given job. In a perfectly competitive labor market, each worker earns the market value of what they contribute

3 Not only are there 867 detailed occupations recognized by the Bureau of Labor Statistics' (BLS) 2018 Standard Occupational Classification, but there are plenty of differences within those occupations. Further, similar jobs offer unique requirements and benefits, which by itself is evidence of some level of monopsony in labor markets.

4 Throughout the paper, we intend compensation or wages to refer to not just money, but also benefits, job quality, and working conditions.

5 In economist jargon, a firm that has an "upward-sloping residual labor supply curve" also has market power. The "residual" part of that phrase distinguishes the firm-specific labor supply curve from the aggregate (market-level) labor supply curve.

to production—known as the "marginal revenue product of labor" (herein, MPL_R). A labor-market monopsonist instead sets its compensation below the MPL_R, which reduces its cost of production and therefore raises profits. Practically, the strength of a firm's market power is indicated by the difference between compensation and MPL_R. Throughout, we refer to this difference—in effect, the amount by which a firm suppresses a worker's compensation—as either a firm's "markdown," or a worker's "lost wages." This is analogous to monopoly's better-known concept of a markup, where a firm charges a price for a good above the firm's costs of production.

Broadly speaking, two distinct classes of economic theories might help explain the source of employers' labor market power. The first class is based on labor market structure: pure monopsony, monopsonistic competition, and oligopsony. These are demand-side counterparts to the more familiar models of monopoly, monopolistic competition, and oligopoly. If only one or a few firms are buying labor in a given labor market, they have the power to set wages in that market and will keep wages below what workers might be able to charge in a competitive market, so workers have nowhere else to turn.

The second class of theories stems from "search and matching" models of labor markets. Search and matching models explicitly account for the frictions and opportunity costs inherent to job searches, both from the worker's and firm's perspectives. In these models, employers account for the worker's difficulties in finding a new job. These difficulties include the direct costs of a job search (e.g., time), as well as indirect costs such as uncertainty about the suitability of a new job, a lack of knowledge about wages or benefits offered by other firms, or foregone pay during unemployment. It also encompasses the fact that jobs are more than just compensation to a worker, who also values the nature of work, company culture, coworkers, managers, and commute times—and different workers may value the same aspects of a job differently. If one worker highly values a specific facet of a job, then they would accept a lower wage than other workers for the same position. Consequently, the employer can reduce its compensation and still maintain many of its workers. For the purposes of this report, both theories share the same core outcome: they result in the reduction of worker compensation.

We now detail those theories and their implications.

Pure Monopsony

Pure monopsony describes a market with a single buyer. This is the mirror image of a monopoly model (a single firm selling final goods and services), except a single firm is purchasing inputs (like labor). In the labor context, monopsony exists if some workers have only one option for employment, such as a "company town" where there is a single dominant employer in the community. As such, it is rarely the ideal model to describe U.S. labor markets.

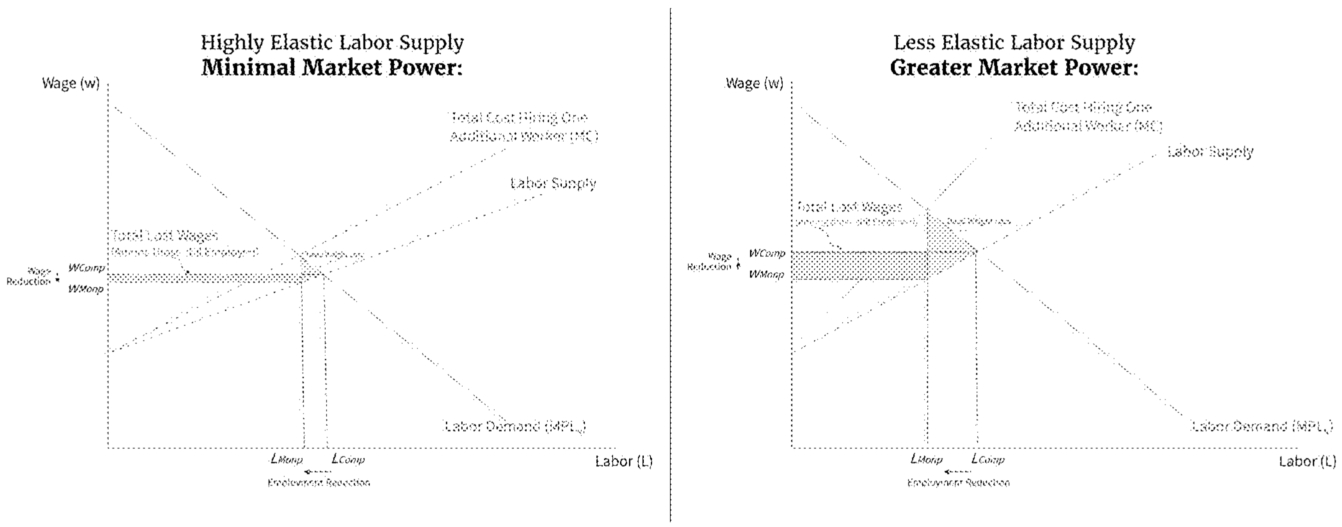

Figure 1 - Pure Monopsony: Elasticity Drives the Scale of Wage Loss

The model nonetheless remains useful, both to help understand the market power problem in a simple context and to establish nearly all the foundation for the more realistic model of monopsonistic competition.

Practically, an upward-sloping labor supply curve implies two costs to hiring a new worker: the first is the wages directly paid to the new worker, and the second is the increased wages paid to workers already employed by the firm. By the same logic, a monopsonist enjoys these two sources of reduced costs by constraining employment below the competitive level.

In market structure models, *the elasticity of labor supply* lives at the heart of market power. Loosely defined, this elasticity measures how strongly the workforce reacts when wages change. In turn, the elasticity of labor supply dictates the markdown in wages. When the labor supply is highly elastic, a small decrease in wages results in a large decrease in the number of workers who are willing to work for the firm. In this case, a monopsonist has little to gain from markdowns since it stands to lose too much of its labor force. With lower elasticities, however, the same decrease in wages prompts a weaker response from the workforce. This effectively grants the monopsonist increased pricing power, as wage cuts induce fewer quits than in a higher-elasticity environment. Simply put, when workers are prepared to walk away from a job, their employer has less power over them.

Monopsonistic Competition

At a national level, pure monopsony is clearly an inappropriate descriptor for labor markets. A more realistic model of labor markets in the United States is that of monopsonistic competition.

Monopsonistic competition is similar to pure monopsony, except the firm faces a residual labor supply curve rather than the aggregate supply curve. To reiterate, a firm's residual labor supply curve is specific to that firm, after accounting for the labor supply curves facing the rest of the market. When wages fall economy-wide, workers will more readily switch from a firm that lowers its wages than out of employment altogether. In other words, residual labor supply curves are more elastic than aggregate labor supply curves. Taken further, the more similar employment is between firms, the more readily workers will switch and the greater the elasticity of residual labor supply curves.

An example of a monopsonistically competitive labor market might be a city with many restaurants. Though there might be many restaurants employing chefs, they are not identical. A chef has skills that can be used in a multitude of restaurants, but this does not mean the chef is indifferent to where they are employed. Some restaurants may provide a more suitable menu, have better or more predictable work schedules, or be more conveniently located. In this case, the chef may be willing to accept a discounted wage to work at a particular restaurant, giving that restaurant some degree of market power.

Search and Matching Models of Labor Markets

Search and matching models introduce important nuance to theories of labor market power.[6] Specifically, these models provide conditions where all employers, to varying degrees, possess market power; but crucially, these models also account for the frictions involved in job searches, among them time and considerable uncertainty. Aware of these frictions, employers can discount wages while retaining their workforce and hiring new employees. A worker will sometimes prefer to accept a job with a discounted wage than to continue a job search that may not yield a better alternative quickly or at all.

A friction is any factor that makes job searches or switches more difficult than the theoretical ideal of switching between two identical consumer goods, such as pantry staples. The job search process is also characterized by

6 For a reference and considered argument, see Manning, Alan. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets.* Princeton: Princeton University Press.

considerable information gaps. For example, consumers can easily compare airfare prices on travel aggregator websites, but it is typically impossible for workers to learn the compensation associated with every potential employment opportunity. Real-world labor markets feature significantly more frictions than consumer markets.

Broadly speaking, there are two types of search and matching models relevant to labor market power. The first is characterized by "ex-ante wage posting," where employers announce their wages with every job offer. This is often applicable to lower wage jobs—think of a sign outside a fast-food restaurant that states, "Positions starting at $15." The second is characterized by "ex-post wage bargaining," where the worker and firm negotiate wages and benefits in the final stage of the hiring process. This is more typical in higher-paying jobs, where the job postings often include an ambiguous statement that the job pays "competitively."

In an "ex-ante wage posting" model[7], workers do not simply pick a job—they must be offered the job first, and the offer comes at a known wage. Upon receiving a job offer, they can accept or decline, which they will do based on their understanding of the rest of the market. If a worker thinks they are likely to receive a significantly better offer elsewhere, they decline the current offer and keep searching. If the worker does not believe they are likely to receive a better offer elsewhere (relative to the continued costs of job search and, for those not currently employed, unemployment), then they will accept the offer. In this way, it is possible for firms offering the same employment to offer different wages—a key characteristic of monopsony models. Firms can choose to raise their wages and induce more workers to accept their offers while simultaneously keeping more of their existing workers, displaying the key characteristic of a monopsonist: to face an upward-sloping residual labor supply curve. One critical insight to these models is that a firm may be *neither large nor dominant* in its market but still exercise market power.

In "ex-post bargaining" models, a jobseeker does not know the wage in advance. The worker and firm bargain over the wage in the final stages of the hiring process. In these models, each job generates a "surplus," defined as the gap between the worker's lowest acceptable wage (their "reservation wage") and the highest wage an employer can profitably pay (i.e., the worker's MPL_R). Firms and workers then bargain over how to allocate that surplus. The share of this surplus going to firms represents profits, while the share accruing to workers represents wages above their reservation wage. If labor markets were perfectly competitive, wages would simply be a function of worker productivity (as wages would be competed upward to the maximum that firms could profitably pay)—meaning workers would be paid their MPL_R. Like the "ex-ante wage posting" models, job search frictions in "ex-post bargaining" models give employers room to pay sub-competitive wages.

Various factors impact how firms and workers allocate the surplus of the worker's employment. Generally, the greater the bargaining power one side has, the larger a share of the surplus they can capture. The bargaining power of employees largely rests on their alternative ("outside") options and the degree to which they are substitutable with other workers. For example, a worker who has unique and highly specialized training that is valued by many other firms generally has greater bargaining power over their share of the surplus than an employee that is relatively easily replaceable and has relatively non-transferable skills. On the other hand, a nurse living in a rural town with only a single hospital within driving distance may have lower bargaining power because that worker lacks alternative local employment options.

While some job search frictions arise naturally, employers can also actively take steps to increase frictions or generate new ones. These frictions are the underlying source of market power in both types of search and matching models, giving employers an incentive to increase frictions. Some frictions are "natural" in the sense that they are not erected by the worker's employers. For example, high costs of moving (including implicit costs like the loss of access to one's social network) may induce someone to stay in their current job despite better alternatives elsewhere. Personal preferences are another natural factor that can give employers leverage. Insofar as a worker

7 For example, Burdett, Kenneth, and Dale T. Mortensen. 1998. "Wage Differentials, Employer Size, and Unemployment." *International Economic Review* 39 (2): 257–273.

is willing to accept a lower wage to work for a given employer, for any personal reason, the firm has the potential power to reduce that worker's wage below MPL_R and still retain the worker. This holds true even if the worker knows that they can be paid more at a rival firm.

Information asymmetry regarding potential wages is another crucial friction. If workers underestimate the wages paid by similar employers, then they will be less likely to actively search for a new employer. For workers, acquiring information about outside options is often more costly than for firms.[8] Recent evidence from Jäger et al. (2021) suggests that worker beliefs about outside options are strongly and unduly influenced by their current wage, which harms the lowest-paid workers the most.[9] They estimate that 10 percent of German jobs could not continue at their current wages if workers had the correct understanding of their outside options. These "non-viable" jobs were concentrated in lower-paid positions. Importantly, these asymmetries arise naturally, but employers can increase them by concealing wages.

Employers can also act to decrease the value of a worker's outside options. For example, restrictive employment agreements that require workers to repay training costs if they leave the firm or non-compete agreements (both discussed in greater detail below) reduce worker power by increasing the costs of leaving the firm. Those costs are explicit in the case of training repayment programs but implicit in non-compete agreements. By preventing a worker from accepting positions well-suited to their skills, firms decrease the expected gains from a worker's job search.

Finally, regulations can also increase the frictions in a job search. Occupational licensing is a notable example, and one that is growing more common over time. These frictions are growing in several ways: the number of occupations covered by licensing; the requirements, costs, and complexity of securing a license; and the patchwork of licenses across states. With non-reciprocity in licensing, two states may have similar goals and standards for a given occupation, yet it remains costly for a worker to move between states.

Licensing does benefit some workers, specifically incumbent workers, in many circumstances. By increasing barriers to entry, licensing restricts the supply of new workers, thereby increasing incumbents' bargaining power. This comes at the expense of other workers who would like to take up the trade, as well as firms and consumers in the form of higher prices. However, licensing *can* harm incumbents too: if licensure differs across states, then a worker who is licensed in one state will find it costly to move, despite professional or personal reasons to want to do so. Licensing can also protect public safety, help consumers distinguish high-quality from low-quality service, and even play a role in ensuring a market for certain goods and services exists (as in Akerlof 1970).[10] On the other hand, licensing can be misused to protect already powerful job occupations and incumbents.

Racial Inequality under Search and Matching Frictions

The frictions arising within search and matching models help explain the link between racial discrimination and racial wage gaps. Models of racial discrimination in the style of Gary Becker's *Economics of Discrimination* (1957) apply within the classical monopsony framework, with the implication that if some *employers* discriminate based on race, then market forces will eventually close the racial pay gaps that result from discrimination.[11] This sanguine

8 This is a result of economies of scale. Firms benefit from information when dealing with every worker they employ or potentially employ. Workers only benefit from this information when it relates to themselves.

9 Jäger, Simon, Christopher Roth, Nina Rousille, and Benjamin Schoefer. 2021. "Worker Beliefs about Outside Options." *National Bureau of Economic Research* Working Paper 29623.

10 Akerlof, George. 1970. "The Market for "Lemons": Quality Uncertainty and the Market Mechanism." *The Quarterly Journal of Economics* 84 (3): 488–500.

11 Becker, Gary S. 1957. *The Economics of Discrimination*. Chicago: University of Chicago Press. Note that the specific source of discrimination is important. The model predicts that discrimination coming from *consumers* (or co-workers) results in a wage gap that will not be rectified by market forces.

result does not hold within search and matching models, as shown by Black (1995).[12] Within a search and matching model, discrimination by even a few employers has a market-wide impact. For example, if some employers discriminate against Black workers, then Black workers face a worse set of potential outside wage offers than their non-Black counterparts. As a direct result, the expected value of a job search is lower for Black workers than it is for non-Black workers.

This lower expected value of search results in a lower average wage through two mechanisms. First, it decreases the returns to a job search for Black workers, meaning they will dedicate fewer resources to search in equilibrium. Second, if employers without proclivity towards discrimination know of the decreased expected returns to search, then they also know they can offer Black workers lower wages than non-Black workers, all while maintaining an equal chance that the offer is accepted.

We have considerable empirical evidence to document discrimination faced by Black workers searching for a job. A substantial literature that has developed submits fake resumes to firms, en masse, with names that are randomized to be "white-sounding" or "Black-sounding."[13] The results consistently show that resumes with stereotypically white names receive callbacks at higher rates than otherwise identical fake resumes with stereotypically Black names. Bertrand and Mullainathan (2004), for example, find that "white-sounding" names receive 50 percent more callbacks than "Black-sounding" names among applications submitted to Boston- and Chicago-area newspapers. Though subsequent papers have typically found smaller effects, the direction of the results have held consistently. To reiterate, this dynamic results in lower wages for Black applicants, all else equal. In search and matching models, wages are a function of outside options—having fewer (or worse) outside options leads to lower average wages, regardless of cause.

Platforms/Regulatory Arbitrage

Regulation is one tool to ameliorate the pernicious effects of monopsonistic power. In a standard example, a judiciously determined price floor (minimum wage) can simultaneously increase wages and employment in the basic monopsony model. For the same reasons, regulations on working conditions can potentially accomplish desirable outcomes without job loss.

Regulatory arbitrage occurs when a company attempts to circumvent enforcement of regulations by availing themselves of different regulatory schemes. Regulatory arbitrage often comes about from ambiguities ("loopholes") in regulations that allow firms to operate in a type of grey space.[14] These ambiguities can weaken regulatory action, including those meant to curb monopsonistic power.

The rise of e-commerce has created new opportunities for regulatory arbitrage as regulatory schemes of the twentieth century meet twenty-first century innovations. Critics argue regulatory arbitrage is widespread in these new markets and gives firms an unfair advantage over their competitors. For example, Amazon was essentially exempt from sales taxes for the first 15 years of its existence, giving it an 8–10 percent price advantage over competitors (Kahn 2017, footnote 204).[15] Such a large price advantage can allow a company to quickly gain

12 Black, Dan A. 1995. "Discrimination in an Equilibrium Search Model." *Journal of Labor Economics* 13 (2): 309–334.

13 See, e.g., Bertrand, Marianne, and Sendhil Mullainathan. 2004. "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination." *American Economic Review* 94 (4): 991–1013; and Banerjee, Rupa, Jeffrey G. Reitz, and Phil Oreopoulos. 2018. "Do large employers treat racial minorities more fairly? An analysis of Canadian field experiment data." *Canadian Public Policy* 44 (1): 1–12.

14 See, e.g., Brief of the United States Department of Justice as Amicus Curiae at 4, The Atlanta Opera, Inc., 10-RC-276292 (NLRB Feb. 10, 2022). Cites potential for the National Labor Relations Board's (NLRB) regulatory ambiguity to "creat[e] opportunities for employers to undercut competition by misclassifying their own employees."

15 Khan, Lina M. 2017. "Amazon's Antitrust Paradox." *The Yale Law Journal* 126 (3): 710–805. https://www.yalelawjournal.org/note/amazons-antitrust-paradox.

dominance in the product space, which may contribute to the firm also gaining increased monopsony power.

Regulatory arbitrage can also weaken worker protections when a firm uses terminology to take advantage of regulatory arbitrage in employment laws. For example, critics of ride-hailing companies, argue that these companies engage in a type of regulatory arbitrage by claiming their drivers are independent contractors when they may more aptly be classified as employees. This distinction, known as misclassification, is discussed in more detail in the next section.

Fissuring of the Workplace

Changes in organizational structure of firms since the 1980s have dramatically reduced the bargaining power of some workers. Prior to the 1980s, large corporations tended to directly employ workers across many occupations.

By the late 1980s, firms began to favor a management style that emphasized firms' focus on the handful of areas where their companies have a comparative advantage, known as their "core competencies."[16] Accordingly, firms began to shed workers by outsourcing, and in some cases offshoring, large parts of their employment, particularly among jobs near the lower end of the income and skill distribution.[17] For example, instead of directly hiring janitorial services, companies began to contract with janitorial service companies. David Weil, former Administrator of the Wage and Hour Division at the Department of Labor (DOL), has termed this process of outsourcing labor as the fissuring of the workplace.[18] Consequently, the modern large business looks more like a "small solar system with a lead firm at its center and smaller workplaces orbiting around it" rather than a large single entity (Weil 2014, 42). At the center of some of the biggest solar systems are firms that Autor et al. (2020) have dubbed "superstar firms."[19]

Jobs that are fissured do not necessarily disappear—they are reorganized, although often under very different terms. Fissured jobs may be restructured in several ways, including sub-contracting, franchising, greater reliance on temporary staffing agencies, and classifying workers as independent contractors.

Fissuring Considerations

Fissuring potentially benefits firms and consumers. Contracting out areas of relative weakness can allow management to focus on areas where they have a comparative advantage. Accordingly, firms are more productive per retained worker, which could lead to lower prices for consumers and potentially more innovation. In certain circumstances, fissuring can benefit smaller businesses as well. Very small firms may lack the funds to hire a full-time custodial employee or accountant and contracting out such tasks could free up mental bandwidth for small firms to focus on their core competencies.

Although it potentially benefits firms and consumers, fissuring can have a detrimental impact on workers. Fissuring can, and empirically does, reduce labor's share of surplus by weakening worker bargaining power and reducing wages for outsourced workers. For example, Dube and Kaplan (2010) estimate that outsourcing among janitors and guards reduced wages by 4–24 percent.[20] They also find substantially lower rates of non-wage benefits, such

16 Prahalad, C. K., and Gary Hamel. 1990. "The core competence of the corporation." *Harvard Business Review* 68 (3): 79–91.

17 Offshoring is a special case of outsourcing. While both involve contracting out tasks or processes to a third party, offshoring specifically refers to contracting out those tasks or processes to entities outside of the country.

18 Weil, David. 2014. *The Fissured Workplace: Why Work Became So Bad for So Many and What Can Be Done to Improve It.* Cambridge: Harvard University Press.

19 Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2020. "The Fall of the Labor Share and the Rise of Superstar Firms." *The Quarterly Journal of Economics* 135 (2): 645–709.

20 Dube, Arindrajit, and Ethan Kaplan. 2010. "Does Outsourcing Reduce Wages in the Low-Wage Service Occupations? Evidence from Janitors and Guards." *Industrial and Labor Relations Review* 63 (2): 287–306.

as health insurance coverage, among outsourced workers. For some workers, this may underestimate the effect of outsourcing if outsourced workers must spend more out-of-pocket to pay for equipment previously supplied by their employer. Using German administrative data that allowed them to follow workers over time, Goldschmidt and Schmieder (2017) show that wages fell by 10–15 percent among outsourced workers in the food, cleaning, security, and logistics service industries compared to similar workers who did not experience outsourcing.[21]

To some extent, the lower wages and decreased benefits that fissured workers receive are the point of fissuring in the first place. Within a firm, a rising tide may lift all boats, but when firms fissure their workforce, they exclude certain people from that boat. Economists have long recognized that there are substantial wage differences between directly employed and outsourced workers doing similar work, even controlling for industry, work environment, and, to some extent, unobserved skills.[22] These "wage premia" are regularly observed to be larger in larger firms, although there is evidence that the scale of the large-firm wage premium may be decreasing over time.[23]

One reason for the higher wages paid to direct employees at some firms is that certain employers, especially profitable ones, pay so-called "efficiency wages" (higher wages than their employees could likely earn elsewhere in the market) to increase retention and worker productivity. Intra-firm dynamics and social norms can discourage providing these higher efficiency wages to only a subset of the firm's workers.[24] In this way, a janitor employed at a large profitable firm may well earn above the market rate for their employment. Efficiency wages can also benefit similarly situated workers in other firms by improving their outside options, thereby strengthening their bargaining position with their current employer. These outside pressures, however, abate when firms contract out their "non-core" workforce.

After having their jobs outsourced, fissured workers lose some of their bargaining power because they no longer benefit from the larger workforce dynamics at that employer. Additionally, fissured workers likely miss out on the internal career opportunities that would have been available if they were considered employees, which compounds the impact of lost career opportunities for intra-firm mobility. Moreover, if workers from multiple firms are outsourced to a single staffing agency, the labor market in which those workers participate will have greater employer market power.

It is difficult to assess exactly which occupations have been the most fissured; however, Weil (2019) provides a compilation of industries where fissuring has been well documented and appears to be widespread.[25] Weil's compilation broadly suggests industries where fissuring has been most prevalent, including telecommunications sub-industries (e.g., telephone call centers), food service industries (e.g., mobile food services), temporary help services, construction subindustries (e.g., landscaping), janitorial services, security services (e.g., security guards), and transportation subindustries (e.g., taxi and limousine services). In some of these industries, women and

21 Goldschmidt, Deborah, and Johannes F. Schmieder. 2017. "The Rise of Domestic Outsourcing and the Evolution of the German Wage Structure." *The Quarterly Journal of Economics* 132 (3): 1165–1217.

22 See e.g., Krueger, Alan B., and Lawrence H. Summers. 1988. "Efficiency wages and the inter-industry wage structure." *Econometrica* 56 (2): 259–293. For a more general empirical view of the large-firm wage premia, see the large literature starting with Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica* 67 (2): 251–333.

23 Bloom, Nicholas, Fatih Guvenen, Benjamin S. Smith, Jae Song, and Till von Wachter. 2018. "The Disappearing Large-Firm Wage Premium." *American Economic Association Papers and Proceedings* 108 (May): 317–22.

24 See, e.g., Piketty, Thomas. 2014. *Capital in the Twenty-First Century*. Cambridge: Harvard University Press. For some firms, especially unionized ones, this aversion to intra-firm income inequality may be mechanical: unions may require that the top paid employee earns no more than some multiple of the lowest earning full-time employee. Fissuring can circumvent such rules by no longer considering the lower-paid workers their employees (Dube and Kaplan 2010).

25 Weil, David. 2019. "Understanding the Present and Future of Work in the Fissured Workplace Context." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 5 (5): 147–165.

minority groups are disproportionately represented.[26] For example, Hispanic workers make up roughly twice as large a share of janitors and building custodians compared to their share of employment in the overall economy (31.5 percent versus 18.0 percent).[27] Hispanic workers also make up a much greater share of construction laborers than their share of employment (48.9 percent versus 18.0 percent). Similarly, women represent approximately 87 percent of registered nurses, even though they only represent about 47 percent of employment.[28] Although fissuring is not exclusively a phenomenon among low-income workers, many of the industries where fissuring appears widespread are industries with low average pay. For example, in November 2021, the average worker in the overall economy earned about $1,100 a week, but telephone call center workers only earned an average of about $775 a week and hotel and motel workers (except casinos) earned only about $650 a week.[29] Janitorial service workers earned even less—about $575 a week.[30]

Fissuring also reduces the power of collective action. By removing the immediate nexus between workers and the firm for which they perform services, workers are prevented from bargaining directly with the entity that has the economic power. Further, workers whose jobs are contracted out typically end up in a much more competitive pool of relatively substitutable workers. As Kaplan and Dube (2010) explain, contracting reduces union power because contracted workers can be permanently replaced by a switch in the contractor of record, even if they are unionized. This reduces the incentive to try to unionize. In some cases, employers use new structures that make it difficult to form unions. For example, in the janitorial services industry, workers are commonly considered independent contractors (Weil 2014). Most worker protection laws, including the National Labor Relations Act, do not cover or protect bona fide independent contractors, so these workers lack collective bargaining rights. Furthermore, they face possible antitrust constraints when they try to act collectively in their economic interest.

The intra-firm dynamics highlighted above have a substantial impact on income inequality. Song et al. (2019) notes that a third of the rise in income inequality from 1978 to 2013 occurred because of changes within firms (as opposed to between them).[31] They further note that one of the two dominant explanations for this increase in inequality within firms was that high-wage workers became more likely to work with each other, which is a natural consequence of fissuring lower-wage workers from the firm.[32] Goldschmidt and Schmieder (2017) similarly find domestic outsourcing deepened income inequality in Germany. We discuss the consequences of rising income inequality later in the paper.

Misclassification of Workers

A firm misclassifies a worker when it treats a worker, who should be classified as an employee, as an independent

26 Weil (2019) reports employment figures by industry. These data do not report demographic data. The demographic data reported below are based on a slightly different classification of employment (based on occupation rather than industry); therefore, demographic decompositions do not perfectly correspond to subindustries identified in Weil (2019). However, both sets of employment estimates originate from surveys conducted or sponsored by BLS.

27 U.S. Bureau of Labor Statistics. 2022. "Labor Force Statistics from the Current Population Survey: Household Data Annual Averages: 11. Employed persons by detailed occupation, sex, race, and Hispanic or Latino ethnicity." Last modified January 20, 2022. https://www.bls.gov/cps/cpsaat11.htm.

28 Nurses are much more likely to work for temporary staffing agencies. See, e.g., Seo, Sukyong, and Joanne Spetz. 2013. "Demand for temporary agency nurses and nursing shortages." *INQUIRY: The Journal of Health Care Organization, Provision, and Financing* 50 (3): 216–228.

29 U.S. Bureau of Labor Statistics. 2022. "Current Employment Statistics – CES (National): Employment and Earnings." Table B-3a. Last modified February 4, 2022. https://www.bls.gov/web/empsit/ceseeb3a.htm. Values rounded to the nearest $25 a week.

30 *Id.*

31 In this context "income inequality" is defined as the variance in the natural log of earnings. Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter. 2019. "Firming Up Inequality." *The Quarterly Journal of Economics* 134 (1): 1–50.

32 The other explanation is the rise of sorting high-wage workers into high-wage firms.

contractor instead.[33] This concept is related to fissuring because both misclassification and fissuring describe a process by which the purchasers of labor attempt to sever what would typically be considered an employee-employer relationship. The employee-employer relationship has historically been the basis for worker protection laws, income tax collection, social security collection, health insurance coverage, and other economic and social constructs. Although fissuring is typically not a per se violation of the law, misclassifying a worker violates some laws.[34]

Firms misclassify workers and outsource labor for similar reasons—it is cheaper and reduces their risk. For example, assigning work to an independent contractor does not entail as many legal obligations, such as tax and overtime obligations, as the hiring of an employee. Classifying workers as independent contractors can especially reduce costs by shifting non-wage costs typically paid by employers (e.g., healthcare benefits) onto the employee.[35] These costs are non-trivial—approximately 30 percent of per-hour employer costs come from costs other than wages and salaries.[36] Accordingly, a misclassified worker and a worker that is outsourced via fissuring face similarly negative consequences. The ability of a firm to misclassify workers without successful pushback from employees (who clearly would have an incentive to not be misclassified) can itself be viewed as a demonstration of the market power firms have over workers.

The distinction between an employee and an independent contractor has developed over time and the legal standards are not uniform. Fundamentally, the difference depends on the nature of the work and the relationship between the firm and worker. In some jurisdictions, courts determine whether a person should be classified as an employee instead of an independent contractor using a three-part ("ABC") test. Under this test, a worker is an independent contractor only if their work relationship allows a "yes" answer to all of the following questions:[37]

- **Part A:** The worker is free from the control and direction of the hiring entity in the performance of the work, both under the contract for the performance of the work and in fact.
- **Part B:** The worker performs work that is outside the usual course of the hiring entity's business.
- **Part C:** The worker is customarily engaged in an independently established trade, occupation, or business of the same nature as the work performed for the hiring entity.

If the answer to any of these questions is "no," the court should classify the worker as an employee. Although different jurisdictions have adopted various exceptions to this ABC test, the test clarifies that, in general, workers are only properly classified as independent contractors if their relationship with the business is sufficiently arm's length and the worker maintains a large degree of autonomy. The ABC test is only one of several types of tests that is used to determine whether a worker is misclassified and is not used under federal law. Other tests include the common-law test and the economic realities test under the Fair Labor Standards Act.

33 Note, worker misclassification involves an incorrect statement by the firm, but does not necessarily imply (nor does it legally need to imply) intentional misclassification on the part of the firm. They may genuinely consider their interaction with a worker to be considered more like an independent contractor relationship than an employee relationship.

34 For example, in the District of Columbia, illegal misclassification is considered a form of payroll fraud. See, e.g., Belman, Dale, and Aaron Sojourner. 2019. "Illegal Worker Misclassification: Payroll Fraud in the District's Construction Industry." Office of the Attorney General for the District of Columbia. https://oag.dc.gov/sites/default/files/2019-09/OAG-Illegal-Worker-Misclassification-Report.pdf.

35 The true cost of such burden shifting largely depends on the sensitivity (elasticity) of each side (employer/employee) to the costs. However, it is unlikely that employees are so sensitive as to effectively make it impossible for employers to reduce employment costs by shifting nominal burdens to the employee.

36 U.S. Bureau of Labor Statistics. 2021. "National Compensation Survey – Employer Costs for Employee Compensation." Civilian workers dataset spreadsheet. Last modified December 16, 2021. https://www.bls.gov/web/ecec/ecec-civilian-dataset.xlsx.

37 The language presented in this test come from Labor & Workforce Development Agency. 2022. "ABC Test." State of California. https://www.labor.ca.gov/employmentstatus/abctest/. Exact language and interpretation of the ABC test will vary from state to state.

Worker misclassification has garnered particular attention around whether so-called "gig workers," especially people working for ride-sharing companies are properly classified. However, worker misclassification expands way beyond gig workers and appears to be becoming more common. A 2018 study in Washington state found that the proportion of employers that misclassify at least one of their workers almost tripled between 2008 and 2017 (from around 5 percent to 14.4 percent).[38] Among firms that misclassify at least some of their workers, they tended to misclassify about 10–25 percent of their workforce. Using administrative data, that study estimated an overall misclassification rate of a little over one percent between 2013 and 2017. Both the incidence and intensity of misclassification varies widely by industry and occupation. The same report found that the industries with the greatest incidence of misclassification were construction, clerical services, and hospitality (hotels and restaurants).

Worker misclassification has broader implications beyond its direct impact on the employee-employer dynamic. Whereas employees' income and Social Security taxes and employers' payments of unemployment insurance and other payroll taxes are managed by the employer, tax compliance among independent contractors, who are required to file taxes on their own, is much lower.[39] Therefore, when an employer misclassifies an employee, payments on that worker's behalf are not made into social safety-net programs that otherwise would have if the employers had properly classified their workers.

The Questionable Tax Employment Practices (QTEP) program, a joint state/federal program that audits tax data to uncover tax non-compliance, has found large-scale misclassification.[40] Among the roughly 30,000 audits conducted between (fiscal years) 2015 and 2020, the program reclassified more than 275,000 workers, resulting in the reclassification of about $4 billion in wages.[41]

Fissured workplaces may result in worker misclassification, and, in turn, worker misclassification impacts labor market competition. Workers that are misclassified as independent contractors are deprived most methods by which they can bargain for a greater share of labor market surplus. When the employer offloads the burdens of labor costs on to the worker (including taxes, unemployment insurance, and social security), while continuing to benefit from their productivity, the worker has very little recourse.

Restrictive Employment Agreements and No-Poach Agreements

Terms of employment contracts often extend well beyond simply defining compensation from the employer and job duties of the employee. Employers often include a variety of clauses that restrict employees' behavior, even going so far as to dictate what they can do after they leave the company.[42] As a result, workers are limited in their ability to—or outright prohibited from—seeking higher-paying work in their field, which reduces their bargaining and earning power. In some cases, such as no-poach agreements (in which employers agree not to solicit or hire each other's employees), employees are not even a party to the agreement.

38 Xu, Lisa, and Mark Erlich. 2019. "Economic Consequences of Misclassification in the State of Washington." Harvard Law School: Labor and Worklife Program. https://lwp.law.harvard.edu/files/lwp/files/wa_study_dec_2019_final.pdf.

39 See, e.g., Bruckner, Caroline, and Thomas L. Hungerford. 2019. "Failure to Contribute: An Estimate of the Consequences of Non- and Underpayment of Self-Employment Taxes by Independent Contractors and On-Demand Workers on Social Security." *Center for Retirement Research at Boston College* Working Paper 2019-1. https://crr.bc.edu/wp-content/uploads/2019/01/wp_2019-1.pdf.

40 See, e.g., Levine, Suzan G. 2021. "Questionable Employment Tax Practices (QETP) Program." *Employment and Training Administration, U.S. Department of Labor* Training and Employment Notice 3-21. https://wdr.doleta.gov/directives/attach/TEN/TEN_03-21.pdf.

41 Note, QETP reclassifications include, but are not limited to, reclassifications due to worker misclassification. For example, they also include reclassification due to the creation of shell companies to avoid tax payments.

42 In some instances, firms may even demand independent contractors to sign such agreements, although some courts may find such clauses unenforceable on public policy grounds.

In practice, restrictive employment agreements can both result from and reinforce employer market power; for example, an employer who has market power for other reasons, such as high market share, may be able to increase its power over both employees and customers by requiring its employees to agree to restrictive clauses. The potential relationship runs in reverse, as well: in a labor market characterized by pervasive use of restrictive agreements, a merger that increases employer concentration may have greater detrimental effects on competition than would otherwise be the case.

The table below outlines several types of restrictive employment agreements.

Clause	Description
Non-compete agreements	Former employee cannot work for a competitor following separation. Typically applies for a certain amount of time, over a certain geographic area, and within a specific industry.
Non-solicitation agreements	Employee agrees to not solicit a company's clients or customers for their own benefit, or the benefit of a competitor, after leaving the company.
Non-recruitment agreements	Employee or former employee is forbidden from recruiting employers' employees away from employer for a period.
Training repayment agreements	Employee must repay the cost of training provided by employer if they leave employment prior to some period. Agreement is typically pro-rated based on length of employment following training.
Non-disclosure agreements	Prevents employee or former employee from disclosing information. Meant to protect information that is both confidential and valuable.
No-poach agreements	Two or more employers agree to not solicit or hire each other's current or former employees.

Heterogeneity in Enforcement and Legality of Restrictive Agreements

The mere statement of a restrictive term in an employment contract does not automatically make it enforceable. Employment contracts are typically evaluated at the state-level pursuant to statute and case law. Therefore, the degree to which courts will enforce such contract provisions varies between states. For example, Texas statutory law allows for non-compete covenants but only "to the extent that it contains limitations as to time, geographical area, and scope of activity to be restrained that are reasonable and do not impose a greater restraint than is necessary."[43] Enforceability also sometimes varies by occupation. For example, Texas places further conditions on the enforceability of non-compete clauses in medical occupations.[44] California, in contrast, prohibits enforcement of non-compete agreements.[45]

Employers who illegally use restrictive covenants rarely face sanctions, such as monetary damages. Instead,

43 Tex. Bus. & Com. Code Ann. §15.50(a) (West 2021).

44 *Id.* at §15.50(b).

45 Cal. Bus. & Prof. Code § 16600 (West 2021).

courts normally either refuse to enforce the covenant or limit the breadth of overly expansive covenants. As such, employers rarely face strong disincentives to including questionable restrictive covenants.

However, federal law has placed limitations on some restrictive employment agreements. For example, in 2016, the Department of Justice (DOJ) and Federal Trade Commission (FTC) jointly issued guidance to human resource professionals explaining (inter alia) that naked wage-fixing or no-poach agreements among competitors are per se violations of the antitrust laws.[46] In early 2021, DOJ announced the first indictments charging naked no-poach or wage-fixing conspiracies.[47] No-poach agreements are common in highly concentrated and high-skilled industries, as well as in the franchise context, although some chains have ended them in recent years amidst legal and public pressure.[48] No-poach agreements are also subject to challenge under state antitrust law.

Theory

Non-compete agreements are among the most common form of restrictive employment agreements, but many of the lessons from that literature also apply to other forms of these agreements.[49] Non-compete agreements (and other similar post-employment restrictive employment agreements) potentially solve a problem that would otherwise limit a firm's investments in their employees—namely, that workers would leave before a firm was able to recoup the value they had invested in training a worker. At the same time, these agreements introduce frictions into the labor market, weaken workers' bargaining positions, and reduce competition over wages (McAdams 2019).[50] Non-compete agreements are also attractive to employers because employers typically cannot subject employees to term contracts (i.e., a contract that requires the employee to work at a firm for a fixed period of time) because courts refuse to issue injunctions compelling employees to stay in a job. The non-compete agreement indirectly accomplishes this goal by depriving the employee of the most attractive alternative employment opportunities.

In theory, non-compete agreements can increase a firm's investment in their employees by reducing the "hold-up" effect, wherein firms face a disincentive to invest in their employees (including training, access to trade secrets, client lists, etc.) for fear of employees quitting and appropriating the value of their investments before the firm can recoup the lost investment value (Rubin and Shedd 1981).[51] This type of agreement could increase the probability

46 Department of Justice Antitrust Division and Federal Trade Commission. 2016. "Antitrust Guidance for Human Resource Professionals." Last accessed March 2, 2022. https://www.justice.gov/atr/file/903511/download. See also, Federal Trade Commission. n.d. "Antitrust Red Flags for Employment Practices." Last accessed March 2, 2022. https://www.ftc.gov/system/files/documents/public_statements/992623/ftc-doj_hr_red_flags.pdf.

47 Department of Justice. 2021. "Health Care Company Indicted for Labor Market Collusion." Press release 21-14. Last modified March 4, 2021. https://www.justice.gov/opa/pr/health-care-company-indicted-labor-market-collusion; and Department of Justice. 2021. "Health Care Staffing Company and Executive Indicted for Colluding to Suppress Wages of School Nurses." Press release 21-284. Last modified March 30, 2021. https://www.justice.gov/opa/pr/health-care-staffing-company-and-executive-indicted-colluding-suppress-wages-school-nurses.

48 Starr, Evan. 2019. "The Use, Abuse, and Enforceability of Non-Compete and No-Poach Agreements: A Brief Review of the Theory, Evidence, and Recent Reform Efforts." Economic Innovation Group. https://eig.org/wp-content/uploads/2019/02/Non-Competes-Brief.pdf. See also allegation contained in United States v. Adobe Systems Inc., et al., No. 1:10-cv-01629, 2011 U.S. Dist. (March 18, 2011). https://www.justice.gov/atr/case/us-v-adobe-systems-inc-et-al; Starr (2019); and Abrams, Rachel. "8 Fast-Food Chains Will End 'No-Poach' Policies." *New York Times*, August 20, 2018. https://www.nytimes.com/2018/08/20/business/fast-food-wages-no-poach-franchisees.html.

49 Balasubramanian, Natarajan, Evan Starr, and Shotaro Yamaguchi. 2021a. "Bundling Employment Restrictions and Value Capture from Employees." *SSRN*, November 14, 2021. http://dx.doi.org/10.2139/ssrn.3814403. Nondisclosure agreements are more common than non-compete agreements, but firm survey data suggest at least some employees have non-compete agreements at approximately two-thirds of firms.

50 McAdams, John M. 2019. "Non-Compete Agreements: A Review of the Literature." *SSRN*, December 31, 2019. https://dx.doi.org/10.2139/ssrn.3513639. Many of the papers cited in the following section were drawn from this literature review.

51 Rubin, Paul H., and Peter Shedd. 1981. "Human capital and covenants not to compete." *The Journal of Legal Studies* 10 (1): 93–110.

that an employer will be comfortable investing in employee human capital, even if those skills are transferable to other firms, rather than simply relying on firm-specific training (Becker 1962).[52] Such training can be mutually beneficial for both the employer and employee.

By design, non-compete agreements limit employees' outside options, which, in turn, weakens workers' bargaining power and raises hiring costs for other firms. The limits are typically within a geographic area for a specific period and within a set of relatively similar occupations or industries but may be much broader. Balasubramanian (2017) models the effects of non-competes to show how this narrowing of outside options reduces employee bargaining power relative to their employer.[53] All else equal, this leads to what they call a "lock-in" effect: lower worker mobility and longer tenure, as well as a flat or declining wage profile.[54]
Both the mitigation of the "hold-up" effect and "lock-in" effect mentioned above can reduce worker mobility. Lower worker mobility increases recruitment costs for all firms as fewer workers are seeking to switch jobs than otherwise would, absent the post-employment restrictive employment agreement. The increases in recruitment costs can lead to worse matches between employers and employees, lowering wages and aggregate productivity (Javanovic 2015).[55]

The "hold-up" and "lock-in" effects can coexist. The net effect of these two mechanisms on wages, tenure, and mobility is theoretically ambiguous since the subset of employees who are aware of being asked to sign non-compete agreements may demand higher wages in return (i.e., a compensating differential). Additionally, since mitigation of the "hold-up" channel can create mutually beneficial investments for both the employee and the employer, longer tenure does not necessarily imply the employee is worse off.

However, the share of people who negotiate over a non-compete agreement appears to be quite small. Starr, Prescott, and Bishara (2021) find only about 10 percent of employees negotiate over their non-compete agreements.56 Therefore, it is unlikely that most employees demand (or receive) a compensating differential from signing a non-compete agreement. Furthermore, a worker with little bargaining power (e.g., low-income workers) or who is unaware they are bound by a non-compete (which may be more likely for less-educated workers) is unlikely to be able to secure a compensating differential in exchange for signing a non-compete agreement. To the extent that a compensating differential requires an explicit negotiation, certain workers may be less willing or able to do so—for example, Babcock and Laschever (2009) argue women are much less likely to negotiate during the hiring process.[57] Accordingly, the share of workers whose wages increase as a result of non-compete agreements is small.

While one of the main justifications for noncompete agreements (as well as other types of restrictive employment agreements) is mitigation of the "hold up" effect, there are far less restrictive means of addressing this problem. For workers with access to genuine trade secrets, there may be overlapping authority with trade secrecy laws, irrespective of the existence of a noncompete agreement.[58] For the broader workforce, sectoral-based training may

52 Becker, Gary S. 1962. "Investment in human capital: A theoretical analysis." *Journal of Political Economy* 70 (5): 9–49.

53 Balasubramanian, Natarajan, Jin Woo Chang, Mariko Sakakibara, Jagadeesh Sivadasan, and Evan Starr. 2017 "Locked In? The Enforceability of Covenants Not to Compete and the Careers of High-Tech Workers." *Center for Economic Studies, U.S. Census Bureau* Working Paper CES-17-09. https://www.census.gov/library/working-papers/2017/adrm/ces-wp-17-09.html.

54 A person's wage profile describes their wages over their lifetime. Typically, a person's wages increase from their 20s through their 60s until falling off as people cut back on work hours and transition into retirement. A flatter wage profile means the increase in wages is slower than otherwise expected, which could have compounding effects on lifetime earnings.

55 Jovanovic, Boyan. 2015. "Matching, Turnover, and Unemployment." *Journal of PoliticalEconomy* 92 (1): 108–122.

56 Starr, Evan, J.J. Prescott, and Norman D. Bishara. 2021. "Noncompete agreements in the US Labor Force." The Journal of Law and Economics 64 (1): 53–84.

57 Babcock, Linda, and Sara Laschever. 2009. *Women don't ask*. Princeton: Princeton University Press.

58 For example, 18 U.S. Code § 1832 criminalizes theft of trade secrets (for use or intended for use in interstate or foreign commerce) by an organization.

provide occupation-specific skills to workers without restricting their mobility.[59] These alternative arrangements have the possibility of meeting a legitimate need of firms (to protect their intellectual property and have access to skilled employees) without some of the detrimental effects noncompete agreements can have on workers.

Since non-compete agreements increase the bargaining power of employers relative to employees, they potentially allow employers to capture a larger share of the surplus generated by the employee-employer match. Johnson and Lipsitz (2020) argues this might be especially true for low-wage workers near the minimum wage because employers are unable to capture additional surplus from offering lower wages but can nonetheless benefit from non-compete agreements in other ways.[60] For example, requiring a worker to sign a non-compete agreement could increase their tenure.[61] Likewise, a non-compete agreement may sufficiently limit an employee's outside options to flatten their wage-tenure profile (that is, how much their wage goes up over time).

Restrictive employment agreements, including non-compete, non-solicitation, and non-recruitment agreements, may reduce firm entry. In aggregate, this tends to lead to reduced demand and wage competition, leading to fewer appealing outside options for similarly situated workers. Samila and Sorenson (2011) find that increases in supply of venture capital funds has a stronger impact on firm start-ups, patent creation, and employment growth in states that have weaker enforcement of non-compete agreements, suggesting non-compete agreements may reduce certain types of entrepreneurial activity.[62] However, Carlino (2017) finds little evidence of this, at least in Michigan.[63] The reduction of firm entry could also reduce innovation and product variety because employees with new ideas may be restrained from capitalizing on new ideas at their current firm in ways they would not be if they could start their own business. On the other hand, this result is theoretically ambiguous since firms may be reluctant to invest in research and development (R&D) if they fear employees can quit and appropriate that research for their own business.

None of the mechanisms described above necessarily require restrictive employment agreements to be enforced, or even enforceable, to have tangible labor market effects.[64] While guaranteed enforcement would strengthen their effects, uncertainty over enforcement can nonetheless affect behavior ("in terrorem" effects). This is true even if the actual probability of a contract being enforced is zero. So long as the *perceived* probability of an employer *attempting* to enforce the contract is non-zero, restrictive employment agreements can create frictions.[65] Consistent with this, Starr, Prescott, and Bishara (2020) present survey evidence that workers with non-compete clauses frequently decline job offers because of their preexisting non-compete agreement, even in states that do not enforce such agreements.[66] Likewise, survey evidence also suggests that the incidence of non-compete clause

59 For an overview, see e.g., Holzer, Harry J. 2022. "Do sectoral training programs work? What the evidence on Project Quest and Year Up really shows." *Brookings*, January 12, 2022. https://www.brookings.edu/research/do-sectoral-training-programs-work-what-the-evidence-on-project-quest-and-year-up-really-shows/.

60 Johnson, Matthew S., and Michael Lipsitz. 2020. "Why are low-wage workers signing noncompete agreements?" *Journal of Human Resources* (May): 0619–10274R2.

61 This is beneficial to employers even in the relative absence of explicit training costs because recruitment costs are non-zero and on-the-job learning makes high turnover less profitable (all else equal) relative to low turnover.

62 Samila, Sampsa, and Olav Sorenson. 2011. "Venture capital, entrepreneurship, and economic growth." *The Review of Economics and Statistics* 93 (1): 338–349. See also Starr, Evan, Natarajan Balasubramanian, and Mariko Sakakibara. 2017. "Screening Spinouts? How Noncompete Enforceability Affects the Creation, Growth, and Survival of New Firms." *Management Science* 64 (2): 552–572.

63 Carlino, Gerald. 2017. "Do Non-Compete Covenants Influence State Startup Activity? Evidence from the Michigan Experiment." *Federal Reserve Bank of Philadelphia* Working Paper 17–30.

64 See, e.g., Starr, Prescott, and Bishara (2021).

65 Because lawsuits can be lengthy, expensive, and mentally taxing, a rational employee may conclude it is not worth trying to switch jobs, even if they are certain they would prevail in court against an attempted enforcement action by their former employer.

66 Starr, Evan, J.J. Prescott, and Norman Bishara. 2020. "The Behavioral Effects of (Unenforceable) Contracts." *The Journal of*

inclusion in employment contracts is not strongly correlated with enforceability of non-compete agreements, which could suggest employers include such clauses even when they do not expect them to be enforceable.[67] This partially occurs because people tend to be risk averse.[68] Therefore, even in places where non-compete contracts are outlawed, the presence of unenforceable non-compete clauses can have a chilling effect on job-switching. The effects may be particularly severe for lower-wage workers, who may have limited access to legal counsel.

Mandatory Pre-Dispute Arbitration and Class Action Waivers

Whereas restrictive employment agreements allow employers to limit how their employees can behave following a separation, mandatory pre-dispute arbitration clauses and class action waivers in employment contracts reduce the options employees or former employees have within the legal system.

Arbitration is a form of alternative dispute resolution in which a third-party, ostensibly neutral, arbitrator resolves the dispute instead of the worker being free to bring a lawsuit through the judicial system. The decision of the arbitrator is binding upon both parties and typically subject to strictly limited subsequent judicial review (i.e., the substance of the decision is generally not appealable). Mandatory arbitration agreements require any dispute ordinarily resolved through a judicial proceeding be, instead, addressed by arbitration, even before the worker has raised any claim that a law has been violated.

Mandatory arbitration agreements are extremely common for non-unionized workers.[69] One recent report estimated about 56.2 percent of non-union employees, or about 60 million workers, are subject to such agreements.[70] The share of workers whose employment contracts contain mandatory arbitration procedures has risen dramatically since the Supreme Court upheld their legality in 1991.[71]

Mandatory arbitration is more common among large firms. Nearly two-thirds of workers at firms with at least 1,000 employees are subject to mandatory arbitration clauses. Likewise, mandatory arbitration clauses are more prevalent in low-wage workplaces and industries disproportionately composed of women and Black workers (Colvin 2018).

Class action waivers in mandatory arbitration agreements are clauses that bar employees from seeking legal redress via collective legal action. The legality of such agreements has been strongly contested, but, in 2018, the Supreme Court ruled that employers could legally require them.[72]

Law, Economics, and Organization 36 (3): 633–687. https://doi.org/10.1093/jleo/ewaa018. See also Starr, Evan, J.J. Prescott, and Norman D. Bishara. 2016. "The in Terrorem Effects of (Unenforceable) Contracts." *University of Michigan Law & Econ. Research Paper 16–032.*

67 Prescott, J.J., Norman D. Bishara, and Evan Starr. 2016. "Understanding Noncompetition Agreements: The 2014 Noncompete Survey Project." *Michigan State Law Review* 2016 (2): 369–464. Note, the weak correlation between the inclusion of non-compete agreements and enforceability would also indicate weak salience of the enforceability of non-compete agreements among employers. This may be especially true among smaller employers who do not have a professional human resource or legal department to craft employment contracts.

68 For example, suppose a person is indifferent between the amenities offered by a competitor relative to their current job. A risk averse person would likely stay at their current job rather than switch to a new job if they were under a non-compete agreement, even if they were highly confident (but not certain) that the non-compete clause was unenforceable. Instead, they would require a premium to account for the possibility that their contract was enforced to their detriment.

69 Unionized employees usually have access to a collectively bargained grievance resolution process that culminates in binding arbitration with the employee represented by the union.

70 Colvin, Alexander J.S. 2018. "The Growing Use of Mandatory Arbitration." *Economic Policy Institute*, April 6, 2018. https://www.epi.org/publication/the-growing-use-of-mandatory-arbitration-access-to-the-courts-is-now-barred-for-more-than-60-million-american-workers/.

71 Gilmer v. Interstate/Johnson Lane Corp., No. 90-18, 500 U.S. 20 (1991).

72 Epic Systems Corp. v. Lewis, No. 16-285, 138 S. Ct. 1612 (2018). Justice Gorsuch strongly suggested in his opinion that

Proponents of mandatory arbitration generally argue the process is faster and less costly than traditional court trials. Additionally, firms may find arbitration a less volatile, more private option than jury trials. Opponents of mandatory arbitration argue arbitrators award smaller awards to employees on average and deprive them of due process. Furthermore, they argue that arbitration is less transparent than traditional litigation. Not only are most arbitration decisions non-public, but the mere existence of a decision is also rarely public, reducing awareness and potential deterrence and compliance effects associated with public results.[73] These information asymmetries allow firms to exert greater monopsonistic power by introducing additional search frictions for workers who may value knowing a firm's prior dispute history with workers (or alternatively, current workers who may update their priors on the quality of their employee if they learned about disputes).

There is some evidence that employees are more likely to win in arbitration disputes than in court, though the awards are lower on average.[74] Larger employers appear to win arbitration cases more often, potentially owing in part to repeat use of arbitrators that ruled favorably for them in the past.[75] Additionally, since employers are more likely to be repeat players than employees, arbitrators may have an incentive to favor employers in order to continue receiving their business.

Due to the lack of quality data on employer arbitration, an empirical analysis of their effect on the labor market is difficult. However, much like non-disclosure agreements, the opaqueness of arbitration agreements can enable employers' continuing bad behavior as disputes and their resolutions are not made public. In this way, they make it harder for jobseekers to identify the positions that are best suited to them or demand adequate compensation for working in sub-par conditions, which can have the effect of inefficiently matching employees and employers. Since class action lawsuits may lower the per-plaintiff cost of dispute resolution, mandatory arbitration agreements with class action waivers tend to discourage employee-driven arbitration. This likewise has the effect of reducing the ability of the dispute resolution system to deter future misconduct.

Occupational Licensing

Occupational licensing is a form of regulation that requires individuals who want to perform certain types of work to obtain permission from the government.[76] Licensing occurs at all levels of government (federal, state, and local), but licenses are primarily issued at the state level.

If markets were competitive, quality was freely observable, and poor (or high) quality imposed no negative (or positive) externalities upon third parties, there would be little justification for occupational licensing.[77] In such a world, consumers who highly valued quality would easily be able to differentiate low- and high-quality providers. Likewise, providers' wages would be differentiated based on their quality—with higher-quality workers commanding greater wages because of their superior skill.

However, quality is typically not easily observable. Nor are the consequences of poor quality always self-evident. Even when quality is observable, it can be costly to consumers in terms of time and resources to obtain such information. This creates a moral hazard problem wherein low-quality workers asymmetrically know their quality, but consumers do not. Low-quality workers, therefore, have an incentive to obfuscate their performance to

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Congress had the ability to change the legality of class action waivers in lawsuits via new legislation.

73 Estlund, Cynthia L. 2018. "The Black Hole of Mandatory Arbitration." *North Carolina Law Review* 96 (3): 679–710.

74 St. Antoine, Theodore J. 2008. "Mandatory Arbitration: Why It's Better Than It Looks." *U. Mich. J. L. Reform* 41 (4): 783–812

75 Colvin, Alex, and Mark Gough. 2015. "Individual Employment Rights Arbitration in the United States: Actors and Outcomes." *Industrial and Labor Relations Review* 68 (5): 1019–1042.

76 The focus of this section is occupational licensing, as opposed to certification. The primary difference between the two is that licensing involves government power whereas certification is typically done by a private actor, such as a non-profit trade group.

77 Quality here is conceived of broadly to include safety.

consumers to extract greater wages than they would in a perfect information environment. Shapiro (1986) shows how licensing that raises the minimum bar for professionals partially alleviates this moral hazard problem by excluding the lowest-quality providers. They show that licensing benefits consumers who value high-quality at the expense of those who do not.[78]

Licensing can be welfare-enhancing if provider quality is not easily observable. Implicitly, this highlights how the strongest theoretical justification for the benefits (to consumers) associated with occupational licensing occur in occupations where quality meaningfully varies, differences in quality are difficult to observe, and the consequence of that variation matters. For example, the potential benefit of occupational licensing is likely higher in an occupation like medicine (where quality could vary dramatically between providers, a layperson would have difficulty in distinguishing between a high- and low-quality provider, and the consequences of being provided poor medical treatment may be large) compared to an occupation like lawn mowing services (where quality may not differ much, could relatively easily be observable by a lay person, and the consequences of poor service are unlikely to be severe).

Note, Shapiro (1986) does not consider the possibility of spillover effects of quality. For example, if a low-quality mechanic poorly fixes a car, that car may break down in the middle of the road. Even if the consumer is willing to take that risk, a broken car in the middle of the road imposes additional costs on third parties. Likewise, a low-quality healthcare provider may fail to properly diagnose a communicable disease, thereby increasing the probability that unrelated third parties are infected (i.e., imposing a negative externality on the third party). In the presence of such externalities, there is a stronger societal benefit to creating a quality floor.

However, gross benefits do not necessarily imply net benefits to consumers as there are potentially large trade-offs to occupational licensing. Licensing imposes barriers to entry into an occupation. Requirements such as continuing or additional training and education, fees, exams, and paperwork can reduce labor supplied in the licensed occupation. Workers who are liquidity constrained may be disproportionately excluded from entering a licensed occupation if these barriers require large upfront investments, even though such training and education would be worth it in the long run due to increased productivity.

Whether licensing enhances or reduces welfare depends not only on its impact on consumers, but workers as well. While benefits of a reduction in labor supply due to licensing may accrue to practitioners in that occupation in the form of higher wages, some or all of those rents may instead flow to licensing entities.[79] Thus, the economic benefit to licensed workers is at least theoretically ambiguous, especially if workers must pay to become licensed.

Since most licensing is done at the state-level, differences in licensing requirements impose inter-state barriers to workplace mobility. That is, even if a worker benefits from licensure in one state, this can come at an implicit cost of reduced mobility. Such restrictions to mobility can increase labor market frictions (i.e., require a much higher offer to induce someone to leave their current work) and reduce search quality (i.e., a place may experience a shortage of otherwise qualified workers simply because those workers live across state lines).

These restrictions to mobility imposed by occupational licensing can be particularly constraining on two-income households facing a so-called "two-body problem" wherein partners of the same (target) household with highly specialized occupations have difficulty in finding suitable work for both partners in the same geographic area. For example, spouses of military members, who frequently move, may find it difficult to find gainful employment when their spouse must relocate. Such barriers can exacerbate pre-existing inequities in household dynamics and lead

78 Shapiro, Carl. 1986. "Investment, Moral Hazard, and Occupational Licensing." *The Review of Economic Studies* 53 (5): 843–862.

79 Department of the Treasury Office of Economic Policy, Council of Economic Advisers, and Department of Labor. 2015. "Occupational Licensing: A Framework for Policymakers." https://obamawhitehouse.archives.gov/sites/default/files/docs/licensing_report_final_nonembargo.pdf.

to worse average job searches, especially when both workers work in licensed occupations.[80]

Once a government entity decides an occupation should be licensed, they must also determine the manner of licensing. Too lax a licensing policy may not adequately screen out low-quality practitioners. This can harm consumers who, believing licensing is an implicit governmental endorsement of quality, may unknowingly visit an under-qualified practitioner. On the other hand, Shapiro (1986) noted licensing may benefit those who value high-quality services, but it harms those who do not. Setting too high of a requirement to get licensed can overly restrict the supply of labor to such a degree that very few consumers would benefit.

If quality is difficult to observe for consumers, it may also be difficult to observe for licensing entities. Therefore, licensing requirements may imperfectly screen for quality, especially when the licensing process is relatively crude. For example, a common requirement for licensing is to train for a certain number of hours before the worker can partake in an occupation. During these trainings, which can take months for some occupations, workers are often unpaid and may even be required to pay for the training.

As mentioned above, these barriers may be infeasible for individuals with less financial resources, which disproportionately includes people of color.[81] Furthermore, if licensing involves a professional examination, as it often does, those tests may reflect underlying biases of the test makers more than actual quality.[82] Thus, even if there is a benefit to screening out lower-quality practitioners, there is no guarantee that licensing entities can do so effectively. Certain types of screening tools may be more effective than others and may thereby avoid some of the limitations of licensing mentioned above. For example, employer-financed training can reduce the liquidity constraints imposed by some licensing bodies. Likewise, union apprenticeships, wherein workers work alongside a professional in preparation for becoming licensed may serve as a better screening mechanism than written tests, where appropriate.

Skill-Biased Technical Change and Job Polarization

As mentioned above, worker bargaining power depends largely on their unique traits. If a firm can easily replace a worker's role in production at a similar cost (i.e., the worker is substitutable), then that worker has minimal leverage during negotiations. Substitutes may come in different forms—for example, an equally qualified worker who would accept the same job at the same wage or perhaps a machine or computer that can do the same work at a similar or lower cost.

80 For example, ex-ante differences in gender pay gaps (due to discrimination or otherwise) can be amplified because a household seeking to maximize household earnings may elect to move to a state if the higher-earning member receives a sufficiently large pay increase from moving, even if the lower-earning member's income suffers. For a modeling example, see, e.g., Rueda, Valeria, and Guillaume Wilemme. 2021. "Career Paths with a Two-Body Problem: Occupational Specialization and Geographic Mobility." *Upjohn Institute for Employment Research* Working Paper 21-346. https://doi.org/10.17848/wp21-346.

81 Even if capital markets allowed workers to borrow against their expected future earnings, most people are risk averse. This risk aversion may make them hesitate to take on debt to finance training in an occupation with uncertain returns. The net result remains the same: workers with fewer means are more likely to be screened out despite their underlying ability relative to workers with greater means.

82 A test may poorly screen for quality, even if it is standardized. For example, the Scholastic Aptitude Test (SAT) is meant to screen for college readiness, but it has long been recognized that it poorly screens students of color disproportionately (see, e.g., Freedle, Roy. 2003. "Correcting the SAT's ethnic and social-class bias: A method for re-estimating SAT scores." *Harvard Educational Review* 73 (1): 1-43.). Some evidence also suggests the SAT is a better predictor of family income than college readiness (see, e.g., Goldfarb, Zachary A. 2014. "These four charts show how the SAT favors rich, educated families." *Washington Post*, March 5, 2014. https://www.washingtonpost.com/news/wonk/wp/2014/03/05/these-four-charts-show-how-the-sat-favors-the-rich-educated-families/.).

As technology changes to develop better substitutes for lower-paid workers, workers see their bargaining positions deteriorate relative to the firm. Whereas a cashier might once have been an indispensable employee at a supermarket or fast-food restaurant, viable substitutes are now available. Intuitively, this limits the worker's bargaining power: if wages grow high enough, the employer may rather pay for kiosks than cashiers.

Many tasks once done by humans are now done by machines. "Skill-biased technical change" refers to changes in technology or production that replace (or substitute) unskilled labor in favor of skilled labor since technology is complementary to skilled labor.[83] This process has especially disrupted routine-based work (where automation is easiest to implement) in occupations with relatively high-paying jobs. This has led to what some economists refer to as job polarization, wherein the labor market is ever more segmented into a low-skilled, low-wage sector and a high-skilled, high-wage sector. This process has contributed to both changes in the marginal product of labor (which would lead to wage divergence under conditions of perfect competition) but also likely had differential impacts on bargaining power across the income distribution.

In this framework, the result is a low-wage sector is characterized by jobs that are not easily replaced by technology (e.g., line cook), while the high-wage sector is characterized by jobs that are complementary to technological advances (e.g. accountants utilizing spreadsheets to tackle more work in a day).[84] The term "polarization" comes from the hypothesis that technology has replaced middle-skilled, middle-wage jobs (e.g., the cashiers mentioned above).[85] That said, both the existence of job polarization (especially after the 1990s) and its impact on income inequality remains hotly debated. For example, Michel et al. (2013) argue that the job polarization found in Acemoglu and Autor (2011) is highly sensitive to measurement error problems, choice of sample period, and empirical design.[86]

Although work pertaining to skill-biased technical change originally focused on the role of education, recent work by Acemoglu and Autor (2011) and others have focused more on the role of tasks, with machine automation primarily able to replace routine non-cognitive based tasks.[87] Acemoglu (2020) built on this framework by modeling not only tasks that are effectively automated away from humans, but also modeling new task formation that flows from automation of older tasks.[88] In their model, the destruction of tasks via automation tends to increase income inequality, but the creation of new tasks resulting from automation has an ambiguous impact on income inequality.

83 This pattern of substitutability and complementarity does not always hold true. Examples of the converse pattern include the power loom during the Industrial Revolution and GPS technology, which substitutes for a detailed knowledge of local geography and traffic routes.

84 Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining job polarization: Routine-biased technological change and offshoring." *American Economic Review* 104 (8): 2509–26.

85 *Id.*

86 Mishel, Lawrence, Heidi Shierholz, and John Schmitt. 2013. "Don't blame the robots. Assessing the job polarization explanation of growing wage inequality." *Economic Policy Institute and Center for Economic Policy and Research Institute* working paper. See also Hunt, Jennifer, and Ryan Nunn. 2019. "Is Employment Polarization Informative About Wage Inequality and Is Employment Really Polarizing?" *National Bureau of Economic Research* Working Paper 26064.

87 Acemoglu, Daron, and David Autor. 2011. "Skills, tasks and technologies: Implications for employment and earnings." *Handbook of Labor Economics*, edited by Orley Ashenfelter and David Card, vol. 4 (Part B), 1043–1171. Elsevier. See also Frey, Carl Benedikt, and Michael A. Osborne. 2017. "The future of employment: How susceptible are jobs to computerisation?" *Technological Forecasting and Social Change* 114 (January): 254-280.

88 Acemoglu, Daron, and Pascual Restrepo. 2020. "Unpacking Skill Bias: Automation and New Tasks." *American Economic Association Papers and Proceedings* 110 (May): 356–361.

LABOR MARKET POWER & COMPETITION: EMPIRICAL EVIDENCE

Having discussed theories of labor market power and related issues, we now turn to the data. Depending on the reader's perspective, several different questions addressed in this section might be deemed 'most important.' Among those questions: how large are wage losses stemming from monopsonic power on average? Have those losses increased or decreased over time? What are the sources of monopsony power, and how do employers exert it in practice?

First, we address the question of causality: does labor market power exist, and does it suppress wages? We find convincing evidence that both questions can be answered in the affirmative. Further, we argue that evidence suggests that this power derives more from labor market frictions than from market frictions. Second, we address the scale of labor market power—on average, how large are the compensation losses which stem from it? We argue that the highest quality estimates suggest wage losses of 15 percent, at minimum. Finally, we address the incomplete evidence on time-trends in labor market power, as well as discussing some alternate perspectives on the source of labor market power.

Does Labor Market Power Suppress Wages, in Practice?

Although theory predicts that labor market power will harm workers, the sources of labor market power often coincide with other market factors that might explain lower wages. For example, small rural communities with a single large factory have both a single dominant employer (the factory) and low costs of living, which can also partially explain low wages. Recent research has nevertheless demonstrated that labor market power *causes* lower wages, though it is not the sole contributing factors. One set of papers, discussed in later sections, argues that estimates of separation elasticities (how much workers respond to wage changes by separating with or joining a firm) directly imply labor market power, a viewpoint which is consistent with the theory discussed above. However, we focus on event-studies to directly address the question of the causal impact of labor market power on wages.

Prager and Schmitt (2021) offer some of the most compelling and nuanced evidence to address this question, although the paper's scope is restricted to hospital employment.[89] The paper studies the effect of employer labor market power by examining the evolution of wages and employment following hospital mergers- mergers that represent a potential source of increased labor market power. The empirical strategy is a "difference-in-differences" framework, which compares changes in markets with one hospital merger from 2000 to 2010 to the changes in markets without mergers during those years. In summarizing the paper, the authors write, "We find evidence of wage slowdowns, but only following mergers that induce large increases in employer concentration, and only for workers whose skills are industry specific."

We highlight two findings from Prager and Schmitt (2021). *First*, it observes wage losses only in those hospital occupations where skills are industry-specific (e.g., doctors, but not cafeteria workers), but only when market concentration substantially increases. There are no detectable wage effects of mergers that only mildly increase employer concentration, but the study does find evidence of slower wage growth following mergers that meaningfully increase concentration. Among the most substantial mergers, the paper estimates a reduction in annual wage growth of between 1.0 and 1.7 percentage points for workers with hospital-specific skills, roughly one-quarter of these occupations' typical wage growth rates. However, detectable wage slowdowns from hospital consolidation are limited to occupations with health-care specific skills, even for the most substantial mergers. For non-health-care specific occupations, those mergers have a less meaningful impact on the number of potential employers and market concentration—leading to lesser or null wage effects. This suggests that occupational-level

89 Prager, Elena, and Matt Schmitt. 2021. "Employer Consolidation and Wages: Evidence from Hospitals." *American Economic Review* 111 (2): 397–427. This paper's results are discussed in further depth below, in the Industry Examples subsection.

markets are more relevant than industry-level markets when analyzing labor market power, a suggestion that is echoed in related papers.

Secondly, insofar as these mergers had detectable employment effects, they were positive.[90] This finding carries particular importance since it is inconsistent with the classical theory of monopsony power, where the monopsonist reduces wages by constricting labor demand, thereby decreasing the number of employees. However, it *is* consistent with a search and matching framework of market power, which does not require a decrease in jobs. Instead, this finding is consistent with a search and matching explanation for market power, where frictions in the labor market shield employers from competition for workers, resulting in sub-competitive wages. As mergers leave fewer potential employers, the employee believes that the benefits of job search are lower, so they put less effort into their search.

Prager and Schmitt (2021) is useful for this report's purposes, as it both (a) convincingly establishes a causal link from mergers to increased labor market power, and (b) furnishes evidence that search and matching is the most relevant framework for understanding monopsonistic power. Other recent papers estimate the wage effects of mergers across a broader range of industries, showing that wage suppression as a result of labor market power is not unique to the health care industry. Notably, Arnold (2021) finds similar effects across a wider range of industries, along with a higher rate of job departures from recently merged employers (the data do not allow an analysis of whether this is due to downsizing, quits, or other mechanisms).[91] However, the wages lost over the course of this study are not meant to be estimates of the current *level* of average wage loss in the U.S. economy. We next turn to papers more suited to estimate those wage losses.

The Extent of Wage Losses due to Labor Market Power

How large are wages losses stemming from the exercise of monopsonist power on average? Before turning to the empirical estimates, it is worth restating a definition for "wage losses.". The "loss" is relative to the wage in a perfectly competitive and frictionless environment where workers would be paid a wage equal to the "marginal revenue product of labor" (MRP_L). Though a technical term, MRP_L reflects a relatively simple idea. If a firm adds one more worker, it can produce a little more of its product. When the firm sells that extra product, the total revenue from that sale is the MRP_L. Put differently: a worker's MRP_L equals the revenue their employer *would* lose *if* they were to quit.

Like with any complex question, studies offer a range of estimates regarding these wage losses. Among recent empirical work, Yeh, Macaluso, and Hershbein (2022) estimate that workers at the average manufacturing plant earn 65 percent of their MRP_L, or 65 cents of every dollar they produce.[92] This is at the higher end of estimates among our selected studies, yet it has plenty of supporting evidence. The paper adopts a direct approach to estimating wage losses, marshalling detailed, plant-level Census data to do so. This is no small feat: due to considerable technical hurdles, nearly all other efforts to estimate wage loss infer the values indirectly by connecting wage loss to theoretically related statistics. One drawback to the paper is its industrial focus: extrapolating the Yeh, Macaluso, and Hershbein (2022) estimate to non-manufacturing sectors is unwarranted, therefore we do not say this is an economy-wide estimate. However, it remains a credible estimate pertaining to a crucial sector of the U.S. economy.

The bulk of our selected studies estimate average wage losses to be on the order of 15–25 cents on the dollar

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90 This positive estimate may well reflect pre-existing trends, rather than an actual effect. After including a linear time-trend in their estimated regression, the employment effects are no longer statistically significant.

91 Arnold, David. 2021. "Mergers and acquisitions, local labor market concentration, and worker outcomes." Working Paper. https://darnold199.github.io/madraft.pdf.

92 Yeh, Chen, Claudia Macaluso, and Brad Hershbein. 2022. "Monopsony in the U.S. Labor Market." *American Economic Review, Forthcoming:* https://www.dropbox.com/s/3qpxons17tuk044/monopsony_draft_January2022.pdf?dl=0.

(alternately, workers earn between 75 and 85 cents for each dollar of value produced). Notable papers that estimate wage losses in this range include Berger, Herkenhoff, and Mongey (2021), who study how competing firms respond to changes in state taxes, leading to estimates of the scale of monopsony power in local labor markets.[93] This paper's estimates suggest an average wage loss of 24 cents per dollar produced. Crucially, workers do not suffer a full 24 percent loss of welfare due to labor market power—a variety of mitigating factors lead to a still-substantial average lifetime welfare loss of 4–9 percent.

Another estimate in this range comes from Bassier, Dube, and Naidu (2021), who study worker responses to changes in firm-wide wage policies.[94] Their estimate of average wage loss is 19 cents on the dollar. This paper's estimates suggest that wage loss due to monopsony power is larger for lower-paid workers—the estimated loss for the bottom quartile of wages is 26 cents on the dollar.

On the lower end of the spectrum, Azar, Berry, and Marinescu (2019) estimate wage losses of 15 cents on the dollar.[95] Focusing on worker preferences between firms – rather than search frictions – Lamadon et al. (2022) also find wage losses on the order of 15 cents on the dollar.[96] Notably, this paper supports the view that across-firm differences in non-pecuniary amenities are both a potential result of labor market power, and a potential source of that power. Kroft et al. (2021) arrive at a similar estimate.[97] Among our selected studies, this is the lower bound of wage losses, meaning we believe the best available empirical evidence suggests that labor market power reduces wages by *at least* 15 percent.

Changes in Labor Market Power and Concentration over Time

Whether labor market power has increased or decreased over the past 50 years remains an unresolved question. Although concentration and market power are not necessarily linked, as argued throughout this report, we do have stronger evidence regarding the trend in labor market concentration. Measured at the national level, the concentration of employers in the labor market has increased since the 1980s. However, at the local level, which is the relevant level for most workers, concentration has consistently decreased over that timeframe (Rinz 2018).[98] From the late 1970s through 2015, the average local labor market Herfindahl-Hirschman Index (HHI) fell by nearly 0.06 (equivalently 600 points).[99]

Nevertheless, concentration remains high. Rinz (2018) finds the average concentration of local labor markets to be around 1,500, the threshold at which DOJ may intervene to block a merger in goods markets. Using job postings from a private jobs website, Azar, Marinescu and Steinbaum (2020) calculate an average HHI of 3,157.[100] Many other

93 Berger, David, Kyle Herkenhoff, and Simon Mongey. 2021. "Labor Market Power." *National Bureau of Economic Research* Working Paper 25719.

94 Bassier, Ihsaan, Arindrajit Dube, and Suresh Naidu. 2021. "Monopsony in Movers: The Elasticity of Labor Supply to Firm Wage Policies." *The Journal of Human Resources,* forthcoming.

95 Azar, José, Steven Berry, and Ioana Elena Marinescu. 2019. "Estimating Labor Market Power." *SSRN*, September 18, 2019. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3456277.

96 Lamadon, Thibaut, Magne Mogstad, and Bradley Setzler. 2022. "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market." *American Economic Review* 112 (1): 169–212. https://www.aeaweb.org/articles?id=10.1257/aer.20190790

97 Kroft, Kory, Yao Luo, Magne Mogstad, and Bradley Setzler. 2021. "Imperfect Competition and Rents in Labor and Product Markets: The Case of the Construction Industry." Working Paper. https://www.bradleysetzler.com/files/Kroft-Luo-Mogstad-Setzler.pdf.

98 Rinz, Kevin. 2018. "Labor Market Concentration, Earnings Inequality, and Earnings Mobility." *Center for Administrative Records Research and Applications, U.S. Census Bureau* Working Paper 2018-10.

99 The HHI is defined as the *sum of squared-market shares,* for some defined market. Higher values of HHI indicate greater market concentration.

100 Azar, José, Ioana Marinescu, and Marshall Steinbaum. 2020. "Labor Market Concentration." *Journal of Human Resources* (May): 1218-9914R1.

studies come to similar results, generally finding that wages are negatively correlated with concentration.[101]

With market power, firms hire fewer workers than they would in a competitive environment. This reduction in employment is more than a curiosity: it informs how we should measure the existence and extent of monopsony power. In particular, it means that the exercise of market power *decreases* market concentration relative to a competitive environment, if larger firms tend to have greater market power. This should give some pause to using labor market concentration as a direct measure of market power. Theoretically, the markdown measures market power most accurately, a point we return to in the empirical section. Unfortunately, markdowns are difficult to measure.

On a related topic, this observation forms the theoretical foundation of how minimum wages can increase aggregate employment.[102] Under monopsony's lower wages, the economy sees fewer jobs than in competitive equilibrium since lower wages mean fewer workers willing to accept jobs. Insofar as a minimum wage does not exceed the competitive wage, it increases employment: more workers will accept employment at the increased wage, while firms still find it profitable to employ all the willing workers.

Decreasing concentration does not necessarily mean increasing labor market competition: the relationship between concentration and labor market power is theoretically *ambiguous*.[103] Indeed, many recent papers on the subject take pains to point this out, including Yeh, Macaluso, and Hershbein (2022); Berger, Herkenhoff, and Mongey (2021); and Bassier, Dube, and Naidu (2021). For example, Berger, Herkenhoff, and Mongey (2021) estimate that labor market power has decreased over that time frame, thereby increasing labor's share of income by 4 percentage points from 1977 to 2013. On the other hand, Yeh, Macaluso, and Hershbein (2022) argue that labor market power decreased from 1977 to 2002, then quickly rose over the ensuing decade. *Figure 2* illustrates this secular trend.

Labor Market Power in U.S. Manufacturing

Markdown Indicies, Relative to 1977

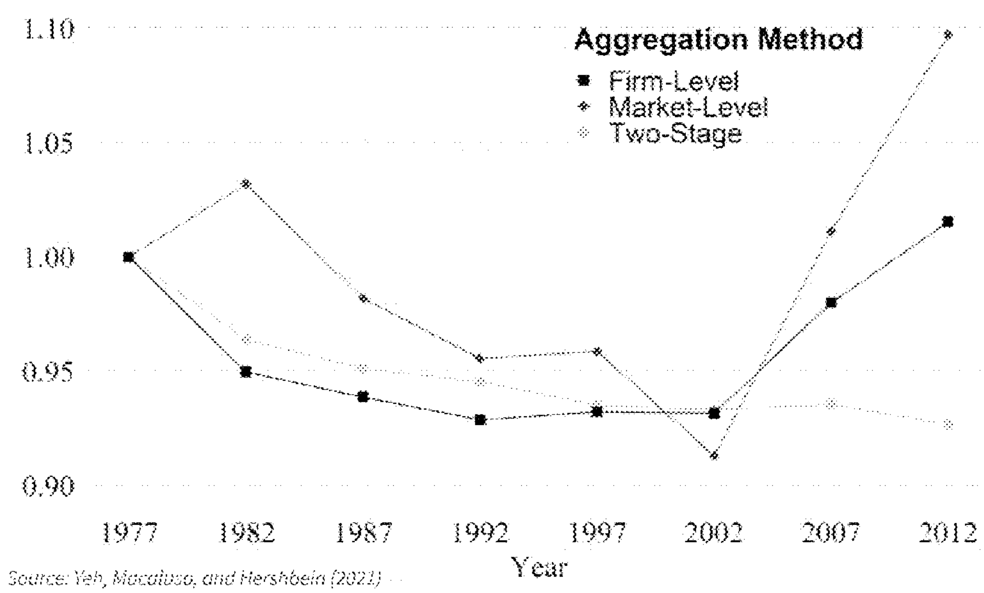


Figure 2 - Labor Market Power in Manufacturing, Measured by Wage Markdowns (Yeh, Macaluso, and Hershbein (2022))

101 See, e.g., Benmelech, Efraim, Nittai K. Bergman, and Hyunseob Kim. 2020. "Strong employers and weak employees: How does employer concentration affect wages?" *Journal of Human Resources* (December): 0119–10007R1.

102 While this white paper does not explicitly address the economics of minimum wages, questions of labor market power are important subtext in the discussion of minimum wages and its potential dis-employment effects.

103 For an overview of the theory, see Syverson, Chad. 2019. "Macroeconomics and Market Power: Context, Implications, and Open Questions." *Journal of Economic Perspectives* 33 (3): 23–43.

Also illustrated by *Figure 2* is the importance of index choice and aggregation method.[104] When we discuss average labor market power at a national level, we are ultimately summing up the positions of many firms and establishments into a single statistic. From the firm's perspective, the plot illustrates that manufacturing labor market power fell from 1977 to 2002, then increased back to roughly 1970s levels over the subsequent decade. The same was not true from the manufacturing workers' perspective, reflected by market-level aggregation (we typically assume that the worker searches within a market, though that is not *strictly* true). From that perspective, markdowns also fell through 2002, but then grew quickly over the past decade, well beyond the levels of the late 1970s.

Note, importantly, that this estimated increase in market power over the last decade was not associated with an increase in concentration. In contrast to the market-level measure of markdown, local concentration in manufacturing labor markets declined since 1977 and remained below the 1977 level all the way through 2012. This observation, combined with observations in the other papers highlighted in this section, suggest that labor market concentration is a flawed proxy for labor market power.

Alternative Perspectives on Market Concentration and Labor Market Power

The previous section featured papers arguing that labor market concentration and labor market power are not necessarily correlated. However, a handful of recent studies have focused on concentration as not only an indicator of market power, but also a cause of it. In a classical monopsony or oligopsony model, some degree of concentration is a prerequisite for market power.[105] For example, Azar, Marinescu, and Steinbaum (2020) measure concentration in local labor markets using data from postings on CareerBuilder.com, estimating that moving from the twenty-fifth to the seventy-fifth percentile of concentration within U.S. local labor markets results in a 5–17 percent decrease in posted wages. Acknowledging that a correlation between concentration and posted wages could be a confounded by productivity differences, the paper uses an "instrument" for market concentration (a common econometric strategy to address these kinds of concerns) of the inverse number of employers that make job postings in the same occupation and quarter, but in different geographic markets. The crucial assumptions are (a) occupation-level concentration in *other* geographic areas is correlated with local concentration, but (b) *not* associated with local occupational wage postings in any other way. If workers commonly look outside their own geographic area for a job, for example, then the second assumption would be violated.

Focusing on the manufacturing sector, Benmelech, Bergman, and Kim (2020) find that increasing local labor market concentration from one standard deviation below the national mean to one standard deviation above the national mean decreases wages between 9.1 percent and 14.4 percent. Notably, they also find that unionization, which provides workers with countervailing market power, decrease how responsive wages are to local labor market concentration by between 29 percent and 45 percent.

This white paper has argued that frictions are a more important source of labor market power than concentration. However, it is important to stress that the two sources are not mutually exclusive. Evidence for one mechanism is not necessarily evidence against the other.

104 Some notes on interpreting *Figure 2*: each of the three series are indexed to 1 in 1977, meaning that all points are relative to that year. For example, the red "Market-Level" series for markdowns is roughly 1.1 in 2012, which can be interpreted as markdowns that are 10 percent greater than they were in 1977. Only changes can be inferred from the figure itself; the figure says nothing about the level of markdowns at any point.

105 In general, it is not true that concentration implies market power. Concentration is consistent with a competitive market featuring differences in productivity. In that context, the most productive firms are the largest employers, and this allocation is efficient—any reallocation of workers would *reduce* wages.

Restrictive Employment Agreements

Both the exposure to and the effect of non-compete agreements and other types of post-employment agreements differ by state, occupation, and workplace status (e.g., entry-level vs executive).

Twenty-one percent of workers in the top income quintile are covered by a non-compete agreement compared to eight percent of workers in the bottom quintile of hourly wages.[106] However, this still leaves millions of workers with minimal employer-specific training subject to non-compete agreements (Starr, Prescott, and Bishara 2021). Top executives may be even more responsive to non-compete agreements. Garmaise (2011) finds that top executives were 47 percent less likely to change jobs within industries as non-competes became more strictly enforced and their tenure also increased by about 16 percent.[107] Additionally, Kini, Williams, and Yin (2021) show that initial CEO compensation is higher when enforceability of non-competes is higher, suggesting CEOs demand a compensating differential in exchange for signing non-compete agreements.[108] The greater responsiveness of compensation to noncompete agreements of top executives compared to lower-wage workers could be due to a number of factors, including that top executives may be more likely to face increased coverage by a non-compete agreement, a bigger relative loss in wages when switching jobs, and higher odds of enforcement of a non-compete agreement.[109]

Unlike higher income workers, lower wage workers likely lack sufficient bargaining power to refuse a non-compete agreement. As a result, whereas non-compete agreements may increase top-earner wages at the expense of mobility, non-compete agreements appear to reduce both wages and mobility for lower-income earners. For example, Lipsitz and Starr (2021) find that the ban on non-compete agreements for hourly workers (who tend to be lower income) in Oregon increased overall hourly wages by 2–3 percent, with a stronger effect for female workers.[110] Johnson, Lavetti, and Lipsitz (2021) likewise find stronger effects from enforcement of non-compete agreements on income of women and people of color.[111] Young (2021) finds that a ban on non-compete clauses for low-to-medium income workers in Austria modestly increased worker's annual job-to-job mobility rate (a 0.27 percentage point increase against a base rate of 16 percent).[112]

Non-compete agreements exist across occupations broadly, though their prevalence varies. For example, non-compete agreements are relatively rare in agricultural occupations compared with sales and management related occupations (Boesch, Lim, and Nunn 2021, fn. 1). Furthermore, employers with multiple locations are more likely to have non-compete agreements (id.).

Balasubramanian, Starr, and Yamaguchi (2021b) show that employers often bundle post-employment restrictive covenants, which in addition to non-compete agreement include non-disclosure agreements, non-solicitation

106 Boesch, Tyler, Katherine Lim, and Ryan Nunn. 2021. "Non-compete contracts sideline low-wage workers." *Federal Reserve Bank of Minneapolis*, October 15, 2021. https://www.minneapolisfed.org/article/2021/non-compete-contracts-sideline-low-wage-workers.

107 Garmaise, Mark J. 2011. "Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment." *The Journal of Law, Economics, and Organization* 27 (2): 376–425.

108 Kini, Omesh, Ryan Williams, and Sirui Yin. 2021. "CEO noncompete agreements, job risk, and compensation." The Review of Financial Studies 34 (10): 4701–4744.

109 Id.

110 Lipsitz, Michael, and Evan Starr. 2021. "Low-Wage Workers and the Enforceability of Noncompete Agreements." *Management Science* 68 (1): 143–170. https://doi.org/10.1287/mnsc.2020.3918.

111 Johnson, Matthew, Kurt Lavetti, and Michael Lipsitz. 2020. "The Labor Market Effects of Legal Restrictions on Worker Mobility." *SSRN*, June 6, 2020. https://ssrn.com/abstract=3455381.

112 Young, Samuel G. 2021. "Noncompete Clauses, Job Mobility, and Job Quality: Evidence from a Low-Earning Noncompete Ban in Austria." *SSRN*, July 5, 2021. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3811459.

agreements, and non-recruitment agreements.[113] Consistent with previous studies, they find that below-median income workers are more likely to be covered by none of these agreements compared to higher-income workers. However, they also find should there be any post-employment restriction covenants low-income are about equally likely as high-income workers to face the full bundle of restrictions. They suggest their estimates are consistent with pure value capture (related to the "lock-in" effect mentioned above) being the dominant reason for bundling agreements for average workers, whereas value creation (related to the "hold-up" effect mentioned above) is a primary reason for top executives, like CEOs.

One type of restrictive employment agreement, the non-disclosure agreement (NDA), has garnered attention recently. In the wake of the #MeToo movement, it was anecdotally argued that NDAs led to underreporting of unlawful conduct resulting from fears of retaliation and lawsuits over breaching these agreements.[114] Sockin, Sojourner, and Starr (2021b) show that changes in laws in three states (California, Illinois, and New Jersey), which prohibited firms from using NDAs to restrict workers from sharing information about unlawful conduct, led to an increase in negative reviews (5 percentage points greater share) on Glassdoor, especially pertaining to workplace harassment (22 percent increase).[115] The authors argue that "by preventing outsiders from learning about undesirable firm employment practices, over-broad NDAs impose potential negative externalities on job seekers and competitor firms."

Starr, Prescott, and Bishara (2021) find that the huge number of low-skill workers subject to non-competes suggests that employers routinely apply them to workers who do not possess trade secrets or customer lists and are not given specialized training. They cite as an example a large sandwich chain, which subjected its workers to extremely broad non-competes. Though these non-competes are not likely enforceable under state law, they point out that they may have an in terrorem effect that deters employees from obtaining jobs at competing employers.

Trends in and Effects of Occupational Licensing

The incidence of occupational licensing has grown dramatically since the 1950s, from about 5 percent to around 20 percent of workers by the mid-2010s.[116]

In 2016, Treasury's Office of Economic Policy, in collaboration with the Council of Economic Advisers (CEA) and DOL, released an extensive report documenting the effects of occupational licensing on labor markets (Department of Treasury, Council of Economic Advisers, and Department of Labor 2015). The report, hereafter referred to as UST (2016), examined dozens of studies on the effects of occupational licensing both broadly and within specific industries.

UST (2016) found little evidence that marginal changes in occupational licensing typically increase quality,

113 Balasubramanian, Natarajan, Evan Starr, and Shotaro Yamaguchi. 2021b. "Bundling Postemployment Restrictive Covenants: When, Why, and How It Matters." Economic Perspectives on Employment & Labor Law Journal (March). Specifically, they look at non-disclosure, non-solicitation, non-recruitment, and non-compete agreements. Among these, they find the most common clause that people are aware of is the non-disclosure agreement.

114 Sockin, Jason, Aaron Sojourner, and Evan Starr. 2021a. "What happens when states limit nondisclosure agreements? Employees start to dish." *Washington Post*, October 4, 2021. https://www.washingtonpost.com/outlook/2021/10/04/non-disclosure-employee-reviews-study/.

115 Sockin, Jason, Aaron Sojourner, and Evan Starr. 2021b. "Externalities from Silence: Non-Disclosure Agreements Distort Firm Reputation." *Institute of Labor Economics* Working Paper. https://conference.iza.org/conference_files/LaborMarkets_2021/sockin_j28322.pdf.

116 Kleiner, Morris M., and Alan B. Krueger. 2013. "Analyzing the extent and influence of occupational licensing on the labor market." Journal of Labor Economics 31 (S1): S173–S202; and Kleiner, Morris M., and Evgeny S. Vorotnikov. 2018. "At What Cost? State and National Estimates of the Economics Costs of Occupational Licensing." *Institute for Justice*. https://ij.org/wp-content/uploads/2018/11/Licensure_Report_WEB.pdf.

safety, or health. Evidence since then tends to corroborate these findings. For example, Kleiner et al. (2016) find that “when nurse practitioners have more independence in their scope of practice, their wages are higher but physicians’ wages are lower, which suggests some substitution between the occupations. Our analysis of insurance claims data shows that more rigid regulations increase the price of a well-child visit by 3–16 percent. However, we find no evidence that the changes in regulatory policy are reflected in outcomes that might be connected to the quality and safety of health services.”[117] Bowblis and Smith (2021) study a federal staffing provision that requires skilled nursing facilities of a certain size to employ licensed social workers and find no evidence that the increase in licensure improves patient care quality, patient quality of life, or quality of social services provided.[118] Meehan and Stephenson (2020) find that changes in the number of hours of education required to become a certified public accountant (CPA) from 150 hours to 120 hours did little to change pass rates or scores on the CPA exam, suggesting the extra hours required had little impact on quality. However, the marginal changes do not necessarily correlate to the overall effect of licensing—some degree of licensing may be welfare enhancing even if a study finds that marginal changes to occupational licensing requirements reduces welfare.[119]

Even if licensing does not objectively increase quality, the perception that it increases quality may nonetheless impact market outcomes (e.g., price). However, it is unclear whether consumers notice or place much value on licensure, especially when other methods for determining quality are available. For example, Farronato et al. (2020) study a large online platform for residential home services and find that consumers are unresponsive to platform-verified licensing status relative to review ratings and price. This suggests that consumers consider reviews from other customers a better signal of quality than licensing (or at least verification of licensing).[120]

Occupational licensing appears to restrict labor supply in some licensed professions (UST 2016). In some contexts, licensing can disproportionately limit the labor supply for subsets of socioeconomically disadvantaged workers. For example, Federman, Harrington, and Krynski (2006) find that state licensing requirements that require proficiency in the English language tend to reduce the number of Vietnamese-American manicurists.[121] Cathles, Harrington, and Krynski (2010) find that licensing laws requiring funeral directors to also be embalmers tended to reduce the share of female funeral directors.[122] These disproportionate impacts on labor supply highlight how the manner of licensing requirements (i.e., inclusion of English language requirements), not just the intensity of licensing (e.g., required number of hours), can affect equity considerations. That said, evidence from Blair and Chung (2018) suggests that occupational licensing may reduce prospective employers’ reliance on race and gender during the hiring process, suggesting licensing can reduce racial and gender inequities in certain contexts.[123]

117 Kleiner, Morris M., Allison Marier, Kyoung Won Park, and Coady Wing. 2016. "Relaxing Occupational Licensing Requirements: Analyzing Wages and Prices for a Medical Service." *The Journal of Law and Economics* 59 (2): 261–291.

118 Bowblis, John R., and Austin C. Smith. 2021. "Occupational Licensing of Social services and Nursing Home Quality: A Regression Discontinuity Approach." *ILR Review* 74 (1): 199–223.

119 For example, Meehan and Stephenson (2020) only identify the effects of a change in intensity (from 150 hours to 120 hours). Meehan, Brian, and E. Frank Stephenson. 2020. “Reducing a Barrier to Entry: The 120/150 CPA Licensing Rule.” *Journal of Labor Research* 41 (December): 382–402. These studies cannot speak to the overall effects of occupational licensing because requiring CPAs to be licensed may increase overall quality of CPAs, even if a reduction in the hours required to obtain a CPA does not reduce quality. For example, this could be the case if 60 hours was sufficient to screen out unqualified candidates.

120 Farronato, Chiara, Andrey Fradkin, Bradley Larsen, and Erik Brynjolfsson. 2020. “Consumer Protection in an Online World: An Analysis of Occupational Licensing.” *National Bureau of Economic Research* Working Paper 26601.

121 Federman, Maya N., David E. Harrington, and Kathy J. Krynski. 2006. “The Impact of State Licensing Regulations on Low-Skilled Immigrants: The Case of Vietnamese Manicurists.” *American Economic Review* 96 (2): 237–241.

122 Cathles, Alison, David E. Harrington, and Kathy Krynski. 2010. “The Gender Gap in Funeral Directors: Burying Women with Ready-to-Embalm Laws?” *British Journal of Industrial Relations* 48 (4): 688–705.

123 Blair, Peter Q., and Bobby W. Chung. 2018. “Job Market Signaling through Occupational Licensing.” *National Bureau of Economic Research* Working Paper 24791. Specifically, they argue one of the main channels for this effect is that

Determining the impact of occupational licensing on wages is difficult. Though a restricted supply of labor can increase wages for those who become licensed, if the most skilled workers are more likely to become licensed, they may have earned more than their unlicensed counterparts even without becoming licensed. UST (2016) found the size of the wage gap attributable to occupational licensing is sensitive to modeling choices. Studies that do not control for underlying differences (e.g., in educational attainment) between licensed and unlicensed workers tend to find a large wage gap—on the order of 10–25 percent. However, studies that control for underlying differences typically find more modest effects of licensing on wages.

Variations in licensing requirements across states may discourage mobility and suppress the wages of licensed workers. However, UST (2016) analysis using 2011 Survey of Income and Program Participation (SIPP) data found weak evidence that licensed workers are less likely than unlicensed workers to move between states. Johnson and Kleiner (2020) find stronger evidence of occupational licensing as a barrier to interstate migration.[124] They find that the interstate migration rate for occupations with state-specific licensing exams are about a third lower than other occupations. Importantly, they do not find similar results for occupations with national exams, highlighting how synchronizing requirements and examinations can reduce mobility barriers created by licensing.[125] That said, Johnson and Kleiner (2020) find that increases in occupational licensing only account for a very small share (about 2.5 percent) of the decline in interstate migration since 1980.

The impact of licensing on the prices of goods and services is clearer. In nine of the eleven studies UST (2016) examined, more restrictive occupational licensing increased prices.[126] This effect increases earnings for licensed workers at the expense of shutting some workers out of an occupation altogether. But the exact impact of licensing on prices varies by occupation or even within individual studies of the same occupation. For example, Kleiner et al. (2016)'s results imply that restricting nurse practitioners from conducting tasks without the supervision of a physician tends to increase the cost of well-child exams by 3–16 percent (Kleiner et al. 2016).

Variation in Licensing

Occupational licensing is substantially more common in some occupations than others. Kleiner and Krueger (2013), along with subsequent research, show that occupational licensing is very common in healthcare, legal occupations, education, and protective services and less common in computer and mathematical, office and administrative support, and art and entertainment occupations.

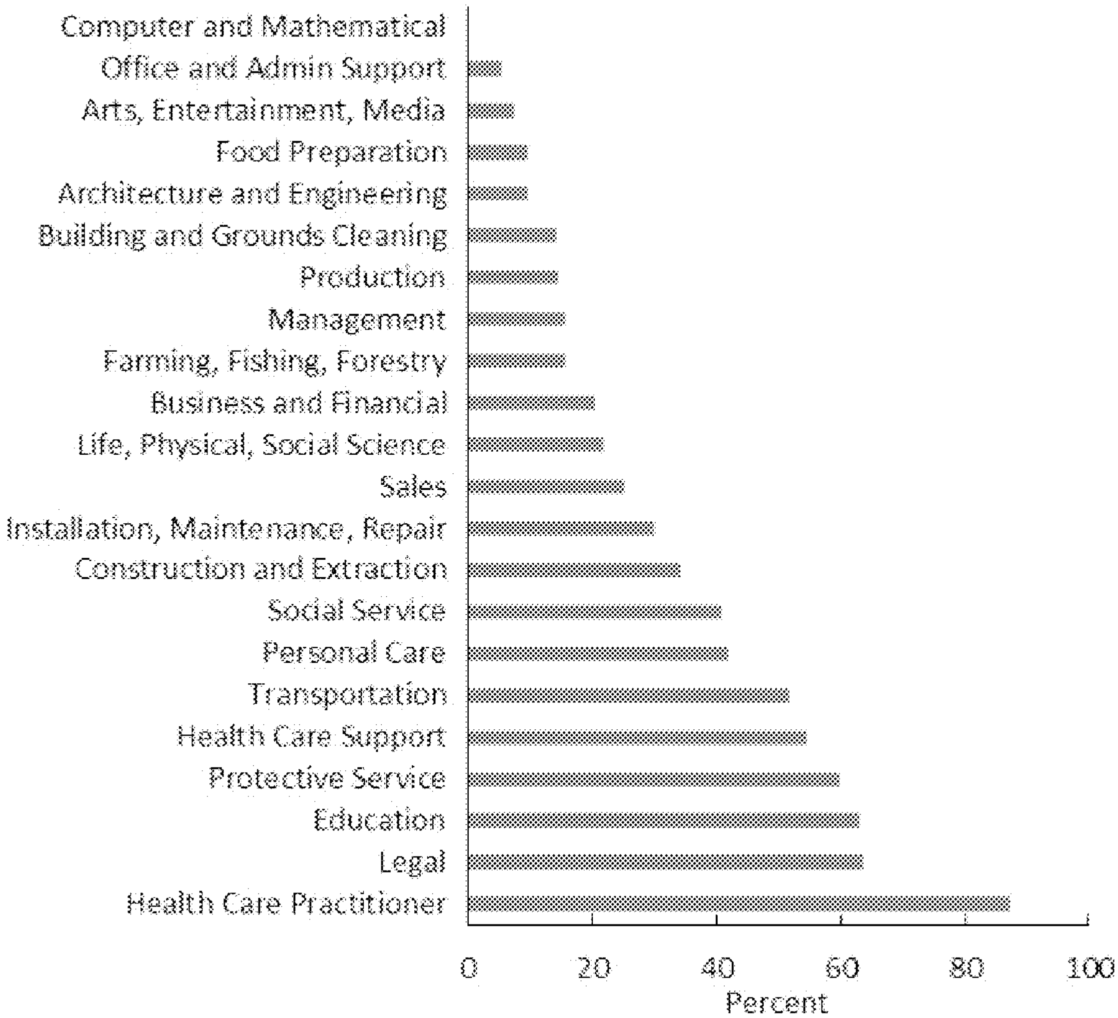
occupational licensing sends a signal to employers of a worker's non-felon status in occupations where only non-felons may become licensed.

124 Johnson, Janna E., and Morris M. Kleiner. 2020. "Is occupational licensing a barrier to interstate migration?" *American Economic Journal: Economic Policy* 12 (3): 347–73.

125 Synchronizing licensing requirements and exams may be more difficult in some occupations than others, depending on the portability of skills. For example, the knowledge and skillsets of lawyers are likely more state-specific than the knowledge and skillsets of bus drivers.

126 However, many of the studies they examined were conducted at least three decades ago and by the same authors. Accordingly, results may be highly correlated with each other.

Percent of Workers Licensed Within Occupations



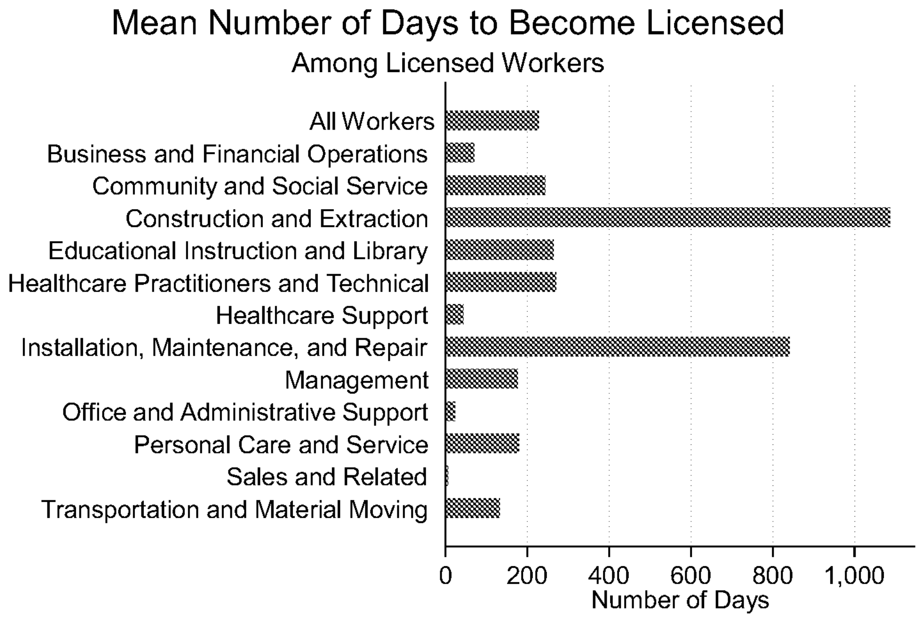
Source: Kleiner and Krueger (2013), Westat data; UST and CEA calculations. Accessed via Department of Treasury, Council of Economic Advisers, and Department of Labor (2015).

Occupational licensing is primarily determined at the state-level and varies considerably between states. For example, Kleiner and Vorotnikov (2018) show that workers are substantially more likely to be licensed in some states than others. For example, they find that Nevada (26.6 percent), Iowa (24.3 percent), and Maine (24.2 percent) have the highest share of workers that are licensed, while Georgia (14.4 percent), Delaware (15.2 percent), and Kansas (16.0 percent) have the lowest share of workers that are licensed (Kleiner and Vorotnikov 2018). While much of the difference between states can be explained by state policies, at least some is explained by underlying differences in the types of occupations within each state (e.g., greater presence of the gambling industry in Nevada than other states).

Differences between states result from differences in both the extensive margin of licensing (who needs to be licensed) and intensive margin of licensing (intensity of requirements to become licensed). For example, to obtain a job as an "electrician," 31 states (including the District of Columbia) require licensing, while 20 states do not. Alaska and Hawaii both require licensing to become an electrician. However, Alaska requires 1,000 hours of training (assuming no previous experience), while Hawaii only requires 240 hours (assuming no previous experience).[127]

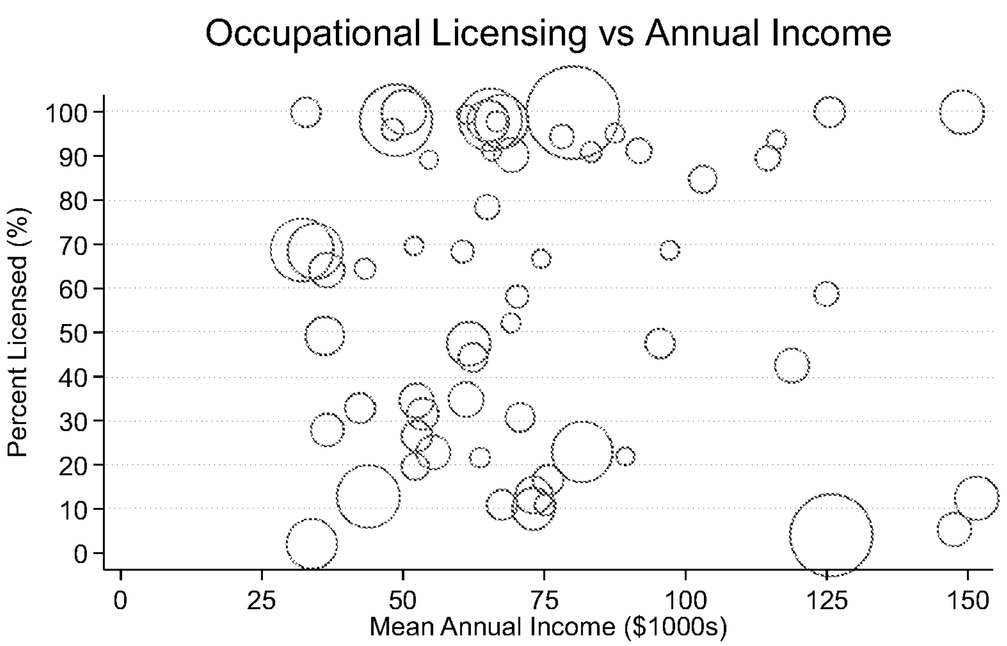
127 Herman, Zach. 2020. "The National Occupational Licensing Database." National Conference of State Legislatures, March 24, 2020. https://www.ncsl.org/research/labor-and-employment/occupational-licensing-statute-database.

While all states require licensing to become a "Nursing Home Administrator," the cost of initial licensure is only $100 in Indiana compared to over $3,500 in Oklahoma.[128] As the figure below shows, while the mean time to obtain a license is about 220 days, there is enormous variation between occupations.



Source: BLS Occupational Requirement Survey, 2020 release. Categories represent major occupation groups.

Occupational licensing is not limited only to workers in high-income occupations. As the figure below shows, there is little obvious correlation between the prevalence of occupational licensure and average income by occupation.



Source: BLS (OES&ORS), authors calculations. Each circle represents an occupation. Size of circles proportional to occupational employment. Note, scatterplot only includes detailed occupations measured by both OES and ORS and with estimated employment of at least 100,000 or more.

aspx#Database.

128 Id.

Wage Transparency

As discussed in the theory section, workers' lack of information on potential outside offers creates an important search friction. Using data they obtained from Denmark, Caldwell and Harmon (2019) find that changes in workers' information about opportunities outside of their current firm spur mobility and wage growth.[129] When workers lack information and are unable to easily find such information, they may stay in jobs they would otherwise leave or fail to ask for a raise when they would otherwise have asked for one (see, e.g., Caldwell and Harmon 2019).

Employers know how much all their employees are compensated, but the converse is often not true. While social taboos around discussing compensation with coworkers plays a role, employer policies and practices play an important role as well. A 2017–2018 survey by the Institute for Women's Policy Research found that workers reported employer policies that either discouraged (35.4 percent) or purported to prohibit (12.8 percent) discussing pay with coworkers. Only about a quarter of workers reported their pay being publicly available, with shares being much higher for public-sector and union workers in their sample.[130] These high rates of pay secrecy policies persist despite legal protections in many jurisdictions for workers who discuss their pay, including anti-retaliation protections, such as the National Labor Relations Act, Executive Order 13665, and 19 state anti-pay secrecy laws. Moreover, while such laws provide important protections, they place the onus on individual workers or jobseekers to seek information via employees or social and professional networks and to invoke legal protections if they face retaliation. This may disadvantage individuals who may not have access to formal and informal professional networks (e.g., those who grew up in low-income households).

Employers likewise often have more information regarding workers' outside options than the workers. Many employers have access to non-public compensation surveys, giving them a better understanding of the wage distribution for a given occupation and geography. Even when information is publicly available, HR departments of firms are in a better position use the data than the typical worker—HR departments have institutional knowledge and a stronger incentive to know where vacancies are posted than a time-constrained worker. Firms can also benefit from asking about applicants' employment and compensation history (where permitted). In contrast, workers very often do not even know what their peers at the same establishment make. For example, Biasi and Sarsons (2021) show that many teachers in Wisconsin did not know how much their colleagues were paid.[131] In their survey, they also found that compared with men, women were 11 percentage points less likely to know how much their colleagues earned (30 percent for women vs 41 percent for men). This highlights how informational asymmetries can have disproportionate impacts on women (Biasi and Sarsons 2021).

There are many ways to mandate greater pay transparency. Some approaches might include: 1) requiring disclosure of *aggregated* income statistics to workers, applicants, or the public, which might be broken out by worker characteristics, like gender; 2) requiring *individual* income disclosure, often only for subsets of workers (e.g., high-paid government workers or managers); and 3) requiring employers to disclose prospective pay ranges in job postings.

Consistent with the logic that pay secrecy exacerbates gender pay gaps, empirical research suggests that pay transparency reduces wage gaps between women and men. For instance, using Canadian administrative data,

129 Caldwell, Sydnee, and Nikolaj Harmon. 2019. "Outside Options, Bargaining, and Wages: Evidence from Coworker Networks." Working Paper. https://sydneec.github.io/Website/Caldwell_Harmon.pdf.

130 Sun, Shengwei, Jake Rosenfeld, and Patrick Denice. 2021. "On the Books, Off the Record: Examining the Effectiveness of Pay Secrecy Laws in the U.S." *Institute for Women's Policy Research* Policy Brief C494. https://iwpr.org/wp-content/uploads/2021/01/Pay-Secrecy-Policy-Brief-v4.pdf. Note: sample sizes for government and union workers are much smaller than the overall sample, so interpret point estimates cautiously.

131 Biasi, Barbara, and Heather Sarsons. 2021. "Information, Confidence, and the Gender Gap in Bargaining." *American Economic Association Papers and Proceedings* 111 (May): 174–78.

Baker et al. (2019) finds that a public sector salary disclosure law, enabling the public to access salaries of individual faculty, reduced the gender pay gap between male and female full-time faculty at Canadian universities by about 20–40 percent.[132] Bennedsen et al. (2019) examine a 2006 Danish law requiring private firms with more than 35 employees to provide salary statistics by gender to an employee representative.[133] Although they find the policy reduced the within-firm gender pay gap by about two percentage points (13 percent relative to the pre-legislation mean), it primarily did so by slowing wage growth for male employees. Using data from Glassdoor, Sockin and Sockin (2019) likewise find that changes in pay transparency laws in the United States reduce the gender pay gap by about 2 percentage points for base earnings, though they detect no change for variable pay (e.g., bonuses and commissions).[134] There is also evidence that wage transparency can reduce the gender wage gap. Roussille (2022) show that when Hired.com started pre-filling job searchers' salary ask with the median offer tendered to applicants with similar qualifications, it resulted in an elimination of the wage ask gap with no impact on the number of offers women received or the likelihood that they receive an offer.[135]

Wage transparency can increase job search and job-to-job transitions. Using a change in pay disclosure laws in California, Mas (2017) finds that a 2010 mandate requiring the online posting of salaries for top municipal managers led to a large (about 75 percent) increase in the quits as well as a 7 percent decline in average compensation for top managers.[136] Using a randomized treatment in access to individual peer-income information for employees at the University of California, Card et al. (2012) find that information about peer pay for workers in their pay unit (specific faculty and staff departments) and occupation increased job searching among workers earning below the median income for their occupation and pay unit (but not for those above the median for their occupation and pay unit).[137]

Though wage transparency may increase job searching and transitions, it plausibly does so partly because it can decrease (current) job satisfaction and overall happiness, at least in the short run, for some workers (especially among relatively lower-paid workers). For example, Card et al. (2012) find that workers above the median income for their occupation and pay unit reported no change in job satisfaction, but workers below the median income for their occupation and pay unit reported lower job satisfaction. More broadly, Perez-Truglia (2020) present evidence that a 2001 law enacted in Norway making individuals' tax records publicly accessible online led to a deepening of the rich-poor (self-reported) happiness and life satisfaction gaps.[138] The author argues the widening of the gap was both a consequence of higher reported happiness and satisfaction among higher-income workers and lower reported happiness and satisfaction among lower-income workers, suggesting the results are driven by income-

132 Baker, Michael, Yosh Halberstam, Kory Kroft, Alexandre Mas, and Derek Messacar. 2019. "Pay Transparency and the Gender Gap." *National Bureau of Economic Research* Working Paper 25834.

133 Bennedsen, Morten, Elena Simintzi, Margarita Tsoutsoura, and Daniel Wolfenzon. 2019. "Do Firms Respond to Gender Pay Gap Transparency?" *National Bureau of Economic Research* Working Paper 25435.

134 Sockin, Jason, and Sockin, Michael. 2019. "A Pay Scale of Their Own: Gender Differences in Variable Pay." *SSRN*, December 16, 2019. http://dx.doi.org/10.2139/ssrn.3512598. Note: Sockin and Sockin (2019) lump together salary history bans and wage transparency laws into one indicator variable; therefore, their results do not distinguish between the effect of a salary history ban (discussed later) and a change in a wage transparency law.

135 Roussille, Nina. 2022. "The Central Role of the Ask Gap in Gender Pay Inequality." Working Paper. https://ninaroussille.github.io/files/Roussille_askgap.pdf.

136 Mas, Alexandre. 2017. "Does transparency lead to pay compression?" *Journal of Political Economy* 125 (5): 1683–1721. Note, top managers in a public-sector job are unlikely to be representative of rank-and-file workers both because wage determination in the public sector differs from the private sector and because top-paid managers are more likely to be near the top of the income distribution.

137 Card, David, Alexandre Mas, Enrico Moretti, and Emmanuel Saez. 2012. "Inequality at Work: The Effect of Peer Salaries on Job Satisfaction." *American Economic Review* 102 (6): 2981–3003.

138 Perez-Truglia, Ricardo. 2020. "The effects of income transparency on well-being: Evidence from a natural experiment." *American Economic Review* 110 (4): 1019–54.

comparison effects. To be clear, decreased job and life satisfaction in the short run may well be more than offset in the longer run for workers who are induced to switch jobs to one that pays them better (or provides a more favorable bundle of non-wage amenities) or successfully press for better pay at their current job. Nonetheless, some workers, especially those who feel they cannot switch jobs or renegotiate their income, may be made worse off by wage transparency.[139]

Prohibiting employers from asking applicants' compensation history (salary history bans) can also reduce the employer's information advantage and increase workers' bargaining power.[140] In a survey of new hires, Hall and Krueger (2012) find that "about half of all workers reported that their employers had learned their pay in their earlier jobs before making the offer that led to the current job."[141] Employers may use such pay history to refine their wage offer. If employers do so by offering whatever the employee made in their previous job plus a moderate raise, reliance on pay history can perpetuate existing income inequalities among workers who have historically been paid less (e.g., women and people of color). Barach and Horton (2021) present some empirical evidence that suggests banning the collection of pay history could lead to employers to "take a chance" on lower-waged and less-experienced workers. Using field evidence from an online labor market, they find that employers tended to hire workers with about 13 percent lower past average wages than the control group that had access to compensation history.[142]

Decline in Department of Labor's Labor Market Enforcement Actions

All else equal, a reduction in the probability of being inspected reduces a firm's incentives to comply with the workplace regulations and standards. Likewise, it affects employee bargaining power because the threat of reporting bad behavior is less credible if the enforcement agency lacks the ability to respond quickly and effectively with inspections and sanctions. Conversely, when workers know their employer's bad behavior is likely to be punished, they gain bargaining power against their employer to improve working conditions.

Labor market enforcement action by government agencies can reduce actions of bad actors directly and indirectly. The direct approach is through actual enforcement actions (inspections, penalties, etc.). However, it is far beyond the ability of any agency to fully monitor all covered workplaces within its purview at any given time. Therefore, the Occupational Safety and Health Administration (OSHA) and similar agencies rely primarily on deterrence actions to enforce workplace standards and regulations.

From an employer's perspective, the cost of being caught failing to comply is weighed against the benefits of not complying. Non-compliance risks fines, penalties, and reputational damage. Firms make this tradeoff by evaluating the likelihood and potential costs of being caught against the potential savings associated with non-

139 Both studies reported above involve individual-level income disclosures. It is possible that the (dis)satisfaction effects reported in these studies would be less severe under a policy of only releasing aggregate statistics instead of individualized income disclosures. This could be the case, for example, if decreased job satisfaction and happiness comes not only from knowledge that a worker earns less than their peers, but knowledge that their peers now know they make more than that worker.

140 Several states and localities have enacted laws that require employers to post salary range information for applicants. Some of these localities include Colorado, Connecticut, Nevada, New York City, Rhode Island, and Washington. Exact details on each of these laws vary—some, such as Rhode Island's law, have been passed but not yet gone into effect.

141 Hall, Robert E., and Alan B. Krueger. 2012. "Evidence on the incidence of wage posting, wage bargaining, and on-the-job search." *American Economic Journal: Macroeconomics* 4 (4): 56–67.

142 Barach, Moshe A., and John J. Horton. 2021. "How do employers use compensation history? Evidence from a field experiment." *Journal of Labor Economics* 39 (1): 193–218. Note, Barach and Horton (2021)'s estimates are based on a "partial equilibrium" approach, i.e., their estimates would likely change if all employers were subject to the types of bans the treated group was subjected to in the experiment.

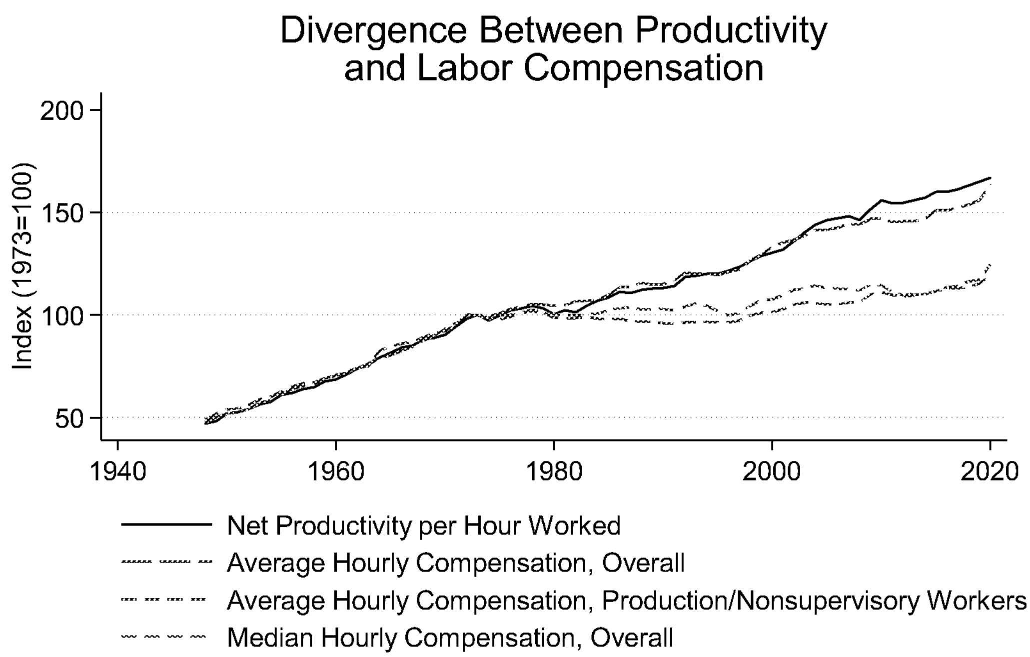
compliance. If firms think the cost or likelihood of being caught in non-compliance is high relative to the benefits, they may comply even absent actual inspections or oversight.

In recent years, the probability of a firm being inspected has decreased sharply. Numerous agencies are responsible for inspections and enforcement actions. However, as an example of how enforcement and inspections have declined, OSHA commenced the largest number of workplace inspections in 1984, at 140,000 inspections. The COVID-19 pandemic sharply reduced the number of inspections conducted in 2020. Even before the pandemic, the number of inspections was much lower than in the 1980s. In 2019, OSHA inspected about 81,000 workplaces, or 40 percent less than it conducted in 1984. From 2013 to 2021, OSHA experienced a 13 percent reduction in Federal enforcement personnel due to reduced budget availability. The workforce is now larger than it was in the mid-1980s, and the nature of workplaces has changed during this time period. With fewer enforcement personnel and a larger workforce, it is increasingly difficult for enforcement actions to reach the same portion of workplaces.

Divergence Between Labor Compensation and Productivity

This section and the next highlights important aggregate trends in wages and labor income. The precise contribution of firm labor market power to these trends remains an open question, but we highlight some of the links established in the literature.

During the first part of the post-World War II period, productivity and average compensation largely moved in tandem. That is, when workers were more productive for each hour they worked, their pay proportionately increased, on average. During this period, gains in productivity appeared to be proportionately dispersed among the compensation distribution.



Source: Economic Policy Institute, BEA, BLS, author's calculations. Productivity is output per hour worked. Net productivity adjusts for depreciation.

However, as the figure above shows, starting around 1980, a divergence in productivity and wages started to emerge, particularly for the lower end of the compensation distribution.[143] This divergence between productivity

143 Note, the figure reports net-productivity rather than gross productivity. Not accounting for accelerated depreciation

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and compensation, particularly among lower-income and non-management workers, has been the subject of considerable debate.[144] Some have noted that part of the divergence may be attributable to differences in how productivity and compensation are adjusted for inflation, possibly due to differences in how the different series account for changes in technological products.[145] However, Stansbury and Summers (2018) argue that some deviation has occurred even after accounting for such measurement issues.[146]

Bivens and Shierholz (2018) argue the difference between typical (median) worker compensation and productivity can be decomposed into two components—declining labor share and income inequality.[147] Using a back-of-the-envelope calculation, they estimate approximately five-sixths of the decline is attributable to rising income inequality and only a sixth attributable to declining overall labor share. The fall in the share of labor, discussed in greater detail in the next section, is partly captured in the above figure as the divergence between average compensation and productivity, especially since 2001. Rising income inequality is reflected in the above figure as the split between mean and median compensation. This divergence suggests that higher-income and supervisory workers have captured a greater share of income over time. A similar schism between compensation of nonsupervisory workers and overall compensation has occurred, likely for similar reasons.

The increase in the share of productivity gains captured by higher-income workers is hotly debated and touches upon the larger debate regarding the causes for the rise in income inequality since the 1980s. In principle, the disparity could be the result of significant increases in productivity among management and stagnation in productivity among lower-income workers. For example, changes in technology could make management substantially more efficient. However, this does not appear to be supported in the literature. Stansbury and Lawrence (2018) argue that a technological change-driven explanation would imply greater divergence during periods of higher productivity gains, however it does not find empirical evidence supporting that implication.

Evidence suggests that declining competition in the labor market coupled with loss of bargaining power among lower-wage workers contributes to income inequality. For example, Furman and Orszag (2018) argue that declining competition for labor has decoupled wage growth from productivity gains as workers face fewer choices and decreased mobility.[148] Consistent with this finding, Benmelech, Bergman, and Kim (2020) use manufacturing plant-level data from 1978 to 2016 to show that wages are noticeably lower in local labor markets that have

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in recent decades tends to overstate the divergence between output per hour worked and compensation. For a critical review, see Lawrence, Robert Z. 2016. "Does Productivity Still Determine Worker Compensation? Domestic and International Evidence." In *The US Labor Market: Questions and Challenges for Public Policy*, edited by Michael R. Strain, 42–62. Washington: American Enterprise Institute." Even here, Lawrence finds declines in labor share post 2000.

144 This debate includes the proper way to account for prices. For details, see discussion in Mishel, Lawrence. 2021. "Growing Inequalities, Reflecting Growing Employer Power, Have Generated a Productivity–Pay Gap Since 1979." *Economic Policy Institute*, September 2, 2021. https://www.epi.org/blog/growing-inequalities-reflecting-growing-employer-power-have-generated-a-productivity-pay-gap-since-1979-productivity-has-grown-3-5-times-as-much-as-pay-for-the-typical-worker/.

145 See Fleck, Susan, John Glaser, and Shawn Sprague. 2011. "The compensation-productivity gap: a visual essay." *U.S. Bureau of Labor Statistics Monthly Labor Review* (January): 57–69. https://www.bls.gov/opub/mlr/2011/01/art3full.pdf. See also, Brill, Michael, Corey Holman, Chris Morris, Ronjoy Raichoudhary, and Noah Yosif. 2017. "Understanding the labor productivity and compensation gap." *U.S. Bureau of Labor Statistics Beyond the Numbers: Productivity* 6 (6): 1–14. https://www.bls.gov/opub/btn/volume-6/pdf/understanding-the-labor-productivity-and-compensation-gap.pdf.

146 Stansbury, Anna, and Lawrence H. Summers. June 2018. "Productivity and Pay: Is the Link Broken?" *Peterson Institute for International Economics* Working Paper 18-5. https://www.piie.com/system/files/documents/wp18-5.pdf.

147 Bivens, Josh, and Heidi Shierholz. 2018. "What labor market changes have generated inequality and wage suppression?" *Economic Policy Institute*, December 12, 2018. https://www.epi.org/publication/what-labor-market-changes-have-generated-inequality-and-wage-suppression-employer-power-is-significant-but-largely-constant-whereas-workers-power-has-been-eroded-by-policy-actions/.

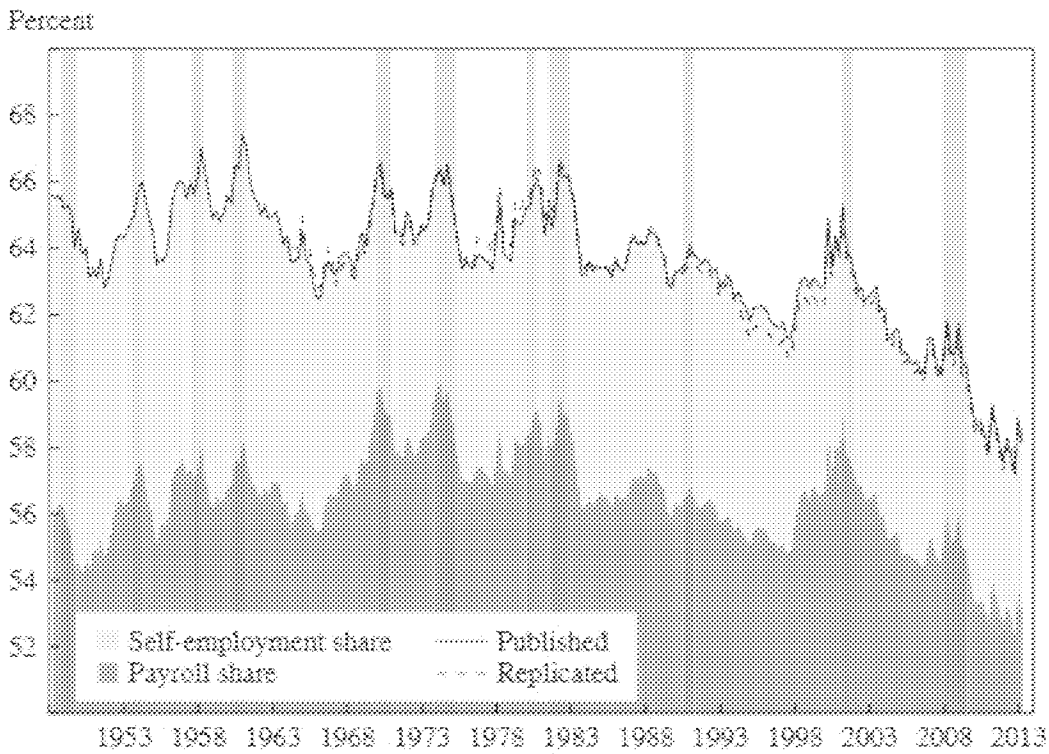
148 Furman, Jason, and Peter Orszag. 2018. "Slower Productivity and Higher Inequality: Are They Related?" *Peterson Institute for International Economics* Working Paper 18-4.

higher employer concentration. Their results also show that this correlation is even more pronounced in areas with low levels of unionization. In a vein like Autor et al. (2020)'s concept of "superstar firms," a 2018 paper by the Organisation for Economic Co-operation and Development (OECD) also noted that the divergence of wages and productivity "at the technological frontier has been accompanied by increasing market shares of frontier firms."[149]

Decline in Labor Share

Economists decompose an economy's aggregate income into that which is attributable to labor (wages and other compensation for work) and capital (i.e., interest, rent, and dividend payments). For decades, labor's share of income was estimated at slightly less than two-thirds.[150] However, starting around the 1980s, this share began to decline not only in the United States, but around the world.[151]

Figure 1. Labor Share, Payroll Share, and Replicated Labor Share in U.S. Nonfarm Business Sector, 1948-2013



Source: Elsby (2016) using data from Bureau of Labor Statistics and Bureau of Economic Analysis.

Numerous theories have been offered for why labor's share of income has declined. Elsby, Hobjin, and Sahin (2016) suggest offshoring of the labor-intensive portion of the United States' supply chain is a leading potential

149 Organisation for Economic Co-operation and Development. 2018. "Decoupling of Wages from Productivity: What Implications for Public Policies?" *OECD Economic Outlook* 2018 (2): 51–65. https://www.oecd.org/economy/decoupling-of-wages-from-productivity/.

150 Kaldor, Nicholas. 1961. "Capital Accumulation and Economic Growth." In *The Theory of Capital*, edited by D.C. Hague, 177–222. London: Palgrave Macmillan.

151 See Karabarbounis, Loukas, and Brent Neiman. 2014. "The global decline of the labor share." *The Quarterly Journal of Economics* 129 (1): 61–103. There is debate whether the share of labor has fallen or the observed changes are due to changes in measurement, such as an increase in self-employment, business owners taking capital instead of labor income, etc. See Autor (2020) for a skeptical overview.

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cause, and note that measurement issues account for a quarter of the observed decline.[152] Karabarbounis and Neiman (2014) suggest rapidly falling prices, especially of capital, may have played a part. Still others, like Weil (2014), suggest fissuring has played a role by decreasing the relative bargaining position of labor. The relative contributions of measurement, technology change, changes in industry composition, and firm wage setting power remain issues of study.

The declining share of labor might also be a result of increasing employer *product* market power. De Loecker, Eeckhout, and Unger (2020) document how markups in product markets have risen nearly three-fold since 1980.[153] They show that this increase primarily came from the very upper end of the markup distribution, i.e., large firms within industries increasing their size, margins, and profitability. Their modeling suggests labor share is inversely proportional to markups, so an increase in markups naturally leads to a decline in the share of labor.[154]

As De Loecker, Eeckhout, and Unger (2020) explain, a natural consequence of increased market power and markups is a decrease in aggregate output.[155] This corresponds with decreases in labor demand, which places downward pressure on wages. The reduction in output also mechanically corresponds to an increase in output price, implying a decrease in real wages (since the same dollars of wages buy fewer goods).

In a related work, Autor et al. (2020) argue that the decline in labor share might be attributable to a rise of what they term "superstar firms" that dominate a particular market and have high markups and low labor share. Using microdata from the U.S. Census Bureau, they document that across many industries, sales are increasingly concentrated among a few firms and industries where this concentration rises most tend to see the largest declines in labor share. The rise of such superstar firms also drives the decline in labor's share of income, even if it does not occur among most firms (which is consistent with the observation of De Loecker, Eeckhout, and Unger (2020) that median markups have not changed much even as the top of the mark-up distribution has increased dramatically).

Autor et al. (2020) argue that the rise of superstar firms could be driven by several factors. They note that the increase could be driven by persistent incumbent dominance. Persistent dominance could be explained by a variety of factors. For example, superstar firms tend to be more productive. To the extent that incumbent firms are more innovative, they could remain dominant because customers prefer their products. Alternatively, persistent dominance can be due to anticompetitive business practices. The authors acknowledge that arguments such as the weakening of antitrust enforcement advocated by Gutierrez and Philippon (2018) could plausibly explain some of their results.[156]

While the increase in market concentration has occurred across numerous industries, the explanation for the rise of superstar firms in each industry need not be the same. The welfare implications of a rise of a superstar firm because of being more innovative compared to one that has engaged in regulatory capture or simply evaded anti-trust enforcement are quite different.

152 Elsby, Michael W.L., Bart Hobijn, and Ayşegül Şahin. 2013. "The Decline of the US Labor Share." *Brookings Papers on Economic Activity* (Fall): 1–63.

153 De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The Rise of Market Power and the Macroeconomic Implications." *The Quarterly Journal of Economics* 135 (2): 561–644.

154 De Loeker, Eeckhout, and Unger (2020) model an economy with imperfect output markets, allowing for firms to extract economic profits. Accordingly, they find that not only does their model imply the share of labor decreases with increased markups, but so does the capital share since profits increase with increased markups.

155 This is a natural consequence because firms can increase their markups/profit by restricting output so long as demand is not perfectly elastic. Intuitively, firms with market power are willing to lose some customers in exchange for charging more per item. Thus, a firm with market power would avoid decreasing output only if consumers did not respond to higher prices.

156 Gutierrez, German, and Thomas Philippon. 2018. "How EU Markets Became More Competitive than US Markets: A Study of Institutional Drift." *SSRN* CEPR Discussion Paper DP12983, June 2018.

Industry Examples

The following subsections highlight the various ways in which developments in example labor markets have harmed workers in their respective occupations or industries. In the hospital and nursing subsection, we show consolidation in the product market (hospitals) can negatively impact workers (nurses). In the agricultural sector, both tacit and explicit collusion between employers has led to highly concentrated markets where workers have little to no bargaining power. In minor league baseball, lobbying efforts, coupled with Supreme Court precedent, have weakened worker pay protections, allowing the monopsonist to extract rents and exert extraordinary control over their worker's mobility.

Hospitals and Nurses

The hospital industry has consolidated in recent decades. Despite a growing population, the number of hospitals decreased from 7,156 hospitals in 1975 to only 6,093 hospitals in 2021.[157] Empirical evidence suggests these consolidations have increased the prices of hospital services with no evidence of quality improvement.[158] Consolidation also impacts the input market. As hospitals consolidate, they gain monopsony power. When the hospital industry consolidates by closing hospitals, it increases monopsony power mechanically by increasing the cost among nurses to finding work elsewhere (i.e., longer commutes). Even when consolidation does not reduce the number of hospitals (e.g., through a merger of hospital systems) it can increase monopsony power by reducing competition among the remaining firms. Krueger (2018) notes that consolidation also increases monopsony power even if hospitals do not have a literal monopoly because fewer players in a market increase the probability of collusion, tacit or otherwise.[159]

Even before the recent wave of hospital consolidation, there was evidence that hospitals exerted considerable monopsony power over healthcare workers. Using changes in wages at Veterans Affairs hospitals, Staiger, Spetz, and Phibbs (2010) found that labor supply to individual hospitals is quite inelastic.[160] Their results imply that a 10 percent decline in the wages of nurses only decrease employment by about 1 percent in the short run, which is a much smaller change in employment than one would expect in a perfectly competitive market where hospitals had little market power. The recent wave of consolidation has likely only increased hospital monopsony power.

Prager and Schmitt (2021), supra, present evidence that certain types of hospital mergers causally decrease wages for certain healthcare workers. They find that mergers that cause the largest increases in hospital concentration (those in the top quartile of increases in the HHI) cause wage growth among skilled workers and nursing and pharmacy workers to slow, particularly among nurses and pharmacy workers. Importantly, they fail to find negative effects on wage growth from smaller mergers (i.e., those that do not increase market concentration much), which suggests the effects they find among larger mergers are caused by the increase in hospital

157 National Center for Health Statistics, Centers for Disease Control and Prevention. 2017. "Hospitals, beds, and occupancy rates, by type of ownership and size of hospital: United States, selected years 1975–2015." Table 89. https://www.cdc.gov/nchs/data/hus/2017/089.pdf; American Hospital Association. 2022. "Fast Facts on U.S. Hospitals, 2022." Last modified January 2022. https://www.aha.org/system/files/media/file/2022/01/fast-facts-on-US-hospitals-2022.pdf. Note: The initial dates are from the Centers for Disease Control and Prevention, while the latest value is from the American Hospital Association. Estimates may not be directly comparable.

158 Beaulieu, Nancy D., Leemore S. Dafny, Bruce E. Landon, and Jesse B. Dalton. 2020. "Changes in Quality of Care after Hospital Mergers and Acquisitions." *New England Journal of Medicine* 382 (January): 51-59. https://www.nejm.org/doi/full/10.1056/NEJMsa1901383.

159 See references in, e.g., Krueger, Alan. 2018. "Reflections on Dwindling Worker Bargaining Power and Monetary Policy." Luncheon address to FRB Kansas City's Jackson Hole Symposium, August 24, 2018. https://www.kansascityfed.org/documents/6984/Lunch_JH2018.pdf.

160 Staiger, Douglas O., Joanne Spetz, and Ciaran S. Phibbs. 2010. "Is there monopsony in the labor market? Evidence from a natural experiment." *Journal of Labor Economics* 28 (2): 211–236.

monopsony power post-merger rather than factors common to most mergers.[161]

Prager and Schmitt (2021) also fail to find that mergers decrease wage growth among hospital workers in jobs requiring little training—which is consistent with these workers having closer employment substitutes outside hospitals, thereby reducing the ability of hospitals to exert monopsonistic power over their wages.[162] The paper does not examine the effects of mergers specifically increasing concentration in the relevant labor markets for these workers in jobs with little hospital-specific skill.

While the antitrust agencies have the authority to challenge hospital mergers,[163] such enforcement efforts are resource-intensive and not always successful.[164] In addition, states may grant Certificates of Public Advantage (COPA), which have the effect of immunizing certain hospital mergers from federal antitrust law.[165] These state COPA laws purport to supplant federal antitrust laws with a regulatory scheme that allows for hospital consolidation even in highly concentrated markets, thereby hindering the ability of the antitrust agencies to challenge anticompetitive mergers. This, in turn, may lead to consolidation among hospital employers that depresses wages and raise health care costs to the public.[166]

For instance, while evaluating a proposed merger of two Texas hospitals that applied for a COPA, FTC staff conducted a labor market analysis and concluded that the merger would likely reduce hospital competition and depress wage growth for registered nurses.[167] The FTC is currently conducting a study of the impact of COPA on competition in healthcare markets, including possible labor monopsony effects.[168]

Agriculture

Food processing is highly concentrated nationally, but its employment is also geographically concentrated. Food processing tends to occur away from urban centers and is more concentrated in low-density areas. For example,

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161 Prager and Schmitt (2021) also show that their results cannot be explained by pre-merger trends—such as poor local economic conditions, which may induce a merger to begin with—explaining why wages decline for nurses and pharmacy workers post-merger.

162 For example, janitorial staff at a hospital may be able to find comparable work outside of a hospital environment, while a nurse has fewer options outside of the hospital industry that would not entail a large pay cut.

163 The federal antimerger law, the Clayton Act, applies to mergers involving non-profits, and the antitrust agencies have opposed several mergers involving non-profit hospitals. See, e.g., Federal Trade Commission v. OSF Healthcare System, 852 F. Supp. 2d 1069, 1081 (N.D. Ill. 2012); United States v. Rockford Memorial Corp., 898 F.2d 1278, 1284-87 (7th Cir. 1990); and Hospital Corp. of America v. Federal Trade Commission, 807 F.2d 1381, 1390-91 (7th Cir. 1986).

164 Federal Trade Commission v. Thomas Jefferson University, No. 20-1113 (E.D. Pa. 2020). https://www.ftc.gov/enforcement/cases-proceedings/181-0128/thomas-jefferson-university-matter.

165 See, e.g., Federal Trade Commission. 2016. "FTC Staff Provides Public Comment and Testimony in Tennessee Opposing Certificate of Public Advantage Application." Press release, November 23, 2016. https://www.ftc.gov/news-events/press-releases/2016/11/ftc-staff-provides-public-comment-testimony-tennessee-opposing.

166 See, e.g., Gaynor, Martin, Kate Ho, and Robert J. Town. 2015. "The Industrial Organization of Health-Care Markets." *Journal of Economic Literature* 53 (2): 236; Gaynor, Martin, and Robert J. Town. 2012. "The Impact of Hospital Consolidation – Update." *Robert Wood Johnson Foundation and the Synthesis Project* Policy Brief 9; and Baicker, Katherine, and Amitabh Chandra. 2006. "The Labor Market Effects of Rising Health Insurance Premiums." *Journal of Labor Economics* 24 (3): 609–634.

167 See Conner, Ian, Andrew Sweeting, and Bilal Sayyed. 2020. "Federal Trade Commission Staff Submission to Texas Health and Human Services Commission Regarding the Certificate of Public Advantage Applications of Hendrick Health System and Shannon Health System." *Federal Trade Commission*, September 11, 2020. https://www.ftc.gov/system/files/documents/advocacy_documents/ftc-staff-comment-texas-health-human-services-commission-regarding-certificate-public-advantage/20100902010119texashhsccopacomment.pdf.

168 See Federal Trade Commission. 2019. "FTC to Study the Impact of COPAs." Press release, October 21, 2019. https://www.ftc.gov/news-events/press-releases/2019/10/ftc-study-impact-copas.

as of the first quarter of 2021, Alabama, Nebraska, Arkansas, and Iowa each employed more animal slaughtering and processing workers than the state of California even though California has approximately three times as many people as those four states combined.[169]

In the agricultural input sector, the use of temporary agricultural workers through the H-2A visa program has received attention because of its increased use in recent years. From 2010 to 2021, the use of this program quadrupled—from about 79,000 jobs certified annually in 2010 to over 317,600 in 2021.[170]

Governed by 8 U.S.C. § 1188 and 20 C.F.R. § 655, Subpart B, the H-2A program is an employer-sponsored temporary visa program that allows agricultural employers to employ nonimmigrant foreign workers to perform agricultural labor or services, as defined by Congress, on a temporary or seasonal basis, typically lasting 10 months or less. While the number of workers that can be admitted and issued an H-2A visa is not capped by Congress, the program does require an employer to offer and provide numerous employment guarantees and protections to H-2A workers and any U.S. workers performing the same work. For example, employers must show that hiring foreign workers will have no "adverse effect" on the wages and working conditions of U.S. workers similarly employed. Employers must provide workers with housing, meals or kitchen facilities for workers to prepare meals, and transportation, and must pay petition and certification fees.[171]

Both employers and workers rights advocates have criticized the H-2A program. Employers have argued the program is too bureaucratic, complex, and expensive. For example, they argue that the requirement that workers obtain visas to enter the United States, which was not a requirement under H-2A's predecessor program, is expensive (about $200 per application). They also often argue that they are required to guarantee a wage rate that is, in their view, artificially high.[172]

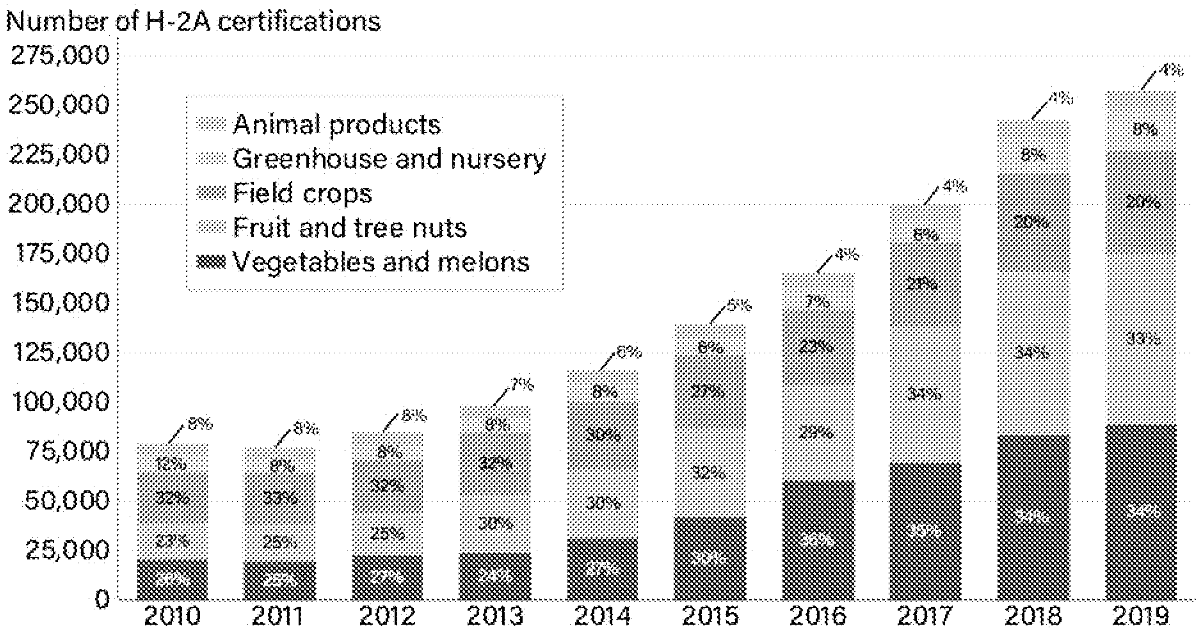
169 Based on Q1 2021 data comparing statewide average employment data for North American Industry Classification System (NAICS) code 3116 in the Quarterly Census of Employment and Wages to 2020 Census population estimates.

170 2010 and 2021 data are from Office of Foreign Labor Certification, U.S. Department of Labor. "Performance Data." Historical Case Disclosure Data for the H-2A Program (file name for FY2021 data: H-2A_Disclosure_Data_FY2021.xlsx; file name for FY2010 data: H-2A_FY2010.xlsx). Last accessed March 4, 2022. https://www.dol.gov/agencies/eta/foreign-labor/performance.

171 Wage and Hour Division. 2010. "Fact Sheet #26: Section H-2A of the Immigration and Nationality Act (INA)." U.S. Department of Labor, February 2010. https://www.dol.gov/agencies/whd/fact-sheets/26-H2A.

172 Per 20 CFR § 655.120, employers must generally offer and pay a wage that is at least the highest of "the AEWR [(Adverse Effect Wage Rate)] the prevailing hourly wage or piece rate, the agreed-upon collective bargaining wage, or the Federal or State minimum wage." The AEWR is set by DOL as a rate that ensures wages of similarly employed U.S. workers are not adversely affected. Typically, the AEWR is the wage that binds, if any.

H-2A certifications increased threefold between 2010 and 2019, growing across product categories



Source: USDA, Economic Research Service using data from U.S. Department of Labor, Office of Foreign Labor Certification.

Workers' rights advocates argue H-2A restricts competition in unfair ways and is rife with employer abuse.[173] Importantly, one way the H-2A program plausibly restricts competition is by allowing employers to coordinate hiring efforts through professional associations, including wage decisions.[174] While such associations allow employers to take advantage of economies of scale in bringing over foreign workers, they also, almost by definition, concentrate labor demand. These associations can account for a large share of hiring by occupation. For example, a recent lawsuit, *Llacua v. Western Range Association*, alleges that two trade associations accounted for the hiring of approximately 91 percent of all shepherds.[175] When in conflict, courts appear to favor the interpretation of immigration law (which is permissive of such monopsony power) over anti-trust law (which, at least in principle, is less permissive of monopsony power) (Riviere 2021, 1581).

173 See, e.g., Farmworker Justice. n.d. "No Way to Treat a Guest: Why the H-2A Agricultural Visa Program Fails U.S. and Foreign Workers." Accessed March 3, 2022. https://www.farmworkerjustice.org/resource/no-way-to-treat-a-guest-why-the-h-2a-agricultural-visa-program-fails-u-s-and-foreign-workers/; National Farm Worker Ministry. n.d. "H-2A Guest Worker Program." Accessed March 3, 2022. https://nfwm.org/farm-workers/farm-worker-issues/h-2a-guest-worker-program/; Lahoud, Raymond G. 2021. "Human Trafficking Indictment Uncovers H-2A Abuses." National Law Review 11 (350); and Mississippi Center for Justice. 2021. "Black Farmworkers Sue Mississippi Farm for Racial Discrimination, Lost Wages, and Abuse of Immigration System to Deny U.S. Workers of Jobs." Press release, September 8, 2021. https://mscenterforjustice.org/black-farmworkers-sue/.

174 See 8 U.S.C. § 1188(d); and Riviere, Candice Yandam. 2021. "The Legal Causes of Labor Market Power in the U.S. Agricultural Sector." *University of Chicago Law Review* 88 (6): 1555–1594. https://lawreview.uchicago.edu/sites/lawreview.uchicago.edu/files/Yandam_LaborMarketPower_88UCLR1555.pdf.

175 Llacua v. Western Range Association, No. 17-1113, 930 F.3d 1161 (10th Cir. 2019). Note, this is an outlier example of concentration, even among H-2A jobs; furthermore, sheep and goat herders account for a small share (about 1 percent) of H-2A certified jobs.

Minor League Baseball

Although it directly impacts a relatively small share of the workforce, minor league baseball provides a useful case study of how a true monopsonist can restrict worker mobility, pay, and even successfully lobby for legislation that further solidifies their dominance over their employees.

In 2014, minor league baseball players brought a class-action lawsuit against Major League Baseball (MLB), the organizer of Minor League Baseball (MiLB), alleging that MiLB's wages and labor practices violate minimum wage laws and overtimes rules set forth in the Fair Labor Standards Act of 1938.[176]The players alleged, among other things, that they routinely worked sixty or more hours in a week but were not paid overtime pay and did not receive pay for certain types of activities that the players considered work-related.

In an apparent attempt to preempt litigation, the MLB lobbied Congress in 2018 to include the Save America's Pastime Act (SAPA) as part of a $1.3 trillion dollar spending package.[177] SAPA explicitly exempts workers in MiLB from minimum wage requirements under FLSA. Furthermore, SAPA purports to be retrospective, applying not only to future MiLB work, but all past work as well. This legislation adds an additional challenge that minor leaguers would have to overcome to prevail on federal employment-law claims.[178]

As of February 2021, MiLB underwent a major reorganization in which 40 minor league teams were cut but wages were raised. Although the percentage raise was significant for many players, absolute salaries remain quite low – players in the highest category are expected to earn approximately $14,700 a season.[179] Players in the lowest tier experienced the largest relative benefit from this restructuring, with their minimum salary increasing by over 70 percent relative to 2019, up to $10,500.[180] MLB also restructured teams to be more geographic-centric, which will hopefully reduce travel burdens.[181]

The MLB still exerts tremendous monopsony power over minor league baseball players, due in part to an "aberrational," judicially-created doctrine that the Supreme Court has called "something that looks a bit like an antitrust exemption for professional baseball," which was first announced by the Supreme Court in 1922.[182] While Congress passed legislation in 1998 to clarify that conduct related to major league baseball players is subject to antitrust laws, the legislation did not address minor leaguers' employment.[183] There are pending lawsuits addressing whether the MLB so-called baseball exemption continues to apply to restraints on minor league players in light of subsequent developments undermining its foundations.

Minor league players are typically unable to receive unemployment insurance (UI) benefits during the off-season

176 Complaint, *Senne et al. v. Office of the Commissioner of Baseball, et al.*, No. 3:14-cv-00608-JCS (N.D. Cal. Feb. 7, 2014), ECF No. 1.

177 It is unclear how much Congressional support SAPA had, as the two-page bill was included on page 1,967 of the 2,323-page spending package.

178 Pannullo, Robert. 2020. "The Struggle for Labor Equality in Minor League Baseball: Exploring Unionization." *American Bar Association Journal of Labor & Employment* 34 (3): 443–476.

179 Blum, Ronald. 2021. "Minor Leagues Get a Reset with 120-Team Regional Alignment." *AP News*, February 12, 2021. https://apnews.com/article/sports-mlb-baseball-rob-manfred-coronavirus-pandemic-f8a0f1c09161e83db87bca8e78219725. A typical season lasts about five months.

180 These reflect minimum salaries. Actual compensation, including bonuses, may be significantly larger, especially for higher-tiered players. Furthermore, these values reflect first-time contracts—second contracts tend to be significantly larger. For more, see Fagan, Ryan. 2021. "Even after overdue salary bump, baseball's minor leaguers still paid far below NBA, NHL counterparts." *Sporting News*, February 12, 2021. https://www.sportingnews.com/us/mlb/news/even-after-overdue-salary-bump-baseballs-minor-leaguers-still-paid-far-below-nba-nhl-counterparts/1gpql94asy7a10uo5nvc3yp4k.

181 Janes, Chelsea. 2021. "MLB overhauled the minors this season. Some advocates say it hasn't been enough." *Washington Post*, July 16, 2021. https://www.washingtonpost.com/sports/2021/07/16/minor-league-baseball-advocacy-mlb-overhaul/.

182 National Collegiate Athletic Association v. Alston, 141 S. Ct. 2141, 2159 (2021).

183 Curt Flood Act of 1998, Pub. L. No. 105-297. 15 U.S.C. Sec. 26b.

because they are classified as seasonal workers. The logic in denying seasonal workers UI benefits is that the end of their employment is predictable and therefore they could plan other job opportunities around the seasonality of their work. Still, some have argued this is unfair, especially since the start of the COVID-19 pandemic.[184]

Ordinarily collective action through unionization can provide a counterbalance to employer power. While major league baseball players have been unionized for decades by the Major League Baseball Players Association, minor league players have no union. A primary reason for union hesitation among the players is a fear of retaliation by MLB (see Pannullo 2020). Additional factors include high turnover of MiLB players, geographic dispersion of MiLB players, and low salaries that discourage existing unions from expanding their membership to include MiLB players.[185]

184 Baccellieri, Emma. 2020. "Minor Leaguers and the Fight to Claim Unemployment." *Sports Illustrated*, June 12, 2020. https://www.si.com/mlb/2020/06/12/minor-league-baseball-players-unemployment.

185 Broshuis, Garrett R. 2013. "Touching Baseball's Untouchables: The Effects of Collective Bargaining on Minor League Baseball Players." *Harvard Journal of Sports & Entertainment* 4 (June): 51–103. https://harvardjsel.com/wp-content/uploads/sites/9/2013/06/Broshius.pdf.

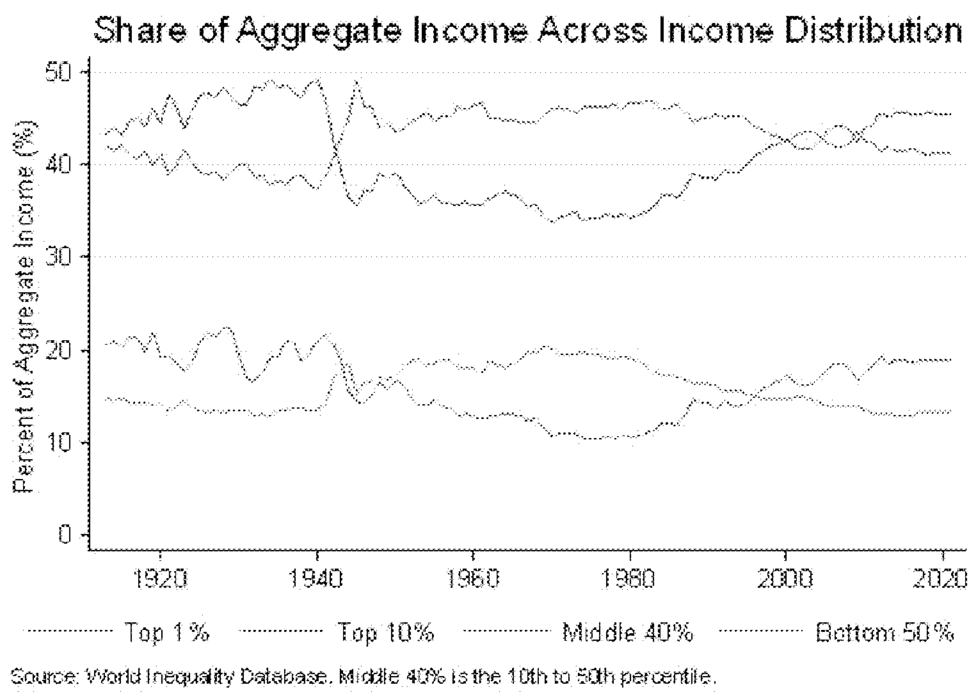
IMPLICATIONS BEYOND THE LABOR MARKET

A decline in the competitiveness of labor markets lowers worker wages, may decouple wages from productivity, and likely diminishes the relative share of income that goes to workers. Moreover, actions of the firm such as requiring workers to sign non-compete agreements and limiting workers' access to information diminishes worker mobility, implicitly reducing workers' bargaining power relative to employers.

These direct effects on workers' wages, employment, and mobility have important broader negative impacts on the economy. Higher inequality likely makes it more difficult to sustain sufficient aggregate demand. Lower wages disproportionately impact women and workers of color. A large pool of low-priced labor likely weakens firm incentives to invest and improve productivity, while lower mobility diminishes productivity growth by hindering the reallocation of labor to more productive firms and industries. Non-compete agreements may prevent workers from starting their own businesses and discourage innovation. In short, a growing body of evidence suggests that declining labor market competition may stymie the drivers of U.S. economic growth. To be clear, labor market competition is unlikely to be the only or even primary driver of broader macroeconomic trends, but, on the margin, likely contributes and exacerbates some drivers of slower economic growth.

Rising Inequality, Low Interest Rate, and Aggregate Demand

Over the last several decades, income inequality has risen sharply. As documented by Piketty and Saez (2003) and Saez and Zucman (2020), the share of income earned by the top 1 percent has risen since 1980 and now approaches levels last seen in the 1920s; the top 1 percent collects nearly one-fifth of national income.[186] Average income growth from 1980 of the top 1 percent has surged at rates well above 2 percent per year, while overall income growth averages just 1.4 percent over the same period and is lower for the bottom 85 percent of the U.S. income distribution.



186 Piketty, Thomas, and Emmanuel Saez. 2003. "Income Inequality in the United States, 1913–1998." *The Quarterly Journal of Economics* 118 (1): 1–41; and Saez, Emmanuel, and Gabriel Zucman. 2020. "The Rise of Income and Wealth Inequality in America: Evidence from Distributional Macroeconomic Accounts." *Journal of Economic Perspectives* 34 (4): 3–26.

Income inequality has several causes; however, inequality in income from labor and slow growth in wages plays an important role in driving overall income inequality. To control for demographic changes that possibly increases in income volatility, Guvenen et al. (2021) measure inequality in male lifetime earnings using Social Security data.[187] They find that median lifetime earnings fell 10–19 percent for men entering the workforce in 1983 versus men entering the workforce in 1957. Put another way, the realized lifetime real income for the typical male worker in 1983 was substantially lower than their 1957 counterparts. For cohorts entering after 1983 (and still working), they find evidence of continued stagnation of income for the median worker and increasing inequality in lifetime earnings. Similar stagnation in lifetime earnings has also been observed for currently working cohorts (gains for female cohorts prior to 1983 came off a very low base).

A growing body of research suggests that rising income inequality carries important implications for the macroeconomy. The secular stagnation hypothesis posits that the natural rate of interest, the interest rate needed to achieve full employment, has been falling for several decades. Several distinct drivers of low interest rates have been suggested, including rising income inequality.[188] As the secular stagnation literature emphasizes, an excessively low natural rate of interest complicates the conduct of monetary policy. In recessions, interest rates must fall to stimulate the investment and maintain aggregate demand. Central banks are generally unable to lower short-term interest rates below zero; when interest rates need to be kept low to sustain full employment, monetary policy can face an inability to lower interest rates sufficiently in recessions before hitting the zero-lower bound.

Since 2000, the zero lower bound has posed an increasing challenge for using monetary policy to boost demand. In the wake of the 2008 financial crisis, the Federal Reserve, European Central Bank, and other central banks had to keep interest rates close to zero for an unprecedented duration to sustain an economic recovery. Prior to the 2020 pandemic, U.S. short-term rates were just 2 percent and, absent an unprecedented increase in fiscal support, appeared insufficient to offset the pandemic's effect on aggregate demand.

While the precise contribution of lower labor market competition to income inequality is open to debate, the rise in inequality has been stark and pronounced. And the link to low interest rates has increasing support as a theoretical mechanism and in empirical evidence. To the extent that increases in labor market competition boost wages and labor share, this would likely imply raised demand and a higher natural rate of interest.

Impacts on Women and Workers of Color

Evidence suggests that the burden of lower worker power fall disproportionately on women and workers of color. Rosenfeld and Kleykamp (2012) estimate that declines in private-sector unionization have contributed to substantial racial wage gaps—up to 30 percent for Black women.[189] Lower rates of unionization may have also left women workers and workers of color more vulnerable to wage theft and other workplace violations (i.e., Bernhardt et al. 2009).[190] Continued labor market power can allow racial discrimination in hiring to persist; Quillian et al.

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187 Guvenen, Fatih, Greg Kaplan, Jae Song, and Justin Weidner. 2021. "Lifetime Earnings in the United States over Six Decades." *Becker Friedman Institute* Working Paper 2021-60. https://bfi.uchicago.edu/working-paper/2021-60/.

188 Eggertsson and Mehrotra (2014) show how low interest rates could contribute to low or negative natural rates of interest. Eggertsson, Gauti B., and Neil R. Mehrotra. 2014. "A Model of Secular Stagnation." *National Bureau of Economic Research* Working Paper 20574. Mian, Sufi, and Straub (2020) show how bequest motives may explain why wealthier households save a larger portion of their income; therefore, higher income inequality lowers the natural rate. Mian, Atif, Ludwig Straub, and Amir Sufi. 2021. "Indebted Demand." *The Quarterly Journal of Economics* 136 (4): 2243–2307.

189 Rosenfeld, Jake, and Meredith Kleykamp. 2012. "Organized Labor and Racial Wage Inequality in the United States." *American Journal of Sociology* 117 (5): 1460–1502.

190 Bernhardt, Annette, Ruth Milkman, Nik Theodore, Douglas Heckathorn, Mirabai Auer, James DeFilippis, Ana Luz González, et al. 2009. "Broken Laws, Unprotected Workers: Violations of Employment and Labor Laws in America's Cities." Center for Urban Economic Development, National Employment Law Project, and UCLA Institute for Research on Labor and

(2017), for example, find no evidence of decreasing discrimination in hiring against Black workers.[191]

More generally, lower wage growth and a declining labor share have had a greater effect on lower- and middle-income workers than high wage workers and business owners. As a result, wage stagnation has a disproportionate impact on women and workers of color who, in any case, receive lower wages than men or white workers. Gould (2020, Table 3) shows that stagnation of wage growth among the lower 90 percent of earners was accompanied by increased within-group wage inequality—wages grew by less within each decile for Black workers.[192] Hispanic workers fared somewhat better, with their wages rising relative to white workers between 2000 and 2019 but earned generally 25 percent less than white workers at every decile.

While the gender wage gap continues to narrow, progress in closing the difference in men and women's earnings has slowed in the last two decades compared to the 1980s and 1990s when female educational attainment improved and wages in male dominated industries faced weaker labor demand. In 2020, the typical woman working full-time, year-round earned only 83 cents for every dollar earned by the typical man working full-time, year-round. And the wage gap is much wider for most women of color, contributing significantly to economic inequality.[193] For example, Hispanic women earned 57 cents and Black women earned 64 cents compared to every dollar earned by white, non-Hispanic men in 2020.[194] The persistent gender wage gap is also tied to increased wage dispersion as wage growth has slowed for all lower and middle wage workers, relative to top earners.

Wage stagnation also has a disproportionate negative impact for minorities because these households derive less income from other sources. Black and Hispanic workers have a much lower homeownership rate than whites—approximately 40 percent and 50 percent respectively compared to over 70 percent for whites. The dramatic wage stagnation after 2000 coincided with the 2008 housing bust that decimated the largest source of wealth for most Americans. The wave of foreclosures in the wake of the 2008 housing crises dramatically lowered minority homeownership rates, meaning that these households are unlikely to have benefited from the recent increase in house prices. Reduced frequency of homeownership leads to less generational wealth, increasing the dependency of Black and Hispanic Americans on wage growth to build income and wealth.

Declining Business Investment and Productivity Growth

Lower employment is a consequence of decreased labor market competition, as discussed in the section on monopsonistic theory. So long as capital and labor are complementary, which they often are, lower employment also results in lower investment. Considered in a different way, the exercise of monopsony power behaves as if it were a tax on labor as an input. This 'tax' leads to lower production and deadweight loss, and therefore lower investment in capital.

More generally, business investment has been relatively weak in recent decades despite a rising profit share and repeated reductions in corporate taxation. Weak wage growth and a large pool of low-priced labor likely dampen business incentives to invest in tangible capital. In a tight labor market, firms would need to find ways to utilize scarce labor more productively and would likely boost investment to make workers more productive.

Employment. https://www.nelp.org/wp-content/uploads/2015/03/BrokenLawsReport2009.pdf.

191 Quillian, Lincoln, Devah Pager, Ole Hexel, and Arnfinn H. Midtbøen. 2017. "Meta-analysis of field experiments shows no change in racial discrimination in hiring over time." *Proceedings of the National Academy of Sciences* 114 (41): 10870–10875.

192 Gould, Elise. 2020. "State of Working America Wages 2019." *Economic Policy Institute*, February 20, 2020. https://www.epi.org/publication/swa-wages-2019/.

193 Bleiweis, Robin, Jocelyn Frye, and Rose Khattar. 2021. "Women of Color and the Wage Gap." *Center for American Progress*, November 17, 2021. https://www.americanprogress.org/article/women-of-color-and-the-wage-gap/.

194 U.S. Bureau of Labor Statistics. 2021. "Highlights of Women's Earnings in 2020." *BLS Reports* Report 1094. https://www.bls.gov/opub/reports/womens-earnings/2020/home.htm. See also, Bleiweis, Frye, and Khattar (2021).

Monopsony power can also decrease aggregate productivity, provided that firm-level productivity and market power are correlated, as Mertens (2020) argues.[195] Given that correlation, higher-productivity firms reduce their output disproportionately, relative to lower-productivity firms. Naturally, this increases low-productivity firms' share of national production, resulting in decreased aggregate productivity. As Gutierrez and Philippon (2017, 2020) show, the largest firms, which hold an increasing share of employment and sales, have stagnant investment rates, and a decreasing relative contribution to aggregate productivity growth.[196] Thus, the largest firms are becoming more profitable while investing less and generating less productivity growth. To be clear, a causal link from lower labor market competition to decreases in investment and productivity growth has yet to be established. However, increased concentration does appear to be a driver of weak investment, low productivity growth, and high profits and likely contributes to lower labor market competition.

Firm Formation and Innovation

Business formation and exits have both declined since the early 1980s. As a share of the total number of firms, about 20 percent fewer firms were created in 2018, compared with 1982.[197] Over the same period, the share of payroll attributable to firms less than 5 years old with at least one employee on payroll declined by almost a quarter, from 38 percent in 1982 to about 29 percent in 2018 (Congressional Budget Office 2020). Accordingly, firms today are, on average, older than they were in the past.

The decline in business formation is likely driven by several factors. In their 2020 analysis, the Congressional Budget Office (CBO) pointed to the aging domestic workforce as a key factor, though they note immigration (especially high skilled immigration) has offset some of that decline. Cyclical factors (e.g., recessions) play a role as well. Moreover, the shift in economic activity to larger and older firms may not necessarily have a negative impact on welfare (Autor et al. 2020).

However, the decline in business formation is potentially troubling because it could suggest that dominant firms maintain their lead status by erecting barriers to entry rather than maintaining their dominance through innovation. Gutierrez and Philippon (2019) provide evidence to this effect, showing that firm entry has become less sensitive to market valuations over time (i.e., high profits do not lead to increasing firm entry). The authors provide evidence that large firms have been able to erect hurdles to the entry of new firms.[198]

As Aghion, Akcigit, and Howitt (2015) note, more intense competition tends to encourage innovation in "frontier" firms (firms that are in sectors at the cutting-edge of technology), whereas barriers to entry become increasingly detrimental to growth as a country approaches the technological frontier.[199] Using a structural model, Akcigit and Ates (2019) find that declines in firm entry and worker reallocation towards new firms reflects slower knowledge

195 Mertens, Matthias. 2020. "Labour Market Power and Between-Firm Wage (In)Equality." *Leibniz Institute for Economic Research Halle* Discussion paper 13/2020.

196 Gutierrez, German, and Thomas Philippon. 2017. "Declining Competition and Investment in the U.S." *National Bureau of Economic Research* Working Paper 23583; and Gutierrez, German, and Thomas Philippon. 2020. "Some Facts about Dominant Firms." *National Bureau of Economic Research* Working Paper 27985.

197 Congressional Budget Office. 2020. "Federal Policies in Response to Declining Entrepreneurship." December 2020. https://www.cbo.gov/system/files/2020-12/56906-entrepreneurship.pdf.

198 Gutierrez, German, and Thomas Philippon. 2019. "The Failure of Free Entry." *National Bureau of Economic Research* Working Paper 26001.

199 Aghion, Philippe, Ufuk Akcigit, and Peter Howitt. 2015. "Lessons from Schumpeterian Growth Theory." *American Economic Review* 105 (5): 94–99. Intuitively, the reason why barriers to entry discourage growth in a "Schumpeterian growth" model is because new firms innovate to gain market share, thus threatening incumbent firms and forcing them to innovate as well. With barriers to entry, incumbent firms face fewer incentives to innovate and, instead, extract monopoly rents from their dominant position.

diffusion from frontier firms to new entrants,[200] which could reflect impediments to worker mobility.

. The use of non-compete clauses, especially among internet-based commerce firms, could be discouraging firm entry (Congressional Budget Office 2020). For instance, Marx, Strumsky, and Fleming (2009) finds that an unintended change in Michigan law boosting the enforceability of non-compete agreements led to sharp declines in the mobility of patent holders.[201] Restricting the use of non-compete agreements and other restrictive employment agreements could allow for new firm creation, as workers at incumbent firms could leave the firm to pursue new ideas, thereby forcing incumbent firms to innovate to stay dominant.

Declining Worker Mobility and Productivity Growth via Reallocation

The reallocation of workers across firms is a key driver of firm-level and overall productivity growth. Workers quit their jobs and search for new jobs that better fit their skills, while firms are seeking the right mix of workers to improve their productivity. A large economic literature provides both theoretical and empirical evidence for linking the pace of reallocation to aggregate productivity growth.

Pre-pandemic, job reallocation (the creation and destruction of new jobs) and worker reallocation (workers quitting and finding new work) have been declining steadily over several decades.[202] Worker mobility across space has also declined over time.[203] Like the literature on declining firm entry rates, demographic factors or the changing industrial composition of the economy may explain some of the decline in reallocation and spatial mobility. Akicigit and Ates (2019) link declining job and worker reallocation to slower diffusion of ideas from market leading firms to new entrants. Davis and Haltiwanger (2014) argue that factors inhibiting competition, including specifically occupational licensing, may account for declining labor market dynamism.[204] They find a particularly large decrease in worker reallocation among younger workers and workers with lower educational attainment. Kleiner and Krueger (2013) also document increasing prevalence of occupational licensing that may inhibit worker switching across occupations and space. It is also likely that restrictive employment agreements are contributing to lower levels of worker mobility.

200 Akcigit, Ufuk, and Sina T. Ates. 2019. "Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory." *National Bureau of Economic Research* Working Paper 25755.

201 Marx, Matt, Deborah Strumsky, and Lee Fleming. 2009. "Mobility, Skills, and the Michigan Non-Compete Experiment." *Management Science* 55 (6): 875–889.

202 Decker, Haltiwanger, Jarmin and Miranda (2020) and Haltiwanger (2015) summarize the decline in job and worker reallocation since 1980 and its implications for aggregate productivity growth. Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda. 2020. "Changing Business Dynamism and Productivity: Shocks versus Responsiveness." *American Economic Review* 110 (12): 3952–3990; and Haltiwanger, John. 2015. "Job Creation, Job Destruction, and Productivity Growth: The Role of Young Businesses." *Annual Review of Economics* 7 (August): 341–358.

203 Molloy, Raven, Christopher L. Smith, and Abigail K. Wozniak. 2014. "Declining Migration within the U.S.: The Role of the Labor Market." *National Bureau of Economic Research* Working Paper 20065.

204 Davis, Steven J., and John Haltiwanger. 2014. "Labor Market Fluidity and Economic Performance." *National Bureau of Economic Research* Working Paper 20479.

BIDEN ADMINISTRATION PROPOSALS TO PROMOTE LABOR MARKET COMPETITION

As this report makes clear, insufficient labor market competition has harmful effects on workers and the economy and worsens inequality. In response, President Biden issued an Executive Order on Promoting Competition in the American Economy, establishing a whole-of-government effort to reduce the trend of corporate consolidation and improve competition for American workers, consumers, and small businesses. Pursuant to this Order, federal agencies are acting to develop and implement several proposals to promote competition in labor markets. Robust labor market competition requires careful maintenance and is a critical component to promoting economic growth, spurring innovation, and addressing economic inequality. The following initiatives and policy proposals will bolster labor market competition and increase workers' bargaining power.

Proposed Legislation

The President is calling on Congress to pass proposed legislation that would promote increased competition in labor markets by improving workers' ability to negotiate fair wages and a larger share of income. The legislative proposals discussed below would greatly enhance the negotiating power of workers and mitigate the decline in wages that have contributed to a historic rise in income inequality. By restoring balance to the labor market, the proposed legislation would force employers to compete for workers on a level playing field and ensure that workers get their fair share of the value they create.

Increasing union representation can help increase workers bargaining power and raise wages. Recent survey data suggests that roughly half of nonunion workers would vote for a union if they had the opportunity and the percent of Americans who support labor unions stands at 68 percent, the highest since the early 2000s. Despite this support, private-sector unionization stood at just 6.1 percent in 2021.[205] Current labor law is a major obstacle to unionization as workers face multiple hurdles and employers can intimidate and coerce workers, often incurring no penalties for retaliatory actions against workers or interfering with union election processes.

Protecting and Expanding Workers' Right to Organize: The President and Vice-President have called for Congress to pass the Richard L. Trumka Protecting the Right to Organize Act and the Public Service Freedom to Negotiate Act (PSFNA). These bills would ensure more private- and public-sector workers nationwide have a genuine right to organize and bargain collectively. They would also promote racial income equality by shrinking the Black-white wage gap by boosting worker power. The PSFNA would establish minimum standards for collective bargaining by state and local public service workers; these workers lack formal bargaining in half of the states. President Biden and Vice-President Harris also have endorsed several proposals to expand labor rights to more workers (especially workers of color, women, and immigrants) and help counteract monopsony power in sectors not covered by current labor laws. These include guaranteeing labor rights to farmworkers and domestic workers—two segments of the labor force excluded from the protections of the National Labor Relations Act. For example, the National Domestic Workers' Bill of Rights, which Vice President Harris championed in the Senate and the President has endorsed, would expand federal labor law to domestic workers and create a new wage and standards board for regulating working conditions in the sector.

Raising the Federal Minimum Wage: Raising the minimum wage is a straightforward approach to addressing lower wages under monopsony and can help increase employment. However, the federal minimum wage has remained unchanged since 2009,[206] during which time inflation has eroded the purchasing power of the minimum wage.

205 Bureau of Labor Statistics. 2022. "Union Members Summary." Last modified January 20, 2022. https://www.bls.gov/news.release/union2.nr0.htm.

206 The Economic Policy Institute. 2022. "Minimum Wage Tracker." Last modified January 1, 2022. https://www.epi.org/

Workers in states that have not enacted meaningful increases to the state's minimum wage have been left behind as a result of this decline in purchasing power. President Biden has endorsed raising the federal minimum wage to $15 per hour, indexing future increases of the federal minimum wage, phasing out the tipped minimum wage, and eliminating the subminimum wage for teen workers and workers with disabilities.[207] Raising the federal minimum wage would give nearly 32 million Americans a raise and would boost the purchasing power of low-income families allowing them the opportunity to more fully participate in the growing economy.[208]

Restricting the Use of Mandatory Arbitration and Class Action Waivers: Legislation restricting the use of mandatory arbitration and limits on class actions would prevent employers from forcing employees into forfeiting the opportunity to have their case heard by a judge and jury or their right to join together in a collective action to remedy collective harms. Congress has already taken a first step to limit the enforceability of mandatory arbitration and class waivers by enacting the Ending Forced Arbitration of Sexual Assault and Sexual Harassment Act of 2021, which makes mandatory arbitration and class waiver provisions invalid and unenforceable in court for claims involving sexual assault or harassment. President Biden signed the Ending Forced Arbitration of Sexual Assault and Sexual Harassment Act into law on March 3, 2022.

Mandatory arbitration agreements undercut labor market competition by effectively reducing wages paid to employees by arbitrarily imposing liability costs on employees. When workers are unable to negotiate for higher pay and are forced into arbitration, their real wage rate is too low, preventing the labor market from functioning efficiently. President Biden supports banning employers' use of forced arbitration and class waivers to restore worker rights and impose accountability on employers. Mandatory arbitration and class action waivers can distort labor markets by insulating businesses from the full costs of doing business, primarily by limiting liability and public exposure. DOL is prioritizing enforcement against employers that employ mandatory arbitration or class action waivers as a check against employers' abuse of their market power. Recently, a court held that DOL's ability to enforce laws through the courts was not limited by an arbitration agreement between an employee and their employer.[209]

Criminal Antitrust Anti-Retaliation Act of 2019: OSHA's Whistleblower Protection Program is implementing the Criminal Antitrust Anti-Retaliation Act of 2019 (CAARA). The law provides legal protections for employees who blow the whistle on criminal antitrust violations by prohibiting employers from taking punitive actions against whistleblowers for reporting these violations to their employer or assisting a federal government investigation into a criminal antitrust violation. In addition to OSHA's ongoing enforcement and outreach, OSHA plans to publish in May 2022 an Interim Final Rule promulgating procedures for the handling and investigation of CAARA claims.

Antitrust Enforcement

In recent years, the federal antitrust agencies—the Antitrust Division of DOJ ("DOJ" or "Antitrust Division") and FTC—have prioritized competition enforcement and advocacy in labor markets by increasing their institutional capacity for labor market enforcement, bringing expertise in-house, and reviewing and, where appropriate, reforming enforcement practices agency-wide to respond to the challenges raised by the modern economy. By leveraging their civil, research, and rulemaking powers, the Antitrust Division and FTC have a significant role to play in improving competitive conditions in labor markets by, among other things, reducing concentration

minimum-wage-tracker/.

207 House Committee on Education and Labor. n.d. "Raise the Wage Fact Sheet." Accessed March 3, 2022. https://edlabor.house.gov/download/hr-603-raise-the-wage-act-fact-sheet

208 Ibid.

209 Department of Labor. 2021. "Court Affirms US Department of Labor's Independent Authority to Recover Unpaid Wages, Damages in Court for Employees Who Signed Private Arbitration Agreements." News release, September 23, 2021. https://www.dol.gov/newsroom/releases/sol/sol20210923

and disciplining the use and abuse of restrictive employment agreements, including non-compete agreements, forced arbitration clauses, non-solicitation clauses, and other covenants that exacerbate bargaining asymmetries between workers and employers. Both agencies can clarify public guidance to bolster labor market competition, and challenge civil action mergers and unilateral conduct that harm labor markets. The Antitrust Division has sole jurisdiction to criminally prosecute conspiracies and other collusive agreements among employers.

DOJ Criminal Enforcement in Labor Markets

The Antitrust Division has both civil and criminal enforcement authority. In particular, the Antitrust Division prosecutes criminal conspiracies among competitors, including price fixing, bid rigging, and market allocation. This includes agreements among employers to fix wages, which is price fixing in the labor market, and to allocate labor markets using no-poach agreements.[210] In recent years, the Antitrust Division's criminal program has become increasingly central to its efforts to prosecute and deter wage fixing and no-poach agreements, which steal from workers by depriving them of competitive wages, benefits, and other terms of employment.

Beginning in October 2016, the Antitrust Division made a series of public statements indicating that it intended to criminally prosecute "naked" no-poach and wage-fixing conspiracies.[211] That decision followed from longstanding caselaw establishing that these restraints are equivalent to agreements to fix product prices and allocate product markets—conduct that the Antitrust Division has prosecuted for over 100 years. Indeed, the Supreme Court held long ago that the Sherman Act applies equally to all industries and markets, including labor markets, and the conduct of employers is not entitled to special treatment under U.S. antitrust laws, except in the context of legitimate collective bargaining and other labor union activities.[212] The Antitrust Division views rooting out criminal collusion in labor markets as part of its overall mission to deter, detect, and prosecute cartels.

Over the last several years, the Division has continued to invest substantial time and resources to ensure vigorous competition in labor markets. These efforts, which included substantial public engagement and awareness building, led to a notable increase in the number of citizens who reported alleged conspiracies to the Antitrust Division since October 2016. Over the same period, labor market investigations have comprised a growing portion of the Antitrust Division's docket. Between December 2020 and December 2021, the Antitrust Division charged five criminal cases for alleged collusion in labor markets, including four companies and nine individuals.[213] In January 2022, the Antitrust Division filed a further indictment charging four managers of home health care agencies with participating in a conspiracy to suppress the wages and restrict the job mobility of essential workers during the COVID-19 pandemic.[214] The Antitrust Division's criminal enforcement program has led to the prosecution of long-running employer conspiracies against workers in multiple critical markets, including physical therapy, dialysis nursing, home health care services, and aerospace, with more active labor market investigations currently underway.

Remedial measures are another important tool for the Antitrust Division in protecting competition for workers. In particular, the Division may require provisions regarding labor market competition in corporate criminal

210 See United States v. Knorr-Bremse AG, et al., 18-747 (D.D.C.) (April 4, 2018).

211 Renata B. Hesse. "The Measure of Success: Criminal Antitrust Enforcement During the Obama Administration." Remarks at the 26th Annual Golden State Antitrust, UCL and Privacy Law Institute, November 3, 2016. Department of Justice, https://www.justice.gov/opa/speech/file/908301/download.

212 See Final Judgement, United Mine Workers of Am. v. Pennington, 381 U.S. 676, 85 S. Ct. 1607, 14 L. Ed. 2d 626 (1965).

213 Indictment, United States v. Jindal, No. 4:20-cr-00358 (E.D. Tex. Dec. 9, 2020); Indictment, United States v. Surgical Care Affiliates, LLC, No. 3-21-CR0011-L (N.D. Tex. Jan. 5, 2021); Indictment, United States v. Hee et al., No. 2:21-cr-00098-RFB-BNW (D. Nev. Mar. 30, 2021); Indictment, United States v. DaVita, Inc., No. 21-cr-00229-RBJ (D. Colo. July 14, 2021); and Indictment, United States v. Patel et al., No. 3:21-cr-00220-VAB (D. CT. Dec. 15, 2021). See also United States v. Jindal, No. 4:20-cr-00358 (E.D. Tex. Nov. 29, 2021) (denying defendants' motion to dismiss).

214 Indictment, United States v. Manahe et al., No. 22-cr-0013-JAW (D. Maine, January 27, 2022).

resolutions where the charged conduct restrained or impacted worker mobility.

At its core, the Antitrust Division is committed to prosecuting naked conspiracies in labor markets because they rob workers of competitive wages, benefits, and other terms of employment. They also deprive honest businesses of talented workers who contribute substantially to the products and services on which Americans rely. While this work is principally criminal enforcement, it also reflects a commitment to ensuring free market competition for workers' labor.

DOJ and FTC Civil Enforcement and Competition Advocacy

Civil enforcement represents an equally important, and in some respects even more expansive, toolset for enforcers to improve labor market competitiveness because it reaches a broader swath of competition concerns. The antitrust agencies are currently committed to using their civil authorities to detect, investigate, and challenge anticompetitive non-compete agreements, mergers that create or enhance monopsony power in labor markets, the anticompetitive exercise of monopsony power, and information sharing by employers. To aid these efforts, the Antitrust Division and the FTC have issued public guidance that reflects the importance the U.S. antitrust agencies place on protecting competition in labor markets and may update that guidance to reflect improved information about market dynamics and competition analysis.

As part of their respective competition advocacy programs, the Antitrust Division and FTC have recently filed statements of interest and amicus briefs in multiple significant labor market matters. In March 2021, the agencies filed an amicus brief in *NCAA v. Alston* on behalf of college athletes.[215] A unanimous Supreme Court decided in the athletes' favor that colleges could not agree to limit the education-related benefits offered to students, rejecting an argument that these limits preserved amateurism and widened consumer choice by providing a unique product—amateur college sports as distinct from professional sports.[216] Before *NCAA v. Alston*, the Antitrust Division filed a number of amicus briefs and statements of interest urging courts to uphold the per se rule for naked restraints in labor markets, including *In re Railway Employee No-Poach Antitrust Litigation*, *Seaman v. Duke University*, and *Aya v. AMN Healthcare*.[217] In April 2020, the agencies warned employers, staffing companies, and recruiters that despite the need for unprecedented cooperation among public and private organizations to respond to the spread of COVID-19, the agencies would be closely monitoring labor markets to challenge any anticompetitive conduct that harms workers.[218] In February 2022, the DOJ filed an amicus brief before the National Labor Relations Board (NLRB) highlighting the potential impacts of misclassification on labor market competition and supporting the NLRB in its efforts to create a "sound, up-to-date, consistent approach to worker classification that adequately protects workers' rights to organize." DOJ also filed a statement of interest in a private non-compete case in Nevada arguing that competition-suppressing agreements should be subject to strict antitrust scrutiny, especially where (as alleged in the pleadings) the effect of enforcement would be to prevent health care workers from earning a living or serving patients in their home metro area.[219]

215 Brief for the United States as Amicus Curiae Supporting Respondents, *NCAA v. Alston*, 141 S. Ct. 2141, 210 L. Ed. 2d 314 (2021).

216 Final Judgement, *National Collegiate Athletic Association v. Alston*, 141 S. Ct. 2141, 210 L. Ed. 2d 314 (2021).

217 Statement of Interest of the United States, In Re: Railway Industry Employee No-Poach Antitrust Litigation, 395 F. Supp. 3d 464 (W.D. Pa. 2019) (No. 2:18-mc-00798-JFC); Statement of Interest of the United States, Seaman v. Duke Univ., No. 1:15-CV-462, 2019 WL 4674758 (M.D.N.C. 2019); and Brief of Amicus United States of America in Support of Neither Party, Aya Healthcare Serv., Inc. v. AMN Healthcare, Inc. et al., 9 F.4th 1102 (9th Cir. 2021).

218 Department of Justice and Federal Trade Commission. 2020. "Joint Antitrust Statement Regarding COVID-19 and Competition in Labor Markets." Press release, April 2020.

219 Brief of the United States Department of Justice as Amicus Curiae at 9, *The Atlanta Opera, Inc.*, 10-RC-276292 (NLRB February 10, 2022); and Statement of Interest of the United States, Beck v. Pickert Medical Group, P.C., No. CV21-02092 (Nev. 2nd. Jud. Dist. Ct. February 28, 2022).

Consistent with the DOJ's recent filing before the NLRB, the agencies intend to continue to seek opportunities to provide guidance to courts in cases that implicate the proper scope of the antitrust exemptions that protect labor organizing. Although multiple federal statutes exempt labor organizing from the antitrust laws' purview, federal courts have held that these protections apply only to workers formally classified as employees.[220] As a result, collective action and organizing by certain workers—including those who have the terms of their work dictated by a firm yet are classified as non-employees—may be susceptible to an antitrust lawsuit, including by private parties. When appropriate, the agencies may consider providing guidance on how they interpret the antitrust laws with respect to organizing activities that are exempt from antitrust prosecution.

In addition to these case-specific interventions, the Antitrust Division and FTC are considering updates to their guidance, particularly in areas where changes in the economy may have led some people to incorrectly interpret the agencies' past guidance in ways that are insufficiently protective of workers' access to robust, competitive labor markets. Currently, the Antitrust Division and FTC are working to revise their joint Antitrust Guidance for Human Resource Professionals, which was published in 2016 to help human resources professionals "implement safeguards to prevent inappropriate discussions or agreements with other firms" (Department of Justice Antitrust Division and Federal Trade Commission 2016). This guidance was primarily intended to educate and inform business and human resource professionals about how the antitrust laws apply to hiring and compensation decisions. However, due to recent case experience and research that have shown that information-sharing, particularly in concentrated markets, may have potentially significant anticompetitive effects even when purportedly anonymized, the agencies are in the process of updating this guidance to reflect this new information.[221]

Similarly, the agencies believe that the principles for addressing and preventing concentration embodied in the Horizontal Merger Guidelines apply just as much to labor markets as to any other market. In January 2022, the agencies announced a joint effort to solicit updated public input on the Horizontal Merger Guidelines in order to better detect and prevent illegal, anticompetitive deals in today's modern markets, including labor markets.[222] As part of this effort, some commentators have suggested that the applicability of antitrust principles to labor markets should be more explicitly articulated, and the Antitrust Division and FTC are considering this feedback as they review the Horizontal Merger Guidelines. The agencies are also considering commentators' contention that labor markets may become subject to market power at more moderate levels of employer concentration than product markets, due to the employee-side search frictions that characterize labor markets.

The agencies' work on the Horizontal Merger Guidelines will reflect lessons learned from multiple recent merger cases brought by the agencies that implicated the rights of workers. In November 2021, the Antitrust Division filed to stop a proposed merger between Penguin Random House and Simon & Schuster, two large book publishers, primarily on the grounds that it would harm competition for author labor by giving Penguin Random House, currently the largest of the five remaining traditional publishers, outsized control over publication opportunities and lead to reduced pay for authors.[223] In 2017, the D.C. Circuit affirmed the Division's successful challenge of

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220 15 U.S.C. § 17.; L.A. Meat & Provision Drivers Union, Local 626 v. United States, 371 U.S. 94 (1962); United States v. Women's Sportswear Mfg. Ass'n, 336 U.S. 460 (1949); and Columbia River Packers Ass'n v. Hinton, 315 U.S. 143 (1942).

221 See Complaint, Kraft Heinz Foods Co. v. Amick Farms et al., 20-cv-02278 (N.D. Ill. April 11, 2020) (alleging use of 3rd party agricultural information to "enabling Defendants to monitor what each producer was doing in furtherance of … concerted action among the producers."); and Complaint, U.S. v. Sinclair Broadcast Group, Inc., 18-cv-02609 (D.D.C. November 13, 2018) (alleging "information exchanges [that] distorted the normal price-setting mechanism in the spot advertising market and harmed the competitive process.").

222 Federal Trade Commission. 2022. "Federal Trade Commission and Justice Department Seek to Strengthen Enforcement Against Illegal Mergers." Press release, January 18, 2022. https://www.ftc.gov/news-events/press-releases/2022/01/ftc-and-justice-department-seek-to-strengthen-enforcement-against-illegal-mergers.

223 Complaint, United States v. Bertelsmann SE & Co. et al., 16-cv-02886 (D.D.C. November 21, 2021).

Anthem's proposed acquisition of Cigna, a merger of two significant health insurers that would have reduced reimbursement rates for physicians in multiple markets.[224] In that case, the labor harms were alleged alongside product-market harms, underscoring the notion that antitrust enforcement in labor markets can complement enforcement in product markets. Similarly, two private duty nursing providers called off their proposed merger after the FTC raised concerns about potential effects on competition for nursing services and for employing nurses in local markets across the country.[225]

The agencies also will be attentive to the over-broad use of non-compete clauses against employees in conjunction with mergers, as they can raise barriers to entry in markets where workers are a key input to effective competition. For instance, the FTC recently issued an order against a national chain of dialysis clinics to remedy concerns that its acquisition of additional clinics would reduce competition for outpatient dialysis services in Provo, Utah. In addition to requiring divestitures, the FTC's order prohibits the company from entering or enforcing any non-compete agreements with physicians that would restrict their ability to work for a competitor.[226]

Research and Rulemaking

To establish a foundation for future efforts to protect workers, in December 2021, the Antitrust Division and FTC concluded a two-day public workshop on the subject, entitled "Making Competition Work: Promoting Competition in Labor Markets." The workshop convened lawyers, economists, academics, policy experts, labor groups, and workers, and covered recent developments at the intersection of antitrust and labor, as well as implications for efforts to protect and empower workers through competition enforcement and rulemaking. Feedback and comments obtained from the workshop will be incorporated into the agencies' efforts going forward, including with respect to enforcement, guidelines, and rulemaking affecting labor market antitrust enforcement.

In addition to its authority to bring law suits to prohibit unfair methods of competition, the FTC Act gives the FTC authority to identify and prohibit unfair methods of competition through a rulemaking process that follows the Administrative Procedure Act.[227] The FTC held a workshop in 2020 to discuss how it could use its rulemaking authority to address the overuse of non-compete clauses, and several organizations, including a group of 19 state attorneys general, have petitioned the agency to initiate a rulemaking to limit their use.[228] As suggested in the President's Executive Order on Competition, the Chair of the FTC is encouraged to work with the rest of the Commission to exercise the FTC's statutory rulemaking authority to curtail the use of non-compete clauses and other clauses that may unfairly limit worker mobility.

Supporting Occupational Licensing Reform Efforts

To better understand and reduce the impacts of inefficient licensing requirements, the DOL has previously awarded several grants for states to review the licensing requirements for various occupations and reduce the

224 Complaint, United States et al. v. Anthem Inc. et al., 16-cv-01493 (D.D.C. July 21, 2016).

225 Federal Trade Commission. 2022. "Statement of FTC Chairman Regarding Announcement that Aveanna Healthcare and Maxim Healthcare Services Terminated Their Acquisition Agreement." Press release, January 30, 2020. https://www.ftc.gov/news-events/press-releases/2020/01/statement-ftc-chairman-regarding-announcement-aveanna-healthcare.

226 In re DaVita Inc., FTC File No. 21-10013 (October 25, 2021).

227 National Petroleum Refiners Association v. FTC, 482 F.2d 672 (D.C. Cir. 1973).

228 Federal Trade Commission. 2020. "Workshop: Non-Competes in the Workplace: Examining Antitrust and Consumer Protection Issues" News release, January 9, 2020. https://www.ftc.gov/news-events/events-calendar/non-competes-workplace-examining-antitrust-consumer-protection-issues; See Petition for Rulemaking to Prohibit Worker Non-Compete Clauses by Open Markets Institute, et al., https://static1.squarespace.com/static/5e449c8c3ef68d752f3e70dc/t/5eaa04862ff52116d1dd04c1/1588200595775/Petition-for-Rulemaking-to-Prohibit-Worker-Non-Compete-Clauses.pdf; and Office of the Attorney General of the District of Columbia. 2020. "Public Comments of 19 State Attorneys General." March 2020. https://oag.dc.gov/sites/default/files/2020-03/FTC-Comment-Letter-Non-Compete-Clauses-Workplace.pdf.

barriers to entry into excessively consolidated occupations. These grants were also intended to improve labor mobility in licensed occupations with an emphasis on transitioning veterans to licensed civilian occupations and improving portability for military spouses. These investments yielded tangible results including a searchable database of licensing requirements for 48 occupations,[229] and comprehensive reports on the barriers facing vulnerable communities, including veterans and military spouses, justice-involved individuals, and immigrants with work authorization. These grants laid a foundation from which to launch future reform efforts.

Several of these grants have since expired; two grants, one to the National Council of State Legislatures and one to the Council of State Governments are set to expire in 2022. These grants have helped reveal the substantial difficulties inherent to occupational licensing reform. Many states are reticent to attempt reforms and, even when reforms are considered, they are occupation specific and not as broad as might be ideal.[230] The federal government, in support of this Executive Order, will do more to support state efforts at reforms, including elevating and disseminating best practices from current and past demonstration investments, directing support for workers pursuing occupational licensing, exploring funding and support that has been shown to be effective in the adoption of meaningful license reforms, and improving labor market competition by increasing worker mobility.

The Department of Defense also has a grant to the Council of State Governments to work with states to promote and expand participation in interstate licensing compacts, another major way to increase license portability. The Licensure Portability Grant Program of the Office for the Advancement of Telehealth, Health Resources & Services Administration, has also supported the development of many interstate licensure portability compacts.[231] A silver lining of the COVID-19 pandemic is that the need to rapidly and safely deploy health care professionals to areas in need has greatly increased support for compacts and other portability initiatives. These initiatives can streamline the process of authorizing practitioners to work across state lines, potentially increasing the supply of practitioners in underserved areas and increasing competition. Accordingly, this is an opportune time for federal support of portability measures, especially in health care.

Administrative Actions to Bolster Worker Power

The Administration has taken steps to increase the level of competition in labor markets, raise the minimum wage for workers involved in federal contracting, protect workers' rights, and incentivize employers not to unlawfully shift costs onto workers and thereby gain unfair competitive benefits. Taken together, these changes will make labor markets more competitive, improve worker negotiating positions, protect workers' rights, and address discriminatory wages.

On April 27, 2021, President Biden issued an Executive Order setting the minimum wage at $15 per hour by January 30, 2022, for workers participating on or in connection with federal contracts. This order also continues the practice

229 National Conference of State Legislatures. 2020. "The National Occupational Licensing Database." Last modified March 24, 2020. https://www.ncsl.org/research/labor-and-employment/occupational-licensing-statute-database.aspx

230 Nunn, Ryan. 2019. "Eliminating the Anti-Competitive Effects of Occupational Licensing." *Brookings*, January 17, 2019. https://www.brookings.edu/opinions/eliminating-the-anti-competitive-effects-of-occupational-licensing/; Avery, Beth, Maurice Emsellem, and Phil Hernandez. 2018. "Fair Change Licensing Reform Takes Hold in the States." *National Employment Law Project*, May 15, 2018. https://www.nelp.org/publication/fair-chance-licensing-reform-takes-hold-states/; Kleiner, Morris. 2015. "Reforming Occupational Licensing Policies." *The Hamilton Project, Brookings* Discussion Paper 2015-01. https://www.brookings.edu/wp-content/uploads/2016/06/THP_KleinerDiscPaper_final.pdf; and The Captured Economy. n.d. "Occupational Licensing." Last accessed March 3, 2022. https://capturedeconomy.com/occupational-licensing/.

231 Health Resources and Services Administration. 2021. "Office for the Advancement of Telehealth." Last modified December 2021. https://www.hrsa.gov/rural-health/telehealth; and Goldman, Karen A.. 2018. "Policy Perspectives: Options to Enhance Occupational License Portability." Federal Trade Commission, September 2018. https://www.ftc.gov/system/files/documents/reports/options-enhance-occupational-license-portability/license_portability_policy_paper_0.pdf.

of indexing the contractor minimum wage to inflation, phases out the tipped contractor minimum wage by 2024, ensures at least a $15 minimum wage for federal contract workers with disabilities, and restores protections to guides operating on federal land.

On January 21, 2022, Secretary Walsh also announced the DOL's Good Jobs Initiative (GJI), which provides critical information to workers, employers, and government agencies as they work to improve job quality and create access to good jobs free from discrimination and harassment for all working people. The efforts undertaken through the GJI, together with the other actions advancing the recommendations of the White House Task Force on Worker Organizing and Empowerment, will help strengthen workers' bargaining power and help mitigate employer power in labor markets. The GJI focuses on empowering working people by:

1) Providing easily accessible information to workers about their rights including the right to bargain collectively and form a union;
2) Engaging employer stakeholders as partners in improving job quality and workforce pathways to good jobs; and
3) Supporting partnerships across federal agencies and providing technical assistance on grants, contracts, and other investments designed to improve job quality.

The GJI coordinates work done since the beginning of this administration (and often for decades before) under one umbrella to promote good jobs and, consistent with applicable legal authority, ensure that other agencies continue to have access to these resources in building job quality standards and equitable pathways to those jobs.

The DOL also announced a final rule, which came into effect on December 28, 2021, placing reasonable limits on when an employer can take credit against its minimum wage obligations, such as when a tipped employee performs non-tipped work. This rule enhances the DOL Wage and Hour Division's capacity to protect the rights afforded to these essential workers, more than half of whom are women, people of color, and immigrants.

With regard to independent contractors, the DOL has withdrawn the Trump Administration's "Independent Contractor Rule" that inappropriately narrowed the interpretation of the Fair Labor Standards Act's coverage and thereby risked excluding workers from minimum wage and overtime protections.[232] As discussed in detail above, misclassification of employees as independent contractors often leaves employees without the benefits and labor protections they are afforded by labor, employment, and tax laws. The National Economic Council has created an interagency policy committee to address worker misclassification (including through legislative solutions) as endorsed in the President's FY 2022 budget proposal. The Wage and Hour Division also has conducted agency-wide training to support efforts to combat misclassification and is partnering with local, state, and federal agencies to identify and address misclassification. Additionally, DOL will conduct research into the impacts related to re-classification on workers, an important step in understanding how misclassification affects the competitiveness of the labor market.

Worker Organizing and Empowerment Task Force

Empowering workers to advocate for better wages and working conditions, as well as enabling them to collectively bargain without fear of reprisal, is a worker-first approach to promoting labor market competition.

Recognizing this, President Biden issued an Executive Order creating the Task Force on Worker Organizing and Empowerment. This Executive Order established the first-ever all-of-government approach to finding ways that executive branch agencies can use their existing authority to facilitate worker organizing and collective

232 Wage and Hour Division. 2021. "Independent Contractor Status under the Fair Labor Standards Act: Withdrawal." Department of Labor, May 6, 2021. https://www.regulations.gov/document/WHD-2020-0007-4330.

bargaining.[233] The Task Force report to the President was published February 7, 2022, and set forth nearly 70 recommended actions for agencies to take to reduce barriers and promote worker organizing among both private and public sector employees.[234] The President approved the recommendations, and the report was released to the public in February 2022. When implemented, the Task Force recommendations should help increase worker organizing and collective bargaining, which will give workers more collective power vis-à-vis their employers.

Reducing Job Lock and Boosting Mobility

As already noted, factors that limit worker mobility diminish bargaining power and limit the effective degree of labor market competition. The ability of workers to quit their job for a better option, move to new locations, or start their own business can strengthen their bargaining power and support fair wages, while fears about inadequate access to childcare and housing can tie workers to locations, boosting the effective monopsony power of firms. Therefore, factors that help workers move freely can be an important component of raising labor market competition and boosting wages.

For many workers, health insurance is provided through their employer, playing an important role in any decision to switch employers or start a business. The passage of the Affordable Care Act in 2010 greatly strengthened the individual health insurance market, providing subsidies for households to purchase insurance and guarantee standards of coverage. By eliminating job lock associated with health insurance, the CBO projected at the time that some workers would start their own businesses or leave their jobs, leading to increased wages.

The American Rescue Plan provided larger tax credits for those purchasing coverage on health insurance exchanges. The Administration proposals—if adopted—would extend these credits to make coverage more affordable and accessible, thus further reducing job lock due to insurance coverage and strengthening worker mobility and bargaining power.

Worker mobility can also be enhanced by better access to childcare and lower housing costs. Though many non-economic factors impact households' decisions of where to live, these decisions are impacted by the general cost of housing and, for parents of young children, proximity to their parents or other caregivers. Investments in affordable housing, childcare support, and universal pre-kindergarten provision can mitigate job lock for housing cost or childcare reasons. These effects are likely to be modest and difficult to quantify, but, even on the margin, higher worker mobility improves bargaining power and raises wages.

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233 The White House. 2021. "Fact Sheet: Executive Order Establishing the White House Task Force on Worker Organizing and Empowerment." News release, April 26, 2021. https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/26/fact-sheet-executive-order-establishing-the-white-house-task-force-on-worker-organizing-and-empowerment/.

234 The White House. 2022. "White House Task Force on Worker Organizing and Empowerment." Report to the President, February 7, 2022. https://www.whitehouse.gov/briefing-room/statements-releases/2022/02/07/white-house-task-force-on-worker-organizing-and-empowerment-report/#:~:text=Today%2C%20the%20Task%20Force%20on,and%20collective%20bargaining%20for%20federal.

Entrepreneurship through Employee Mobility, Innovation, and Growth

Salomé Baslandze

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Abstract: Firm-level productivity differences are big and largely ascribed to ex-ante heterogeneity in the entrepreneurs' growth potential at birth. Where do these ex-ante differences come from, and what can the policy do to encourage the entry of high-growth entrepreneurs? I study empirically and by means of a quantitative growth model the spinout firms: the firms founded by former employees of the incumbent firms. By focusing on innovating spinouts identified through the inventor mobility in the patent data, I document that spinout entrants significantly outperform regular entrants throughout their life. Firms with a bigger technological lead spawn more successful spinouts. Building on these observations, I build a structural model of innovation and firm dynamics, where firm heterogeneity arises from endogenous decisions of innovation workers to become entrepreneurs and create spinouts. The spinout dynamics affect productivity growth through four main channels: direct entry, incumbents' disincentive effect, knowledge diffusion, and the firm composition channel. Growth decompositions show that accounting for spinout dynamics is quantitatively important for our understanding of the growth process. I analyze the role of noncompete laws affecting employee entrepreneurship for aggregate innovation and growth.

JEL classification: O30, O43

Key words: innovation, spinouts, entrepreneurship, noncompete laws, firm dynamics

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Please address questions regarding content to Salomé Baslandze, Research Department, Federal Reserve Bank of Atlanta, salome.baslandze@atl.frb.org.

1 Introduction

Firm-level productivity differences are large, with only a handful of high-growth firms accounting for the majority of innovation and productivity growth in the U.S. (Bartelsman and Doms, 2000; Haltiwanger, Hurst, Miranda and Schoar, 2017). Although recent empirical evidence suggests that these firm-level differences are largely ascribed to ex-ante heterogeneity in growth profiles at birth (Pugsley, Sedlacek and Sterk, 2018), the models of growth and firm dynamics are mute on sources of this ex-ante heterogeneity. Where do these ex-ante differences come from? In this paper, I focus on a specific type of ex-ante heterogeneity often overlooked in the growth and firm dynamics literature – the heterogeneity coming from the prior employment background of firms' founders. I show both empirically and by means of a quantitative growth model that *spinout* entrants – the firms established by former employees of incumbent firms – play an important role in innovation, growth, and firm dynamics. By better understanding aggregate implications of spinout dynamics, we can better design policies aimed at fostering high-growth entrepreneurship, innovation, and growth.

Spinout entrants often turn into exceptionally productive high-growth firms, often reshaping the whole industries (Klepper, 2002; Klepper and Sleeper, 2005; Franco and Filson, 2006). Examples of transformational spinout firms are ample. Figure 1 shows a small part of a large spinout family tree spawned by Bell Telephone Laboratories established in 1952. After the stages of prolific spawning of new and exceptionally productive spinouts, the semiconductor industry grew, achieving sales of more than $400 billion today. A more recent example is Zoom Video Communications – entrepreneurial venture by a former head of Cisco Webex engineering team, that swept the crowded communications market and saw unprecedented growth during the 2020 pandemic.

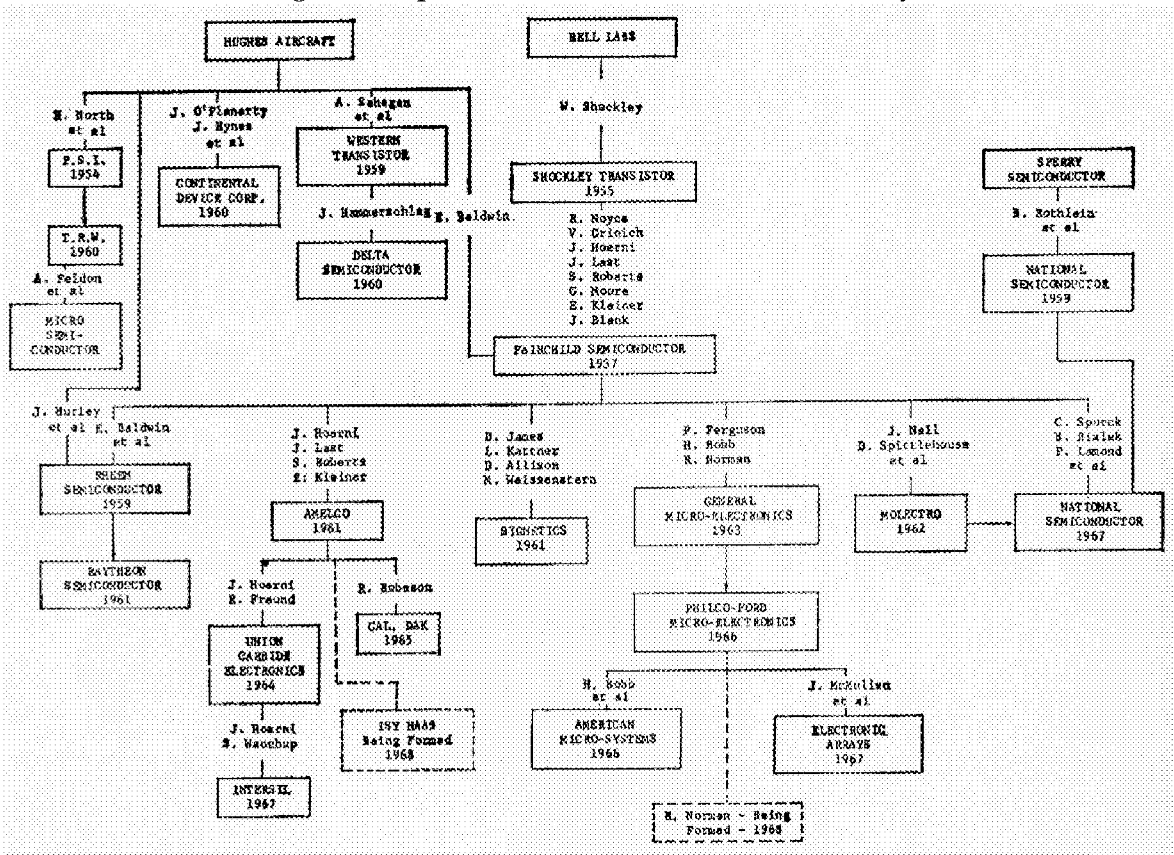
Although spinout entrants may be more productive, the process of spinout creation entails a tension between incumbents and the employees leaving their firms to pursue their own entrepreneurial ventures.[1] Indeed, employers are increasingly concerned about the harm to their businesses caused by employee mobility, as manifested by existing employer protection regulations such as non-compete policies and the continual demands to strengthen them.[2] If this tension results in incumbents' lower appropriability of innovation investments, their innovation incentives will decline.

To understand this interaction between spinout entry and incumbents' innovation incen-

[1]See Pakes and Nitzan (1983) and Anton and Yao (1995) for the first theoretical treatments of this tension between inventors and employers.

[2]There is an ongoing debate around non-compete regulations limiting the employee mobility, as reflected by a recent House Bill requesting to strengthen existing regulations (Bill S.998, "An Act relative to the judicial enforcement of noncompetition agreements", 2017-2018 legislative session) and a later bill which prohibits the use of non-compete agreements (S.2614 - Workforce Mobility Act of 2019, introduced in the 116th Congress, 2019-2020.).

Figure 1: Spinouts in Semiconductor Industry



Source: "Semiconductor Family Tree", *Electronic News*, July 8, 1968.

tives and the quantitative implications for aggregate innovation and growth, I build a rich structural model of innovation and firm dynamics, where firm heterogeneity arises from endogenous decisions of innovation workers to become entrepreneurs and create spinouts. With this model at hand, I quantitatively analyze the role of non-compete laws (NCL) hindering the employee mobility, in promoting aggregate innovation and growth.

I begin the study by empirically analyzing spinout firms and by providing motivating stylized facts that guide the modeling. To identify the innovating spinout firms, I use a detailed datasets on patents and the universe of patenting firms from NBER-USPTO and combine it with the disambiguated inventors dataset from Harvard Patent Network Dataverse project (Lai, D'Amour, Yu, Sun and Fleming, 2011) to track individual inventor across firms. A firm is defined as a spinout if at least one inventor on a patent application filed in the firm's entry year has worked in a different firm before that year. A sizable share of innovating firms enter as spinouts: 30% of the patenting entrants, the total of 17,295 firms.

The advantage of using patents and inventors dataset to analyze spinout firms is twofold. First, the model in this paper focuses on the innovating firms that drive technological progress in the economy; and patents have been widely used in the literature as the main systematic metric to identify the innovating firms (Griliches, 1981; Hall, Thoma and Torrisi, 2007; Kogan, Papanikolaou, Seru and Stoffman, 2017; Argente, Baslandze, Hanley and Moreira, 2020). Second, the data on rich patent characteristics offers the possibility to proxy for individual's innovation quality as well as quality and technological capabilities of a firm –objects that are hard to get with other datasets and that are crucial to discipline the model. On the downside, this approach provides just a proxy for spinout firms and can potentially mismeasure the true number of spinouts. In addition, inventors moving to the new firms may not formally be the entrepreneurs or owners of the spinout firms. In this sense, our empirical definition of spinouts is broader than the definition of spinouts just based on owners and in addition includes the founding team of the early inventors in the firm. This approach is similar to Choi, Goldschlag, Haltiwanger and Kim (2019) who show that not just the founders but the early employees play a key role in the firms' subsequent performance.

I provide a set of validation exercises for the identification of spinouts in the data. First, I compare the external sample of 40 spinout firms reported in Franco and Filson (2006) against my data and show that for the overlapping sample of the patenting firms, the spinout status is correctly identified. Second, I show that the main data moments and stylized facts that emerge from this data on innovating firms are very consistent with the existing empirical studies in other settings (described in detail in the literature review). Hence, main motivating empirical facts that emerge from my data are general and support well the broad modeling assumptions.

The two main stylized facts emerge from the data. First, spinout entrants significantly outperform regular entrant firms throughout their entire life. Spinouts file more and higher-quality patents, live longer, grow faster, are more R&D-intensive, and generate more patents per R&D dollars spent. Second, firms with a bigger technological lead spawn more successful spinouts. Specifically, spinout firms are more innovative on many dimensions if their parent firms are in the top percentiles of patent quality distribution in their technology classes. Hence, the data supports a sort of learning or inheritance, whereby working in the leading firm is linked with the probability of creating a high-quality spinout firm.

In the second part of the paper, I build a general equilibrium endogenous growth model consistent with main empirical facts from the data. Building on the Schumpeterian growth models (Aghion and Howitt, 1992; Acemoglu and Akcigit, 2012; Peters, 2020) with entry and incumbents' innovation, I introduce new features of individuals occupation choice, spinout entry, and non-compete restrictions.

In the model, skilled people are allocated into three groups: entrepreneurs running the firms, R&D managers conducting innovation in the firms, and outsiders contemplating entry into one of the above occupations. Motivated by the first empirical fact that spinouts significantly outperform regular entrant firms throughout their entire life, I introduce heterogeneous firm-specific quality types determined at entry. Some firms enter as high-type, while others enter as low-type firms. Entrepreneurs decide on innovation efforts that push the technology frontier forward. The heterogeneous quality types of entrepreneurs' firms determine their efficiency in the innovation process. By innovating, the firms move up the technological ladder and increase their market power. R&D managers bargain with entrepreneurs over their wages and, while being on the job, can search for ideas and outside opportunities to create their own spinout firms. Importantly, building on the second fact that better firms spawn better spinouts, R&D managers learn on the job – more technologically advanced is their employer, higher are the chances that their start-up quality is of a better type.[3] Hence, an important new characteristic of this model is that the entry distribution of the firm quality types is endogenous through the feedback from the incumbents' type distribution, their innovation decisions, and the employees' entrepreneurial choices. Finally, the model builds in the non-compete restrictions that influence the expected costs of spinout formation by employees.

The four main channels through which spinout formation affects aggregate innovation and growth operate in the model. First is the *direct entry effect* on growth, where more entry positively contributes to innovation and hence growth. Second is the *disincentive effect* of spinout formation on incumbent firms' innovation incentives: similar to the standard appropriability problem, ex-ante incentives of incumbents are lower if they expect their R&D managers to leave and compete with their firms. The third channel is *knowledge diffusion*, whereby spinout entry increases the share of high-type firms in the market. Finally, spinout entry also influences the *firm composition*: more spinout entry promotes more competition and, as a result, increases aggregate innovation efforts.

In the last part of the paper, I quantitatively evaluate these various channels to understand the role of spinout formation for aggregate innovation and growth and to conduct counterfactual policy analysis. By calibrating the model to match growth, innovation, entry, and workforce composition targets in the data, I first demonstrate that the model is successful at replicating several important non-targeted data moments. The model quantitatively matches the observed declining spinout entry rate in the states with weaker non-compete restrictions, as well as facts on competition, spinout separation, and the dynamics of wages with firm size.

Using growth decompositions, I first show that accounting for spinout dynamics is quantitatively important for our understanding of growth process. The static growth decomposition shows that 7% of productivity growth is accounted for by direct entry by spinouts. However, the dynamic growth decomposition that takes into account both entry

[3]This setup also does not rule out the possibility of positive sorting between the firms and the R&D managers. More discussion is in Section 3.

and an increase in the share of high-quality entrepreneurs through knowledge diffusion increases the contribution of spinouts to aggregate productivity growth. If the spinout dynamics are important for growth, could we design the policies to foster spinout entrepreneurship without distorting the incumbents' innovation incentives?

To understand which policies can boost high-quality entrepreneurship and productivity growth, I provide a set of counterfactual policy experiments. The first policy explores the current non-compete laws in the U.S. Recent evidence indicates that the use of non-compete agreements– the clauses in employee contracts that prohibit the employees from working for a competitor or forming a new firm, has been on the rise, with an estimated 28%-47% of private-sector workers being subject to non-compete restrictions.[4] The high-skill employees are even more likely to be subject to non-competes, indicating that for inventors, these restrictions on establishing own ventures might be even more severe.[5] Currently, the U.S. states vary widely in the degree of enforcement of (Garmaise, 2011; Starr, 2019). For example, in California, the courts would not enforce any non-compete agreements, while in Florida they would enforce them in many cases. The policy analysis shows that abolishing non-compete restrictions is welfare-maximizing, mainly due to resulting higher aggregate innovate and growth. State-by-state, the gains from the optimal policy adoption have a wide range, reaching the maximum gain of 11 basis points in growth rate in Florida, Montana, and Tennessee.

Related Literature This paper is related to the large literature on firm dynamics, entrepreneurship, innovation, and growth. Motivated by a large productivity dispersion across firms (Dunne et al., 1988), the basic models of firm dynamics have long incorporated exogenous productivity differences across firms (Hopenhayn, 1992; Hopenhayn and Rogerson, 1993). Although underlying productivity differences between firms have been empirically shown to be largely driven by initial differences at entry (Abbring and Campbell, 2005; Guzman and Stern, 2015; Belenzon et al., 2017; Pugsley et al., 2018; Azoulay et al., 2020; Guzman and Stern, n.d.), the firm dynamics models are mostly silent about the sources of this ex-ante heterogeneity. In this paper I endogenize ex-ante productivity differences based on the employees' choices of entrepreneurship and the dynamics of knowledge diffusion. As a result, the paper considers a new mechanism of endogenous knowledge diffusion that speaks to the recent works on knowledge diffusion and growth (Perla and Tonetti, 2014; Lucas and Moll, 2014; Benhabib et al., 2021).

I build on the general equilibrium models of innovation, firm dynamics, and growth (Aghion and Howitt, 1992; Grossman and Helpman, 1991; Klette and Kortum, 2004; Lentz

[4]The Economic Policy Institute Report on Noncompete Agreements, December 10, 2019.

[5]Interviews of patent holders from Marx (2011) show that non-compete agreements play important role in career paths of the technical professionals.

and Mortensen, 2008; Akcigit and Kerr, 2018; Acemoglu and Akcigit, 2012; Acemoglu and Cao, 2015; Acemoglu, Akcigit, Alp, Bloom and Kerr, 2018; Peters, 2020). While these models are only concerned about firm's innovation decisions, I incorporate the problem of the firm's R&D manager/inventors and analyze the firm's and inventor's interaction and its effects on aggregate firm dynamics and growth. This framework can also be used to jointly analyze various labor market and innovation policies.

This paper also relates to theoretical studies of employee entrepreneurship. The first works in this direction are classic papers by Pakes and Nitzan (1983) and Anton and Yao (1995) who study the optimal contracting problem in an environment where a researcher can learn an idea and decide between continuing working for the firm or creating own firms. These studies do not consider industry dynamics and aggregate outcomes. The closest to my study is Franco and Filson (2006). They study the evolution of an industry where employees can imitate the know-how of the employers and establish new firms. In Franco and Filson (2006), competitive equilibrium is efficient, while here due to monopoly distortions and intertemporal knowledge spillovers from the improved firm type composition in the economy, the equilibrium is not generally efficient. In another related study, Franco and Mitchell (2008) analyze spinouts and industry dynamics with non-compete laws to explain the initial dominance of Route 128 over Silicon Valley and its subsequent reversal. These models provide important intuitions, but they are stylized and do not allow for quantitative analysis of the spinout formation and its implications for productivity growth and policy. To the best of my knowledge, the only related quantitative macro study is the concurrent work by Sohail (2021).[6] Different from that work, I develop a framework to study the interaction of incumbents' innovation incentives with spinouts' entry, its effect on the evolution of the distribution of firms' qualities and competition, and resulting effect on aggregate growth. This structural framework then allows me to quantify importance of various channels and evaluate optimal innovation and non-compete policies.

Theoretical analysis in this paper is guided by the set of stylized facts that I document using inventors and patent data. These facts are consistent with the growing empirical literature on employee spinouts identified in different datasets[7] hence lending a wide support to the empirical underpinnings of the structural model considered in this paper. For example, a number of papers empirically study characteristics of spinout firms in the automobile industry, laser, disk drive, medical device, legal services, and biotech industries – Klepper (2002), Agarwal et al. (2004b), Klepper and Sleeper (2005), Franco and Filson (2006), Chatterji (2009), Klepper and Thompson (2010), Campbell et al. (2012). The follow-

[6]Using data from Mexico, Sohail (2021) shows that spinout spawning is lower for larger firms. My study is mute on firm size, and it shows that conditional on size, firms with higher technological leadership are more likely to spawn spinouts, lending support to the knowledge inheritance hypothesis, similar to Agarwal et al. (2004a).

[7]Literature often uses word "spinoff" instead of "spinout" that I use here.

ing set of broad facts emerges from the empirical studies. Spinouts account for a sizable share of entry – across industries, the share of spinout entrants ranges from 17% to 26%, and it increases over time as industry matures. Spinout firms usually performing well, often become industry leaders (oftentimes beating their parents), and usually have low failure rates. Spinouts also tend to separate from the firms that are industry leaders, and better firms spawn even better spinouts. In this paper, I find that similar empirical patterns emerge when I consider innovating spinouts across all industries using micro-level data on inventors and firms from the patent data. The contribution of this paper is to incorporate these common stylized facts in the micro-founded macro model to understand aggregate implications of spinout formation for innovation, firm dynamics, and growth.

Finally, a large and mainly empirical literature studies various effects of non-compete laws. Empirically, the studies have documented that stricter enforcement of non-competes limits labor mobility (Fallick, Fleischman and Rebitzer, 2006; Marx, Strumsky and Fleming, 2009; Garmaise, 2011) and firm entry (Samila and Sorenson, 2011; Starr, Balasubramanian and Sakakibara, 2018; Jeffers, 2019); stricter non-competes are also related to higher or riskier investment by firms, especially in knowledge-intensive industries, supporting the idea that employee mobility reduces firms' incentives to invest (Conti, 2014; Jeffers, 2019; Barnett and Sichelman, 2020). Consistent with the observed empirical tradeoff between increased firm entry and job-to-job mobility on the one hand and lower firm investment incentives on the other hand, scholars and policymakers have had diverse opinions on aggregate implications and overall desirability of non-competes (Saxenian, 1994; Gilson, 1999; Barnett and Sichelman, 2020). To the best of my knowledge, this is the first paper that attempts to quantify these opposing effects of non-competes on the aggregate innovation and growth and evaluates optimal non-compete policies. A concurrent paper by Shi (2021) also studies non-compete policies in a structural macro model, but her focus is on the job-to-job mobility and wage contracts of executives, while the effect through spinout entry, innovation, and knowledge diffusion is the focus of the current work. Nevertheless, both of our analyses show that optimal policy is not to enforce the non-competes.

2 Data and Motivating Empirical Facts

To identify and characterize innovating spinout firms, I use micro-level datasets on patents, firms, and inventors. The data serves two major purposes: first, it helps the theory to build on empirically motivated assumptions; and second, it helps to calibrate the model, quantify relevant channels, and conduct counterfactual policy experiments. Hence, after describing the data, Section 3.2 documents two main empirical facts underpinning the model assumptions; while Section 5 then matches the model to the data and presents counterfactual exercises.

2.1 Patent and Inventors Data and Identification of Spinouts

Data Sources This section details data sources, identification of spinout firms, and other variables construction.

NBER-USPTO Patent Data (PD). The core of the empirical analysis relies on the USPTO patent dataset drawn from the NBER Patent Data Project (Hall et al., 2001). The NBER patent data contains all granted patents by the U.S. Patent and Trademark Office during the 1976-2006 period. I use a detailed information on 1,841,499 patents assigned to 1,457,121 U.S. entities (assignees). For each patent, I use the following patent characteristics: patent's technology classification, patent claims, the number of forward patent citations received – a widely-used measure of the economic and technological significance of a patent (Trajtenberg, 1990; Harhoff et al., 1999; Kogan et al., 2017), as well as information on the assignees that file a patent. For the analysis, I focus on patents of the U.S. corporate assignees.[8] For each patenting firm, I use its location (state) and define its technology classification based on the most common technology classification of the patents this firm files.

Disambiguated Inventors Data (DID). The second source of data on the U.S. patent inventors comes from the Harvard Patent Network Dataverse (HPND) project (Lai et al., 2011). Each patent application, in addition to listing patent assignees, also lists names of all individual inventors of the patent. The HPND project disambiguates inventor names to provide unique identifiers for each inventor in the USPTO data. As a result, by matching PD and DID datasets, we obtain the matched firm-inventor dataset from 1976 to 2006 for nearly a million of innovating firms in the U.S. and more that 650 thousands unique inventors working in those firms. The advantage of this data match is that it allows us to measure firm's innovative output quality as well as track individual inventors over time across different firms.

Firms are classified into incumbent and entrant firms by identifying firm's entry year as the year the firm makes its first patent application. Since the data does not contain information on patents granted before 1976, to decrease the left truncation problem, I identify entrants starting from 1981. Likewise, since the data ends in 2006, due to the time lag between patent application and its grant, we naturally observe fewer patents closer to the end of the sample. Hence, to reduce the right truncation problem, the last year in which entrants are identified is 1999. As a result, the benchmark sample focuses on entrants who are born in the years 1981-1999. This allows for considerable time to observe entrants' future activities and measure their performance and potential exit. A firm applying for a patent prior to 1981 is classified as an incumbent. A firm's exit year is defined as the grant year of its last patent in the data.

The firm entry and exit dates defined based on the patent application/grant dates do

[8]Using extensive firm name cleaning and tracking firm reorganizations, PD provides unique company identifiers for each corporate assignee.

not necessarily coincide with the exact entry and exit dates of the firm in the economy. Nevertheless, these are good proxies to measure firm's entry and exit into innovation – the focus of this paper. The first patenting year well describes the entry of the firm into the innovation stage – similar to the firm entry in the model; while the firm's last patent describes its exit from the innovation stage – again, in line with firm exit in the model.

Compustat North American Fundamentals. In order to measure other outcome variables at the firm level, such as firm sales, total employment, assets, and R&D expenditures, I link the matched dataset to the financial data for publicly listed firms from the Compustat North American Fundamentals (Annual).[9] As a result, the empirical section will consistently refer to two data samples: "Patent Data" is the sample on all the patenting firms in our data, and "Compustat + Patent Data" refers to the subsample of the firms matched to Compustat.

The identification of spinout firms To identify spinouts, I track inventors' mobility across firms by following inventors' patenting records. A firm is defined as a *spinout entrant* if at least one inventor on a patent application made in the firm's entry year has worked in a different firm before that year.[10] [11] To reduce the measurement error, I exclude spinouts if the time gap between the inventor's last date in the previous firm and in a new spinout firm is greater than 5 years. However, I illustrate robustness of the empirical results keeping these firms in the sample. Alternatively, the entrant is classified as a *regular entrant*. The following example illustrates the spinout identification. Computer Memories Inc. was a California-based manufacturer of hard disks during the 1980's. The firm has seven granted patents in the data. Ara W. Nazarian was an inventor on two of those patents filed in 1983 (*US*4578625 and *US*4685007). In 1986, this inventor filed *US*4786995 under Peripheral Technology Inc.; and *US*4786995 is also the first patent by this firm. Hence, Peripheral Technology Inc. is classified as a spinout entrant.[12]

Discussion and the validation exercises The identification of spinout firms using patents and inventors data offers several advantages as well as has certain limitations. In terms of advantages, first, theory in this paper focuses on innovating firms that drive technological progress in the economy; and patents have been widely used in the literature as the main

[9] NPDP project provides the linking procedure between patent data and the Compustat database.

[10] An alternative definition that leads to similar empirical results looks at the background of all inventors in the firm's first two years after entry.

[11] I discard the inventor mobility cases if they occur because of mergers or acquisitions and between subsidiaries of the same firm. *Dynass* file from NPDP database helps to identify these types of reorganizations.

[12] Indeed, using alternative data sources, Franco and Filson (2006) analyze the history of hard disc drive industry in the U.S., and list Peripheral Technology Inc. as a firm established by a former employees of other firms. Peripheral Technology enters the economy in 1985 and exits in two years through acquisition. In our data, this firm enters in 1986 and exits in 1988 – the year of its last patent application. It is also worth noting that Computer Memories Inc. announced its departure from the hard disc drive industry in 1986, coinciding exactly with the last year it files a patent in the data.

systematic data on innovation across firms and over time (Griliches, 1981; Hall et al., 2007; Kogan et al., 2017; Argente et al., 2020). Hence, the analysis of the large dataset on the universe of patenting firms and identification of spinout firms within these innovating firms maps the data well to the model. Second, the data on rich patent characteristics offers the possibility to proxy for individual's innovation quality as well as quality and technological capabilities of a firm – objects that are hard to get with other datasets and that are crucial to discipline the model.

On the other hand, there are several reasons for why identification of spinouts using inventors' mobility could mismeasure true number of spinouts, even within innovating firms. First, an inventor who moves to the new firm may not formally be an owner of the spinout firm. However, to the extent that the first inventors in a new firm define the technological abilities and innovation direction of a firm, this approximates well our model where mobility happens via R&D workers. In this sense, our empirical definition of spinouts is broader than the definition of spinouts just based on owners of the firms and in addition entails the founding team of early inventors in the firm. This approach is similar to Choi et al. (2019) which shows that not just founders but initial employees at the firm play a crucial role in determining firm's future success. Second, this definition would miss the spinouts established through the mobility of non-inventor employees, which might be an important channel of knowledge transfer as well. However, through the lens of the model, mobility and knowledge diffusion occur through the moves of R&D workers, and the data on inventors should capture well these moves.

Nevertheless, it is useful to provide certain benchmark and assess our identification of spinouts relative to that benchmark. For that, I provide two layers of validation. The first validation exercise is to compare my definition of spinouts with the external sources defining spinout firms. Franco and Filson (2006) analyze rigid disk drive industry and using detailed industry reports, obtain the history of all entrants in 1977-1993. The authors identify and list the names of 40 spinout entrants, their founding year, life span, and the names of their parents. Among these, for 76% (19 firms) of innovating spinouts that match to the USPTO data (the total of 25 firms), my data confirms the firms' spinout type. In addition, the non-matches mainly come from the spinouts established in the early years of the sample, which because of the left truncation in my sample, do not allow me to accurately define firm type.[13]

Second, the main data moments and stylized facts that emerge from this data on innovating firms are very consistent with the existing studies in the literature (described in details in the literature review). For example, the share of spinout entrants among all en-

[13]As expected, firms' entry years in my sample are lagging compared to true founding years on average by 1.3 years.

Table 1: Summary Statistics

Patent data	Spinout Entrants	Regular Entrants	Incumbents
Number of firms	17295	46888	11452
Years in sample	4.28	3.69	23.07
Number of spinouts spawned	0.29	0.14	0.82
Number of parents	1.22	.	.
Lifetime number of patents	11.09	4.55	67.77
Lifetime number of cit-weighted	199.85	77.11	950.64
Patent + Compustat data			
Number of firms	777	2229	2249
Years in sample	9.70	9.19	29.82
Number of spinouts spawned	0.91	0.41	2.25
Number of parents	1.36	.	.
Lifetime number of patents	79.39	28.58	244.32
Lifetime number of cit-weighted patents	1618.07	585.40	3605.18
Sales(yearly)	919.65	938.10	3283.89
Sales growth (yearly)	23.62%	17.95%	10.13%
Employees (yearly)	3.77	3.61	12.34
Assets(yearly)	1219.56	1569.49	4361.11
R&D Expenditure (yearly)	61.12	47.76	108.46

Note: The table presents summary statistics for spinout entrants, regular entrants, and incumbent firms in 1981-2006 along various dimensions. The entrants are identified in the period 1981-1999, while incumbents are defined as firms filing at least one patent before 1981. The first panel presents statistics for all the innovating firms in the data, while the second panel presents statistics for firms matched to Compustat.

trants in my sample is 24.8%[14], which is in the range of other studies in the literature. Likewise, the facts on the superior performance of spinouts, knowledge inheritance, and spinout separation probabilities are also supported by the existing patterns from other data sources. These studies are discussed in Section 1, while Sections 2.2 and 5 describe these empirical facts in details. Taking all together, these validations assure that the data on patenting firms and inventors' mobility presents a good laboratory to analyze the innovating spinout dynamics and to discipline the theoretical model.

Summary statistics Table 1 provides summary statistics of the data. During years 1981-1999, we observe 64,183 entrant firms with the average longevity of 3.8 years and on average 6.3 patents and 110 citations-weighted patents.[15] Among these entrants, 17,295 firms are spinouts. Spinout and regular entrants account for nearly equal share of patents in 1981-2006 – for 16% and 17% of the total patent filings by all firms, respectively. The comparison of the share of spinouts and regular entrants with their respective patenting shares already

[14]Using the spinout definition not restricting to the 5-year gap between inventor's last year in the parent firm and the entry year of the spinout results in 32.0% of entrants

[15]Due to the nature of forward citations that take time to accumulate, I use the truncation-adjusted number of citations from Hall et al. (2001)

hints to the superior patenting activity of the spinout firms compared to regular entrants. Patents-Compustat data match reduces the sample size, but the share of spinout firms remains similar. Spinout firms are also larger and spend more on R&D, on average.

2.2 Motivating Empirical Facts

Two main building blocks of the model are empirically motivated here. First, I document that firm quality is significantly higher if it enters as a spinout; and second, spinout's quality is even higher if it is spawned from a firm with a bigger technological lead.

Spinouts vs Regular Entrants

I start the analysis by documenting substantial differences in outcomes of entrant firms depending on prior experience of their founders. Table 2 compares lifetime outcome variables for spinouts and regular firms. Panel A is based solely on the patent data sample, while Panel B considers the sample of firms that also appear in Compustat. As seen, conditional on being in the same cohort, operating in the same technology class and the state, spinout firms file 46% ($= exp(0.376)$) more patents during their lifetime. These firms issue not just larger number of patents, but also more impactful patents: spinouts have both more citations-weighted patent counts and more of high-quality patents in the top percentiles of the quality distribution of patents. Likewise, the number of years they are present in the patent data is also higher. A better performance of spinout firms is also reflected in the Compustat data. Spinout firms that become publicly traded are more R&D-intensive and have on average 3.4 percentage points higher sales growth than regular firms that are publicly traded. In addition, their R&D spending is more efficient as measured by the citations-weighted patents and the number of top patents per R&D dollar spent.

Overall, these findings indicate that firms established as spinouts from other innovating firms are more productive and innovative relative to firms established with no such prior background. This finding indicates that differences in entry type highlighted in this paper explain at least part of the large persistent ex-ante productivity differences across firms (Dunne et al., 1988; Pugsley et al., 2018; Guzman and Stern, n.d.).

Spinouts Quality and Parent's Technology Lead

Next, I document that within spinout firms, the characteristics of parent firms matter for the quality of spinouts. Figure 2 compares spinouts spawned from parents with different technological leads. First, I construct firms' patent quality distribution based on the citations-weighted patent counts in the last 5 years in their technology class, and then define parents' technological lead based on 20 quantiles of this distribution. Panel (a) of Figure 2 then shows the estimated coefficients of lifetime citations-weighted patent counts of a spinout as a function of parent's technological lead at the time of spinout separation.

Table 2: Spinouts vs Regular Entrants

	-Panel A. Patent Data-			
	Log Patents	Log Cit-Patents	Log Top Patents	Log Lifespan
Spinout entrant	0.384^{***}	0.511^{***}	0.187^{***}	0.131^{***}
	(0.009)	(0.013)	(0.009)	(0.005)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	64176	61303	64176	64176
Mean	0.752	3.111	0.198	0.812
	-Panel B. Compustat + Patent Data-			
	log R&D/Empl	Mean growth	Cit-Patent/R&D	Top patent/R&D
Spinout entrant	0.155^{***}	0.0461^{***}	176.9^{***}	1.141^{***}
	(0.051)	(0.014)	(39.08)	(0.272)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	2269	2609	2316	2316
Mean	3.135	0.247	162.64	1.035

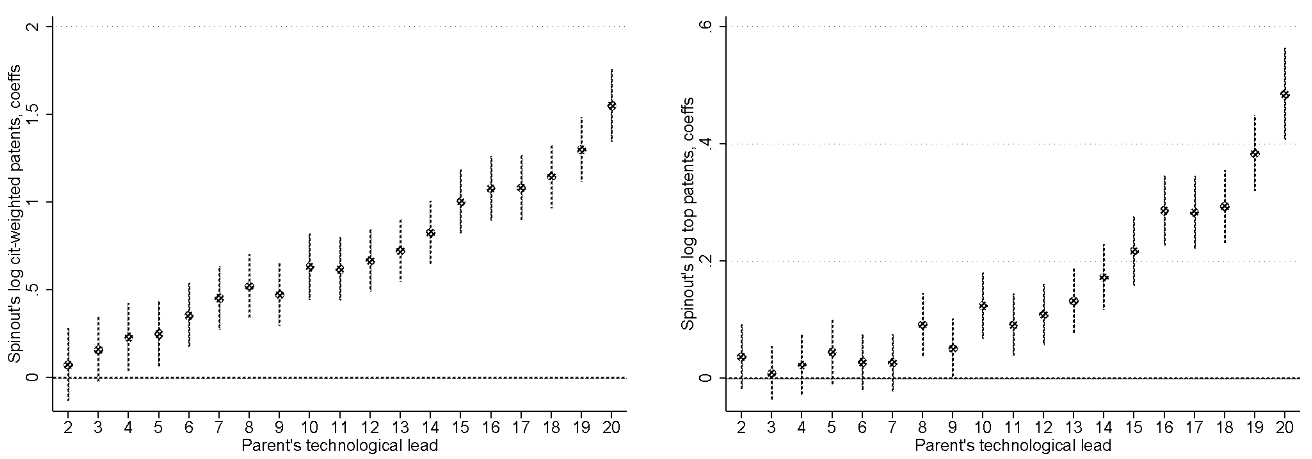
Note: The table compares spinout and regular entrants along various outcome variables in different columns. Each observation corresponds to a firm that enters in the data in 1981-2000 period. *Spinout entrant* is a dummy equal to one if a firm is a spinout. Panel A considers all firms in the patent data, while Panel B limits the sample to those firms that match to Compustat. Patents, cit-patents, and top-patents are the total number of all patents, citations-adjusted patents, and top patents granted to the firm during the whole period, respectively. Top patents are defined as the patents whose truncation-adjusted citations are above the 90th percentile of the citations distribution of patents filed in the same year and technology class. Lifespan is the difference between the last and the first year the firm appears in the data. The variables in Panel B are averages over all years the firm is present in the Compustat data. Mean growth refers to the average sales growth of the firm. Regressions control for entrants' cohort, their technology class (*nclass*), and state fixed effects.

The regressions also control for the number of parents, parent's number of patents in the last 5 years, technology class, state, and spinouts' cohort fixed effects. Panel (b) illustrates similar results where outcome variable is the lifetime number of top patent counts of the spinout.

We see that spinouts are significantly more innovative when they are spawned from parents who hold bigger technological lead. Since the regressions control for the stock of patents, the estimated coefficients show additional effect associated with the *quality* of parents' patent stock and its relative technological lead. In fact, as Appendix Table A.2 illustrates, parents' quality of patents, measured in different ways, is an important correlate with spinouts' performance, but not the quantity. These results should not be necessarily interpreted as spinouts learning from a specific patent filed by the parent, but rather as a broader parents-to-spinouts knowledge inheritance, similar to the relationship built in the model. It is easier to identify high-quality ideas, to learn about entrepreneurial opportunities, or how to successfully implement these ideas in the market by working in the firms at the technology frontier (Chatterji, 2009).[16] Further robustness checks to spinouts' other outcome variables and the definition of parents' technological lead are given in Appendix Tables A.4 and A.3.

Figure 2: Parent's Technological Lead and Performance of Spinouts

(a) Lifetime cit-patent count (b) Lifetime top patent count



Notes: The figures plot the estimated coefficients from the regressions of spinout outcome variables on their parents' technological lead. Technological lead is defined as 20 quantiles of the patent quality distribution based on the citations-weighted patent counts in the last 5 years in the technology class of the firm. The outcome variable in Panel (a) is spinout's lifetime log citations-weighted patent counts; the outcome variable in Panel (b) is spinout's lifetime log number of top patents. The plots show the point estimates with the corresponding 95% confidence intervals. The regressions also control for the number of parents, parent's number of patents in the last 5 years, technology class, state, and spinouts cohort fixed effects.

[16]These results are also consistent with additional stories, such as the positive sorting, better access to financing, or different motivation and effort of employees of leading firms (Dahl and Sorenson, 2013).

3 Model

Overview— To understand the role of spinouts for innovation and firm dynamics, I build a general equilibrium endogenous growth model consistent with main empirical facts from the data. Building on Schumpeterian growth models (Aghion and Howitt, 1992; Acemoglu and Akcigit, 2012; Acemoglu and Cao, 2015; Akcigit and Kerr, 2018; Peters, 2020) with entry and incumbents' innovation, I introduce new features of individuals occupation choice, spinout entry, and non-compete restrictions. An important new characteristic of the model is that entry distribution of firm types is endogenous through feedback from the incumbents' type distribution, their innovation decisions, and workers' entrepreneurial choices.

Two main stylized facts documented in Section 2.2 guide the main building blocks of this model. First, spinout entrants significantly outperform regular entrant firms throughout their entire life. This heterogeneity motivates me to introduce heterogeneous firm-specific quality types determined at entry. Second, firms with bigger technological lead spawn more innovative spinouts. This motivates modeling a type of learning or inheritance, whereby working in the leading firm increases the probability of creating a high-type entrant.

In the model, skilled people are allocated into three groups: entrepreneurs running the firms, R&D managers conducting innovation in the firms, and outsiders contemplating entry into one of the above occupations. Entrepreneurs, heterogeneous in their quality types, decide on innovation efforts that push the technology frontier forward. By innovating, they acquire technological leadership and market power. R&D managers collect wages and while being on the job, can search for ideas and outside opportunities to create their own spinout firms. Importantly, R&D managers learn on the job – more technologically advanced is their employer, higher are the chances that their start-up quality is of a better type. The model also introduces a parameter for NCL that affects the cost of establishing a spinout firm. After presenting the model and validating it against other empirical regularities in the data, the model will be used to understand both qualitatively and quantitatively the effects of spinout entry and non-compete laws on aggregate innovation and growth in the U.S.

3.1 Preferences and Final Good Technology

Time is continuous. The representative household consists of a measure L of unskilled and $2 + S$ measure of skilled people and has logarithmic preference over consumption good C_t. Household maximizes expected lifetime discounted utility of

$$U = \int_0^\infty e^{-\rho t} \ln C_t dt,$$

where ρ is household's discount rate. Household holds a balanced portfolio of all the firms in the economy, $\mathcal{A}_t$. Hence, its budget constraint can be written as $C_t + \dot{\mathcal{A}}_t = r_t\mathcal{A}_t + \mathcal{W}_t$, where r_t is interest rate and $\mathcal{W}_t$ is the total wage bill.

Final good is produced by combining intermediate goods using the following logarithmic aggregator:

$$\ln Y_t = \int_0^1 \ln y(j,t)dj, \tag{1}$$

where $y(j,t)$ is the intermediate good from product line j at time t.

Market for final good production is perfectly competitive, and the final good price is the numeraire. Denote the price of the intermediate good produced in product line j at time t by $p(j,t)$. Profit-maximizing final good producers choose intermediate input to solve:

$$\max_{y(j,t)} \left[\exp \int_0^1 \ln y(j,t)dj - p(j,t)y(j,t), \right] \quad \forall t$$

This maximization leads to the following unit-elastic demand function:

$$y(j,t) = \frac{Y_t}{p(j,t)}. \tag{2}$$

3.2 Intermediate Goods Market

An intermediate good in product line $j \in [0,1]$ can be produced by two firms competing *á la* Bertrand. Firm i has the following production technology utilizing labor input scaled by time-variant firm-specific productivity:

$$y_i(j,t) = q_i(j,t)l_i(j,t), \tag{3}$$

where $l_i(j,t)$ is unskilled labor input and $q_i(j,t)$ is firm-specific productivity in product line j that evolves endogenously as described below.

Index by i a firm with a leading technology, and a follower by $-i$, such that $q_i(j,t) > q_{-i}(j,t)$. Products of these competing firms are perfect substitutes, hence Bertrand competition between the two firms ensures that the only active producer is firm i. Furthermore, this leading firm sets a price equal to the marginal cost of a follower, such that[17]

$$p(j,t) = \frac{w_t^u}{q_{-i}(j,t)}, \tag{4}$$

where w_t^u denotes an equilibrium wage rate of unskilled labor. As a result of the demand curve given by (2) and the price in (4), profit of an intermediate goods producer in product

[17] We can also interpret this structure as the pricing decision of a firm facing a competitive fringe that is able to produce at some base level of technology $q_{-i}(j,t)$ freely accessible to everyone.

line j is

$$\Pi_i(j,t) = \left(1 - \frac{q_{-i}(j,t)}{q_i(j,t)}\right) Y_t \tag{5}$$

Notice that profits of a firm are scaled by total output in the economy (a standard market size effect) and only depend on the ratio of current leading technology over the follower's technology in the product line. Hence, the incentive of the leading firm is to widen this technology gap in order to increase profits. This, in turn, can be achieved through costly research and development (R&D). Next section describes this process of R&D.

3.3 Firm Heterogeneity and the Productivity Dynamics

To advance their current level of productivity, intermediate good firms[18] need to invest in R&D. Firms are heterogeneous in their R&D efficiency. Each firm has a permanent *quality type* $\tau \in \{H, L\}$, where H denotes more R&D efficient high-type firms and L corresponds to less R&D efficient low-type firms.

R&D process requires hiring an R&D manager and spending resources proportional to the intensity of innovation chosen. In particular, to generate z Poisson arrival rate of innovation, firm needs to pay the following

$$\text{R\&D cost} = w^s(j,t) + \frac{z^\gamma(j,t)}{\gamma B^\tau} Y_t \tag{6}$$

where first part, $w^s(j,t)$, is a fixed cost – wage bill for the R&D manager. The second part of the cost is a variable cost that increases and is convex in the chosen intensity of innovation arrival rate z ($\gamma > 1$). $B^H > B^L$ and shows that high-type firms are more productive at research than low-type firms. In other words, high-type firms are more likely to upgrade their productivity, for the same amount of resources spent.

If the firm's innovation is successful, within a small time interval Δt, it improves the previous productivity by a step size λ, where $\lambda > 1$:

$$q_i(j, t + \Delta t) = \lambda q_i(j,t)$$

In the model, inactive followers act as competitive fringe, and it is convenient to index productivity improvements relative to their productivity. Say, the productivity of a competitive fringe in product line j is $q_{-i}(j,t) = \lambda^{n_{-ij}} q_0$, and the productivity of an incumbent is $q_i(j,t) = \lambda^{n_{ij}} q_0$, where q_0 is some initial level of productivity. Then denote the number of step improvements made by the incumbent relative to the competitive fringe in its product line by $n_j(t) \equiv n_{ij}(t) - n_{-ij}(t)$, which we refer to as product line j's *technology gap*. This

[18] In what follows, intermediate good firms are just referred to as firms.

technology gap will be endogenously evolving as a result of entry, and exit, and innovation by incumbents in each product line. For example, if the incumbent successfully innovates, the gap in the product line increases by one: $n_j(t+\Delta t) = n_j(t) + 1$. Going back to equation (5), we can rewrite incumbent's static profit as

$$\Pi_i(j,t) = \left(1 - \lambda^{-n_j(t)}\right) Y_t \tag{7}$$

Hence, the model produces a convenient structure for profits as a function of the technology gap n. This technology gap and its evolution will be the main objects of interest in what follows.[19]

3.4 The Allocation of Skilled Labor

This section describes the allocation of skilled labor in the economy and an optimization problem of each type of labor separately. At any point in time, a constant measure of skilled people in the economy is allocated into three groups:

$$\textit{Skilled people} = \underbrace{\textit{Entrepreneurs}}_{1} + \underbrace{\textit{R\&D managers}}_{1} + \underbrace{\textit{Outsiders}}_{S}$$

The measures of entrepreneurs and of R&D managers are equal to one each: there is measure one of product lines in the economy, and each producing (leader) firm is associated with one entrepreneur and hires one R&D manager. In addition, measure S of outsiders can enter as R&D managers or try to become entrepreneurs.

Denote by $V_t^{firm}(n,\tau)$ a discounted present value of entrepreneur (incumbent firm) who possesses a technology gap n and has a permanent quality type τ. Entrepreneurs (firms) decide on investment in R&D and hiring unskilled labor. Denote by $V_t^{manager}(n,\tau)$ the value of an R&D manager who works for a firm with (n,τ) characteristics. R&D managers collect wages and decide on separation rate – *spinout entry*. As will be clear below, $V_t^{manager}(n,\tau)$ depends on the characteristics of the employee firm for two reasons: because of the differences in wages and because of the differences in the probabilities of high-type spinout formation. Finally, denote the value of being an outsider by V_t^{out}. Outsiders can start a job as R&D managers or they can enter the market as entrepreneurs – *regular entry*.

From this point onward, we only focus on the economy in a stationary equilibrium where all values grow at the same rate as the aggregate output. Hence, we will normalize all values by Y_t and denote the normalized values by their respective lower-case letters (e.g., $v^{firm}(n,\tau) = \frac{V_t^{firm}(n,\tau)}{Y_t}$). Hence, the time subscript t is dropped where it does not cause a confusion. Next sections separately describe in details the problems of each group

[19]In what follows, for brevity, subscript i is dropped.

of skilled people.

3.4.1 Outsiders

An outsider faces two options – either to attempt to start an entrepreneurial venture or to become an R&D manager. Denote the value of entrepreneurial entry by v^{entry} and the value of entry to the labor market as v^{work}. Then,

$$v^{out} = \max\{v^{entry}, v^{work}\} \tag{8}$$

To become an entrepreneur, the outsider has to successfully implement an idea. Success is uncertain. Paying cost $\frac{e\nu^2}{2}$ ensures Poisson arrival rate of idea ν. If the idea is implemented successfully, the entrepreneur enters into a random product line and improves existing technology level in that product line by λ. As a result, the entering firm creatively destroys the existing incumbent and starts production with the minimal technology gap of $n = 1$.[20] Upon entry, the entrepreneur draws a permanent type of its firm τ: probability of drawing a high type H equals to $\tilde{\mu}$. If the idea is not successfully implemented, outsider remains in the group of outside skilled people. Using the standard Euler equation derived from household optimization, $g = r - \rho$, we can write the Bellman equation for the value of entry in the following way:[21]

$$\rho v^{entry} = \max_{\nu \geq 0} \left(-\frac{e\nu^2}{2} + \nu(\tilde{\mu} v^{firm}(1, H) + (1 - \tilde{\mu}) v^{firm}(1, L) - v^{entry}) \right) \tag{9}$$

The flow value of entry consists of the following terms on the right-hand side. First, an entrant incurs instantaneous cost of developing an idea (first term on the right-hand side). Next, upon a successful entry with probability ν, the entrant gets an expected value of holding a product line, where expectation is taken over the firm's type τ. If firm is not successful at entry, it retains its value of v^{entry}. Hence, the incremental value is the term in the brackets. ν is chosen to maximize the total value. Denote aggregate entry from outsiders by I^o:

$$I^o = S\nu \tag{10}$$

Next, consider the value of becoming an R&D manager. First, as will become clear below, the only new demand for R&D managers in this economy comes from firms with a technology gap $n = 1$: these are either the newly-created firms – regular entrants established by outsiders or spinout entrants, or existing firms losing their R&D managers who spawned spinouts. Second, I assume that outsiders find jobs instantaneously and are ran-

[20] Since the previous incumbent turns into a competitive fringe, the new gap relative to the previous technology is 1.

[21] A detailed derivation of this continuous-time value function representation is in Appendix A.

domly matched to the firms demanding R&D managers. As a result, if we denote by α the (endogenously determined) share of firms demanding R&D managers who are of type H, we can express v^{work} as following:[22]

$$v^{work} = \alpha v^{manager}(1, H) + (1 - \alpha)v^{manager}(1, L) \tag{11}$$

In equilibrium, outsiders have to be indifferent between the two options open to them. As a result, from equation (8) we get:

$$v^{out} = v^{entry} = v^{work} \tag{12}$$

3.4.2 R&D Managers and Spinout Entry

An R&D manager who works in a firm with (n, τ) characteristics earns wage $w(n, \tau)$. While on the job, the manager can search for outside opportunities to create her own start-up – a spinout firm.[23] For that, she chooses a separation rate $a(n, \tau)$, where $a(n, \tau)$ can also be zero, indicating that the worker chooses not to separate. The separation effort is costly and it costs $\frac{ka(n,\tau)^2}{2}$ in terms of final output. One can think of this cost as the time or monetary cost necessary to develop an idea and implement it into a new start-up.

If separation effort is successful, a new spinout firm is created. It enters into a random product line, improves upon the existing level of the productivity by λ, and hence replaces the incumbent in that product line. Because there is a continuum of product lines, the probability of spinout landing on the product line of her former employee is zero. In this sense, the new spinout firm will not directly threat the former employer by replacing it. However, once the R&D manager leaves, the employer loses part of its current value, and its technological lead diminishes from n to 1. One way to think about this structure is to think of new technologies as being largely embedded in the human capital of a firm; once the main part of the firm's human capital – the R&D manager, leaves a firm, firm has to rebuild its technological advantage from scratch. Alternatively, one could model competitive threat from spinouts by assuming spinouts replace parents in their product lines. However, this creative destruction of a parent would be an extreme assumption not well-supported by the data. First, evidence shows that many spinout firms do not directly compete in the same narrow technologies as their parents (Chatterji, 2009). Second, although existing work shows that spinouts often outperform their parents and harm their performance (Wezel et al., 2006; Campbell et al., 2012), this process does not usually result in instantaneous exit of the parent firms. Hence, a more appropriate intermediate approach is to model this

[22]Note that once matched with a firm, the manager does not have an incentive to destroy the match by joining the pool of outsiders and searching again. Section 3.5 shows that this is not optimal since the value of being an outsider is not higher than the lowest value that an R&D manager can get.

[23]The model abstracts away from job-to-job transitions.

negative effect on parents as a gradual process where parent firm loses its technology gaps upon spinout entry.

When a new spinout is created, it incurs costs associated with non-compete restrictions. In particular, a spinout pays the fixed cost $F \geq 0$ (in terms of final output) which depends on the strength of the existing non-compete laws.[24] In reality, there is a wide range of legal outcomes that founders of spinout firms may face (Garmaise, 2011): in some cases, spinouts would have to pay the fees, in others they may need to shut down the operations completely, and in others they may not incur any legal costs. In the model, one can think of the parameter F representing an average of all these possibilities.

New spinouts may have successful ideas and enter the market with a high quality type $\tau = H$. Alternatively, they draw quality type $\tau = L$. As in the data, the probability of drawing high type depends on the firm an R&D manager works for: better spinout ideas are generated in technologically leading firms. Formally, a spinout draws a type $\tau = H$ with probability $\mu(n)$, where $\mu(n') > \mu(n)$ if $n' > n$. Hence, the model features a type of spinout-parent knowledge inheritance: over time, as employers acquire higher technological leadership, workers' entrepreneurial ventures are more successful. This inheritance can come through the direct learning of technical knowledge or through a non-technical experience that helps to identify high-quality ideas and knowing how to successfully bring them to the market. This channel resembles the knowledge diffusion channels emphasized in recent literature (Lucas and Moll, 2014; Perla and Tonetti, 2014), but in the current model, spinout firms do not replicate the ideas of their parents but rather diffuse knowledge by creating new high-quality start-ups.

As a result of workers' separation decisions, each firm in the economy faces the probability of creative destruction from spinouts separating from other product lines. Denote this aggregate spinout entry rate by I^s. We are now ready to write down the value of an R&D manager who works at (n, τ) firm as follows:

$$\rho v^{manager}(n,\tau) = \max_{a(n,\tau)\geq 0} \left\{ \begin{aligned} & \omega(n,\tau) - \frac{ka^2(n,\tau)}{2} \\ & + a(n,\tau)[\mu(n)v^{firm}(1,H) + (1-\mu(n))v^{firm}(1,L) - F - v^{manager}(n,\tau)] \\ & + (I^s + I^o)[v^{out} - v^{manager}(n,\tau)] \\ & + z(n,\tau)[v^{manager}(n+1,\tau) - v^{manager}(n,\tau)] \end{aligned} \right\} \tag{13}$$

This continuous-time value function can be interpreted as following. The left-hand side is the flow value of an R&D manager at (n, τ) firm. The right-hand side includes the components that make up this value. The first line is instantaneous wage bill (where $\omega(n, \tau) = w(n, \tau)/Y$) less the separation cost. The second line shows the change in the

[24] In Section **??**, F will also vary with the employer firm's technology gap.

worker's value when the separation is successful at the rate $a(n,\tau)$. In particular, this change is equal to the expected value of a new start-up less the legal costs associated with non-compete restrictions minus the current value. The third line shows a change in the worker's value if the employer firm is replaced by an entrant (spinout or outside entrant). This happens at rate $I^s + I^o$. In such a case, employer firm exits the market, and the R&D manager joins the pool of outsiders in the economy. Finally, the last term indicates the possibility of the employer's innovation. If this innovation is successful at the rate $z(n,\tau)$, employer advances one step ahead and the worker's value changes to $v^{manager}(n+1,\tau)$. The first-order condition of the problem implies:

$$a(n,\tau) = \max\left\{0, \frac{\mu(n)v^{firm}(1,H) + (1-\mu(n))v^{firm}(1,L) - F - v^{manager}(n,\tau)}{k}\right\} \tag{14}$$

This condition indicates that on the one hand, R&D manager has an incentive to separate if the probability of drawing the high type $\mu(n)$ is high. On the other hand, the R&D manager faces the opportunity cost of separation: if she waits, she has an opportunity to learn more on the job and increase the future probability of a better spinout ($v^{manager}(n+1,\tau) - v^{manager}(n,\tau)$ term in equation (13)).[25] Hence, the choice to separate crucially depends on the shape of the learning schedule $\{\mu(n)\}_n$. Finally, all else equal, more stringent non-compete restrictions (higher F) reduce workers' incentives to separate.

3.4.3 Entrepreneurs

An entrepreneur who runs an incumbent firm with (n,τ) characteristics gets the following value. She collects instantaneous profits from production, pays the R&D manager, and incurs variable R&D cost. Successful innovation at rate $z(n,\tau)$ increases firm's value one step ahead on a technological ladder to $v^{firm}(n+1,\tau)$. At the rate $I^s + I^o$, entrants hit the incumbent's product line replacing it and forcing the entrepreneur to join the pool of outsiders. Finally, the R&D manager may successfully leave the firm by creating a spinout. As described above, this destroys the firm-R&D manager match and brings down the incumbent's technological lead to $n = 1$. All these cases are reflected in the following specification for entrepreneur's value:

$$\rho v^{firm}(n,\tau) = \max_{z(n,\tau)\geq 0} \left\{ \begin{array}{l} \pi(n) - \omega(n,\tau) - \dfrac{z(n,\tau)^{\gamma}}{\gamma B^{\tau}} + z(n,\tau)(v^{firm}(n+1,\tau) - v^{firm}(n,\tau)) \\ + (I^s + I^o)(v^{out} - v^{firm}(n,\tau)) + a(n,\tau)(v^{firm}(1,\tau) - v^{firm}(n,\tau)) \end{array} \right\} \tag{15}$$

[25]In addition, by staying with he firm, her wages will also increase if firm innovates: as we will see, $\omega(n+1,\tau) - \omega(n,\tau) > 0$.

where $\pi(n) = 1 - \lambda^{-n}$ is the normalized flow profit (equation (7)). The first-order condition of the entrepreneur's maximization problem gives:

$$z(n,\tau) = \max\{0, B^{\tau\frac{1}{\gamma-1}}(v^{firm}(n+1,\tau) - v^{firm}(n,\tau))^{\frac{1}{\gamma-1}}\} \tag{16}$$

This condition states that innovation incentives depend on the incremental value that an entrepreneur can get from advancing one step ahead. H-type entrepreneurs invest in innovation and grow more, as reflected by positive dependence on B^{τ}. In addition, the future spinout possibility reduces the firm's value and decreases innovation incentives, similar to the standard R&D investment appropriability problem.

3.5 Wage Determination and the Summary of the Dynamics

In this section, I describe how the wages $\omega(n,\tau)$ are set and summarize the dynamics between the firm and the R&D manager. The wage rate is determined by Nash bargaining. At the beginning of each period, an R&D manager and an entrepreneur bargain over the wages. If both agree on the wage, firm and R&D manager collaborate and get the values $v^{firm}(n,\tau)$ and $v^{manager}(n,\tau)$, respectively. If they disagree, the manager can walk away and get an outside value of v^{out}, while the firm loses its match-specific productivity and its technology gap diminishes to 1 (similar to the case of spinout separation), so entrepreneur gets the value of $v^{firm}(1,\tau)$. Linear sharing rule prescribed by Nash bargaining implies:

$$\beta(v^{firm}(n,\tau) - v^{firm}(1,\tau)) = (1-\beta)(v^{manager}(n,\tau) - v^{out}) \tag{17}$$

where β denotes R&D manager's bargaining weight. Or, in other words, an R&D manager gets a β share of the joint net surplus.

Notice that equation (17) for $n = 1$ implies that

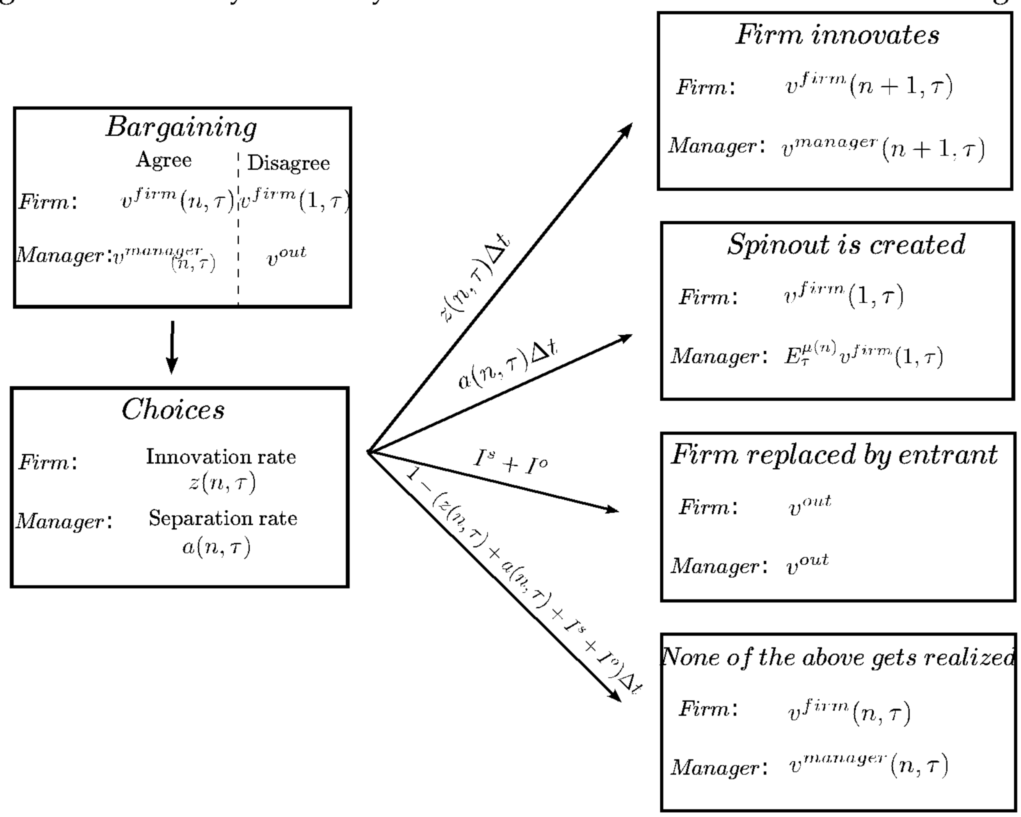
$$v^{manager}(1,H) = v^{manager}(1,L) = v^{out} \tag{18}$$

This ensures that the R&D manager who ends up working in a L-type firm will not have an incentive to search again to land a job in a H-type firm. Notice also that in expectation H-type firms offer higher learning opportunities to their managers – since high-type firms are more likely to increase their technological lead, R&D managers working in the high-type firms are more likely to get high-quality draws for their potential entrepreneurial ventures. This implies that in order for (18) to hold, low-type firms have to pay higher wages. Hence, in this model R&D managers pay for the possibility to move up the technological ladder with an employer.[26] We will come back to this point in Section 5.

[26]This implication is similar to the results from the models where workers pay for on-the-job training in the firms Acemoglu (1997).

The summary of the dynamics between a firm and its R&D manager is illustrated in the diagram in Figure 4. In the beginning of a period, manager and the firm bargain. The manager and the firm negotiate over the wage but not over the worker's separation intensity that is unobservable to the firm. After the agreement, worker may still find it profitable to choose a positive separation intensity $a(n, \tau)$. Hence, the next step within the time interval t is for the firm to choose the innovation rate $z(n, \tau)$ and for the R&D manager to choose the separation rate $a(n, \tau)$.

Figure 3: Summary of the Dynamics between a Firm and its R&D manager



Within a small time interval Δt, the following scenarios may get realized. First, with probability $z(n, \tau)\Delta t$, the firm advances one step ahead and gets the value of $v^{firm}(n + 1, \tau)$, while the manager gets $v^{manager}(n + 1, \tau)$. Second, with probability $a(n, \tau)\Delta t$, in period $t + \Delta t$ worker separates, pays the cost of separation and gets expected value of the spinout entry – $\mu(n)v^{firm}(1, H) + (1 - \mu(n))v^{firm}(1, L)$ that is denoted on the diagram as $E^{\mu_n}_{\tau} v^{firm}(1, \tau)$. In this case, the firm gets $v^{firm}(1, \tau)$. Third, the incumbent firm may get replaced by an entrant that improves upon its technology. In this case, both the entrepreneur and its R&D manager get the exit values of v^{out}. Because time is continuous, probability of two or more of these events being realized at the same time is zero. As a result, the remaining possibility is for none of the scenarios to get realized. In such a case, both the manager and the firm continue getting same values in state (n, τ).

3.6 The Stationary Distribution

As a result of entry, exit, and the innovation process, firms move up and down the technology ladder. Denote by $\xi(n,\tau)$ the measure of firms that currently possess a technology gap of n and are of τ-type. In the stationary equilibrium, although individual firms enter, exit and constantly change their position in the technology space, the overall measure of firms in different states stays the same. This implies that the inflow and outflow into and from each state should balance each other.

In particular, for all $n \geq 2$, the following should hold:

$$\xi(n-1,\tau)z(n-1,\tau) = \xi(n,\tau)(a(n,\tau) + I^s + I^o + z(n,\tau)) \tag{19}$$

The left-hand side of the equation (19) represents inflow into (n,τ) state. This only comes from the successful innovation efforts of firms that are one step behind at $n-1$ and are of type τ. The right-hand side of the equation is the outflow from (n,τ) state. It can happen for three reasons: if spinouts separate from (n,τ)-firms, if (n,τ)-firms are replaced through creative destruction by entrants – at rate $I^s + I^o$, or if firms in (n,τ) state successfully innovate and advance ahead.

The entry into state with $n = 1$ is different. The left-hand side of Equation 20 shows the inflow into $(1,H)$ state. The first term comes from the spinout separation from all firms taking into account that only μ fraction of spinouts draw high-quality ideas and create H-type firms. The second term stands for the entry of firms that were high-type, had a technology gap n but because of spinout separation lost their technological advantage to $n = 1$. Finally, the third term comes from the outside entry with I^o intensity; fraction $\tilde{\mu}$ of them draw type H. The right-hand side of the (20) is similar to the description of outflow in equation (19): outflow happens because of spinout separation, creative destruction, or successful innovation by incumbents.

$$\sum_{n,\tau}\xi(n,\tau)a(n,\tau)\mu(n) + \sum_{n}\xi(n,H)a(n,H) + I^o\tilde{\mu} = \xi(1,H)(a(1,H) + I^s + I^o + z(1,H)) \tag{20}$$

Similar logic applies to the case with $\tau = L$:

$$\sum_{n,\tau}\xi(n,\tau)a(n,\tau)(1-\mu(n)) + \sum_{n}\xi(n,L)a(n,L) + I^o(1-\tilde{\mu}) = \xi(1,L)(a(1,L) + I^s + I^o + z(1,L)) \tag{21}$$

3.7 The Steady State Equilibrium

Before summarizing the steady state equilibrium, let us lay out final components of the equilibrium. Aggregate spinout entry rate comes from the separation efforts by R&D managers in all firms in the economy and is equal to

$$I^s = \sum_{n,\tau} \xi(n,\tau) a(n,\tau). \tag{22}$$

Labor Market. The labor allocation for skilled people has been already described; it is clear that by construction it is always balanced.[27] However, the market for unskilled labor has to be cleared by the equilibrium wage. Demand for unskilled labor comes from the production decisions of firms, while the supply is inelastic and is equal to L. Combining equations (2), (3), and (4), and denoting by ω^u the normalized equilibrium wage rate of unskilled labor, we get

$$q_j l_j \;=\; \frac{1}{\omega^u} q_{-j},$$

hence the labor demand of the incumbent in product line j is

$$l_j = \frac{1}{\omega^u} \lambda^{-n_j} \tag{23}$$

This implies the following market clearing condition:

$$L = \sum_{\tau,n} \frac{\xi(\tau,n)}{\lambda^n \omega^u}. \tag{24}$$

The definition below summarizes the steady state equilibrium:

Definition (Steady-State Equilibrium) *Given the non-compete policy F, a steady-state equilibrium is a tuple*

$$\{v^{firm}(n,\tau),\ v^{manager}(n,\tau), v^{out}, v^{work}, v^{entry},\ z(n,\tau),\ a(n,\tau),\ \nu,\ I^o,\ I^s,\ \omega(n,\tau),\ \omega^u,\ \xi(n,\tau), g, r\}$$

such that

(i) $v^{firm}(n,\tau)$, $v^{manager}(n,\tau)$ *satisfy equations (13) and (15);*

(ii) v^{out}, v^{work}, *and* v^{entry} *are given by equations (8), (9), and (12);*

(iii) $a(n,\tau)$ *and* $z(n,\tau)$ *satisfy first-order conditions (14) and (16);*

(iv) *Entry rate by outsiders, I^o, satisfies equation (10), where ν maximizes (9);*

(v) *Spinout entry rate I^s is given by equation (22);*

(vi) *Wages of R&D managers satisfy equations (11), (12), (17), and (18);*

[27] At each point in time, if a firm is replaced by a regular entrant, two skilled people (an entrepreneur and an R&D manager of an exiting firm) join outsiders' pool, and two skilled people exit the pool of outsiders (an entrepreneur and an R&D manager of an entering firm). Similar accounting holds for spinout entry. Hence, in the total pool of skilled people which is measure $2 + S$, measure one is always running a firm, another measure one is always employed as R&D manager, and measure S is in the outsider's pool.

(vii) *Wage of unskilled labor clears labor market in (24);*
(viii) *Stationary distribution $\xi(n,\tau)$ satisfies (19), (20), and (21);*
(ix) *Aggregate growth rate is given by equation (25);*
(x) *Interest rate satisfies Euler equation, $\rho = g - r$.*

Proposition 1 *Steady-state growth rate can be expressed as*

$$g = \ln \lambda (I^s + I^o + \sum_{n,\tau} \xi(n,\tau) z(n,\tau)). \tag{25}$$

The proof is in Appendix C. This Proposition makes it clear that the steady state growth rate of the economy is determined by four factors: i) innovation decisions of incumbent firms at different levels of the technology gap; ii) the distribution of firms across the technology gaps; iii) entry by spinouts; and iv) entry by outsiders. All these innovations increase aggregate productivity by λ.

At this point, we can summarize the main channels through which non-compete policies affecting spinout separation influence growth. Because the possibility of spinout negatively affects incentives of parent firms to innovate, evaluating the benefits of spinout formation depends on the quantitative importance of various channels in the model. Four main channels operate in the model. First is the *direct entry effect* on growth, where more spinout entry positively contributes to innovation and growth. Second is the negative *disincentive effect* of spinout formation on incumbent firms' innovation incentives that is similar to standard appropriability problem. The third channel is *knowledge diffusion*, whereby spinout entry increases the share of high-type firms in the market. Finally, spinout entry also influences the *firm composition*: higher spinout entry shifts the composition of firms towards lower technology gaps hence promoting more competition and as a result aggregate innovation efforts.

3.8 Welfare

Consider the steady-state welfare of a representative household at time $t = 0$:

$$\text{Welfare}(0) = \int_0^\infty e^{-\rho t} lnC_t dt, \tag{26}$$

The final output is divided into consumption and investment. Denote the total investment (normalized by output) by I. There are four types of investment activities in this economy: 1) Outsiders invest into developing new ideas to enter as entrepreneurs; 2) R&D managers invest into developing new ideas to spin-out; 3) Founded spinouts pay non-compete costs; and 4) entrepreneurs invest in innovation. These lead to the following equation for the total investment undertaken in this economy:

$$I = \frac{ev^2}{2}S + \sum_{n,\tau}\frac{ka^2(n,\tau)}{2}\xi(n,\tau) + \sum_{n,\tau}\xi(n,\tau)a(n,\tau)F + \sum_{n,\tau}\frac{z(n,\tau)^\gamma}{\gamma B^\tau}\xi(n,\tau) \tag{27}$$

As a result, we can write the aggregate consumption as $C = (1-I)Y$ and rewrite equation (26) in the following way:

$$\text{Welfare}(0) = \frac{\ln Y(0)}{\rho} + \frac{g}{\rho^2} + \frac{1-I}{\rho}$$

Next, we can derive steady-state value of $\ln Y(0)$ from equations (1) and (4) and use in the previous equation to get (see the detailed derivations in Appendix B):

$$\text{Welfare}(0) = \frac{\ln Q(0) - \ln\lambda\sum_{n,\tau} n\xi(n,\tau) - \ln\omega^u}{\rho} + \frac{g}{\rho^2} + \frac{\ln(1-I)}{\rho} \tag{28}$$

In the steady state, all the equilibrium variables entering this expression are constant. For the steady state comparisons of different economies with different non-compete policies, it is sufficient to compare two economies with the same levels of initial productivity level $Q(0)$ and different policies F. Our non-compete policies will affect aggregate growth by providing different innovation incentives to incumbents and spinouts. This growth rate has the first-order effect on welfare, as seen from the above. In addition, non-compete policies will alter the steady-state distribution of firms across technology gaps as well as equilibrium labor share. If the economy has a low entry and creative destruction, more firms will enjoy higher technology gaps and, hence, higher markups leading to lower welfare (as seen by negative terms in the expression (28)). It is worth noting that $Q(0)$ is an arbitrary number and hence the proportional changes in welfare resulting from the changes in the policy are not informative. However, ordinal rankings are well defined and hence welfare-maximizing policies can be found by comparing the welfare numbers from (28).

4 Quantitative Analysis

This section takes the model to the data. First, I lay out the model solution algorithm and describe the calibration. Next, I characterize the model fit and explore quantitative properties of the model. Finally, I quantitatively analyze the role of various policies in promoting aggregate innovation and growth.

4.1 Calibration

This section describes the calibration of structural parameters of the model. The model has the following parameters: $\rho, \lambda, \gamma, \beta, \tilde{\mu}, \{\mu_n\}_{n=1}^N, B^H, B^L, L, S, e, F, \kappa$. The calibration proceeds in two steps. First, a set of parameters is fixed externally based on estimates from the literature or estimated directly from the data. Second, the remaining set of parameters is calibrated internally by minimizing the distance between important empirical moments and the corresponding moments generated by the model.

The first panel of Table 3 lists externally calibrated parameters. The annual discount rate is set to 4%, so $\rho = 0.04$. Curvature of the R&D cost function γ determines the elasticity of innovation with respect to R&D. Several papers have empirically evaluated this elasticity. Following Acemoglu et al. (2018) who discuss this evidence in detail, I set $\gamma = 2$. In the benchmark calibration, I set β to 0.05 following Hagedorn and Manovskii (2008).

Table 3: Calibrated Parameters

Parameter	Meaning	Value
	EXTERNALLY CALIBRATED PARAMETERS (24)	
ρ	Discount rate	0.04
γ	R&D cost curvature	2
β	R&D manager's bargaining weight	0.05
$\{\mu_n\}_{n=1}^N$	Prob. of H-type spinout entry from firm n	Figure 4
$\tilde{\mu}$	Prob. of H-type outside entry	0.20
	INTERNALLY CALIBRATED PARAMETERS (8)	
B^H, B^L	R&D cost efficiency	2.74, 0.049
L, S	Skill composition	19, 0.60
e	Entry cost parameter	6.07
F	NCL parameter	0.60
κ	Separation cost parameter	12.52
λ	Step size of innovation	1.08

Notes: The table reports the calibrated parameter values consistent with moments reported in Table 4.

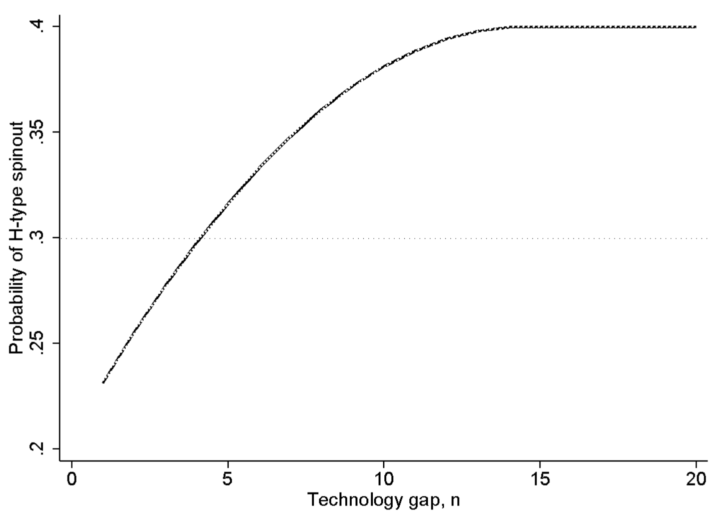
I estimate the probability of spinouts entering as high-type firms, $\{\mu_n\}_{n=1}^N$, directly from the data. Figure 2 already provides the first evidence on the positive relationship between the parent's technological lead and spinouts' performance. Here, I map the data closer to the primitives of the model. First, I define H-type and L-type firms in the data. In the model, firm's type is constant over time, and high-type firms are more innovative than their low-type competitors. As a result, I define a firm as H-type if it ranks in the top quartile based on its lifetime innovation output, proxied by the lifetime citations-adjusted patent count of the firm, residualized for firms' cohort and technology class fixed effects. Second, I proxy for n – technological gap of the firm. In the model, technology ladder has N equidistant innovation steps. The value of N, the maximum achievable technology gap, is set to 20.[28] In the data, I consider the patent quality distribution based on the citations-weighted patent counts in the last 5 years in the technology class of the firm, and split it into 20 equal intervals.

Finally, I estimate μ_n – the probability of spawning a H-type spinout from a firm with technology gap n, using the following regression specification:

$$Y_i = \beta_0 + \gamma_1 n + \gamma_2 n^2 + \boldsymbol{X_i \beta} + \varepsilon_i, \tag{29}$$

where Y_i is a dummy equal to one if a spinout i is H-type, and n is a technology gap of spinout's parent.[29] Other controls in $\boldsymbol{X_i}$ include log number of parents, parent's log number of patents in the last 5 years, as well as the cohort and technology class fixed effects. μ_n is then calculated as $\gamma_1 n + \gamma_2 n^2$ plus a constant equal to the average probability of H-type entry from a parent with $n = 1$. The resulting profile for μ_n is plotted in Figure 4. Similarly, I compute the share of regular entrants from the data that are H-type, resulting in $\tilde{\mu} = 0.20$.

Figure 4: Calibration: μ_n estimates



Notes: The figure reports the estimates for the μ_n parameters used in the model calibration. The estimates are based on equation (29). μ_n is then calculated as γ_n plus a constant equal to the average probability of H-type entry of a spinout from a parent with $n = 1$.

The second panel of Table 3 lists internally calibrated parameters. The parameter L can be directly pinned down from the data on labor force composition in the U.S. economy. The share of scientists and engineers in the total employment is about 5%.[30] This implies

[28]Setting N higher does not alter the results since, as will be seen from the equilibrium solution, the share of firms achieving the gap close to $N = 20$ is very low.

[29]If the spinout has multiple parents, I take the maximum technology gap among them.

[30]"Individuals in Science and Engineering Occupations as a Percentage of All Occupations." National Science Foundation.

that $\frac{1}{1+L} = 0.05$, resulting in $L = 19$. The remaining seven parameters are calibrated jointly by matching a set of moments. Below, I provide heuristic discussion of the identification and of the role each moment plays in pinning down the model parameters.

Together with L, a parameter S is related to the skill composition in the economy. Hence, in addition to the labor force composition, I match the moment on relative compensation of production and R&D workers in the U.S. economy. Based on the data on average earnings in S&E occupations relative to all the U.S. workers, I match the ratio of the average high-skill wage to the average wage $\frac{\overline{w(n,\tau)}}{w^u \frac{L}{1+L} + \overline{w(n,\tau)} \frac{1}{1+L}}$ to 2.27.[31]

R&D cost parameters B^H and B^L affect both the overall level of R&D intensity by firms as well as innovation differences between high- and low-type firms. The firm-level R&D intensity, measured as R&D-to-sales ratio, in the model is $\omega(n,\tau) + \frac{z(n,\tau)^\gamma}{\gamma B^\tau}$. This value, averaged across all the firms in the economy is then matched to the average R&D spending per sales computed in the sample, which is 0.127.[32]Relative innovation by high- and low-type firms $\frac{\overline{z^H(n,\tau)}}{\overline{z^L(z,\tau)}}$ is mapped to the ratio of average innovation outputs by H-type and L-type firms in the data, proxied, as before, by the lifetime citations-adjusted patent count of the firm, residualized for firms' cohort and technology class fixed effects. This ratio in the data is 9.5. The step size of innovation λ affects how innovation translates into aggregate growth (equation (25)). I match the aggregate growth rate of 3.1%, which is the average growth of the U.S. GDP during the sample period.[33]

The remaining three parameters in the model will directly affect entry rates. Entry cost parameter e affects the outside entry rate. Similarly, k affects cost of separation and as a result the spinout entry, while F is a policy parameter that will impact the spinout entry rate across locations with different NCL policies. To pin down these parameters, I will target the outside and spinout entry rates in the data. Average entry rate in the economy during the sample period is 11%.[34] In my data, spinout entrants account for 28.9% of entry, leading to the average outside entry of $I^o = 7.8\%$ and spinout entry of $I^s = 3.2\%$. Finally, I target the spinout entry rate in the states with no NCL restrictions ($F = 0$) of 4.31%. Data on NCL restrictions across states come from Garmaise (2011) and are described in detail in the Appendix Section F.

The calibration procedure then is to search for the unknown parameters $\Theta \equiv [\lambda, B^H, B^L, L, S, e, F, \kappa]$ to minimize the distance between model-implied moment values m_i^{model} and data moments m^{data} described above. Specifically,

[31]OES Survey, Bureau of Labor Statistics. Science and Engineering Indicators, 2018.

[32]R&D data reported in Compustat often contains zeros. It is not necessarily clear that these missing values always represent zeros. I compute statistics under two alternative scenarios imputing all missing values with zeros and, alternatively, imputing zeros only if firm issues zero patents in recent 5 years and average the resulting values.

[33]Because of large outliers, both lifetime citations-adjusted patent count and R&D-to-sales ratio are winsorized at 1%-95% levels.

[34]Business Dynamics Statistics Dataset, U.S. Census Bureau.

Table 4: Moments: Model vs Data

Description	Data	Model
Growth rate	3.1%	3.08%
Average R&D intensity	0.127	0.096
Ratio of H- to L-type firm innovations	9.5	6.72
Wage ratio $\overline{\frac{w(n,\tau)}{w^u}}$	2.27	1.42
Percent of S&E in workforce	5%	5%
Average outside entry rate	7.8%	8.77%
Average spinout entry rate	3.2%	3.76%
Spinout entry rate with no NCL	4.31%	5.36%

Notes: The table reports data moments and corresponding model counterparts from the calibration exercise.

$$\Theta^* = argmin\Big[\sum_{i=1}^{8} \omega_i \Big(\frac{m_i^{model}(\theta) - m_i^{data}}{m_i^{data}}\Big)^2\Big]^{0.5},$$

where ω_i denotes moment-specific weight. I weight all the moments equally except for the moment on spinout entry that I overweight twice. Resulting estimates of the parameters are given in the second panel of Table 3, and the implied match to the data is illustrated in Table 4. Model does quite well in matching all the moments from the data.

5 Solution Properties and Model Validation

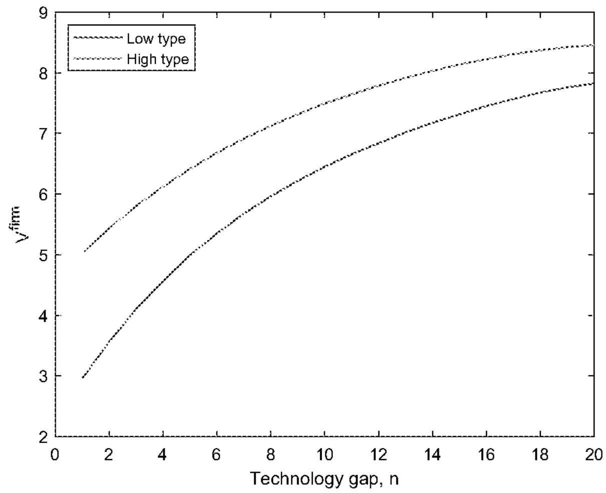
In this section, I discuss basic properties of the equilibrium solution and validate the model against non-targeted moments in the data.

Solution properties Figure 5 shows the value functions of the firm, R&D manager, and the wage rate of the R&D manager over the firm's technology gap.

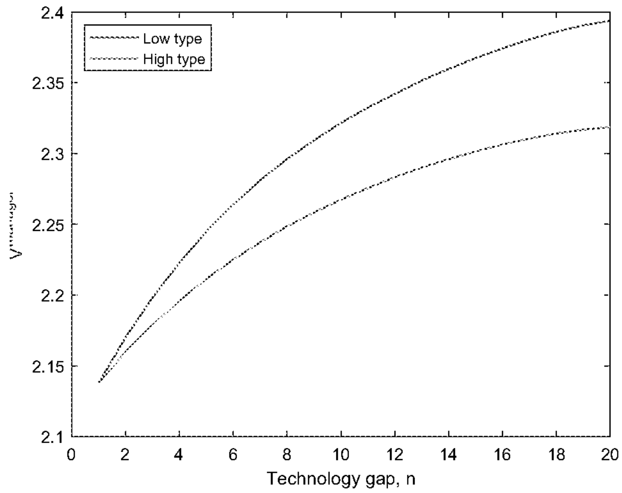
The value of a firm increases with technology gap, reflecting higher profits with higher n. At the same time, the value of an high-type firm is higher than the value of the low-type firm, since the high-type firms have higher probability to innovate and grow in the future. The value function of the R&D manager increases with technology gap, too. There are two reasons for this. First, when total surplus increases, because of bargaining, the share of surplus going to the R&D manager increases, too. However, importantly, there is another reason for higher wage growth. Recall that $\mu(n)$ – the probability of establishing a high-type firm if the R&D manager spawns a spinout, grows with the employer's technology gap. This increases the employee's surplus further. Unfortunately, my data do not contain information on R&D workers' wages, hence I cannot quantitatively validate the results. However, this increasing wage premium property is consistent with a large

Figure 5: Value Functions and R&D manager's Wages

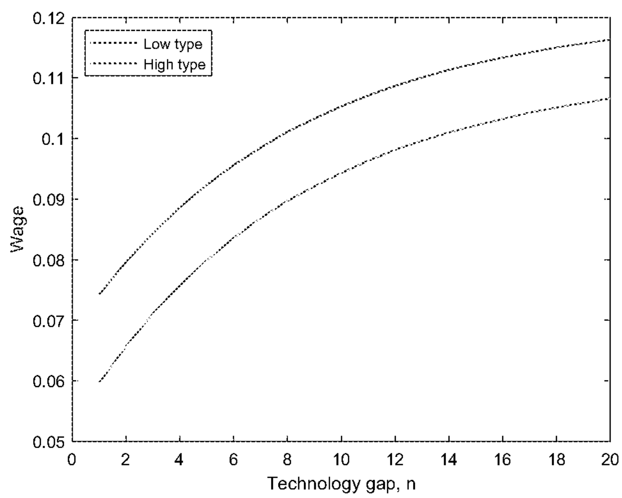
(a) Value function of the firm



(b) Value function of R&D manager



(c) Wages of R&D manager



Notes: Equilibrium solution of the model given the calibrated parameter values.

literature studying a large-firm wage premium (Brown and Medoff, 1989; Card et al., 2013; Song et al., 2019). In addition, Aghion et al. (2018) show that inventors earn more after the firm applies for a patent, especially a highly cited patent, getting closer to the relationship between higher technological leadership and R&D manager's wage documented here.

An interesting feature of the equilibrium wage function is that conditional on the technology gap wage in the low-type firm is higher than the wage in the high-type firm. Why is this the case? Conditional on n, R&D managers in the high-type firm are more likely to move up the technology ladder when firm innovates next period, hence increasing the probability of establishing a high-type spinout in the future. As a result, similar to the intuition from Acemoglu (1997), R&D managers pay for the possibility to move up the technological ladder with an employer. This result is also consistent with wage backloading documented by Moen (2005): the technical staff in RD-intensive firms take lower wages early in the career to pay for the knowledge they accumulate on the job. Lastly, it is worth noting that as seen from Appendix Figure 11, high-type firms reach the high levels of n more frequently than the low-type firms. As a result, since wages are growing with n, employees of high-type firms, on average (unconditional on n), would be more likely to obtain higher wages than the employees of low-type firms.

Next, I quantitatively compare the model-implied average innovation rate, R&D manager's separation rate, and firm size distribution with data. Appendix Figure 11 contains a more detailed description of these functions over technology gaps split by firm type.

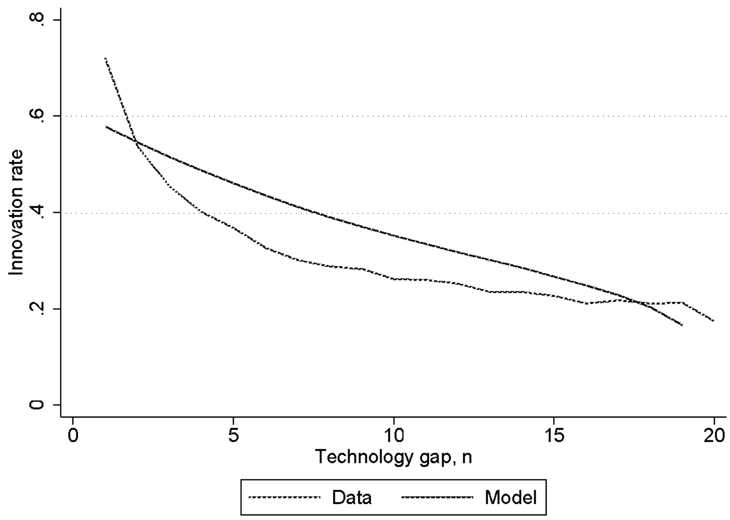
Innovation. Model and data. Figure 6 shows innovation rates of firms from the model and data. For the model, I plot $z(n, \tau)$ averaged over τ. In the data, I calculate the innovation rate of the firm as new citations-adjusted patents over the stock of firm's citations-adjusted patents and plot it over n as calculated in Section 4.1. We see that both in the model and the data, innovation rate declines with firm's technological leadership.[35] In the model, the decline in innovation rate is more gradual than in the data, but overall, the two profiles match well, especially given that the calibration procedure does not not match any moment related to the technology gaps.

Spinout separation. Model and data. Next, I examine the spinout separation rate in the model and the data. Since this function is an important and a new feature of this model, I start by presenting a detailed empirical analysis of spinout separation rate in the data.

Table 5 shows the relationship between spinout spawning and firm's technological leadership proxied by the quality of its patent filings. As earlier, Panel A presents results based on the patent data only, and Panel B includes results for the sample of patenting firms in Compustat. The first two columns present logit regressions for the yearly probability of

[35] This is also consistent with empirical evidence from Akcigit and Kerr (2018) and Argente et al. (2020).

Figure 6: Innovation Rate. Model and Data



spinout separation, while the last two columns show negative binomial regressions for the number of spinouts separating from the firm in a year. Across these different samples and specifications, the coefficient on log citations-adjusted patents in the last 5 years is positive and significant. Since the regressions also include the count of patents, this indicates that spinouts are more likely to separate after the firms file higher-quality patents. The regressions in addition control for the number of inventors to avoid mechanical dependence between firm size and spinout separation, firm age, year, industry, state, and firm fixed effects (columns 2 and 4). Additional controls are included in the regressions based on Compustat sample.[36]

This finding on higher spinout separation in more technologically advanced firms is also consistent with earlier findings by Klepper and Sleeper (2005) and Franco and Filson (2006) from the rigid disk drive and laser industries. Using administrative data from Sweden, a recent study by Engbom (2020) finds generally a negative relationship between employer's productivity and a probability of starting a firm. This relationship flips the sign, however, when the employer is in the top decile of the productivity distribution in the economy. Since my data focus on innovating firms who are in the very top of the productivity distribution in the economy, my evidence is also consistent with Engbom (2020).[37]

Consistent with the data, the model also generates a largely increasing relationship

[36]Appendix Tables A.5 and A.6 confirm robustness of these results to different definitions of the employer's technological leadership.

[37]A related evidence on spinout separation comes from Sohail (2021). Using individual-level data from Mexico and the U.S., the study shows a negative relationship between firm size and spinout entry. Notice that unlike Sohail (2021), here I focus on the technological leadership (patenting) of the firm, *conditional* on firm size. In addition, the data in this study contain firms that innovate which is a special sample of the firms where learning and technological knowledge diffusion is presumably more important.

Table 5: Technological Leadership and Spinout Separation

-Panel A: Patent data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents (parent)	0.141***	0.155***	0.139***	0.145***
	(0.0123)	(0.0337)	(0.0115)	(0.0299)
Patents, Inventors, Age	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	179313	50292	179547	50606

-Panel B: Patent + Compustat data

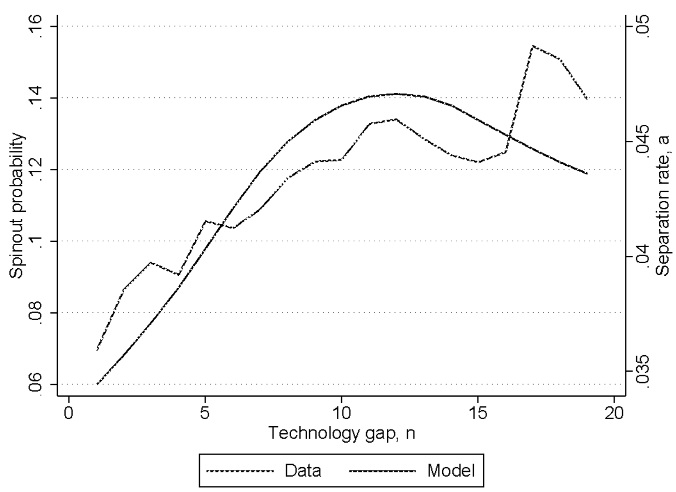
	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents (parent)	0.092*	0.193**	0.158***	0.204***
	(0.0492)	(0.0927)	(0.0392)	(0.0717)
Patents, Inventors, Age, R&D, Sales, Assets, Num. employees	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	15796	9797	16422	9984

Note: The table presents firm-level regressions of the probability of spinout separation (logit models in columns 1 and 2) and the count of spinouts (negative binomial models in columns 3 and 4) as a function of the technological leadership of the firm (parent) and other firm characteristics. Technological leadership is proxied by the firm's citations-adjusted patent count filed within the last 5 years. Panel A estimates the results on the sample of all patenting firms. Additional controls are the log number of patents, number of inventors and firm age together with fixed effects. Panel B shows the same kind of estimates for the merged sample with Compustat. Additional control variables are log sales, assets, number of employees, and the log R&D expenditures, log number of employees, sales growth and log assets value. The sample covers the period 1981-2000.

between the technology gap of the employer and the spinout separation rate of R&D managers, a. Interestingly, this separation rate declines at high levels of n. Overall, there are two main forces that drive R&D manager's decisions to form a spinout. The first force – a growing probability $\mu(n)$ of creating a high-type entrepreneurial venture, leads to a positive dependence between n and a.[38] The second force – growing wages, leads to a negative dependence between n and a. For high n, wages still grow (see Figure 5) but learning opportunities subside ($\mu(n)$ is stalling in Figure 4), leading on net to the declining incentives for separation.

Figure 6 compares model-implied separation rate over n and the probability of spawning a spinout by n from the data. In the data, we do not observe the declining tail for spinout probability. However, notice that this part of the technology gap distribution contains very few firms and, as a result, quantitatively plays a little role in aggregate dynamics.

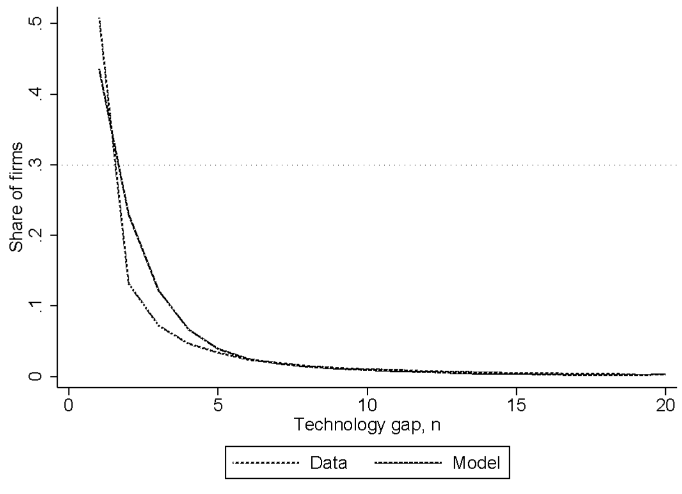
Figure 7: Spinout Separation Rate. Model and Data



Distribution of firms We can also compare the model-implied equilibrium distribution of firms across technology gaps to the distribution in the data. Figure 8 presents the distributions and shows that the entry, innovation, an exit dynamics in the model generate the stationary distribution that matches data well.

[38]Another consideration is also an option value of waiting and increasing the chances of forming a high-type spinout in the next period. This consideration effectively increases the opportunity cost of waiting. Hence, when learning curve is steep, incentives to separate are low.

Figure 8: Distribution of Firms over Technology Gaps. Model and Data



Non-compete laws. Model and Data Lastly, we explore spinout entry as a function of the strength of the non-compete laws both in the data and the model. The laws governing the enforcement of non-compete clauses in employee contracts that prohibit the employees from working for a competitor or forming a new firms vary across U.S. states. I rely on empirical measures of the strength of state-level non-compete laws, *NCL index*, from Garmaise (2011) and Starr (2019).[39]

Table 6 shows that stricter enforcement (a higher NCL index) is associated with lower spinout formation. These regressions look at the probability of spinout separation from the firm (logit models in columns 1 and 2) and the count of established spinouts (negative binomial models in columns 3 and 4) as a function of parent firm characteristics – the log number of patents and citation-adjusted patents filed in the last 5 years, the log number of inventors, firm age, and fixed effects (columns 2 and 4), as well as state-level characteristics – competition over time (the number of innovating firms in the same technology class and state), GDP per capita, and population.

Table 6: Non-Compete Laws and Spinout Separation

	(1) Logit	(2) FE Logit	(3) Neg. Binomial	(4) FE Neg. Binomial
NCL index	-0.623***	-0.077*	-0.425**	-0.101***
	(0.1996)	(0.0416)	(0.1772)	(0.0341)
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	179253	50153	179485	50465

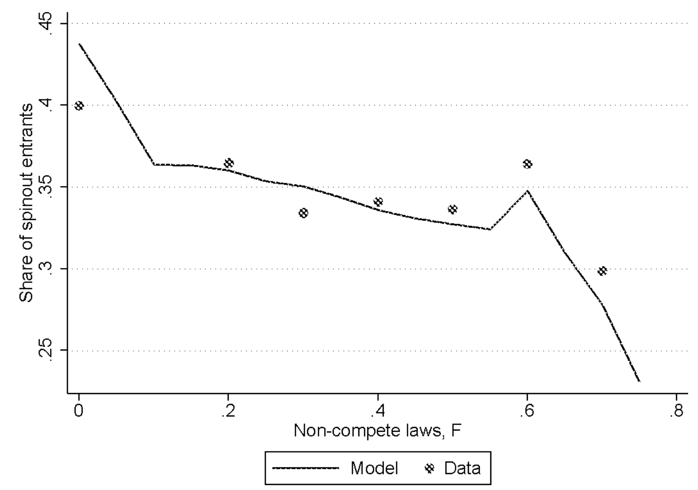
Note: The table presents firm-level regressions of the probability of spinout separation (logit models in columns 1 and 2) and the count of spinouts (negative binomial models in columns 3 and 4) as a function of the NCL index and other firm characteristics. *NCL index* is the non-competition index defined in (31). Other controls are the log number of patents and citation-adjusted patents filed in the last 5 years, the log number of inventors, firm age as well as the measures of state-level competition over time (number of innovating firms in the same technology class and state), GDP per capita, and population. The sample includes all patenting firms in the period 1981-2000.

Figure 9 shows a similar evidence at the macro level: in the states with stricter enforcement, the share of spinout entrants among all entrants is lower (red dots in the figure). In the model (blue line), the entry of spinouts decline, too. An important caveat in this comparison between the model and the data is that the model treats different states with different strength of laws as separate economies, but in the data the mobility across states

[39]See Appendix F for more details about data.

may affect the relationship between state-level laws and entry. Despite these considerations, the quantitative magnitudes of the decline in the share of spinout entrants over F are very similar. In addition, Appendix Figure 12 illustrates that the model also generates an interesting empirical observation highlighted by previous studies (e.g. Starr et al., 2018): although fewer spinouts enter in states with stricter a non-compete enforcement, the average quality of these entrants is higher. The model has a simple selection mechanism that accounts for this result: when cost of entry is higher, R&D managers wait longer on the job[40] to find a better-quality idea and separate only when in expectation this idea covers higher entry costs.

Figure 9: The Share of Spinout Entrants over Non-compete Laws. Model and Data



6 Growth Decomposition and Policy Counterfactuals

6.1 Growth Decompositions

I now use the structure of the model to analyze sources of aggregate productivity growth. From equation (1), we can decompose growth into productivity improvements coming from entrants and incumbents. Decomposing growth into these two margins in Table 7 shows that entry accounts for 23% of aggregate growth. This share is large given the overall low fraction of entrants. This number, however, is comparable to the estimates from recent studies showing large contribution of entrants to growth (Foster et al., 2008; Lentz and Mortensen, 2008; Acemoglu et al., 2018). Spinouts account for about the third of this direct contribution by entrants, resulting in 7% aggregate growth contribution. Table 7 also shows

[40]See Balasubramanian et al. (2017) for the evidence on longer job attachments of high-tech workers with stricter NCL.

that 46% of aggregate growth is accounted for by high-type firms, while the low-type firms contribute 31% of growth.

These direct growth contributions by spinouts and high-type firms are not taking into account dynamic effects. The high-type firms tend to achieve higher technological gaps and spawn more spinouts; these spinouts are in turn more likely to be high-type themselves. This sort of the proliferation effect is an important dynamic characteristic of this problem and increases the indirect contribution of spinout formation to growth. In the following section, we will see a more nuanced analysis of growth contribution of spinouts via channels of knowledge diffusion, firm composition, and incumbents' innovation. Finally, smaller firms (here, defined as $n \leq 5$) contribute more to growth compared to larger firms.

Table 7: Growth Decomposition

Aggregate growth: $g = 3.08\%$			
Entrants 23%		Incumbents 77%	
		High-type firms 46%	Low-type firms 31%
Spinout entrants 7%	Regular entrants 16%	Small firms ($n \leq 5$) 59%	Large firms ($n > 5$) 18%

6.2 Policy Analysis

The first column of Table 8 reports some illustrative equilibrium statistics from the benchmark economy matched to the average statistics from the U.S. To find the growth-maximizing value of F, I recalculate the steady state equilibrium of the economies characterized by different parameter values of F and search for F that maximizes aggregate growth given in equation (25). It turns out that relationship between g and F is close to monotonic, and $F = 0$ is the value that maximizes growth. In particular, moving from the benchmark estimate of non-compete laws to the case with no non-compete restrictions increases growth by 7 basis points. Notice that this gain is for the average value of non-compete restrictions, and there are larger gains for the states with stricter existing protection. Figure 10 lists the gains across different states from moving from their existing levels of regulations to the optimal level with zero protection. Across states, the gains range from zero to 11 percentage points. The welfare calculation using equation (28) shows that $F = 0$ also maximizes the consumer welfare.

Next, I explore the main channels that drive these results. The channels through which non-compete laws affect growth can be divided into *direct entry effect, composition effect, knowledge diffusion, and disincentive effect*. *Direct entry effect* refers to the direct effect of non-compete restrictions on separation incentives of R&D managers. From Table 8, we see that spinout entry rate I^s is larger in the case of no-restrictions. Because entry directly contributes to growth, this largely determines higher overall growth rate in the economy with no non-compete protection. *Composition effect* refers to the effect of non-compete laws on distribution of firms across technology gaps, n. In Table 8 it can be seen by comparing the total share of firms with $n = 1$ ($\xi(1, \cdot)$) to the total share of firms with $n = 10$ ($\xi(10, \cdot)$). Because of higher entry, in the economy with no non-compete restrictions, distribution of firms is shifted to the left. This, in turn, has a positive effect on growth as more competitive firms with lower markups innovate more. The third *knowledge diffusion* effect refers to the fact that because bigger share of entry comes from spinouts, there are more high-type firms in the economy with weaker non-competes. The table illustrates that although this effect is present (see $\xi(\cdot, H)$), it is not quantitatively large.

Finally, non-compete laws impact the incumbents' innovation incentives. The *disincentive effect* refers to the fact that for each n, incentives of firms to innovate are lower because of lower appropriability of returns from R&D investments. This effect can be clearly seen by comparing innovation rates $z(1, \cdot)$ and $z(10, \cdot)$ in the columns with benchmark and no non-compete protection. This negative disincentive effect is quite large and significantly dampens positive impact from the other effects. In particular, notice that the average innovation rate in the economy (see *Mean z* row) is somewhat lower in the economy with no restrictions. On net, however, the positive effect dominates, and it is both growth- and welfare-enhancing to abolish non-compete enforcement.

Given that the disincentive effect is quantitatively large, I next ask if it is possible to design the state-dependent policies that could diminish the disincentive effect, while not largely affecting the spinout entry rate. I focus on particular type of state-dependent policies that offer non-compete protection based on incumbent's current technological leadership. In other words, instead of considering the uniform F, I consider F as a function on n. The last column of Table 8 considers the effect of the policy that gives the highest protection to the firms with $n \leq 5$ and no protection afterwards. We see that this policy clearly reduces both growth and welfare. It turns out that setting the protection the opposite way is more beneficial. In particular, as the third column illustrates, giving the full protection to the firms with the highest five technology gaps is actually growth-enhancing. Why does this happen? This can be explained by a *trickle-down effect*: when policies provide higher protection to more advanced firms, this gives incentives to the firms below the threshold to catch up and reach the state with higher protection. This can be clearly seen by looking at the innovation rates of firms $z(1, \cdot)$ and $z(10, \cdot)$ from the Table. At the same time, spinout entry is not affected negatively too much. This results in the higher aggregate growth. However, notice that while maximizing growth, this policy reduces welfare relative to no-protection case. This largely happens because giving protection to technolog-

Table 8: Non-compete Policy Experiments

	Benchmark NCL	No NCL	Protection of Higher n	Protection of Lower n
$z(1,\cdot)$	1.0790	1.0115	1.0395	1.1224
$z(10,\cdot)$	0.8174	0.7797	0.9034	0.7503
$\xi(1,\cdot)$	0.3180	0.3964	0.3798	0.2464
$\xi(10,\cdot)$	0.0128	0.0088	0.0101	0.0168
$\xi(\cdot,H)$	0.2816	0.2822	0.2765	0.2824
Mean z	0.3534	0.3417	0.3487	0.3513
$a(1,\cdot)$	0.0515	0.1059	0.1081	0
$a(10,\cdot)$	0.0926	0.1329	0.0761	0.0974
I^s	0.0317	0.0560	0.0504	0.0127
I^o	0.0706	0.0674	0.0687	0.0742
w^u	0.0197	0.0205	0.0201	0.0192
w^s	0.0848	0.0692	0.0745	0.0961
g^*	3.08%	3.15%	3.17%	2.96%
$Welfare$	120.0126	126.7576	123.4354	115.6200

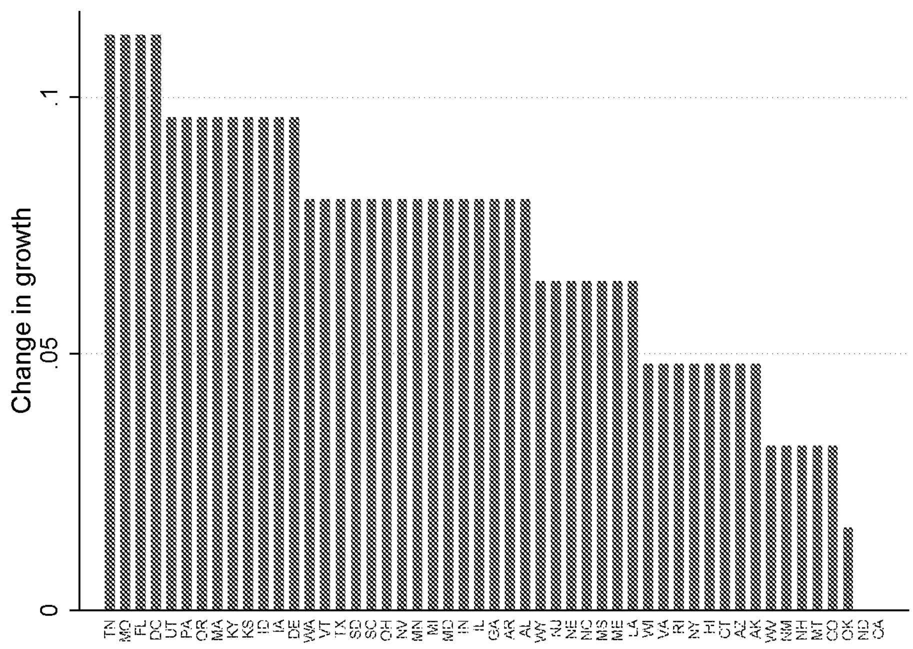
ical leaders shifts firm's distribution to the right, and higher markups are associated with welfare losses for consumers.

7 Conclusion

This paper theoretically and empirically studies the role of employee entrepreneurship in innovation and productivity growth. Using the newly constructed data on innovating spinouts from the USPTO patent filings, I find evidence of the superior quality of spinout firms and the strong correlation between spinout quality and the technological leadership of a parent firm. Motivated by these observations, I study the interaction between incumbents' innovation incentives and spinout entry in a dynamic general equilibrium endogenous growth framework. The developed model provides rich grounds to analyze multiple channels through which the process of employee entrepreneurship affects industry dynamics and aggregate growth. I find that it is welfare improving to abolish existing non-compete restrictions; however, the policy protecting firms with high technological leadership is growth-maximizing.

The dynamics of employee entrepreneurship is an important and understudied question in growth theory. The theoretical framework developed in this work can be applied to jointly study various innovation and labor market policies.

Figure 10: Gains from the Optimal Uniform Policy Adoption across States



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Theoretical Appendix

A Derivation of Bellman Equation (13)

As an example, I derive Bellman equation for R&D managers. Other equations are derived in a similar way. We start by writing down the value of being an R&D manager $V_t^{manager}(n,\tau)$ as

$$V_t^{manager}(n,\tau) = \max_{a_t(n,\tau)\geq 0} \left\{ \begin{array}{c} \left[w_t(n,\tau) - \frac{ka_t^2(n,\tau)}{2}Y_t\right]\Delta t + o(\Delta t) \\ +e^{-r_{t+\Delta t}\Delta t} \left[\begin{array}{c} a_t(n,\tau)\Delta t\left(\mu(n)V_{t+\Delta t}^{firm}(1,H) + (1-\mu(n))V_{t+\Delta t}^{firm}(1,L) - FY_{t+\Delta t}\right) \\ +(I^s+I^o)\Delta t V_{t+\Delta t}^{out} + z_t(n,\tau)\Delta t V_{t+\Delta t}^{manager}(n+1,\tau) \\ +(1-a_t(n,\tau)\Delta t - (I^s+I^o)\Delta t - z_t(n,\tau)\Delta t)V_{t+\Delta t}^{manager}(n,\tau) \end{array} \right. \end{array} \right.$$

The value at time t consists of wages minus incurred cost of separation during a time interval Δt. Next is the discounted continuation value after Δt. This continuation value is made up of the following parts: the first line in square brackets is a net continuation value from forming a spinout which happens with probability $a_t(n,\tau)\Delta t$ during a time interval Δt. The second line comes from the possibility of creative destruction of an employer firm with probability $(I^s + I^o)\Delta t$, in which case the manager gets $V_{t+\Delta t}^{out}$, and from the possibility of employer's innovation with probability $z_t(n,\tau)\Delta t$, in which case a manager gets $V_{t+\Delta t}^{manager}(n+1,\tau)$. Finally, on the third line, with the remaining probability, manager continues working in the same firm and gets $V_{t+\Delta t}^{manager}(n,\tau)$.

Now, subtract $V_t^{manager}(n,\tau)$ from both sides and divide everything by Δt:

$$\frac{o(\Delta t)}{\Delta t} = \max_{a_t(n,\tau)\geq 0} \left\{ \begin{array}{c} w_t(n,\tau) - \frac{ka_t^2(n,\tau)}{2}Y_t \\ +e^{-r_{t+\delta t}\Delta t} \left[\begin{array}{c} a_t(n,\tau)\left(\mu(n)V_{t+\Delta t}^{firm}(1,H) + (1-\mu(n))V_{t+\Delta t}^{firm}(1,L) - FY_{t+\Delta t}\right) \\ +(I^s+I^o)V_{t+\Delta t}^{out} + z_t(n,\tau)V_{t+\Delta t}^{manager}(n+1,\tau) \\ -(a_t(n,\tau) + (I^s+I^o) + z_t(n,\tau))V_{t+\Delta t}^{manager}(n,\tau) \end{array} \right] \\ +\frac{e^{-r_{t+\Delta t}\Delta t}V_{t+\Delta t}^{manager}(n,\tau) - V_t^{manager}(n,\tau)}{\Delta t} \end{array} \right\}$$

Take limits when $\Delta t \to 0$:

$$
0 = \max_{a_t(n,\tau)\geq 0} \left\{ \begin{array}{c}
w_t(n,\tau) - \frac{k a_t^2(n,\tau)}{2} Y_t \\
+a_t(n,\tau) \left(\mu(n) V_t^{firm}(1,H) + (1-\mu(n)) V_t^{firm}(1,L) - F Y_t \right) \\
+(I^s + I^o) V_t^{out} + z_t(n,\tau) V_t^{manager}(n+1,\tau) \\
-(a_t(n,\tau) + (I^s + I^o) + z_t(n,\tau)) V_t^{manager}(n,\tau) \\
+ \lim_{\Delta t \to 0} \frac{e^{-r_{t+\Delta t}\Delta t} V_{t+\Delta t}^{manager}(n,\tau) - V_t^{manager}(n,\tau)}{\Delta t}
\end{array} \right\}
$$

Notice that $\lim_{\Delta t \to 0} \frac{e^{-r_{t+\Delta t}\Delta t} V_{t+\Delta t}^{manager}(n,\tau) - V_t^{manager}(n,\tau)}{\Delta t}$ is indetermined, so using the l'Hopital's rule, we get $-r_t V_t^{manager}(n,\tau) + \dot{V}_t^{manager}(n,\tau)$. Hence,

$$
r_t V_t^{manager}(n,\tau) - \dot{V}_t^{manager}(n,\tau) = \max_{a_t(n,\tau)\geq 0} \left\{ \begin{array}{c}
w_t(n,\tau) - \frac{k a_t^2(n,\tau)}{2} Y_t \\
+a_t(n,\tau) \left(\mu(n) V_t^{firm}(1,H) + (1-\mu(n)) V_t^{firm}(1,L) - F Y_t \right. \\
+(I^s + I^o)(V_t^{out} - V_t^{manager}(n,\tau)) \\
+z_t(n,\tau)(V_t^{manager}(n+1,\tau) - V_t^{manager}(n, \\
-(a_t(n,\tau) + (I^s + I^o) + z_t(n,\tau)) V_t^{manager}(n
\end{array} \right.
$$

Since we are focusing on the steady state equilibrium in which decision rules are constant over time and value functions grow at the same rate as the whole economy, g, we can divide the above equation by Y_t and rewrite in the following way:

$$
\rho v^{manager}(n,\tau) = \max_{a(n,\tau)\geq 0} \left\{ \begin{array}{c}
\omega(n,\tau) - \frac{k a_t^2(n,\tau)}{2} \\
+a(n,\tau) \left(\mu(n) v^{firm}(1,H) + (1-\mu(n)) v^{firm}(1,L) - F - v^{manager}(n,\tau) \right) \\
+(I^s + I^o)(v^{out} - v^{manager}(n,\tau)) \\
+z(n,\tau)(v^{manager}(n+1,\tau) - v^{manager}(n,\tau)) \\
-(a(n,\tau) + (I^s + I^o) + z(n,\tau)) v^{manager}(n,\tau)
\end{array} \right\}
$$

where we used the fact that $\frac{\dot{V}_t^{manager}(n,\tau)}{Y(t)} = g v^{manager}$ and by Euler equation, $\rho = r - g$. This gives us equation (13).

B Proof of Equation (28)

Expanding the expression for the welfare (26) and taking into account that in the steady state equilibrium Y_t grows at rate g, we get

$$
\begin{aligned}
Welfare(0) &= \int_0^\infty e^{-\rho t} lnC_t dt \\
&= \int_0^\infty e^{-\rho t} ln(1-I)Y_t dt \\
&= \int_0^\infty e^{-\rho t} ln(1-I)dt + \int_0^\infty e^{-\rho t} \ln e^{gt} Y_0 dt \\
&= -\left.\frac{\ln(1-I)e^{-\rho t}}{\rho}\right|_0^\infty + \ln Y_0 \int_0^\infty e^{-\rho t} dt + \int_0^\infty gte^{-\rho t} dt \\
&= \frac{\ln(1-I)}{\rho} + \frac{\ln Y_0}{\rho} + g\left[-\left.\frac{te^{-\rho t}}{\rho}\right|_0^\infty + \frac{\int_0^\infty e^{-\rho t}dt}{\rho}\right] \\
&= \frac{\ln(1-I)}{\rho} + \frac{\ln Y_0}{\rho} - g\frac{e^{-\rho t}|_0^\infty}{\rho^2} \\
&= \frac{\ln(1-I)}{\rho} + \frac{\ln Y_0}{\rho} + \frac{g}{\rho^2}
\end{aligned}
$$

Now, let us expand $\ln Y_0$:

$$
\begin{aligned}
\ln Y_0 &= \int_0^1 \ln y(j,0)dj \\
&= \int_0^1 \ln q(j,0)dj + \int_0^1 \ln l(j,0)dj \\
&= \ln Q(0) + \int_0^1 \ln \frac{1}{\omega^u \lambda^{n_j}} dj \qquad (30) \\
&= \ln Q(0) - \ln \lambda \int_0^1 n_j dj - \ln \omega^u \\
&= \ln Q(0) - \ln \lambda \sum_{n,\tau} n\xi(n,\tau) - \ln \omega^u
\end{aligned}
$$

The second line used (3) and the third line used labor demand (23). Hence, we arrived at equation (28).

C Proof of Proposition 1

Similar derivation as above gives us that $\ln Y_t = \ln Q(t) + \textit{constant terms}$ in steady state. Hence, growth in output is the same as growth in productivity $Q(t)$:

$$g = \lim_{\Delta t \to 0} \frac{\ln Q(t+\Delta t) - \ln Q(t)}{\Delta t}$$

.

Growth in Q comes from successful innovation by incumbents, spinout entry, or entry by outsiders. In a time interval Δt, probability of a successful innovation by incumbents is equal to $\Delta t \sum_{n,\tau} \xi(n,\tau) z(n,\tau)$, while probability of a successful spinout entry is equal to $I^s \Delta t$ and probability of a successful entry by outsiders is $I^o \Delta t$. All these innovations improve productivity by λ.

Hence,

$$\begin{aligned} g &= \frac{\Delta t(I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln \lambda Q(t) + (1 - \Delta t(I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln Q(t) - \ln Q(t)}{\Delta t} \\ &= (I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln \lambda Q(t) - (I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln Q(t) \\ &= (I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln \lambda \end{aligned}$$

D Computational Algorithm

To quantitatively solve for the steady state equilibrium of the model, I use the following computational algorithm.

Step 1. Guess the firm's and manager's value functions $v^{firm}(n,\tau)$ and $v^{manager}(n,\tau)$.

Step 2. Given $v^{firm}(n,\tau)$ and $v^{manager}(n,\tau)$, compute optimal policies $z(n,\tau)$ and $a(n,\tau)$ using the first-order conditions in (14) and (16).

Step 3. Find v^{entry} and optimal entry rate ν using the value function definition in (9). This reduces to solving a quadratic equation in v^{entry} unknown. The resulting solution is:

$$v^{entry} = M + e\rho - \sqrt{2Me\rho + e^2\rho^2},$$

where $M = \tilde{\mu} v^{firm}(1,H) + (1-\tilde{\mu}) v^{firm}(1,L)$.

Given v^{entry}, compute the resulting aggregate entry by outsiders, I^o, from equation (10).

Step 4. Given the policy functions and entry rate by outsiders, find the stationary distribution $\xi(n, \tau)$ by solving the quadratic system of equations given in equations (19), (20), (21), and (22). Compute spinout entry rate I^s from equation (22).

Step 5. Solve for $v^{firm}(n, \tau)$, $v^{manager}(n, \tau)$, and wages $\omega(n, \tau)$ using equations (12), (13), (15), (17), and (18). Use the fact that v^{work} is equal to v^{entry}, which has already been calculated.

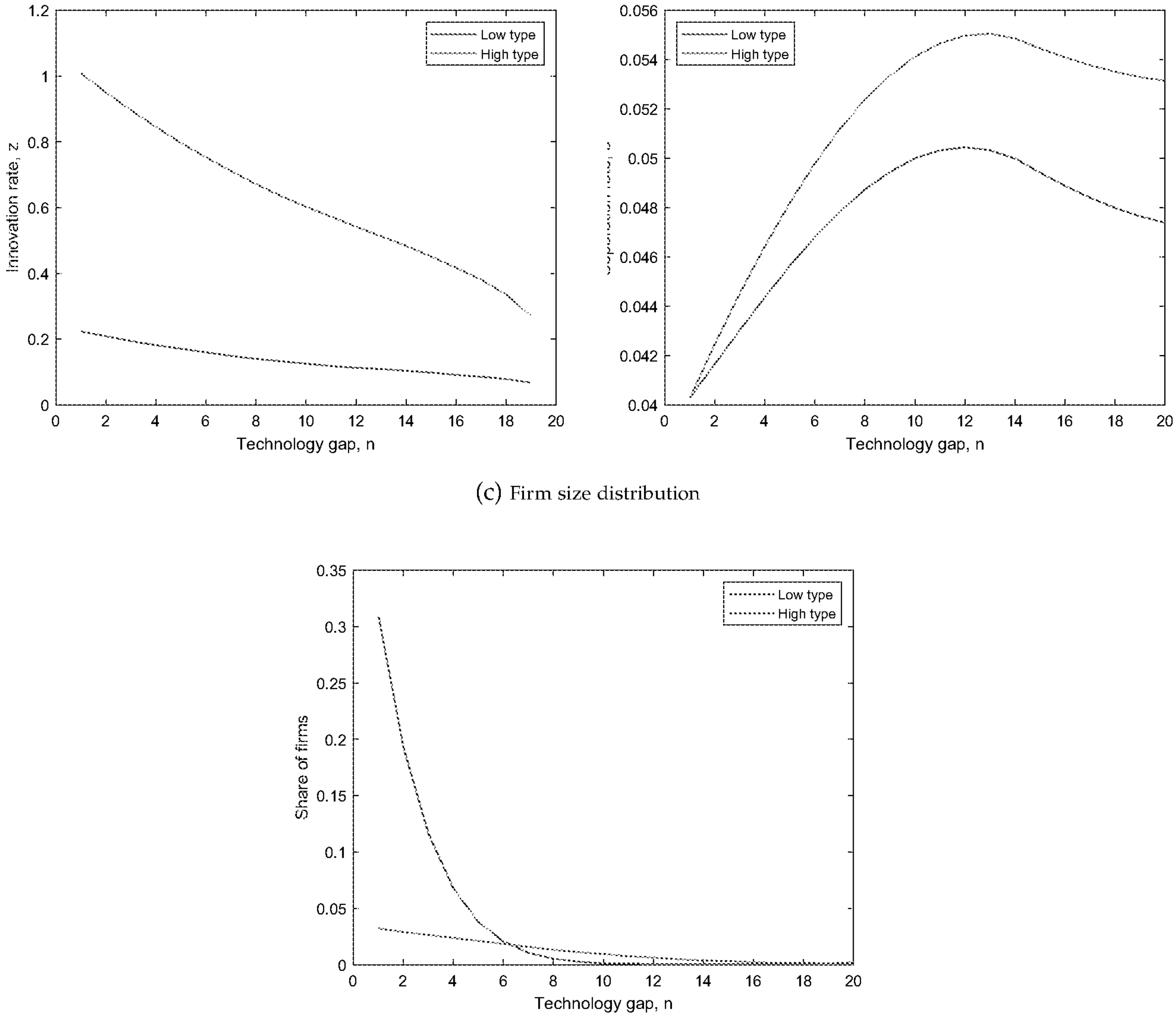
Step 6. Compare $v^{firm}(n, \tau)$ and $v^{manager}(n, \tau)$ to the previous guesses. Iterate this algorithm until both value functions converge.

E Additional Results from the Model

Figure 11: Innovation, Separation, and Firm Size Distribution in the Model

(a) Innovation rate of the firm

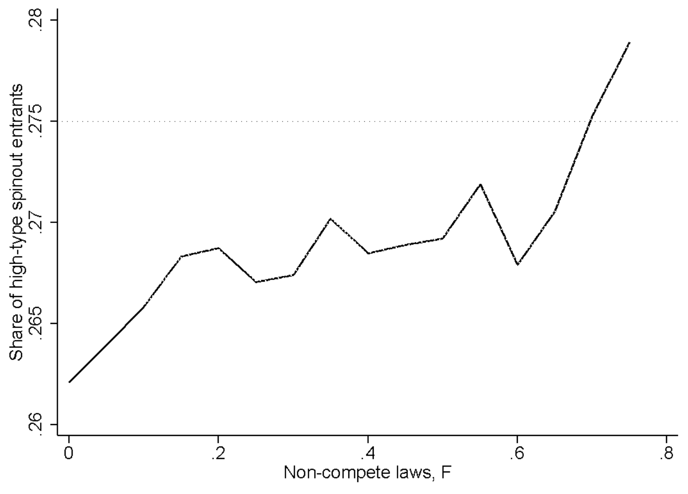
(b) Spinout separation rate



(c) Firm size distribution

Notes: Equilibrium solution of the model given the calibrated parameter values.

Figure 12: The Share of High-type Spinouts among Spinout Entrants



Notes: The figure plots the equilibrium share of H-type entrants among all spinout entrants over different values of F correnponding to the *NLC index* range across the U.S. states.

F Additional Data Details. Non-compete Laws

Non-compete covenants are the clauses in employee contracts that prohibit the employees from working for a competitor or forming a new competing firm. The laws governing the enforcement of non-compete agreements, the non-compete laws (NCL), vary greatly across the U.S. states. Malsberger (2004) conducted a state-by-state survey analyzing twelve questions on different aspects of enforcement of non-compete agreements. There are two states which completely void the non-compete agreements: California and North Dakota. Other states largely vary by the types of contracts enforceable in terms of the scope, geographic area, length, time restriction, and others. Based on the questions analyzed in the survey, Garmaise (2011) derived state-specific non-competition index. Over the U.S. states, the index varies from 0 to 9, with a higher index indicating a stricter enforcement. More recently, Starr (2019) builds on Bishara (2011) and provides a different index for non-compete laws across states for the years 1991 and 2009. Table A.1 lists these three indexes for each state. These indexes are highly correlated, but since the NCL index from Starr (2019) has more time variation, I use this index as the benchmark in the regression analysis. More specifically, I combine the 1991 and 2009 versions of the index and define the final index over time as

$$NCL(t) = NCL_{1991} + \frac{NCL_{2009} - NCL_{1991}}{18}(t - 1991) \tag{31}$$

Notice that, as required by the Full Faith and Credit Clause in the United States Constitution, states within the United States have to respect "public acts, records, and judicial proceedings of every other state". This should mean that even if the spinout founded a new start-up in a state different from the state of the previous employer, the laws of the previous state should be still important. In 1998 though, California set the precedent (Application Group, Inc. vs Hunter Group, Inc.) where the court stated that California law is applicable to non-California employees seeking employment in California. In general, despite the Full Faith and Credit statement, there is still some ambiguity as to which laws should be applicable in each case. This uncertainty though ex-ante may work in favor of employers so that the employees take less risk in trying to compete with the employer.

G Additional Empirical Results

Appendix Table A.1: Non-competition Indexes across the U.S. States

State	NCL Garmaise'11	NCL1991 Starr'19	NCL2009 Starr'19	State	NCL Garmaise'11	NCL1991 Starr'19	NCL2009 Starr'19
Alabama	5	0.36	0.36	Montana	2	-0.63	-0.65
Alaska	3	-1.33	-0.98	Nebraska	4	-0.13	-0.13
Arizona	3	-0.16	0.15	Nevada	5	-0.62	0.03
Arkansas	5	-0.62	-0.58	New Hampshire	2	0.26	0.26
California	0	-3.76	-3.79	New Jersey	4	0.47	0.9
Colorado	2	0.38	0.38	New Mexico	2	0.74	0.74
Connecticut	3	0.62	1.26	New York	3	-0.73	-1.15
Delaware	6	0.18	0.52	North Carolina	4	0.18	0.18
DC	7	0.12	0.12	North Dakota	0	-4.23	-4.23
Florida	7	1.15	1.6	Ohio	5	-0.18	0.08
Georgia	5	0.45	0.02	Oklahoma	1	-0.8	-0.94
Hawaii	3	-0.83	-0.17	Oregon	6	0.14	0.14
Idaho	6	-0.01	0.77	Pennsylvania	6	-0.14	0.14
Illinois	5	0.55	0.95	Rhode Island	3	-0.67	-0.33
Indiana	5	0.7	0.7	South Carolina	5	-0.2	-0.27
Iowa	6	0.19	1.01	South Dakota	5	0.37	1.02
Kansas	6	0.69	1.21	Tennessee	7	0.22	0.45
Kentucky	6	0.61	0.85	Texas	5	-0.04	-0.28
Louisiana	4	-0.7	0.5	Utah	6	1	1
Maine	4	0.06	0.41	Vermont	5	0.3	0.6
Maryland	5	0.15	0.6	Virginia	3	0.09	-0.29
Massachusetts	6	0.87	0.48	Washington	5	0.64	0.34
Michigan	5	0.07	0.46	West Virginia	2	-0.8	-0.8
Minnesota	5	-0.07	-0.07	Wisconsin	3	0.16	-0.09
Mississippi	4	-0.2	0.04	Wyoming	4	-0.65	0.23

Note: The Table presents the non-competition indexes from Garmaise (2011) and Starr (2019).

Appendix Table A.2: Parent's Characteristics and Performance of Spinouts

-Panel A-

	Log number of cit-weighted patents of spinout			
Log num of parents	0.558***	0.556***	0.551***	0.559***
	(0.041)	(0.041)	(0.042)	(0.041)
Log parents' patents	0.063***	-0.337***	-0.063***	-0.029**
	(0.005)	(0.016)	(0.008)	(0.012)
Log parents' cit-patents		0.392***		
		(0.015)		
Parents' tech lead pctile			0.067***	
			(0.003)	
Log parents' top patents				0.138***
				(0.017)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	16672	16582	16672	16672

-Panel B-

	Log number of top patents of spinout			
Log num of parents	0.190***	0.189***	0.188***	0.191***
	(0.021)	(0.021)	(0.021)	(0.021)
Log parents' patents	0.022***	-0.110***	-0.013***	-0.032***
	(0.002)	(0.007)	(0.004)	(0.005)
Log parents' cit-patents		0.129***		
		(0.007)		
Parents' tech lead pctile			0.019***	
			(0.001)	
Log parents' top patents				0.081***
				(0.007)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	17268	17166	17268	17268

Note: The table shows the regressions of spinouts' outcome variables as a function of various parental characteristics at the time of spinout separation. Each observation is a spinout firm entering in the period 1981-2000. The outcome variable in Panel A is spinout's lifetime log citations-weighted patent counts; the outcome variable in Panel B is spinout's lifetime log number of top patents. Top patents are the patents whose truncated-adjusted citations are above the 90th percentile of the citations distribution of patents filed in the same year and technology class. Control variables include the log number of parents, parents' log number of patents, log number of citations-weighted patents, technological lead percentiles, and log number of top patents. Technological lead percentile is a categorical variables with 20 quantiles of the patent quality distribution based on the citations-weighted patent counts in the last 5 years in the technology class (*cat-ocl*) of the firm. The regressions also control for spinout's cohort, technology class, and state fixed effects.

Appendix Table A.3: Parent Characteristics and Performance of Spinouts. Other Outcome Variables

-Panel A-

	Log longevity of spinout			
Log num of parents	0.197***	0.197***	0.196***	0.197***
	(0.024)	(0.024)	(0.024)	(0.024)
Log parents' patents	0.029***	-0.064***	-0.013***	0.030***
	(0.003)	(0.011)	(0.005)	(0.008)
Log parents' cit-patents		0.091***		
		(0.010)		
Parents' tech lead pctile			0.023***	
			(0.002)	
Log parents' top patents				-0.001
				(0.010)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	17268	17166	17268	17268

-Panel B-

	Log number of patents of spinout			
Log num of parents	0.475***	0.474***	0.471***	0.475***
	(0.034)	(0.034)	(0.034)	(0.034)
Log parents' patents	0.057***	-0.078***	-0.005	0.058***
	(0.004)	(0.013)	(0.006)	(0.010)
Log parents' cit-patents		0.132***		
		(0.011)		
Parents' tech lead pctile			0.032***	
			(0.002)	
Log parents' top patents				-0.002
				(0.013)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	17268	17166	17268	17268

Note: Table repeats the analysis of Table A.2, but for other outcome variables. The outcome variable in Panel A is the log longevity of the spinout; the outcome variable in Panel B is spinout's lifetime log number of patents.

Appendix Table A.4: Parent Characteristics and Performance of Spinouts. Robustness

-Panel A

Log number of citations-weighted patents of spinout

	(1)	(2)	(3)
Log num of parents	0.539***	0.556***	0.622***
	(0.042)	(0.042)	(0.046)
Log parents' patents	-0.046***	-0.065***	-0.056***
	(0.008)	(0.008)	(0.010)
Parents' tech lead pctile	0.060***	0.070***	0.073***
	(0.003)	(0.003)	(0.006)
Cohort FE	YES	YES	YES
Tech class FE	YES	YES	YES
State FE	YES	YES	YES
Observations	16672	16672	9701

-Panel B

Log number of top patents of spinout

	(1)	(2)	(3)
Log num of parents	0.185***	0.190***	0.215***
	(0.021)	(0.021)	(0.025)
Log parents' patents	-0.009***	-0.013***	-0.016***
	(0.003)	(0.004)	(0.005)
Parents' tech lead pctile	0.017***	0.019***	0.025***
	(0.001)	(0.001)	(0.002)
Cohort FE	YES	YES	YES
Tech class FE	YES	YES	YES
State FE	YES	YES	YES
Observations	17268	17268	10005

Note: Table presents the specifications similar to column (3) of Table A.2, but with various robustness checks. The first column redefines parent's technological lead percentile based on the citations distribution with more narrow technology classification (*nclass*); the second column redefines technological lead percentile based on the citations distribution of all firms, irrespective of their technology classification. The third column considers robustness to the definition of the spinout separation time by defining the parental variables in the entry year of the spinout firm.

Appendix Table A.5: Probability of spinout separation. Different proxy for parent's technological leadership.

-Panel A: Patent data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log top patents	0.259***	0.127***	0.219***	0.076***
	(0.0151)	(0.0343)	(0.0125)	(0.0275)
Patents, Inventors, Age	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	184009	50660	184213	50978

-Panel B: Patent + Compustat data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log top patents	0.230***	0.174**	0.182***	0.092*
	(0.0357)	(0.0685)	(0.0262)	(0.0478)
Patents, Inventors, Age, R&D, Sales, Assets, Num. employees	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	15796	9797	16422	9984

Note: The Table repeats the analysis in Table 5, but using the log top patents as measure of parent's technological leadership. Panel A of the table shows annual panel estimates of the probability of an entrant firm being a spinout as a function of various firm characteristics in different rows for all firms in the patent data, for the time period 1981-2000. Patents and top patents are the total number of all patents and top patents granted to the firm during the last 5 years for each year, respectively. Inventors is the total number of inventors of the firm during the last 5 years for each year. Panel B shows the same kind of estimates of Panel A for the merged databases between Patents and Compustat. Control variables in Panel B are firm's annual log R&D expenditures, log number of employees, sales growth and log assets value.

Appendix Table A.6: Probability of spinout separation. Contemporaneous measure of parent's technological leadership.

-Panel A: Patent data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents yr	0.111***	0.055***	0.104***	0.037**
	(0.0107)	(0.0178)	(0.0099)	(0.0156)
Patents, Inventors, Age	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	175352	48983	175632	49285

-Panel B: Patent + Compustat data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents yr	0.022	0.058	0.077***	0.046
	(0.0353)	(0.0479)	(0.0280)	(0.0378)
Patents, Inventors, Age, R&D, Sales, Assets, Num. employees	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	15796	9797	16422	9984

Note: The Table repeats the analysis in Table 5, but using the contemporaneous (instead of last 5-year) quality-adjusted patent count of parent firms. Panel A of the table shows annual panel estimates of the probability of an entrant firm being a spinout as a function of various firm characteristics in different rows for all firms in the patent data, for the time period 1981-2000. "Patents yr" and "cit-patents yr" are the total number of all patents and adjusted citation patents granted to the firm for each year, respectively. Inventors is the total number of inventors of the firm for each year. Panel B shows the same kind of estimates of Panel A for the merged databases between Patents and Compustat. Control variables in Panel B are firm's annual log R&D expenditures, log number of employees, sales growth and log assets value.

Appendix Table A.7: Non-compete Laws and Spinout Formation. Alternative NCL index.

	(1) Logit	(2) Logit	(3) Neg. Binomial	(4) Neg. Binomial
NCL index	-0.037*	-0.056***	-0.027	-0.046***
	(0.0196)	(0.0203)	(0.0175)	(0.0156)
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	179253	50153	179485	50465

Note: The table repeats the regressions in Table 6 but using a different measure of non-compete laws from Garmaise (2011). Other controls are the log number of patents and citation-adjusted patents filed in the last 5 years, the log number of inventors, firm age as well as the measures of state-level competition over time (number of innovating firms in the same technology class and state), GDP per capita, and population. The sample includes all patenting firms in the period 1981-2000.

Appendix Table A.8: Non-Compete Laws and Spinout Separation. Within-state and within-industry spinouts.

-Panel A-

Within-state spinouts

	(1) Logit	(2) Logit	(3) Neg. Binomial	(4) Neg. Binomial
NCL index	-0.403	-0.223***	-0.396	-0.169**
	(0.3260)	(0.0728)	(0.3062)	(0.0665)
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	168908	23264	170599	23402

-Panel B-

Within-industry spinouts

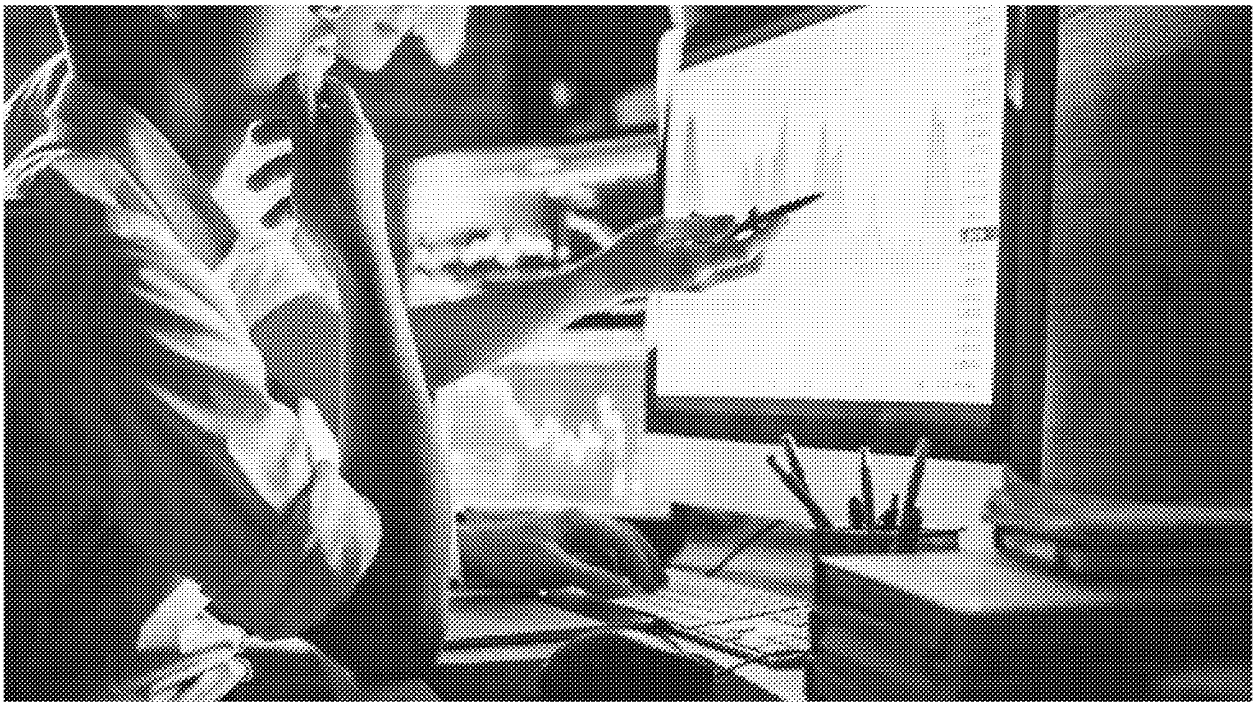
	(1) Logit	(2) Logit	(3) Neg. Binomial	(4) Neg. Binomial
NCL index	-0.236	-0.173***	-0.129	-0.168***
	(0.2772)	(0.0611)	(0.2586)	(0.0536)
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	170673	26993	170673	27120

Note: The table repeats the regressions in Table 6 but only considering the within-industry spinouts (Panel A) and within-industry spinouts (Panel B). *NCL index* is the non-competition index defined in (31). Other controls are the log number of patents and citation-adjusted patents filed in the last 5 years, the log number of inventors, firm age as well as the measures of state-level competition over time (number of innovating firms in the same technology class and state), GDP per capita, and population. The sample includes all patenting firms in the period 1981-2000.

The brokered patent market in 2022

The 2022 Richardson Oliver Patent Market Report, “Every Patent, Everywhere, All at Once”, gives a snapshot of 2022 buy-sell activity, including sourcing, diligence, pricing, buyers, litigation and market size.

Kent Richardson, Erik Oliver and Michael Costa
19 April 2023



- **Patent market growing as the economic downturn encourages operating companies to sell assets**
- **Data shows broker community is critically important to the success of the patent market**
- **Software-related technologies dominate patent market; biggest increase in hardware related packages**

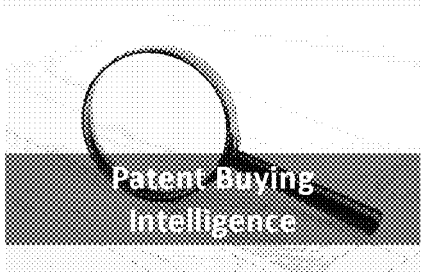
The patent market is growing a lot as the economic downturn places more assets for sale. Companies are exiting markets and their assets are being listed: for example, GoPro Inc is selling its drone portfolio and Intel Corp is selling its wireless portfolio.

"Like Zillow for patents"

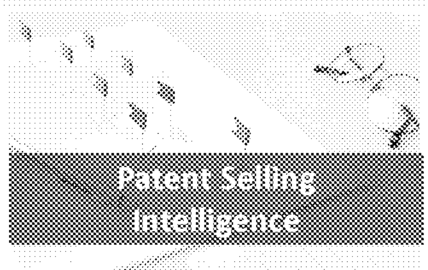
Patent Market Data and Analytics Solutions

Richardson Oliver Insights offers a suite of data and analytics solutions providing patent buyers, sellers, and executives access to patent market data covering over 250,000 patent assets and 16,500 deals. The data spans hundreds of technologies and market sectors including smartphones, wireless communications, cloud computing, social networking, video streaming, and semiconductors.

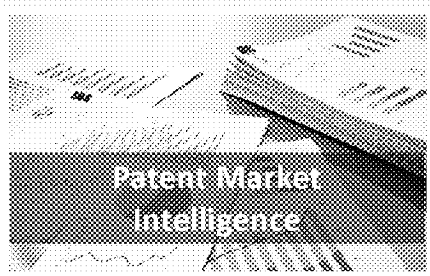
Our Services



A well-executed patent buying patent program can give your company the leverage needed to win tough negotiations or settle litigation, but buying the right patents is difficult and time-consuming. Our proprietary data allows us to analyze thousands of deals to find assets that are valuable to you.



How should I price the deal? How should I package the deal to maximize value? Who is likely to buy the assets? Our data includes asking prices, selling rates, time to sale, technology areas, and much more. We offer data-driven insights on how to best structure your deals, what prices to ask for, and what to expect from a sales process.



Developing a data-driven patent strategy is key to creating value from your IP, but devising a strategy is easier said than done. IP managers and business leaders need to make decisions about how to best use their patent assets, how to seize opportunities in the market, and how to mitigate risk.

Our Data

$41B	16,500	$2B
Total Deal Value	Number of Deals	Transacted Deals

Our database of patent market deals dates back to 2009, when we first began helping customers navigate the patent market. We now track over $41 billion worth of deals, 16,500 packages, and more than 250,000 patent assets. Our deal database includes asking price data, sales dates, and seller and buyer identification.

Testimonials

Richardson Oliver Insights provides us with actionable data allowing us to make timely, business-driven decisions when screening and assessing patents

- Fergal Clarke, Director IP Business Analysis , Lenovo

Richardson Oliver Insights provides actionable patent market information that enables our strategic decisions.

- Allen Lo, Head of IP, Facebook

Richardson Oliver Insights represents the next critical step in providing patent market information directly to patent holders and patent buyers, like Zillow did for the real estate market.

- Suzanne Harrison, Author of 'Edison in the Boardroom'

Discover more at ROIpatents.com

It's a great time to be a buyer. NPEs know this and litigation funders are chasing them.

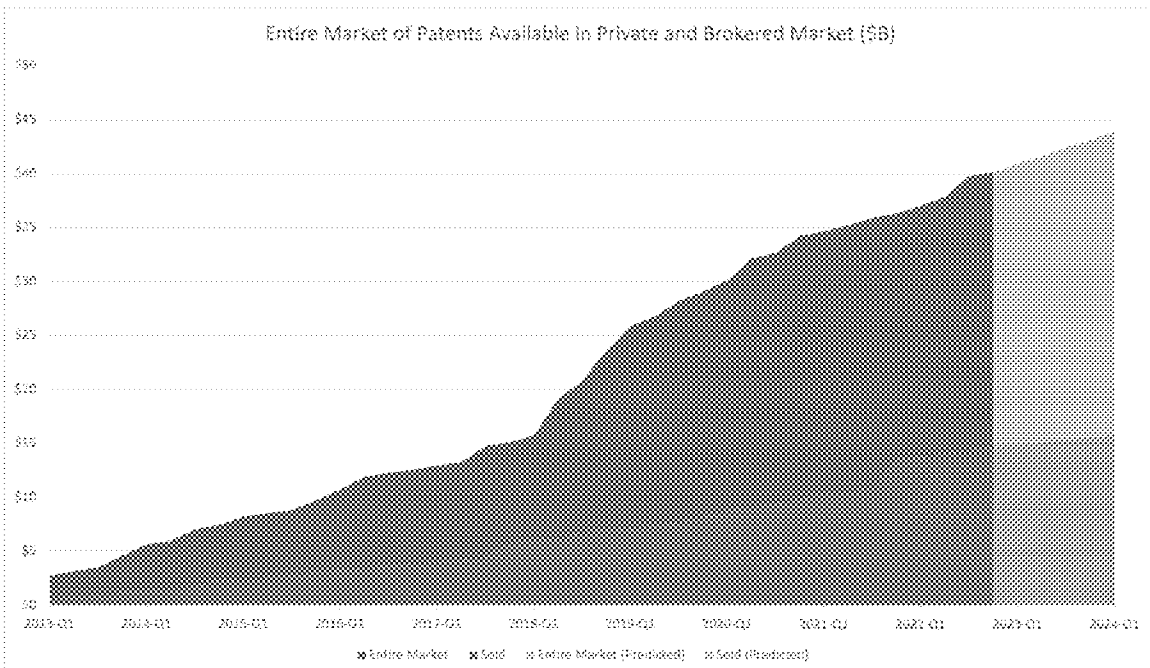
Richardson Oliver Insight's 11th patent market report, "Every Patent, Everywhere, All at Once", covers the slice of it that we see. We changed things this year to expand our data set to include a broader set of available patents, effectively more than doubling our datapoints for some topics. We believe that enhances the transparency of the patent market. We now track over 16,000 packages representing over 283,000 patent assets. The database grows by about 2,000 packages per year.

One note of caution: comparing last year's numbers to this year's numbers is fraught with problems. Last year's 10-year analysis is valid for the open brokered market; this year's analysis is valid for the broader patent market.

Key takeaways

Figure 1 shows the cumulative asking price of all the assets that we track, which currently stands at about $40 billion. We wrote and maintain tools that parse assignment records, where available, to identify sales. Sales represent $14.7 billion in asking prices. Projecting through to Q1 2024, we expect cumulative total sales to reach close to $16 billion. As a reminder, this is the sum of asking prices for the sold packages without adjustments or discounts to estimate actual closing prices.

Figure 1: cumulative sum of all asking prices for all deals in billions



This year's report has key takeaways:

- We apologise to the broker community. We knew you were critically important to the success of the patent market; we just did not appreciate how much. Read on to find out why;
- Asking prices have declined but the asking prices of packages that sell have been more stable;
- Operating companies continue to supply most assets and NPEs keep buying them; and
- Patents that hit the open market are incredibly dangerous; litigation rates are orders of magnitude higher once a patent hits the market.

Summary of 2022 patent market data	
Annual sales	$197 million
Asking price per family	$250,000
Asking price per US-issued patent	$173,000
Asking price per patent asset	$100,000
Package sales rate (cy projected)	27%
Sold package litigation rate (tt)	17.5%
Unsold package litigation rate (tt)	3%
All package litigation rate (tt)	5%
Packages listed	1,934
US-issued patents	10,988
Patent assets	28,957
Average number of assets per package	15.4
Median number of assets per package	2
Packages with 10 or fewer US-issued patents	90%

Note: All data is 2022 calendar year unless otherwise note. (tt) is total tracked data.

As we have done in the past, the flow of this article matches the general flow of patents from first offering to sale and beyond. We cover sourcing, diligence, pricing, buyers, and litigation. We end with an estimate of the market size. A detailed explanation of our methodology is at the bottom of the page.

Brokers matter

We apologise to the broker community. We already knew and reported that they were critical to the functioning of this market. Brokers act as stewards to sellers who are unfamiliar with the process of selling patents. They also sell, buy, market, negotiate, evangelise, and promote patents in the market. They have enormous experience in two critical areas: identifying patents of value and setting buyer and seller expectations. Brokers leverage their networks of connections to find interesting patents to sell and to find willing buyers. None of this is why we are apologising to the broker community.

We have reported in the past that the number of brokers in the market has declined and although that is true for generally available patent packages (packages made available to all buyers), this does not paint the entire picture. Some brokers work exclusively on packages that are offered to only a few potential buyers.

When we look at the broader broker community we find:

1. more brokers than we have reported in the past; and
2. a shift in broker practices to more limited distributions of their packages.

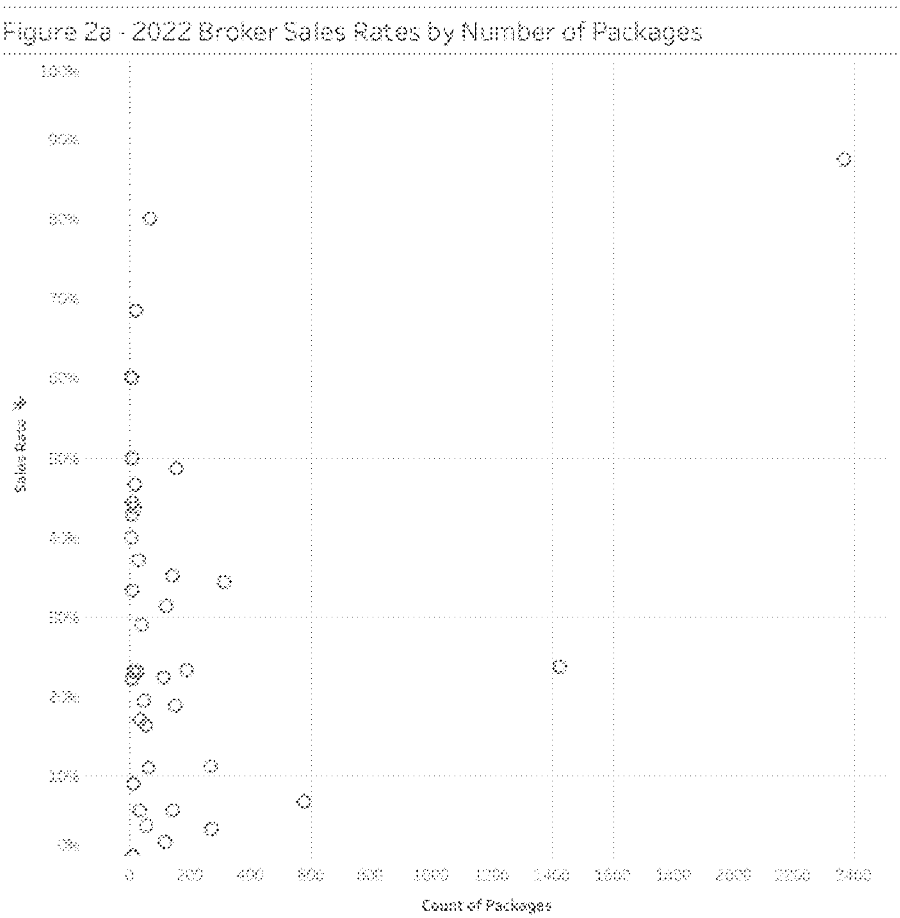
Table 1 lists, in alphabetic order, brokers who brought five or more packages to the market in 2022.

Table 1: brokers with five or more packages in 2022

Adapt IP Ventures	N&G Consulting
Dynamic IP Deals LLC	OCEAN TOMO, LLC
G1 IP Law Firm	Red Chalk Group
GTT Group	Reliance Capital
Huang Partners IP Advisory	Rui Zhi Ventures Limited
ICAP	Santibu
Iceberg	Silver Bullet IP
IP Approach, LLC	Tangible IP
IP Offerings	TransactionsIP LLC
IP Pioneer Group	Uninno IP Limited
IPInvestments Group	Value Kium Corp
KangHan International Patent & Law Firm	Vitek Intellectual Property

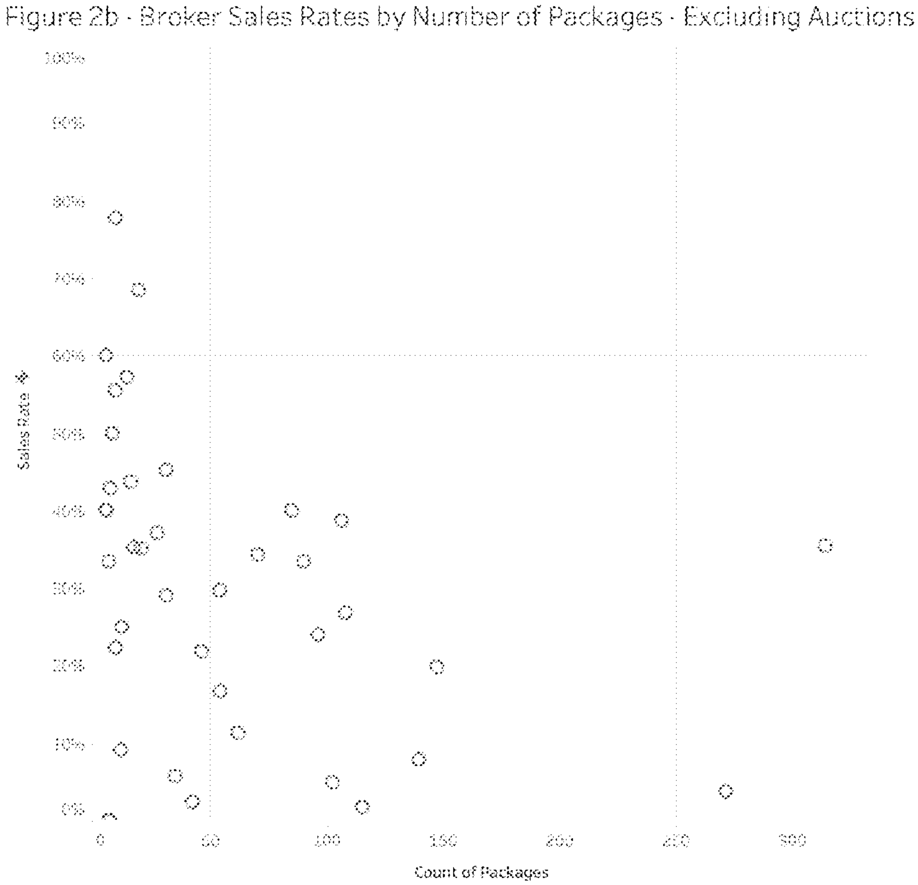
Figures 2a and 2b show the overall success of brokers. We include two versions of this graph for reasons that will become abundantly clear. Each circle represents a single broker with the y-axis representing their close rates (the percentage of their packages they have sold) from 2017 through to 2021. The x-axis represents the number of packages they brought to market during the same period. Up and to the right means the broker is more successful.

Figure 2a: sales rates of brokers (all packages)



The broker in the upper right corner of 2a appears to be crushing the entire field with an almost 90% close rate on over 2,300 packages. That broker is Quinn Pacific and they represented Provenance in the sale of their approximately 2,300 packages. Congratulations to the Quinn Pacific team, however, as all of these packages sold as one deal, we do not believe that this image accurately represents what is really going on. So, Figure 2b shows the close rates excluding auctions and Provenance deals. Here you see a concentration of successful brokers who brought between 25 and 50 packages to market from 2017 to 2021 with close rates above 40%.

Figure 2b: sales rates of brokers (Provenance and auctions omitted)



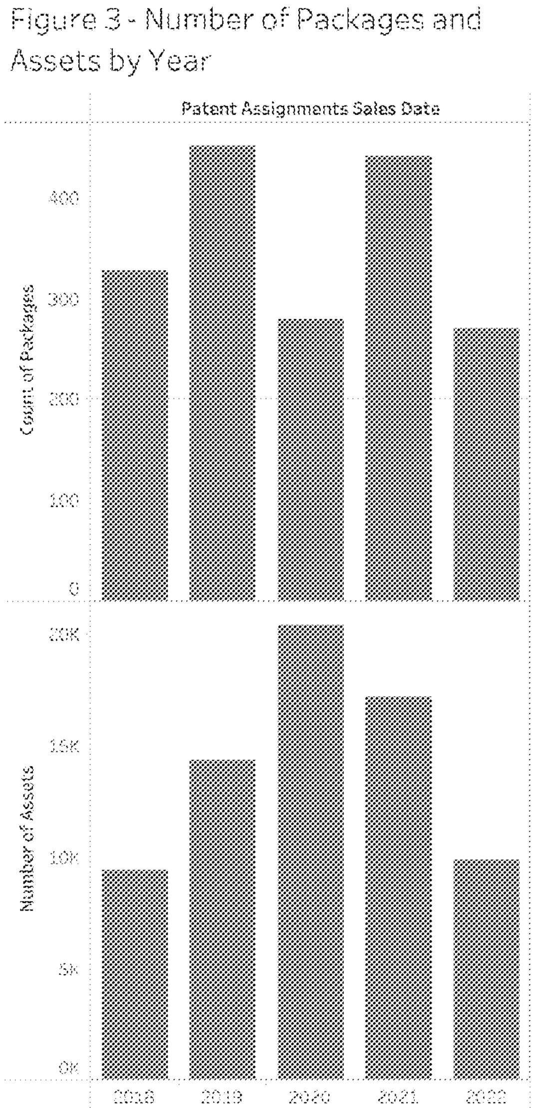
One additional metric we reviewed this year was the number of unique brokers closing a deal in any calendar year. In short, the number of unique brokers has slightly increased from 55 in 2017 to 63 in 2022.

Brokers represented over 90% of the sold packages over the past five years (80% if you exclude Provenance packages). Brokers are responsible for 90% of the assets that sold in the same five-year period, even excluding Provenance. Frankly, 90% is astounding. Congratulations to the broker community for being the engine that drives this market. Our apology to the broker community is for not presenting this data sooner; we knew you were important, just not this important.

Total sales over time

Given the covid-19 pandemic, we expected sales rates to drop through the floor and we thought we were seeing some of that in 2021, but this is why we wait for sales data to settle down. In short, sales did not fall off. Figure 3 shows the number of packages sold in the 2018 to 2022 calendar years. Overall, 2021 looks pretty good. While 2022 is down a bit, we expect that a few more 2022 sales will become public in the next few months. So, if you were expecting covid-19 to wipe out the market, that did not happen.

Figure 3: number of packages and assets sold by year



New ways to buy or sell patents continue to emerge: some combine the current skills of brokers with platforms, while others offer completely new models. The following are the most noteworthy:

- IAM Market is a market provided by IAM where sellers can list their patents and anyone can browse the packages, contact the sellers, and close patent purchases.
- IP3 by AST is a fast-close patent buying programme. Sellers list their assets for a set price and AST member companies decide whether to purchase, all on an accelerated schedule. AST continues to try new models for buying patents and we expect additional leadership from them here.
- Brokers are offering more and more "license if you don't want to buy" options. At least three of the top brokers are offering licences like this.
- RPX has switched to almost exclusively obtaining licences for its members, rather than buying the patents outright.

Package and asset counts recovered from the 2021 drop: 2022 asset counts increased 50% from 2021 and exceeded even 2020 counts. Table 2 shows the three-year package and asset counts. Note: we see publicly available packages (ones offered to every buyer) and a significant number, but not all, of the private packages. Table 2 necessarily underestimates the total number of packages and assets on the market each year.

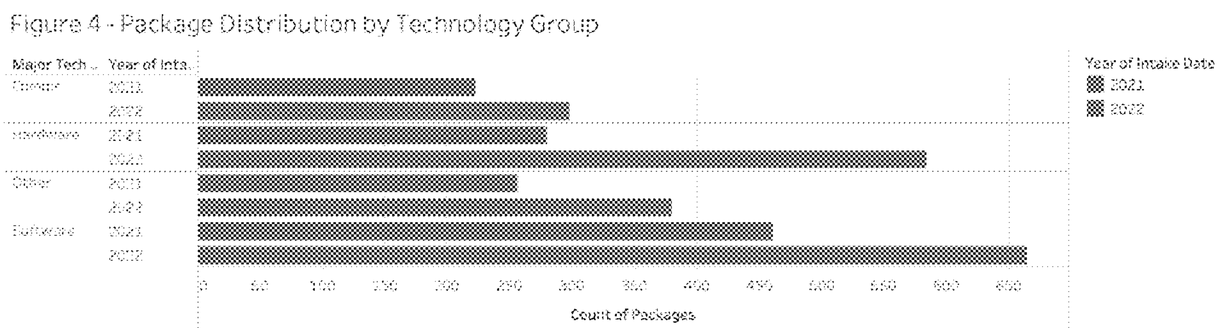
Table 2: packages and assets listed by year

	2020	2021	2022	% Difference 2022 vs 2021
Count of Packages	2,242	1,239	1,934	56%
Number of Issued US Patents	10,317	8,638	10,988	27%
Number of Assets	24,788	19,241	28,957	50%

The market continues to provide buying opportunities in a diverse range of technologies that are used (or purported to be used) in a wide variety of products and by strategically important companies. With the breadth of technologies and asset characteristics, risk mitigation strategies and other business needs can be addressed in almost any tech category. When we receive a package, we use the package materials, along with any assets highlighted by the seller, to categorise the package according to our taxonomy of technical areas. We have developed a two-tiered classification taxonomy with 17 general technical categories and 108 sub-categories. We continue to modify this taxonomy as new technologies come onto the brokered market and supplement them with machine-learning classifications. We also use machine learning classifiers to classify individual patent families within packages to provide a different view of the content. We then roll these technology classifications into four larger categories: communications, hardware, software, and other.

Figure 4 shows that all technology categories saw increased package counts from 2021 to 2022. Software-related technologies continue to dominate the patent market. The biggest increase was in hardware related packages. Software tends to sell better than other categories. The "other" category includes medical devices, automotive and energy related patents.

Figure 4: package distribution by technology group

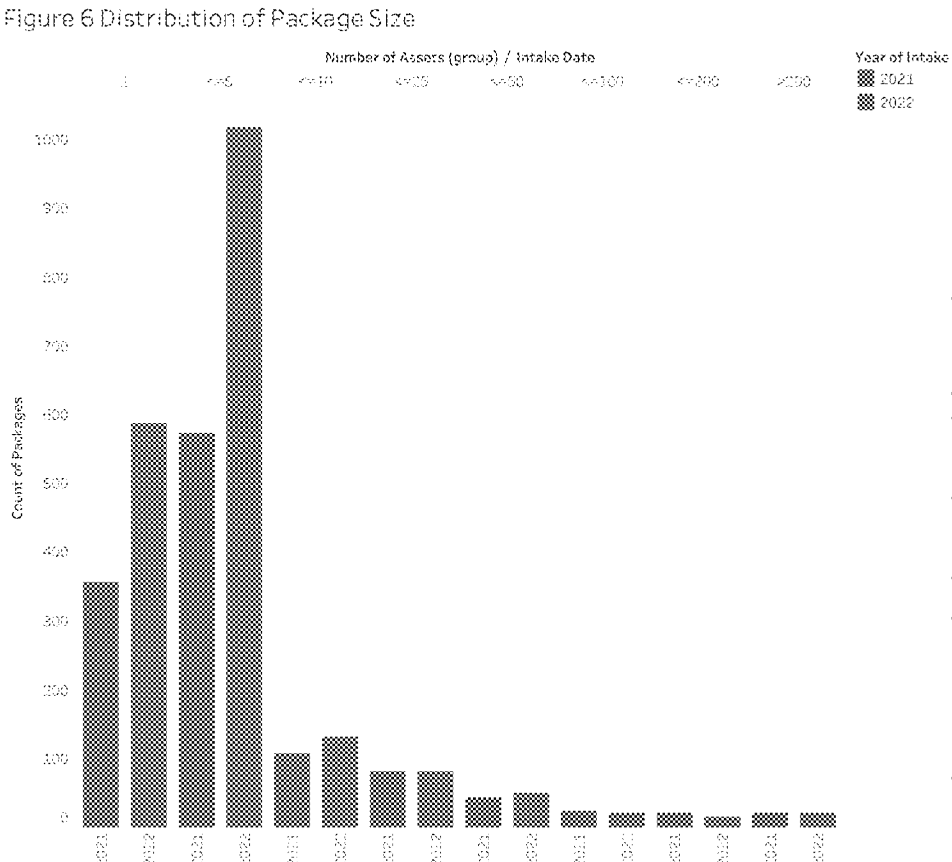


The word cloud in Figure 5 provides another way to visualise the focus of the patent market. The relative size of the words highlights the hot companies, technologies and products identified in the evidence of use (EOU) and marketing materials provided by the seller of the packages. Examining the word cloud gives a sense of how packages were marketed in 2022. It should come as no surprise that the biggest technology companies (Google, Apple and Microsoft) continue to be the favourite targets of patent sellers' EOU materials. The focus products and technologies shift over time, but the focus companies have generally stayed the same.

Figure 5: word cloud of hot companies and technologies

The distribution of package sizes (see Figure 6) continues to be one of the most consistent metrics describing pricing and other deal dynamics in the market. Bigger deals have higher close rates (at least for some assets and partial sales) and prices tend to decline as more assets are added to a deal. When comparing 2022 to 2021, we do see a large increase in the number of smaller package (five or fewer assets), but the median number of assets in a package remains the same for both years: two assets.

Figure 6: distribution of package size



Pricing

Price. What is the price? Am I paying too much? Is this going for too little? How do I prove that we are getting a decent deal for these assets? No one wants to look like they got a bad deal. We have worked hard to bring greater transparency to this market. With this, our 11th market report, we hope to continue the work of clarifying asset pricing of the market.

For those new to the idea of pricing patents, maybe the most important thing to understand is that pricing is complex in every industry; if knowing the numbers alone was sufficient, lots of product marketing jobs would disappear. So, you are not alone in feeling uncomfortable when pricing patents. An important aspect of price is that it is different than value – critically different. For a patent to sell, the value of a patent to the seller must be less than the sales price. Similarly, the value of a patent to the buyer must be greater than the purchase price. Value and price are often interchanged, but the difference in their meanings is critical when discussing "market pricing". We recommend that when determining the price at which to sell a patent that you focus exclusively on market data. Once the price is established, compare the price to the value to you to determine if the transaction is desirable.

As in the past, as a starting point for discussions, we recommended referencing average and median pricing, and making some adjustments for specific factors related to the deal, recognising that there is a long-tail distribution to pricing histograms. Understanding what the characteristics of an average patent are, and why your patents might differ, helps you to adjust the price from the averages and medians. For an example of how to quickly ballpark the price of a package of patents, a critical step in your diligence process, see our 2020 IAM article, "A Rapid Analysis of Intel's Connected Devices Patent Portfolio".

We have helped clients buy patents priced at above $1 million per asset and at a small fraction of that price. In both cases we think the prices were justified and, importantly, the deviation from the average was supported by deal-specific factors.

With reference to Table 3, in 2021 the median asking price per asset dropped 30% from $143,000 to $100,000, the lowest price in the past five years. But, as we highlighted in the introduction, when analysing the price of sold patents, greater stability of pricing is evident than in the broader market.

Note we are focusing on median prices because average prices are not as effective with the long tail curve of the pricing histograms for patents.

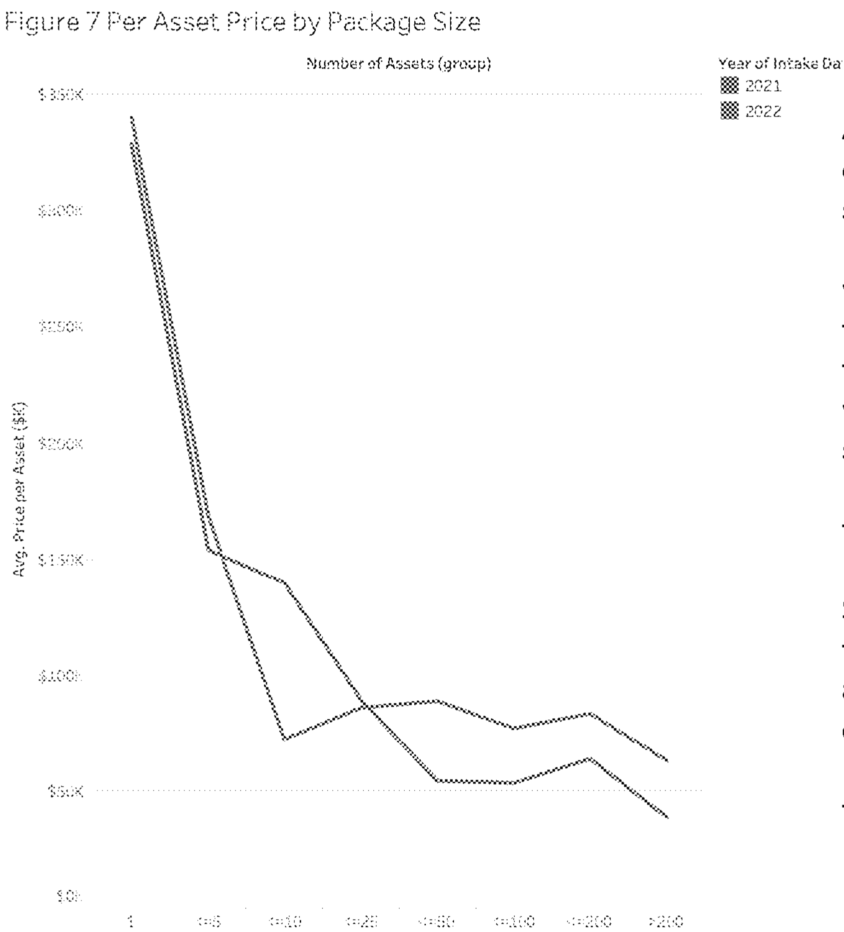
Table 3 – Median asking prices of all assets v sold assets

Asking Prices of All Assets	**2018**	**2019**	**2020**	**2021**	**2022**
Price per Asset ($K)	$149K	$108K	$150K	$143K	$100K
Price per US Issued ($K)	$219K	$185K	$250K	$225K	$173K
Price per Family ($K)	$325K	$285K	$325K	$325K	$250K
Asking Prices of Sold Assets	**2018**	**2019**	**2020**	**2021**	**2022**
Price per Asset - Sold Only ($K)	$70K	$54K	$63K	$55K	$77K
Price per US Issued - Sold Only ($K)	$95K	$90K	$100K	$96K	$92K
Price per Family - Sold Only ($K)	$125K	$125K	$125K	$100K	$253K

An important reminder here: these are asking prices. We conduct other independent studies of closing prices and see average discounts of between 0% and more than 75%. Discounts tend to increase the longer the assets stay on the market, so if a deal is new, you can expect a smaller discount, while older deals can have much higher discounts.

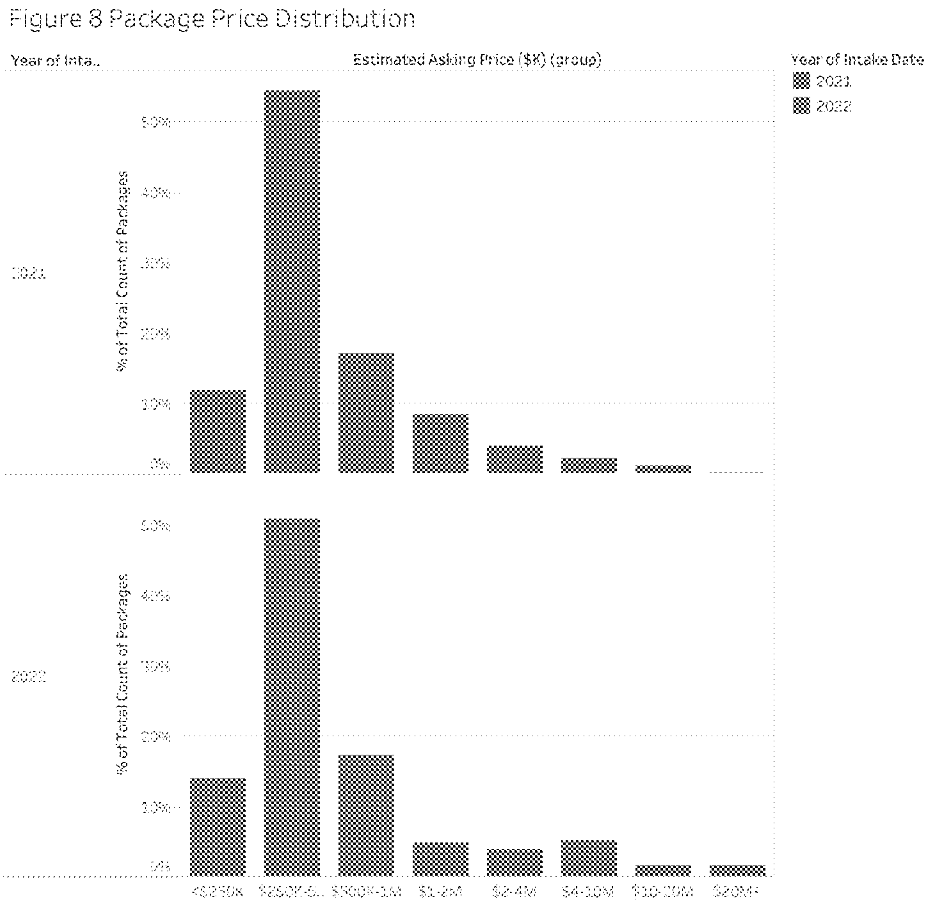
One of the most significant factors in pricing assets is the number of patent assets in a particular package. Figure 7 shows the price per asset compared to the size of the package. Larger packages mean a lower price per asset. Overall, we see a greater dip in pricing from 1 asset packages to 10 asset packages, compared with 2022.

Figure 7: per-asset price by package size



Another consideration is the overall price of a deal. Not surprisingly, not only do buyers have a maximum that they are willing to pay per asset, but they also have a maximum total number that they are willing to spend. Figure 8 shows the distribution of pricing of all the packages in the study. There is a clear preference for deals in the $250,000 to $500,000 range; this is down from five years ago. Signing authorities at companies start to cap out ("I have to get permission from the CEO if I go over $2 million") and people become less comfortable closing high-price deals.

Figure 8: package price distribution



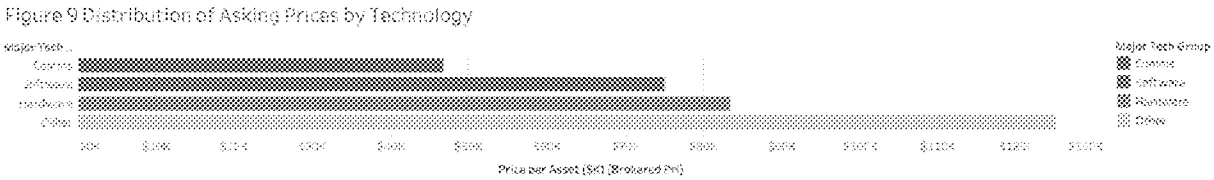
Packages that lack pricing guidance are one of the most frustrating aspects of the patent market. When we look at all the packages, sellers provide asking prices about 63% of the time. This is higher than what we have reported in the past because public deals come with less pricing guidance than private deals. We do not know why. The fact that any deals come without an asking price is still shocking to us. We have reported in the past that buyers deprioritise packages that do not have pricing information. As a result, nearly 40% of all packages are ignored by many buyers simply because the deal lacks any pricing guidance.

One additional note, we changed our practice to allow for "market price" as pricing guidance. Although not many sellers take advantage of this, at least the seller is stating that they have thought about the price and are OK with the going rate for the package. Why asking prices matter, even if they are "market price"? If you are a buyer, and the seller provides absolutely no guidance, the buyer thinks some version of: "What if the seller wants $10 billion for the patents? Why am I going to spend my time diligencing a deal that can't get done? I can just move on to the next deal."

Technology categories continue to drive asking price variations but this signal for specific tech areas is often buried in the noise of other factors. For the more specific technology areas, we use a normalisation procedure to calculate the impact on pricing. For more detail, please see our 2020 Brokered Market Report.

More generally (see Figure 9), the major tech groupings show significant differences in pricing. When it comes to top asking prices, the 'other' category, including medical devices, automotive and energy related patents, has been consistently getting more and more expensive relative to the other categories and became the highest priced category in 2021. Software on the other hand is below hardware for the first time since 2018. Comms has also been dropping in price relative to other categories.

Figure 9: distribution of asking prices by technology



There are ways that a seller can show that its package has high value and should have a high price. Evidence of Use or a claim of infringement is a great way to do that. Overall, the percentage of deals with an EOU has stayed about the same (this year at 31%). The price premium for an EOU varies greatly by package size and is another opportunity to dig into normalised data. Over the full data set, we observe substantial pricing premiums for EOUs in packages, anywhere from 25% to 75% higher. We also know that sales rates are higher for deals with an EOU (see below), so the value of preparing an EOU is even greater.

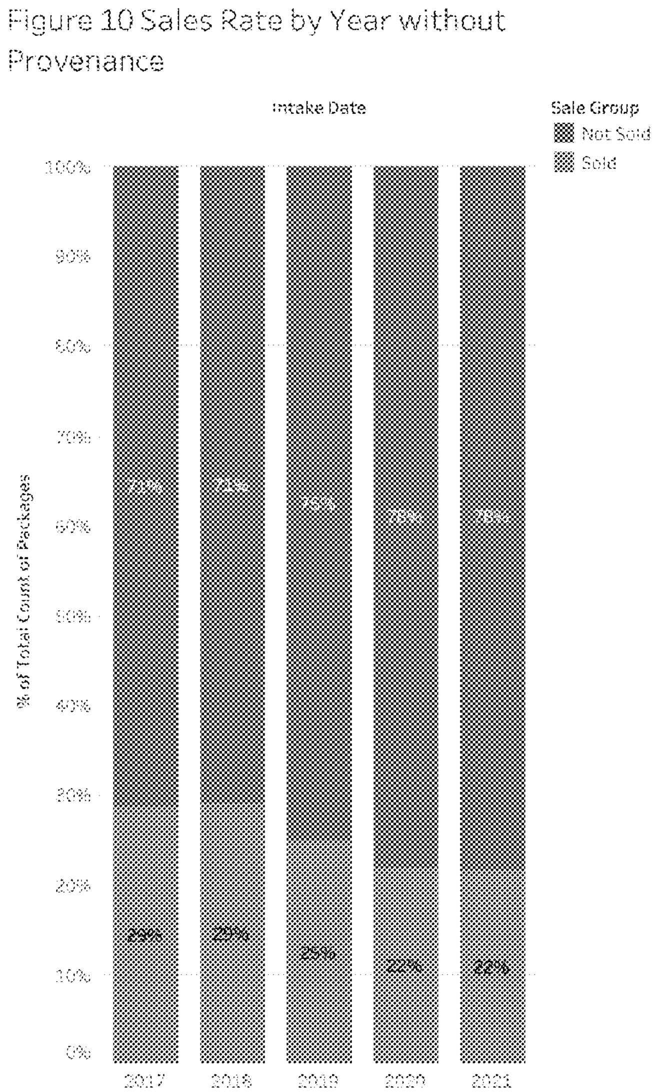
Sales

Sales rates typically exceed 30% of all packages from any one year. That is, eventually the sales rate hits 30%. Figure 10 shows the annual sales rates. For packages first listed in 2017, the rates are just about to hit 30% sold. So even some very old packages will sell eventually. For buyers, one advantage of old packages is that the discount from asking price can be very high. So, if you passed on a package because of price before, you may want to revisit it.

We have a process for tracking whether a package has sold. Generally, if any asset is found to be sold, we consider the entire package as "sold". This has both good and bad implications for our buyers and sellers. Importantly for buyers, this prevents them from spending money on diligencing a patent that someone already bought.

We only look at sales rates for packages that have had enough time to sell – a package that just hit the market is not a good predictor of sales rates. Our sales rate for 2022 listings stands at 5%, so we do not include that year in our analysis as many of the packages are simply too new to have sold.

Figure 10: sales rate by year (Provenance omitted)



Sellers

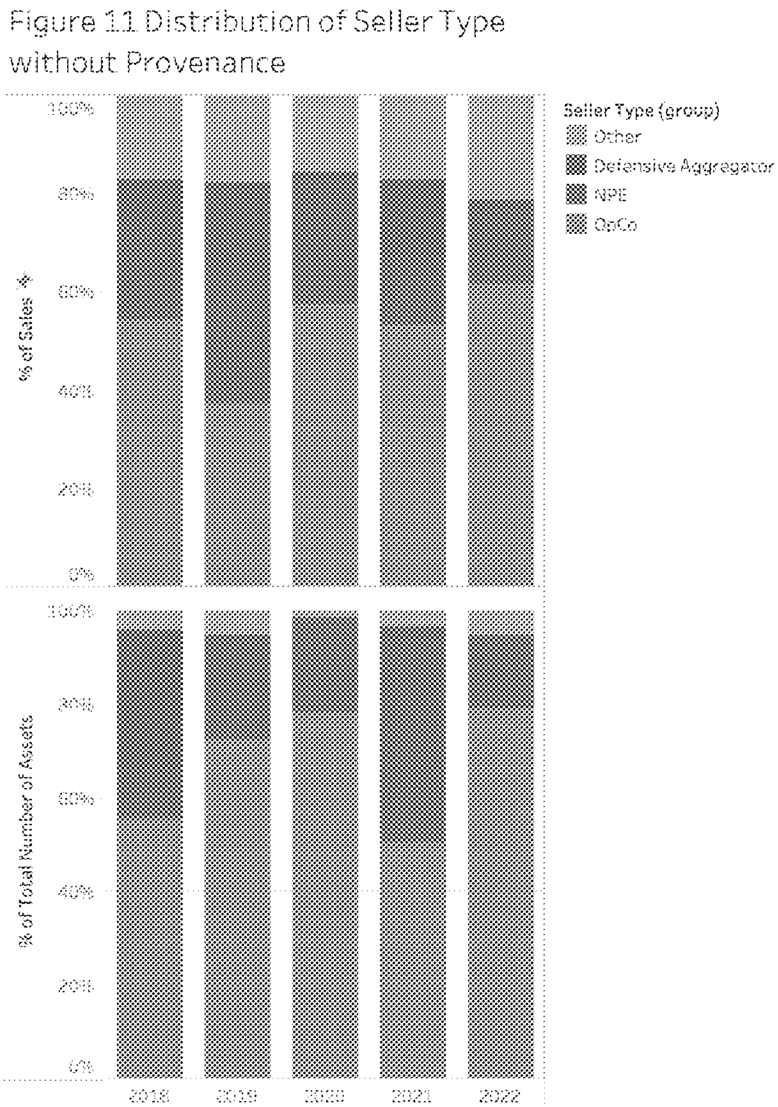
As a buyer, tracking the behaviours of sellers, both in aggregate and individually, allows you to operationalise your buying activities. Knowing who is willing to sell and the type of assets available not only allows you to review listings faster, but also gives you the opportunity to make a direct approach for a private deal. This is especially true for repeat sellers, which can account for more than 40% of available packages in any given listing year. Keeping track of a seller's listings, package sizes and asking prices can also help in negotiations because you know their negotiation parameters before you sit down at the table.

Similarly, if you are a seller, it is important to get the word out that you are selling. Listing packages on your website or through the IAM Market, sending targeted email blasts and working with brokers all help to attract buyers to you, rather than you having to spend the time and effort to find them. And, as a reminder, our data clearly shows that brokers close an enormous percentage of the deals on the market.

Figure 11 shows that on average 40% to more than 60% of the packages and assets came from operating companies. Considering that operating companies file the most patents, this is not particularly surprising; where those patents end up is surprising for those who have not seen our reports in the past (more on this in the buyers section).

Operating companies that are buying to mitigate risk may want to monitor sellers to try to determine who is starting to sell before they fully ramp up their sales programme. Ask yourself: "How can I mitigate the risk of these patents without purchasing them?" Taking an early licence to a seller's portfolio may be significantly less expensive than taking one after the assets have sold. Additionally, solutions such as the LOT Network may help to mitigate NPE risk across companies that currently have no intention to sell assets. James Kovacs and Nader Mousavi cover these options in "Why smart corporate IP strategies need license on transfer", IAM March/April 2017.

Figure 11: distribution of seller type (Provenance omitted)



Digging in more deeply, Table 4 lists sellers who sold more than one package in 2021 or 2022. You will find a mix of corporations, NPEs, defensive aggregators and universities. An important observation is that this is not a long list – a little proactive cross-licensing may go a long way in reducing risk.

Table 4: repeat sellers in 2021 and 2022

AJOU University
Allied Security Trust (AST)
ATT
Beijing Metis Technology Service Center
Collective Dynamics
Flextronics International Ltd.
France Brevets SAS
Health Tracker Systems LLC
Hewlett Packard Enterprise (HPe)
Hewlett Packard Inc (HP inc)
Huawei
Intel Corporation
IoT and M2M Technologies LLC
JVC Kenwood Corporation
Mobiwee Inc.
NEC
Ofinno Technologies
Pioneer Corporation
Prism Technologies, LLC
Provenance
Siemens Healthineers
Silicon Image, Inc. (now Lattice Semiconductor)
Sisvel International S.A.
TeleCommunication Systems, Inc. (TCS)
Tower Semiconductor, LTD.
Wipro Limited

Buyers

Patent buyers place bets on the future. Often, they consider patents as an option on the future. Whether to mitigate some future risk, backstop a new technology, counter-sue a competitor, or simply license the patents for money, the buyer is betting that the money they pay for the patents is lower than the value of those patents to the buyer.

Figure 12 shows that on average 25% to more than 50% of assets were purchased by NPEs. Operating companies purchased a similar number of packages (24% to 48%), but more assets (44% to 67%). Considering that operating companies are selling significantly more assets than NPEs, the patent market represents a shift of assets from operating companies to NPEs. Defensive aggregators do clear a lot of risk as they are also buying 24% to 36% of the packages, but the packages they buy are often smaller. This is why the percent of assets purchased by defensive aggregators is much smaller.

A few interesting things to note: in 2020, many operating companies were focused on figuring out remote work and how to exist during a global pandemic. As such, patent purchasing seems to have been deprioritised and this removed market competition for NPEs. The highest percentage of packages purchased by NPEs was in 2020 when they purchased more than 50% of the assets sold. Also, were one to include the sale of the Provenance assets to RPX in the 2021 numbers, the graphs look wildly different for that year. That inclusion more than doubles the percentage of assets purchased by defensive aggregators to 36% and because Provenance assets were listed as thousands of single-family packages, would show defensive aggregators purchasing 82% of packages.

Figure 12: distribution of buyer type (Provenance omitted)

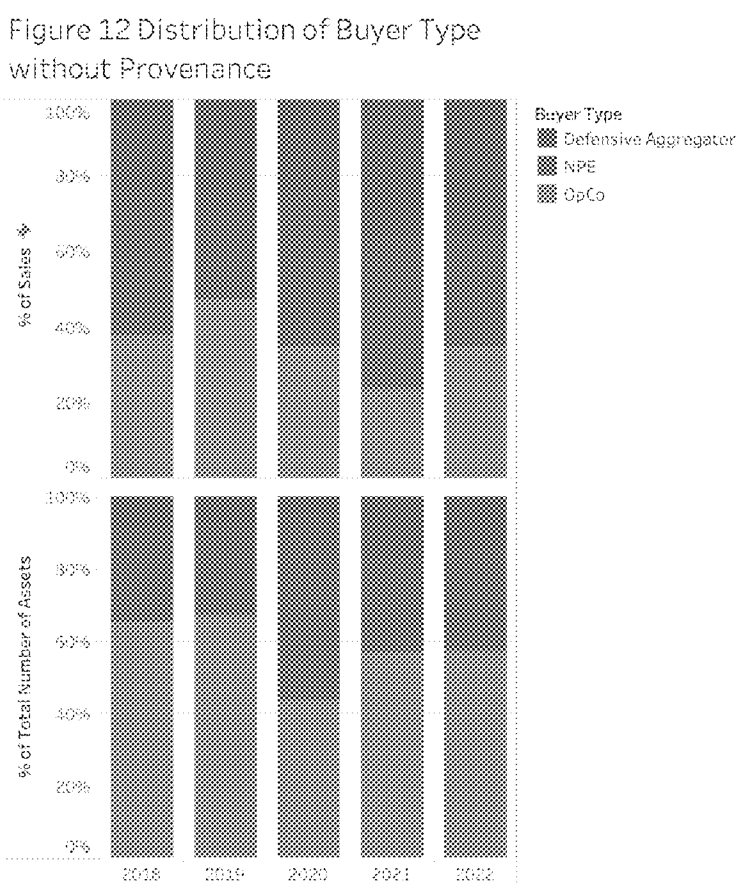


Table 5 shows repeat buyers from 2021 and 2022. We see a mix of operating companies, NPEs, and defensive aggregators in the list. One heuristic that is helpful: "LLCs" are usually NPEs.

Table 5: repeat buyers in 2021 and 2022

Advanced Coding Technologies LLC	MODENA NAVIGATION LLC
Allied Security Trust (AST)	Ollnova Technologies Ltd.
ARTAX, LLC	OMNISLASH DIGITAL LLC
Auth Token LLC	Patent Asset Management Advisors, LLC
Beijing Xiaomi Mobile Software Co., Ltd.	Proven Networks, LLC
Bright Machines, Inc.	RPX
Burley Licensing LLC	Snowflake Inc.
Crowdstrike, Inc.	Stripe, Inc.
Crown Electrokinetics Corp.	Toyota Motor Corporation
Dawncrest IP LLC	Universal Connectivity Technologies, Inc.
Emergent Mobile LLC	UNM RAINFOREST INNOVATIONS
Facebook, Inc.	Valtrus Innovations Limited
HYPERQUERY LLC	Workday, Inc.
Hyundai Motor Company	Xero Corporation
IPValue Management Group	YUKKA MAGIC LLC
KEYSTONE INTELLECTUAL PROPERTY MANAGEMENT LIMITED	Zama Innovations LLC
Mindset Licensing LLC	Zoom Video Communications, Inc.

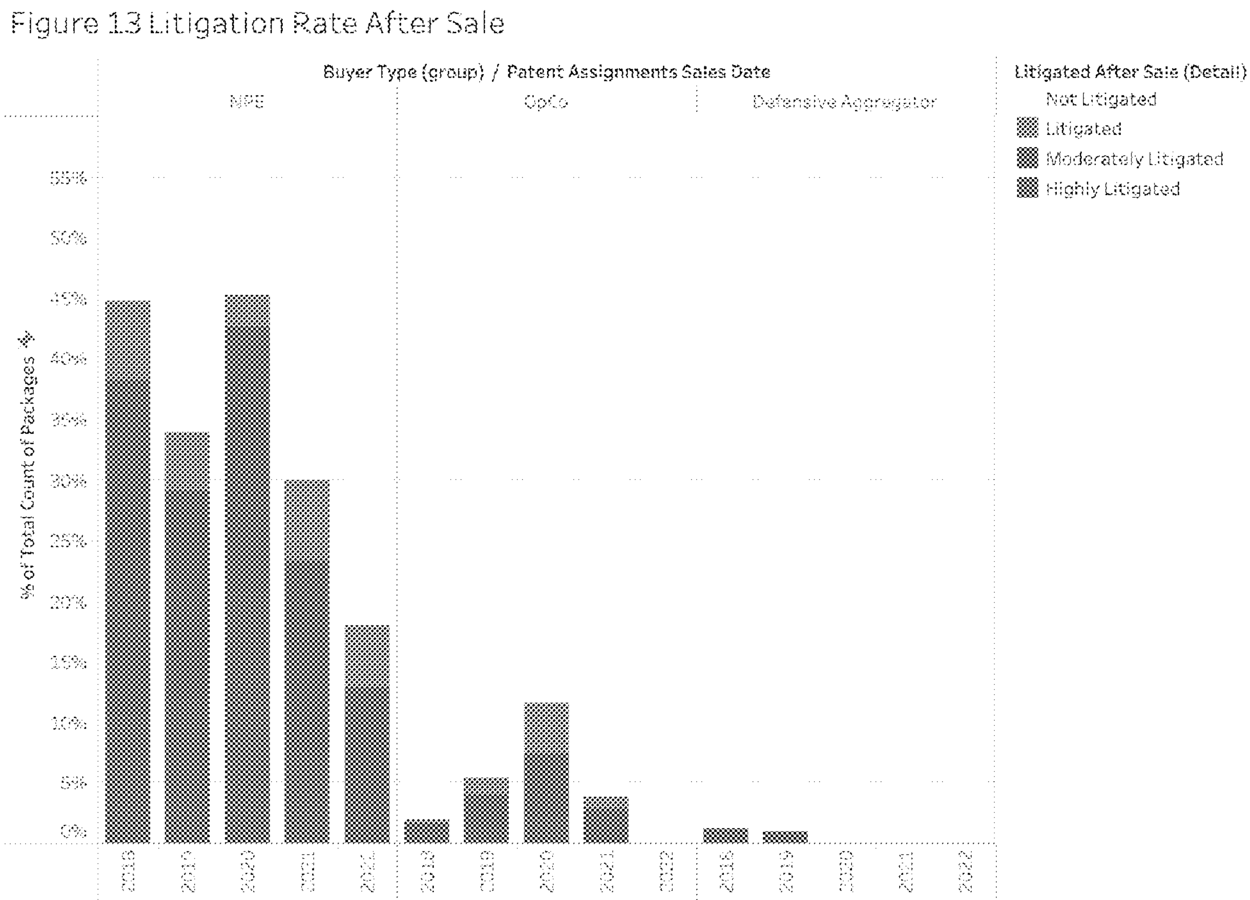
Litigation: the most dangerous patents in the world

Patents offered for sale are the most dangerous in the world. These patents are orders of magnitude more likely to be used in litigation than a patent chosen at random. Patents that are sold to NPEs are unsurprisingly the most perilous, but even when the assets never sell, the chance that they will be litigated goes through the roof. This is why we watch all patents for litigations after listing, but especially those that sold.

Figure 13 demonstrates just how dangerous sold patents can be. Around 30% to 45% of packages that sell to an NPE will have at least one patent litigated. We expect the 2022 numbers to rise significantly as more cases are filed over time. Further, these numbers do not include private assertions that result in a licence before a litigation is filed. Additionally, the number of cases filed in a litigation campaign can be impressive. We define "litigated" as having one case, "moderately litigated" as having two to nine cases, and "highly litigated" as having 10 or more cases. Of packages sold to NPEs in 2020, over 20% are highly litigated.

Despite this number being extremely high relative to other patents, we are surprised that they are not higher. More than 50% of packages sold to NPEs do not get litigated for one reason or another.

Figure 13: litigation rate after a sale



As for the market overall, when we look at all the packages we track (excluding the Provenance packages), over 6% of listed packages are litigated after they were listed for sale. Sold packages, regardless of the buyer type, are litigated just over 17.5% of the time with 6.2% being highly litigated and even packages that have not sold are litigated 3% of the time. As a reference, it's estimated that 1% or less of all patents are ever litigated.

Full market size

We estimate the 2022 market size to be $197 million. To estimate this, we use the discounted asking price of deals that we see which have sold in 2022. We used a different methodology this year which better reflects discounts that we expect would be applied to packages that have been on the market a long time. For comparison, the 2021 market size using the new approach

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Deliverables	• Analyze existing deals • Identify characteristics of desirable deals • Identify buyers, sellers, & types of deals • Develop deal filtering rules	• Monthly deal capture • Filtering deals based on deal filtering rules	• Sourcing directly from corporate holders	• Proven and efficient diligence process • Deal pricing and valuation analysis • Deal negotiation and close
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would have been about $265 million. In 2022, we found 246 sold packages, compared to 410 sold packages in 2021. Overall, the market is down this year, likely due to ongoing impacts from covid-19 and some of the downturn in the high-tech sector.

Opportunities, insights and reflections

Brokers fundamentally enable the patent market. Responsible for 90% of all the closed deals, brokers make the patent market. When you consider that brokers now charge anywhere from 15% to 35% of the closing price, you might wonder why more people do not get into the business. Some do, but it is still a tough business. Although 90% of closed sales is extremely high, the overall closing rate is still around 30% of all deals.

Google, Apple, Samsung, and Microsoft continue to be favourite targets of patent sellers, whose marketing materials name their products as infringing the assets, thereby making them a potential target of litigation for the patent buyers. What we do not see selling much are technologies that are working their way through the hype cycle and have not hit volume production. So, while augmented reality and virtual reality (AR/VR) and blockchain are technologies of interest, we do not see a lot of sales because the products are not in high enough volume.

Asking prices continue a downward trend, but not when we look at the asking prices of packages that sell. Asking prices of sold packages are lower than unsold packages and we think that this means that the market is getting better at pricing. That is, people are bringing their asking prices more in line with those deals that sell.

Litigation rates remain high for NPEs. Patents that hit the market are so much more dangerous than other patents. If your company is named as someone of interest in a patent sales package, it pays to have a good relationship with the defensive aggregators.

Methodology

This year we used our entire data set of 16,225 patent packages for sale on the patent market. This includes more than 280,000 patent assets.

We are not going to kid you; our paper only shines some light on the complex and opaque patent market. We pull data together for multiple sources dozens of times a year to try to keep up with the changing state of the market. Tracking the data, the changes, and analysing the results is complex and we could not do this without a great internal team and our data partners and vendors.

Our data sources include our proprietary patent package database, the USPTO patent data (Public-Pair), the USPTO Assignment database, Cipher, Derwent Innovation and litigation data.

This data is then combined on both a per-patent and per-package basis, using tools that we have developed over the past 11 years. The result is a proprietary database of hundreds of thousands of records across nearly 500 fields.

We also internally track asking prices, bidding dates and clients' specific diligence decisions, and maintain a list of unique entities that are buying and selling and keep track of standardised names. Standardising the names of buyers and sellers is awful. We also classify these entities by entity type, which means that we have our own internal list of companies that we believe to be NPEs. Although this process is quite time consuming, we believe that using real data to back up our conclusion is the best way to provide accurate analyses to our clients and lower the barrier to entry for companies joining the market.

Vertical Restraints and Labor Markets in Franchised Industries *

BRIAN CALLACI,† SÉRGIO PINTO,‡

MARSHALL STEINBAUM,§ & MATT WALSH¶

March 10, 2023

Abstract

This paper combines 530 digitized Franchise Disclosure Documents and standard contracts with employer-identified job ads from Burning Glass Technologies to establish stylized facts about franchising labor markets and their relation to the vertical restraints and contractual provisions that limit the autonomy of franchisees vis a vis their franchisors. We report novel findings about the application of vertical restraints like Resale Price Maintenance, Exclusive Dealing, and No-poaching Restrictions, among many others, to a low-wage workforce. A legal regime that favors the franchising business model incentivizes franchisees to profit at the expense of workers and to limit egalitarian tendencies operating in the workplace.

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†Open Markets Institute, callaci@openmarketsinstitute.org

‡University of Maryland at College Park and Instituto Universitário de Lisboa (ISCTE-IUL), DINAMIA'CET, Lisbon, Portugal, stpinto@umd.edu.

§University of Utah, marshall.steinbaum@utah.edu

¶Burning Glass Technologies

1 Introduction

The franchising business model consists of legally independent but economically interrelated firms. The franchisor is typically a nationally- or regionally-known brand, and local franchisees either distribute the franchisor's centrally-manufactured output or perform the function associated with its brand, offering standardized products and services (sometimes at standardized retail prices) and operating by a standard set of procedures.

Vertical restraints incorporated in a standard contract and operators' manual issued by the franchisor to its franchisees are integral to the business model. The term vertical restraints refers to contracts or other arrangements between actors in adjacent markets that preempt a material business decision by one or the other party (e.g. with whom to deal, or what prices to set), pertaining to a transaction or economic relationship other than the bilateral one between the contracting parties themselves (Paul, 2023). Their legality and scope has historically been the subject of competition policy. In the United States, between 1967 and 1977, the legal status of vertical non-price restraints such as exclusive dealing, exclusive supply contracts, and exclusive territories shifted from de facto illegality to de facto legality (Callaci, 2021*a*). By 2007, vertical price restraints ("Resale Price Maintenance") had also become legal in functionally all cases, at least under federal antitrust jurisprudence.[1]

The economic justification for the shift in policy toward vertical price and non-price restraints was that they typically serve to enhance rather than reduce competition. "Restricted dealing is a way to compete," according to Judge Frank Easterbrook, because "restricted dealing is a form of cooperation. One firm (the retailer) agrees to do things the way a manufacturer specifies, just as an employee does things within an integrated firm. The agreement is not a displacement of the market. Such contracts are the market at work." (Easterbrook, 1984) The reasoning is that vertical restraints are analogous to within-firm coordination, and within-firm

[1] *Leegin v. PSKS* held that minimum RPM would be evaluated under the Rule of Reason, for which defendants have a win rate between 97 and 99% (Carrier, 2009). Vertical price restraints are still evaluated under a per se standard in the antitrust statutes of some states.

coordination is by definition efficiency-enhancing or else it wouldn't take place within the firm (Coase, 1937). Ergo vertical restraints between legally separate but economically-related firms are also efficiency-enhancing and by dint of that, pro-competitive.

Much of the literature on vertical restraints focuses on "product distribution" franchising, in which one firm (for example General Motors or Exxon) enters an exclusive contracting arrangement with a downstream distributor to sell its branded goods. In contrast, under "business format" franchising, of which the archetype is the fast food industry, a firm licenses a franchisee to operate an entire "business format" under its brand name. McDonalds franchisees are not dealers of McDonalds manufactured goods, but are rather units of a chain operating under a shared brand. While much of the economic logic carries over from product distribution to business format franchising, the reader should keep in mind that the evidence presented in this paper comes almost exclusively from business format franchising contracts. For example, when we use the phrase "resale price maintenance" to refer to the vertical restraint in the McDonalds franchise chain we mean a centrally-imposed retail price. No good is actually "resold."

Exactly what constitutes the greater efficiency of within-firm coordination, or in the case of franchising, within-franchising-chain coordination, enabled by vertical restraints? Vertical restraints are posited as the solution to a principal-agent problem wherein the franchisee wishes to sell less, at a higher price and markup, than the franchisor would want, and thus legally enabling the franchisor to mandate lower prices and margins for the franchisee would cause more product to be sold in the final output market, so-called "Elimination of Double Marginalization" or EDM (Spengler, 1950). For example: "When double marginalization is an issue, the imposition of vertical restraints will not only increase the overall efficiency of the vertical structure but also lead to lower prices for customers. Thus restraints are usually welfare enhancing when used to solve the successive-monopoly problem" (Lafontaine and Slade, 2005). Alternatively, the greater efficiency may come from obtaining more effort from franchisees the more dependent they are on a single franchisor. For example: "The supplier may get improved product promotions from those with exclusive contracts. There will be added incentive to promote the seller's product vigorously if that is all the buyer has to sell to the final consumer" (Blair and Kaserman, 1983).

The above posits the efficiency as arising from the franchisee's greater dependence on the franchisor if the franchisee lacks alternative sources of supply. Models that predict efficiencies from the imposition of vertical restraints typically assume that production cost and technology are exogenous, and hence the competitive effect of a given restraint is entirely summarized by the retail markup, i.e. the discretionary retail price over the exogenous marginal cost, which may or may not be a double margin. What this overlooks is that the dependence, and the greater control that franchisors may derive from it, shifts the incentives for franchisees toward making their margins in other ways, i.e. by reducing labor costs, as opposed to raising prices by constraining output.

Franchisees are frequently managers of workers, and one of the types of opportunism they may engage includes "overpaying" workers. For that reason, franchising contracts that give franchisee owner-managers a stake in establishment profits incentivize such managers to discipline their workforce more closely (Krueger, 1991). Vertical restraints therefore may align distributor incentives with suppliers at the expense of workers.

A more recent interpretation of vertical restraints concerns their use as a means of excluding rivals at the upstream level from the market by cutting off their channels of distribution (Asker and Bar-Isaac, 2014). The idea is that incumbent dominant suppliers would bind their distribution network to themselves using price- and non-price restraints that reward retailers with higher profits for excluding upstream rivals. The restraints then operate to share the franchisor's monopoly profit with its affiliated distributors, which works if that shared profit is larger than what the distributors would earn from accommodating entry at the upstream level. The mechanism modeled by Asker and Bar-Isaac (2014) contraposes the "Chicago" critique of antitrust liability for exclusive dealing provisions or their equivalents, namely that they cannot have the anticompetitive effect of excluding a discounting entrant, because the incumbent wouldn't be willing to pay the retailers it's trying to bind enough to make it worth their while to cooperate in the exclusion. But Asker and Bar-Isaac (2014)'s mechanism is similar to the account in Blair and Kaserman (1983), albeit portraying the restraints as carrots rather than sticks for disciplining distributors to be exclusive to their supplier. And the implications for workers are the same: franchisees earn higher profits the less they have to pay.

In this paper we focus on the application of vertical restraints to franchising labor markets. We bring a novel dataset to bear on the question: We link 530 digitized standard Franchise Disclosure Documents and their appended standard contracts (at the chain/franchisor level) with employer-identified job ads that are informative about the workers and labor markets out of which franchisees hire. That enables us to characterize the presence or absence of an array of vertical restraints used in franchising. We also use the job ads data to describe the franchising labor force by industry, occupation, and job title. We report employer concentration in heavily-franchised industries and occupations, as well as *prima facie* findings about the effect of vertical restraints on labor market competition in franchised industries.

This paper contributes to the rather sparse empirical literature on vertical restraints between related business entities (Lafontaine and Slade (2005), Blair and Lafontaine (2005), MacKay and Smith (2014), Overstreet (1983), and Felstead (1993), among others), all of which focus their welfare analysis on consumer-facing effects. Krueger and Ashenfelter (2022) and Callaci (2021*b*) are the closest analogs to this paper, in that they both use digitized franchising contracts to characterize the share of workers subject to different types of vertical restraints. Krueger and Ashenfelter (2022) focus solely on no-poaching provisions of franchising contracts, and includes only about 25% of the contracts/franchising chains covered here. This paper uses the same dataset of digitized contracts as Callaci (2021*b*), covering many different restraints in addition to no-poaching. Unlike either paper, the dataset this paper introduces links franchise chains directly to job ads posted by employers affiliated with the chain, whereas both of the prior papers rely on labor market data from publicly-available, non-employer-identified sources at the industry level.

Our findings could thus be viewed as a contribution to the labor literature on firm-specific pay-setting: why do some firms pay more and some less, even in the same industry or occupation and to workers who appear to be quite comparable? In short, what determines firm-level pay policies? (Song et al., 2019; Card, 2022)

These findings also speak to the growing literature on labor market market monopsony and employer market power, driven by finite firm-level labor supply elasticities (Webber, 2015; Dube et al., 2020; Dube, Giuliano and Leonard, 2019; Bassier, Dube and Naidu, 2022; Azar, Berry and Marinescu, 2022; Yeh, Macaluso and Hershbein, 2022). Employer concentration in particular appears to be associated with market power and firm-level discretion to set pay (Azar, Marinescu and Steinbaum, 2022, 2019; Benmelech, Bergman and Kim, 2022; Rinz, 2022; Prager and Schmitt, 2021; Arnold, 2021; Guanziroli, 2022; Thoresson, 2021), partly summarized in Ashenfelter et al. (2022)). And beyond the concentration of employers, both horizontal no-poach agreements between them and noncompete clauses, which are conditions of employment that forbid workers from working for a different employer after the employment relationship is ended, are potential mechanisms by which competition in labor markets for workers appears to be less than perfect (Gibson, 2022; Callaci et al., 2023; Lipsitz and Starr, 2022; Starr, Prescott and Bishara, 2021; Balasubramanian et al., 2022).

This paper can be seen as building on the latter literature by investigating the prevalence of all sorts of vertical restraints and contractual provisions, in addition to no-poaching and noncompete agreements, that might suppress labor market competition in the franchising sector and, through that mechanism or otherwise, shift bargaining surplus in favor of employers. Part of the motivation for this work is to expand the definition and indicia of employer power in labor markets beyond the focus on either the horizontal concentration of employers in a labor market, or the explicit limits on worker mobility implied by both horizontal no-poaching agreements or vertical noncompete clauses explicitly binding workers to one employer, to consider other mechanisms that either create employer market power or are themselves constitutive of the exercise of employer power, such as vertical restraints and other contractual provisions in the franchising context that incentivize employers to extract surplus from workers.

This work also builds on Wilmers (2018), which investigates the effect of vertical market power in supply chains on wages. In that case, the question is whether workers are paid less in supply networks where downstream retailers or manufacturers are more dominant. This paper looks at the labor market on the other end of the supply chain, namely, among the retailers and distributors who are subject to the control of dominant franchisors. The use of vertical control techniques that disadvantage workers is central to the narrative of the "Fissured Workplace" recounted by Weil (2014), wherein a lead firm is able to control and direct the labor of a network of contractors who worsen labor standards and working conditions, compared to a model in which all the work that a lead, branded firm does is done by employees of that lead firm.

Vertical restraints in an important sense create the fissured workplace, since without the ability to control franchisee operations through vertical restraints, lead firms would be forced to directly own and operate local establishments to present a uniform brand image to the public, or else cede valuable consumer-facing brand recognition to retailers. Franchising in particular is a type of fissured workplace that has long been characterized by low wages and bad working conditions. Krueger (1991) finds that franchised restaurants pay lower wages and offer workers a flatter tenure-earnings profile than company-owned restaurants. Meanwhile Ji and Weil (2015) find that franchised fast food outlets are more likely to violate labor laws than comparable company-owned establishments. Vertical restraints, especially price restraints, seem likely candidates for mechanisms contributing to bad working conditions at franchised establishments. For example, a McDonalds franchisee reports that the company told her to "just pay your workers less" to maintain profitability in the face of the franchisor's mandatory cut-price promotions (DePillis, 2014).

A related motivation for franchising is to ring-fence unionization and collective bargaining efforts by workers, since the enterprise bargaining system that is dominant under US labor law prohibits workers from formally negotiating with, or taking action against, entities that are not their legal employer. The currently-ongoing unionization effort at Starbucks offers a telling example of the utility of franchising as a means of curtailing worker organization, since Starbucks does not employ the franchising model, unusually for its industry. If it did, it would be hard or impossible to spark a unionization "wave." If a franchised establishment were to unionize, a franchisor would probably face no legal bar to simply terminating it, whereas closing stores that are in fact part of a national chain like Starbucks faces legal risk for retaliation. And the benefits to workers from unionizing a franchised establishment are far lower even absent overt retaliation, since workers at the franchisee cannot bargain with the franchisor, and the purpose of the franchising contract is to direct most of the profits to the franchisor. Moreover, some of the chains reported on in this paper have existing collective bargaining agreements covering employees in the core aspect of their business, and so one motivation to employ a franchising business model for other parts of it is likely to exclude some of its workforce from having collective bargaining or other labor rights, and associated collectively-bargained pay scales.

Patterns such as this motivate the present project and research agenda: to document the effect of franchising restraints on outcomes for workers, as well as labor markets generally, not just consumers, as has been typical in the economic analysis of vertical restraints. This paper makes a start on that by reporting on characteristics of the labor force working in franchised industries and the application of the many restraints and contractual provisions embedded in the franchising relationship to that labor force.

Section 2 describes the matched franchise contract-job ads dataset. Section 3 reports the industry, occupation, and job title-level breakdown of the matched dataset, computes industry- and occupation-level labor market concentration in that dataset, and most importantly, reports the prevalence of each restraint or contractual provision in the dataset, as well as by industry and occupation. Section 4 reports on the competitive significance of franchise no-poach clauses specifically, building on Krueger and Ashenfelter (2022). Section 5 reports regression results for the effect of each restraint/contractual provision on chain-level wages, net of controls. Section 6 places our findings in a larger discussion of f competition policy. Section 7 concludes.

2 Data

This paper relies on matching two datasets: a dataset of digitized Franchise Disclosure Documents (FDDs) and appended contracts taken from Callaci (2021*b*), and a dataset of employer-identified job advertisements from Burning Glass Technologies (BGT).[2]

Franchising is regulated by the Federal Trade Commission under its Franchise Rule, which requires franchisors to provide an FDD to all prospective franchisees in advance of entering into any agreement. Some state regulatory agencies further require franchisors to register these FDDs. The chains included in this study are all those with over 80 locations nationwide who registered their FDDs with the State of Wisconsin in 2016 (containing information for the year 2015). Those FDDs are coded for franchisor and industry characteristics, as well as numerous binary and some continuous variables representing the presence and extent of various types of contractual provisions, some of which correspond to received notions of competition-relevant vertical restraints and some to more general aspects of the franchisor's business model, its degree of control over the franchisee, and how much control the franchisee is also expected to exert over the business. Appendix A explains what each restraint or provision is in detail and gives sample contract language interpreted as signifying the presence or absence of each restraint.

FDDs also include the name of the franchisor, plus sufficient other identifying information, that it is possible to match the chain-level contract data to employer-identified job ad data from BGT, covering the entire year 2007 and the period January 2010-December 2021. The BGT data includes employer names where available (approximately 65% of postings), industry, occupation, job title, location, and annual wages for around 15% of postings until early 2018, when the share of job ads reporting salaries jumps to around 30%. The dataset created by this matching consists of all the online job ads posted by the chains whose FDDs are in the Callaci

[2]See Hershbein and Kahn (2018), Modestino, Shoag and Ballance (2016), and Azar et al. (2020) for prior studies using the BGT job ads data.

(2021*b*) dataset. We treat each FDD as corresponding to a separate franchisor/national chain, even though in many cases there is common ownership of chains by a given holding company or investor. We do not analyze that higher level of ownership in this paper.

Throughout this paper, we refer to the dataset of job ads created by that matching procedure as the "matched dataset." It does not include job ads from other employers that may be affiliated with chains whose contracts are not included in that dataset, nor employers hiring in the same industries or occupations that are not affiliated with any chain whose FDD we have digitized.

Typically, job ads posted by the franchisee will feature the name or brand of the franchisor, since the franchisor's trademark and brand are exactly what's valuable to the franchisee.[3] Our matching procedure consists of parsing the employer name variable in the BGT data for identifying strings that relate that employer to the chain in the FDD data, then sifting out false positives of employer names that match those strings but which are not part of the franchising chain. Thus, we identify job ads that are related to the entire franchising network (though we may overlook false negatives in which the job ad does not identify the franchisor with which the job in question is, in fact, associated, because the employer named in the job ad does not use any trademark associated with the overall chain with which that employer is affiliated.) We cannot differentiate between ads posted by franchisees and franchisors (in particular, for company-owned units in the franchising network). But typically the vast majority of jobs posted throughout a given chain will be in occupations that correspond to that chain's core function, as opposed to "corporate" jobs posted by the franchisor for its central operations. Some chains operate solely through franchised outlets, some have a mix, and for some, the franchised aspect of the business is a subset of the chain's overall operations.

To give one example, we designate a job ad as being affiliated with the franchise chain Panera Bread if the employer name in the job ad data includes the string "panera," including "Panera Bread" and "Panerabread." We then weed out employers that have that string in their

[3]We drop job ads that do not identify an employer.

name but which appear not to be affiliated with that franchise chain, such as "Paneratech." According to Panera Bread's 2016 FDD, it had 1906 outlets nationwide, 861 of which were company-owned and 1045 operated by franchisees. This procedure is designed to designate job ads posted by both company-owned and franchisee-owned establishments as affiliated with the chain.

Figure 1 plots the number of job ads in the matched dataset as a monthly time series. The prevalence of online recruitment has expanded since 2010, particularly in low-wage occupations, though the coverage of online recruitment differs across occupations and industries even now. That is probably the main reason for the upward trend, although a secondary reason may be the increasing importance of franchising chains, and specifically the chains covered in our dataset, since there has been consolidation in many heavily-franchised industries like fast food and hotels.

3 Results

Since different chains operate in different industries and make use of workforces with different occupational breakdowns, there is a good deal of variation in the types of jobs they post. For example, the restaurant industry accounts for almost half the jobs posted, but even so, fast-food workers appear to be hired through online recruiting at a lower rate than workers in other low-wage sectors. Job ads for the restaurant sector are also less likely to include posted wages. Figure 2 plots the share of all job ads in the matched dataset that include a posted wage, over time. The discontinuous increase in the percent of job postings reporting a wage in 2018 and 2019 is driven by the introduction of new job boards with a higher prevalence of including such information than other scraped job posting sources into the source material for the Burning Glass web crawler.

Before describing the coverage of each restraint or contractual provision in the FDDs, we first report on the characteristics of the top industries, occupations, and job titles represented in the matched dataset. Industry is a characteristic of a firm or employer, while occupations are a characteristic of a worker (hence, a job ad connecting an employer to a vacancy or a worker are classified both by industry and occupation.) Job titles, which are subordinate to occupations, are also reported in the BGT data.

We follow the Burning Glass data in using 6-digit occupations according to the Standard Occupational Classification ("SOC-6"), which enables us to compare the matched dataset to Bureau of Labor Statistics Occupational Employment and Wage Statistics (OEWS) data, a nationally-representative survey of establishments. Table 1 lists the top 20 occupations in the matched dataset, average wages according to both BGT and OEWS data, the share of job ads that report salary information for each of the top occupations in the matched dataset, and the ratio of the count of job ads for each occupation to the total occupational employment count in OEWS, a measure of how representative the BGT data is for each occupation. In addition to variation in turnover (and hence the frequency of recruitment) across occupations, some occupations are more frequently recruited with online job postings.

Table 1 appears to suggest that among restaurant occupations, BGT data frequently miscodes non-managerial occupations as managerial (SOC 11-9051), given the outsize ratio of BGT job ads to total OEWS employment in that occupation and the fact that the average earnings of BGT job ads in that occupation are substantially below average earnings in that occupation according to OEWS (shown in Table 2). This anomaly likely reflects the restaurant industry's tendency to classify non-managerial workers as managers to avoid paying them overtime. Cohen, Gurun and Ozel (2023) document this phenomenon in much greater detail, also using the BGT data. Those authors show that it is more prevalent at employers where workers have fewer outside options and employers who face a greater likelihood of being penalized for overtime violations.

Table 2 reports the top ten most-frequently-appearing NAICS four-digit industries among all the job ads in the matched dataset and the prevalence of each industry in both the job ads and franchising chains/FDDs. We use the industry associated with the franchising chain, according to the FDD data, as opposed to the industry reported in the job ads. There is a much larger range of industries reported in the latter, but since industry is a characteristic of an employer and the point of the matching procedure is to link together job ads posted by different nominal employers to the same chain, we prefer the industry classification reported in the FDD. 49% of the matched dataset is from the restaurant industry, and a further 13% from Traveler Accommodation. Every other industry accounts for 5% or less of the matched dataset, with 15% of job ads from industries outside the top ten.

For each of the top ten industries, table 2 then reports the top three occupations which employers affiliated with chains in that industry hire for, the share of job ads associated with that occupation (where the denominator is all job ads in the industry), and average annual salaries for that occupation-within-industry. (The same occupation can appear in multiple industries. For example, "Sales Representatives" is a top occupation for several different industries in the matched dataset.)

Table 3 is structured similarly, except it lists the top ten most-frequently-appearing occupations (6-digit SOC) in the matched dataset (regardless of industry) and the top three most-frequently-appearing job titles within each occupation, along with average salaries for each occupation and job title. As previously mentioned, we can compare salaries from BGT job ads to the nationally-representative salaries in OEWS. There is no equivalent nationally-representative data on job titles.

The top occupations are nearly all from the restaurant/food service, hospitality, or retail sectors. None of the top occupations has an average salary over $50,000. The highest, for Supervisors of Retail Sales Workers, is $47,613. Altogether, the labor force in franchised industries is a low-wage workforce.

Finally, in tables 4 and 5, we compute national chain-level market shares (of job ads), as well as concentration at both the national and commuting zone levels in the top 10 industries and occupations in the matched dataset. The reported local Herfindahl-Hirschman Index (HHI) of concentration reports a simple average of HHIs across commuting zones, by either industry or occupation. Since industry is a characteristic of a chain, industry concentration tends to be significantly higher than occupational concentration. Several industries are only represented by a few chains in the contracts data, and all of the job ads associated with a given chain are interpreted as being within that chain's industry (as with previous tables and industry-level statistics). By contrast, the same chain frequently hires workers in multiple occupations, which de-concentrates occupation-defined labor markets by construction. Because these computations are undertaken *only* using the matched dataset, they should not be interpreted as representing overall employer concentration in a given industry or occupation (unlike Azar et al. (2020), for example).

Concentration is lowest in the restaurant industry and its associated occupations, reflecting the prevalence of franchising in that sector and hence the inclusion of many chains from that sector in the matched dataset. One important point made by Krueger and Ashenfelter (2022) is that the use of franchise no-poach agreements within chains increases the effective concentration of employers in a sector by a significant degree. In these computations of concentration, we assume that all franchisees affiliated with the same chain constitute a single employer, whether or not the chain uses a franchise no-poach provision. We relax that assumption to examine the effect of franchise no-poach provisions on effective concentration, and employer market power more broadly, in Section 4. But before we get to that, the following subsection explains what each of the vertical restraints and contractual provisions in the digitized FDDs signifies for the organization and balance of power in labor markets in the franchising sector.

3.1 Restraints

The restraints and contractual provisions that characterize the subordination of franchisees to franchisors in the FDDs and appended contracts are as follows:

1. **No poaching of employees within franchising network**: Franchisees are enjoined from hiring workers currently- or recently-employed by other franchisees (or the franchisor) in

the same chain.

2. **Resale Price Maintenance**: Franchisors have the power to dictate maximum or minimum retail prices for products offered to consumers by franchisees, including mandating they honor chain-level promotions. Note that "resale" in this context is inexact, since most franchising chains are not strictly manufacturers selling to distributors to resell to consumers, but rather trademark-holders licensing a brand and operators' manual to local service-providers.

3. **Franchisor Selects Inventory**: Franchisees are obliged to offer only those products or services prescribed by the franchisor. This restraint subsumes what is known in the Industrial Organization literature as "exclusive dealing" (the franchisor is itself the supplier of the inventory) and "exclusive supply" (the franchisee must source inventory from a third party per a contract negotiated with the franchisor, not the franchisee).

4. **Full Line Forcing**: Franchisees are mandated to carry the entire product line offered by the franchisor, and cannot decline to offer disadvantageous products.

5. **Independent Franchisee Association**: an organization of franchisees exists and is not under the control of the franchisor. Formal collective bargaining is prohibited for franchisees,[4] but associations can advocate to franchisors on behalf of their member franchisees.

6. **Mandatory Opening Hours**: Franchisees are required to maintain hours as prescribed by the franchisor, for example 24-hour service.

7. **Franchisor Access to Franchisee Data**: Franchisees are required to grant the franchisor access to point-of-sale data.

[4] Pending litigation in California and Massachusetts, and possibly in other states that employ an "ABC test" for employment status, allege misclassification of franchisee-employees as independent contractors on the grounds that the degree of control exercised by franchisors is tantamount to an employment relationship. If the plaintiffs' allegation is correct, that could lead to permissible collective bargaining by franchisees against dominant franchisors. See Dolan et al. (2021).

8. **Franchisor Selects or Must Approve Franchisee Site**: The franchisee's specific place of business is subject to the franchisor's approval (or prior selection).

9. **Franchisee Must Operate Directly**: The franchisee must personally manage the franchise establishment(s).

10. **Mandatory Arbitration**: Disputes arising under the franchisor-franchisee contract are referred to arbitration rather than litigation.

11. **Franchisor right to terminate without cause**: The franchisor has the right to terminate the franchise without cause. This is atypical in franchising contracts, but state-level franchising laws vary in whether just-cause termination is required. Over time franchisors have had increasing success defending themselves in improper termination suits (Emerson, 2016).

12. **Franchisor right to assign the contract to a different franchisor**: The franchisor can transfer the franchise contract and its rights to a different franchisor. In effect, the franchisor has the right to merge or transfer its assets without gaining the franchisee's approval for the new counterparty.

13. **Franchisor right to purchase assets at expiration**: A right of first refusal to purchase the franchisee's assets if the franchise is not renewed. This can be understood as a partial noncompete clause, since it precludes the franchisee from transferring to a different franchisor when one franchising relationship expires, without the prior franchisor's consent.

14. **Automatic withdrawal of franchisee fees**: The franchisor is granted access to the franchisee's bank account for the purpose of automatically withdrawing franchise fees.

15. **Franchisee Personal Guarantee**: The franchisee is required to put up a personal (and, in some cases, spousal) guarantee for obligations to the franchisor, even if the franchisee is incorporated.

16. **Franchisor Restriction on Transfers**: The franchisee cannot transfer its obligations to a different franchisee without the franchisor's approval.

Appendix A gives a more complete explanation of the meaning of each restraint/contractual provision, including sample language from the FDD and appended contract that signifies the presence or absence of each.

Table 6 reports the prevalence of each restraint or contractual provision among the franchising contracts and job ads (the latter from the matched dataset), irrespective of industry or occupation. Prevalence in the job ads data can be understood loosely as employment-weighted prevalence of each restraint, 'loosely' because the number of job ads posted by a chain isn't necessarily exactly proportional to its employment share among franchising chains.

Tables 7 and 8 report the prevalence of each restraint for the top ten industries and the top ten occupations in the matched dataset.[5] It's difficult to summarize how "controlled" franchisees are by industry or occupation since the many restraints/contractual provisions don't reduce to a single index, but there are big differences across industries in the use of each restraint/contractual provision individually, suggesting that franchising performs somewhat different functions across industries. On the other hand, most industries, and most chains, use exclusive dealing and/or supply provisions, suggesting that franchisees play the role of captive distributors operating to bring the franchisor's branded goods or services to market as though vertically integrated while segmenting the labor force that actually performs that function in the economy from formal affiliation with the franchisor, or in Weil (2014)'s parlance, the 'lead firm.' Keeping in mind Asker and Bar-Isaac (2014)'s interpretation of vertical restraints, then, in addition to exclusive territories or maximum RPM as a means of ensuring distributor loyalty by sharing monopoly profits, we could also see no-poaching clauses as similar carrots by which franchisors guarantee a profit to franchisees in return for loyalty and cooperation.

[5]Several other publications in this literature, including Callaci (2021*b*), Blair and Lafontaine (2005), and Krueger and Ashenfelter (2022) report the frequency of different restraints and contractual provisions at the franchising chain level using FDD-derived data, but to our knowledge, this is the first to do so using a dataset that in effect weights by each chain's, and therefore each provision's, importance in the labor market or the overall economy.

By contrast, Blair and Lafontaine (2005) write that "franchisors occasionally require that their franchisees buy a variety of inputs from the franchisor or its dedicated supplier." Those authors find that around 30% of franchising contracts included mandatory purchase requirements such as these in 1988 and 1989, whereas we find around 90% have exclusive dealing or supply contracts in 2015 and 86% have full-line forcing. The possibility that exclusive dealing-type provisions have increased in prevalence over time is an intriguing possibility suggesting shifting bargaining power toward franchisors. That bears further investigation.

Moreover, about half of the contracts, and 42% of job ads, include the Franchisor Right to Purchase Assets at Expiration provision. That breaks out as 48% of the restaurant industry, 98% of personal care services, and 68% of individual and family services (home healthcare agencies and the like). Franchisees subject to that provision are bound to their current franchisor by the equivalent of a non-compete clause, which bears on the inferred balance of power between franchisor and franchisee. Blair and Lafontaine (2005) claim that franchisors rarely possess market power because franchisees can always switch to a different chain, and many chains offer franchising contracts to qualified applicants. These results suggest otherwise.

4 Competitive Effects of Franchise No-poach Clauses

Section III of Krueger and Ashenfelter (2022) analyzes the competitive effect of franchise no-poach clauses in light of two different theories of power imbalance in labor markets. First, in what might be called an "old monopsony" model, no-poach agreements may increase effective employer concentration by combining each franchisee-employer in the market. Without a no-poach agreement, the franchisees would be bidding against one another for workers. Put differently, a worker employed by any one franchisee loses access to outside franchisee-employers in the same franchising chain if there is a franchise no-poach in place, reducing her residual labor supply elasticity vis a vis her current employer by virtue of the elimination of otherwise-available outside options. Second, in a dynamic "new monopsony" model, a no-poach provision has the effect of pushing down the wage-turnover tradeoff schedule. In other words, employers can get away with paying lower wages for a given level of turnover, since workers have fewer other places to go. Card (2022) elaborates on each of these classes of theories and their scholarly antecedents. Most importantly, both theories hinge on the concept of finite residual labor supply elasticity: any one employer can unilaterally dictate a wage reduction without losing all of his workers. For that reason, the two theories are entirely consistent with one another, in fact complementary.

In this section, we report *prima facie* evidence of the empirical plausibility of each theory. Earlier, in tables 4 and 5, we assumed that each franchising chain constitutes a unitary employer for the purposes of computing labor market concentration, which amounts to the assumption that every chain has a perfectly-enforceable franchise no-poach in place covering all workers at any franchisee, or at the franchisor. Here, we instead attempt to measure employer concentration at the *franchisee* level, then see how that measure of employer concentration changes when we combine all the employer-franchisees in a chain into a single employer only if that chain has a franchise no-poach reported in its FDD.

This analysis is complicated by the fact that we do not observe distinct franchisees. In fact, most employers affiliated with a chain will use the franchisor's trademark in recruiting workers, just as they do marketing to consumers. That is the basis of the franchising business model, not to mention the text-based matching procedure we employ to construct the matched dataset. Thus, to assume each separate employer name constitutes a separate franchisee (as, for example, is done in Azar et al. (2020) for employers more broadly) would erroneously combine distinct franchisees because they appear with the same name in the BGT data.[6] Instead, we assume that each distinct combination of employer name and employer location in the BGT data constitutes a separate employer, implicitly that these two job-ad-level variables signify unique franchisees. However, many franchisees in fact operate multiple locations and likely

[6]Employer names by themselves are standardized within national chains in the BGT data, even though in some cases employer names signify geographic specificity (e.g. "McDonalds of Fourteenth Street").

appear with the same employer name for each location, so a definition of franchisee-employer that distinguishes each employer name-by-geographic-location underestimates the degree of employer concentration operating at the franchisee level.

Notwithstanding this weakness, the results shown in Tables 9 (for the top 20 industries) and 10 (for the top 20 occupations) are consistent with the mechanism outlined by Krueger and Ashenfelter (2022). Effective concentration increases significantly when franchisees are combined in chains that use no-poach restraints. For example, the average local (commuting zone level) concentration in the restaurants industry when franchisees are distinct employers is 109, and it is 731 when franchisees are combined for chains that use no-poaches. That is close to the HHI of 1086 for chain-level concentration, because 81% of that industry uses no-poaches (per table 7). By contrast, franchisee-level concentration is 820 for the traveler accommodation industry, and only slightly higher, 888, when franchisees in chains with no-poaches are combined, much less than the 2489 computed for chain-level concentration. That is because only 5% of the industry employs franchise no-poaches. By and large, for industries and occupations where no-poaches are prevalent, effective employer concentration increases significantly as a result.

Testing the second, dynamic monopsony theory produces more ambiguous results. In this case we construct wage-turnover schedules by chain as follows. For each observable, wages and turnover, we perform a first stage. This is straightforward in the case of wages: we first regress posted annual wage at the job ad level on occupation, commuting zone, and year-quarter fixed effects, to compute a chain-by-month-level average residual from that regression.

Turnover is not observable in the job ads data. Instead we take the job ads themselves to be evidence of turnover, regressing the chain-by-month count of total job ads posted on industry and year-month fixed effects, as well as a single chain-level variable in the FDD data that records the number of outlets in the chain. The idea is that chains may post different numbers of job ads for a variety of reasons: whether they perceive that as an efficacious recruitment mechanism (which we implicitly assume varies at the 4-digit industry level), their demand for labor (which we assume varies at a monthly frequency), and the size of the chain (which is proxied by the number of outlets). We assume that residual variation in the number of job ads posted captures chain-specific turnover. The biggest weakness of this estimation of chain-level turnover, in our view, is that we are missing a time-varying estimate of chain size (i.e., total employment, or total number of outlets). Thus, our residual variation in job-ad-posting may also be capturing variation in chain size.

Finally, we compare the residual chain-by-month variation in posted wages to the residual chain-by-month variation in total job ads posted, which we take to approximate the wage-turnover tradeoff that is the focus of the new monopsony model in Krueger and Ashenfelter (2022). These results are depicted in figure 3, for the period before January 2018, and figure 4, for the period after June 2018. The reason we split the sample in this way is that starting in January 2018, the Washington State Attorney General commenced an investigation and eventually an enforcement campaign against franchise no-poach provisions that secured national settlements enjoining their further use. We describe that campaign and evaluate its impact in separate work, Callaci et al. (2023). For our purposes here, if the effect of the no-poach provisions is to push down the wage-turnover relationship, that effect should disappear after the no-poach provisions cease to be in effect. The first settlements were reached in June 2018.

The results are mostly ambiguous. First of all, the best fit lines in most of the scatterplots are upward-sloping, whereas in a dynamic monopsony model they would slope downward, reflecting that lower turnover comes at the expense (for employers) of higher pay. And in general, there is no difference between the estimated wage-turnover relationship for chains with and without a no-poach provision.

We report separate scatterplots for the top three most frequently-appearing industries in the matched dataset: restaurants, traveler accommodation, and personal care services. For the restaurant industry, 81% of job ads are in chains with no-poaches, whereas in traveler accommodation, only 5% are. Thus, there is not very much variation in no-poach presence between chains in either industry. For personal care services, on the other hand, 49% of job ads are in chains with no-poaches, suggesting meaningful variation between chains in that industry as to whether they use no-poaches. In that sense, the personal care service scatterplots may be most informative, and if you squint, these plots provide evidence consistent the dynamic monopsony theory: chains that use no-poaches post lower salaries for a given level of job posting than chains that don't use no-poaches for the period prior to January 2018. After June 2018, when the no-poach settlements started to go into effect, that difference is reversed.

We perform one final analysis testing the dynamic monopsony theory: we link franchising chains in our dataset to chain-level financial revenue data from Compustat, as a proxy for time-varying chain size. Then the first stage regression to compute residual variation in chain-level job ad count includes chain-level financial revenue at a quarterly frequency. The idea is that in that case, residual variation in the monthly count of job ads is a better proxy for chain-level turnover.

For the top three industries previously reported, we match only 25 chains to Compustat revenue data, likely because most of the 204 chains in those industries are privately-held. In figure 5, we report similar scatterplots for those 25 chains, before January 2018 and after June 2018. Because of the small number of chains, we do not break these scatterplots out by industry. The findings are mostly unchanged, although the best fit line for the chains without no-poaches is mostly above the line for chains that use no-poaches before the Washington AG settlements were reached (as well as downward-sloping), and the two appear more similar after June 2018. This is, again, consistent with the dynamic monopsony model, but hardly dispositive.

5 Wage Regressions

In this section we report on binary regressions of (log) posted wage on an indicator for whether the chain posting a vacancy does or does not have a given restraint or provision in its FDD/franchising contract. For each regression, the identifying variation is between jobs posted by different chains that either do or do not include a given provision.

The regression equation is as follows:

$$log(w_{ijkmt}) = \alpha + \beta D_j + \gamma_k + \delta_m + \lambda_t + \epsilon_{ijmt} \tag{5.1}$$

where $log(w_{ijkmt})$ is the log wage in job i by franchisor (chain) j for occupation k in commuting zone m at time t. We observe a binary variable D_j at the chain (j) level, which is constant over job ads, occupations, commuting zones, and time (since we observe this for FDDs governing all franchisees in a network, filed by each chain at a single point in time). We include fixed effects (γ, δ & λ) designed to filter out overall market characteristics, like business cycles, geographic earnings premia, and occupation average earnings from chain-specific pay. This specification implicitly defines a labor market by commuting zone, occupation, and quarter, drawing on Azar et al. (2020) and Azar, Berry and Marinescu (2022). ϵ_{ijmt} is an error term.

The coefficient estimate on each restraint is reported in Figure 6, where the covariates in each case are fixed effects for year-quarter, commuting zone, and 6-digit SOC occupation. Overall, most of the restraints that give franchisors greater control over the operation of the franchisee's business correlate with lower wages for workers, including no poaching provisions, resale price maintenance, exclusive dealing/supply ("franchisor selects inventory"), full-line forcing, mandatory opening hours, and franchisor access to franchisee data. For the restraints that pertain more directly to the contract between franchisor and franchisee, the coefficient estimates are negative but the confidence intervals overlap zero, which is not surprising given the only variation is between chains (and standard errors are clustered at the chain level). Franchisor restriction on transfers and franchisor right to terminate without cause both correlate positively with earnings, but in each case there is little variation between chains: almost every chain restricts transfers between franchisees, and few chains reserve an explicit right to terminate franchises without cause.[7]

[7] In fact, the right to terminate without cause differentiates an employment relationship from a contractual franchising relationship in some legal applications, in which case franchisors would not want to claim an explicit right to terminate franchisees without cause, lest they be liable for employment misclassification.

Figure 7 complicates any inference from the earnings regressions by also including fixed effects for NAICS 4-digit industries. As a result, very few of the coefficient estimates are significantly different from zero, since in many cases there are few chains per industry and thus little variation in the application of each restraint within labor markets defined by quarter, commuting zone, occupation, and industry. And because it is difficult to disentangle industry-level wage effects from the effect of each restraint, given strong patterns in the use of restraints by industry, we can't form any conclusion about the effect of restraints on wages by varying their application and holding industry constant.

The results reported here are not causal estimates of the effect of vertical restraints between franchisors and franchisees on wages for workers in franchise chains. For that, we need plausibly-exogenous variation in the application of each of the vertical restraints over time or across workers, which we leave to further work, including Callaci et al. (2023).

6 Discussion

The franchising business model is to a large extent the creation of the post-1970s revolution in antitrust jurisprudence that legalized vertical restraints between dominant upstream franchisors and subordinate downstream franchisees (Callaci, 2021*a*). Paul (2019) refers to this as the extension of antitrust's "firm exemption" (permitting economic coordination within a firm) across the legal boundary of the firm, to economic subordinates under a logic of hierarchy-as-economically-efficient visible in Coase (1937) and analyzed more overtly by Williamson (1980). Part of the rationale for that legal revolution is that consumers benefit when economic production takes place under a unified locus of control, and that regulatory regimes, including antitrust, should not throw up obstacles to the exercise of that control. To take the most ideologically extreme rendition of this principle, the idea that franchisees should retain legal independence has been viewed as elevating the uneconomic principle of promoting small business at the expense of the "economic" preference for productive efficiency inherent in large firm domination.[8]

Notably, that legal revolution never rested on a basis of empirical verification for its core theories: that vertical control by dominant firms in supply chains benefits consumers by making the process of production and distribution more efficient, reducing prices and markups. Recently, the conclusions of that legal revolution have been brought into question. In December 2021, the Federal Trade Commission indicated its interest in rule-making on the subject of exclusive contracting provisions such as those documented in this paper (Federal Trade Commission, 2021*b*). In response, critics have maintained that questioning the legal status quo is not grounded in any empirical documentation of the harms from those provisions (Wilson, 2021), notwithstanding the significant public comment the FTC's call for evidence about their effects garnered (Federal Trade Commission, 2021*a*). This paper begins to fill the gap documenting the coverage of such provisions (as well as others), but since policy has historically veered wildly in response to theoretical innovations without very much empirical verification, there is scope for a good deal of further research regarding their effects.

Legalizing vertical restraints while simultaneously weakening standards for joint employer liability in labor law draws an inconsistent conceptual boundary of the firm: antitrust grants broad powers to a lead firm to control its subordinates, as though they are part of the same economic entity, while labor law narrows the responsibility of lead firms to those workers who work directly for it. Franchisors erect franchisees as middle-men tasked with supervising and controlling workers essential to the franchisor's core function, but which the franchisor prefers to keep outside the legal boundary of the firm lest it otherwise be responsible for providing minimum labor standards, since a single workplace can create egalitarian social expectations, which it is easier for employers to transgress when workers are nominally (and legally) segmented (Weil, 2017).

Furthermore, the formal schematization of the franchising relationship as vertical immu-

[8]For examples of this view, see Shapiro (2018) and especially Muris and Nuechterlein (2019). For intellectual-historical analysis of it, see Popp Berman (2022).

nizes practices like no-poaching agreements from antitrust liability, even where they are standardized across a chain and thus have identical economic effects as a horizontal no-poaching agreement would. A recent ruling in *Deslandes v. McDonalds* exemplifies this point (Alonso, 2022), holding that franchise no-poach provisions are vertical and hence to be analyzed under antitrust's Rule of Reason, requiring that the defendant's market power be shown as part of making the case. Since franchising labor markets are unconcentrated, so the ruling goes, franchise employers must not have market power, hence the no-poach provisions are not presumptively anti-competitive. This reasoning belies the economic intuition that agreements between employers not to hire one another's workers, especially where the parties to the agreement are the most likely but-for source of outside job offers, are very likely to reduce labor market competition. But it is one example of the reasoning under which control exercised across the legal boundary of the firm is virtually unregulated.

This paper considers the effect of franchising on workers, empirically grounding intuitions about the incentive structure facing franchisees (to exploit workers) when their profit-maximization decision is attenuated by the application of obligations that close off their autonomy over most business decisions.

Insofar as the Industrial Organization literature contemplates competitive harm arising from vertical restraints imposed by dominant firms in a supply chain, the scope for harm has been limited to cases where the terms of one bilateral economic relationship or contract affects the terms of third-party transactions. For example, in the standard case of foreclosure, a contract that says one supplier must be exclusive to a dominant distributor is deemed anti-competitive only if it withholds must-have inputs from a competing distributor (i.e., a would-be third party), weakening price competition at the distributor level. If it merely disadvantages the bound supplier (counterparty to the bilateral contract), then that is not sufficient to establish harm to competition. The implication of analyzing the labor market impact of vertical restraints in franchise chains (and more generally) is that workers are a relevant third party, and labor market competition is an arena where the anti-competitive effect of vertical restraints may be manifested.

7 Conclusion

This paper creates a novel dataset by matching 530 digitized Franchise Disclosure Documents and appended franchising contracts with employer-identified job ads. It thus permits a novel empirical investigation in two respects: first, a comprehensive picture of the provisions of franchising contracts, across all major US chains and sectors in which the franchising form is used. Second, the ability to match those provisions to labor market outcomes.

We report on characteristics of workers and labor markets in franchised industries and occupations, including average earnings and national-level labor market concentration. Following and building on Krueger and Ashenfelter (2022) and Callaci (2021*b*), we associate the restraints and contractual provisions contained in each franchise chain's FDD with workers employed in that chain, which enables us to estimate the share of workers subject to each provision by industry and occupation. We investigate the mechanisms by which franchise no-poach provisions in particular contribute to employer power and worker dependence. We also conduct correlational regressions of annual earnings on each restraint, but any causal interpretation of the restraints awaits further work.

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Table 1. Top occupations in the matched dataset. This table reports the top 20 most-frequently-appearing occupations in the matched dataset, along with average salaries in both the BGT and Occupational Employment and Wage Statistics (OEWS) data, as well as the ratio of the count of job ads to total employment in the occupation, according to OEWS. That ratio is computed using the OEWS annual data in 2007 and 2010-2021, and all of the BGT job ads posted in those years.

Rank	Occupation	SOC-6 code	Average annual earnings (BGT)	Average annual earnings (OEWS)	BGT ads / Total employment in OEWS (%)	BGT ads with salary info (%)
1	Food Service Managers	11-9051	39,622	55,643	48	11
2	Food Prep/Serving Workers	35-3021	25,156	19,435	1	13
3	Food Prep/Serving Supervisors	35-1012	33,550	34,124	3	12
4	Driver/Sales Workers	53-3031	33,303	28,631	6	16
5	Waiters/Waitresses	35-3031	26,425	23,485	1	9
6	Customer Service Representatives	43-4051	31,589	34,928	1	14
7	Retail Salespersons	41-2031	37,318	27,124	1	16
8	Supervisors of R/S Workers	41-1011	47,613	43,059	2	18
9	Cooks, Restaurant	35-2014	26,694	25,601	1	11
10	Hospitality desk clerks	43-4081	26,038	23,527	7	21
11	Personal Care Aides	39-9021	31,046	21,664	1	21
12	Auto Technician/Mechanic	49-3023	37,690	41,529	2	23
13	Hairdressers/Hairstylists	39-5012	38,486	29,253	4	6
14	Maids/Housekeepers	37-2012	28,073	23,847	1	21
15	Janitors/Cleaners	37-2011	28,906	26,992	0	24
16	Maintenance/Repair Workers	49-9071	34,660	39,761	1	15
17	Sales Representatives	41-4012	53,691	66,988	1	18
18	Tax Preparers	13-2082	56,382	44,434	12	6
19	Hosts/Hostesses (Rest/Cafes)	35-9031	23,723	21,424	2	12
20	Bakers	51-3011	28,251	27,196	4	10

Table 2. Industry & occupational breakdown of the matched dataset. This table gives the top 10 NAICS 4-digit industries represented in the matched contracts-job ads dataset, the top three most-frequently-appearing occupations within each industry, and the average annual salary for each occupation among those employed in that industry, not for the occupation in general.

Industry name	NAICS code	Contracts share (%)	Job ads share (%)	Top occupations	Occ. share of industry ads (%)	Average salary ($)
Restaurants & similar	7225	28	49	Food Service Managers Food Prep/Serving Workers Food Prep/Serving Supervisors	29 20 8	39,476 25,089 29,679
Traveler Accommodation	7211	7	13	Hospitality desk clerks Maids/Housekeepers Waiters/Waitresses	16 11 7	25,715 24,587 24,217
Personal Care Services	8121	3	4	Hairdressers/Hairstylists PS Workers' Supervisors Massage Therapists	40 17 14	38,499 42,275 57,146
Individual and Family Services	6241	3	4	Personal Care Aides Nursing Assistants Home Health Aides	53 14 10	31,032 30,771 31,409
Accounting-Tax-Bookkeeping	5412	1	3	Tax Preparers Receptionists/Information Clerks Office/admin support Supervisors	42 15 12	56,451 34,012 46,686
Automotive Parts and Accessories	4413	1	3	Auto Technician/Mechanic Retail Salespersons Tire Repairers and Changers	43 12 12	37,639 64,457 30,736
Travel Arrangement & Reservation	5615	1	2	Managers (all other) Sales Managers Software Developers	8 8 8	81,090 90,797 96,935
Automotive Equip. Rental & Leasing	5321	2	2	Supervisors of R/S Workers Vehicle Operators (all other) Sales Representatives	14 10 10	38,785 19,752 54,536
Building Equipment Contractors	2382	3	2	Janitors/Cleaners Maintenance/Repair Workers Sales Representatives	34 5 4	25,315 46,618 66,668
Automotive Repair and Maintenance	8111	3	2	Auto Technician/Mechanic Customer Service Representatives First-Line Supervisors of Mechanics, Installers, and Repairers	44 17 5	37,004 37,078 53,635
Other	N/A	49	15	Retail Salespersons Supervisors of R/S Workers Customer Service Representatives	12 9 8	30,543 41,627 35,680

Table 3. Occupation & job title breakdown of the combined dataset. This table gives the top 10 SOC 6-digit occupations represented in the matched contracts-job ads dataset (not conditional on industry), the top three most-frequently-appearing job titles within each occupation, and the average annual salary for each job title among those employed in that occupation, not for the job title in general.

Rank	Occupation (SOC-6)	Job ads share (%)	Average salary ($)	Top job titles	Job title share of occ. ads (%)	Average salary ($)
1	Food Service Managers	15	39,622	Assistant Manager	21	35,484
				Assistant Restaurant Manager	17	41,650
				Restaurant General Manager	14	47,652
2	Food Prep/Serving Workers	10	25,156	Restaurant Crew	6	23,834
				Fast Food Team Member	3	24,794
				Food team member	2	23,883
3	Food Prep/Serving Supervisors	5	33,550	Restaurant Shift Supervisor	8	34,285
				Restaurant Manager	2	43,871
				Restaurant Shift Leader	2	26,085
4	Driver/Sales Workers	4	33,303	Delivery Driver	89	33,133
				Pizza Delivery Driver	8	33,232
				Catering Driver	0	27,781
5	Waiters/Waitresses	3	26,425	Restaurant Server	18	27,446
				Skating Carhop	5	22,692
				Banquet Server	5	25,166
6	Customer Service Representatives	3	31,589	Customer Service Representative	45	33,723
				Customer Service Associate	11	29,058
				Customer Service Advisor	6	43,424
7	Retail Salespersons	3	37,318	Sales Associate	40	30,048
				Retail Sales Associate	18	29,731
				Store Team Member	17	23,257
8	Supervisors of R/S Workers	3	47,613	Store Coordinator	18	36,987
				Store Manager	16	50,604
				Retail Store Manager	10	63,133
9	Cooks, Restaurant	2	26,694	Cook	46	25,850
				Line Cook	25	27,037
				Prep Cook	13	24,794
10	Hospitality desk clerks	2	26,038	Front Desk Agent	19	25,603
				Night Auditor	17	26,079
				Guest Service Agent	12	26,556

Table 4. Market shares and market concentration by industry. This table gives the market share (of job ads) of each of the top 10 chains, by industry, as well as the national and commuting-zone-average ("local") Herfindahl-Hirschman Index in each industry. In several industries among the top 20, there are fewer than 10 chains in the matched dataset. All chains are included in the HHI calculation, even where there are more than the top 10 market shares reported here.

Industry	1	2	3	4	5	6	7	8	9	10	HHI (national)	HHI (local)
Restaurants and Other Eating Places	14	11	7	7	5	4	3	3	3	3	516	1086
Traveler Accommodation	36	21	7	5	5	4	4	4	2	2	1861	2489
Personal Care Services	50	28	7	5	3	3	1	1	1	1	3356	5139
Individual and Family Services	46	13	8	6	6	4	4	4	3	2	2468	4405
Accounting, Tax Preparation, Bookkeeping, and Payroll Services	91	8	1	0							8380	8132
Automotive Parts, Accessories, and Tire Stores	96	3	1	0							9227	9276
Travel Arrangement and Reservation Services	100	0	0	0							9905	9400
Automotive Equipment Rental and Leasing	90	9	1	0	0	0	0	0			8136	9276
Building Equipment Contractors	77	11	5	3	1	1	1	1	0	0	6144	6595
Automotive Repair and Maintenance	45	23	8	5	5	3	3	2	2	1	2728	4596
Other Amusement and Recreation Industries	29	29	11	6	5	3	2	2	2	2	1894	3946
Health and Personal Care Stores	63	34	2	0	0	0	0	0	0		5166	7942
Gasoline Stations	51	48	1								4887	7883
Furniture Stores	98	2	0								9584	9495
Offices of Other Health Practitioners	91	5	2	1	1	0	0				8378	8502
Other Financial Investment Activities	65	35									5456	7527
Services to Buildings and Dwellings	23	9	9	9	8	7	6	6	4	4	1023	2608
Employment Services	77	14	4	4	1	0	0				6112	7481
Offices of Real Estate Agents and Brokers	31	29	14	10	5	5	3	1	1	1	2126	4452
Other Schools and Instruction	39	12	11	10	7	6	5	3	3	1	1982	3904

Table 5. Market shares and market concentration by occupation. This table gives the market share (of job ads) of each of the top 10 chains, by occupation, as well as the national and commuting-zone-level ("local") Herfindahl-Hirschman Index in each occupation. In several industries among the top 20, there are fewer than 10 chains in the matched dataset. All chains are included in the HHI calculation, even where there are more than the top 10 market shares reported here.

Occupation	1	2	3	4	5	6	7	8	9	10	HHI (national)	HHI (local)
Food Service Managers	19	11	11	6	5	4	4	4	3	3	746	1288
Food Prep/Serving Workers	16	9	6	6	6	5	4	4	4	3	576	1095
Food Prep/Serving Supervisors	11	9	8	6	6	5	5	4	3	3	460	1043
Driver/Sales Workers	36	21	11	11	6	5	2	1	1	1	2035	3231
Waiters/Waitresses	20	11	9	8	7	7	6	4	4	3	874	2166
Customer Service Representatives	17	14	10	6	6	6	3	3	3	3	747	1612
Retail Salespersons	24	17	14	11	9	5	2	2	2	1	1277	2100
Supervisors of R/S Workers	19	15	11	10	9	7	5	4	2	1	956	1759
Cooks, Restaurant	15	11	7	6	5	4	4	3	3	2	561	1544
Hospitality desk clerks	20	10	10	9	8	4	3	3	3	2	808	1645
Personal Care Aides	53	7	6	6	4	3	3	3	3	2	2984	4496
Auto Technician/Mechanic	55	18	7	4	4	3	2	2	1	1	3447	4780
Hairdressers/Hairstylists	81	14	2	2	1	0	0	0	0	0	6745	7193
Maids/Housekeepers	23	14	7	7	5	4	4	4	3	3	927	1841
Janitors/Cleaners	50	6	4	4	4	3	3	3	3	2	2617	3084
Maintenance/Repair Workers	40	10	6	4	4	4	3	2	2	1	1772	2788
Sales Representatives	20	14	7	5	3	3	3	3	3	3	765	1964
Tax Preparers	86	13	1	0	0	0	0	0	0	0	7592	7809
Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	16	14	12	7	7	7	6	5	4	3	858	2049
Bakers	72	5	4	3	2	2	2	2	1	1	5321	5408

Table 6. Share of observations in each dataset for which a given restraint or contractual provision is present. The first column gives the share of franchising chains imposing each restraint. The second column gives the share of job ads in the matched dataset which are subject to each restraint. The shares differ between the two columns because of variation in the number of job ads associated with each chain.

	(1) Chains	(2) Job ads
No Poaching of Employees within Franchising Network	0.592	0.601
Resale Price Maintenance	0.442	0.416
Franchisor Selects Inventory	0.908	0.918
Full Line Forcing	0.868	0.864
Independent Franchisee Association	0.123	0.291
Mandatory Opening Hours	0.643	0.766
Franchisor Access to Franchisee Data	0.790	0.851
Franchisor Selects or Must Approve Franchisee Site	0.819	0.955
Franchisee Must Operate Directly	0.349	0.371
Mandatory Arbitration	0.579	0.382
Franchisor Right to Terminate w/o Cause	0.023	0.044
Franchisor Right to Assign Contract to Different Franchisor	0.845	0.842
Franchisor Right to Purchase Assets at Expiration	0.491	0.424
Automatic Withdrawals of Franchisee Fees	0.815	0.829
Franchisee Personal Guarantee	0.932	0.868
Franchisor Restriction on Transfers	0.994	0.999
Observations	530	8,691,518

Table 7. Share of observations in each of the top ten industries for which a given restraint/contractual provision is present. This table gives the share of job ads in each of the top industries which are covered by a given restraint. The restraints are sorted into two categories for ease of presentation. The first set concerns restrictions on franchisee autonomy. The second set concerns the contractual relationship between franchisors and franchisees.

Industry	No Poaching	RPM	Excl. Dealing	Full Line Forcing	Indep. Franchisee Assoc.	Mand. Hours	Data Access	Franchisor Site Approval	Franchisee Must Operate	Transfer Restriction
Restaurants & similar	81	35	99	100	43	81	91	100	43	100
Traveler Accommodation	5	89	81	99	2	91	98	93	7	100
Personal Care Services	49	87	100	99	78	95	100	100	28	100
Individual and Family Services	86	57	100	54	13	44	86	88	60	100
Accounting-Tax-Bookkeeping	99	8	100	100	1	100	100	100	91	100
Automotive Parts and Accessories	0	0	3	4	0	3	4	100	0	100
Travel Arrangement & Reservation	0	0	100	0	0	100	0	100	100	100
Automotive Equip. Rental & Leasing	91	1	90	1	0	90	91	100	0	100
Building Equipment Contractors	4	4	18	84	2	1	6	88	9	100
Automotive Repair and Maintenance	85	16	97	71	38	96	90	100	14	100

Industry	Mandatory Arbitration	Franchisor Right to Terminate w/o Cause	Franchisor Right to Merge	Franchisor Right to Purchase Assets	Automatic Fee Withdrawal	Franchisee Personal Guarantee
Restaurants & similar	31	7	89	48	90	83
Traveler Accommodation	22	0	53	2	47	100
Personal Care Services	90	1	100	98	100	100
Individual and Family Services	41	0	78	68	94	94
Accounting-Tax-Bookkeeping	8	0	99	9	99	9
Automotive Parts and Accessories	4	1	100	3	100	100
Travel Arrangement & Reservation	100	0	100	0	100	100
Automotive Equip. Rental & Leasing	90	0	91	91	0	91
Building Equipment Contractors	86	0	95	6	84	100
Automotive Repair and Maintenance	51	0	100	86	76	100

Table 8. Share of observations in each of the top ten occupations for which a given restraint/contractual provision is present. This table gives the share of job ads in each of the top occupations which are covered by a given restraint. The restraints are sorted into two categories for ease of presentation. The first set concerns restrictions on franchisee autonomy. The second set concerns the contractual relationship between franchisors and franchisees.

Occupation	No Poaching	RPM	Excl. Dealing	Full Line Forcing	Indep. Franchisee Assoc.	Mand. Hours	Data Access	Franchisor Site Approval	Franchisee Must Operate	Transfer Restriction
Food Service Managers	77	27	99	99	48	77	93	100	37	100
Food Prep/Serving Workers	71	32	98	100	34	85	90	100	50	100
Food Prep/Serving Supervisors	66	33	97	98	29	92	91	100	55	100
Driver/Sales Workers	97	42	99	99	84	63	97	100	48	100
Waiters/Waitresses	69	60	96	100	34	71	92	99	9	100
Customer Service Representatives	85	38	98	88	49	86	93	98	42	100
Retail Salespersons	60	50	89	86	32	73	86	98	20	100
Supervisors of R/S Workers	69	29	90	78	45	81	89	99	14	100
Cooks, Restaurant	66	69	97	99	15	91	80	99	19	99
Hospitality desk clerks	21	78	77	98	10	85	95	90	13	100

Occupation	Mandatory Arbitration	Franchisor Right to Terminate w/o Cause	Franchisor Right to Merge	Franchisor Right to Purchase Assets	Automatic Fee Withdrawal	Franchisee Personal Guarantee
Food Service Managers	24	3	85	36	90	87
Food Prep/Serving Workers	33	6	84	41	86	79
Food Prep/Serving Supervisors	37	11	77	49	86	85
Driver/Sales Workers	28	6	99	59	98	99
Waiters/Waitresses	30	0	80	37	79	92
Customer Service Representatives	42	8	92	79	89	93
Retail Salespersons	41	1	95	21	93	99
Supervisors of R/S Workers	36	0	97	45	86	98
Cooks, Restaurant	30	1	80	48	77	82
Hospitality desk clerks	24	0	69	16	57	100

Table 9. Change in effective labor market concentration due to franchise no-poach clauses, by industry. This table reports three different concepts of labor market concentration by industry in the matched dataset, both nationally (columns 1-3) and by commuting zone (columns 4-6). Columns 1 and 4 report concentration based on franchisee-level job ad shares, where each franchisee is an employer name-location combination. Columns 3 and 6 report chain-level (franchisor-based) concentration, thus identical to the right-most two columns of Table 4. Columns 2 and 5 report a combination of the two, in which franchisees linked to the chains that use no-poach clauses are combined for the purposes of computing market shares. For the chains that don't use no-poaches, market shares are computed at the franchisee level.

Industry	HHI (national, franchisee-based)	HHI (national, franchisor-based if no-poach chain)	HHI (national, franchisor-based)	HHI (local, franchisee-based)	HHI (local, franchisor-based if no-poach chain)	HHI (local, franchisor-based)
Restaurants and Other Eating Places	0	471	516	109	731	1086
Traveler Accommodation	10	34	1861	820	888	2489
Personal Care Services	3	881	3356	677	1760	5139
Individual and Family Services	2	2410	2468	537	2910	4405
Accounting, Tax Preparation, Bookkeeping, and Payroll Services	6	8379	8380	1197	8155	8132
Automotive Parts, Accessories, and Tire Stores	8	8	9227	1608	1608	9276
Travel Arrangement and Reservation Services	145	145	9905	4171	4173	9400
Automotive Equipment Rental and Leasing	23	8056	8136	2198	8674	9276
Building Equipment Contractors	13	21	6144	1339	1378	6595
Automotive Repair and Maintenance	5	2650	2728	838	3519	4596
Other Amusement and Recreation Industries	4	1851	1894	634	2967	3946
Health and Personal Care Stores	20	4047	5166	1357	5744	7942
Gasoline Stations	9	2310	4887	1091	2683	7883
Furniture Stores	7	9580	9584	1768	7729	9495
Offices of Other Health Practitioners	11	13	8378	1144	1167	8502
Other Financial Investment Activities	276	276	5456	2331	2331	7527
Services to Buildings and Dwellings	3	734	1023	460	1399	2608
Employment Services	16	50	6112	1716	1953	7481
Offices of Real Estate Agents and Brokers	20	865	2126	786	1611	4452
Other Schools and Instruction	3	327	1982	468	1078	3904

Table 10. Change in effective labor market concentration due to franchise no-poach clauses, by occupation. This table reports three different concepts of labor market concentration by occupation in the matched dataset, both nationally (columns 1-3) and by commuting zone (columns 4-6). Columns 1 and 4 report concentration based on franchisee-level job ad shares, where each franchisee is an employer name-location combination. Columns 3 and 6 report chain-level (franchisor-based) concentration, thus identical to the right-most two columns of Table 5. Columns 2 and 5 report a combination of the two, in which franchisees linked to the chains that use no-poach clauses are combined for the purposes of computing market shares. For the chains that don't use no-poaches, market shares are computed at the franchisee level.

Occupation	HHI (national, franchisee-based)	HHI (national, franchisor-based if no-poach chain)	HHI (national, franchisor-based)	HHI (local, franchisee-based)	HHI (local, franchisor-based if no-poach chain)	HHI (local, franchisor-based)
Food Service Managers	0	670	746	136	920	1288
Food Prep/Serving Workers	0	466	576	124	753	1095
Food Prep/Serving Supervisors	0	298	460	172	680	1043
Driver/Sales Workers	1	2034	2035	361	2952	3231
Waiters/Waitresses	2	668	874	410	1540	2166
Customer Service Representatives	1	734	747	260	1339	1612
Retail Salespersons	1	875	1277	307	1250	2100
Supervisors of R/S Workers	1	773	956	296	1186	1759
Cooks, Restaurant	2	371	561	409	1127	1544
Hospitality desk clerks	2	102	808	443	639	1645
Personal Care Aides	2	2916	2984	542	3171	4496
Auto Technician/Mechanic	3	422	3447	761	1487	4780
Hairdressers/Hairstylists	6	199	6745	1009	1369	7193
Maids/Housekeepers	4	64	927	551	700	1841
Janitors/Cleaners	5	85	2617	640	883	3084
Maintenance/Repair Workers	1	1592	1772	412	1998	2788
Sales Representatives	5	450	765	646	1256	1964
Tax Preparers	2	7592	7592	1095	7780	7809
Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	2	739	858	525	1592	2049
Bakers	3	5285	5321	982	5165	5408

Figure 1. Total number of job ads in the matched dataset over time. The prevalence of online job ads as a recruitment mechanism generally increased from 2010 to 2022, particularly among low-wage industries. This plots the time series of the count of job ads in the matched dataset, at a monthly frequency.

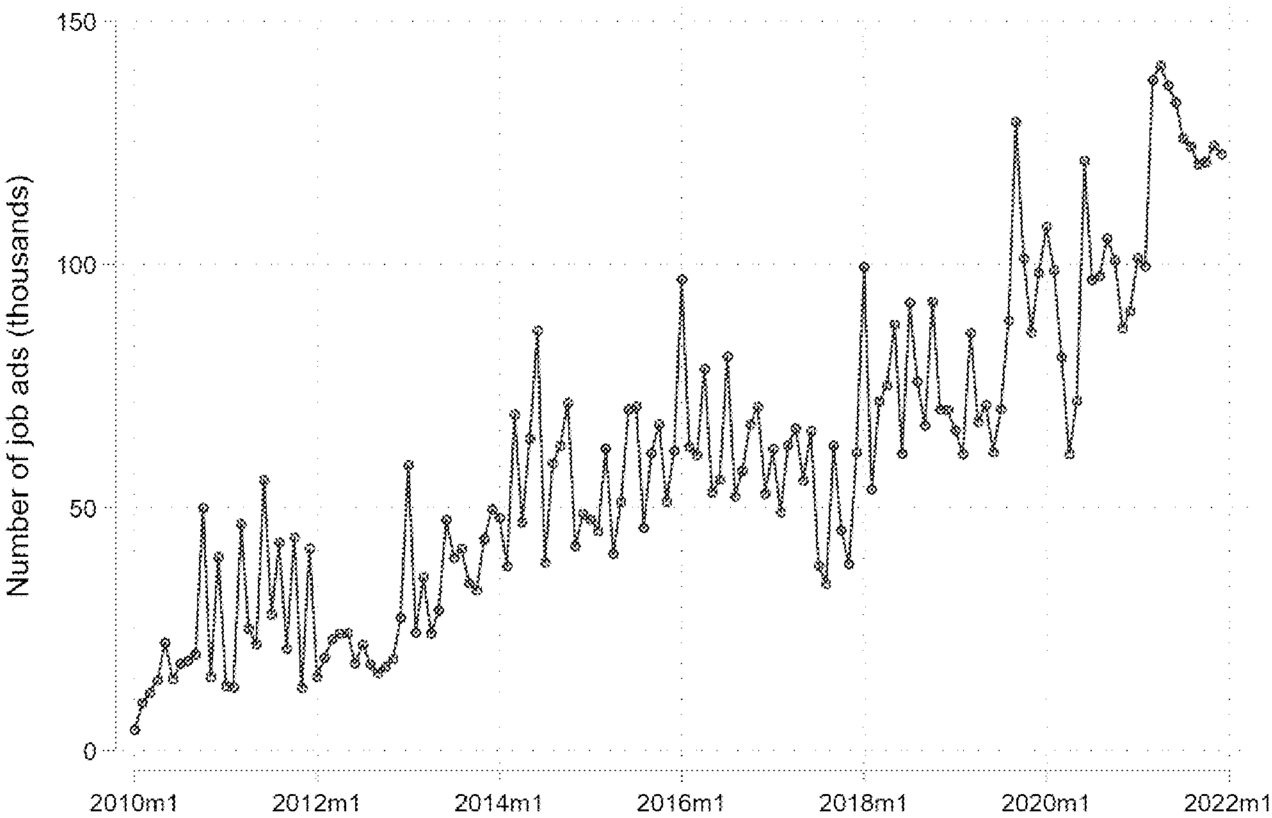


Figure 2. Share of job ads with salary information. The share of the posted job ads that contain salary information hovers just under 10% until 2018, when it increases to between 30-40%.

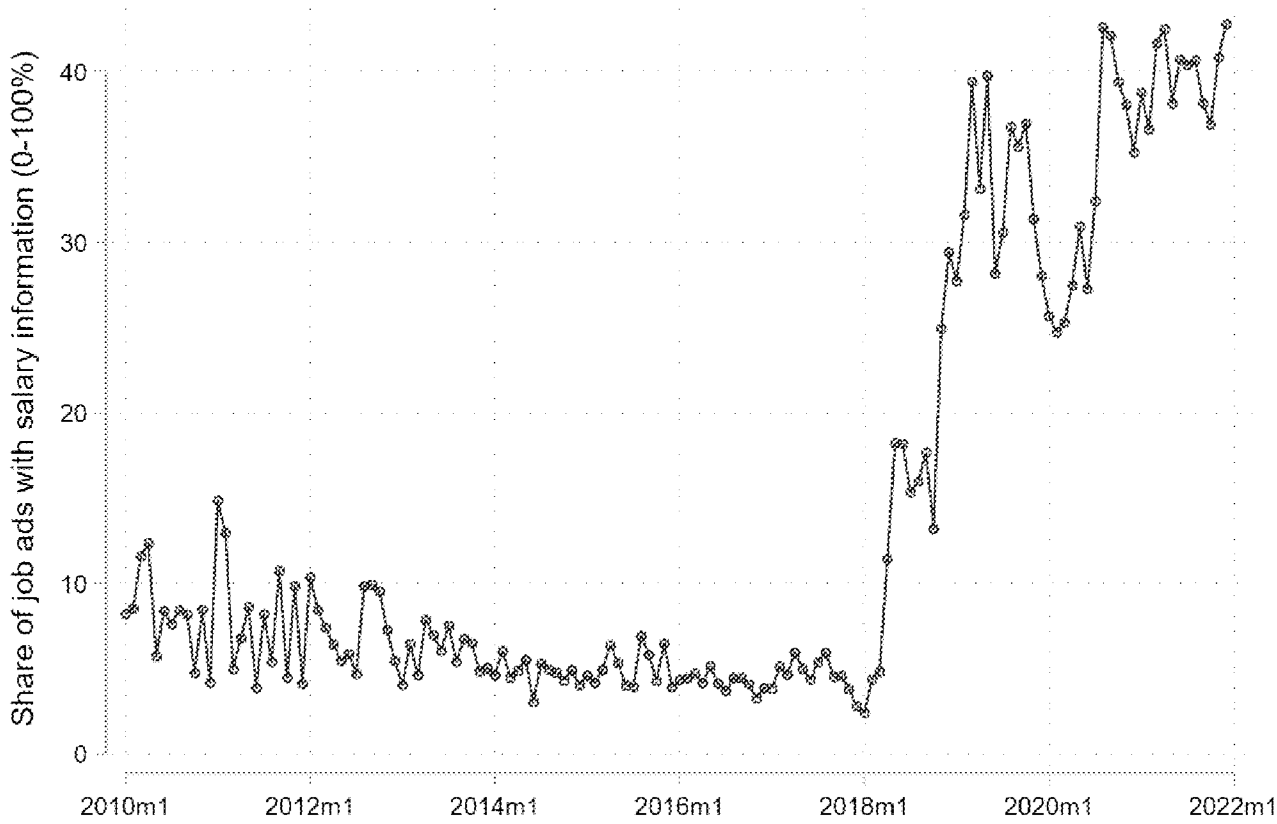


Figure 3. Wage-turnover scatterplot, pre-January 2018. These plot the chain-by-month residual variation in posted salaries against the residual variation in job turnover, as described in section 4. The first plot pools all chains, and the second breaks out the chains in the top three most frequently-appearing franchising industries.

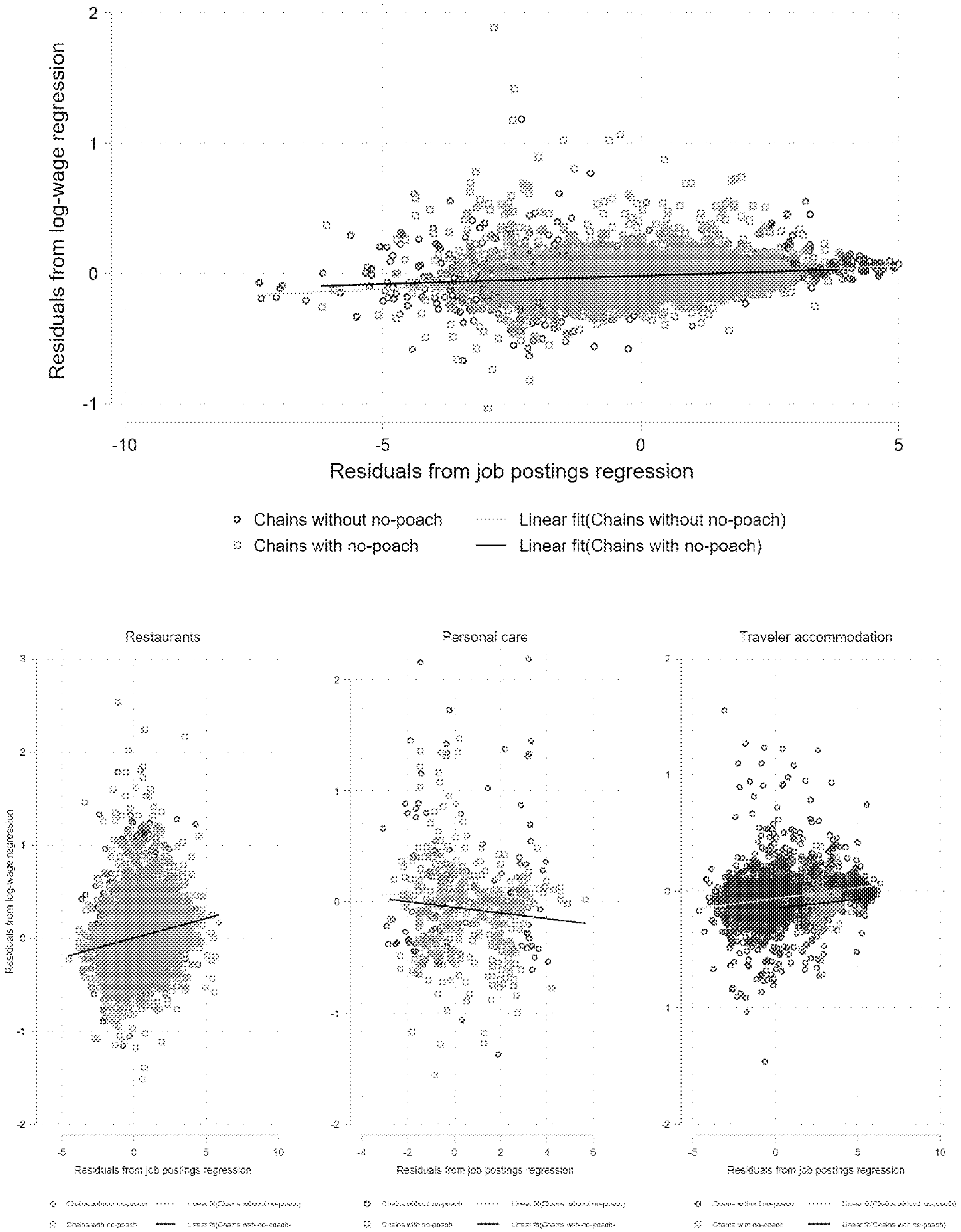


Figure 4. Wage-turnover scatterplot, post-June 2018. These plot the chain-by-month residual variation in posted salaries against the residual variation in job turnover, as described in section 4. The first plot pools all chains, and the second breaks out the chains in the top three most frequently-appearing franchising industries.

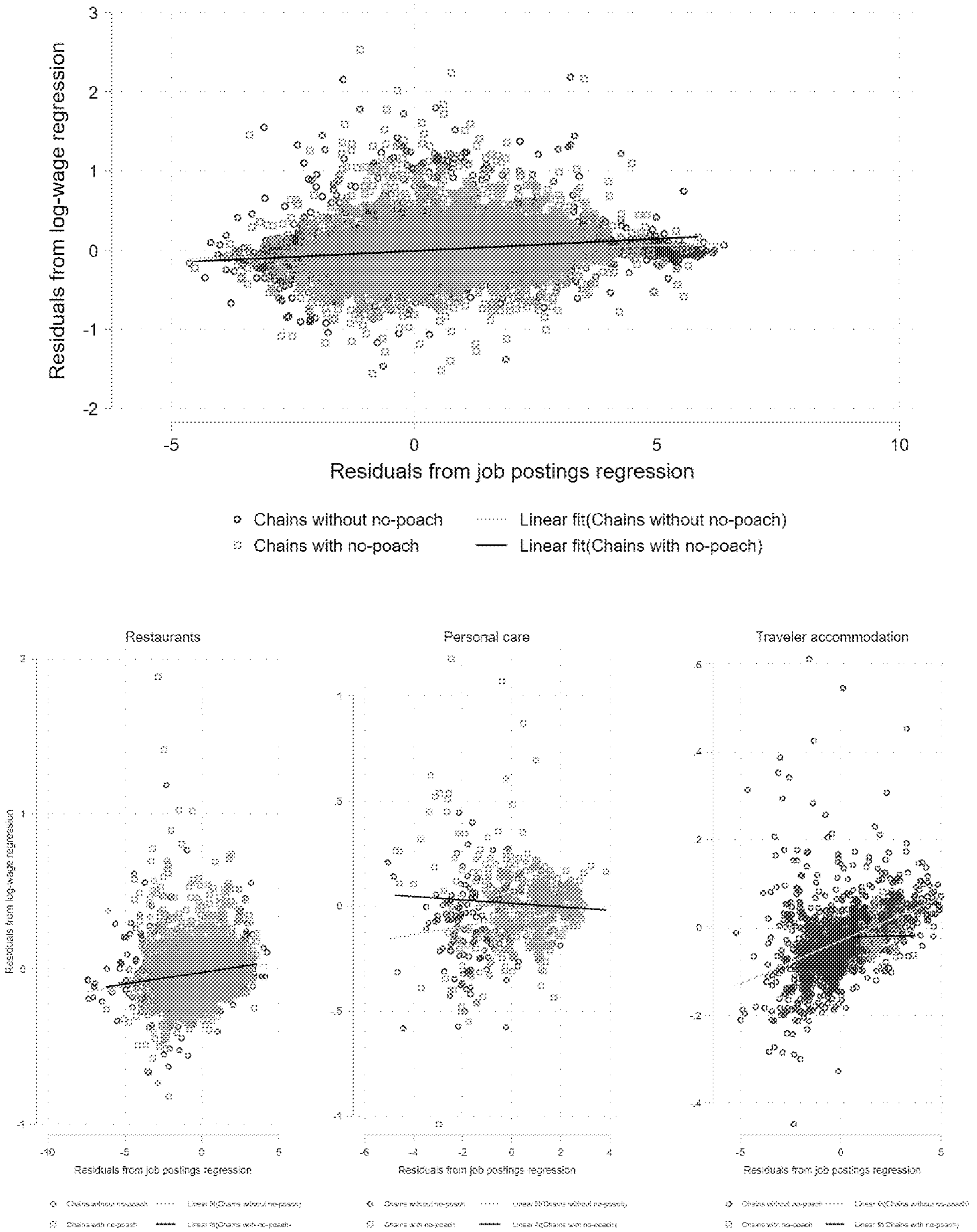
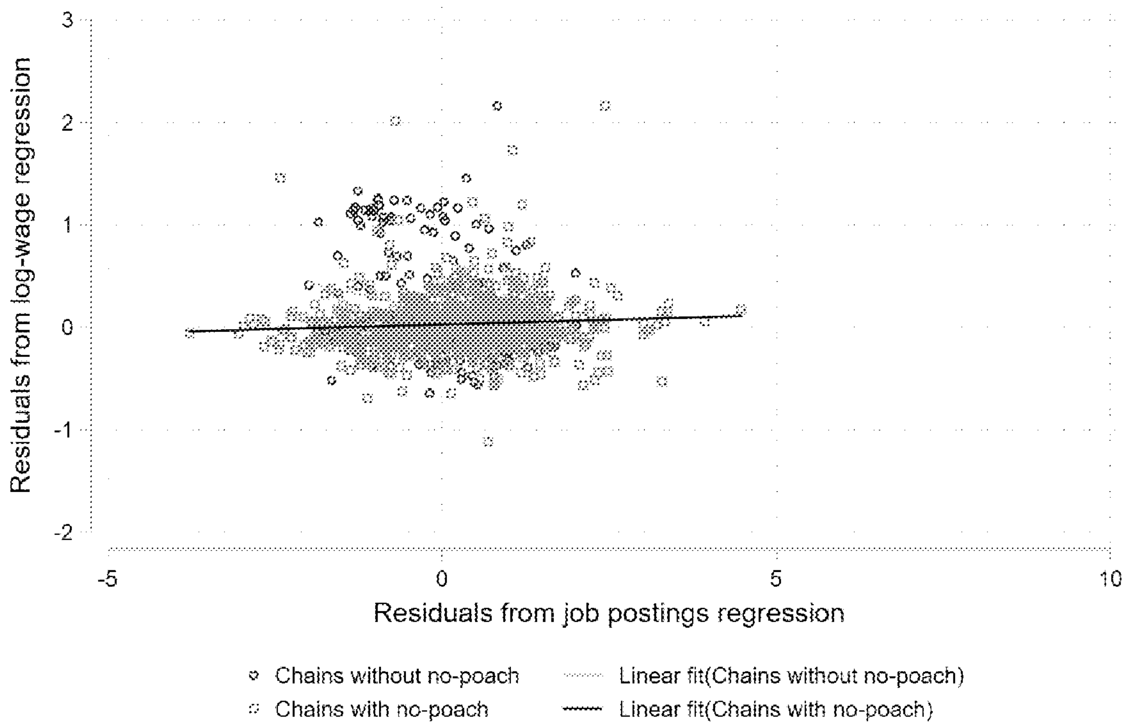


Figure 5. Wage-turnover scatterplots with time-varying chain revenue regressor, pre-January 2018 and post-June 2018. These plot the chain-by-month residual variation in posted salaries against the residual variation in job turnover, as described in section 4. The first plot pools all chains for the pre-January 2018 period, and the second pools all chains for the post-June 2018 period.



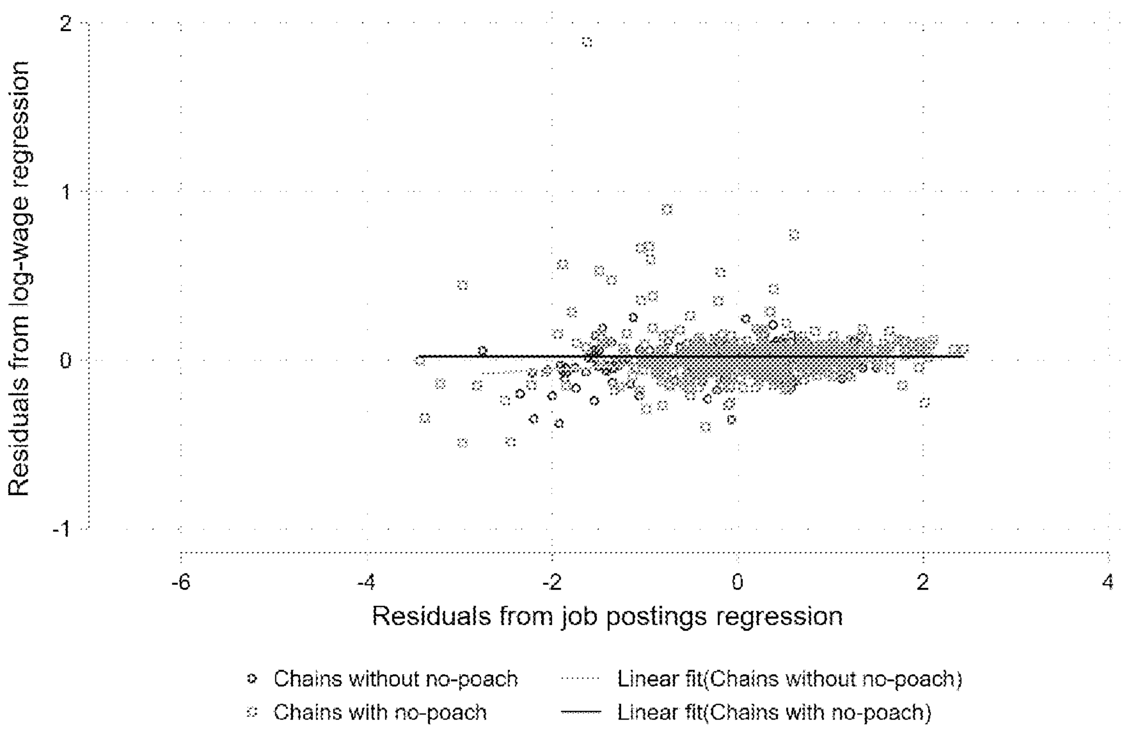


Figure 6. Summary of coefficient estimates on each restraint. This figure plots the coefficient estimates on each binary restraint listed in Table 6 in a regression where the outcome of interest is log annual earnings. Variation is within labor markets defined by commuting zone, SOC-6 occupation, and quarter, between chains.

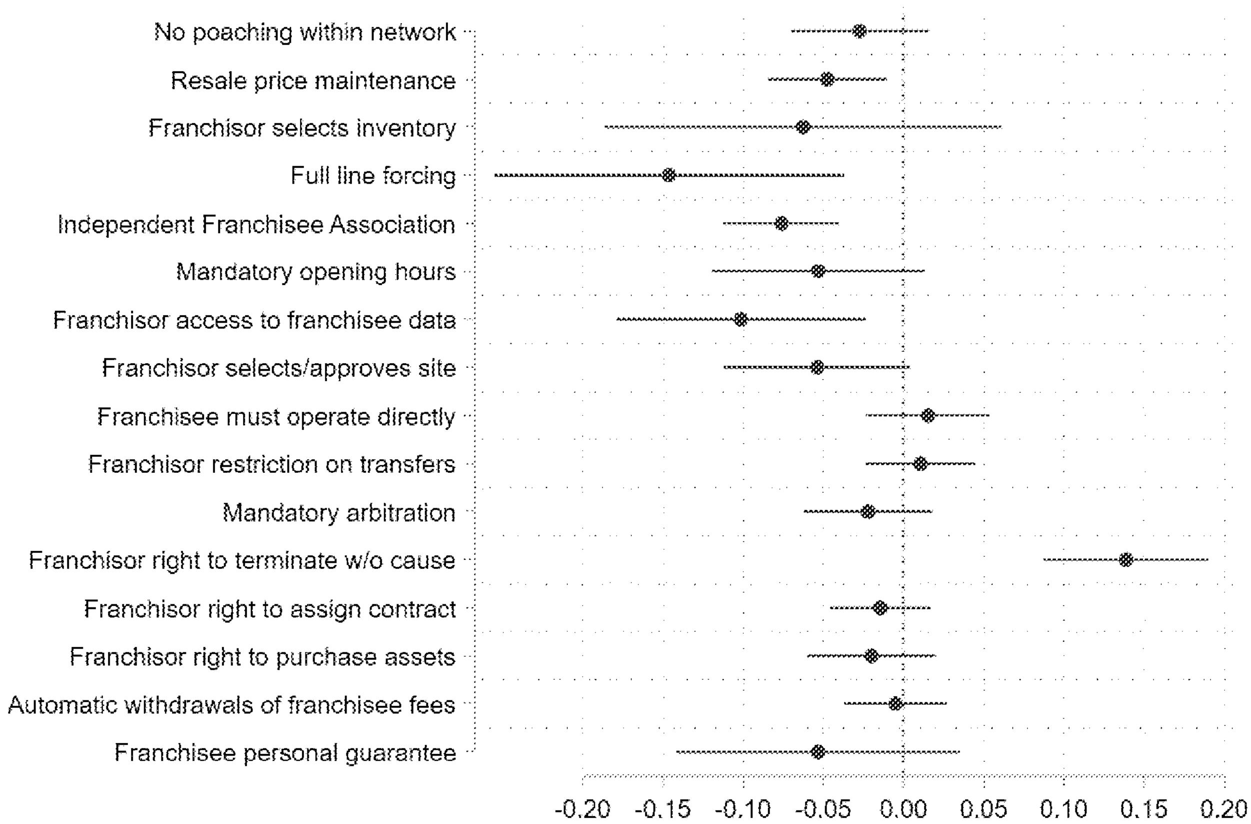
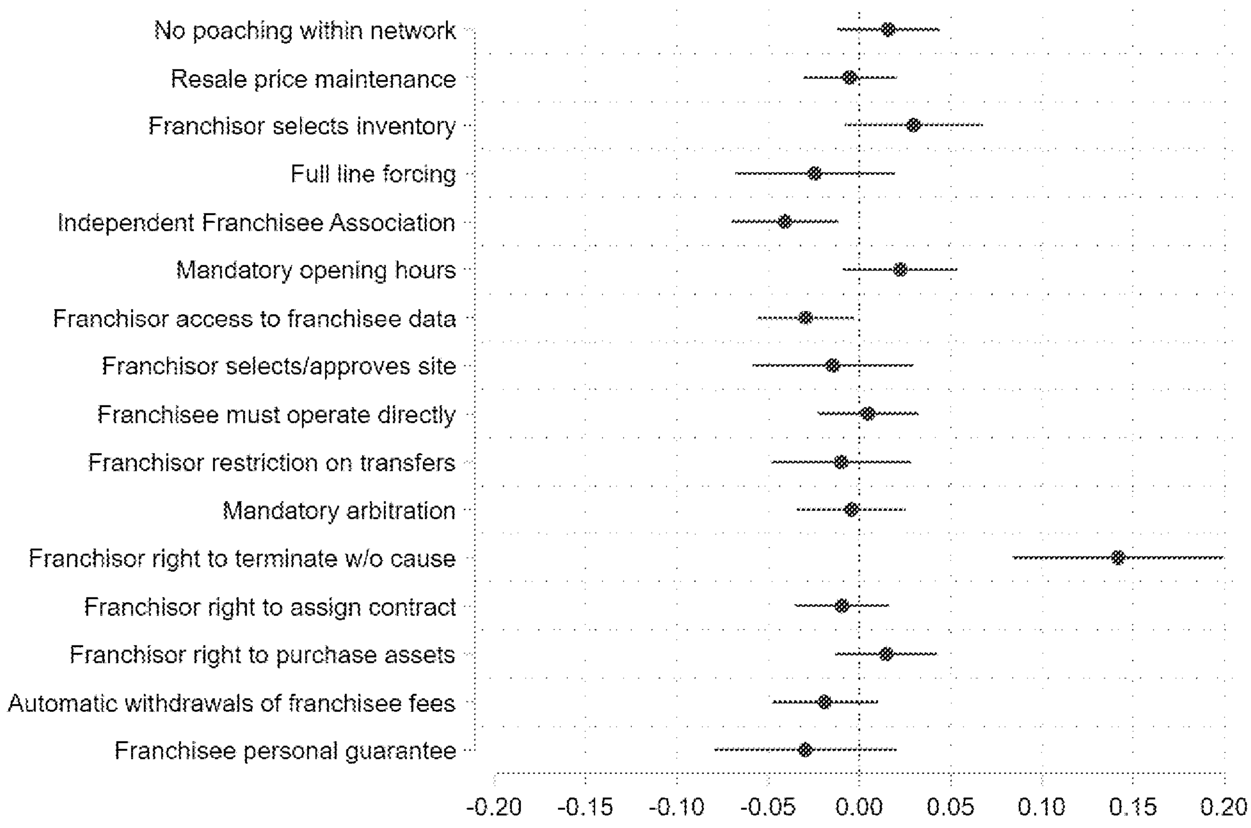


Figure 7. Summary of coefficient estimates on each restraint, with industry fixed effects. This figure plots the coefficient estimates on each binary restraint listed in Table 6 in a regression where the outcome of interest is log annual earnings. Variation is within labor markets defined by commuting zone, SOC-6 occupation, NAICS 4-digit industry, and quarter, between chains.



A Description of Franchise Disclosure Document Variables

Under the Federal Trade Commission's Franchise Rule, 16 CFR Parts 436 and 437, franchisors must provide prospective franchisees with a Franchise Disclosure Document (FDD) containing information about the offered franchise, its officers, and other franchisees. Certain mandatory disclosures are contained in a series of twenty-three "items." Item 22 contains a complete copy of the franchise contract. This Appendix describes our coding decisions for each FDD-derived variable in the data set.

A.1 Item 11: Franchisor's Assistance, Advertising, Computer Systems, and Training

Item 11 includes the disclosure on site selection. We code this variable a 1 if the franchisor must approve the site of the franchisee's business, 0 otherwise. We are interested in whether the franchisee must seek approval for the specific site of their establishment, so it is not sufficient for the franchisor to merely specify a geographic zip code or other more general territory.

As an example of contract language that we code a 0, see the Item 11 disclosure of Caring Transitions:

> Before you open your business, we will: Approve or disapprove the boundaries that you submit for your franchise territory. Your territory must be a single, undivided geographic area delineated by postal ZIP Code. If the U.S. Postal Service alters the boundary or number of the ZIP Code(s) assigned to you, we will re-define the boundaries of your territory to correspond as nearly as possible to your original territory. Our decision on this matter will be final.

Because the language specifies a zip code and not a specific site, we code this a 0.

As an exapmle of contract language that we code a 1, see the Item 11 disclosure of Aireserv:

You are responsible for finding and purchasing or leasing a site that meets our site selection guidelines and standards and is located in the Territory.

Because the franchisor specifies site guidelines in addition to a territory, and presumably checks to ensure the site meets those guidelines, we code this a 1.

A.2 Item 15: Obligation of the Franchisee to Participate in the Actual Operation of the Franchise Business

Item 15 contains the language we rely on to code our "Franchisee Must Operate Directly" variable. In Item 15, franchisors must disclose to franchisees whether franchisees are obligated to personally manage the establishment. Put another way, Item 15 tells franchisees whether they must supply labor in addition to investment capital to the franchisor.

We code this variable a 1 if the franchisee does have an obligation to participate directly in the operation of the establishment, 0 otherwise. In coding this variable, we set the following criteria:

- We code a 1 only if the franchisee has the obligation to personally operate the establishment throughout the contract term. We code a 0 if at any time in the franchise term the franchisee does not have the obligation to operate. For example, if the franchisor only requires the franchisee to personally operate the establishment for the first year of the contract term, we code a 0.
- We code a 1 if the franchisor retains the right to decide whether the franchisee can delegate to a non-owner. Since in such cases the ultimate discretion lies with the franchisor, the franchisor can impose the obligation to operate at any time.
- If there are differing criteria for single vs. multi-unit franchisees, we take the criteria for a single unit franchisee, since these are the bulk of the franchisees.

As an example of contract language where we code a 0, see Nhance Wood Restoriation's Item 15 disclosure:

> While you are not required to participate in the direct or daily operation of the business, at least one of the franchise owners must successfully complete NHI's training program.

As an example of contract language where we code a 1, see the Item 15 disclosure of AdvantaClean Systems:

> As an AdvantaClean franchise owner, you must personally participate in the direct operation of your AdvantaClean franchise. The agreement requires that you be directly involved in the day to day operations and work in your business for at least forty (40) hours per week during the first two years you are in business. In certain situations, we may permit you to employ a manager that has completed our Initial Training Program to operate the day to day operations of your Franchised Business (the "Designated Manager"). Your Designated Manager must be approved by us prior to commencing management duties of your Franchised Business and you must notify us within five business days if the Designated Manager leaves your employ. Any replacement Designated Manager you hire must also be approved by us prior to taking over the operations of your Franchised Business in any manner.

According to our criteria, because the decision to delegate to a manager must be approved by the franchisor, the franchisor retains the right to re-impose an obligation to operate at any time.

A.3 Item 16: Restrictions on Goods and Services Offered by the Franchisee

Item 16 contains information on vertical restraints pertaining to product offerings. We are concerned with two types of product restrictions. In the first, the franchisor *prohibits* the franchisee from offering any products the franchisor has *not* approved. In the second, the franchisor *requires* the franchisee to offer all the products (the "full line") that the franchisor *has* approved.

A.3.1 Franchisor Selects Inventory

We code this a 1 if the franchisor retains the right to prohibit the franchisee from offering products not specifically approved by the franchisor, 0 otherwise. For example, we code Floors to Go a 0:

> With regard to the FTG System, there are no restrictions on the goods and services which may be offered by you, including competing floor covering products, except that you may not participate in a competing marketing and merchandising system which offers products similar to those offered by the FTG System while a member of the FTG System.

Because the franchisee is permitted to offer products not specifically approved by the franchisor, we code a 0.

As an example of an instance where we code a 1, see Firehouse Subs: "You may not offer for sale any products or perform any services that we have not authorized." The majority of FDDs contain straightforward bans on non-approved products similar to this.

A.3.2 Full Line Forcing

In addition to disclosing whether the franchise contract bars the franchisee from offering any products the franchisor has not approved, it also discloses whether the franchisee must offer *all* the products and services that are part of the franchisor's system. This is sometimes known as "full line forcing." We code this a 1 if the franchisee is required to offer the franchisor's full line of products, 0 otherwise. Because a franchisor that has the right to change the list of required products retains the right to force the franchisee to carry the full line at any time, we code cases where a franchisor can alter the list of required products as a 1. Vision Trends provides an example of language that we code as a 0:

> We do not restrict the goods or services that you may offer. However, we require that you offer and sell only those goods and services that relate to the practice of

> optometry and eye care. You may not offer any products or services that have are deemed [sic] unacceptable or disapproved by any government or professional agency. The Company does not have the right to require you to dispense any particular brand of product in your store, and we cannot change the nature of your office in that your office will always carry eye care dispensary items and products.

Because the franchisor does not have the right to require the franchisee to sell specific brands of products, we do not consider this full-line forcing and code a 0.

Sbarro, meanwhile, provides an example of language that we code as a 1:

> A Franchisee must sell those items for which the franchise has been granted, and all other food, menu items and other products required by Sbarro. ... Franchisees must participate in Sbarro's promotional programs for all Restaurants operating under the System, as prescribed by Sbarro in the Manuals or otherwise in writing, including all limited time offerings and selling and offering for sale gift cards which may be used at any Sbarro Restaurant for menu items or products, and permitting customers who purchased gift cards from another Sbarro Restaurant or Sbarro to use their gift cards for menu items or products at your Restaurant. There is no limit in the Franchise Agreement on the number of programs in which you must participate or the costs that you must incur. Sbarro has the right (without limitation) to modify these requirements from time to time in its sole discretion.

In this case, the franchisor has the right to force the franchisee to sell any product or participate in any promotion the franchisor chooses. We code a 1.

A.4 Item 17: Renewal, Termination, Repurchase, Modification and/or Transfer of the Franchise Agreement, and Dispute Resolution

Item 17 of the FDD informs the franchisee of the conditions under which either party may terminate the contract, obligations on both parties after the contract is terminated or expires, and spells out the conditions under where either party can renew, sell, or assign the franchise to others. From Section 17, we code each contract for whether the franchisor can terminate the contract without cause, whether the franchisor has the right to purchase the franchisee's assets at expiration of the contract term, whether the franchisor has the right to assign the contract to a different franchisor, and whether the franchisor imposes a mandatory arbitration clause on the franchisee.

A.4.1 Franchisor Termination Without Cause

Item 17(e) contains the conditions under which the franchisor may terminate the relationship. We code this a 1 if the franchisor has the right to terminate without cause, 0 otherwise. For an example of where we code a 0, the Pure Barre franchise agreement contains the following language in Item 17(e): "We may not terminate without cause." The language is typically as straightforward as that.

For an example of a case where we code a 1, see the Medicap Pharmacy FDD:

> Subject to state law, we may terminate your franchise agreement, without cause, on 90 days notice to you.

Since the franchisor can terminate without cause, with only a notice requirement, we code a 1.

A.4.2 Franchisor restriction on transfers

Item 17(m), "conditions for franchisor's approval of transfer," details the conditions under which the franchisee may transfer the franchise to another franchisee. We code this a 1 if the franchisor's approval is required before the franchisee can transfer the franchise, 0 otherwise.

For an example of where we code a 0, see Newpoint Learning Centers:

> You must be in compliance with the agreement, pay the transfer fee and all amounts owed by you, and execute a general release of any claims against us. Any financing you offer the transferee shall be subordinate to any obligations of the transferee to

> us. The transferee must promptly provide all information we request and meet all of our qualifications. The transferee must agree to assume your liabilities, assume your Franchise Agreement (subject to our consent) or otherwise execute the current form of Franchise Agreement, complete our training program, pay the transfer fee and all other applicable fees.

Because these are all objective criteria, not contingent upon the franchisor's judgment, we code this a 0.

For an example of a case where we code a 1, see Pandora:

> New franchisee qualifies, you agree to comply with all post-term obligations, you are not in default under the Franchise Agreement, transfer fee paid, all amounts owed by you are paid, training completed, new franchise agreement signed, you and new franchisee supply information we request and you sign a general release (subject to state law).

Because "franchisee qualifies" is a subjective criterion, over which the franchisor has some discretion, we code this a 1.

A.4.3 Franchisor Right to Purchase Assets at Expiration

Item 17(O) contains information on whether the franchisor has the right to purchase the franchisee's business upon expiration of the contract. There is some variety among FDDs in what "franchisee's business" means. While it does not include goodwill (which always accrues to the franchisor), it may include the land, building, equipment, fixtures, inventory, or some combination of those. There is also variety in the valuation methods: liquidation value, book value, or fair market value. We code Item 17(O) a 1 for any instance where the franchisor has a right to acquire some or all of the franchisee's assets upon expiration of the agreement, 0 otherwise. Baskin Robbins is an example of Item 17(O) coded a 0:

> If your Franchise Agreement is terminated due to your default, you must sell to us (if we elect) any or all equipment, signs, trade fixtures, and furnishings used in the Restaurant, at the then- current fair market value less any indebtedness on the equipment, and indebtedness to us.

Because the right to purchase is only triggered in the event of a default, not contract expiration at the end of the term, we code this a zero.

An example of a contract that we code a 1, see Batteries Plus: "When the Franchise Agreement expires or terminates, we may purchase assets at book value."

A.4.4 Franchisor Right to Assign Contract to Different Franchisor

Item 17(J) contains information on the franchisor's right to assign the contract to another franchisor, as in the event of a merger or buyout of the franchisor by another firm. As some FDDs spell out the conditions under which the franchisor may assign the contract, we simplify matters by coding a 1 if and only if the franchisor's right to assign is absolute and unrestricted. If the FDD places any conditions on the franchisor's right to assign, we code it a 0. As an example of where we code a 0, see Hobby Town's FDD:

> The Company can assign and transfer the Franchise Agreement to a third party as long as third party assumes obligations.

As the right to assign requires the the third party assume obligations, and is therefore not absolute and unrestricted, we code a 0.

Mister Sparky is an example of a contract that we code a 1:

> We can sell, assign, transfer or otherwise dispose of the Franchise Agreement, or any or all of our rights and obligations under the Franchise Agreement, to any one in our sole discretion.

As this right to assign is absolute and unrestricted, we code a 1.

A.4.5 Mandatory Arbitration

Item 17(U) contains information on dispute resolution. There is some variation in which disputes must be arbitrated, so for simplicity we code a 1 if any type of dispute must be arbitrated, 0 otherwise.

An example of 17(U) coded a 0 is Maid Brigade, which simply states "No provision" in the required field. As an example of Item 17(U) coded a 1, see Acti-Kare:

> Except for certain claims, all disputes must be arbitrated at the office of the American Arbitration Association closest to our headquarters.

A.5 Item 20: Information About Franchise Outlets

Item 20 of the FDD includes a disclosure of whether an independent franchisee association (that is, an association not affiliated with or controlled by the franchisor) is present at the chain. For an example of where we code a 0, see Jet's Pizza: "To the best knowledge of Jet's, currently there is not a franchisee organization associated with the franchise system being offered." For an example of where we code a 1, see Church's Chicken:

> The following independent franchisee association has requested that we include their contact information in this Franchise Disclosure Document: Church's Independent Franchisee Association.

A.6 Contractual Provisions Not Disclosed in Franchise Disclosure Documents

Six further contract provisions: No Poaching of Employees within Franchising Network, Resale Price Maintenance, Mandatory Opening Hours, Franchisor Access to Franchisee Data, Automatic Withdrawal of Franchise Fees, and Franchisee Personal Guarantee are not among the mandatory disclosures included in the 23 Items of the franchise agreement. Fortunately, Item 22 of the franchise agreement requires that a copy of the full franchise contract be attached to the FDD. By searching the full text of the contract for key words and reading the surrounding prose in context, we can code for the presence or absence of these contract provisions.

A.6.1 No Poaching of Employees within Franchising Network

This is a contract provision wherein a franchisee pledges not to hire employees that are currently employed at another establishment of the same franchisor. Under no poaching agreements, the McDonalds on the east side of town promises it will not consider for employment workers who are employed by the McDonalds on the west side of town.

To code the presence or absence of this contract provision, we run a text search of each FDD, including the contract, for the word stem "employ" and synonym word stems "work," and "staff." We code each contract a 1 if there is language restricting the franchisee's ability to hire employees of other franchisees in the chain, and 0 if, after searching the entire document for the relevant word stems, we can find no such language. We code a 1 if hiring of employees from other franchisees is restricted in *any* way. That includes outright prohibition, or financial penalties for doing so. We also code a 1 if *any* class of employee is covered by a no-poaching agreement. We code a 0 if franchisees are enjoined from hiring workers employed by the franchisor, but not restricted from hiring workers employed by other franchisees.

Some examples of language of no-poaching agreements, all of which we code 1:

AlphaGraphics:

> You and we covenant and agree that, during the term of this Agreement, and for a period of two (2) years thereafter, you and your Owners will not, directly or indirectly: ... employ or seek to employ any person employed by you or us, or any other person who is at that time operating or employed by or at any other ALPHAGRAPHICS Business Center, or otherwise directly or indirectly induce such persons to leave their employment.

Five Guys:

> If you employ any individual as general manager or in a managerial position who is at the time employed in a managerial position by us or by another of our franchisees, you must pay the former employer for the reasonable costs and expenses the employer incurred for the training of the employee.

Mosquito Squad:

> During the Initial Term (including any Interim Period) of this Agreement and for a period of 2 years thereafter, Franchisee, Franchisee owners, and the Designated Business Manager shall not attempt to attain an unfair advantage over other franchisees or Franchisor or any Affiliates thereof by soliciting for employment any person who is, at the time of such solicitation, employed by Franchisor, other franchisees or any Affiliates, nor shall Franchisee directly or indirectly induce or attempt to induce any such person to leave his or her employment as aforesaid.

World Gym:

> During the term of this Agreement and for one year after its Termination, you may not disrupt, damage, impair or interfere with our business or that of any member of the Franchise Network by directly or indirectly soliciting their employees to work for you or their members to join your Facility or any individual or company then in competition with the Franchise Network.

A.6.2 Resale Price Maintenance

Resale price maintenance is a practice in which a franchisor reserves the right to set maximum or minimum prices for the franchisee's products and services. To code the presence or absence of this contract term, we run a text search of each FDD, including the contract, for the terms or word stems "pric," "rate," "charg," and "fare." We code the contract a 1 if the franchisor retains the right to set maximum or minimum prices across all customers, 0 otherwise.

We code a 0 if the franchisor only has the right to set maximum or minimum prices for a subset of customers, such as corporate clients of the chain. We code a 1 if the franchisor has the right to compel the franchisee to participate in pricing promotions and discounts, such as a "dollar menu."

Some examples of language imposing resale price maintenance:

Ascend Hotels:

> [Franchisee must] Participate in and honor the terms of any loyalty, discount or promotional program ... that we offer to the public on your behalf and any room rate quoted to any guest at the time the guest makes an advance reservation.

Jamba Juice

> Company reserves the right, to the fullest extent allowed by applicable law, to establish maximum, minimum or other pricing requirements with respect to the prices Franchisee may charge for products or services.

Screen Mobile:

> We may, from time to time, make suggestions to you regarding your pricing policies in compliance with applicable laws. We retain the right to establish minimum and maximum prices to be charged by you, subject to applicable laws, but any exercise of that right will be specifically set forth in writing. It is furthermore understood and agreed that any list or schedule of prices furnished to you by us may, unless otherwise specifically stated as to the minimum or maximum price, be treated as a recommendation only, and failure to accept or implement any such suggestion may not in any way affect the relationship between you and us.

Tutor Doctor:

> We may periodically suggest prices to be charged by you that, in our judgment, would constitute good business practice. You do not need to accept this advice or guidance and you have the sole right to determine the prices to be charged. The integrity and goodwill developed in your business and the System may depend upon the sale of Products and Services at competitive prices and that, therefore, we may specify maximum or minimum prices for your Products and Services and you must comply with these directions from us concerning maximum and minimum prices. If we set a maximum price on a particular Product or Service, then (subject to applicable law) you may charge any price for that Product or Service, up to and including the maximum price we have set. If we impose a minimum price on a particular Product or Service, then (subject to applicable law) you may charge any price for that Product or Service, down to and including the minimum price we have set. The suggested retail price for Products and Services may vary from region to region if necessary to reflect differences in costs and other factors applicable to these regions.

A.6.3 Mandatory Opening Hours

A mandatory opening hours restriction exists when the franchisor retains the right to specify specific hours of operation that the franchisee must be open. To code the presence or absence of this contract term, we run a text search of each FDD, including the contract, for the terms "hour," "tim," "open." We code the contract a 1 if the franchisor retains the right to require specific opening hours, 0 otherwise. Some examples of language imposing a mandatory opening hours restriction:

Charles Schwab:

> In operating the Independent Branch, you must adhere to the comprehensive standards and specifications comprising the Schwab System, including: (i) client service standards; (ii) privacy policies; (iii) appearance, design and trade dress standards

for the Independent Branch; (iv) use of the Schwab Marks; and (v) minimum operating hours. By setting minimum service requirements and uniform standards, we strengthen customer confidence in the Charles Schwab® brand. We explain these specifications in the Confidential Manuals. We may revise our specifications in our discretion as frequently as we believe is necessary through written or electronic bulletins or supplements to the Confidential Manual or through communications sent or available to you on our Intranet. You must conform to all changes in our specifications at your cost within the time we allow.

Krispy Kreme:

> Franchisee agrees that the STORE will not be closed for five (5) or more consecutive days without Franchisor's prior written consent and that the STORE will be open and in operation during such hours and such days as Franchisor may specify from time to time in writing.

Planet Fitness:

> A PLANET FITNESS franchise offers fitness training facilities, including exercise machines and free weights, fitness training services, tanning services, related services and ancillary related merchandise as we may authorize periodically. The PLANET FITNESS franchisee must provide these services on a 24 hour per day 7 day per week basis unless prohibited by law or authorized by us in writing.

Thrifty Car Rental:

> You shall keep each Location open the hours and days specified in the Operations Guide.

A.6.4 Franchisor Access to Franchisee Data

Some franchise contracts give franchisors independent, remote access to data stored on franchise computer systems, such as through the "point-of-sale" system employees use to process customer orders. To code the presence or absence of this contract term, we run a text search of each FDD, including the contract, for the terms and stems "data," "computer," "access," "point of," "point-of." We code the contract a 1 if the franchisor has automatic access to franchisee data, 0 otherwise. Some examples of language that we code a "1":

Applebee's:

> All Applebee's Restaurants must have a POS [Point of Sale] computer system that meets Applebee's specifications. The POS systems approved by Applebee's are specifically designed for tracking information relevant to the Restaurant's business. The POS systems are integrated with support and reporting tools that enable us to have independent immediate access to the information monitored and stored by the POS system, and there is no contractual limitation on our use of the information we obtain.

Mister Sparky:

> We will use the SuccessWare21 (ASP Option) software program or other software package we specify to gather information on the entire franchise system. We may use this information to monitor your compliance with Minimum Sales Performance Standards (as defined below) and may use it to develop a financial performance representation for our Disclosure Document. We have independent access to the information and data. By signing the Franchise Agreement, you grant us the right to access that data. We reserve the right to independently access, gather, use, and share customer data maintained in the SuccessWare21 (ASP Option) software program (or other software program specified by us and which may be modified, updated, or replaced from time to time) for any legitimate business purposes, including, but not limited to, cross-selling One Hour and Ben Franklin products and services. You will be required to take all action necessary to allow us to access, gather, use, and share such information as we may specify in the Operations Manual. (Franchise

Agreement, Section 9.2.) There are no contractual limits on our independent access to the information and data stored on your computer.

College Nannies:

The computer system will be used in the day-to-day operation of the business primarily to access our proprietary internet based database system named CNeT and must utilize the supported browser of our discretion. The system will also be used to report and communicate with us for your accounting and record keeping and for other uses as we designate. You must maintain your systems network and you must promptly update and otherwise change your computer hardware and software systems as we require, at your expense. You must pay all amounts charged by any supplier or licensor of the systems and programs used by you, including charges for use, maintenance, support and/or update of these systems or programs. We will have direct access to the data regarding the Franchised Business.

CRDN:

You must purchase a "Point of Sale Software System" or "POS" that we approve and that meets our requirements, as may be modified from time to time in the Operations Manual, from such vendor as we require. You will also need to purchase certain other software and hardware in connection with this interface, as we require from time to time. You may also need to pay to install the POS and related software and hardware. Your POS must interface with our current proprietary software system and you may need to purchase certain other software or hardware in connection with such interface, as we require from time to time. We will have independent access to all data recorded or stored in your POS.

A.6.5 Automatic Withdrawal of Franchise Fees

Some franchise contracts require franchisees to give franchisors the right to withdraw money directly and automatically from franchisee bank accounts. To code the presence or absence of this contract term, we run a text search of each FDD, including the contract, for the terms "account," "debit," "automatic clearing," "electronic funds," and "withdraw." We code the contract a 1 if the franchisor has the right to automatically withdraw money from franchisee bank accounts, 0 otherwise. Some examples of language that we code a "1":

Minuteman Press:

> Upon execution of this Agreement and/or at any other time thereafter at Minuteman's request, Franchisee shall sign an authorization substantially in the form attached to this Agreement as Schedule B and all other documents necessary to permit Minuteman to withdraw funds from your designated bank account by electronic funds transfer in the amount of the Royalty Fee and all other fees and amounts described in this Agreement.

Transworld Business Advisors:

> Upon execution of this Agreement and/or at any other time thereafter at Franchisor's request, You shall sign an authorization substantially in the form attached to this Agreement as Schedule C and all other documents necessary to permit Franchisor to withdraw funds from Your designated bank account by electronic funds transfer in the amount of the Royalty Fee, the Marketing Fee and all other fees and amounts described in this Agreement.

Worldwide Express:

> WWE may require Franchisee to execute an Authorization Agreement for Direct Deposits (Attachment 6 or any comparable document) to allow WWE to effect an automatic bank draft or electronic funds transfer on all future freight obligations. If

> the designated due date is not a business day, WWE will draft Franchisee's account on the next business day. If Franchisee's account does not have sufficient funds to pay the draft on the designated date, Franchisee's failure to pay is an event of default that will result in immediate suspension of access to the freight program technology and will result in a notice of default under Section 26.3(a) and/or (d) of the Agreement.

IHop:

> Upon request of Franchisor, Franchisee must participate in Franchisor's then-current electronic funds transfer program authorizing Franchisor to receive payments from Franchisee by pre-authorized bank draft, wire transfer, automated clearinghouse (ACH) transfer, or otherwise, as Franchisor specifies from time-to-time in Franchisor's sole and absolute discretion, in accordance with procedures that may be set forth in the Operations Bulletins.

A.6.6 Personal Guarantee

Some franchise contracts require franchisees to sign a personal guarantee, meaning that even if the franchisee incorporates, they still grant the franchisor recourse to their personal assets for all obligations under the franchise agreement. Some chains also require the franchisee's spouse to sign a personal guarantee as well. To code the presence or absence of this contract term, we run a text search of each FDD, including the contract, for the stem "guarant." If the franchise agreement states that the franchisor refuses to accept incorporated entities as franchisees and only franchises to natural persons, we code that as a 1. Some examples of language that we code a 1:

Little Caesar's (personal and spousal guarantee):

> Any individual or entity that owns any direct or indirect interest in your entity must sign the Guarantee included as Exhibit A to the Franchise Agreement. In addi-

tion, we require any individual who is or becomes the spouse of any natural person who signs the Guarantee to also sign the Guarantee, jointly and severally with the spouse. If you or any owner holds or later acquires any interest in any other Little Caesars® restaurant, you and your owners must also unconditionally guarantee full performance and discharge of all of the franchisee's obligations under the franchise agreement for the other Little Caesars® restaurant, including the payment of all royalty fees, advertising fees, and other obligations.

Culver's (personal and spousal guarantee):

If you are a corporation, partnership, or limited liability company, each shareholder, partner or member owning a 10% or greater interest in the franchisee entity, along with his or her spouse, must personally guarantee your obligations under the Franchise Agreement (or, if applicable, the Development Agreement) and also agree to be personally bound by, and personally liable for the breach of, every provision of the Franchise Agreement (or, if applicable, the Development Agreement). A copy of this "Guaranty" is included as an exhibit to the Franchise Agreement attached to this disclosure document.

Fresh Healthy Vending (personal guarantee only):

If you are a corporation, partnership, limited liability company or other entity, we will require all of your owners to sign a guaranty of your obligations under your Franchise Agreement and your owners' spouses may be required to consent to the guaranty.

Jimmy John's (personal guarantee only):

If you are a corporation, limited liability company, or partnership, your owners must personally guarantee your obligations under the Franchise Agreement and agree to be bound personally by every contractual provision, whether containing monetary or non-monetary obligations, including the covenant not to compete. This "Guaranty and Assumption of Obligations" is the last 2 pages of the Franchise Agreement.

STOCKS AAPL +0.29%

StockMarket.com

What Is Market Cap In Stocks?

August 12, 2022 — 04:02 pm EDT

Written by **Josh Dylan** for **StockMarket.com →**

Market Capitalization (Cap) D

If you're new to the stock market, you've likely been c
terms that investors use. In this article, we're going tc

market. Simply put, Market cap, or market capitalization, is a measure of the value of a

How To Understand Market Capitalization (Cap)

In order to understand market cap, it is important to first understand what the stock market is. The stock market is a collection of all the stocks that are being traded on the stock exchange. The stock exchange is where companies list their stocks and investors can buy and sell them.

Understanding market cap is important for understanding the overall value of a company. It also helps us compare companies within the same industry. It can also be useful for understanding the risk involved in investing in a particular company. A high market cap indicates that a company is large and stable. On the other side, a low market cap indicates that a company is small and riskier. Knowing the market cap can help you make informed investment decisions.

[Read More] The Most Frequently Asked Questions About The Stock Market In 2022

How To Calculate Market Capitalization (Cap)

×

Now we know now that the market cap is a measure (
ompany's shares. Market cap is calculated by multip
y the current market price per share. For example, if
utstanding with a share price of $20, the market cap

Additionally, the market cap is often used to categori:
large-cap companies have a market cap of $10 billion
have a market cap of less than $2 billion.

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Bottom Line

Though market cap is a useful metric, it should not be the only factor to consider when making investment decisions. A company with a large market cap may be overvalued by the market, while a small-cap company may be undervalued.

In addition, the market cap does not take into account other important factors. This includes the company's financial health, competitive advantage, and growth potential to name a few. As such, it is important to consider all available information when making investment decisions.

Below you will find a list of the 10 largest publicly traded companies in order by market cap. The current share price is as of Friday, August 12, 2022 afternoon.

1. **Apple, Inc.** (NASDAQ: AAPL)
   - **Market Cap:** $2.762 Trillion
   - **Current Share Price:** $171.90

- **Current Share Price**: $290.95

3. **Alphabet** (NASDAQ: GOOG)
    - **Market Cap**: $1.591 Trillion
    - **Current Share Price**: $122.48
4. **Amazon.com, Inc.** (NASDAQ: AMZN)
    - **Market Cap**: $1.455 Trillion
    - **Current Share Price**: $142.84
5. **Tesla, Inc.** (NASDAQ: TSLA)
    - **Market Cap**: $938.51 Billion
    - **Current Share Price**: $898.54
6. **Berkshire Hathaway** (NYSE: BRK.B)
    - **Market Cap**: $661.45 Billion
    - **Current Share Price**: $300.34
7. **UnitedHealth Group, Inc.** (NYSE: UNH)
    - **Market Cap**: $506.05 Billion
    - **Current Share Price**: $541.01
8. **Meta Platforms Inc.** (NASDAQ: META)
    - **Market Cap**: $484.45 Billion
    - **Current Share Price**: $180.26
9. **Taiwan Semiconductor Manufacturing Co. Ltd** (NYSE: TSM)
    - **Market Cap**: $472.06 Billion
    - **Current Share Price**: $91.03
10. **NVIDIA Corporation** (NASDAQ: NVDA)
    - **Market Cap**: $464.23 Billion
    - **Current Share Price**: $186.29

Subjective Beliefs about Contract Enforceability

J.J. Prescott
Univ. of Michigan
jprescott@umich.edu

Evan Starr[†]
Univ. of Maryland
estarr@umd.edu

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Abstract

This article assesses the content, role, and adaptability of subjective beliefs about contract enforceability in the context of postemployment covenants not to compete ("noncompetes"). We show that employees tend to believe that their noncompetes are enforceable, even when they are not. We provide evidence for both supply- and demand-side stories that explain employees' persistently inaccurate beliefs. Moreover, we show that believing that unenforceable noncompetes are enforceable likely causes employees to forgo better job options and to perceive that their employer is more likely to take legal action against them if they choose to compete. Finally, we use an information experiment to inform employees about the enforceability of their noncompete. While this information matters for employee beliefs and prospective behavior, it does not appear to eliminate an unenforceable noncompete as a factor in the decision to take a new job. We discuss the implications of our results for the policy debate regarding the enforceability of noncompetes.

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1. INTRODUCTION

How individuals behave in response to law depends on their particular and sometimes mistaken beliefs about the law's content, including the probability of enforcement. Under many circumstances, individuals are likely to have accurate beliefs about the law, such as in economic settings where the stakes are high and information is easy to access. Contracting may be one such setting. In other environments, however, baseline access to facts can be limited, and information gathering can be costly. Moreover, we know that a counterparty can sometimes benefit by investing in maintaining an individual's specific mistaken beliefs (Gabaix and Laibson 2006). For this reason, the extent to which individual beliefs are inaccurate, the reasons they are inaccurate, and the implications of these inaccuracies, especially when they are systematic, remains an important area of research (Salop and Stiglitz 1977, Kim 1997, Wilkinson-Ryan 2017, Stantcheva 2020, Jäger et al. 2022). When persistently mistaken beliefs relate to the content of policies or law and are socially costly, interventions designed to disrupt such an equilibrium may be able to change behavior and improve welfare (Chetty 2015).

In this article, we consider beliefs regarding the legal enforceability of covenants not to compete ("noncompetes") and the role such beliefs may play in explaining employee behavior. Noncompetes are employment provisions that prohibit departing employees from joining or starting a competitor under certain conditions. Our work is motivated by two recent findings that point to the possible influence of mistaken beliefs in this domain. First, employers use noncompetes heavily in states that explicitly refuse to enforce them (Starr et al. 2021, Colvin and Shierholz 2019). Second, noncompetes appear to influence employee mobility even in states where such provisions are unenforceable (Starr et al. 2020). While there are several reasons why employers might use and employees might comply with noncompetes even when employees *know* that a court will not enforce them (e.g., reputational harm or disutility from breaking a "promise"), one explanation for these results is that employees have mistaken beliefs about noncompete policies and that these beliefs matter to their choices.[1]

The possibility that employees are systematically uninformed or perversely misinformed about the law has important implications for the interpretation of existing noncompete research. Nearly all studies of the consequences of noncompetes leverage state-level policy changes to identify the effects of these provisions, essentially assuming that employees and employers are aware of, understand, and react to such policy changes.[2] Policy advocates also almost invariably (if implicitly) assume that em-

[1] Catherine Fisk (2002) highlights this possibility when she writes: "In California, covenants not to compete have been unenforceable against employees since 1872. Employers have nevertheless sought to restrict their employees from working for competitors … presumably counting on the *in terrorem* value of the contract when the employee does not know that the contract is unenforceable." Another possibility is that employees are well informed about the law but other terms in their contract make any noncompete de facto enforceable (Sanga 2018).

[2] Bishara and Starr (2016) review this literature on "enforceability." See, e.g., Garmaise (2009), Marx et al. (2009), Samila and Sorenson (2011), Marx et al. (2015), Starr (2019), Kang and Fleming (2020), Balasubramanian et al. (2022),

ployees respond rationally to—or at least with awareness of—existing law when navigating noncompete-related choices. In fact, one common starting point has been the view that enforceable noncompetes must be beneficial to both employees and employers (Rubin and Shedd 1981, Posner et al. 2004) because otherwise they would not agree to such provisions. And yet the potential consequences of assuming that employees understand the legal ramifications of their noncompetes are significant. For example, mistaken beliefs about unenforceable noncompetes can be welfare reducing when they inhibit employees from moving to jobs in which they would be more productive.[3] Also, from a policy perspective, simply prohibiting court enforcement of such clauses—the traditional reform proposal—is unlikely to be effective if the *in terrorem* power of noncompetes remains available to employers notwithstanding any such enforcement "ban" (Starr et al. 2020).[4]

Our study uses detailed, nationally representative survey data and an information experiment involving 11,505 labor force participants to examine what employees believe about the enforceability of noncompetes and to identify the causal effects of such beliefs on prospective decisions.[5] We document that employees tend to believe their noncompetes are enforceable regardless of actual noncompete enforceability. Specifically, 70% of employees with unenforceable noncompetes mistakenly believe their noncompetes are enforceable. Moreover, we find that subjective beliefs about the probability that a court will enforce a noncompete, conditional on an employer bringing a lawsuit, are not even positively correlated with actual enforceability. Surprisingly, and in contrast to the prevailing assumption, better-educated employees also appear largely misinformed about enforceability (Friedman 1991, Callahan 1985). Our data offer support for both supply- and demand-side hypotheses that might explain these persistently mistaken beliefs. First, individuals who mistakenly believe their noncompete to be enforceable are less likely to search for employment with a competitor, reducing their

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Lipsitz and Starr (2022), and Young (2020). It is also likely that prior research pays scant attention to beliefs about noncompete enforceability because data on employee beliefs are difficult to obtain.

[3] While it is beyond the scope of this paper to assess the welfare consequences of noncompetes and noncompete enforceability generally, it is worth noting that, to the extent noncompete efficiency benefits—including greater investment in or the development of valuable information—*depend* on a court enforcing such agreements (Rubin and Shedd 1981), unenforceable noncompetes are unlikely to lead to such investments in the first place. This concern dovetails with research that finds that noncompete *enforceability* generates training and investment benefits (Starr 2019, Starr et al. 2021, Jeffers 2019). More broadly, recent empirical work has identified significant negative externalities associated with noncompetes (Starr, Frake, and Agarwal 2019, Johnson, Lavetti, and Lipsitz 2020), implying that the use and enforcement of noncompetes is not merely a transfer of rights that affects only the contracting parties.

[4] Somewhat ironically, proponents of banning noncompete *enforcement* often make their case by alluding to the lack of sophistication or bargaining power on the part of employees subject to such provisions. At least with respect to uninformed applicants and employees, it seems optimistic to believe that these individuals will become aware of and be able to take advantage of subtle changes in state law when they are uninformed about the content or implications of the noncompete clause contained in their employment contract.

[5] We use data from the 2014 Noncompete Survey Project, the first nationally representative survey of noncompetes (Prescott et al. 2016). In previous work using these data, we describe the incidence of noncompetes across the U.S. labor force (Starr et al. 2021), how noncompetes relate to mobility (Starr et al. 2020), and how noncompetes create externalities even among those not bound by such agreements (Starr, Frake, and Agarwal 2018).

access to potentially correcting information. Second, we find that employees who do interact with competitors are actually *more* likely to believe their noncompete is enforceable, in part because individuals in states that do not enforce noncompetes are more likely to receive "reminders" of their supposed noncompete obligations from their current employer.

We next establish that mistaken beliefs can be countered by providing employees with accurate information about the law and, further, that such information causes employees to change their prospective employment mobility decisions. We find that employees with a noncompete update their beliefs markedly to more closely align with the information they receive—especially employees in states that do not enforce noncompetes. In this same vein, employees with unenforceable noncompetes report feeling much less constrained by their noncompete after receiving accurate information about noncompete enforceability in their state.[6] Using our information experiment as an instrument for an individual's beliefs about noncompete enforceability, we estimate that believing noncompetes are enforceable increases the likelihood that an employee anticipates their noncompete would be a factor in choosing to start or join a competitor by approximately 60 percentage points relative to an employee who believes noncompetes are unenforceable.

To build on our evidence that an employee's beliefs about noncompete enforceability influence whether the employee is willing to pursue or consider a job with their employer's competitors, we also assess whether these beliefs might affect (prospective) negotiation over a noncompete provision during contracting as well as the extent to which our results are driven by changes in the perceived likelihood of being sued for violating a noncompete. Among those presently bound by noncompetes, we find no evidence that believing that a noncompete is enforceable causes employees to be more likely to negotiate over these provisions. We also estimate that 20–30% of the effect that enforceability beliefs have on whether a noncompete matters for accepting a new employment offer is attributable to changes in whether the employee anticipates a subsequent enforcement lawsuit. Nevertheless, we also find that among employees with unenforceable noncompetes who believe their noncompetes are unlikely to be enforced and who view the likelihood of being sued as low, 12–25% still consider their noncompete to be a factor in whether to take a position with a competitor—perhaps because of moral, reputational, or relational costs from breaking their word.

This research enriches our understanding of (mistaken) beliefs about law (Kim 1997, Wilkinson-Ryan 2017), "information shrouding" (Gabaix and Laibson 2006), and the use of unenforceable contract terms (Furth-Matzkin 2017, Koszegi 2014, Tirole 2009). It also contributes to the body of work

[6] Interestingly, again, the effects of correcting beliefs in our information experiment appear to be concentrated among individuals in states that do not enforce noncompetes (versus individuals who initially view noncompetes as unenforceable in states that actually *do* enforce them). This asymmetry suggests that inaccurate initial beliefs that a noncompete is unenforceable may be driven less by some mistaken understanding about a state's law than by other beliefs not affected by the new information—for example, that a lawsuit brought by a former employer is practically unlikely or that a court would likely find the respondent's particular noncompete to be unreasonable.

on the behavioral effects of noncompete agreements and related reform proposals. To begin with, although prior research has documented mistaken beliefs about the law in other settings (e.g., Darley et al. 2001, Rowell 2017), we find that these mistaken beliefs can persist even when the stakes are high—i.e., when they operate to limit an employee's professional opportunities. Moreover, consistent with firms "shrouding" information on prices to keep consumers in the dark (Ellison and Ellison 2009, Brown et al. 2010), we present evidence that employers may actively reinforce ignorance about the law when it benefits them.[7] Mistaken beliefs may also be self-reinforcing if employees who believe their noncompetes are enforceable simply opt out of searching for jobs with competitors. Second, we show that mistaken beliefs about enforceability explain at least some of the behavioral response of employees to *unenforceable* noncompetes (Sullivan 2009, Fisk 2002). Alternative theories, such as concern about reputation or the moral or relational costs of breaking a promise, also appear to have some merit (MacLeod 2007). One implication of these findings is that existing studies that exploit bans on noncompetes (Balasubramanian et al. 2022, Lipsitz and Starr 2022, Fallick et al. 2006) likely understate the effects of noncompetes themselves because some employees continue to adhere to newly unenforceable noncompetes (Starr et al. 2020). Third, given that beliefs and prospective decisions change when we supply people with information about the law, our research implies that educational campaigns as a form of regulation offer some promise—more effective, perhaps, than statutes that simply render noncompetes unenforceable in court. Alternatively, policymakers may succeed with laws that directly target the use of noncompetes, such as penalties for use or garden leave obligations.[8]

We organize the remainder of our article as follows: In Section 2, we review relevant literature—particularly research exploring ignorance about the law, the consequences of this ignorance, the surprisingly common use of unenforceable contractual provisions, and their behavioral effects—and motivate our particular research questions and hypotheses. In Section 3, we introduce our survey data and our empirical design. Section 4 presents the results of our empirical work. In Section 5, we conclude by discussing the implications of our findings for reform and future research.

2. RELATED LITERATURE AND RESEARCH MOTIVATION

Despite the common casual assumption that people either correctly gauge the content of the law from the get-go or that they will otherwise quickly self-correct whenever it matters (i.e., when they have an incentive to get things right), mistaken beliefs about law appear to be common and to have

[7] While we focus in this paper on noncompetition agreements, our results also have implications for other policies and provisions that limit *within-industry* mobility of employees, including the inevitable disclosure doctrine (Flammer and Kacpercyk 2019, Contigiani et al. 2018), trade secret laws (Png 2017), and other restrictive covenants in employment contracts (Balasubramanian et al. 2021).

[8] Garden leave refers to an employer keeping an employee on payroll but away from work obligations during the prohibition period of a noncompete—i.e., a soon-to-be-former employee is compensated to tend their proverbial garden (see Oregon Revised Statutes 653.295) while they wait out their noncompete term, after which they are free to work for their prior employer's competitors.

serious ramifications. For example, Kim (1997) finds that job-seekers overwhelmingly overestimate the legal protections afforded by default (at-will) employment contracts. Mistaken beliefs of this sort are especially relevant to our work. In contrast to some consumer settings where the consumer's interest is modest and protecting oneself requires near-constant (unrealistic) vigilance, an employment relationship is central to many people's lives, the stakes are high, and there are relatively few salient and predictable points in time (e.g., hiring, promotion) when employment contract terms are negotiated and resolved. Thus, good reasons exist to predict that people will "read the fine print" of employment contracts. Yet Kim's study reveals that employees enter into employment relationships systematically misinformed about the extent of their protection from discharge. Kim's research also implicitly undermines an alternative theory that justifies the at-will rule as a reflection of the parties' preference for internal, non-contractual norms to prevent welfare-reducing terminations.

Kim (1997) identifies a particular legal doctrine about which most employees are mistaken, but her finding is no anomaly: other empirical research confirms that systematic mistakes about the content of law are a general phenomenon. Some of this work also makes progress at sketching the mechanisms that might explain the direction and character of these mistakes. Darley et al. (2001) survey respondents across four states on four areas of law, explicitly testing whether people are aware of any "minority" rules that apply to them in their jurisdictions. They find that respondents in minority- and majority-rule states do not differ in their subjective beliefs about the content of law, indicating that mistakes may be the result of reasonable "best guess" estimates across jurisdictions with different laws. (This interpretation is consonant with the direction of mistaken beliefs in our data.) Darley et al. also uncover support for the idea, aligning with Kim (1997), that mistaken views of what the law *is* can be driven by beliefs about what the law *should be*. Rowell (2017) likewise finds that normative beliefs about what the law should be are better predictors of beliefs about the content of law in some areas than the "true" content of law.[9] Rowell also detects varying degrees of informedness across six states regarding ten relevant state laws, from relatively high (the requirement to file an income tax return) to relatively low (a constitutional right to a clean environment). Rowell fails to discover any relationship between the perceived importance of the law and the accuracy of respondents' beliefs, again consistent with the existence of systematic mistakes about weighty legal issues (Kim 1997).[10]

[9] There is evidence that cuts against this view, however; at least in some contexts, legal intuitions do not seem to align with normative intuitions (Furth-Matzkin and Sommers 2020).

[10] Other studies examine the problem of inadequate knowledge among actors who seek to assert their legal rights or entitlements. For example, in another context, Grisso (1980) empirically measures the capacity of juveniles to understand their *Miranda* rights and finds, overwhelmingly, that they could not understand these protections. Grisso contends that the law should adapt to this widespread confusion by developing a per se rule excluding juvenile waivers. Other studies, exposing similarly widespread misapprehensions about rights, maintain that governments can improve understanding of the law by simply enhancing "notice." For instance, Tymchuk et al. (1986) finds that user-friendly methods like the use of large print or videos can increase comprehension of patient rights by the elderly. Similarly, DeChiara (1995) argues that requiring employers to disseminate more and better legal information may reduce employee ignorance relating to their right to bargain.

These studies point to two conclusions. First, people are broadly misinformed about important areas of the law, including laws that affect them directly. Second, the direction of mistaken beliefs may not be arbitrary but a function of views about what the law should be or of what seems most familiar. One implication of these conclusions is that people's beliefs, and potentially their behavior, can be shaped, either unintentionally or with a particular purpose in mind. Relatedly, Stolle and Slain (1997), Hoffman and Ryan (2013), Wilkinson-Ryan (2015), Wilkinson-Ryan (2017), Furth-Matzkin and Sommers (2020), and Furth-Matzkin (2019), among others, demonstrate that actors can strategically influence beliefs about law and related behavior, showing in experimental settings that the inclusion of erroneous law (specifically, unenforceable provisions) in contracts and leases (or manipulating whether people believe they are a party to a contract or a lease with similar language) can deter individuals from exercising their actual legal rights—rendering them "demoralized by contractual fine print" (Furth-Matzkin and Sommers 2020).[11]

Research also indicates that the inclusion of terms in formal contracts in particular (as opposed to, say, an online policy containing the same information) influences people's beliefs about the enforceability of the terms in question and deters action that conflicts with these beliefs (Wilkinson-Ryan 2017). In a lab experiment close in flavor to our own research in a real-world employment setting, Wilkinson-Ryan (2017) studies whether exposing individuals to information at odds with contract language can counter mistaken beliefs about the presumptive enforceability of contract terms. She shows that giving individuals information that a court previously held a term in a contract to be unenforceable reduces an individual's beliefs that the same term in their contract will be enforced. But without such guidance there is considerable scope for sophisticated parties to generate and take advantage of mistaken beliefs about the law and, specifically, the enforceability of unenforceable terms in contracts. Darley et al.'s (2001) findings hint that such manipulation will likely be easier to accomplish when unenforceable terms are actually enforceable in many or most other places.

Together, these lines of research imply that employers in jurisdictions where noncompetes are unenforceable may nonetheless include them in their employment contracts, and that employees may be likely to hold inaccurate beliefs about noncompete enforceability (and guide their behavior at least in part on the basis of these inaccurate beliefs)—though the character of any such mistakes is unclear

[11] It is now well established that the use of unenforceable contractual provisions is anything but rare. In the noncompete setting, Prescott et al. (2016) and Starr et al. (2021) demonstrate that noncompetes are virtually as common in jurisdictions that do not enforce noncompetes as they are in jurisdictions that do enforce them. Furth-Matzkin's (2017) seminal work in the residential lease context shows that this finding is no fluke. In Boston, she finds widespread inclusion of either misleading or flat-out invalid terms within these lease agreements. Her work confirms empirically, at least in the residential lease context, what the literature had long contemplated: that offerors have much to gain and little to lose by including beneficial yet unenforceable terms (Kuklin 1988). Furth-Matzkin's more recent work (including with Sommers) establishes that "gain" is the more likely outcome, with unenforceable terms apparently influencing beliefs and behavior in experimental settings involving consumer scenarios. In related work, Hoffman and Strezhnev (2022) offer a different explanation to explain the existence of unenforceable terms. Our work here extends this literature to real-world, long-term employment contracts/relationships and future mobility intentions.

ex ante. If employees generally take noncompetes to be unfair, they may view them as unenforceable. Alternatively, because any noncompete is part of an employment contract, and because most states do enforce noncompetes, the typical employee in a state where noncompetes are unenforceable may nevertheless assume that employers in their state can lawfully enforce such provisions.

The potential benefits to employers of using unenforceable noncompete provisions when employees may mistakenly assume they are enforceable call to mind profitable "information shrouding" by firms under conditions of costly information acquisition (Salop and Stiglitz 1977, Gabaix and Laibson 2006). In these models, firms take advantage of consumers' inaccurate beliefs and avoid debiasing them. Mistaken consumer beliefs can give retailers some degree of market power; the costs of obtaining correct information from the market prevent consumers from switching to another seller. In our context, employers wield "monopsony" power (Manning 2020). The cost of uncovering accurate information about enforceability may prevent employees from contravening unenforceable restrictions, allowing employers to reduce turnover and inhibit labor market competition with competitors. For instance, if the prevailing industry wage were to rise, employees who rely on the mistaken beliefs that their noncompete is enforceable when it is actually unenforceable will be less likely to take advantage of better outside options (Johnson, Lavetti, and Lipsitz 2020).

Extensive research indicates that unenforceable noncompetes are very common (Prescott et al. 2016, Colvin and Shierholz 2019, Starr et al. 2021, Balasubramanian et al. 2021), and Starr et al. (2020) find that unenforceable noncompetes affect employee mobility. These two findings suggest that noncompetes operate through channels other than actual enforceability. Below, we test whether mistaken beliefs about enforceability at least partially explain these two patterns.[12] Additionally, we seek to understand why, in the noncompete context, mistaken beliefs about the law appear to be persistent, focusing both on employee-side behaviors that may insulate or even reinforce inaccurate beliefs and employer-side behaviors that aim to keep employees misinformed. We also assess the consequences for beliefs, predictions, and intentions of directly providing employees with relevant and accurate information on noncompete enforceability in their jurisdiction.[13] All of this matters because the strategic (or just lazy, form-driven) use of unenforceable provisions may be quite socially costly in the context

[12] Of course, there are alternative explanations. First, employees may not be mistaken about their noncompete being unenforceable and yet may comply because of the reputational or relational costs of not following through on their "promise" (MacLeod 2007). Second, even if there are no reputational consequences, employees may not violate a noncompete they *know* to be unenforceable because of some subjective cost of breaking one's word (Sullivan 2009, Fried 2015). We are able to separate out these competing theories to some degree in our information experiment based on whether and how receiving accurate information changes behavior. An employee's decision to continue to adhere to a noncompete after learning that noncompetes are unenforceable indicates that something beyond "enforceability" is driving compliance.

[13] In doing so, we extend Wilkinson-Ryan's (2017) research by evaluating the impact of providing a more reform-friendly summary of settled state law about entire categories of provisions rather than a past court case finding a particular hypothetical term unenforceable.

of noncompete agreements (Sullivan 2009).[14] At the very least, unenforceable noncompetes may inhibit productivity-enhancing employee mobility without providing the proper incentives for employers to make investments in employees (Rubin and Shedd 1981). Accordingly, evidence that speaks to the potential value of an information campaign to reduce or eliminate mistaken beliefs about enforceability may be of particular policymaking significance.

3. SURVEY DATA AND ENFORCEABILITY MEASURES

Our data come from a proprietary survey that we developed and implemented in 2014 to examine the use and consequences of noncompetes in the U.S. (Prescott et al. 2016).[15] The sample population consists of individuals aged 18 to 75 who are either unemployed or employed in the private sector or in a public healthcare system. The full sample comprises 11,505 respondents drawn from all states, industries, occupations, and other demographic categories.[16] Using these data, Starr, Prescott, and Bishara (2021) provide the first systematic evidence on the incidence of noncompetes across the U.S. labor force, finding that noncompetes bind roughly one in five labor force participants. Starr, Prescott, and Bishara (2020) add by demonstrating how noncompetes can and do influence the process of employee mobility, independent of whether noncompetes are actually enforceable.

To examine what employees believe about noncompete enforceability and the consequences of violating their noncompete, as well as how those beliefs matter to their forward-looking intentions and expectations, we take advantage of several novel aspects of our survey data. First, we analyze employees' *beliefs* about whether, if they took a job with a competitor and their prior employer sued them for violating their noncompete, a court would ultimately enforce their noncompete.[17] Second, we examine the results of an information experiment that we built into our survey in which we informed a random selection of respondents of the *actual* noncompete enforcement policies of their state. In our view, our information experiment can be taken as a rough simulation of an educational

[14] Sullivan (2009) reviews how the approach courts take toward unenforceable noncompete clauses encourages their use by employers. Courts, Sullivan argues, seek to do justice among the parties before them and often construe these clauses in ways that strike the unenforceable portions but salvage the contract as a whole, leaving the contract drafter no worse off. He argues that this approach by courts does little to address the actual problem of these unenforceable provisions: the *in terrorem* deterrence of the many who view these terms in these contracts as enforceable.

[15] We provide a brief discussion of the data here and refer the interested reader to our Online Appendix for further information, with an even more detailed description appearing in Prescott et al. (2016).

[16] To ensure that the data are nationally representative, we create weights for our analysis using iterative proportional fitting ("raking") to match the marginal distributions of key variables in the 2014 American Community Survey. We considered many weighting schemes. See Tables 16 and 17 in Prescott et al. (2016) for more details.

[17] We can gauge these beliefs in two ways using our survey data. First, the survey asks, "*Are noncompetes enforceable in your state*?" Second, the survey asks respondents to assign a probability that a court would enforce their noncompete were they to violate it and their employer were to sue: "*If you were to quit your current job to work for or start a competing company, how likely is it that a court would actually enforce your noncompete (assuming your employer took legal action to try to enforce your noncompete)?*" Third, the survey asks respondents to assess how likely their employer is to sue to try to enforce their noncompete: "*If you were to quit your current job to work for or start a competing company, how likely is it that your employer would take legal action to try to enforce your noncompete?*"

campaign or as improved access to legal information, but the experiment also functions as a source of exogenous variation in beliefs about noncompete enforceability, which allows us to identify the effects of *beliefs* about enforceability on prospective behavior.

To study how beliefs vary by noncompete enforceability—and to implement our information experiment—we build a measure of actual enforceability using contemporaneous state noncompete policies (Beck 2014),[18] which captures the conditions under which states will (and will not) enforce noncompetes, including any exemptions under state law. We summarize these dimensions in Table OA1,[19] which shows which states have adopted which policies and the score that each policy receives in our overall measure. In the table, we report policy variation with respect to 1) how states treat overbroad noncompete clauses, 2) whether states enforce noncompetes when an employer terminates an employee without cause, and 3) whether noncompetes require additional consideration beyond continued employment. For each policy, a score of "1" is associated with the highest likelihood that a court will enforce a noncompete coming before it (e.g., even scenarios in which an employer terminates the employee without cause), and "0" is associated with the lowest likelihood that a court will enforce a noncompete. We then add a fourth dimension: whether the state will enforce noncompetes at all (the three states that essentially do not enforce at all are California, North Dakota, and Oklahoma). Next, we aggregate across all four measures for each state, such that the maximum score a state can receive is "4" for robust enforceability. Finally, we take into account any exemptions associated with specific professions (e.g., physicians) in the state (meaning that employees with different occupations in the same state may have different enforceability measures) and divide by the maximum score possible for each state. Thus, the final score for each respondent is between "0" and "1."[20]

For purposes of this article and in our analysis, we classify state-occupation combinations with a score of "0" as "no enforceability," scores between "0" and "1" as "medium enforceability," and scores of "1" as "high enforceability." Table 1 shows which states (and state-occupations) fall into each category and provides summary statistics across the full sample and the sample of individuals with a noncompete, which will be our focus in most of our analyses. In Figure OA1, we present a map of the U.S. shaded according to the level of enforceability.

[18] See our Online Appendix C for the exact documentation in Beck (2014).

[19] The language we use to describe enforceability in Table OA1 with respect to each particular aspect of noncompete policy is also identical to the language we use in our information experiment.

[20] If a state does not have a policy on any particular dimension of enforceability (e.g., whether the state will enforce a noncompete for an employee terminated without cause), we exclude that dimension from the calculation of that state's overall index, dividing the state-specific score by the maximum of the non-missing scores for that state. There are other ways to aggregate these measures into a useful index (see, e.g., Bishara 2011 and Starr 2019), but our approach cleanly identifies nonenforcing states and does not presume any linear relationships.

4. EMPIRICAL ANALYSIS AND RESULTS

In this section, we study what individuals believe about the enforceability of their noncompetes, the accuracy of those beliefs, and why, if at all, employees may be persistently misinformed. We also describe and report the results from our information experiment, which effectively "shocks" employees' beliefs with accurate information about noncompete enforceability. We use the experiment not only to determine whether and how accurate information alters preexisting mistaken beliefs about noncompete enforceability—as well as to see whether mistaken beliefs can fully account for the behavioral effects of unenforceable noncompetes (Starr et al. 2020)—but also to identify the causal relationship between an employee's beliefs about enforceability and their future expectations and intentions regarding their noncompete-related behavior. Our various research questions require a range of empirical tools, so we describe our empirical methods as needed along the way.

4.1 Employee Beliefs about Noncompete Enforceability

To begin, Table 2 tabulates responses to the following survey question: "*Non-competition enforcement policy is determined at what level?*" Notwithstanding recent federal noncompete policy proposals (beginning circa 2015) and conversations about regulation by the Federal Trade Commission, noncompete policies are and historically have been under the purview of states (Bishara 2011). Only 24% of respondents—just four percentage points higher than guessing at random—are aware of the legal primacy of states in this domain. The proportion of respondents who answer correctly in our survey scales somewhat with education; a larger share of those with education beyond a bachelor's degree recognize that noncompetes are enforced at the state level (32%) in comparison to those with less than a bachelor's degree (21%). A slightly larger share of those who have a noncompete with their current employer recognize that state law governs their noncompete (30%) relative to those who are not bound by a noncompete (23%). Taken together, Table 2 suggests that the majority of employees, regardless of their education level and even if they are presently subject to a noncompete, are unaware that noncompete enforceability is state-level policy.

Panel A of Table 3 presents a summary analysis of answers to the following question: "*Are noncompetes enforceable in your state?*" In the full sample, 59% believe that noncompetes are enforceable, compared to just 5% who believe that they are unenforceable (which is low, considering that 13% of the population resides in states that either do not enforce noncompetes) and 37% who report that they do not know the answer to the question. While there is relatively little heterogeneity across education levels, 76% of those bound by a noncompete believe that noncompetes are generally enforceable, compared to 61% of those who do not have a noncompete (and just 37% of those who are not sure if they are bound). For each cut of the data, less than 10% of the sample believes that noncompetes are unenforceable, suggesting that the conventional set of beliefs in the population are that noncompetes are enforceable—especially for those presently subject to one (Wilkinson-Ryan 2017).

Panel B of Table 3 investigates the accuracy of these beliefs, using our broad classification in which we treat California, North Dakota, and Oklahoma as the only states that refuse as a policy matter to enforce noncompetes.[21] We refer to those who report not knowing their state's law in Panel A as the "uninformed," and their proportions are unchanged in Panel B. The "misinformed" are those who incorrectly estimate noncompete enforceability in their state. They make up 11% of the full sample and 13% of those presently bound by noncompetes.[22] In contrast, the "informed"—those who correctly estimate noncompete enforceability in their state—amount to 53% of the population and 67% of those working under noncompetes. The apparently high proportion of "informed" employees may be illusory and just a function of chance and the relevant shares; most states happen to enforce noncompetes, and the majority of employees appear to believe that their states will enforce noncompetes. The proportion could simply be the result of individuals going with what they sense is the "majority" rule and just happening to be correct most of the time (Darley et al. 2001).

Figure 1 depicts the level of employee "informedness" about the law among individuals with a noncompete according to actual state policies, where the "no enforceability" states are those that entirely deny enforcement for all categories of employees (i.e., California, North Dakota, and Oklahoma) and where medium/high enforceability states are the complement. The figure shows that while 74.8% of those with a noncompete in states that enforce noncompetes are informed, 70.2% of those with a noncompete in states that do not enforce noncompetes are misinformed (8.4% are uninformed). Figure 2 presents these patterns by education level (among those affirmatively bound by a noncompete). While highly educated employees appear to be slightly better informed in states that do not enforce noncompetes, more than 70% of those with above a bachelor's degree are either misinformed (64.6%) or uninformed (6.5%). Taken together, Table 3 and Figures 1 and 2 establish that employees bound by noncompetes tend to believe that noncompetes are enforceable in their state—even when they are not—and confirm that this pattern is relatively stable across education levels.[23]

We can assess the robustness of these findings by turning to a more nuanced measure of beliefs about noncompete enforceability that is specific to the employee's current employment situation. The survey asks respondents to answer the following question using a scale of 0–100: "*If you were to quit*

[21] We do not incorporate the occupation-specific carve-outs in this measure because the question refers to state law broadly and is not specific to the respondent's occupation. Also, it is important to note that these states will enforce noncompetes incident to the sale of business but not for an employee's move between employers. Our survey is limited to employees (we drop self-employed individuals), making this omission less of a concern. Our main continuous measure of enforceability is specific to employee mobility (as opposed to business sales).

[22] We classify as misinformed those in California, Oklahoma, or North Dakota who answer that noncompetes *are* enforceable and those in the rest of the states who state that noncompetes are *not* enforceable. Note that not all noncompetes are enforceable even in states that will generally enforce them; the terms of any noncompete in an enforcing state must still survive the state's "reasonableness" test before a court will enforce it (Bishara 2011).

[23] See Figure OA2 for a cut by occupation, conditional on having more than 20 individual respondents in that occupation in both enforcing and non-enforcing states. Lawyers are the most likely to be aware that their noncompete is unenforceable. However, because these estimates are underpowered, we recommend viewing them with caution.

your current job to work for or start a competing company, how likely is it that a court would actually enforce your noncompete (assuming your employer took legal action to try to enforce your noncompete)?" An answer to this question thus provides a continuous and subjective assessment of the employee's beliefs that a court, if asked, would enforce their specific noncompete. Figure 3 documents a strong, positive relationship between this continuous measure of beliefs and the blunt, categorical beliefs we document in Table 3. The graph plots subjective beliefs as a function of categorical beliefs and whether the employee is presently bound by a noncompete. Figure 3 shows that employees who believe noncompetes are unenforceable also estimate the likelihood of enforcement in their case to be much lower than those who believe noncompetes are enforceable, with those who are uncertain falling in the middle (see Table OA2, columns (1) and (2) for regression results with and without "basic" controls).[24]

Using this individual-specific measure of enforceability (i.e., respondent's beliefs about likely enforcement in their own situation), Figure 4 assesses whether beliefs about enforceability unconditionally correspond with actual enforceability by noncompete status.[25] Generally speaking, if employees are accurately informed about noncompete enforceability, the lines in Figure 4 should be at least weakly upward sloping. But the relationships we uncover are relatively flat. Employees with a noncompete believe that a court will enforce their noncompete somewhere between 40% and 46% of the time, regardless of actual enforceability in their jurisdiction (with the highest estimate of enforceability coming from those in states that do *not* enforce noncompetes). Employees without noncompetes report similarly invariant beliefs across jurisdictions, though the levels differ (see columns (3) and (4) of Table OA2). These figures suggest that, as before, employees living in states where courts would not countenance their noncompete agreements remain generally unaware of the unenforceability of such provisions. To explore this pattern more closely, Figure 5 addresses only the noncompete population to determine whether more highly educated employees are more likely to be informed. As in Figure 2, we find that employees of all education levels seem to be mistaken about the law, at least in states where noncompetes are unenforceable (see columns (5) and (6) of Table OA2).[26]

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[24] In our regression work, "basic" controls include employee gender, employee education, employee race, a third-degree polynomial in employee age, the class of the employer (e.g., for-profit), the type of occupation (2-digit SOC), industry (2-digit NAICS), employee class (e.g., hourly vs. salary), hours worked per week, weeks worked per year, the interaction of hours and weeks worked, employer size, whether the employer has multiple establishments, and the log of number of establishments in the employee's county-industry. The 95% confidence intervals reflect standard errors clustered at the state level, the level at which courts and legislatures determine noncompete enforcement policy (Abadie et al. 2017). We use the adjective "basic" because, in prior papers using these data, we distinguish between more plausibly exogenous "basic" controls and other "advanced" controls that may be endogenous to the contracting process and therefore potentially problematic to include (Starr et al. 2020, Starr et al. 2021).

[25] In contrast to the broad state-level measure of actual enforceability (i.e., do vs. do not enforce) that we use in the previous section, in this analysis and in all work below that relies on these individual-specific, continuous beliefs, we incorporate the occupation-specific exemptions under the law from Table 1 into the "no enforceability" group.

[26] One potential critique of our approach here is that employers with establishments in multiple states could use noncompetes with choice-of-law clauses incorporating another state's law. We find no evidence that beliefs about noncompete enforceability vary by whether the employer is a multi-state operation, an employer characteristic that we collect

4.2 The Persistent Inaccuracy of Employee Beliefs

The prior section establishes that employees with unenforceable noncompetes are largely unaware that courts will refuse to enforce their agreement not to compete. Importantly, employee beliefs are not random. Descriptively, employee mistakes about enforceability favor mistaken beliefs that unenforceable noncompetes are enforceable rather than beliefs that enforceable noncompetes are unenforceable. Hypotheses that would explain this pattern include 1) the existence of a default presumption among employees that contracts generally and noncompetes specifically are enforceable and 2) a pervasive inference that any particular noncompete is likely enforceable given that noncompetes are enforceable in a "majority" of jurisdictions (Darley et al. 2001). However, both of these hypotheses fly in the face of traditional views about the advantages of learning the truth (which seem significant), the relatively low costs of obtaining freely available information, and the information-diffusing benefits of labor markets. Employment contracts are high stakes, and employees looking for a new position will presumably meet potential new employers who *do* know when a provision is unenforceable. In this section, we consider two hypotheses—one supply side and one demand side—to explain why employee beliefs about enforceability may be persistently and asymmetrically inaccurate.

Our supply-side hypothesis is simply that many employees who mistakenly believe their noncompete is enforceable may opt out of searching for a position with a competitor, thereby short-circuiting the labor market's ability to correct their mistaken beliefs. To assess this possibility, we study the extent to which an employee reports searching for jobs at competing firms within the last year (measured on a scale from 0–10). In the sample of employees with a noncompete, we regress this measure of search effort on indicators for whether the employee is informed about the law, interacted with actual noncompete enforceability, and employer and employee controls. The results, shown in Figure 6, offer some support for this hypothesis. Conditional on our basic controls, employees who are informed that their noncompetes are unenforceable exert 50% more search effort towards competitors relative to those who are misinformed (mistaken) or uninformed (3.74 vs. 2.48). In contrast, among employees with enforceable noncompetes, we observe little difference between these two groups (see columns (1) and (2) of Table OA3 for unconditional and conditional model estimates).

An important limitation of this analysis is that it does not exploit any exogenous variation in an employee's beliefs or in the accuracy of their beliefs about enforceability. Accordingly, these results should be interpreted as descriptive; some unobservable factor may exist that affects *both* how well informed an employee is about the enforceability of their noncompete *and* their level of search effort toward competitors. Reverse causation may also drive the relationship we observe—those who exhibit more search effort toward competitors may be more likely to learn about the law. While we

using our survey instrument. We classify employees based on the state where they work, however, and we do not know if their contract invokes another state's law.

acknowledge these concerns, our results nevertheless make clear that those who do not know that their noncompete is unenforceable—approximately 80% of those living in states where noncompetes are unenforceable per Figure 1—put less effort into searching for new positions at competing firms, necessarily limiting their ability to learn about the law governing their contract from competitors. This finding reminds us that certain mistakes—even mistakes about the law—may cause agents to refrain from activities that facilitate error correction and thus can become persistent.

Our demand-side hypothesis emerges from the information-shrouding literature. Employers in states that do not enforce noncompetes may have relatively weak incentives to inform employees at competing employers about the lack of enforceability of their noncompetes—even when they wish to poach these employees. At first blush, this possibility seems counterintuitive. If a competing employer wants to poach employees with unenforceable noncompetes, one would guess it need only give these employees offers and inform them that their existing noncompetes are unenforceable. However, such "informative" recruiting may be either unattractive to the poaching employer or unlikely to succeed without substantial effort (Gabaix and Laibson 2006). The recruiting employer may not benefit on net from successfully informing a prospective employee about their noncompete's unenforceability for two reasons. For one, once the focal employee appreciates the unenforceability of their noncompete, the recruiting employer may face greater competition for that employee, who might now be more open to offers from, for instance, more obvious competitors to their current employer. Moreover, the recruiting employer may itself use unenforceable noncompetes with its existing employees, who may *also* mistakenly believe such provisions are enforceable (as seems likely given Section 4.1). Thus, "informative" recruiting may produce a pyrrhic victory—i.e., higher turnover and wage costs—if the new hire eventually informs the employer's entire workforce about the unenforceability of noncompetes (from the employer's "own mouth," as it were). Finally, convincing a prospective employee that their unenforceable noncompete is actually unenforceable may be too difficult to justify in many cases. For example, an employee's current employer may implicitly (or explicitly) threaten potentially departing employees with litigation by reminding them that they agreed to a noncompete clause (or by actually suing them), which may render employees *more* (not less) likely to believe their noncompete is enforceable—perhaps specifically when it is unenforceable.

To assess whether there is potential for competitor recruitment to inform employees about the law, we exploit two unique aspects of our survey data. The first is an indicator for whether the employee reports receiving a job offer from a competitor in the last year. The second is an indicator for whether, if an employee's present employer became aware of the employee's job offer from a competitor, the employer reminded the employee of their noncompete obligations. Figure 7 displays the results from a regression using data from noncompete-bound employees, including basic controls, of employee beliefs regarding the level of noncompete enforceability interacted with whether the employee in question received a job offer from a competitor within the last year. The results furnish some support for the demand-side hypothesis: we find that employees who receive offers from competitors actually believe their noncompetes are enforceable to a somewhat greater degree on average relative to those who do not receive offers from competitors (55% vs 47%), though the difference is not statistically significant (see columns (3) and (4) of Table OA3).

Figures 8 and 9 attend to the potential role of strategic reminders by current employers in keeping employees misinformed about the unenforceability of their noncompete. Figure 8 shows that, comparing two observationally equivalent employees (per our basic controls) who are subject to a noncompete and who have received job offers from competitors, an employee with an *unenforceable* noncompete is approximately 40 percentage points more likely to receive a reminder about their (unenforceable) noncompete (71% vs 32%, 34%) from their employer.[27] Figure 9 documents that reminders alone are associated with stronger beliefs about the enforceability of noncompetes, regardless of the level of enforceability (see columns (1)–(4) of Table OA4).[28] Taken together, Figures 7, 8, and 9 imply that rather than operating to inform employees when they have an unenforceable noncompete, recruitment activity by competitors—and subsequent reminders or threats from current employers—may actively prevent employees from learning that their noncompete is unenforceable.

A key limitation of our analysis of noncompete reminders is that relatively few employees with a noncompete in our sample received offers from competitors that became known to their employer—which is necessary for their employer to respond to the competing offer by issuing a reminder (237 total observations). To supplement our analysis, we turn to a question in the survey that asks all individuals with a noncompete: "*Are you aware of any instances in which your employer sued an employee for violating a non-competition agreement?*"[29] Logically, reminders are a likely precursor to a lawsuit, so knowledge of a prior lawsuit (or at least a letter threatening legal action) may operate much the same as a reminder in terms of reinforcing an employee's beliefs in enforceability. It also reflects the idea that employee beliefs may respond not only to what the employee experiences personally (as in the reminders analysis) but also to the experiences of their present and former coworkers. Figure OA3 shows that approximately 20–24% of individuals with a noncompete are aware of (or believe they are aware of) their employer suing others over noncompetes, and this relationship is relatively flat with respect to actual enforceability (see columns (5) and (6) of Table OA4). Interestingly, however, Figure OA4 shows that employees who believe their employer has sued former employees are significantly more likely to believe that their noncompete is enforceable (see columns (7) and (8) of Table OA4), and this effect appears to be especially pronounced for employees with a noncompete that is actually *unenforceable*.

[27] These results are robust to dropping observations from California. Without data from California, 62.2% of employees still receive reminders about unenforceable noncompetes.

[28] Both Figures 8 and 9 graph results from the regression estimates we report in Table OA4.

[29] We acknowledge that it is not entirely clear whether respondents interpreted this question as asking whether their employer actually filed a legal complaint or, alternatively, whether hearing that one or more fellow employees had received a "threatening letter" or other warning would suffice for respondents to answer "yes."

Thus, with reminders and hints of (frivolous) lawsuits, employers seem endowed with at least some ability to convince individuals with an unenforceable noncompete that their noncompete is in fact enforceable, countering whatever effect competing firms may have if they attempt to disabuse these employees of their mistaken beliefs about enforceability.[30]

4.3 Information Experiment Design and Balance Tests

Whatever the *reasons* for persistently mistaken beliefs about noncompete enforceability among employees, an important question is whether effective policy responses exist. Policymakers might deter employers from using unenforceable noncompetes by imposing financial penalties for their use or by requiring compensation during any noncompete prohibition period (i.e., garden leave). An alternative, possibly more effective solution to inaccurate beliefs about enforceability is an educational campaign—such as the regular posting of employee contractual rights and information at the workplace or elsewhere—and mandatory legal disclosures that are comprehensible, easy to verify, and conspicuous. There is considerable debate over the value of disclosures as a means of positively influencing behavior. Ben-Shahar and Schneider (2011), for example, describe many of the drawbacks—indeed the harms—of such an "educational approach," and yet other work, for example, Wilkinson-Ryan (2017), Furth-Matzkin (2019), and Furth-Matzkin and Sommers (2020), finds clear benefits. To gauge the potential effects of providing accurate information to employees about enforceability, we simulate a (rough) disclosure policy for correcting mistaken beliefs via an information experiment within our survey. Researchers use this empirical strategy in many contexts. Recent studies, for example, examine the impact of information on business economic expectations over time (Coibion et al. 2018), college major choices (Wiswall and Zafar 2015), and settlement decisions (Sullivan 2016).

Our information experiment analysis proceeds in three steps. First, we assess our respondents' baseline expectations about noncompete enforceability (which we describe and analyze at length above) and how they regard the effects of any noncompete on their behavior. Next, we randomly assign approximately 50% of respondents (50.1% and 52.43% of the unweighted full and noncompete samples, respectively) to receive legal information about the actual enforceability of noncompetes, individualized for a given respondent based on their state of employment. Finally, we reevaluate their beliefs about the enforceability of noncompetes and the potential influence of these provisions on the respondent's behavior by re-administering questions from the first stage of the information experiment—even to those who do not receive the information treatment.[31]

[30] An employer bringing a lawsuit to enforce a clearly unenforceable term can, at least in some jurisdiction, be subject to a countersuit on the part of the employee for unfair labor practices (as in California). However, taking advantage of this right of action can be costly and risky for an employee, leaving employers at least some room to posture in a way that might reduce mobility that conflicts with the terms of a noncompete.

[31] By asking those who do not receive information the same questions, we can alleviate concerns that those in the treatment group are changing their answers simply because they must answer the same questions twice.

We gather the specific information about the law that we supply to respondents in the experiment from the characterization of state-level noncompete regimes contained in Beck (2014), which we provide in some detail in Online Appendix C. We summarize these laws in Table OA1. We outline the actual information that we present to those who receive information (treatment) in Figures OA5 and OA6. In the survey, the information appears in the order indicated in those figures. Figure OA5 explains that noncompete policy is designed and enforced at the state level and that only a few states do not enforce such provisions.[32] It also describes the typical reasonableness test that state courts employ when they decide whether to enforce a noncompete in a particular case. Figure OA6 displays all of the state-specific information the survey delivers to respondents, where the blue arrows indicate our experiment's "display logic" by which we ensure that we introduce only appropriate information (depending on the state in which the respondent works) to respondents as part of the treatment (see Table OA1 to link specific policies to individual states).[33]

In Table 4, we present the results of a balance test to verify that individuals with a noncompete are balanced between treatment and control groups, both overall and within each of the state enforceability levels. With the exception of the gender variable—men are five percentage points more likely to be in the group that receives information (and the medium enforceability category drives this difference)—there are no statistically significant differences between the (unweighted) treatment and control groups in the full sample or any subsample.

4.4 Information Effects on Employee Beliefs

Figure 10 reports the distribution of beliefs among individuals with a noncompete across the treatment and control groups—i.e., according to whether the individual receives information on actual noncompete enforceability in their state. The top row of Figure 10 shows, not surprisingly but reassuringly, that the distributions of beliefs before and after the experiment among those who do not receive any information are nearly identical. In contrast, for those who receive information in the "no enforceability" group, we observe a large leftward shift in the distribution of beliefs. This swing indicates that employees can actually read and absorb the information in our treatment. In medium and high enforceability states, we see slight shifts rightward in the distribution. Figure 11 presents the simple mean effects corresponding to the post-experiment beliefs by treatment status (corresponding

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[32] In Figure OA5, we only list California and North Dakota as nonenforcing states. This is discordant with Beck (2014), which includes Oklahoma as a nonenforcing state. We exclude Oklahoma from Figure OA5 because, in the literature, we found competing views on whether Oklahoma is truly a nonenforcing state in 2014 (see Bishara 2011). Nevertheless, we include Beck's (2014) characterization in the state-specific information we provide regarding Oklahoma. As a result, employees in Oklahoma (we only have 118 such individuals in the full sample—of whom only 13 indicate having a noncompete) may be *undertreated* by our experimental choices.

[33] We made one error in carrying out our information experiment. According to Beck (2014), Alabama does not enforce noncompetes for professionals. Our information experiment unintentionally excludes that information. There are only 25 respondents with a noncompete from Alabama, although 12 of these are professionals. Fortunately, this error does not materially influence our results.

to regression results in Table OA5 columns (1) and (2)). Consistent with Figure 10, we find that those who receive information that their noncompete is unenforceable are far less likely to believe that their noncompete is enforceable (24%) relative to those who do not receive information (46%). These effects appear muted for the medium and high enforceability groups. Taken together, Figures 10 and 11 demonstrate that information delivery is most effective at changing beliefs among those with an entirely unenforceable noncompete, which is the population entertaining the bulk of mistaken beliefs in this domain. Notably, providing information that noncompetes are unenforceable—at least as we do in our experiment—does not completely free the informed from their mistaken beliefs.

Importantly, the raw distributions and mean effects we present in Figures 10 and 11 may mask heterogeneity in whether and how much respondents update their beliefs after the experiment *relative to their initial beliefs*. Figure 12 addresses this issue by presenting an unconditional binned scatterplot of the relationship between pre-experiment beliefs and post-experiment beliefs (Starr and Goldfarb 2020). If respondents estimate the same level of enforceability before and after receiving information, their responses would line up along the 45-degree line (shown in thick black in Figure 12). Matching estimates along the 45-degree line is primarily what we observe for those who do not receive information, regardless of the level of actual enforceability (left panel of Figure 12). In contrast, Figure 12's right panel indicates that those who receive information update *differently* given initial beliefs and actual enforceability. For example, respondents who initially estimate their noncompete to be enforceable with certainty reduce their post-experiment beliefs considerably: those with an unenforceable noncompete reduce their estimate to approximately 35%, while those in medium and high enforceability states reduce their beliefs to 75–80%. These latter shifts imply that accurate and precise information even for medium and high enforceability states may give employees some doubt that their noncompete can or will be enforced. We see a similar pattern among those who initially view their noncompete as largely unenforceable—these individuals update their beliefs upward, especially if they live in a state where noncompetes are moderately or easily enforceable.

Figure 13 characterizes the mean effects of information on beliefs among individuals with a noncompete that we document in Figure 12 by splitting the sample by pre-experiment beliefs above or below the median (50%) and then regressing post-experiment beliefs on a treatment indicator that we interact with actual enforceability and basic controls (see Table OA5 columns (3) and (4)). The results show that the drop in mean beliefs in Figure 11 is almost entirely attributable to the changing beliefs of those who initially view their noncompete as enforceable. For example, for those with above-median pre-experiment beliefs about enforceability in their state, information receipt causes beliefs to fall from 81% to 26% when their noncompete is actually unenforceable, and even causes drops of 8–10 percentage points in medium and high enforceability states. In contrast, those who initially believe their noncompete is unenforceable (left panel of Figure 13) are largely unmoved by the information—even in medium and high enforceability states.[34]

4.5 Information Effects on Prospective Employee Behavior

In this section, we examine whether the delivery of accurate information about noncompete enforceability produces changes in an employee's prospective mobility behavior. Unfortunately, we are unable to track employee decisions or behavior over time. Instead, we estimate an employee's very short-run reaction to exposure to enforceability information using their answers to questions that appear after the experimental treatment in the survey. We cannot know whether the outcomes we study below will ever translate to actual changes in mobility at some point in an employee's future. However, it is reasonable to assume that changes in prospective mobility outcomes are a necessary precursor to behavioral change.[35] In other words, if information has no apparent effect on an employee's expectations or predictions, it seems unlikely to matter to actual behavior. Moreover, because our information treatment is less polished and credible than a professionally designed educational campaign would be, our assumption is that our estimates are conservative.

To collect a broad measure of how a noncompete might influence employee mobility, our survey presents respondents with the following question both before and after our experimental treatment: *"If you received a much better offer from a comparable, competing employer, would your noncompete be a factor in preventing you from moving?"* (Starr et al. 2020). In Figure 14, we calculate how responses to this question differ depending on treatment status and the level of enforceability.[36] For individuals with an unenforceable noncompete, 51% of those who do *not* receive information indicate that their noncompete would be a factor in whether they would accept the job offer, versus 26% among those who receive accurate information about lack of enforceability. For individuals with a moderately enforceable noncompete, the difference is smaller (46% vs 38%), while there is no difference for those with a highly enforceable noncompete. Figure 15 breaks out this analysis based on individual responses to this same question before the experiment, conditional on basic controls (see Table OA6 columns (3) and (4)). In the right panel, we find that individuals who initially report that their noncompete *would* be a factor in leaving their current employer but who live in a state where noncompetes are actually unenforceable experience the largest drop to 51%. Notably, the control group (which does not receive information)

[34] Figure OA7 shows the same heterogeneity for the sample of employees not bound by a noncompete. Those who receive information and mistakenly believe pre-treatment that any noncompete would have been enforceable (had they agreed to one in their current job) also dramatically update their beliefs about enforceability (right panel). In contrast to the sample of individuals with a noncompete, however, those who mistakenly believe any noncompetes would not have been enforceable also update their beliefs moderately when those noncompetes are highly enforceable (left panel).

[35] Anecdotally, several of the survey participants who received information thanked us at the end of the survey for letting them know that their noncompete was unenforceable. This suggests that real learning about the content of the law in such a format can affect future employment-related decisions.

[36] The sample is limited to individuals with a current noncompete, and the underlying regression specification includes basic controls. We report the full results in Table OA6.

also shifts downward a little as well, suggesting that control respondents answer the question differently the second time. In the left panel, we detect fewer differences by treatment status in the sample of individuals who initially report that their noncompete would not be a factor.[37]

One important and interesting result of this analysis is that, even after employees learn that their noncompete is unenforceable, many still indicate (in our survey, at least) that they will weigh their noncompete as a factor in deciding whether to take a better job at a competing employer. This result implies that while mistaken beliefs about enforceability explain a relatively large portion of how unenforceable noncompetes succeed at deterring employees from taking better jobs, noncompetes—even unenforceable ones—may influence employee mobility decisions through other channels as well.[38] Formally agreeing to a noncompete, for example, might increase the subjective cost of violating one's word, the reputational cost of breaking a nonbinding "promise," or even the financial cost of defending oneself against a frivolous lawsuit (Sullivan 2009). We return to this issue in Section 4.7.

4.6 Effects of Beliefs about Enforceability on Employee Behavior

In the previous section, we examine the effects of our simple information treatment on (1) beliefs about noncompete enforceability and on (2) various prospective mobility outcomes. These findings are relevant to policymaking discussions about how best to correct mistaken beliefs about enforceability and about whether such interventions can influence mobility, either by changing beliefs or through other mechanisms. In this section, we study the relationship between (1) and (2) directly. Specifically, we leverage our information treatment to identify the causal effects of *beliefs* about noncompete enforceability on prospective mobility outcomes (as opposed to the effects of the information treatment itself). If someone believes that their noncompete is more rather than less enforceable, how much does that matter to their prospective mobility decisions? In theory, beliefs about enforceability might matter very little, if questions about enforceability are absent from an employee's mobility-related decision making, perhaps because many other considerations (like reputation) matter far more.[39] Alternatively, employees may put weight on enforceability in making their mobility decisions, either in the abstract or by breaking down the separate practical facets of "enforceability," like whether their employer might sue them if they depart to a competitor or, if a lawsuit does occur, whether a court would enforce their noncompete. In that case, employee *beliefs* about enforceability seem likely to matter to mobility, though how *much* they might matter remains unclear.

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[37] Figures OA8 and OA9 show the same patterns hold for whether a noncompete will be a factor in starting a new business. The precise question in the survey is: "*If you developed an idea to start a new company that competes with your current employer, would your noncompete be a factor in preventing you from starting the competing firm?*"

[38] We acknowledge that one concern with this conclusion is that our respondents (in the right panel) initially state affirmatively that their noncompete *would* be a factor in deciding whether to leave their employer for one of its competitors, whereas in a real-world educational campaign, no preliminary mental choice would be required. Therefore, any post-educational choice would not be a "change" from a prior position.

[39] Of course, this possibility seems remote, given the results we report in Section 4.5.

To study the relationship between beliefs about noncompete enforceability and employee mobility decisions, we could simply check to see whether one correlates with the other. Controlling for observables, for instance, we might find that an employee's beliefs that their noncompete is enforceable are positively correlated with an employee's reporting that their noncompete would be a factor in their decision to leave for a competitor. This approach suffers from endogeneity concerns, however. For example, relatively sophisticated employees may be both more likely to believe that noncompetes are unenforceable (because such employees may be more knowledgeable about the law in jurisdictions where noncompetes are unenforceable) and more likely to attract outside offers. Another possibility is that relatively mobile employees who have had many conversations with friends about transitioning to other jobs may be more likely to have accurate beliefs about enforceability—i.e., low or at least lower estimates of enforceability in states where noncompetes are unenforceable.

Due to these endogeneity concerns, we use an instrumental variable approach that exploits the fact that the information experiment exogenously causes employees to update their beliefs about noncompete enforceability. The idea is that randomly deploying information causes some employees to update their beliefs when their initial beliefs are wrong, as in Figure 13. Accordingly, we instrument for post-experiment beliefs with a set of instrumental variables that capture the main effect of the information experiment and its interaction with the actual enforceability of the respondent's noncompete and an indicator for the respondent's pre-experiment beliefs about enforceability (above or below 50%).[40] Figure 13 (which effectively reports the first-stage 2SLS estimates) reveals that the compliant subpopulation driving any local average treatment effects is primarily individuals who have an unenforceable noncompete but who initially believe their noncompete is enforceable. The identifying assumption underlying these instruments is that the information shock affects mobility only through its effects on beliefs about the enforceability of noncompetes. In our view, this assumption seems at least plausible because the content of the information relates only to the circumstances under which a court in their state would enforce a noncompete. That is, it is difficult to conceive of a reasonable way in which new information about the content of law would affect mobility through some channel that does not depend on a change in what individuals believe about the law.[41]

[40] This approach produces four total instruments: (1) receipt of information; (2) receipt of information×pre-experiment beliefs; (3) receipt of information×actual enforceability; (4) receipt of information×pre-experiment beliefs×actual enforceability. Note that we include the respondents' pre-experiment beliefs, actual state law, and the interaction of these two variables as controls in the 2SLS model.

[41] In Section 4.7, we explore one potential mechanism for how changing beliefs about enforceability might influence mobility—through changing beliefs about the likelihood of an employer filing a lawsuit. We acknowledge that there may be other ways that changing beliefs can affect mobility outcomes and that some of these scenarios might not be particularly policy relevant. One possibility is that the information in our experiment might engender an emotional response in respondents, such as anger, because they learn that their employer has been threatening them over an entirely unenforceable contract, which may then cause them to be more likely to want to leave their employer as they continue with the survey. While this anger response only arises because the information treatment changes these individuals' beliefs about

Table 5 documents the 2SLS results for a variety of relevant behavioral outcomes. Columns (1)–(3) examine whether beliefs that a noncompete is enforceable cause an employee to conclude that their future job options are limited and whether an employee's noncompete would be a factor in deciding to take a better job or start a competing enterprise. In all cases, we find that believing that a noncompete is enforceable causes a sizable increase in feelings that the noncompete limits job opportunities. These estimates are also quite large in magnitude. For example, an employee who believes their noncompete is enforceable with certainty is 43 percentage points more likely to feel like their noncompete limits their future job options (186% of the sample mean) and 66 percentage points more likely to report their noncompete would be a factor in joining a competitor (159% of the sample mean) relative to an employee who does not believe their noncompete is enforceable.[42]

If believing that a noncompete is enforceable causes employees to forgo job opportunities (at least prospectively), an important question is whether these ex post consequences might lead at least some employees to negotiate over the terms of their noncompete or to seek other benefits in exchange for agreeing not to compete. That is, if employees who believe their noncompete is enforceable are more likely to see their noncompete as limiting their job opportunities in the future, do they negotiate in the hope of obtaining some compensating differential up front? Starr et al. (2021) find that only 10% of workers overall negotiate over the terms of their noncompete,[43] so large effects seem unlikely, unless most or many of these bargaining employees were to live in states that do not enforce noncompetes. In Figure 16, we show that, comparing observationally equivalent individuals with a noncompete, the likelihood that people report negotiating over their noncompete does not differ dramatically across states that do and do not enforce noncompetes.[44] Column (4) of Table 5 reports IV results for the effects of beliefs in noncompete enforceability on negotiation expectations. Consistent with Figure

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the law's content (otherwise, why an angry response?), such a mechanism may only operate in environments in which some employers engage in actively misleading their employees in equilibrium.

[42] Table OA7 explores the robustness of these relationships by exploiting answers to a series of questions about the importance of various factors in an employee's decision whether to move to a comparable competing company. Columns (1), (2), and (3) show that believing that a noncompete is enforceable increases the importance of the employee simply having a noncompete, the importance of the possibility their employer will sue to enforce the noncompete, and the importance of the likelihood that the court will enforce it. Columns (4), (5), and (6) examine how beliefs about noncompete enforceability change the relative importance of entering into a noncompete as compared to a range of employment amenities. In each specification, believing that a court would enforce a noncompete following litigation causes an employee to more heavily weight the importance of agreeing to a noncompete relative to job amenities such as compensation, lifestyle benefits, or opportunities for greater prestige or training.

[43] Rothstein and Starr (2022) find that employees with a noncompete do not appear more likely to bargain over wages, conditional on employee and employer characteristics, though they have relatively higher wages.

[44] Figure OA10 examines whether an information treatment might lead employees to update their estimate of the likelihood that they would negotiate in the future over noncompetes. While there is an enormous difference in levels between Figure 16 (which reflects actual reported negotiation behavior) and Figure OA10 (which reflects prospective negotiation behavior), the information treatment does not appear to differentially cause individuals to change their negotiation predictions relative to the control group. A likely reason that the mean levels of negotiation are different is that the second question asks about whether the employee *would* negotiate over a noncompete as opposed to whether those with a noncompete *actually* negotiated over their current noncompete.

16, we detect no evidence that believing noncompetes are enforceable causes employees to change their negotiating patterns—at least for those bound by noncompetes. This set of results calls into question freedom-of-contract arguments often made in favor of enforcing noncompetes—that applicants and employees are rational and reasonably sophisticated agents with the power to negotiate for compensating differentials.[45]

4.7 Beliefs about the Likelihood of a Lawsuit as a Mechanism

Whether and how such beliefs about the enforceability of noncompetes matter to an employee's behavior may depend in part on what the employee believes about the likelihood that their employer will actually sue them for violating their noncompete in the first place—whether or not a court would enforce the noncompete. Employers may sue an employee even when a noncompete is unenforceable simply to force the employee to defend at significant personal cost, and an employer who has an employee dead to rights for violating an enforceable noncompete may choose not to litigate. In other words, legal enforceability does not translate one-to-one to the costs and consequences that might follow from deviating from the terms of a noncompete—distinct beliefs about the practical likelihood of a lawsuit may be important, too. Furthermore, a noncompete may still matter even when an employee believes it to be unenforceable and *further* believes that, regardless, their employer would never attempt to litigate over it. For example, employees may experience moral or reputational costs for violating the provision's spirit. We are able to use our rich data to investigate these ideas.

We begin by assessing whether noncompetes appear to influence job mobility choices even when employees believe both that a noncompete is unenforceable *and* that, in any event, their employer will not cause a fuss by litigating the point. Figure 17 considers this question by categorizing employees based on whether they view their noncompete as enforceable and on whether employees perceive a lawsuit as likely (based on whether the reported likelihood of litigation is above or below 25%). We then cut the data by actual noncompete enforceability and further by whether a respondent receives information on the actual noncompete policies in their state.[46]

We uncover two strong patterns, both for those who do and do not receive information. First, individuals with a noncompete who believe that their noncompete is enforceable and that their employer is likely to sue them for breaching it are much more likely to see their noncompete as a factor in deciding whether to join a competitor (57%–78% depending on the level of actual enforceability)

[45] In contrast, column (5) of Table 5 shows that those who are not bound by a noncompete would be more likely to negotiate over a new noncompete when they believe it would be enforceable. This shift appears to be driven by the fact that those not bound by a noncompete report being less likely to negotiate when they receive information about noncompetes being unenforceable (Figure OA11). It is not clear ex ante why these answers differ from the noncompete sample in both direction and statistical significance. One possibility is that because these employees do not have a noncompete, they may be unfamiliar with the typical contracting process around noncompetes and therefore may make different assumptions about the costs and effectiveness of negotiation.

[46] As before, we include our basic controls and cluster standard errors at the state level.

relative to those who see neither possibility as very likely (5%–25%). Second, even when employees know that their noncompete is unenforceable in court and do not believe their employer is likely to sue them anyway if they depart, a non-negligible proportion of employees still view their noncompete as a factor in deciding whether to accept a competitor's offer: 12% among those who are informed about the law and 25% among those who do not receive information.[47] This evidence indicates that while beliefs about enforceability and the likelihood of an enforcement lawsuit can explain a substantial proportion of the variation in whether employees view their noncompete as a factor in deciding whether to accept a position with a competitor, other reasons likely remain important in their viewing a noncompete as an impediment. Two natural explanations, which we unfortunately cannot address further with our data, are the subjective disutility and the reputational costs of breaking a promise or otherwise upsetting a relational contract.

This joint analysis of beliefs about court enforcement and beliefs about employer litigation propensity is limited, however, because it treats the two as independent; it ignores the potential for beliefs about noncompete enforceability to *influence* beliefs about the likelihood of a lawsuit. It may be, for instance, believing that noncompetes are legally enforceable causes one to believe that their employer will sue them for violating one. We examine binned scatterplots in Figure OA12 relating beliefs about enforceability to beliefs about the likelihood of facing a lawsuit. The left and middle panels reveal an (unconditional) positive correlation between beliefs about noncompete enforceability and the likelihood of a lawsuit, both before and after the information experiment. The right panel, in turn, shows that this positive relationship holds within-individual, both for those who do and do not receive information. Because we randomly shock the former group's beliefs with information, we can interpret this positive relationship causally. More formally, in column (1) of Table 6, we use the same instrumental variables strategy we deploy in prior sections to examine how a change in beliefs about enforceability causally affects an employee's perception of the likelihood that their employer will sue them to enforce their noncompete. The results indicate that an employee who believes with certainty that their noncompete is enforceable will also believe that their employer is 41.1 percentage points (106% of the sample mean) more likely to take legal action relative to an employee who is certain noncompetes are unenforceable. Put another way, employees appear to assume that law at least partially determines employer litigation behavior.

Given that changes in an employee's beliefs about enforceability cause changes in beliefs about litigation risk—and that both seem to relate to whether a noncompete will be a factor in an employee's decision to transition to a competitor per Figure 17—we next explore to what extent beliefs about the

[47] We note that these percentages may be too low when we take into account the fact that answering a survey is not the same as breaking a promise made to coworkers with whom one has had a long relationship. The latter is likely to be more socially or morally costly than the former.

likelihood of a lawsuit mediate the relationship between beliefs about enforceability and mobility intentions. Specifically, we test whether the relationship between beliefs about enforceability and mobility is driven entirely, in part, or not at all by changes in an employee's beliefs about the possibility of being sued over their noncompete. Practically speaking, all this requires is that we examine models both with and without a post-experiment control for the perceived likelihood of a lawsuit.

First, we explore the robustness of our earlier information experiment results to the inclusion of controls for post-experiment beliefs about the likelihood of an employer lawsuit. We present our findings in columns (2) and (3) of Table 6. To reiterate our earlier results, we estimate that those who receive information on the lack of enforceability of their noncompetes are 25 percentage points less likely to report that their noncompete would be a factor in deciding to leave to work for a competitor. However, once we hold fixed an employee's post-experiment beliefs about the likelihood of a lawsuit in column (3), the estimate falls to 15 percentage points. Thus, changes in employee beliefs about litigation risk account for 40.5% ((0.252 – 0.150)/0.252) of the overall effect of information about unenforceable noncompetes. Our analysis also indicates that beliefs about the threat of a lawsuit mediate the effect of information in medium and high enforceability states to a similar degree. We find that the mere inclusion of the perceived likelihood of a lawsuit causes the interaction between information in medium enforceability states to fall from 0.164 to 0.071, while the interaction between high enforceability and information falls from 0.256 to 0.171.

We perform one final test to assess how strongly the perceived threat of a lawsuit mediates the relationship between beliefs about enforceability and behavioral outcomes. Columns (4)–(7) examine OLS and 2SLS models, comparing whether beliefs about noncompete enforceability relate to whether a noncompete would be a factor in accepting an offer with a competitor. The OLS specifications suggest that 32.5% of the overall relationship between beliefs and our prospective mobility measure can be explained by how much employee beliefs about enforceability drive changes in beliefs about litigation risk (i.e., the effect of P(Enforce) falls from 0.578 to 0.390 when controlling for P(Lawsuit)). Columns (6) and (7) report the same analysis, except in those specifications, we use the instrumented measure for post-experiment beliefs.[48] A similar pattern arises, with the likelihood of a lawsuit accounting for approximately 32.8% of the relationship between beliefs about the law and the extent to which noncompetes matter for taking a competing job.

Taken together, this section documents three facts regarding how beliefs about a lawsuit relate to beliefs about enforceability and mobility choices. First, a boost in one's beliefs that a noncompete is

[48] To perform the mediation analysis in column (7), we follow the Instrumental Variable mediation approach in equations (10) and (11) of Dippel et al. (2020). As an alternative, we construct the 2SLS estimate in column (7) of Table 6 "by hand" (i.e., taking the predicted values from the first stage and including them in the second stage manually), so that we can include the beliefs about the likelihood in the second stage but not the first stage With this approach, the coefficient on post-experiment beliefs falls 18%.

enforceable also increases one's beliefs that their employer will sue in response to a violation of the noncompete. Second, perceptions about the likelihood of a lawsuit mediate the relationship between beliefs about enforceability and mobility outcomes, explaining roughly 20–30% of the overall effect. Third, a nontrivial minority (12–25%) of those who see it as unlikely that their employer will sue them and *also* see it as unlikely that a court will enforce their noncompete still treat their noncompete as a factor in whether to take a job with a competitor. This last result suggests that being a party to a noncompete can still have chilling effects on an employee's mobility decisions, perhaps for reputational or relational reasons, even when the employee assumes a court would not uphold the noncompete and, in any event, the employer would never seek to enforce it.

5. DISCUSSION AND CONCLUSION

In this study, we examine the beliefs employees possess about the enforceability of noncompetes, the accuracy of those beliefs, and how those beliefs influence behavior. We find that employees of all education levels tend to believe that noncompetes are enforceable even when they are not, a result that adds to existing work about mistaken beliefs about the law. We study mechanisms that may support persistently mistaken beliefs by circumventing normal pathways for correction. First, employees who are unaware that their noncompete is unenforceable may opt out of important "corrective" labor market activity by searching for jobs at competitors less often. We also build on the information shrouding literature, which emphasizes that firms can benefit from hiding certain pricing information from consumers, to show that recruiting employers may counterintuitively have reasons to keep applicants in the dark about the law. Finally, employers can (and often do) remind their employees of their noncompete—especially those with unenforceable noncompetes—to render them more likely to (mistakenly) believe their noncompete is enforceable.

We also show that an information treatment, which roughly simulates an educational campaign, can cause employees to update their beliefs—especially employees whose noncompetes are unenforceable. After receiving information, employees with unenforceable noncompetes report that their noncompete would be less of a factor in their choice whether to accept employment with a competitor than they indicate under mistaken beliefs of enforceability. However, employees as a group do not *fully* adjust their mobility intentions (i.e., they do not report that their noncompete would no longer be a factor whatsoever in leaving for a competitor). In fact, a nontrivial fraction of employees who see their noncompetes as unenforceable and who view a lawsuit as unlikely continue to consider their noncompete to be a factor in deciding whether to take a job offer at a competitor. This result suggests that moral, reputational, and perhaps financial costs remain for violating even entirely unenforceable contract provisions. We also show that stronger beliefs in enforceability cause employees to be more concerned about their noncompete when considering an offer from a competitor, and we present evidence that this effect may be due in part to perceptions that a lawsuit is more likely. At the same time, noncompete-bound employees appear no more likely to negotiate over the terms of their noncompete or for other benefits in exchange for agreeing not to compete when they believe their noncompete is enforceable.

Our study has several limitations. First, because we cannot follow employees over time, we can only estimate very short-term elasticities. We hope future work will address this shortcoming by collecting and analyzing the long-term outcomes of similar information experiments. Second, our experiment is convoluted in its design and specific to the context of a survey. To the extent that the medium and the specifics of the language itself were responsible for our findings (or lack thereof), our results may not extend to other types of educational campaigns (Armantier et al. 2016, Hertwig et al. 2014). Third, our study is one about *employee* beliefs. We know little about what employers know about the law and how their beliefs matter (or do not) for their choices. Finally, while we took great pains to clean and weight our data appropriately, our analysis nevertheless builds on a selected sample. Future work should examine these issues using alternative samples.

Our empirical results contribute to the important and growing literature on postemployment restrictive covenants. This body of work relies mostly on the legal enforceability of noncompetes, exploiting bans or other smaller changes in noncompete laws at the state level (Marx et al. 2009, Garmaise 2009, Balasubramanian et al. 2022, Lipsitz and Starr 2022, Johnson et al. 2020, Jeffers 2020). One goal of this article is to emphasize that researchers pay too little attention to the impact of *unenforceable* noncompetes and the role of individual beliefs about the law (Starr et al. 2020). Our work stresses—with respect to noncompete research as well as all research examining state policy shocks without accounting for underlying beliefs—that voiding contracts in court ex post may have little practical effect if employees continue to believe that anything that appears in a contract must be enforceable (Chetty 2015). As a result, studies examining bans on noncompetes (Balasubramanian et al. 2022, Marx et al. 2009, Marx et al. 2015, Lipsitz and Starr 2022) that assume such bans end the use of noncompetes may understate the effect of noncompetes since (a) employers may still use noncompetes and (b) employees may still view these noncompetes as enforceable.

As a result, policymakers and antitrust agencies (Posner 2020) concerned about the potential ill effects of (unenforceable) noncompetes may need to consider reforms that induce employers to reduce the *use* of noncompetes in the first place as opposed to policies that limit their enforceability in court or simply inform employees that they are unenforceable (since at least some employees seem likely to continue to adhere to them). Two natural options include statutory penalties for inappropriate noncompete use or requiring employers to pay former employees during the prohibition period (known as garden leave). Oregon, for example, adopted garden leave in 2008 (see Lipsitz and Starr 2022) and Virginia's recent noncompete law (Va. Code Ann. § 40.1-28.7:8) requires employers to pay $10,000 for each illegal noncompete. Both of these policies are not without their challenges, however—employers may skirt paying garden leave, and it may be difficult to identify employers using unenforceable noncompetes. A third approach, recently highlighted in California, is for state bars to view using unenforceable contractual clauses as unethical, which may encourage lawyers to actively eliminate such restrictions (Gerstein and Shearer 2019). The effectiveness of each of these approaches in deterring the use of unenforceable provisions is an important avenue for future research.

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Tables

Table 1. Summary Statistics By Actual Enforceability

	(1)	(2)	(3)	(4)	(5)	(6)
	No Enforceability		Medium Enforceability		High Enforceability	
States	Arizona (Physicians), California, Colorado (Non-Professionals, Physicians), Delaware (Physicians), Illinois (Physicians), Massachusetts (Physicians), Tennessee (Physicians), North Dakota, Oklahoma, Texas (Physicians)		Arizona, Arkansas, Indiana, Louisiana, Maryland, Minnesota, Montana, Nebraska, New Mexico, North Carolina, Oregon, Pennsylvania, Rhode Island, South Carolina, Texas, Utah, Vermont, Virginia, West Virginia, Washington, Wisconsin, Wyoming		Alabama, Alaska, Colorado (Professionals), Connecticut, Delaware, Florida, Georgia, Hawaii, Idaho, Illinois, Iowa, Kansas, Kentucky, Maine, Massachusetts, Michigan, Mississippi, Missouri, Nevada, New Hampshire, New Jersey, New York, Ohio, South Dakota, Tennessee	
Sample	Full Sample	Noncompete Sample	Full Sample	Noncompete Sample	Full Sample	Noncompete Sample
Observations	1,484	205	4,376	685	5,645	857
Age	40.51	42.43	40.11	39.33	40.48	40.45
Hours Worked Per Week	39.25	42.44	37.24	40.61	37.34	41.50
Weeks Worked Per Year	48.79	49.84	47.90	47.46	47.41	48.65
$\mathbb{1}$(Male)	0.56	0.72	0.52	0.55	0.52	0.56
$\mathbb{1}$(Multi-Unit Employer)	0.64	0.78	0.64	0.77	0.62	0.67
$\mathbb{1}$(Employer > 1K Employees)	0.39	0.49	0.38	0.45	0.37	0.40
$\mathbb{1}$(Highest Degree is $\geq$ BA)	0.44	0.68	0.27	0.47	0.30	0.52
Pre-Experiment P(Enforce)	0.43	0.46	0.42	0.40	0.43	0.44

Note. We present sample means for each sample, cut by actual noncompete enforceability.

Table 2. Beliefs about the Locus of Noncompete Enforcement Policy

	Overall	Education Level			Agreed to Noncompete?		
		<BA	BA	>BA	Yes	No	Maybe
Don't know	0.44	0.48	0.39	0.32	0.33	0.45	0.52
Citywide	0.05	0.05	0.05	0.07	0.05	0.05	0.06
Countywide	0.05	0.04	0.05	0.07	0.06	0.04	0.04
Nationally	0.23	0.22	0.24	0.23	0.26	0.23	0.19
Statewide	0.24	0.21	0.27	0.32	0.30	0.23	0.19
Unweighted Observations	9,460	4,116	3,717	1,627	1,747	6,344	1,369

Note. Survey Question: "Non-competition policy is determined at what level?" The table displays percentages that sum to 100% within each column. Education level refers to employee's highest educational degree (BA = bachelor's degree).

Table 3. Beliefs about Noncompete Enforceability in Employee's State

Panel A. "Are noncompetes enforceable in your state?"

	Overall	Education Levels			Agreed to Noncompete?		
		<BA	BA	>BA	Yes	No	Maybe
Don't know	0.37	0.38	0.33	0.34	0.21	0.36	0.54
No	0.05	0.05	0.04	0.07	0.04	0.04	0.09
Yes	0.59	0.57	0.63	0.60	0.76	0.61	0.37

Panel B. Accuracy of Beliefs

	Overall	Education Levels			Agreed to Noncompete?		
		<BA	BA	>BA	Yes	No	Maybe
Uninformed	0.37	0.38	0.33	0.34	0.21	0.36	0.54
Misinformed	0.11	0.10	0.13	0.15	0.13	0.10	0.12
Informed	0.53	0.52	0.54	0.52	0.67	0.54	0.34
Unweighted Observations	9,460	4,116	3,717	1,627	1,747	6,344	1,369

Note. The table displays percentages that sum to 100% within each column. Education level refers to employee's highest educational degree. Uninformed includes those respondents who do not know, while misinformed includes those who select the wrong policy. We consider California, Oklahoma, and North Dakota to be states that do not enforce noncompetes. All others enforce them (to some degree).

Table 4. Balance Test

Panel A: Full Sample of Individuals with a Noncompete	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	No Info	Info	*p*-value						
Age	41.87	41.47	0.51						
Hours Worked Per Week	42.16	42.59	0.38						
Weeks Worked Per Year	48.63	48.91	0.33						
$\mathbb{1}$(Male)	0.53	0.58	0.05						
$\mathbb{1}$(Multi-Unit Employer)	0.74	0.72	0.21						
$\mathbb{1}$(Employer > 1K Employees)	0.46	0.43	0.32						
$\mathbb{1}$(Highest Degree is BA)	0.68	0.67	0.90						
Pre-Experiment P(Enforce)	0.44	0.43	0.55						

Panel B: Cut by Actual Enforceability

	No Enforceability			Medium Enforceability			High Enforceability		
	No Info	Info	*p*-value	No Info	Info	*p*-value	No Info	Info	*p*-value
Age	41.85	41.10	0.67	41.50	41.14	0.70	42.17	41.83	0.69
Hours Worked Per Week	41.58	41.67	0.96	42.64	42.35	0.71	41.90	43.02	0.12
Weeks Worked Per Year	48.21	49.42	0.18	48.65	48.79	0.76	48.71	48.88	0.69
$\mathbb{1}$(Male)	0.58	0.59	0.94	0.49	0.56	0.07	0.55	0.58	0.31
$\mathbb{1}$(Multi-Unit Employer)	0.76	0.77	0.82	0.77	0.74	0.34	0.72	0.69	0.31
$\mathbb{1}$(Employer > 1K Employees)	0.43	0.45	0.79	0.49	0.46	0.36	0.43	0.41	0.48
$\mathbb{1}$(Highest Degree is ≥ BA)	0.73	0.74	0.85	0.65	0.64	0.66	0.68	0.69	0.95
Pre-Experiment P(Enforce)	0.40	0.44	0.47	0.42	0.40	0.64	0.48	0.46	0.41

Note. Our sample is limited to 1,747 individuals who have a noncompete. The *p*-value column reports the results of a test of the null hypothesis of no mean difference between the information and no-information groups. We construct these unweighted comparisons using Stata's "orth_out" command.

Table 5. Instrumenting for Post-Experiment Enforceability Beliefs

	(1)	(2)	(3)	(4)	(5)
Model: 2SLS	𝟙(Current Noncompete Limits Future Job Options)	𝟙(Noncompete Is a Factor in Joining Competitor)	𝟙(Noncompete Is a Factor in Starting Competitor)	𝟙(Employee Would Negotiate Over Noncompete)	
Instrumented P(Enforce)	0.434**	0.659**	0.577**	-0.121	0.286**
	(0.163)	(0.127)	(0.121)	(0.136)	(0.081)
Sample	Noncompete	Noncompete	Noncompete	Noncompete	No Noncompete
Controls	Yes	Yes	Yes	Yes	Yes
Pre-Experiment Dependent Variable	Yes	Yes	Yes	Yes	No
Observations	1,747	1,747	1,747	1,709	9,758
F-Stat	54.29	51.49	50.25	51.64	51.86
Mean of Dependent Variable	0.233	0.415	0.523	0.603	0.744

Note. We report robust standard errors in parentheses, clustered at the state level. Our sample for columns (1)–(4) is limited to individuals with a noncompete, while column (5) focuses on those without a noncompete. All models except for column (5) include main effects of the pre-experiment measure of the particular dependent variable, which we measure a second time after the experiment (both for those who do and do not receive enforceability information). The instrument for post-experiment beliefs is a three-way interaction of an indicator for pre-experiment beliefs about enforceability being greater than 50%, indicators for living in a no, medium, or high enforceability state, and whether the individual randomly receives information. Controls include pre-experiment beliefs about enforceability, indicators for enforceability (no, medium, high) interacted with an indicator for pre-experiment enforceability beliefs being greater than 50% (as in the instrument), and other demographics we describe in text. The F-Stat reports the Kleibergen-Paap Wald rk F statistic, which tests for weak instruments with clustered standard errors.
** $p < .01$.

Table 6. The Mediating Effect of the Likelihood of Lawsuit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	P(Employer Would Sue Over Noncompete if Violated)	𝟙(Noncompete Is a Factor in Joining Competitor)					
Post-Experiment P(Enforce)	0.411**			0.578**	0.390**	0.659**	0.443*
	(0.087)			(0.036)	(0.051)	(0.127)	(0.191)
Post-Experiment P(Lawsuit)			0.570**		0.287**		-0.363
			(0.056)		(0.071)		(0.389)
𝟙(Information)		-0.252**	-0.150*				
		(0.064)	(0.056)				
𝟙(Medium Enforceability)		-0.050	-0.051				
		(0.079)	(0.071)				
𝟙(High Enforceability)		-0.083	-0.105+				
		(0.065)	(0.057)				
𝟙(Medium Enforceability) × 𝟙(Information)		0.164*	0.071				
		(0.077)	(0.072)				
𝟙(High Enforceability) × 𝟙(Information)		0.256**	0.171*				
		(0.081)	(0.073)				
Model	2SLS	OLS	OLS	OLS	OLS	2SLS	2SLS
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,747	1,747	1,747	1,747	1,747	1,747	1,747
F-Stat	42.67					51.49	
Mean of Dependent Variable	0.389	0.415	0.415	0.415	0.415	0.415	0.415
% of Main Effect Driven by P(Lawsuit)			40.5		32.5		32.8

Note. We report robust standard errors in parentheses, clustered at the state level. Our sample is limited to individuals with a noncompete. The instrument for post-experiment beliefs is a three-way interaction of an indicator for pre-experiment beliefs about enforceability being greater than 50%, an indicator for living in a no, medium, or high enforceability state, and whether the individual randomly receives information. Controls include pre-experiment beliefs about enforceability, indicators for enforceability (no, medium, high) interacted with an indicator for pre-experiment enforceability beliefs greater than 50% (as in the instrument), and other demographics we describe in text. The F-Stat reports the Kleibergen-Paap Wald rk F statistic, which tests for weak instruments with clustered standard errors. For column (7), we apply the IV Mediation analysis recommended by Dippel et al. (2020).

$^{+}p < .10$.
$^{*}p < .05$.
$^{**}p < .01$.

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Figures

Figure 1. Accuracy of noncompete enforceability beliefs by actual enforceability

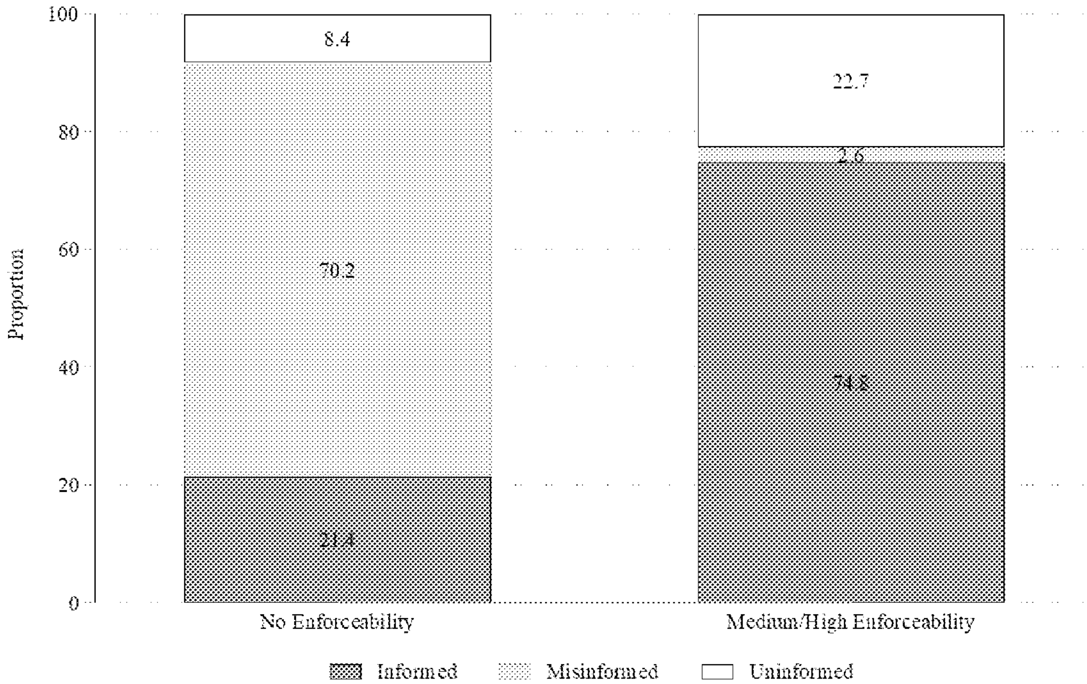

Figure 2. Accuracy of noncompete enforceability beliefs
by actual enforceability and education

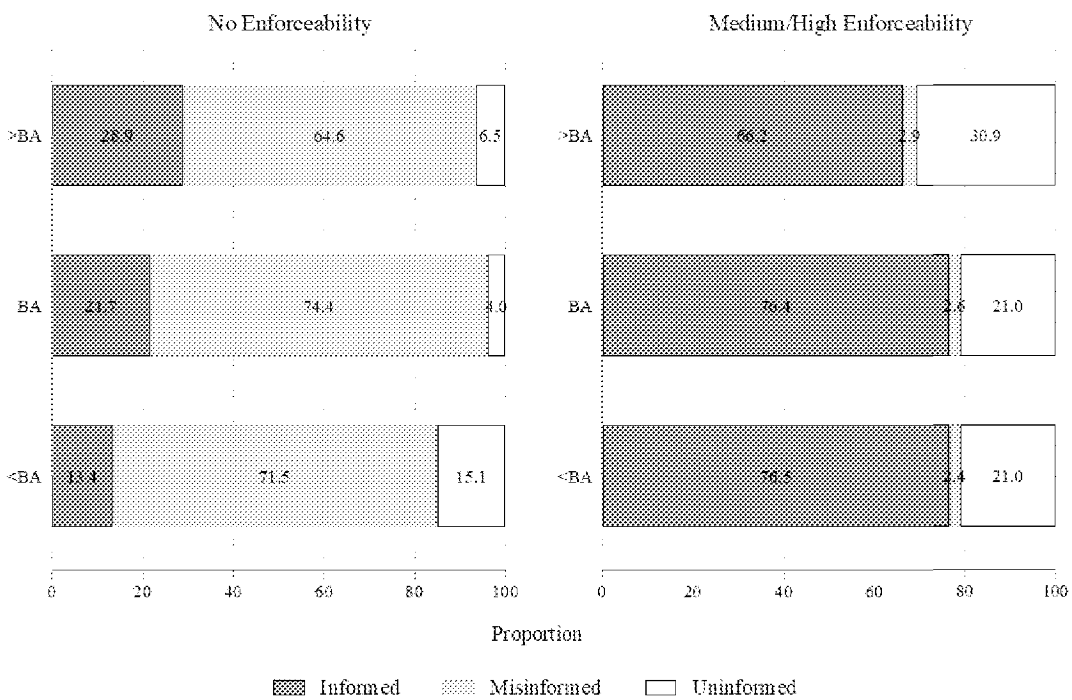

Figure 3. Categorical and continuous beliefs about noncompete enforceability

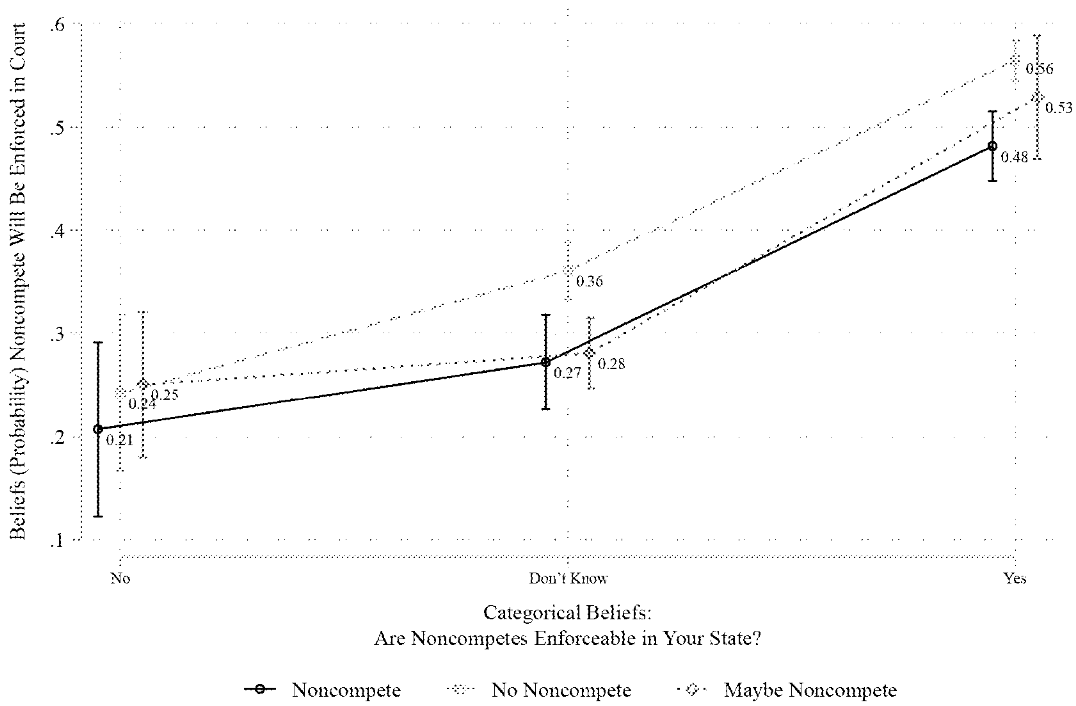

Figure 4. Noncompete enforceability beliefs by actual enforceability and noncompete status

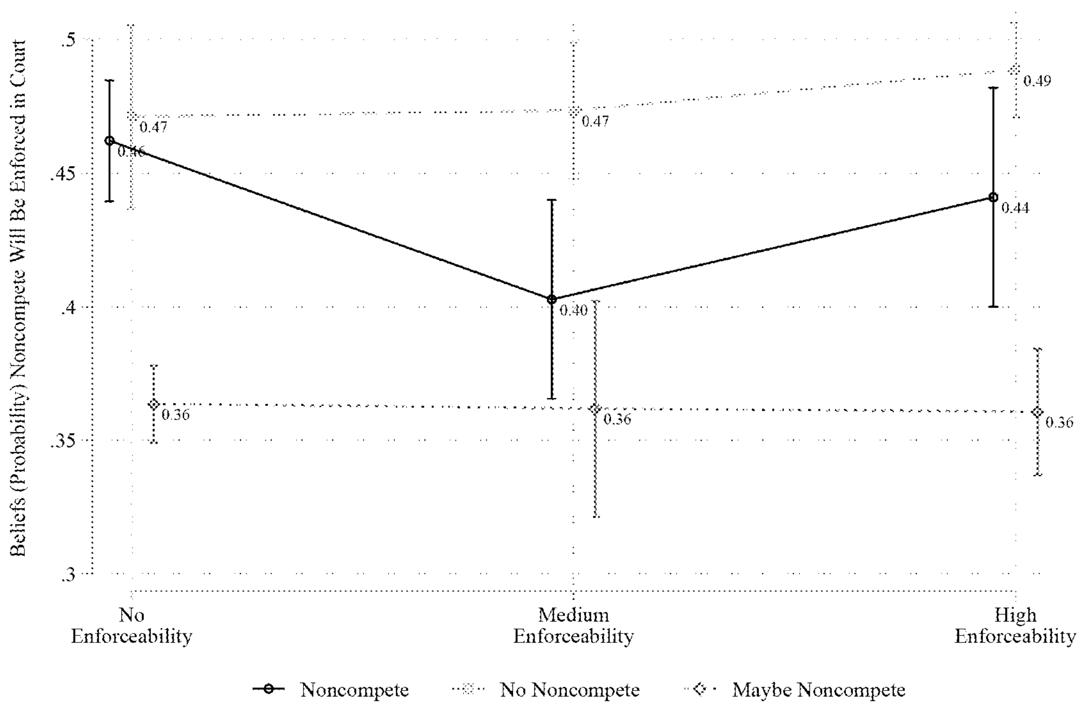

Figure 5. Noncompete enforceability beliefs held by individuals with a noncompete by actual enforceability and education

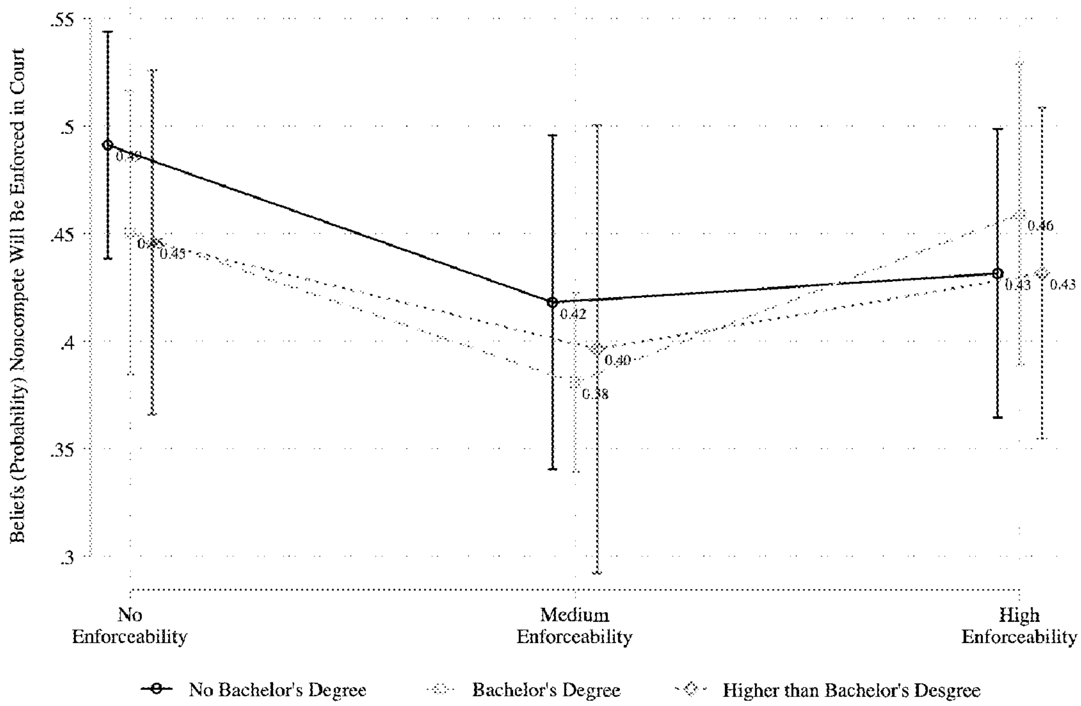

Figure 6. Search effort toward competitors and noncompete enforceability beliefs

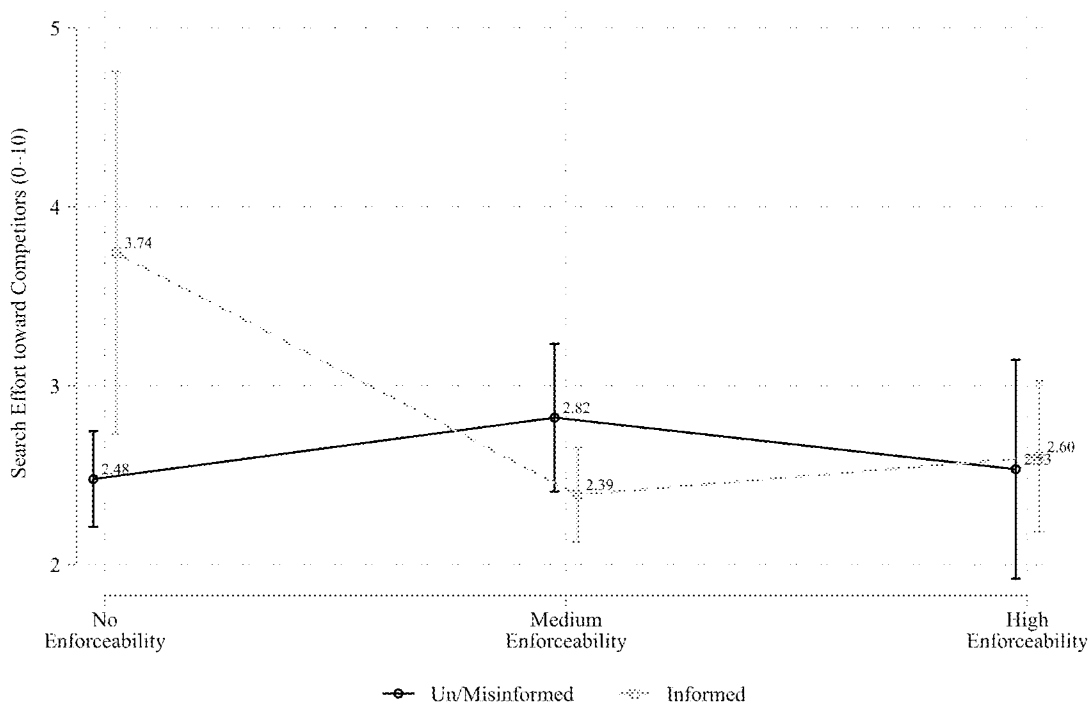

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Figure 7. Noncompete enforceability beliefs by actual enforceability and competitor-offer receipt

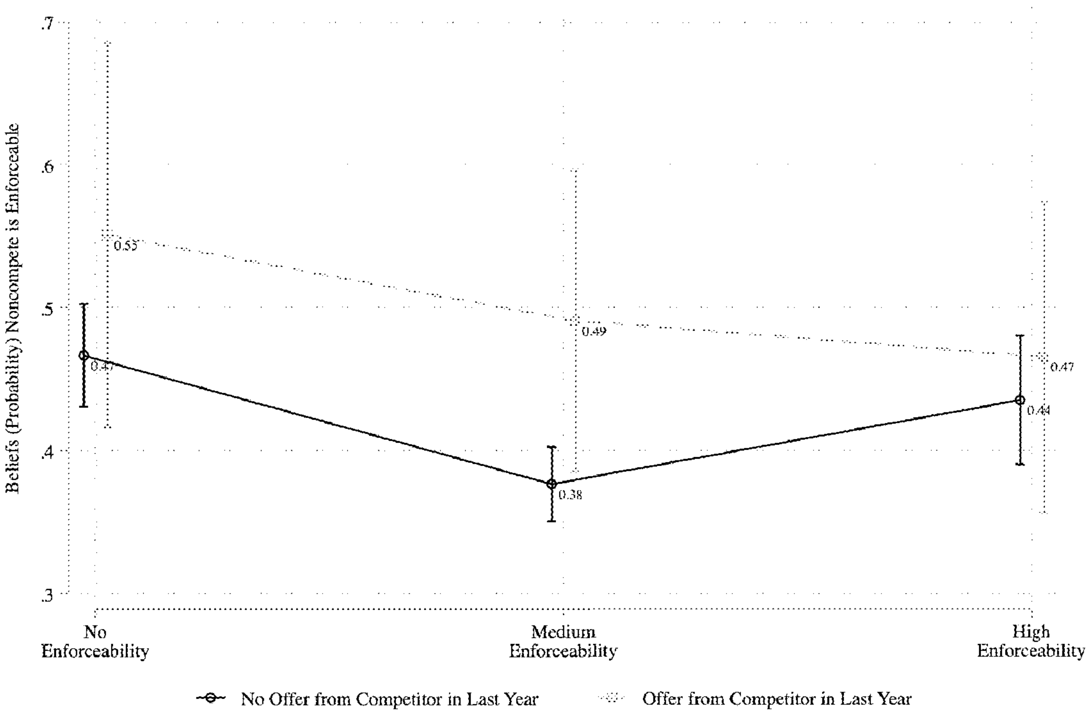


Figure 8. Probability employer reminded employee about noncompete by actual enforceability

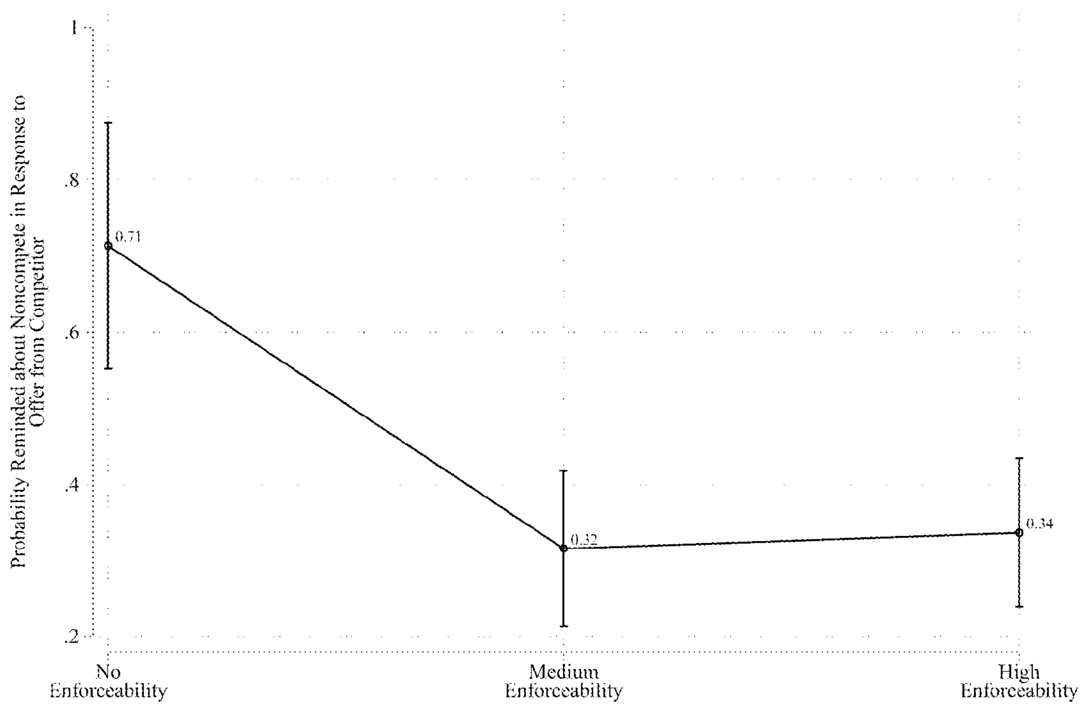


Figure 9. Reminders and beliefs about noncompete enforceability

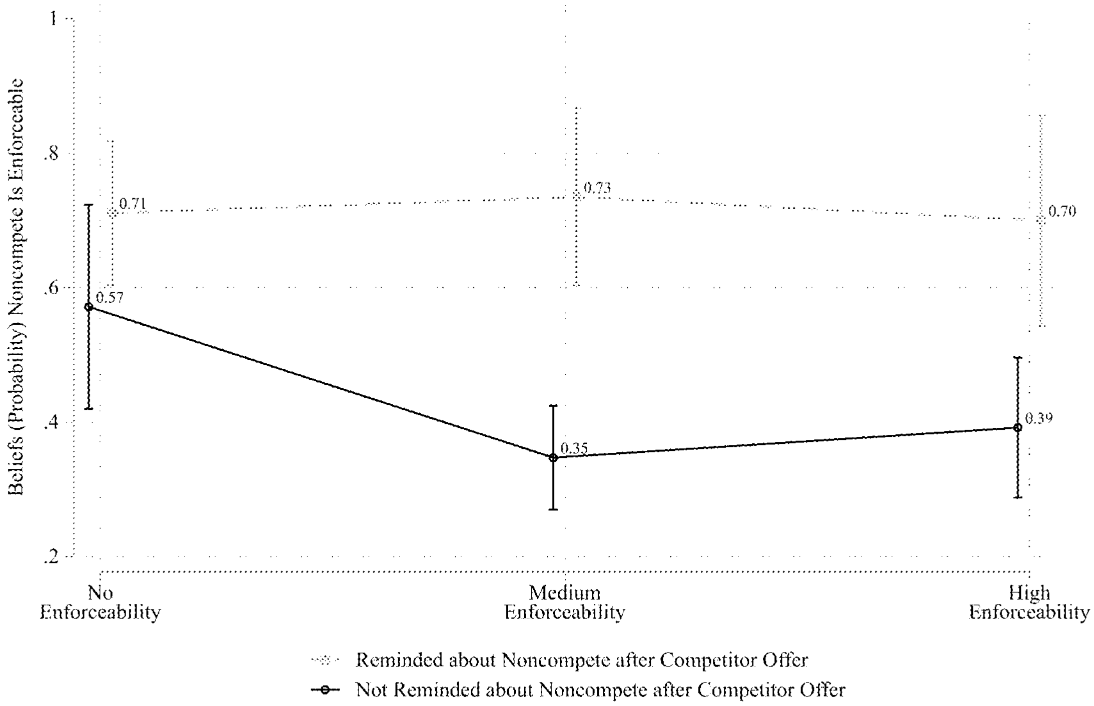


Figure 10. Distribution of noncompete enforceability beliefs before and after experiment

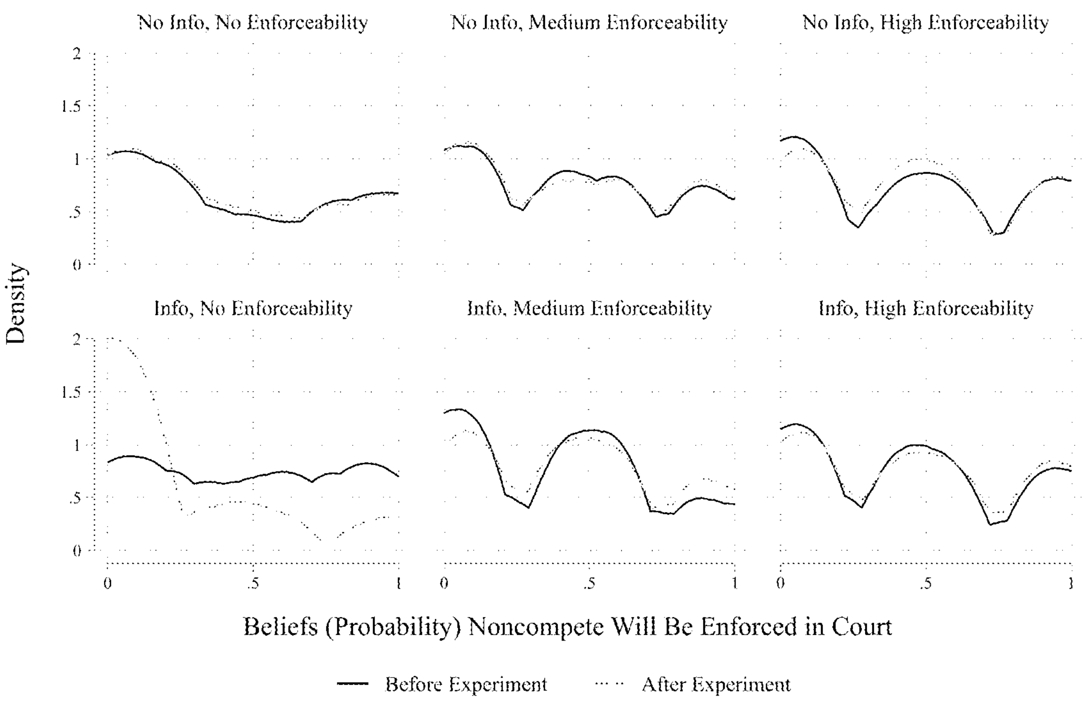


Figure 11. Average post-experiment beliefs by actual enforceability and treatment status

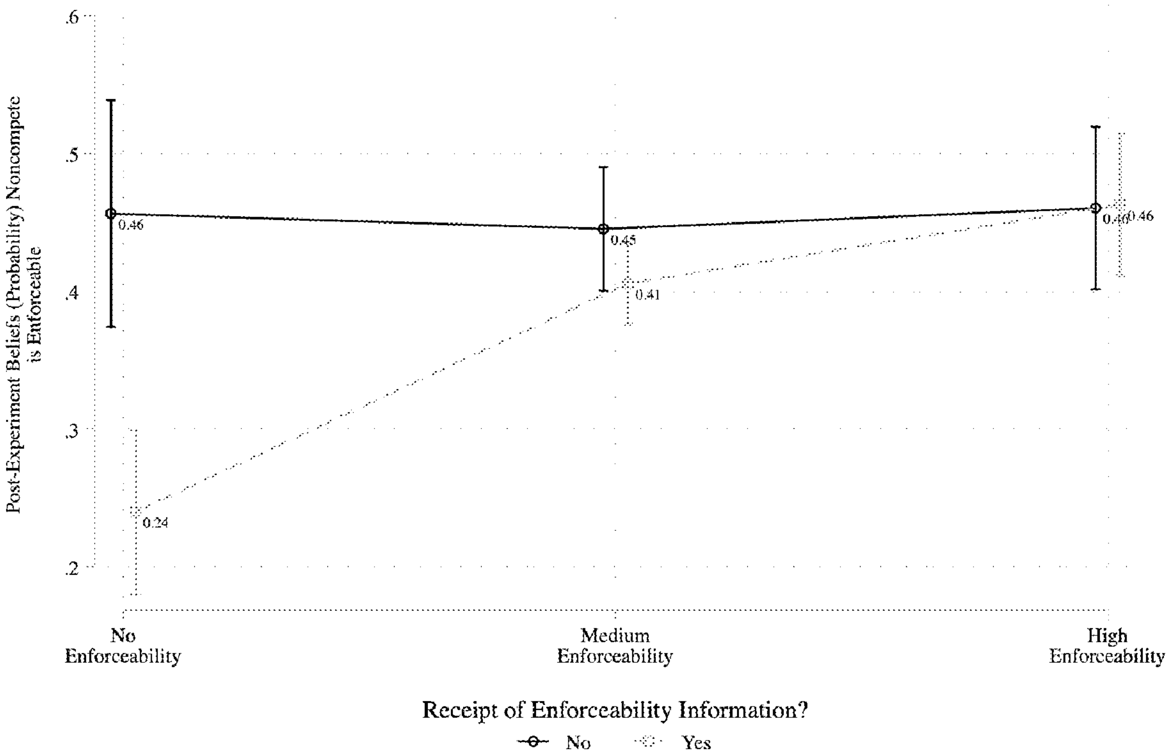


Figure 12. Relationship between pre-experiment and post-experiment beliefs

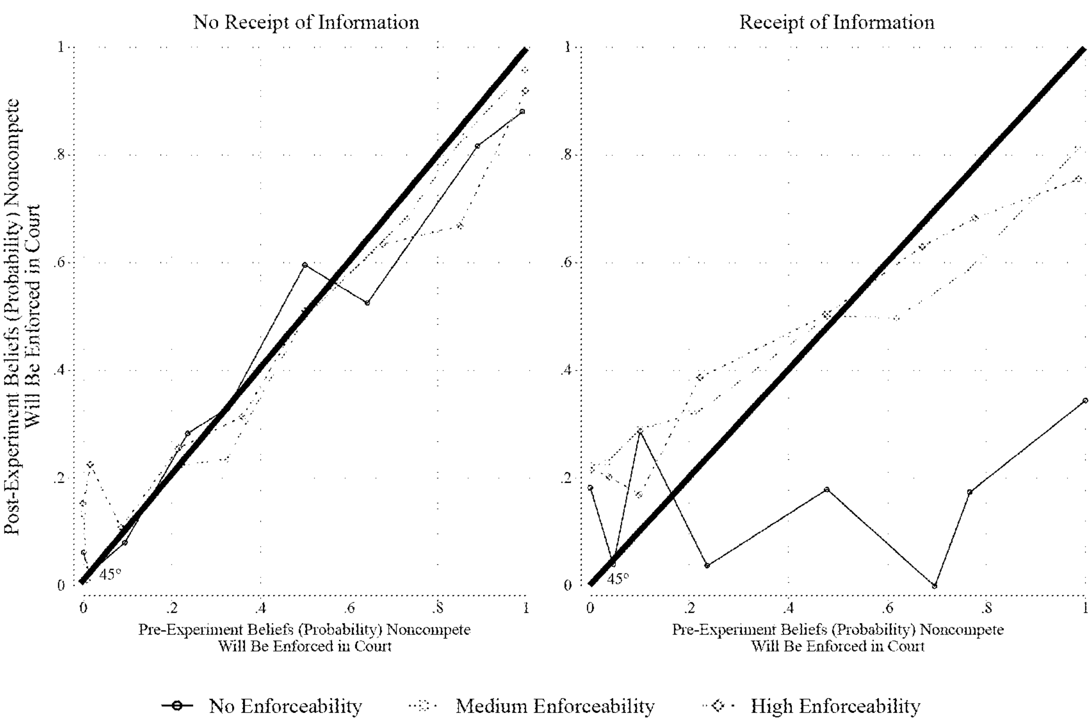


Figure 13. Heterogeneity in post-experiment beliefs and pre-experiment beliefs among employees with a noncompete

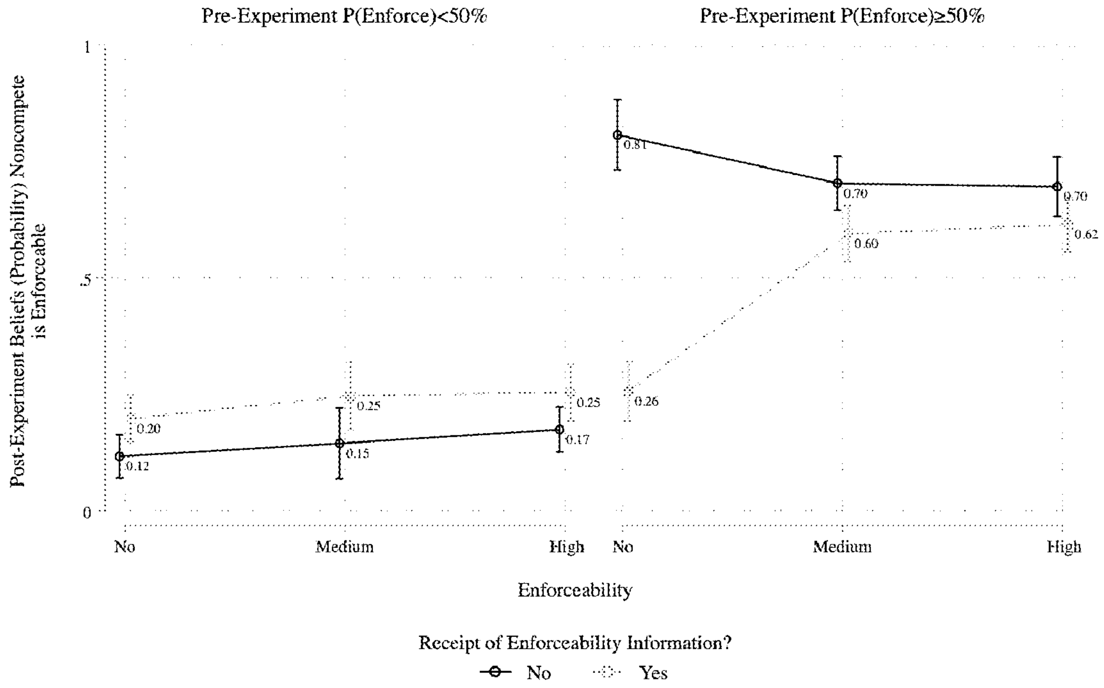


Figure 14. Noncompete as a factor in leaving by noncompete enforceability and treatment status

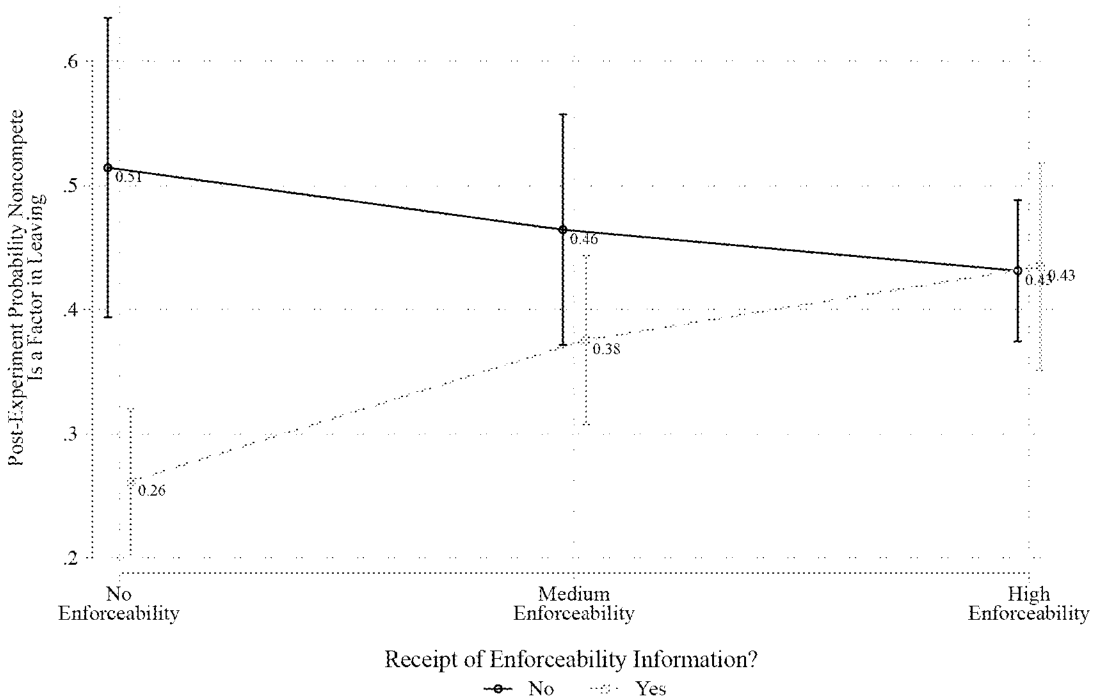


Figure 15. Post-experiment heterogeneity in noncompete as a factor in leaving by pre-experiment answer

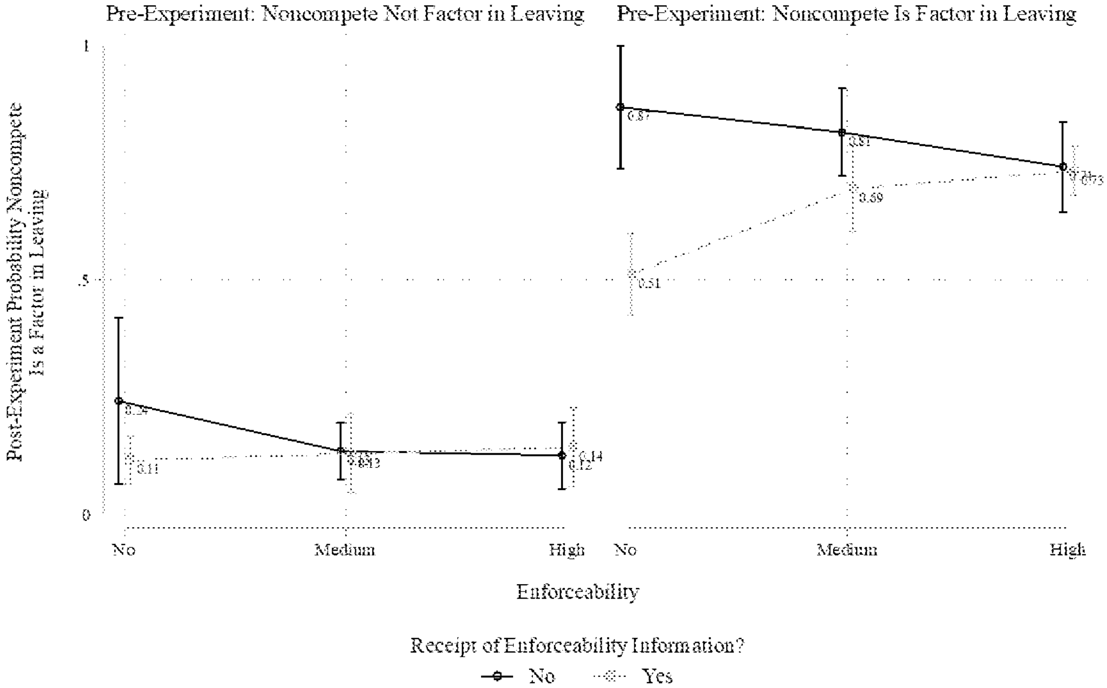


Figure 16. Negotiation over noncompetes and noncompete enforceability among employees with a noncompete

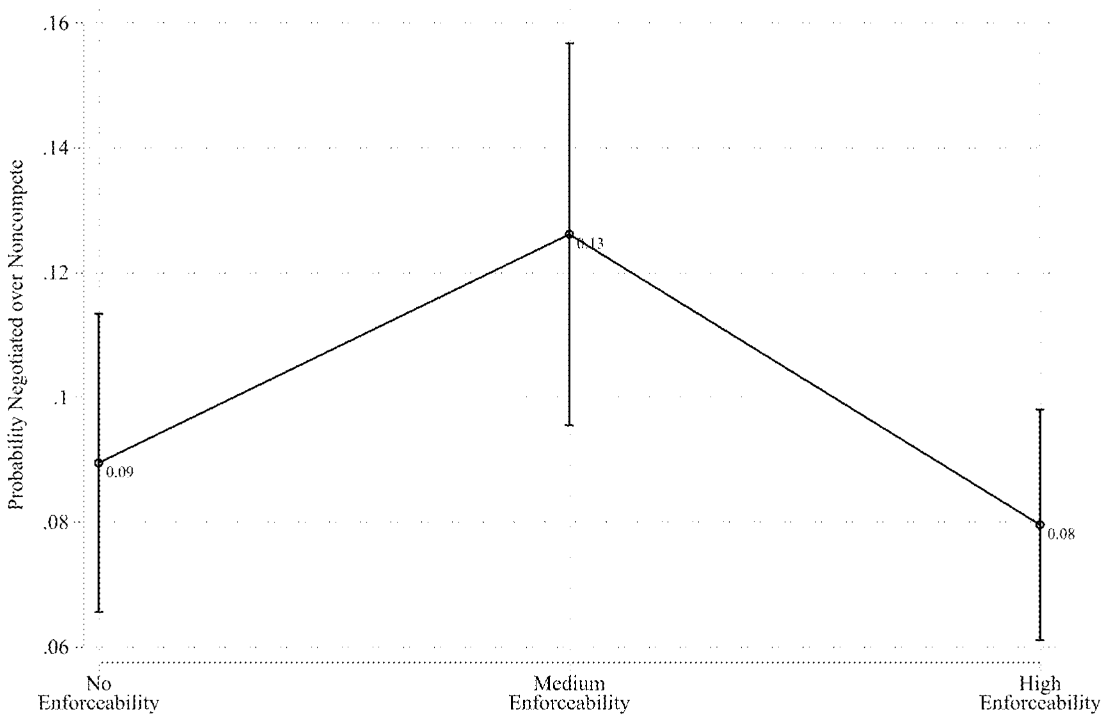
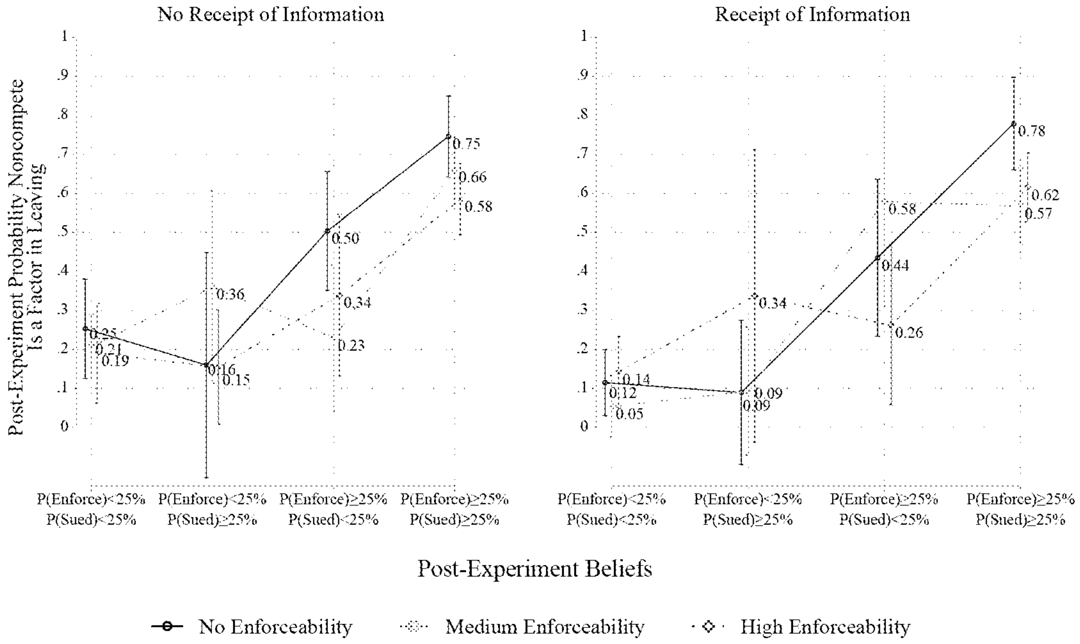


Figure 17. Noncompete as a factor in leaving by beliefs about enforceability and likelihood of lawsuit



Online Appendix A. Additional Figures and Tables

Table OA1. Noncompete Policies by State

Score		*Panel A. Handling of Overbroad Covenants*
1	Rewrite unreasonably overbroad noncompete terms to make the terms reasonable and enforce the revised noncompete against the employee	Alabama, Alaska, Colorado, Connecticut, Delaware, DC, Florida, Georgia, Hawaii, Idaho, Illinois, Iowa, Kansas, Kentucky, Maine, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Nevada, New Hampshire, New Jersey, New York, Ohio, Oregon, Pennsylvania, South Dakota, Tennessee, Texas, Washington, West Virginia, Wyoming
0.5	Remove unreasonably overbroad terms from a noncompete contract but enforce the rest of the provision	Arizona, Indiana, Louisiana, Maryland, Montana, North Carolina, Rhode Island
0	Refuse to enforce a noncompete against an employee if *any* part of the contractual provision is unreasonably overbroad	Arkansas, Nebraska, South Carolina, Virginia, Wisconsin
		Panel B. Enforce if Employee is Terminated Without Cause?
1	Enforce a noncompete against an employee even when the employee is terminated from their job without cause	Alabama, Connecticut, Delaware, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Louisiana, Maine, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, New Jersey, New York, North Carolina, Ohio, Pennsylvania, South Dakota, Texas, Utah, Vermont, Virginia, Washington, Wyoming
0	Refuse to enforce a noncompetes against an employee unless the employee voluntarily leaves their job or is terminated without cause	DC, Maryland, Montana
		Panel C. Enforcement Dependent on Consideration?
1	Enforce a noncompete against an employee even if the employee *only* received continued employment in exchange for agreeing to the noncompete	Alabama, Arizona, Arkansas, Colorado, Connecticut, Delaware, DC, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Mississippi, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, Ohio, South Dakota, Tennessee, Utah, Vermont
0	Refuse to enforce a noncompete against an employee unless the employee is given additional consideration (such as additional compensation, training, or other	Minnesota, Montana, North Carolina, Oregon, Pennsylvania, South Carolina, Texas, Washington, West Virginia, Wisconsin, Wyoming

	benefits) *beyond* continued employment in exchange for agreeing to the noncompete	
0	Refuse to enforce a noncompete against an employee if the employer did not notify the employee at least 14 days before the start of employment that the employer would request the noncompete	Oregon
		Panel D. Exemptions
1	Enforce a noncompete against an employee *only* if the employee is an executive or management-level employee or related professional staff	Colorado
0	Refuse to enforce (or be very unlikely to enforce) a noncompete against an employee who is a physician	Arizona, Colorado, Delaware, Illinois, Massachusetts, Tennessee, Texas
0	Refuse to enforce a noncompete against an employee who leaves to join or start a competing business, regardless of the circumstances	California, North Dakota
0	Refuse to enforce a noncompete against an employee who leaves to join or start a competing business but restrict the ability of the employee to directly solicit clients from their former employer	Oklahoma

Note. We report the actual language we use in the experimental treatment in Figure OA6. We derive this classification from Beck (2014). See Online Appendix C for more details. The overall measure of enforceability adds each score for each state and adds an additional one (1) point for states that enforce noncompetes under any circumstances. As a result, the maximum score a state can receive is four (4). We normalize this measure by dividing by the maximum score for each state, such that nonenforcing states (or nonenforcing state-occupation combinations) receive a score of zero (0) and states that robustly enforce noncompetes receive a score of one (1).

Table OA2. Enforceability Beliefs by Categorical Beliefs, Noncompete Status, and Education

Dependent Variable: Probability Noncompete Enforced	(1) Categorical Beliefs	(2)	(3) Noncompete Status	(4)	(5) Education	(6)
Constant	0.207**	0.682	0.462**	0.456*	0.491**	0.792
	(0.042)	(0.592)	(0.011)	(0.201)	(0.026)	(0.569)
𝟙(Don't Know if Noncompete Enforceable)	0.065	0.082*				
	(0.043)	(0.033)				
𝟙(Believe Noncompete Is Enforceable)	0.274**	0.296**				
	(0.048)	(0.032)				
𝟙(Medium Enforceability)			-0.059**	-0.079**	-0.073	-0.077
			(0.020)	(0.023)	(0.052)	(0.047)
𝟙(High Enforceability)			-0.021	-0.038	-0.060	-0.057
			(0.027)	(0.029)	(0.042)	(0.046)
𝟙(No Noncompete)			0.009	0.008		
			(0.018)	(0.021)		
𝟙(Maybe Noncompete)			-0.099**	-0.107**		
			(0.014)	(0.019)		
𝟙(Medium Enforceability) × 𝟙(No Noncompete)			0.062*	0.074*		
			(0.030)	(0.029)		
𝟙(Medium Enforceability) × 𝟙(Maybe Noncompete)			0.058+	0.070*		
			(0.031)	(0.028)		
𝟙(High Enforceability) × 𝟙(No Noncompete)			0.039	0.048		
			(0.031)	(0.030)		
𝟙(High Enforceability) × 𝟙(Maybe Noncompete)			0.018	0.028		
			(0.031)	(0.030)		
𝟙(Bachelor's Degree)		-0.019		-0.028**	-0.041	-0.035
		(0.025)		(0.010)	(0.049)	(0.053)
𝟙(Above Bachelor's Degree)		-0.010		-0.067**	-0.045	-0.045
		(0.029)		(0.013)	(0.049)	(0.046)
𝟙(Medium Enforceability) × 𝟙(Bachelor's)					0.003	-0.026
					(0.069)	(0.062)
𝟙(Medium Enforceability) × 𝟙(Above Bachelor's)					0.024	-0.005
					(0.100)	(0.084)
𝟙(High Enforceability) × 𝟙(Bachelor's)					0.068	0.034
					(0.065)	(0.056)
𝟙(High Enforceability) × 𝟙(Above Bachelor's)					0.045	0.010
					(0.074)	(0.069)
Controls	No	Yes	No	Yes	No	Yes
Observations	1,747	1,747	11,505	11,505	1,747	1,747
Mean R-Squared	0.066	0.155	0.022	0.048	0.006	0.0967

Note. We report standard errors in parentheses, clustered at the state level, using least squares estimation. Our sample is limited to individuals with a noncompete for columns (1), (2), (5), and (6). Basic controls include employee gender, employee education, employee race, a third-degree polynomial in employee age, the class of the employer (e.g., for-profit), the type of occupation (2-digit SOC), industry (2-digit NAICS), employee class (e.g., hourly vs. salary), hours worked per week, weeks worked per year, the interaction of hours and weeks worked, employer size, whether the employer has multiple establishments, and the log of number of establishments in the employee's county-industry. Mean R-Squared is the mean of R-Squared statistics generated by our multiple-imputation analysis as we explain in Online Appendix B.

$^{+}p < .10$.
$^{*}p < .05$.
$^{**}p < .01$.

Table OA3. Search Effort and the Receipt of Job Offers from Competitors

	(1)	(2)	(3)	(4)
Model: OLS	Search Effort Toward Competitor		P(Enforce)	
Constant	2.759**	-0.442	0.459**	0.766
	(0.131)	(3.988)	(0.011)	(0.548)
𝟙(Medium Enforceability)	-0.324	0.343	-0.079**	-0.090**
	-0.307	(0.253)	(0.018)	(0.024)
𝟙(High Enforceability)	-0.276	0.055	-0.022	-0.031
	(0.343)	(0.352)	(0.024)	(0.030)
𝟙(Information)	1.535**	1.265*		
	(0.350)	(0.476)		
𝟙(Medium Enforceability) × 𝟙(Information)	-1.651**	-1.696**		
	(0.486)	(0.486)		
𝟙(High Enforceability) × 𝟙(Information)	-1.359**	-1.195*		
	(0.466)	(0.589)		
𝟙(Received Competitor Offer)			0.018	0.084
			(0.067)	(0.062)
𝟙(Medium Enforceability) × 𝟙(Competitor Offer)			0.113	0.030
			(0.082)	(0.084)
𝟙(High Enforceability) × 𝟙(Competitor Offer)			0.010	-0.054
			(0.091)	(0.086)
Controls	No	Yes	No	Yes
Observations	1,747	1,747	1,747	1,747
Mean R-Squared	0.014	0.178	0.012	0.102
Mean of Dependent Variable	2.573	2.573	0.428	0.428

Note. We report robust standard errors in parentheses, clustered at the state level. Our sample is limited to individuals with a noncompete. Basic controls include employee gender, employee education, employee race, a third-degree polynomial in employee age, the class of the employer (e.g., for-profit), the type of occupation (2-digit SOC), industry (2-digit NAICS), employee class (e.g., hourly vs. salary), hours worked per week, weeks worked per year, the interaction of hours and weeks worked, employer size, whether the employer has multiple establishments, and the log of number of establishments in the employee's county-industry. Mean R-Squared is the mean of R-Squared statistics generated by our multiple-imputation analysis as we explain in Online Appendix B.

* $p < .05$.

** $p < .01$.

Table OA4. Reminders and Lawsuits

Model: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	𝟙(Employer Reminded Employee about Noncompete)		P(Enforce)		𝟙(Employee Aware of Employer Suing Others Over Noncompete)		P(Enforce)	
Constant	0.591**	3.683**	0.383**	2.077	0.208**	-0.670	0.415**	0.874
	(0.067)	(1.248)	(0.078)	(1.400)	(0.031)	(0.471)	(0.008)	(0.557)
𝟙(Medium Enforceability)	-0.239*	-0.398**	0.048	-0.224*	0.022	0.042	-0.043	-0.063*
	(0.093)	(0.113)	(0.094)	(0.084)	(0.040)	(0.042)	(0.029)	(0.029)
𝟙(High Enforceability)	-0.242*	-0.377**	0.010	-0.180*	-0.003	0.005	-0.010	-0.018
	(0.092)	(0.088)	(0.123)	(0.087)	(0.034)	(0.042)	(0.019)	(0.027)
𝟙(Employer Reminded about Noncompete)			0.331**	0.140				
			(0.088)	(0.098)				
𝟙(Medium Enforceability) × 𝟙(Noncompete Reminder)			-0.074	0.248*				
			(0.123)	(0.115)				
𝟙(High Enforceability) × 𝟙(Noncompete Reminder)			-0.052	0.169				
			(0.196)	(0.130)				
𝟙(Employee Aware of Other Suits)							0.224**	0.280**
							(0.045)	(0.041)
𝟙(Medium Enforceability) × 𝟙(Employee Aware of Other Suits)							-0.092	-0.142*
							(0.080)	(0.060)
𝟙(High Enforceability) × 𝟙(Employee Aware of Other Suits)							-0.050	-0.119
							(0.086)	(0.094)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	237	237	237	237	1,747	1,747	1,747	1,747
Mean R-Squared	0.034	0.522	0.151	0.601	0.001	0.141	0.038	0.129
Mean of Dependent Variable	0.392	0.392	0.519	0.519	0.216	0.216	0.428	0.428

Note. We report robust standard errors in parentheses, clustered at the state level. Our sample is limited to individuals with a noncompete. Our sample for columns (1)–(4) is limited to individuals with a noncompete who received job offers from competitors. Basic controls include employee gender, employee education, employee race, a third-degree polynomial in employee age, the class of the employer (e.g., for-profit), the type of occupation (2-digit SOC), industry (2-digit NAICS), employee class (e.g., hourly vs. salary), hours worked per week, weeks worked per year, the interaction of hours and weeks worked, employer size, whether the employer has multiple establishments, and the log of number of establishments in the employee's county-industry. Mean R-Squared is the mean of R-Squared statistics generated by our multiple-imputation analysis as we explain in Online Appendix B.

* $p < .05$.

** $p < .01$.

Table OA5. Information Experiment and Post-Experiment Beliefs About Enforceability

	(1)	(2)	(3)	(4)
Model: OLS	Post-Experiment Beliefs P(Enforce)			
Constant	0.418**	0.619	0.101**	-0.015
	(0.040)	(0.384)	(0.018)	(0.307)
𝟙(Medium Enforceability)	0.026	-0.011	0.051	0.028
	(0.047)	(0.047)	(0.040)	(0.051)
𝟙(High Enforceability)	0.045	0.004	0.076+	0.058+
	(0.049)	(0.053)	(0.039)	(0.031)
𝟙(Information)	-0.215**	-0.216**	0.068*	0.082*
	(0.032)	(0.034)	(0.026)	(0.038)
𝟙(Medium Enforceability) × 𝟙(Information)	0.202**	0.177**	0.041	0.020
	(0.037)	(0.039)	(0.075)	(0.084)
𝟙(High Enforceability) × 𝟙(Information)	0.214**	0.219**	0.022	-0.002
	(0.045)	(0.051)	(0.070)	(0.058)
𝟙(P(Enforce)≥50%)			0.665**	0.691**
			(0.032)	(0.044)
𝟙(P(Enforce)≥50%) × 𝟙(Medium Enforceability)			-0.109+	-0.132+
			(0.055)	(0.076)
𝟙(P(Enforce)≥50%) × 𝟙(High Enforceability)			-0.142*	-0.169**
			(0.059)	(0.063)
𝟙(P(Enforce)≥50%) × 𝟙(Information)			-0.604**	-0.632**
			(0.046)	(0.066)
𝟙(P(Enforce)≥50%) × 𝟙(Medium Enforceability) × 𝟙(Information)			0.380**	0.422**
			(0.109)	(0.126)
𝟙(P(Enforce)≥50%) × 𝟙(High Enforceability) × 𝟙(Information)			0.437**	0.471**
			(0.096)	(0.089)
Controls	No	Yes	No	Yes
Observations	1,747	1,747	1,747	1,747
Mean R-Squared	0.039	0.122	0.400	0.460
Mean of Dependent Variable	0.425	0.425	0.425	0.425

Note. We report robust standard errors in parentheses, clustered at the state level. Our sample is limited to individuals with a noncompete. The independent variable 𝟙(P(Enforce)≥50%) is the pre-experiment measure. Basic controls include employee gender, employee education, employee race, a third-degree polynomial in employee age, the class of the employer (e.g., for-profit), the type of occupation (2-digit SOC), industry (2-digit NAICS), employee class (e.g., hourly vs. salary), hours worked per week, weeks worked per year, the interaction of hours and weeks worked, employer size, whether the employer has multiple establishments, and the log of number of establishments in the employee's county-industry. Mean R-Squared is the mean of R-Squared statistics generated by our multiple-imputation analysis as we explain in Online Appendix B.

+ $p < .10$.
* $p < .05$.
** $p < .01$.

Table OA6. Information Experiment and Noncompetes as a Factor in Moving to Competitor

	(1)	(2)	(3)	(4)
Model: OLS	Post-Experiment 𝟙(Noncompete Factor in Moving)			
Constant	0.467**	2.721**	0.194+	1.871**
	(0.054)	(0.665)	(0.106)	(0.560)
𝟙(Medium Enforceability)	-0.015	-0.050	-0.089	-0.107
	(0.087)	(0.079)	(0.124)	(0.093)
𝟙(High Enforceability)	-0.015	-0.083	-0.057	-0.116
	(0.066)	(0.065)	(0.112)	(0.092)
𝟙(Information)	-0.251**	-0.252**	-0.105	-0.126
	(0.046)	(0.064)	(0.104)	(0.103)
𝟙(Medium Enforceability) × 𝟙(Information)	0.205*	0.164*	0.170	0.121
	(0.098)	(0.077)	(0.121)	(0.109)
𝟙(High Enforceability) × 𝟙(Information)	0.224**	0.256**	0.130	0.144
	(0.063)	(0.081)	(0.130)	(0.124)
𝟙(Noncompete Factor in Moving)			0.629**	0.627**
			(0.089)	(0.071)
𝟙(Noncompete Factor in Moving) × 𝟙(Medium Enforceability)			0.081	0.054
			(0.104)	(0.086)
𝟙(Noncompete Factor in Moving) × 𝟙(High Enforceability)			0.004	-0.011
			(0.117)	(0.108)
𝟙(Noncompete Factor in Moving) × 𝟙(Information)			-0.304**	-0.230**
			(0.104)	(0.080)
𝟙(Noncompete Factor in Moving) × 𝟙(Medium Enforceability) × 𝟙(Information)			0.116	0.115
			(0.117)	(0.088)
𝟙(Noncompete Factor in Moving) × 𝟙(High Enforceability) × 𝟙(Information)			0.229	0.204
			(0.160)	(0.138)
Controls	No	Yes	No	Yes
Observations	1,747	1,747	1,747	1,747
Mean R-Squared	0.019	0.150	0.372	0.464
Mean of Dependent Variable	0.415	0.415	0.415	0.415

Note. We report robust standard errors in parentheses, clustered at the state level. Our sample is limited to individuals with a noncompete. The independent variable 𝟙(Noncompete Factor in Moving) is the pre-experiment measure. Basic controls include employee gender, employee education, employee race, a third-degree polynomial in employee age, the class of the employer (e.g., for-profit), the type of occupation (2-digit SOC), industry (2-digit NAICS), employee class (e.g., hourly vs. salary), hours worked per week, weeks worked per year, the interaction of hours and weeks worked, employer size, whether the employer has multiple establishments, and the log of number of establishments in the employee's county-industry. Mean R-Squared is the mean of R-Squared statistics generated by our multiple-imputation analysis as we explain in Online Appendix B.

+ $p < .10$.
* $p < .05$.
** $p < .01$.

Table OA7. Beliefs about Enforceability and the Importance of a Noncompete

	(1)	(2)	(3)	(4)	(5)	(6)
"Suppose that at your current job you receive an offer to perform your same duties in a comparable, competing company. How important are the following factors in determining whether or not you decide to move to the comparable, competing company? (7 Extremely important to 1 Not at all important)"						
				Column (4)–(6) Dependent Variable: Importance of _____ minus Importance of the "fact that I signed a CNC"		
Model: 2SLS	Importance of *"The fact that I signed and agreed to the CNC"*	Importance of *"The chance my employer would take legal action to try to enforce my CNC"*	Importance of *"The chance the court will enforce my noncompete"*	*"The increase in prestige, training, or opportunity to do more exciting work"*	*"The increase in my compensation or other benefits"*	*"The location of the new job and other lifestyle benefits"*
Instrumented P(Enforce)	2.100**	1.751**	2.925**	-1.344**	-2.023**	-2.591**
	(0.629)	(0.419)	(0.557)	(0.340)	(0.457)	(0.725)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Experiment Dependent Variable	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,747	1,747	1,747	1,747	1,747	1,747
F-Stat	50.30	46.48	46.34	55.03	53.50	51.86
Mean of Dependent Variable	4.448	4.525	4.543	1.038	1.566	1.277

Notes. We report robust standard errors in parentheses, clustered at the state level. Our sample is limited to individuals with a noncompete. All models include main effects of the pre-experiment measure of the particular dependent variable, which we measure a second time after the experiment (both for those who do and do not receive enforceability information). The instrument for post-experiment beliefs is a three-way interaction of an indicator for pre-experiment beliefs about enforceability being greater than 50%, indicators for living in a no, medium, or high enforceability state, and whether the individual randomly receives information. Controls include pre-experiment beliefs about enforceability, indicators for enforceability (no, medium, high) interacted with an indicator for pre-experiment enforceability beliefs being greater than 50% (as in the instrument), and other demographics we describe in text. The F-Stat reports the Kleibergen-Paap Wald rk F statistic, which tests for weak instruments with clustered standard errors.
** $p < .01$.

Figure OA1. Noncompete enforceability in 2014 for contiguous United States

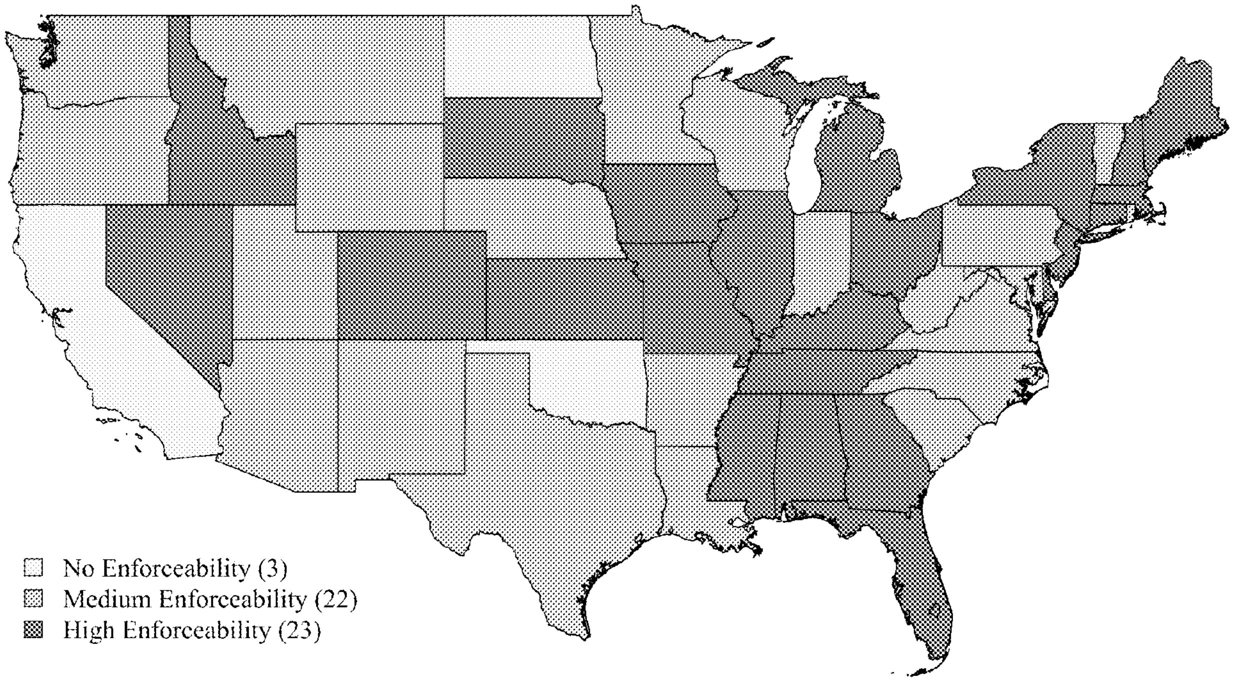


Figure OA2. Beliefs about noncompete enforceability in state by occupation

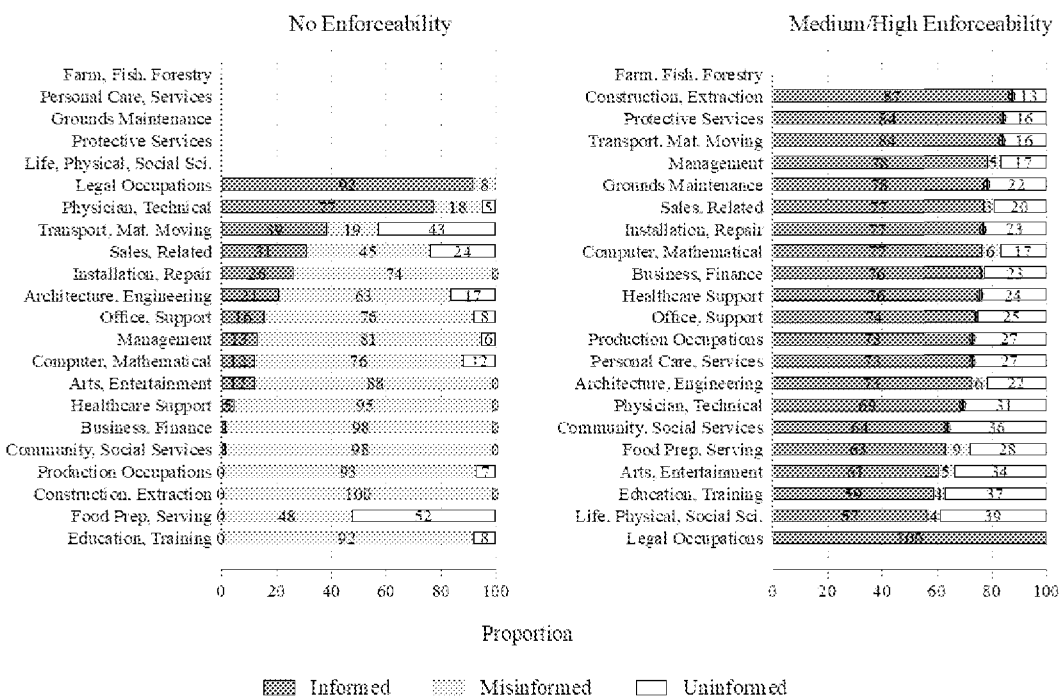
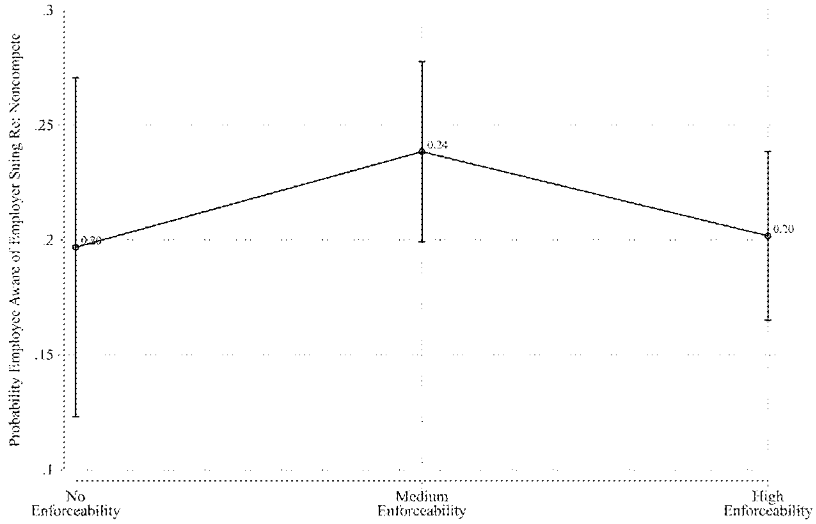
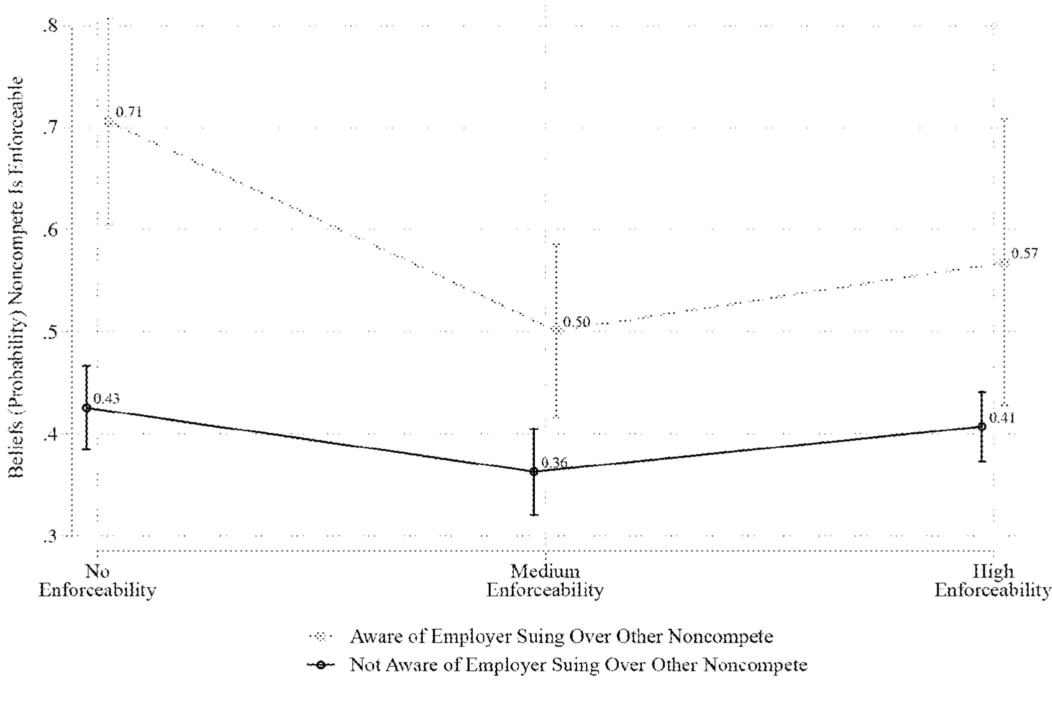


Figure OA3. Awareness that employer has sued others to enforce a noncompete



Note. The figure shows how actual noncompete enforceability relates to the likelihood that an employee reports their employer has legally pursued others for violating a noncompete. Our sample is limited to individuals with a noncompete. We present results as predicted values (with 95% confidence intervals) from a model with basic controls (corresponding to Table OA4 column (6)—see column (5) for an uncontrolled model), using sample weights.

Figure OA4. Awareness of other noncompete lawsuits and beliefs about enforceability



Note. The figure shows how employee beliefs about noncompete enforceability relate to the likelihood that an employee reports their employer has legally pursued others for violating a noncompete, cut by actual enforceability. Our sample is limited to individuals with a noncompete. We present results as predicted values (with 95% confidence intervals) from a model with basic controls, an interaction between awareness of respondent's employer suing another over a noncompete and actual enforceability (corresponding to Table OA4 column (8)—see column (7) for an uncontrolled model), using sample weights.

Figure OA5. General noncompete enforceability information treatment

General Noncompete Enforcement Information:

-- Noncompete policy is conducted at the state level. States have very different noncompete enforcement polices

-- California and North Dakota have bans on enforcing noncompetes, without exceptions.

-- Every other state enforces noncompetes, but under different circumstances.

-- To be enforceable, noncompetes must generally satisfy each of the following conditions:

(1) The worker must leave the employer in which the noncompete was signed and join or start a **competing** business;

and

(2) The employee must possess valuable, non-public information, that would cause harm to the initial employer's legitimate business interests if competitors had access to it. This information can come in the form of client relationships, client lists, client specific information, trade secrets, or other types of sensitive information such as business strategy or future plans;

and

(3) The scope of the noncompete must be reasonable so as not to unduly harm the worker or the public interest.

Figure OA6. State-specific noncompete enforceability information treatment

Noncompete Enforcement Information Specifically For *${q://QID406/ChoiceGroup/SelectedChoices}*

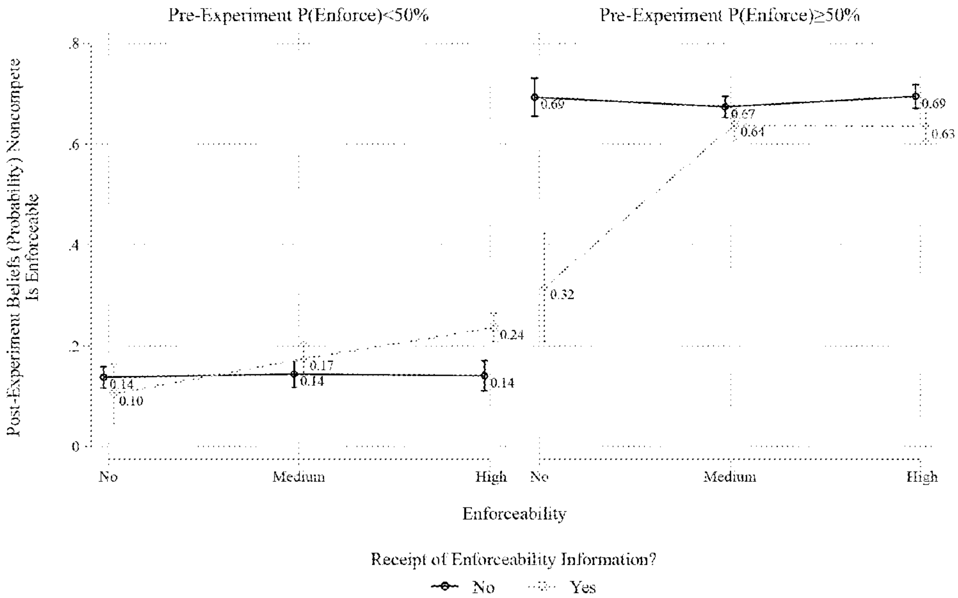
Under ${q://QID406/ChoiceGroup/SelectedChoices}'s noncompete policy, courts will typically:

(The bullet points below are information about your state's noncompete policies. This is not a question.)

- Rewrite unreasonably overbroad noncompetes terms to make the terms reasonable and then enforce the revised agreement
- Remove unreasonably overbroad terms from the noncompete contract, but enforce the rest
- Not enforce a noncompete if *any* part of the contract is unreasonably overbroad
- Enforce the noncompetes of workers who are fired from their jobs without cause
- Enforce *only* the noncompetes of workers who either voluntarily leave or are fired for cause (not enforced if fired without cause)
- Enforce a worker's noncompete even if the worker *only* received continued employment in exchange for signing
- Only enforce the noncompete of a worker who is given additional benefits (such as additional compensation, training, or other benefits) *beyond* continued employment in exchange for signing a noncompete
- Enforce *only* the noncompetes of executive or management-level employees and related professional staff
- Either will not enforce or are unlikely to enforce noncompetes for physicians
- Not enforce noncompetes for employees who leave to join or start a competing business, regardless of the circumstances
- Not enforce noncompetes for employees leaving to join or start a competing business, but will restrict the ability of the employee to directly solicit clients from his/her former employer
- Not enforce a signed noncompete if the employer did not notify the employee at least 14 days before the start of employment that a noncompete would be requested.

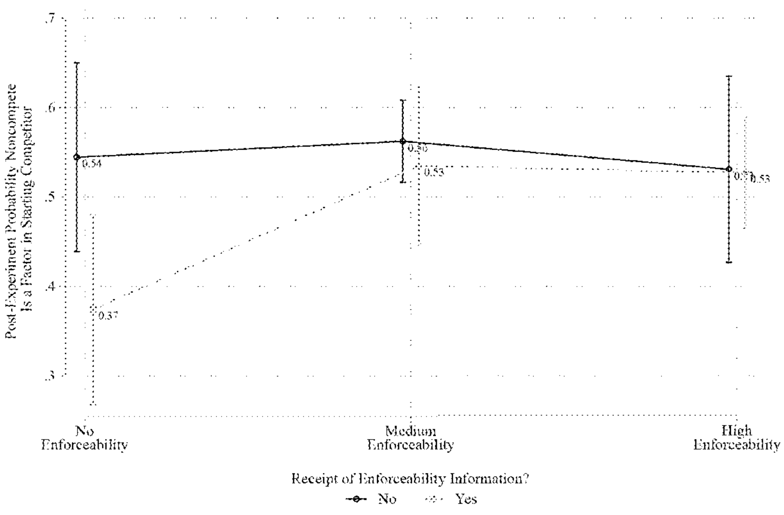
Note. Blue arrows indicate that the survey will only display the bullet point if the respondent's answers and demographics meet certain criteria. The survey shows the respondent only the bullet points that are relevant for a given respondent-selected state using the classification in Beck (2014).

Figure OA7. Heterogeneity in post-experiment beliefs and pre-experiment beliefs among employees without noncompetes



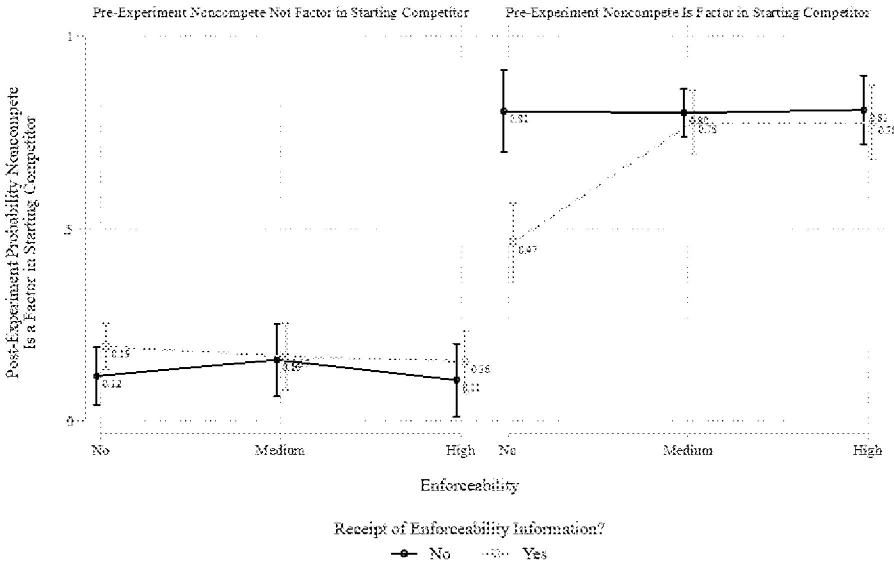
Note. The figure shows how average post-experiment beliefs about noncompete enforceability differ between those who receive enforceability information and those who do not receive information, cut by actual enforceability and by pre-experiment beliefs (above or below 50%). Our sample is limited to individuals without a noncompete. We present results as predicted values (with 95% confidence intervals) from a model with basic controls, a three-way interaction (with all the double interactions as well) between actual enforceability, an indicator for receiving information, and an indicator for pre-experiment beliefs about enforceability being greater than 50%, using sample weights.

Figure OA8. Noncompete as a factor in starting a competitor by actual enforceability and treatment status



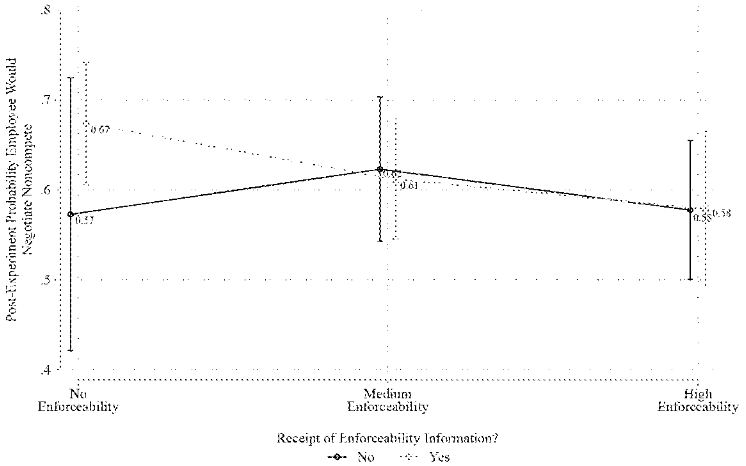
Note. The figure shows how the post-experiment likelihood a noncompete would be a factor in starting a competitor differs between those who receive enforceability information and those who do not receive information, cut by actual enforceability. Our sample is limited to individuals with a noncompete. We present results as predicted values (with 95% confidence intervals) from a model with basic controls and an interaction between receiving information and actual enforceability, using sample weights.

Figure OA9. Heterogeneity in noncompete as a factor in starting a competitor by pre-experiment answer



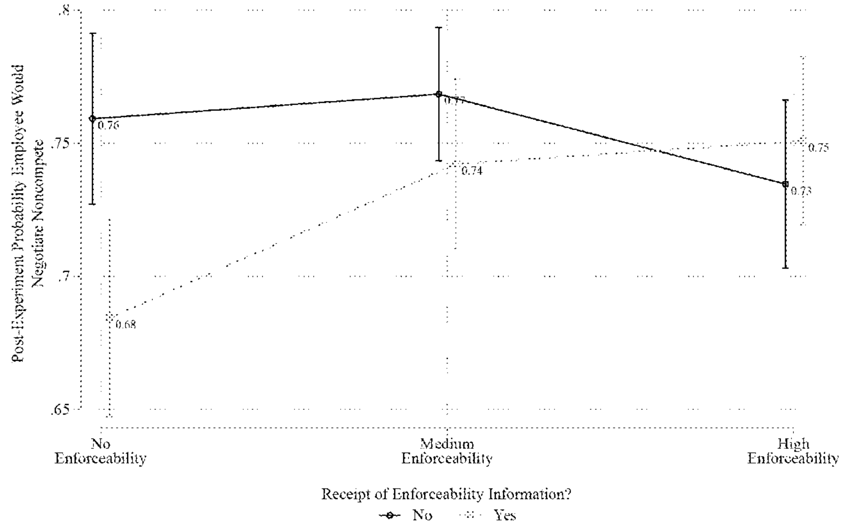
Note. The figure shows how the post-experiment likelihood a noncompete would be a factor in starting a competitor differs between those who receive enforceability information and those who do not receive information, cut by actual enforceability and by the respondent's pre-experiment answer to the same question about whether their noncompete would be a factor in starting a competitor. Our sample is limited to individuals with a noncompete. We present results as predicted values (with 95% confidence intervals) from a model with basic controls, a three-way interaction (and all the double interactions) between actual enforceability, receiving information, and a pre-experiment indicator for whether the noncompete would be a factor in starting a competitor, using sample weights.

Figure OA10. Post-experiment negotiation over noncompetes by treatment status among employees with a noncompete



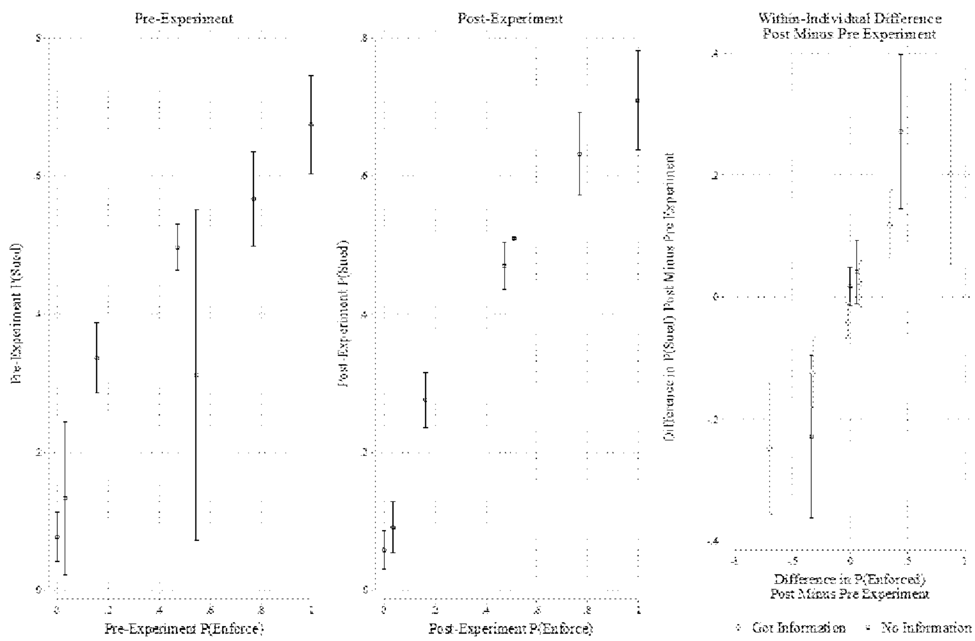
Note. The figure shows how the post-experiment likelihood of negotiating over a prospective noncompete differs between those who receive enforceability information and those who do not receive information, cut by actual enforceability. Our sample is limited to respondents without noncompetes. We present results as predicted values (with 95% confidence intervals) from a model with basic controls, an interaction between getting information and actual enforceability, using sample weights.

Figure OA11. Post-experiment negotiation over noncompetes by treatment status among employees without a noncompete



Notes. The figure shows how the post-experiment likelihood of negotiating over a prospective noncompete differs between those who receive enforceability information and those who do not receive information, cut by actual enforceability. Our sample is limited to individuals without noncompetes. We present result as predicted values (with 95% confidence intervals) from a model with basic controls and an interaction between receiving information and actual enforceability, using sample weights.

Figure OA12. Correlation between beliefs about the likelihood of enforceability and lawsuit



Notes. The figure shows the unconditional relationship between beliefs about the likelihood of enforceability and the average beliefs about the likelihood that a respondent's employer would legally pursue them if they violate the terms of their noncompete, before the experiment (left panel), after the experiment (middle panel), and the within-individual difference before and after the experiment (right panel, cut by whether they receive information). The sample is limited to individuals with a noncompete. We show 95% confidence intervals and use sample weights.

Online Appendix B

OB. Data Appendix

This article's data derive from a labor force (i.e., employee) survey that we designed and implemented between April and July 2014. Our goal in conducting the survey was to understand the use and effects of covenants not to compete ("noncompetes"), both in a respondent's current job and over the course of a respondent's career. In this appendix, we describe the survey's origin, design, and sampling frame as well as our cleaning and processing of the data to clarify important aspects of this article's analysis. We draw heavily on an earlier technical article that describes these issues in meticulous detail (Prescott et al. 2016) and those who are interested can find virtually identical content in the appendices of Starr et al. (2020) and Starr et al. (2021).

OB1. Sampling Frame and Data Collection Methodology

The sampling frame for this study are U.S. labor force participants aged 18–75 years who are working in the private sector (for profit or nonprofit), working for a public health system,[49] or unemployed and looking for work. We exclude individuals who report being self-employed, government employees, non-U.S. citizens, or out of the labor force. To collect the data, we considered a few possible survey platforms and collection methods, including using RAND's American Life Panel (ALP), conducting a random-digit-dial survey, and adding questions to ongoing established surveys like the NLSY or the PSID. Ultimately, we concluded that our work required a nationally representative sample that was larger than the ALP could provide. We also determined that, to obtain a complete picture of an employee's noncompete experiences, we needed to collect too many different pieces of new information to build on existing surveys. Instead, it made more sense to design and draft a noncompete-specific survey ourselves so that we would be able to ask all of the potentially relevant questions. In the end, we settled on using Qualtrics, a reputable online survey company with access to more than 10 million *verified* panel respondents.[50]

The target size for this data-collection project was 10,000 completed surveys. We were able to control the characteristics of the final sample through the use of quotas, which are simply constraints on the numbers of respondents with particular characteristics or sets of characteristics. In particular, we sought a final sample in which respondents were 50% male; 60% with at least a bachelor's degree; 50% with earnings of at least $50,000 annually from their current, highest paying job; and 30% over the age of 55 years. We chose these particular thresholds either to align the sample with the corresponding sample moments for labor force participants in the 2012 American Community Survey (ACS) or to oversample certain populations of interest.

[49] We initially considered focusing only on the private sector, but we recognized that public health systems (e.g., those associated with public universities) also use noncompetes extensively.

[50] The difference between verified and unverified survey respondents is important. The use of unverified survey respondents means that there is no external validation of any information the respondent provides (e.g., a Google or Facebook survey), while verified survey respondents have had some information verified by the survey company. We signed up with a number of these companies to see how they vetted individuals who agreed to respond to online surveys. A typical experience involves filling out an intake form and providing fairly detailed demographic information, including a contact number. A day or so after completing the intake form, the applicant receives a phone call from the survey company at the number the applicant provided. On the call, the applicant is asked a series of questions related to the information previously provided on the intake form. Verified respondents are those who are reachable at the phone number supplied and who corroborate the information initially supplied.

Respondents who completed the survey were compensated differently depending on the panel provider: some were paid $1.50 and entered into prize sweepstakes; others were given tokens or points in online games that they were playing. Respondents took a median time of approximately 28 minutes to complete the survey. Due to the length of the survey, we used three "attention filters" spaced evenly throughout the survey to ensure that respondents were paying attention to the questions. Before we describe the cleaning process for our survey data, we briefly outline the costs and benefits of using online surveys.[51]

OB2. Costs and Benefits of Online Surveys

Online surveys come with a variety of benefits. Relative to random-digit-dial or in-person surveys, the cost per respondent is orders of magnitude lower and the data-collection time is orders of magnitude faster. The interactive survey interface also allows the survey designer to write complicated, nested questions that are easy for respondents to answer through an online platform. Online surveys also allow individuals to respond at their leisure via their preferred method (e.g., computer, phone, tablet, etc.) from wherever they wish (e.g., work, home, or coffee shop). For these reasons, Reuters, the well-known national polling company, has conducted all of its polling since 2012 online, including its recent Presidential election polling.[52]

However, these benefits come at a potentially high cost: a sample of online survey takers may not be representative of the population of interest to researchers or policymakers. There are four sample selection concerns in particular. First, not all people in the U.S. labor force are online. Second, not all of those online register to take surveys. Third, not all of those who register to take surveys receive any particular survey. Fourth, not all of those who are invited to take a survey finish it. Among these sample selection concerns, only the second one is unique to online surveys.[53] With respect to the fourth, alternatives seem unlikely to be better. Kennedy and Hartig (2019) find that survey response to random-digit dialing fell to 6% in 2018, raising the very important question whether a sample resulting from a random-digit-dial survey is still a random sample of the population. We address each of these selection concerns in Prescott et al. (2016) and discuss the second concern in particular in Section OB4.

OB3. Survey Cleaning

Qualtrics fielded the survey and obtained 14,668 completed surveys. When we began to review this initial set of responses, we recognized that individuals with the same IP address may have taken the survey multiple times given there were incentives. To address this, we retained only the first attempt to take the survey from a given IP address and only if that attempt resulted in a completed survey, which produced a sample of 12,369 respondents. We next detected, by inspecting the raw data by hand, that some individuals appeared to have the exact same responses, even for write-in questions, despite the fact that the IP addresses recorded in the survey data were different. To weed these out, we compared individual responses for those with the same gender, age, and race, living in the same state and zip code, and working in the same county. We found 665 possible repeat survey takers; the majority of these respondents took the survey with two different panel partners. We reviewed these potential repeat survey takers by hand, and, among those identified as repeat takers

[51] The information contained in the following sections can be found in Tables 1–18 in Prescott et al. (2016).

[52] See the methodology discussion linked at http://polling.reuters.com/.

[53] For example, random-digit-dial surveys miss those without a phone, those who have a phone but do not receive the survey call, and those who receive the call but decline to take the survey.

from different IP addresses, we kept the first observation and dropped all others, leaving us with a sample of 12,090 respondents.[54]

In the next round of cleaning, we examined individual answers to identify any that were internally inconsistent or unreasonable in substance. In doing so, we developed a "flagging" algorithm that flagged individuals for making mistakes within or across questions, in addition to manually reading through text entry answers. In analyzing these answers, we discovered that some individuals were intentionally noncompliant (e.g., writing curse words or gibberish instead of their job title), while others simply made idiosyncratic errors (e.g., noting that their entire employer was smaller than their establishment—that is, their particular office or factory). We dropped respondents entirely if we deemed them to be intentionally noncompliant because their singular responses indicated that they did not take the survey seriously. This step left us with 11,529 survey responses.[55]

In the last round of cleaning, we began with those who had clean surveys and those who had made some sort of idiosyncratic error. From our flagging algorithm, we determined that 82.2% had no flags and that 16.05% had just one flag (see Table 6 in Prescott et al. (2016)). The most common flag was reporting earnings below the minimum wage (often 0), which was true for 1,007 of the 11,529 respondents. The challenge we faced was how to handle these flagged variables. We adopted four approaches: the first was to do nothing—simply, retain all of offending values as they were. The second was to drop all observations with any flag. The third was to replace offending values as missing. The fourth was to impute or otherwise correct offending values. Our preferred method, and the one we use in this article (although our findings are not very sensitive to this choice), is to impute or correct these offending values. Specifically, we "repaired" entries that were marred by idiosyncratic inconsistency by replacing the less reliable, offending value with the value closest to the originally submitted value that would not be inconsistent with the respondent's other answers. When an answer was clearly unreasonable or missing, and there was no workable single imputation procedure, we applied multiple imputation methods to calculate substitute values for the original missing or unreasonable survey entries.

We also reviewed by hand the values of reported earnings, occupations, and industries, due to their importance in our work. With regard to compensation, we manually reviewed all reported earnings greater than $200,000 per year and cross-checked them with the individual's job title and duties to ensure the amount seemed appropriate. We also examined potential typos in the number of zeros (e.g., the sizable real-world difference between $20,000 and $200,000 may be missed on a screen by survey respondents) by comparing reported annual earnings to expected annual earnings in subsequent years. If a typo was made by omitting a zero or by including an extra zero, we would expect to see a ratio of 0.1 or 10. We imputed earnings that were unreasonable if we were unable to correct the entry in a reliable way. With regard to occupation and industry, we had respondents self-select two-digit NAICS and SOC codes within the survey and also report their job title, occupational duties, and employer's line of business. To verify the two-digit NAICS and SOC codes—which are crucial for both weighting and fixed effects in our empirical work—we had four sets of RAs independently code the 11,529 responses by taking job titles, occupational duties, and employer descriptions and matching them with the appropriate two-digit NAICS and SOC codes.[56] As part of this process, we found that 24 individuals in the sample were self-employed, worked for the government, or were retired, thus reducing our total number of respondents to 11,505.

[54] See Tables 3–5 in Prescott et al. (2016) for more details.

[55] See pp.412–14 in Prescott et al. (2016) for more details.

[56] See p.422 of Prescott et al. (2016) for details.

OB4. Sample Selection

As we observe above, there are four primary sample selection concerns with an online survey like ours: (1) not everybody is online; (2) not everybody online signs up for online surveys; (3) not everybody who signs up for online surveys receives a particular survey; and (4) not everybody who receives a survey manages to complete it. We describe these issues in greater detail in Section II.E in Prescott et al. (2016). All survey research must confront issues (1), (3) and (4)—the only unique selection concern for online surveys is (2). The key question is why individuals sign up to take online surveys and whether that reason is associated with their noncompete status or experiences.[57] To understand why the individuals who responded to our survey agreed to take online surveys, we asked them directly, and their responses were tabulated in Table 13 in Prescott et al. (2016). The two most common reasons individuals report to explain their interest in taking online surveys are that they enjoy the rewards (59%) and sharing their opinions (58%). Only 40% indicated that they wanted money, and only 23% claimed that they needed money. Taking these responses seriously, the crucial selection question is, conditional on observables, whether individuals who like the available rewards or sharing their opinions are less likely to be in jobs that require noncompetes. We believe it is certainly plausible that there is no such relationship.

A related sample selection concern is that individuals who participate in a survey may for some reason lie or otherwise provide inaccurate information in a systematic way. We designed our cleaning strategy with the explicit goal of weeding out such individuals. However, in any surveying effort, legitimate concerns remain about the validity of the responses of the individuals who remain in the sample. To assuage these concerns, we present in Table OB1 the self-described job title, self-described job duties, and self-described industries for 15 randomly selected observations. These randomly selected respondents include a sales rep, a nurse, an analyst, a pizza delivery driver, an optometrist, and a programmer analyst. Reading their job-duty descriptions reveals a striking amount of detail, suggesting not only that these respondents answered the survey's questions carefully but also that they were responding truthfully.

[57] A look at the population of online survey takers (see Table 12 of Prescott et al. (2016)) shows that relative to the average labor force participant they tend to be female and less likely to be in full-time employment.

Table OB1. Self-Described Job Title, Duties, and Industry for 15 Randomly Selected Respondents

	Self-Described Job Title	Self-Described Job Duties	Self-Described Industry
1	Associate Analyst	My current job duties are to review and evaluate telephone recordings between our customers and customer contact representatives.	My current employer is a regional utilitiy company which provides/sells electricity and natural gas to residential and commercial customers.
2	project manager	Design and staff community health clinics, write proposals, seek funding, evaluate and educate	Ensure children of low income families get preventive health and treatment if necessary
3	Quality Assurance Director	Review reports before going to our clients	Insurance Inspection Services
4	optometrist	Care for patient's ocular health	Optometry
5	purchasing clerk	I have receptionist duties including purchasing office supplies and filing the shipping department's paperwork.	retail art gallery
6	sales rep	account manager for a sales base	sells office supplies and equipment
7	Sales Associate	Sell phones and other communication devices, assist customers and resolve issues.	Retail sales company for cell phone business
8	Programmer analyst	Software developer	IT Consulting
9	Customer Service	I take phone calls from Customers.	My employer provides Health Insurance.
10	Certified Medical Assistant	Assist the doctor in the office and minor office procedures while making sure the office runs efficiently.	Healthcare provider
11	Analyst	researching our site's traffic	Publishing
12	Registered Nurse	I am responsible for providing dialysis services to current inpatients	It is a rehabilitation hospital
13	Title Coordinator	Process recorded deed of trust	Issue title policies
14	LEGAL ASSISTANT	INTERACT W/STATE BOARD OF WORKERS'COMP, PROVIDE PERSONAL INJURY REPRESENTATION, INVOLVES HIPAA LAWS	PERSONAL INJURY/WORKERS' COMP ATTORNEY
15	delivery driver	deliver food to people	pizza

OB5. Weighting and Imputation

In this section, we describe our approach to 1) weighting our survey data and 2) imputing values that are missing in our data or that we identified as problematic and marked as missing during the data cleaning process. The fact that weights need to be incorporated into the imputation step to impute unbiased population values complicates these two tasks. In line with current survey methods, we generated our analysis data by weighting our nonmissing data elements, imputing the missing variables (including the weights in the imputation step), and then reweighting the data given the imputed values so that the resulting analysis data are nationally representative. Below, after discussing our weighting approach, we explain how we combined weighting and multiple imputation methods to assemble our data.

With respect to weighting, we considered and compared several candidate approaches,[58] including post-stratification, iterative proportional fitting (also called raking), and propensity score weighting. Details on these methods can be found in Kalton et al. (2003). For each method, we evaluated a variety of potential weighting variables, and then we examined the ability of each weighting scheme to match the distributions of variables within the 2014 American Community Survey (ACS) (see Table 17 in Prescott et al. (2016)). Iterative proportional fitting, or raking, performed clearly better than alternatives in matching our data to the distributions of key variables in the ACS.

To assemble our analysis data, we began by using raking to calculate weights for our original nonmissing survey data. Next, we imputed our missing data. Our goal was to impute values for many different variables (see Table 18 in Prescott et al. (2016) for details), some of which were missing because of the cleaning process we describe above in Section A4 and others because we added the relevant question to the survey while the survey was in the field. In addition, as we explain in the article, we also aimed to impute whether the "maybe" individuals are currently or have ever been bound by a noncompete. Because we sought to impute missing values across multiple variables, we employed Stata's chained multiple imputation command, which imputes missing values for all variables in one step. As suggested in Sterne et al. (2009), we incorporated all of the variables that we planned to use in our empirical analyses into our imputation model. Doing otherwise would have produced attenuated estimates.[59] Indeed, a general rule of thumb is that all variables involved in the analysis should be included in the imputation model.

While imputing missing values just one time will allow for unbiased coefficient estimates, the associated standard error estimates will be too small because the predicted values will not convey the uncertainty implicit in those estimates (King et al. 2001). To generate unbiased standard error estimates, Graham et al. (2007) recommend conducting at least 20 imputations when the proportion missing is 30% (relevant for our "maybe" group). We added another 5 to increase power.

The exact mechanics for a given imputation step are as follows: First, we fit a regression model with our initial nonmissing data. Second, we simulate new coefficients based on the posterior distribution of the estimated coefficients and standard errors—this step is what gives us variation across the 25 datasets. Third, we combine these coefficients with the observed values of the covariates for the missing observations to generate a predicted value. For continuous variables, we used predictive mean matching in the third step. Specifically, we took the average of the 15 nearest neighbors to the

[58] See pp.436–46 in Prescott et al. (2016) for more details.

[59] Dependent variables should be included as controls in the imputation of an independent variable to avoid attenuation in the imputed estimates (Sterne et al. 2009). See also http://thestatsgeek.com/2015/05/07/including-the-outcome-in-imputation-models-of-covariates/.

predicted value. For binary variables, we employed a logit model to create the predicted value. We repeated this process 25 times for all missing values, creating 25 separate datasets.

Once we had 25 imputed datasets in hand, we reweighted within each dataset using the raking procedure we discuss above, so that each individual dataset is nationally representative. In Table 2 of Starr et al. (2021), we present a comparison of the distribution of demographics between the 2014 ACS and our weighted and unweighted data. The table shows that the weighted data quite accurately match the distribution of contemporaneous ACS data and that the unweighted data indicate a much more skilled workforce, one that does not align closely with the U.S. labor force. This occurs because we employed quotas to ensure that more than 50% of our sample was composed of respondents with a bachelor's degree.

Estimation of our main analysis via multiple imputation involves running the regression model in question on each individual dataset and then aggregating the 25 different estimates using Rubin's rules, combining the within-imputation variance and the between-imputation variance into our standard error calculations. We note that standard regression statistics, like R-Squared, are not typically reported for regressions conducted with multiple-imputation data because there are 25 distinct estimates of each statistic. To give a rough approximation of fit, we report the mean of our R-Squared estimates.

Additional References

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Online Appendix C. State Policies According to Beck (2014)

State	Permitted	Protectable / Legitimate Interests	Standards	Exemptions	Continued Employment is Sufficient Consideration	Reformation Blue Pencil Red Pencil	Enforceable Against Discharged Employees
AL	Yes. Ala. Code Sec. 8-1-1	Trade Secrets; Customer Relationships	Protectable Interest; Restriction is Reasonably Related to the Interest; Restriction is Reasonable in Time and Space; No Undue Hardship on Employee	Professionals	Yes	Reformation	Yes
AK	Yes	Trade Secrets; Confidential Information; Customer Relationship (where employee was sole contact)	Factors: Limitations in Time and Space; Whether Employee Was Sole Contact with Customer; Employee's Possession of Trade Secrets or Confidential Information; Whether Restriction Eliminates Unfair or Ordinary Competition; Whether the Covenant Stifles Employee's Inherent Skill and Experience; Proportionality of Benefit to Employer and Detriment to Employee; Whether Employee's Sole Means of Support is Barred; Whether Employee's Talent Was Developed During Employment; Whether Forbidden Employment Is Incidental to the Main Employment.	-	Undecided	Reformation	Undecided
AZ	Yes	Trade Secrets; Confidential Information; Customer Relationships	No broader than necessary to protect the employer's legitimate business interest; not unreasonably restrictive; not contrary to public policy; ancillary to another contract.	Broadcasters; maybe Physicians	Yes	Blue Pencil	Undecided

FTC_AR_0001753

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

Beck Reed Riden LLP

State	Permitted	Protectable / Legitimate Interests	Standards	Exemptions	Continued Employment is Sufficient Consideration	Reformation Blue Pencil Red Pencil	Enforceable Against Discharged Employees
AR	Yes	Special Training; Trade Secrets; Confidential Business Information; Customer Lists	Ancillary to Employment Agreement; Protectable Interest; Geographic Reach is not Overly Broad; Reasonable in Time; Not greater than reasonably necessary and does not injure a public interest.	-	Yes	Red Pencil	Undecided
CA	No, except maybe as to trade secrets. Cal. Business & Professions Code sec. 16600	Trade Secrets	Uncertain status as to trade secrets.	-	-	-	-
CO	Yes, as to executive or management employees and professional staff; limited as to rest. Colo. Rev. Stat. sec. 8-2-113.	Trade Secrets; Recovery of Training Expenses for Short- term Employees	Must fall within statutory exception; be reasonable; and be narrowly-tailored.	-	Yes	Reformation	Undecided
CT	Yes.	Trade Secrets; Confidential Information; Customer Relationships	Factors: time; geographic reach; fairness of protection afforded to employer; extent of restraint on employee; extent of interference with public interest.	Broadcasters; Security Guards	Yes, likely	Reformation	Yes
DE	Yes	Trade Secrets; Confidential Information; Customer Relationships	Reasonable in time and geographic reach; protects legitimate economic interests; survives balance of equities.	Physicians	Yes	Reformation	Yes

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Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

B|R|R Beck Reed Riden LLP

State	Permitted	Protectable / Legitimate Interests	Standards	Exemptions	Continued Employment is Sufficient Consideration	Reformation Blue Pencil Red Pencil	Enforceable Against Discharged Employees
DC	Yes	Trade secrets; confidential knowledge; expert training; fruits of employment	Reasonable in time and geographic area; necessary to protect legitimate business interests; promisee's need outweighs promisor's hardship. [Follows Restatement (Second) of Contracts, secs. 186-88.]	Broadcasters	Likely	Reformation or Blue Pencil	No
FL	Yes. Fla. Stat. Ann. Sec. 542.335	Trade secrets; confidential business information; substantial customer relationships and goodwill; extraordinary or specialized training	Legitimate business interest; reasonably necessary to protect legitimate business interest. [Rebuttal presumptions exist.]	Mediators	Yes	Reformation (mandatory)	Undecided
GA	Yes. Ga. Const., Art. III, Sec. VI, Par. V(c), as amended.	Proprietary Confidential Information and Relationships; Goodwill; Economic Advantage; Time and Monetary Investment in Employee's Skill and Training	Not overbroad in time, space, and scope; interest of individuals in gaining and pursuing a livelihood; commercial concerns in protecting legitimate business interests; public policy.	-	Yes	Reformation	Yes, but it's a factor to be considered.
HI	Yes. Haw. Rev. Stat. sec. 480-4(c)	Trade Secrets; Confidential Information; Customer Contacts	Reasonable in time, space, scope.	-	Undecided	Reformation	Undecided
ID	Yes	Trade Secrets; Confidential Information; Customer Contacts	No broader than necessary to protect the employer's legitimate business interest; reasonable as to covenantor, covenantee, and public; not contrary to public policy.	-	Yes	Reformation	Yes

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

State	Permitted	Protectable / Legitimate Interests	Standards	Exemptions	Continued Employment is Sufficient Consideration	Reformation Blue Pencil Red Pencil	Enforceable Against Discharged Employees
IL	Yes.	Legitimate business interests are based on the totality of the facts and circumstances of the case. Trade secrets, confidential information, and near permenant business relationships are factors.	Ancillary to a valid employment relationship; no greater than required to protect a legitimate business interest; does not impose undue hardship on the employee; not injurious to the public; and reasonable in time, space, and scope. [May require two years of continued employment before any noncompete can be enforced.]	Broadcasters; Government Contractors; Physicians	Yes (if employment continued for sufficient duration)	Reformation	Yes
IN	Yes.	Trade Secrets; Confidential Information; Goodwill; Special Training or Techniques	Clear and specific (not general) restraint must be reasonable in light of the legitimate interests to be protected; reasonableness is measured by totality of interrelationship of the interest, and the time, space, and scope of the restriction, judged by the needs for the restriction, the effect on the employee, and the public interest.	-	Yes	Blue Pencil	Yes
IA	Yes.	Trade Secrets; Goodwill; Specialized Training	Whether the restriction is reasonably necessary to protect the employer's business, unreasonably restrictive (time and space), and prejudicial to the public interest.	Franchisees (where franchisor does not renew)	Yes	Reformation	Yes, but it's a factor to be considered.
KS	Yes.	Trade Secrets; Loss of Clients; Referral Sources; Reputation; Special Training	Protects a legitimate business interest; not undue burden on employee; not injurious to public welfare; reasonable in time and space.	Accountants (limited)	Yes	Reformation	Yes

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

State	Permitted	Protectable / Legitimate Interests	Standards	Exemptions	Continued Employment is Sufficient Consideration	Reformation Blue Pencil Red Pencil	Enforceable Against Discharged Employees
KY	Yes.	Confidential Business Information; Customer Lists; Competition; Employee Raiding; Investment in Training	Reasonable in scope and purpose; reasonableness determined by the time, space, and "charter" of the restriction; no undue hardship; does not interfere with public interest	-	Yes (if long enough and employee resigns)	Reformation	Undecided (but it can be a factor)
LA	Yes. La. Rev. Stat. Ann. Sec. 23:921.	Trade Secrets; Financial Information; Management Techniques; Extensive (Unrecouped Through Employee's Work) Training	No more than two years; specifies the specific geographic reach (by parishes, municipalities, or their respective parts); defines employer's business; strict compliance with statute.	Automobile Salesman; Real Estate Broker's Licensees (procedural requirements)	Yes	Blue Pencil, if allowed by the noncompete	Yes, likely.
ME	Yes	Trade Secrets; Confidential Information; Goodwill	No broader than necessary to protect the employer's legitimate business interest; reasonable as to time, space, and interests to be protected; no undue hardship to employee.	Broadcast Industry (presumption)	Yes	Reformation	Yes, likely.
MD	Yes	Trade Secrets; Routes; Client Lists; Established Customer Relationships; Goodwill; Unique Services	Duration and space no broader than reasonably necessary to protect legitimate interests; no undue hardship to employee or public; ancillary to the employment.	-	Yes	Blue Pencil, but undecided as to whether more flexible	No, likely.
MA	Yes	Trade Secrets; Confidential Information; Goodwill	Narrowly tailored to protect legitimate business interest; limited in time, space, and scope; consonant with public policy; harm to employer outweighs harm to employee.	Broadcasters; Physicians; Nurses; Social Workers; Psychologists	Yes	Reformation	Yes

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Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

Beck Reed Riden LLP

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MI	Yes. Mich. Comp. Laws sec. 445.774a.	Trade Secrets; Confidential Business Information; Goodwill	Must have an honest and just purpose and to protect legitimate business interests; reasonable in time, space, and scope or line of business; not injurious to the public.	-	Yes	Reformation	Yes
MN	Yes	Trade Secrets; Confidential Business Information; Goodwill; Prevention of Unfair Competition	No broader than necessary to protect the employer's legitimate business interest; does not impose unnecessary hardship on employee.	-	No	Reformation	Yes
MS	Yes	Trade Secrets; Confidential Business Information; Goodwill; Ability to Succeed in a Competitive Market	Reasonableness and specificity of restriction, primarily, in time and space; hardship to employer and employee; public interest.	-	Yes (though questioned if employee terminated shortly after)	Reformation	Yes
MO	Yes. 28 Mo. Stat. Ann. Sec. 431.202 (related)	Trade Secrets; Confidential Business Information; Customer or Supplier Relationships, Goodwill, or Loyalty; Customer Lists; Protection from Unfair Competition; Stability in the Workforce	Reasonably necessary to protect legitimate interests; reasonable in time and space; not an unreasonable restraint on employee; purpose served; situation of the parties; limits of the restraint; specialization of the business. [Absence of legitimate business interest impacts duration, which can be no more than one year.]	Secretaries (limited); Clerks (limited)	Yes, generally.	Reformation	Yes
MT	No. Mont. Code Ann. Secs. 28-703-05	Likely confidential information and goodwill; may be more broad.	Reasonable in time or space; reasonable protection for employer; does not impose unreasonable burden on the employee or public.	-	Undecided, likely requires additional consideration.	Blue Pencil, likely	No

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

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NE	Yes	Trade Secrets; Confidential Information; Goodwill	Reasonably necessary to protect legitimate interests; not unduly harsh or oppressive to employee; not injurious to the public. Considerations include: inequality in bargaining power; risk of loss of customers; extent of participation in securing and retaining customers; good faith of employer; employee's job, training, health, education, and family needs; current employment conditions; need for employee to change his calling or residence; relation of restriction to legitimate interest being protected.	-	Yes	Red Pencil	Undecided
NV	Yes. Nev. Rev. Stat. sec. 613.200	Trade Secrets; Goodwill	Not greater than reasonably necessary to protect the business and goodwill of the employer; no undue hardship on employee. Time and space are considerations for reasonableness.	-	Yes	Reformation	Undecided
NH	Yes. RSA 275:70	Trade Secrets; Confidential Business Information; Goodwill; Employee's Special Influence Over the Employer's Customers	Not greater than necessary to protect the employer's legitimate business interests; no undue or disproportionate hardship to employee; not injurious to public interest; employee must be given a copy of the noncompete in with offer for employment or change in job classification.	-	Yes	Reformation	Undecided

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

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NJ	Yes	Trade Secrets; Confidential Business Information; Goodwill in Existing Customers; Preventing Employee from Working with Customer at Lower Cost than Working through Employer	Protects a legitimate business interest; not undue burden on employee; not injurious to the public; not overbroad in time, space, and scope.	In-House Counsel; Psychologists.	Yes	Reformation	Yes
NM	Yes	Maintaining Workforce; Limitation of Competition (but not to stifle competition); Customer Relationships	Reasonable as applied to the employer, employee, and public; not great hardship to employee in exchange for small benefits to employer.	-	Yes, likely	Undecided	Undecided
NY	Yes	Trade Secrets; Confidential Information; Goodwill; On-Air Persona of Broadcasters; Employee's Unique or Extraordinary Services	Necessary to protect legitimate business interest; reasonable in time and space; not harmful to general public; not unreasonably burdensome to the employee.	-	Yes	Reformation	Yes, with exceptions.
NC	Yes. N.C. Gen. Stat. sec. 75-4; 21 N.C. Admin. Code sec. 29.0502(e)(5) (limitations on locksmiths)	Trade Secrets; Confidential Business Information; Goodwill	In writing; part of an employment contract; reasonably necessary to protect legitimate business interest; reasonable in time and space; not against public policy.	-	No	Blue Pencil	Yes, likely.
ND	No. N.D. Cent. Code sec. 9-08-06	-	-	-	-	-	-

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Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

Beck Reed Riden LLP

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OH	Yes	Trade Secrets; Confidential Information; Customer Relationships; Prevention of the Use of Proprietary Customer Information to Solicit Customers	Not greater than necessary to protect the employer's legitimate business interests; no undue hardship to employee; not injurious to public interest. Considerations: absence or presence of limitations as to time and space; whether employee is sole contact with customer; employee's possession of trade secrets or confidential information; purpose of restriction (elimination of unfair competition vs. ordinary competition and whether seeks to stifle employee's inherent skill and experience); proportionality of benefit to employer as compared to the detriment to the employee; other means of support for employee; when employee's talent was developed; whether forbidden employment is merely incidental to the main employment.	-	Yes	Reformation	Yes
OK	No. Okla Stat. ti. 15, sec. 219A	-	-	-	-	-	-

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

Beck Reed Riden LLP

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OR	Yes. Or. Rev. Stat. sec. 653.295	Trade Secrets; Confidential Business or Professional Information; Investment in Certain On-Air Broadcasters; Customer Contacts and Goodwill	Noncompete provided at least two weeks before employment or with bona fide advancement; employee meets minimum compensation threshold; no longer than two years; restricted in time or space; application of restriction should afford only a fair protection of the employer's interests; must not interfere with public interest. [Qualifying garden leave clauses are enforceable.]	-	No.	Reformation	Undecided
PA	Yes	Trade Secrets; Confidential Information; Goodwill; Investment in Specialized Training; Unique or Extraordinary Skills	Ancillary to employment relation or other transaction; reasonably necessary to protect the employer's legitimate interests; reasonable in time and space.	-	No	Reformation	Yes, but it's a factor to be considered.
RI	Yes	Trade Secrets; Confidential Information; Customer Lists; Goodwill; Special Training or Skills	Reasonable in light of protectable interests.	-	Undecided	Blue Pencil, but may allow Reformation	Undecided
SC	Yes	Business and Customer Contacts; Existing Employees; Existing Payroll Deduction Accounts.	Necessary to protect legitimate business interest; reasonably limited in time and space; not unduly harsh and oppressive to employee's efforts to earn a living; reasonable from standpoint of public policy.	-	No	Red Pencil, likely. (SC S.Ct rejected blue pencil doctrine by name, but case involved reformation.)	Undecided

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

B | R | R
Beck Reed Riden LLP

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SD	Yes. S.D. Codified Laws sec. 53-9-8, *et seq*.	Trade Secrets; Protection from Unfair Competition; Existing Customers	Restriction is in the same business or profession as that carried on by employer and does not exceed two years and in a specified geographic area; reasonableness in time, space, and scope is a factor only in certain circumstances.	-	Yes	Reformation, likely.	Yes, but it's a factor to be considered.
TN	Yes	Trade Secrets; Confidential Information; Retention of Existing Customers; Investment in Training or Enhancing the Employee's Skill and Experience	Restriction must be reasonable in time and space and necessary to protect legitimate interest; public interest no adversely affected; no undue hardship to the employee.	Physicians (in certain circumstances).	Yes (if employment continued for appreciably long period)	Reformation	Undecided
TX	Yes. Tex. Bus. & Com. Code secs. 15.50-.52	Trade Secrets; Confidential or Proprietary Information; Goodwill; Special Training or Knowledge Acquired During Employment;	Ancillary to an otherwise enforceable agreement; reasonable in time, space, and scope; does not impose a greater restraint than necessary to protect legitimate business interest. **In December 2011, the Texas Supreme Court withdrew its June 2011 landmark decision, but still eliminated the requirement that the consideration given by the employer in exchange for the noncompete must give rise to the interest protected by the noncompete, and held that the consideration for the noncompete agreement must be reasonably related to the company's interest sought to be protected.*	Physicians (in certain circumstances).	No	Reformation (mandatory)	Yes

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

Beck Reed Riden LLP

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UT	Yes	Trade Secrets; Good-will; Extraordinary Investment in Training or Education	No bad faith in the negotiations; necessary to protect legitimate business interest; reasonable in time, space, and scope; consideration of hardship.	-	Yes	Undecided	Yes
VT	Yes	Proprietary Confidential Information; Goodwill; Relationships with Customers; Investments in Special Training	Necessary to protect legitimate business interest; not unnecessarily restrictive to employee; limited in time, space, and/or industry; not contrary to public policy.	Beauticians and Cosmetologists (by their school)	Yes	Undecided	Yes, but it's a factor to be considered.
VA	Yes	Trade Secrets; Confidential Information; Knowledge of Methods of Operation; Protection from Detrimental Competition; Customer Contacts	No broader than necessary to protect the employer's legitimate business interest; reasonable in time, space, and scope; not unduly harsh in curtailing employee's ability to earn a living; reasonable in terms of public policy.	-	Yes	Red Pencil	Yes
WA	Yes	Customer Information and Contacts; Goodwill	Restriction is necessary to protect employer's business or goodwill; restriction is no greater than reasonably necessary to secure employer's business or goodwill; reasonable in time and space; injury to public does not outweigh benefit to employer.	Broadcasters (under certain circumstances)	No	Reformation	Yes, likely.

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

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WV	Yes	Trade Secrets; Confidential or Unique Information; Customer Lists; Direct Investment in Employee's Skills; Goodwill	Ancillary to a lawful contract; not greater than reasonably necessary to protect legitimate business interest; reasonable in time and space; no undue hardship on employee; not injurious to public.	-	No, likely.	Reformation	Undecided
WI	Yes. Wis. Stat. Ann. Sec. 103.465	Trade Secrets; Confidential Business Information; Customer Relationships.	Necessary to protect legitimate business interest; reasonable in time and space; not harsh or oppressive to the employee; not contrary to public policy.	-	No, likely.	All or nothing. But, recent case law may suggest a judicial move toward a more tolerant approach. *See Star Direct, Inc. v. Dal Pra*, 767 N.W.2d 898 (Wis. 2009).	Undecided
WY	Yes.	Trade Secrets; Confidential Information; Special Influence of Employee Over Customers to the Extent Gained During Employment	Restraint must be ancillary to otherwise valid agreement and fair; no greater than necessary to protect legitimate business interests; reasonable in time and space; no undue hardship on employee; employer's need outweighs harm to employee and public; not injurious to public.	-	No	Reformation	Yes, likely.

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Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

Beck Reed Riden LLP

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		Customer lists are frequently considered trade secrets or confidential information. Some states, however, separately identify them as protectable interests.	Consideration for the noncompete is always a requirement. That requirement is not typically an issue when the agreement is entered into at the inception of an employment relationship.	Attorneys and certain persons in the financial services industry are subject to industry regulations not addressed in this chart.	The continued employment issue addresses only at-will employment relationships.	Reformation is also sometimes called "Judicial Modification," the "Rule of Reasonableness," the "Reasonable Alteration Approach," or the "Partial- Enforcement" rule. Red Pencil is also sometimes called the "All or Nothing" rule.	Assumes no breach or bad faith by the employer.

Russell Beck
Beck Reed Riden LLP
155 Federal Street, Suite 1302
Boston, MA 02110
617-500-8670
rbeck@beckreed.com

Quarterly Census of Employment and Wages

QCEW HOME

Employment and Wages Data Viewer

Private, 10 Total, all industries, All States and U.S.
2022 Annual Averages, All establishment sizes
Source: Quarterly Census of Employment and Wages - Bureau of Labor Statistics

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State	Annual Establishments	Annual Average Employment	Total Annual Wages	Annual Average Weekly Wage	Annual Wages per Employee	Annual Average Employment Location Quotient	Total Annual Wages Location Quotient
V Λ	V Λ	V Λ	V Λ	V Λ	V Λ	V Λ	V Λ
U.S. TOTAL	11,215,668	128,718,060	$9,054,842,577,232	$1,353	$70,346	1.00	1.00
Alabama	142,581	1,660,156	94,188,552,072	1,091	56,735	0.96	0.94
Alaska	22,327	241,031	15,626,534,624	1,247	64,832	0.89	0.88
Arizona	203,253	2,689,673	173,939,638,194	1,244	64,669	1.02	1.01
Arkansas	94,817	1,056,644	57,242,157,555	1,042	54,174	0.99	0.98
California	1,670,259	15,438,555	1,304,497,083,695	1,625	84,496	1.01	1.00
Colorado	241,934	2,384,337	180,226,670,540	1,454	75,588	0.99	1.00
Connecticut	136,171	1,426,728	117,522,769,513	1,584	82,372	1.01	1.02
Delaware	40,175	392,082	26,971,747,152	1,323	68,791	1.00	1.00
District of Columbia	48,172	514,487	56,288,735,348	2,104	109,408	0.80	0.77
Florida	845,932	8,308,654	528,910,710,487	1,224	63,658	1.03	1.03
Georgia	370,748	4,062,791	270,647,015,817	1,281	66,616	1.01	1.02
Hawaii	50,348	501,744	29,748,952,403	1,140	59,291	0.94	0.90
Idaho	84,171	699,084	38,323,305,059	1,054	54,819	0.99	1.00
Illinois	387,675	5,161,095	380,459,313,865	1,418	73,717	1.02	1.02
Indiana	180,517	2,733,492	160,166,848,132	1,127	58,594	1.02	1.03
Iowa	104,388	1,297,333	74,575,339,085	1,105	57,484	0.98	0.98
Kansas	88,348	1,151,446	66,369,714,552	1,108	57,640	0.96	0.98
Kentucky	137,021	1,640,191	91,941,535,636	1,078	56,055	1.00	0.99
Louisiana	143,196	1,571,606	89,609,944,331	1,097	57,018	0.98	0.98
Maine	58,994	530,043	30,939,839,645	1,123	58,372	0.99	0.99
Maryland	185,715	2,156,462	153,474,536,350	1,369	71,170	0.95	0.91
Massachusetts	282,469	3,168,350	289,698,284,237	1,758	91,435	1.03	1.04
Michigan	287,758	3,749,727	239,927,537,862	1,230	63,985	1.02	1.01
Minnesota	193,074	2,483,988	174,967,291,765	1,355	70,438	1.01	1.02
Mississippi	77,261	919,857	43,098,331,795	901	46,853	0.94	0.92
Missouri	224,172	2,424,908	145,877,680,285	1,157	60,158	1.00	1.01
Montana	57,863	413,058	22,400,888,086	1,043	54,232	0.97	0.96
Nebraska	73,799	824,945	47,425,308,816	1,106	57,489	0.98	0.98
Nevada	103,366	1,315,007	80,335,908,930	1,175	61,092	1.04	1.02
New Hampshire	59,864	589,213	43,592,819,794	1,423	73,985	1.02	1.04
New Jersey	307,423	3,581,671	282,503,401,520	1,517	78,875	1.01	1.01
New Mexico	63,668	660,670	35,476,916,053	1,033	53,698	0.92	0.89
New York	669,545	7,908,130	716,637,284,658	1,743	90,620	0.99	1.00
North Carolina	339,053	4,018,296	255,730,519,363	1,224	63,642	1.00	1.00
North Dakota	32,060	339,203	20,810,769,388	1,180	61,352	0.96	0.97
Ohio	313,656	4,684,897	284,086,513,719	1,166	60,639	1.01	1.00
Oklahoma	117,212	1,304,605	70,105,516,627	1,033	53,737	0.94	0.93
Oregon	177,635	1,675,632	109,531,423,551	1,257	65,367	1.00	0.98
Pennsylvania	371,182	5,210,459	350,863,056,973	1,295	67,338	1.04	1.03
Rhode Island	45,438	420,969	26,511,469,596	1,211	62,977	1.02	0.99
South Carolina	162,148	1,833,574	101,350,510,551	1,063	55,275	0.98	0.97
South Dakota	36,373	368,476	20,173,250,239	1,053	54,748	0.97	0.98
Tennessee	197,747	2,741,025	172,279,178,538	1,209	62,852	1.01	1.02

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State	Annual Establishments	Annual Average Employment	Total Annual Wages	Annual Average Weekly Wage	Annual Wages per Employee	Annual Average Employment Location Quotient	Total Annual Wages Location Quotient
Texas	788,032	11,337,527	804,028,623,667	1,364	70,917	1.00	1.01
Utah	128,186	1,407,806	86,767,195,072	1,185	61,633	0.99	1.00
Vermont	28,549	250,086	14,841,570,398	1,141	59,346	0.97	0.96
Virginia	319,638	3,258,793	232,368,907,788	1,371	71,305	0.96	0.96
Washington	252,068	2,955,687	251,959,354,170	1,639	85,246	0.98	0.99
West Virginia	51,829	539,694	28,547,108,981	1,017	52,895	0.93	0.92
Wisconsin	189,729	2,505,934	149,568,315,401	1,148	59,686	1.02	1.02
Wyoming	28,130	208,246	11,706,695,354	1,081	56,216	0.89	0.89
Puerto Rico	48,839	729,767	22,464,400,321	592	30,783	0.92	0.88
Virgin Islands	3,510	24,037	1,064,131,946	851	44,271	0.81	0.69

Last Modified Date: September 7th, 2022

U.S. BUREAU OF LABOR STATISTICS OEUS/DASLT, PSB Suite 4860 2 Massachusetts Avenue NE Washington, DC 20212-0001
Telephone: 1-202-691-6567 www.bls.gov/CEW Contact QCEW

DEPARTMENT OF COMMERCE

Bureau of Industry and Security

15 CFR Parts 734, 736, 740, 742, 744, 762, 772, and 774

[Docket No. 220930–0204]

RIN 0694–AI94

Implementation of Additional Export Controls: Certain Advanced Computing and Semiconductor Manufacturing Items; Supercomputer and Semiconductor End Use; Entity List Modification

AGENCY: Bureau of Industry and Security, Department of Commerce.

ACTION: Interim final rule; request for comments.

SUMMARY: In this rule, the Bureau of Industry and Security (BIS) is amending the Export Administration Regulations (EAR) to implement necessary controls on advanced computing integrated circuits (ICs), computer commodities that contain such ICs, and certain semiconductor manufacturing items. In addition, BIS is expanding controls on transactions involving items for supercomputer and semiconductor manufacturing end uses, for example, this rule expands the scope of foreign-produced items subject to license requirements for twenty-eight existing entities on the Entity List that are located in China. BIS is also informing the public that specific activities of "U.S. persons" that 'support' the "development" or "production" of certain ICs in the PRC require a license. Lastly, to minimize short term impact on the semiconductor supply chain from this rule, BIS is establishing a Temporary General License to permit specific, limited manufacturing activities in China related to items destined for use outside China and is identifying a model certificate that may be used in compliance programs to assist, along with other measures, in conducting due diligence. '

DATES:

a. Effective on October 7, 2022, are the following instructions: 7 (§ 740.2), 9 (§ 740.10), 11 (§ 742.6), 17 (§ 744.23), and 25 (supplement no. 1 to part 774).

b. Effective on October 12, 2022, is the following instruction: 15 (§ 744.6).

c. Effective on October 21, 2022, are the following instructions: 2 (§ 734.9), 3 (supplement no. 1 to part 734), 5 (supplement no. 1 to part 736), 8 (§ 740.2), 12 (§ 742.6), 14 (§ 744.1), 16 (§ 744.11), 18 (§ 744.23), 19 (supplement no. 4 to part 744), 21 (§ 762.2), 23 (§ 772.1), and 26 (supplement no. 1 to part 774).

d. Comments must be received by BIS no later than December 12, 2022.

ADDRESSES: Comments on this rule may be submitted to the Federal rulemaking portal (*www.regulations.gov*). The regulations.gov ID for this rule is: BIS–2022–0025. Please refer to RIN 0694–AI94 in all comments.

All filers using the portal should use the name of the person or entity submitting the comments as the name of their files, in accordance with the instructions below. Anyone submitting business confidential information should clearly identify the business confidential portion at the time of submission, file a statement justifying nondisclosure and referring to the specific legal authority claimed, and provide a non-confidential version of the submission.

For comments submitted electronically containing business confidential information, the file name of the business confidential version should begin with the characters "BC." Any page containing business confidential information must be clearly marked "BUSINESS CONFIDENTIAL" on the top of that page. The corresponding non-confidential version of those comments must be clearly marked "PUBLIC." The file name of the non-confidential version should begin with the character "P." Any submissions with file names that do not begin with either a "BC" or a "P" will be assumed to be public and will be made publicly available through *https://www.regulations.gov.*

FOR FURTHER INFORMATION CONTACT: For questions on the license requirements in this interim final rule, contact Eileen Albanese, Director, Office of National Security and Technology Transfer Controls, Bureau of Industry and Security, Department of Commerce, Phone: (202) 482–0092, Fax: (202) 482–482–3355, Email: *rpd2@bis.doc.gov.* For emails, include "Advanced computing controls" or "Semiconductor manufacturing items control" as applicable in the subject line.

For questions on the Entity List revisions, contact: Chair, End-User Review Committee, Office of the Assistant Secretary for Export Administration, Bureau of Industry and Security, Department of Commerce, Phone: (202) 482–5991, Email: *ERC@bis.doc.gov.*

SUPPLEMENTARY INFORMATION:

I. Background

With this interim final rule, the Commerce Department's Bureau of Industry and Security (BIS) makes critical changes to the Export Administration Regulations (EAR) in two areas to address U.S. national security and foreign policy concerns. First, BIS imposes additional export controls on certain advanced computing semiconductor chips (chips, advanced computing chips, integrated circuits, or ICs), transactions for supercomputer end-uses, and transactions involving certain entities on the Entity List. Second, BIS adopts additional controls on certain semiconductor manufacturing items and on transactions for certain IC end use. Additional information about both areas of change is provided in the Overview of New Controls section. Some changes made in this interim final rule to address these two areas involve the same EAR provisions; in those cases, the preamble provides cross references to other areas in the rule that provide relevant additional information. This rule also solicits public comments on the changes included in this rule.

The restrictions implemented in this rule follow extensive United States government consideration of the impact of advanced computing ICs, "supercomputers," and semiconductor manufacturing equipment on enabling military modernization, including the development of weapons of mass destruction (WMD), and human rights abuses. The Government of the People's Republic of China (PRC or China) has mobilized vast resources to support its defense modernization, including the implementation of its military-civil fusion development strategy, in ways that are contrary to U.S. national security and foreign policy interests.

A. Additional Export Controls: Certain Advanced Computing Integrated Circuits (ICs); Supercomputer End-Uses; Entity List Modifications

With this rule, BIS imposes new export controls on certain advanced computing semiconductor chips and computer commodities that contain such chips. Further, this rule implements an end-use control for certain items intended for a "supercomputer" located in or destined to the PRC.

Advanced computing items and "supercomputers" can be used to enhance data processing and analysis capabilities, including through artificial intelligence (AI) applications. The PRC is rapidly developing exascale supercomputing capabilities and has announced its intent to become the world leader in AI by 2030. These advanced systems are capable of sophisticated data processing and analysis that has multiple uses, and are enabled by advanced ICs. These systems are being used by the PRC for its military modernization efforts to improve the speed and accuracy of its military decision making, planning, and logistics, as well as of its autonomous military systems, such as those used for cognitive electronic warfare, radar, signals intelligence, and jamming. Furthermore, these advanced computing items and "supercomputers" are being used by the PRC to improve calculations in weapons design and testing including for WMD, such as nuclear weapons, hypersonics and other advanced missile systems, and to analyze battlefield effects. In addition, advanced AI surveillance tools, enabled by efficient processing of huge amounts of data, are being used by the PRC without regard for basic human rights to monitor, track, and surveil citizens, among other purposes. With this rule, BIS seeks to protect U.S. national security and foreign policy interests by restricting the PRC's access to advanced computing for its military modernization, including nuclear weapons development, facilitation of advanced intelligence collection and analysis, and for surveillance. BIS intends to impose controls on items subject to the EAR and U.S. person activities to limit the PRC's ability to obtain advanced computing chips or further develop AI and "supercomputer" capabilities for uses that are contrary to U.S. national security and foreign policy interests.

These controls are being imposed through this interim final rule to address immediate concerns with the PRC's demonstrated intent and ability to use these items for activities of national security and foreign policy concern to the United States. As such, the advanced computing ICs and computer commodities that contain such ICs identified by this rule have been controlled for Regional Stability (RS) purposes. This rule also expands the scope of licensing requirements for 28 existing entities on the Entity List in supplement no. 4 to part 744 of the EAR that are located in China and were added to the Entity List between 2015 and 2021 to further address the national security and foreign policy concerns described above. BIS is interested in receiving comments regarding whether a broader or different scope of control is warranted for these ICs.

B. Additional Export Controls: Certain Semiconductor Manufacturing Items; Integrated Circuits End Use

Also with this rule, BIS imposes new export controls on certain semiconductor manufacturing items and activities involving the "development" or "production" of advanced integrated circuits (packaged or unpackaged) in the PRC that meet specified criteria.

Semiconductor manufacturing equipment can be used to produce ICs (packaged or unpackaged) for commercial applications, which has helped to transform the world and holds great commercial promise across a wide variety of industries and applications, including communications, health care, and transportation. However, semiconductor manufacturing equipment can also be used to produce various ICs (packaged or unpackaged) for WMD or other military applications, as well as applications that enable human rights violations or abuses, including but not limited to the advanced systems and "supercomputers" described above. Similar to their use in commercial products, the use of semiconductors has become vital in the "production" of military systems, particularly for advanced military systems, and may be used for purposes that are contrary to U.S. national security and foreign policy interests. The PRC government expends extensive resources to eliminate barriers between China's civilian research and commercial sectors, and its military and defense industrial sectors. It also is developing and producing advanced integrated circuits (packaged or unpackaged) for use in weapons systems.

Under the Export Control Reform Act of 2018 (ECRA), the United States shall control U.S. person activity related to nuclear explosive devices, missiles chemical or biological weapons, whole plants for chemical weapons precursors, foreign maritime nuclear projects, and foreign military intelligence services; BIS has already imposed some of these controls in § 744.6 of the EAR. But these controls generally only apply when the "U.S. person" has knowledge that their activities are contributing to prohibited end uses or end users. China's military-civil fusion effort makes it more difficult to tell which items are made for restricted end uses, thereby diminishing the effect of these existing controls. Accordingly, with this rule the United States is taking additional steps to inform the public that 'support' by "U.S. persons" related to the provision of items used to produce the most advanced semiconductors necessary for military programs of concern, such as missile programs or programs related to nuclear explosive devices, requires a license, even when the precise end use of such items cannot be determined by the "U.S. person."

BIS has already identified on the Entity List 28 entities in the PRC that are of concern for the national security and foreign policy reasons identified in this rule. For example, four of these entities were determined to be involved with supercomputers in the PRC that are believed to be used in nuclear explosive activities. See 80 FR 8527, Feb. 18, 2015. Five of the other entities were added to the Entity List due to their involvement in exascale high performance computing and ties to military end uses and end users. See 84 FR 29373, June 24, 2019. Finally, seven of the remaining entities were added to the Entity List due to their involvement in activities that support China's military actors, its destabilizing military modernization efforts, and/or its WMD programs. See 86 FR 18438, April 9, 2021.

In addition, BIS notes that according to the April 9, 2021, Annual Threat Assessment of the U.S. Intelligence Community, China "will continue the most rapid expansion and platform diversification of its nuclear arsenal in its history, intending to at least double the size of its nuclear stockpile during the next decade and to field a nuclear triad" and "is building a larger and increasingly capable nuclear missile force that is more survivable, more diverse, and on higher alert than in the past, including nuclear missile systems designed to manage regional escalation and ensure an intercontinental second-strike capability." The types of semiconductor manufacturing items controlled in this rule under new item-based and end-use-based controls produce advanced integrated circuits that can be used in the "development," "production," or "use" of such military items with WMD application. In particular, the ability to produce indigenously within China these types of advanced ICs (packaged or unpackaged) would be contrary to U.S. national security and foreign policy interests.

As more fully discussed in Section IV.C below, this rule will more comprehensively control "U.S. persons" 'support' for the "development" or "production" of ICs (packaged or unpackaged) that could contribute to WMD applications. Advanced logic, certain NOT AND (NAND), and dynamic random-access memory (DRAM) chips have more significant military, intelligence, and security applications, including missile, nuclear, and conventional weapons applications. Advanced ICs (packaged or unpackaged) with smaller physical dimensions (*e.g.*, produced at more advanced technology nodes) are of national security concern because of the faster and more efficient microelectronic operation, greater data storage capability, and greater computational efficiencies that these ICs (packaged or unpackaged) possess.

For example, a BIS rule from August 15, 2022 (87 FR 49981), stated that reasons why Gate-All-Around transistor technology are the key to next generation integrated circuits. This architecture allows for higher current capability and lower parasitic capacitances that enable 50 percent faster chip operation compared to bulk technologies. It is also inherently radiation hardened. Chips with these characteristics would advance many commercial as well as military applications, including defense and communication satellites. Because faster and more efficient chip operation enables superior processing and aggregation critical for WMD applications (*e.g.,* data volumes and computational loads necessary to model nuclear explosions, and missile simulations), it is necessary and consistent with the Export Control Reform Act of 2018 (ECRA) to impose this ''U.S. persons'' activity control under the EAR for 'support,' including the provision of services and foreign-produced items not subject to the EAR, but capable of producing such integrated circuits (*e.g.,* advanced logic, NAND, and DRAM integrated circuits).

With this rule, BIS intends to limit the PRC's ability to obtain semiconductor manufacturing capabilities to produce ICs (packaged or unpackaged) for uses that are contrary to U.S. national security and foreign policy interests.

II. Item-Based Controls on Semiconductor Manufacturing Equipment

As of the effective date of this rule on October 7, 2022, the specified semiconductor manufacturing equipment is controlled for RS reasons under the EAR, in order to immediately address concerns with the PRC's demonstrated intent and ability to use the specified items for activities of U.S. national security and foreign policy concern. Due to the urgent need for this rule to counter China's actions, it will not be published as a Section 1758 technology rule, which would include a notice and comment period (50 U.S.C. 4817(a)(2)(C)). However, BIS is interested in hearing from the public about the items in this rule and the scope of the new control.

III. Overview of New Controls for Certain Advanced Computing Integrated Circuits (ICs); Supercomputer End-Uses; Entity List Modifications

This rule addresses U.S. national security and foreign policy concerns by: (1) adding to the Commerce Control List (CCL) (supplement no. 1 to part 774 of the EAR) certain advanced computing chips and the computers, ''electronic assemblies,'' and ''components'' that contain them; (2) establishing a new end-use control for certain CCL items destined for ''supercomputers''; and (3) creating two new Foreign Direct Product (FDP) rules related to advanced computing and ''supercomputers'' and expanding an existing FDP rule for certain entities listed on the Entity List.

A. Addition of Advanced Computing Chips, Computer Commodities That Contain Them, and Associated ''Software'' and ''Technology'' to the Commerce Control List (Supplement no. 1 to Part 774 of the EAR)

In the CCL, this rule adds new Export Control Classification Numbers (ECCNs) 3A090 for specified high-performance ICs and 4A090 (computers, ''electronic assemblies,'' and ''components,'' not elsewhere specified (n.e.s.), containing ICs in ECCN 3A090). Both new ECCNs are controlled for RS reasons for exports or reexports to the PRC, through the addition of a new RS control in § 742.6(a)(6) of the EAR. The two ECCNs are also controlled for anti-terrorism (AT) reasons when destined to a country that has an AT:1 license requirement (Iran § 742.8, Syria § 742.9, or N. Korea § 742.19); see also parts 744 and 746 of the EAR for additional controls on items controlled for AT reasons. Associated ''software'' and ''technology'' controls on the CCL for the items controlled in ECCNs 3A090 and 4A090 are found in ECCNs 3D001, 3E001, 4D090, and 4E001, respectively, this rule controls the ''software'' and ''technology'' for RS reasons when destined to the PRC, in addition to the other reasons described in those ECCN entries.

This rule revises Category 3, Product Group A, Note 3 because controls for wafers (finished or unfinished) are now in multiple ECCNs in Category 3.

As discussed above, to align the new RS license requirements for ECCNs 3A090 and 4A090 in the associated ''technology'' and ''software'' ECCNs, the new RS license requirement has been added to the License Requirement tables within ECCNs 3D001, 3E001, and 4E001 for these items. Additionally, BIS is adding RS license requirements to the License Requirement tables within ECCNs 5A992 and 5D992 to address circumstances when these ECCNs meet or exceed the performance parameters of ECCN 3A090 or 4A090.

New ECCN 4D090 is also created to accommodate the software associated with the items controlled in ECCN 4A090, as such controls could not be readily added to ECCN 4D001.

B. License Requirements for New Advanced Computing Items

This rule establishes a new unilateral RS control and brings the newly identified advanced computing integrated circuits and related computers under the control. If a relevant multilateral export control regime adopts controls for the identified technology, BIS will adopt multilateral controls in place of the unilateral control. This rule also adds a new basis for RS controls to § 742.6 of the EAR. This newly added RS control imposes a license requirement for exports, reexports, and transfers (in-country) of identified items to or within the PRC. The license requirements under this new RS control for advanced computing chips and computer commodities that contain them found in new § 742.6(a)(6). The license requirements in § 742.6(a)(6) do not apply to deemed exports or reexports.

In addition, this RS control imposes a license requirement for the export from the PRC to any destination worldwide of technology for the design, development, or production of advanced computing chips (*i.e.,* 3E001 for 3A090), which has been developed by an entity headquartered in the PRC, is the ''direct product'' of certain software subject to the EAR, and is for the ''production'' of certain advanced computing integrated circuits and computers or assemblies containing them, consistent with § 734.9(h)(1)(i)(B)(*1*) and (h)(2)(ii). BIS is implementing this license requirement given the historical precedent of chips designed by PRC entities being diverted for use in the PRC to support PRC military modernization, and the inherent risk of this occurring with these advanced computing chips. Parties to such transactions should consider obtaining proof of the ultimate end use, such as the Model Certificate described in supplement no. 1 to part 734. Entities outside of the PRC that receive 3E001 for 3A090 technology from China should consider confirming that a license was obtained to export such technology from China. If no such license was obtained, General Prohibition 10 (§ 736.2(b)(10) of the EAR) prohibits any person from taking any further action with respect to such technology that has been exported without a required BIS license.

The license review policy for this new RS control is added to a new § 742.6(b)(10) of the EAR. Most license applications for items controlled under this RS control will be reviewed under a presumption of denial based on the risk of these items being used contrary to the national security or foreign policy interests of the United States, including the foreign policy interest of promoting the observance of human rights throughout the world. The exception to the presumption of denial is for license applications for semiconductor manufacturing items destined to end users located in China that are headquartered in the United States or in a country in Country Group A:5 or A:6; license applications involving such end users will be considered on a case-by-case basis, taking into account factors including technology level, customers and compliance plans.

C. Anti-Terrorism Controls for Lower-Level Computing ICs and Computer Commodities That Contain Them

In the CCL, this rule also revises ECCN 3A991 by adding a new paragraph 3A991.p (specified high-performance ICs) and revises ECCN 4A994 by adding new paragraph 4A994.l (computers, "electronic assemblies," and "components," not elsewhere specified (n.e.s.), containing ICs in 3A991.p). These ECCNs, including these new paragraphs, are controlled for anti-terrorism (AT Column 1) reasons. Associated "software" and "technology" controls for ECCNs 3A991.p and 4A994.l are found in ECCNs 3D991, 3E991, 4D994, and 4E992, respectively. The Related Control Notes of ECCNs 3A991 and 4A994 are amended to alert the reader about associated technology and software ECCNs. As noted above, license requirements for AT Column 1 items are identified in parts 742, 744, and 746 of the EAR.

Deemed exports and reexports of technology and software that previously did not require a license, but now require a license because of the controls implemented by this rule, will only require licenses if the technology or software release exceeds the scope of the technology or software that the foreign national already had lawful access to prior to the controls implemented in this rule, *e.g.,* a foreign national who lawfully accessed technology or software specified in new ECCN paragraphs 3A991.p or 4A994.l items prior to the effective date would not need a new license to continue receiving the same technology or software for ECCN paragraphs 3A991.p or 4A994.l items, but would require a license for the release of controlled technology or software different from that previously release, even if the technology or software is classified under the same ECCNs.

This rule makes an editorial revision to the heading of ECCNs 3D001 and 4D994 by replacing the word "equipment" with "commodities." This is to ensure that these ECCNs control software for not only equipment, but also parts, components, and assemblies.

D. License Exception Eligibility for New Advanced Computing Items

The only license exceptions available for exports or reexports of items controlled under the new ECCNs (3A090, 4A090, and the associated software and technology in 3D001, 3E001, 4D090, and 4E001) are listed in new § 740.2(a)(9) of the EAR. Similar to existing paragraph (a)(8), this new paragraph contains a list of appropriate license exceptions for the license requirements implemented in this rule. This restriction on the availability of license exceptions also applies to any integrated circuit, computer, or assembly meeting the performance parameters of new ECCNs 3A090 and 4A090 but classified elsewhere on the CCL (*e.g.,* under ECCN 5A002 due to encryption functionality). The only license exceptions available for the foregoing items are: Servicing and replacement of parts and equipment (RPL) under § 740.10; Governments, international organizations, International Inspections Under the Chemical Weapons Convention, and the International Space Station (GOV), restricted to eligibility under the provisions of § 740.11(b)(2)(ii) (exports, reexports, and transfers (in-country) made by or consigned to a department or agency of the United States Government); and Technology and Software Unrestricted (TSU), under the provisions of § 740.13(a) and (c). License Exceptions RPL and TSU require that the equipment or software must have been shipped to their current location in accordance with U.S. law and continue to be legally used, therefore these license exceptions will authorize support, *i.e.,* repairs and software updates, for items that were lawfully exported. These license exceptions will not overcome the new license requirement imposed in this interim final rule under new § 744.23 "Supercomputer" and semiconductor manufacturing end use")," implemented in this interim final rule, because no license exceptions are available to overcome the license requirement in that provision of the EAR. As discussed further below, new § 744.23 applies restrictions on the use of license exceptions to or within China.

BIS estimates these new license requirements will result in an additional 1,600 license applications being submitted to BIS annually.

E. Revising the Entity List Foreign Direct Product Rule Under § 734.9(e) and Establishing Two New Foreign Direct Product Rules for Advanced Computing and "Supercomputers" Under § 734.9(h) and (i)

In § 734.9 (Foreign-Direct Product (FDP) Rules), this rule revises § 734.9(e) (Entity List FDP rule) to add a new product scope and end-user scope for entities on the Entity List identified with a new footnote 4 and adds new paragraphs (h) (Advanced computing FDP rule) and (i) ("Supercomputer" end-use FDP rule) to the EAR. As with the other FDP rules, these new FDP rules define when certain foreign made items are subject to the EAR. License requirements associated with these foreign direct products are found in § 742.6(a)(6) of the EAR, as well as in new § 744.23, described below. The license requirement for the Entity List entities designated with footnote 4, is found in a new § 744.11(a)(2)(ii) of the EAR and in such entities' entries in supplement no. 4 to part 744, as described below.

1. Revised Entity List FDP Rule

The revised Entity List FDP rule, set forth in § 734.9(e), now identifies two footnotes on the Entity List that indicate application of an Entity List FDP rule. The revision made in this interim final rule does not alter the scope or requirements of the existing Entity List FDP rule that applies to entities designated with footnote 1 on the Entity List, but this revision required BIS to renumber the paragraphs of the existing Entity List FDP rule. This rule also revises the heading of paragraph (e)(1)(i)(B) to reflect alignment with the unchanged scope of the paragraph, as the plant or 'major component' of the plant that must be a "direct product" of U.S.-origin "technology" or "software." This new Entity List FDP rule states that any foreign-produced item is subject to the EAR if: (1) it meets the product scope in § 734.9(e)(2)(i)—either paragraph (e)(2)(i)(A) or (B); and (2) there is "knowledge" that an entity designated with footnote 4 on the Entity List is either involved in any of the activities in paragraph (e)(2)(ii)(A) or is a party to the transaction as described in paragraph (e)(2)(ii)(B).

2. Advanced Computing FDP Rule

The new "Advanced computing FDP rule" under paragraph (h) indicates that any foreign-produced item is subject to the EAR if it meets the product scope in § 734.9(h)(1)—either paragraph (h)(1)(i) or (ii)—and destination scope in paragraph (h)(2). Paragraph (h)(1)(i) (''Direct product'' of ''technology'' or ''software'') specifies that a foreign-produced item meets the product scope of this new advanced computing FDP rule if it meets the conditions identified in (both) paragraphs (h)(1)(i)(A) (*i.e.,* the foreign-produced item is the ''direct product'' of certain specified ''software'' or ''technology'' subject to the EAR) and (B) (the foreign-produced item is specified in new ECCN 3A090 or 4A090 or is an integrated circuit, computer, ''electronic assembly,'' or ''component'' specified elsewhere on the CCL which meets or exceeds the limit in the performance parameters of ECCN 3A090 or 4A090, or is an item used in the ''development,'' ''production,'' ''use,'' operation, installation (including on-site installation), maintenance (checking), repair, overhaul, or refurbishing of any item in the PRC used in the ''development'' or ''production,'' of certain integrated circuits).

The product scope in § 734.9(h) also includes foreign-produced items specified in ECCN 3A090 or 4A090 or other specified items that are products of a complete plant or 'major component' of a plant, whether made in the United States or a foreign country, that itself is a ''direct product'' of certain specified U.S.-origin ''technology'' or ''software.''

Paragraph (h)(2) (Destination scope) specifies that a foreign-produced item meets the destination scope of this paragraph if there is ''knowledge'' that the foreign-produced item is being exported, reexported, or transferred (in-country) to or within the PRC, or being incorporated into any ''part,'' ''component,'' ''computer,'' or ''equipment'' destined to the PRC.

3. Supercomputer End-Use FDP Rule

The new ''Supercomputer end-use FDP rule'' under § 734.9(i) of the EAR makes any foreign-produced item subject to the EAR if it meets the product scope in paragraph (i)(1)—either paragraph (i)(1)(i) or (ii)—and the end-use and country scope in paragraph (i)(2) of § 734.9. Paragraph (i)(1)(i) (''Direct product'' of ''technology'' or ''software'') of this new Supercomputer end-use FDP rule specifies that a foreign-produced item meets the product scope if it meets the conditions identified in paragraph (i)(1)(i), *i.e.,* meaning the foreign-produced item is the ''direct product'' of certain specified ''technology'' or ''software'' subject to the EAR. The product scope also includes foreign-produced items that are the products of a complete plant or 'major component' of a plant, whether made in the United States or a foreign country, that itself is a ''direct product'' of certain specified U.S.-origin ''technology'' or ''software.'' The product scope for this FDP rule generally matches the product scope for the new ''supercomputer'' end use rule in § 744.23 of the EAR.

Paragraph (i)(2) (Country and end-use scope) of § 734.9(i) specifies that a foreign-produced item meets the country and end-use scope if there is ''knowledge'' that the foreign produced items will be 1) used in the design, ''development,'' ''production,'' operation, installation (including on-site installation), maintenance (checking), repair, overhaul, or refurbishing of a ''supercomputer'' located in or destined to the PRC; or 2) incorporated into, or used in the ''development,'' or ''production,'' of any ''part,'' ''component,'' or ''equipment'' that will be used in a ''supercomputer'' located in or destined to the PRC.

The end-use scope for this FDP rule generally matches the end-use requirement for the new ''supercomputer'' end-use control in § 744.23 of the EAR. Because the product scope, end-use scope, and country scope of this FDP rule generally match the license requirements in § 744.23 of the EAR, items that meet the terms of this foreign direct product rule should also require a license under § 744.23 of the EAR.

Relatedly, § 772.1 of the EAR is amended by adding a definition for ''supercomputer,'' as follows: ''A computing ''system'' having a collective maximum theoretical compute capacity of 100 or more double-precision (64-bit) petaflops or 200 or more single-precision (32-bit) petaflops within a 41,600 ft^3 or smaller envelope.''

F. Instituting a New End-Use and End-User Control for ''Supercomputers'' Under § 744.23 of the EAR

In part 744 (End-Use and End-User Controls), this rule adds a new § 744.23 (''Supercomputer'' and semiconductor end use). New § 744.23 imposes an end-use control that is supplemental to CCL-based license requirements and adds two prohibitions under paragraphs (a) and (b). Paragraph (a) specifies that you may not export, reexport, or transfer (in-country) an item meeting the product scope in paragraph (a)(1) when you have ''knowledge'' at the time of export, reexport, or transfer (in-country) that the item will be used, directly or indirectly, in an applicable end use in paragraph (a)(2). In addition, new paragraph (a)(1)(iii) imposes a license requirement on any item subject to the EAR when you have ''knowledge'' at the time of the export, reexport, or transfer (in-country) that the item is destined for a specified end use, *i.e.,* the ''development'' or ''production'' of integrated circuits at a semiconductor fabrication ''facility'' located in China that fabricates certain integrated circuits.

Paragraph (a)(1) sets forth the product scope, which generally aligns with the new Supercomputer FDP rule in § 734.9(i), but this license requirement also applies to U.S.-origin items and other items subject to the EAR—not just the foreign-produced items subject to the EAR under the Supercomputer FDP rule.

Paragraph (a)(2) specifies the end-use scope, which includes the design, ''development,'' ''production,'' operation, installation (including on-site installation), maintenance (checking), repair, overhaul, or refurbishing of a ''supercomputer'' located in or destined to the PRC; incorporation of an item meeting the product scope of paragraph (a)(1) into any ''component'' or ''equipment'' that will be used in a ''supercomputer'' located in or destined to the PRC; the ''development'' or ''production,'' of integrated circuits at a semiconductor fabrication ''facility'' located in the PRC that fabricates integrated circuits with specified parameters or if you do not know whether such semiconductor fabrication ''facility'' can produce such integrated circuits; or the ''development,'' ''production,'' ''use,'' operation, installation (including on-site installation), maintenance (checking), repair, overhaul, or refurbishing of any item in the PRC used in the ''development'' or ''production,'' of integrated circuits.

This rule adds paragraph (b) (Additional prohibition on persons informed by BIS) to new § 744.23 to include an ''is informed'' process similar to other part 744 end-use controls. New paragraph (b) specifies that BIS may inform persons, either individually by specific notice or through amendment to the EAR, that a license is required for certain exports, reexports, or transfers (in-country) of any item subject to the EAR to a certain end user because there is an unacceptable risk of use in, or diversion to, the activities specified in paragraph (a)(1) of § 744.23. Consistent with other ''is informed'' provisions of the EAR, this rule specifies in paragraph (b) that a specific notice may be given only by, or at the direction of, the Deputy Assistant Secretary for Export Administration. In addition, paragraph (b) specifies that when such notice is provided orally, it will be followed by a written notice within two working days. This rule also clarifies that the absence of any such notification under paragraph (b) does not excuse persons from compliance with the license requirements of paragraph (a)(1) or (2) of § 744.23 of the EAR.

This rule also adds paragraph (c) to new § 744.23 to specify that no license exceptions are available to overcome the license requirements in § 744.23. As with other end-use controls in part 744 of the EAR, this limitation on license exceptions applies even if the items also require a license under another provision of the EAR that is not so limited. For example, even if an item categorized under ECCN 3A001 is ordinarily eligible for export to China under License Exception RPL (for replacement parts), it would not be eligible for License Exception RPL if it is for a "supercomputer" that is located in or destined to the PRC.

Finally, this rule adds paragraph (d) (License Review Standards) to specify that there is a presumption of denial for applications to export, reexport, or transfer (in-country) of items that meet the product scope in paragraph (a)(1) of § 744.23 and the end use scope of paragraph (a)(2) of that section, except for certain end users in China that are headquartered in the United States or in a Country Group A:5 or A:6 country. This license review standard applies even though the items subject to this end-use control may require licenses to the PRC or other destinations for multiple reasons, including for reasons that have a more favorable licensing policy (*e.g.,* 3A001 items require a license for China and would normally be reviewed under the license review policy described in § 742.4(b)(7), but for an end-use described in new § 744.23, BIS will review the license application under the presumption of denial policy described above). The new paragraph also specifies that when an entity listed under supplement no. 4 to part 744 of the EAR (*i.e.,* the Entity List) and designated with a reference to footnote 4 are a party to the transaction, the license review policy for foreign-produced items subject to a license requirement is set forth in such entity's entry in supplement no. 4 to part 744 of the EAR.

BIS estimates new license requirements under § 744.23 will result in an additional five (5) license applications being submitted to BIS annually.

In § 744.1 (General provisions), as a conforming change to addition of § 744.23, this rule adds one sentence to specify that the end use and end-user controls in part 744 also extend to those in new § 744.23.

Provisions of this paragraph regarding the "development" or "production," of integrated circuits at certain semiconductor manufacturing "facilities" located in China are described below in Section IV.B of this preamble.

G. Revisions to the Entity List Under Supplement No. 4 to Part 744 of the EAR

1. Overview of Entity List

The Entity List (supplement no. 4 to part 744 of the EAR) identifies entities for which there is reasonable cause to believe, based on specific and articulable facts, that the entities have been involved, are involved, or pose a significant risk of being or becoming involved in activities contrary to the national security or foreign policy interests of the United States. The EAR imposes additional license requirements on and limits the availability of most license exceptions for exports, reexports, and transfers (in-country) to listed entities.

The license review policy for each listed entity is identified in the "License Review Policy" column on the Entity List, and the impact on the availability of license exceptions is described in the relevant **Federal Register** document that added the entity to the Entity List. Any license application for an export, reexport, or transfer (in-country) involving an entity on the Entity List that is subject to an additional EAR license requirement will also be reviewed in accordance with the license review policies in the sections of the EAR applicable to those license requirements. For example, for Russian entities on the Entity List, if the export, reexport, or transfer (in-country) is subject to a license requirement in § 746.6, § 746.8, or § 746.10, the license application will be reviewed in accordance with the license review policies in those sections in addition to the specified license review policy under the Entity List entry.

BIS places entities on the Entity List pursuant to parts 744 (Control Policy: End-User and End-Use Based) and 746 (Embargoes and Other Special Controls) of the EAR. Paragraphs (b)(1) through (5) of § 744.11 include an illustrative list of activities contrary to the national security or foreign policy interests of the United States.

The End-User Review Committee (ERC), composed of representatives of the Departments of Commerce (Chair), State, Defense, Energy and, where appropriate, the Treasury, makes all decisions regarding additions to, removals from, or other modifications to the Entity List. The ERC makes all decisions to add an entry to the Entity List by majority vote and makes all decisions to remove or modify an entry by unanimous vote.

2. Entity List Decisions: Revisions to the Entity List

This rule expands the scope of licensing requirements for 28 existing entities on the Entity List that are located in the PRC and were added to the Entity List between 2015 and 2021. Certain of the entities are developing supercomputers believed to be used in nuclear explosive activities; these entities have been placed on the Entity List triggering license requirements for items destined to those specific entities. For example, see 80 FR 8527, Feb. 18, 2015 ("National University of Defense Technology (NUDT) has used U.S.-origin multicores, boards, and (co)processors to produce the TianHe-1A and TianHe-2 supercomputers located at the National Supercomputing Centers in Changsha, Guangzhou, and Tianjin. The TianHe-1A and TianHe-2 supercomputers are believed to be used in nuclear explosive activities as described in § 744.2(a) of the EAR.") Similarly, BIS has added multiple other Chinese entities involved in the "development" and "production" of integrated circuits to the Entity List based on their involvement with WMD as well as military end uses and end users. For example, on April 9, 2021 (86 FR 18437), BIS added seven Chinese entities to the Entity List "on the basis of their procurement of U.S.-origin items for activities contrary to the national security and foreign policy interests of the United States. Specifically, these entities are involved in activities that support China's military actors, its destabilizing military modernization efforts, and/or its [WMD] programs." The types of computing facilities located at these entities are used for designing stealth technologies, space planes, hypersonic missiles, and other military applications including nuclear weapons design. Most specifically, with the April 9 rule, BIS added chip developer Tianjin Phytium Information Technology (also known as Phytium) to the Entity List.

Even though the license requirement for these entities remains all items subject to the EAR, this rule changes the scope of items subject to the EAR for transactions involving these entities through the revised Entity List FDP rule in § 734.9(e)(2) of the EAR and adds a new license requirement in § 744.11 of the EAR that is specific to foreign produced items for these entities, both discussed elsewhere in this interim final rule. This rule adds a footnote 4 to the entities, and a reference to the Entity List FDP rule in the license requirements column of the Entity List. With these changes, additional foreign-produced items will now be subject to the EAR and require a license when destined to or for these 28 entities. The agencies represented on the ERC have approved the changes.

The 28 revised entities are:

• Beijing Institute of Technology;
• Beijing Sensetime Technology Development Co., Ltd.;
• Changsha Jingjia Microelectronics Co., Ltd.;
• Chengdu Haiguang Integrated Circuit;
• Chengdu Haiguang Microelectronics Technology;
• China Aerospace Science and Technology Corporation (CASC) 9th Academy 772 Research Institute
• Dahua Technology;
• Harbin institute of technology;
• Higon;
• IFLYTEK;
• Intellifusion;
• Megvii Technology;
• National Supercomputer Center Zhengzhou;
• National Supercomputing Center Changsha (NSCC–CS);
• National Supercomputing Center Guangzhou (NSCC–GZ);
• National Supercomputing Center Jinan;
• National Supercomputing Center Shenzhen;
• National Supercomputing Center Tianjin (NSCC–TJ);
• National Supercomputing Center Wuxi (NSCC–WX);
• National University of Defense Technology;
• New H3C Semiconductor Technologies Co., Ltd.;
• Northwestern Polytechnical University;
• Shanghai High-Performance Integrated Circuit Design Center;
• Sugon;
• Sunway Microelectronics;
• Tianjin Phytium Information Technology;
• Wuxi Jiangnan Institute of Computing Technology; and
• Yitu Technologies.

To assist with clarity, this rule revises § 744.11 by making editorial changes to the paragraph that imposes a license requirement on foreign-produced items for footnote 1 entities. This rule adds double quotes around the term ''direct product'' in the paragraph heading for footnote 1 entities, because that term is defined in part 772, and updates the citation and description of the prohibition for footnote 1 entities in paragraph (e)(1)(i). This rule also adds paragraph (a)(2) to impose a license requirement on foreign-produced items for footnote 4 entities. The new paragraph prohibits, without a license, the reexport, export from abroad, or transfer (in-country) of any foreign-produced item subject to the EAR pursuant to § 734.9(e)(2)(i) of the EAR when an entity designated with footnote 4 on the Entity List in supp. no. 4 to part 744 of the EAR is a party to the transaction. This prohibition on foreign-produced items for these identified Chinese entities is necessary because many supercomputer parts and components based on U.S. technology and software are not produced in the United States, and more conventional export control measures would not effectively limit the U.S. contribution to Chinese advanced computing efforts by these entities.

IV. Overview of New Controls: Certain Semiconductor Manufacturing Items; and Integrated Circuits End Use

This rule further addresses U.S. national security and foreign policy concerns by making three changes related to semiconductor manufacturing equipment. First, BIS adds to the CCL certain advanced semiconductor manufacturing equipment under a new ECCN 3B090, controlled for RS and AT reasons of control with limited license exception availability. It also adds references to the new ECCN 3B090 under the related ''software'' and ''technology'' controls under ECCNs 3D001 and 3E001. Second, this rule establishes a new end-use control for any item subject to the EAR when the exporter, reexporter, or transferor knows the item is for ''development'' or ''production'' of ICs (packaged or unpackaged) at a semiconductor fabrication ''facility'' located in the PRC that fabricates ICs (packaged or unpackaged) that meet certain specified criteria under § 744.23. Finally, this rule informs the public that certain specific ''U.S. persons'' activity to 'support' the ''development'' or ''production'' of ICs (packaged or unpackaged) that meet certain criteria under § 744.6 of the EAR requires a license.

A. Addition of Semiconductor Manufacturing Equipment, and Associated ''Software'' and ''Technology'' to the Commerce Control List (Supplement No. 1 to Part 774 of the EAR)

This rule adds new ECCN 3B090 to the CCL for specified semiconductor manufacturing equipment. The new ECCN is controlled for RS reasons and a license is required when the items it controls are destined to the PRC. This rule imposes this license requirement by adding ECCN 3B090 to an RS control in § 742.6(a)(6) of the EAR. ECCN 3B090 will also be controlled for AT reasons when destined to a country that has AT:1 license requirement (Iran § 742.8, Syria § 742.9, or North Korea § 742.19); see also parts 744 and 746 of the EAR for additional controls on items controlled for AT reasons.

Associated ''software'' and ''technology'' controls in the CCL for items in ECCN 3B090 are found in ECCNs 3D001 and 3E001, respectively; the ''software'' and ''technology'' is also controlled for RS reasons (which this rule adds as a new reason for control) when destined to the PRC, and for other reasons described in the ECCN entries. Specifically, this rule adds the new RS license requirement to the License Requirement tables within ECCNs 3D001 and 3E001.

As described in new § 742.6(b)(10), license applications for semiconductor manufacturing items, such as semiconductor equipment, destined to end users in China that are headquartered in the United States or in a country in Country Group A:5 or A:6 will be considered on a case-by-case basis, taking into account factors including technology level, customers and compliance plans.

License requirements for AT Column 1 items are identified in part 742 of the EAR; the items subject to these requirements are also subject to the end-use and end-user controls in part 744 of the EAR as well as many of the country and sector controls imposed in part 746 of the EAR, including controls that apply to Russia and Belarus under § 746.8(a)(1) of the EAR. If, in the future, a multilateral export control regime adopts controls for the specified items controlled in this interim final rule, BIS will amend the controls implemented in this rule as needed to implement multilateral controls in place of the unilateral control.

The only license exception available for exports or reexports of items controlled under new ECCN 3B090 (and the associated software and technology in ECCNs 3D001 and 3E001) is listed under § 740.2(a)(9) of the EAR, which is an existing paragraph that contains a list of license exceptions that are appropriate for the license requirements implemented in this rule. The only available license exception is License Exception Governments, International organizations, international inspections under the Chemical Weapons Convention, and the International Space Station (GOV), restricted to eligibility under the provision of § 740.11(b)(2)(ii) (exports, reexports, and transfers (in-country) made by or consigned to a department or agency of the United States Government).

BIS estimates these new license requirements and the restrictions on license exceptions described below will result in an additional fifty (50) license applications being submitted to BIS annually.

B. Instituting a New End-Use Control for Any Item Subject to the EAR for the "Development" or "Production," of Integrated Circuits at Certain Semiconductor Manufacturing "Facilities" Located in the PRC

In part 744 (End-Use and End-User Controls), this rule adds § 744.23 ("Supercomputers" and semiconductor manufacturing end use), to impose an end-use control that is supplemental to CCL-based license requirements. BIS imposes the new end-use control by adding prohibitions under paragraphs (a)(1)(iii) through (v). Paragraph (a) specifies that you may not export, reexport, or transfer (in-country) an item meeting the product scope in paragraph (a)(1) when you have "knowledge" at the time of export, reexport, or transfer (in-country) that the item will be used, directly or indirectly, in an applicable end use in paragraph (a)(2).

As with all end-use controls under the EAR, exporters, reexporters, and transferors are responsible for reviewing their transactions in accordance with the "Know Your Customer" Guidance in supplement no. 3 to part 732 of the EAR. If your customer is a semiconductor manufacturing "facility" involved in the end uses set forth in paragraph (a)(2) of § 744.23, in addition to the best practice of obtaining and end-use statement from your customer, you should also evaluate all other available information to determine whether a license is required pursuant to § 744.23. If your customer is a reseller, distributor, or other intermediary transaction party, it is a good compliance practice to attempt to obtain confirmation of the actual end use and end user of your products. If the intermediary party (*e.g.*, reseller, distributor) cannot furnish these details at the time of the proposed export or reexport because it is a prospective order and no specific customer has yet been identified, as a good compliance practice you may attempt to obtain a written statement that the intermediary party understands the license requirements in § 744.23 and will either: (a) inform you of the actual end use and end user, once known, so you may evaluate whether a license is required for any proposed in-country transfer, or (b) evaluate the end use and end user and apply for any required license for any proposed in-country transfer. The new prohibition this rule adds to § 744.23(a)(1)(iii) through (v) and (a)(2)(iii) through (v) is subject to BIS's "is informed" process under paragraph (b) (Additional prohibition on persons informed by BIS).

As specified under paragraph (c) to newly added § 744.23, no license exceptions are available to overcome the license requirements in § 744.23.

Paragraph (d) (License Review Standards) specifies that there is a presumption of denial for applications to export, reexport, or transfer (in-country) items subject to the license requirements of § 744.23, which will also apply for the "development" or "production," of integrated circuits at a semiconductor fabrication "facility" located in the PRC that fabricates certain integrated circuits and the "development" or "production" in the PRC of any "parts," "components" or "equipment" specified under certain ECCNs. This license review standard applies even though the items subject to this end-use control may require licenses to the PRC or other destinations for multiple reasons, including for reasons that have a more favorable licensing policy.

BIS estimates new license requirements under § 744.23(a)(1)(iii) through (v) and (a)(2)(iii) through (vi) will result in an additional twenty-five (25) license applications being submitted to BIS annually.

Provisions of this paragraph regarding "supercomputers" are described above in Section III.F of this preamble.

C. Providing Public Notice That "U.S. Person" 'Support' for "Development" or "Production," of Integrated Circuits That Meet Certain Specified Criteria Implicates the General Prohibitions in § 744.6(b) of the EAR

In part 744, this rule revises § 744.6 (Restrictions on specific activities of "U.S. persons") to inform "U.S. persons" that 'support' for the "development" or "production," of integrated circuits that meet certain specified criteria in the PRC implicates the general prohibitions set forth in § 744.6(b) of the EAR and is therefore subject to a BIS license requirement. As authorized in ECRA (50 U.S.C. 4812(a)(2)), § 744.6 specifies that no "U.S. person" may without a license from BIS 'support' the WMD- and military-intelligence-related end uses and end users set forth in paragraphs (b)(1) through (5). 'Support' is defined in paragraph (b)(6) to encompass a number of activities, including, but not limited to, shipping, transmitting, or transferring (in-country) items not subject to the EAR; facilitating such shipment, transmission, or transfer (in-country); or servicing items not subject to the EAR.

As described above, semiconductor manufacturing items enable the "development" or "production" of advanced ICs that may contribute to the WMD-related end uses set forth in § 744.6(b). Section 744.6(c) of the EAR provides that BIS may inform "U.S. persons" through amendment to the EAR published in the **Federal Register** that a license is required because an activity could involve the type of 'support' defined in paragraph (b)(6) to the end uses and end users set forth in paragraphs (b)(1) through (5). Accordingly, BIS is amending the EAR in this rule to set forth the current text of § 744.6(c) in new § 744.6(c)(1) and to add a new § 744.6(c)(2) to inform "U.S. persons" of activities related to the "development" or "production" of ICs that could involve 'support' to WMD and missile end uses set forth in paragraph (b) and are therefore subject to a BIS license requirement.

Specifically, new paragraph (c)(2) informs "U.S. persons" that the shipment, transmission, or transfer (in-country) to or within the PRC of any item not subject to the EAR; facilitation of such shipment, transmission, or transfer (in-country); or servicing of any item not subject to the EAR to or within the PRC when such activity would assist the "development" or "production" of ICs meeting certain parameters is subject to a license requirement. Likewise, BIS is informing "U.S. persons" that the shipment, transmission, or transfer (in-country) of certain items not subject to the EAR that meet specific technical parameters set forth on the CCL; facilitation of such shipment, transmission, or transfer (in-country); or servicing of such items to or within the PRC when such activity would assist the "development" or "production" of ICs, but you cannot determine the technical parameters of those ICs requires a license. A license is also required for "U.S. persons" activities involving shipping, transmitting, or transferring (in-country) or facilitating the shipment, transmission, or transfer (in-country) to or within the PRC any item not subject to the EAR and meeting the parameters of ECCN 3B090, 3D001 (for 3B090), or 3E001 (for 3B090) regardless of end use or end user; or servicing any item not subject to the EAR located in the PRC and meeting the parameters of ECCN 3B090, 3D001 (for 3B090), or 3E001 (for

3B090), regardless of end use or end user.

This is consistent with the scope of the end-use restriction for items subject to the EAR in new § 744.23(a)(2)(iii).

As specified under paragraph (d)(1) (Exceptions), no license exceptions are available to overcome the license requirements in § 744.6(b)(1) through (4) or (c)(2).

Under paragraph (e)(3) (License Review Standards), there is a presumption of denial for applications to export, reexport, or transfer (in-country) items subject to the license requirements of § 744.6(c)(2) except for license applications for end users in China headquartered in the United States or in a country in Country Group A:5 or A:6, which will be considered on a case-by-case basis taking into account factors including technology level, customers and compliance plans.

BIS estimates new license requirements under § 744.6(c)(2)(i) will result in an additional five (5) license applications being submitted to BIS annually.

V. Measures To Minimize Short Term Impacts on Supply Chains

BIS is imposing the controls described in this rule to protect critical U.S. national security and foreign policy interests. BIS is aware that the new controls being imposed in this rule may result in the disruption of certain companies' activities involving China, in particular in relation to their supply chains. In order to give companies time to become familiar with the new controls being implemented, this rule implements two changes to minimize the short term impact on supply chains in transactions that do not appear to implicate national security or foreign policy concerns.

A. Certification of Compliance With New FDP Rule

In § 734.9(h), this rule adds a new paragraph (h)(3) (*Certification*) to assist exporters, reexporters, and transferors in determining whether the items being exported, reexported, or transferred (in-country) are subject to the EAR based on the advanced computing FDP rule under § 734.9(h). The model certificate provided by BIS in new supplement no. 3 to part 734, is not required under the EAR, but is provided to assist exporters, reexporters, and transferors with the process of resolving potential red flags regarding whether an item is subject to the EAR based on § 734.9(h). The model certificate contemplates inclusion of information described in paragraph (b) of supplement no. 1 to part 734 and the signature by an official or designated employee of the certifying company. If a person in the supply chain is unable to obtain the certification due diligence is suggested and a BIS authorization may be required for the next set of recipients in the supply chain. While BIS expects that this certificate will be useful in facilitating understanding the application of the EAR to an item, BIS does not view use of this certificate alone to be a comprehensive due diligence process.

BIS has determined that use of the certificate will protect U.S. national security and foreign policy interests. BIS expects it will also limit the burden on entities participating in supply chains by allowing them to proceed with transactions within their supply chains.

In § 762.2 this rule revises paragraph (b) to add a reference to the FDP supply chain certification that this rule added under new § 734.9(h). This interim final rule makes this change by redesignating paragraphs (b)(3) through (31) as paragraphs (b)(4) through (32) and adding new paragraph (b)(3). In § 740.10 (Servicing and replacement of parts and equipment (RPL)), this interim final rule makes a conforming change to paragraph (c)(2) in § 762.2 to remove the references to § 762.2(b)(4), (47), and (48) and instead include a reference to § 762.2(b).

B. Temporary General License—Supply Chain

This rule establishes a temporary general license (TGL) in new paragraph (d) of supplement no. 1 to part 736 that allows, from October 21, 2022, through April 7, 2023, exports, reexports, in-country transfers, and exports from abroad destined to or within China by companies not headquartered in Country Groups D:1 or D:5 or E to continue or to engage in integration, assembly (mounting), inspection, testing, quality assurance, and distribution of items covered by ECCN 3A090, 4A090, and associated software and technology in ECCN 3D001, 3E001, 4D090, or 4E001; or any item that is a computer, integrated circuit, "electronic assembly" or "component" and associated software and technology, specified elsewhere on Commerce Control List (supplement no. 1 to part 774), which meets or exceeds the performance parameters of ECCN 3A090 or 4A090. The purpose of this TGL is to avoid disruption of supply chains for items covered by ECCNs that are ultimately destined to customers outside of China. This TGL does not authorize the export, reexport, in-country transfer, or export from abroad to "end-users" or "ultimate consignees" in China. This TGL is only for companies that engage in the specific activities authorized under this TGL. The TGL does not overcome any license requirements set forth in the EAR involving an entity on the Entity List or other prohibited end use and end user restrictions (*e.g.,* those applicable to military end uses and end users). Prior to any export, reexport, or transfer (in-country) to China pursuant to this TGL, the exporter, reexporter, or transferor, must retain the name of the entity receiving the item and the complete physical address of where the item is destined in China and the location of that company's headquarters.

In response to this interim final rule, BIS welcomes comments on the temporary general license, including comments on how important the temporary general license is for supply chains to continue functioning, comments on dependency of certain aspects of the supply chain on companies in China, overview of steps taken by companies to reduce dependency on China for those aspects of their supply chains, and if a request to extend the temporary license is made to provide a rationale for why an extension may be warranted. BIS, in consultation with the other agencies, will solely determine whether any extension or modification of the TGL is warranted, but comments from the public are welcome and may help inform any subsequent decisions on the TGL. Upon expiration of the TGL, exporters will need to apply for an individually-validated export license to export such advanced computing chips, assemblies containing them, and related software and technology to the PRC for supply chain-related activities, such as assembly, inspection, quality assurance, and distribution. Such license applications will be reviewed consistent with the licensing policy set forth in new § 742.6(b)(10), as described above in Section III.B.

Savings Clause

Shipments of items removed from license exception eligibility or eligibility for export, reexport or transfer (in-country) without a license as a result of this regulatory action that were on dock for loading, on lighter, laden aboard an exporting carrier, or en route aboard a carrier to a port of export, on October 7, 2022, may continue to the destination under the previous license exception eligibility or without a license so long as they have been exported, reexported or transferred (in-country) before November 7, 2022. Any such items not actually exported, reexported or transferred (in-country) before midnight, on November 7, 2022, require a license in accordance with this interim final rule.

Deemed exports and reexports of technology and software related to ECCNs 3A991.p and 4A994.l that previously did not require a license, but now require a license because of the controls implemented by this rule, will only require licenses if the technology or software release exceeds the scope of the technology or software that the foreign national already had access to prior to the implementation of controls in this rule.

Export Control Reform Act of 2018

On August 13, 2018, the President signed into law the John S. McCain National Defense Authorization Act for Fiscal Year 2019, which included the Export Control Reform Act of 2018 (ECRA) (codified, as amended, at 50 U.S.C. Sections 4801–4852). ECRA provides the legal basis for BIS's principal authorities and serves as the authority under which BIS issues this rule. To the extent it applies to certain activities that are the subject of this rule, the Trade Sanctions Reform and Export Enhancement Act of 2000 (TSRA) (codified, as amended, at 22 U.S.C. Sections 7201–7211) also serves as authority for this rule.

Rulemaking Requirements

1. This interim final rule is not a "significant regulatory action" because it "pertain[s]" to a "military or foreign affairs function of the United States" under sec. 3(d)(2) of Executive Order 12866.

2. Notwithstanding any other provision of law, no person is required to respond to, nor shall any person be subject to a penalty for failure to comply with, a collection of information subject to the requirements of the Paperwork Reduction Act of 1995 (44 U.S.C. 3501 *et seq.*) (PRA), unless that collection of information displays a currently valid Office of Management and Budget (OMB) Control Number.

This rule involves the following OMB-approved collections of information subject to the PRA:

• 0694–0088, "Multi-Purpose Application," which carries a burden hour estimate of 29.4 minutes for a manual or electronic submission;

• 0694–0096 "Five Year Records Retention Period," which carries a burden hour estimate of less than 1 minute; and

• 0607–0152 "Automated Export System (AES) Program," which carries a burden hour estimate of 3 minutes per electronic submission.

BIS estimates that these new controls under the EAR imposed by this rule will result in an increase of 1,700 license applications submitted annually to BIS. However, the additional burden falls within the existing estimates currently associated with these control numbers. Additional information regarding these collections of information—including all background materials—can be found at *https://www.reginfo.gov/public/do/PRAMain* by using the search function to enter either the title of the collection or the OMB Control Number.

3. This rule does not contain policies with federalism implications as that term is defined in Executive Order 13132.

4. Pursuant to section 1762 of the Export Control Reform Act of 2018 (50 U.S.C. 4821) (ECRA), this action is exempt from the Administrative Procedure Act (APA) (5 U.S.C. 553) requirements for notice of proposed rulemaking, opportunity for public participation, and delay in effective date. While section 1762 of ECRA provides sufficient authority for such an exemption, this action is also independently exempt from these APA requirements because it involves a military or foreign affairs function of the United States (5 U.S.C. 553(a)(1)).

5. Because a notice of proposed rulemaking and an opportunity for public comment are not required to be given for this rule by 5 U.S.C. 553, or by any other law, the analytical requirements of the Regulatory Flexibility Act, 5 U.S.C. 601, *et seq.*, are not applicable. Accordingly, no regulatory flexibility analysis is required, and none has been prepared.

List of Subjects

15 CFR Part 734

Administrative practice and procedure, Exports, Inventions and patents, Research, Science and technology.

15 CFR Parts 736 and 772

Exports.

15 CFR Part 740

Administrative practice and procedure, Exports, Reporting and recordkeeping requirements.

15 CFR Part 742

Exports, Terrorism.

15 CFR Part 744

Exports, Reporting and recordkeeping requirements, Terrorism.

15 CFR Part 762

Administrative practice and procedure, Business and industry, Confidential business information, Exports, Reporting and recordkeeping requirements.

15 CFR Part 774

Exports, Reporting and recordkeeping requirements.

For the reasons stated in the preamble, parts 734, 736, 740, 742, 744, 762, 772, and 774 of the Export Administration Regulations (15 CFR parts 730 through 774) are amended as follows:

PART 734—SCOPE OF THE EXPORT ADMINISTRATION REGULATIONS

■ 1. The authority citation for part 734 continues to read as follows:

Authority: 50 U.S.C. 4801–4852; 50 U.S.C. 4601 *et seq.;* 50 U.S.C. 1701 *et seq.;* E.O. 12938, 59 FR 59099, 3 CFR, 1994 Comp., p. 950; E.O. 13020, 61 FR 54079, 3 CFR, 1996 Comp., p. 219; E.O. 13026, 61 FR 58767, 3 CFR, 1996 Comp., p. 228; E.O. 13222, 66 FR 44025, 3 CFR, 2001 Comp., p. 783; E.O. 13637, 78 FR 16129, 3 CFR, 2014 Comp., p. 223; Notice of November 10, 2021, 86 FR 62891 (November 12, 2021).

■ 2. Effective on October 21, 2022, § 734.9 is amended by revising paragraph (e) and adding paragraphs (h) and (i) to read as follows:

§ 734.9 Foreign-Direct Product (FDP) Rules.

* * * * *

(e) *Entity List FDP rule.* A foreign-produced item is subject to the EAR if it meets the product scope and end-user scope in either Entity List FDP rule footnote 1 provision in paragraph (e)(1) of this section or the Entity List FDP rule Footnote 4 provision in paragraph (e)(2) of this section.

(1) *Entity List FDP rule: Footnote 1.* A foreign-produced item is subject to the EAR if it meets both the product scope in paragraph (e)(1)(i) of this section and the end-user scope in paragraph (e)(1)(ii) of this section. See § 744.11(a)(2)(i) of the EAR for license requirements, license review policy, and license exceptions applicable to foreign-produced items that are subject to the EAR pursuant to this paragraph (e)(1).

(i) *Product Scope Entity List FDP rule: Footnote 1.* The product scope applies if a foreign-produced item meets the conditions of either paragraph (e)(1)(i)(A) or (B) of this section.

(A) "*Direct product*" *of* "*technology*" *or* "*software.*" A foreign-produced item meets the product scope of this paragraph (e)(1)(i)(A) if the foreign-produced item is a "direct product" of "technology" or "software" subject to the EAR and specified in ECCN 3D001, 3D991, 3E001, 3E002, 3E003, 3E991, 4D001, 4D993, 4D994, 4E001, 4E992, 4E993, 5D001, 5D991, 5E001, or 5E991 of the Commerce Control List (CCL) in supplement no. 1 to part 774 of the EAR; or

(B) *Product of a complete plant or 'major component' of a plant that is a "direct product."* A foreign-produced item meets the product scope of this paragraph (e)(1)(i)(B) if the foreign-produced item is produced by any plant or 'major component' of a plant that is located outside the United States, when the plant or 'major component' of a plant, whether made in the U.S. or a foreign country, itself is a "direct product" of U.S.-origin "technology" or "software" that is specified in ECCN 3D001, 3D991, 3E001, 3E002, 3E003, 3E991, 4D001, 4D993, 4D994, 4E001, 4E992, 4E993, 5D001, 5D991, 5E001, or 5E991 of the CCL.

Note 2 to paragraph (e)(1)(i): A foreign-produced item includes any foreign-produced wafer whether finished or unfinished.

(ii) *End-user scope of the Entity List FDP rule: Footnote 1.* A foreign-produced item meets the end-user scope of this paragraph (e)(1)(ii) if there is "knowledge" that:

(A) *Activities involving Footnote 1 designated entities.* The foreign-produced item will be incorporated into, or will be used in the "production" or "development" of any "part," "component," or "equipment" produced, purchased, or ordered by any entity with a footnote 1 designation in the license requirement column of the Entity List in supplement no. 4 to part 744 of the EAR; or

(B) *Footnote 1 designated entities as transaction parties.* Any entity with a footnote 1 designation in the license requirement column of the Entity List in supplement no. 4 to part 744 of the EAR is a party to any transaction involving the foreign-produced item, *e.g.,* as a "purchaser," "intermediate consignee," "ultimate consignee," or "end-user."

(2) *Entity List FDP rule: Footnote 4.* A foreign-produced item is subject to the EAR if it meets both the product scope in paragraph (e)(2)(i) of this section and the end-user scope in paragraph (e)(2)(ii) of this section. See § 744.11(a)(2)(ii) of the EAR for license requirements, license review policy, and license exceptions applicable to foreign-produced items that are subject to the EAR pursuant to this paragraph (e)(2).

(i) *Product Scope Entity List FDP rule: Footnote 4.* The product scope applies if a foreign-produced item meets the conditions of either paragraph (e)(2)(i)(A) or (B) of this section.

(A) *"Direct product" of "technology" or "software."* The foreign-produced item is a "direct product" of "technology" or "software" subject to the EAR and specified in ECCN 3D001, 3D991, 3E001, 3E002, 3E003, 3E991, 4D001, 4D993, 4D994, 4E001, 4E992, 4E993, 5D001, 5D002, 5D991, 5E001, 5E002, or 5E991 of the CCL; or

(B) *Product of plant or 'major component' that is a "direct product."* The foreign-produced item is produced by any plant or 'major component' of a plant when the plant or 'major component' of a plant, whether made in the U.S. or a foreign country, itself is a "direct product" of U.S.-origin "technology" or "software" that is specified in ECCN 3D001, 3D991, 3E001, 3E002, 3E003, 3E991, 4D001, 4D993, 4D994, 4E001, 4E992, 4E993, 5D001, 5D991, 5E001, 5E991, 5D002, or 5E002 of the CCL.

(ii) *End user scope of the Entity List FDP rule: Footnote 4.* A foreign-produced item meets the end-user scope of this paragraph (e)(2)(ii) if there is "knowledge" that:

(A) *Activities involving Footnote 4 designated entities.* The foreign-produced item will be incorporated into, or will be used in the "production" or "development" of any "part," "component," or "equipment" produced, purchased, or ordered by any entity with a footnote 4 designation in the license requirement column of the Entity List in supplement no. 4 to part 744 of the EAR; or

(B) *Footnote 4 designated entities as transaction parties.* Any entity with a footnote 4 designation in the license requirement column of the Entity List in supplement no. 4 to part 744 of the EAR is a party to any transaction involving the foreign-produced item, *e.g.,* as a "purchaser," "intermediate consignee," "ultimate consignee," or "end-user."

* * * * *

(h) *Advanced computing FDP rule.* A foreign-produced item is subject to the EAR if it meets both the product scope in paragraph (h)(1) of this section and the destination scope in paragraph (h)(2) of this section. See § 742.6(a)(6) of the EAR for license requirements and license exceptions and § 742.6(b)(10) for license review policy applicable to foreign-produced items that are subject to the EAR under this paragraph (h).

(1) *Product scope of advanced computing FDP rule.* The product scope applies if a foreign-produced item meets the conditions of either paragraph (h)(1)(i) or (ii) of this section.

(i) *"Direct product" of "technology" or "software."* A foreign-produced item meets the product scope of this paragraph (h) if it meets both the following conditions:

(A) The foreign-produced item is the "direct product" of "technology" or "software" subject to the EAR and specified in 3D001, 3D991, 3E001, 3E002, 3E003, 3E991, 4D001, 4D090, 4D993, 4D994, 4E001, 4E992, 4E993, 5D001, 5D002, 5D991, 5E001, 5E991, or 5E002 of the CCL; and

(B) The foreign-produced item is:

(*1*) Specified in ECCN 3A090, 3E001 (for 3A090), 4A090, or 4E001 (for 4A090) of the CCL; or

(*2*) An integrated circuit, computer, "electronic assembly," or "component" specified elsewhere on the CCL and meets the performance parameters of ECCN 3A090 or 4A090.

(ii) *Product of a complete plant or 'major component' of a plant that is a "direct product."* A foreign-produced item meets the product scope of this paragraph (h) if it meets both of the following conditions:

(A) The foreign-produced item is produced by any complete plant or 'major component' of a plant that is located outside the United States, when the plant or 'major component' of a plant, whether made in the United States or a foreign country, itself is a "direct product" of U.S.-origin "technology" or "software" that is specified in ECCN 3D001, 3D991, 3E001, 3E002, 3E003, 3E991, 4D001, 4D090, 4D993, 4D994, 4E001, 4E992, 4E993, 5D001, 5D991, 5E001, 5E991, 5D002, or 5E002 of the CCL; and

(B) The foreign-produced item is:

(*1*) Specified in ECCN 3A090, 3E001 (for 3A090), 4A090, or 4E001 (for 4A090) of the CCL; or

(*2*) An integrated circuit, computer, "electronic assembly," or "component" specified elsewhere on the CCL and meets the performance parameters of ECCN 3A090 or 4A090.

(2) *Destination or end use scope of the advanced computing FDP rule.* A foreign-produced item meets the destination scope of this paragraph (h)(2) if there is "knowledge" that the foreign-produced item is:

(i) Destined to the PRC or will be incorporated into any "part," "component," "computer," or "equipment" not designated EAR99 that is destined to the PRC; or

(ii) Technology developed by an entity headquartered in the PRC for the "production" of a mask or an integrated circuit wafer or die.

(3) *Certification.* Exporters, reexporters, and transferors may obtain a written certification from a supplier that asserts an item being provided would be subject to the EAR if future transaction meet the destination scope in paragraph (h)(2)(i) or (ii) of this section. The model certificate provided

by BIS in supplement no. 1 to this part is not required under the EAR, but through its provision, the certificate may assist exporters, reexporters, and transferors with the process of resolving potential red flags regarding whether an item is subject to the EAR based on this paragraph (h). The model certificate provided by BIS contemplates signature by an official or designated employee of the certifying company and inclusion of all the information described in paragraph (b) of supplement no. 1 to this part. If the exporter, reexporter, or transferors has not obtained such a certification, due diligence needs to be conducted to determine if the items meets the scope in this paragraph (h). While this certificate is expected to be useful for a company to understand the application of the EAR to an item, BIS does not view this as the only step to be completed during a company's due diligence process. *See* supplement no. 1 to this part and supplement no. 3 to part 732 of the EAR.

(i) ''*Supercomputer*'' *FDP rule.* A foreign-produced item is subject to the EAR if it meets both the product scope in paragraph (i)(1) of this section and the country and end-use scope in paragraph (i)(2) of this section. See § 744.23 of the EAR for license requirement, license review policy, and license exceptions applicable to foreign-produced items that are subject to the EAR pursuant to this paragraph (i).

(1) *Product scope.* The product scope applies if a foreign-produced item meets the conditions of either paragraph (i)(1)(i) or (ii) of this section.

(i) ''*Direct product*'' *of* ''*technology*'' *or* ''*software.*'' The foreign-produced item meets the product scope of this paragraph (i)(1)(i) if the foreign-produced item is a ''direct product'' of ''technology'' or ''software'' subject to the EAR and specified in ECCN 3D001, 3D991, 3E001, 3E002, 3E003, 3E991, 4D001, 4D993, 4D994, 4E001, 4E992, 4E993, 5D001, 5D991, 5E001, 5E991, 5D002, or 5E002 of the CCL; or

(ii) *Product of a complete plant or 'major component' of a plant that is a* ''*direct product.*'' A foreign-produced item meets the product scope of this paragraph (i)(1)(ii) if the foreign-produced item is produced by any plant or 'major component' of a plant that is located outside the United States, when the plant or 'major component' of a plant, whether made in the United States or a foreign country, itself is a ''direct product'' of U.S.-origin ''technology'' or ''software'' that is specified in ECCN 3D001, 3D991, 3E001, 3E002, 3E003, 3E991, 4D001, 4D994, 4E001, 4E992, 4E993, 5D001, 5D991, 5E001, 5E991, 5D002, or 5E002 of the CCL.

(2) *Country and end-use scope.* A foreign-produced item meets the country and end-use scope of this paragraph (i)(2) if there is ''knowledge'' that the foreign produced item will be:

(i) Used in the design, ''development,'' ''production,'' operation, installation (including on-site installation), maintenance (checking), repair, overhaul, or refurbishing of, a ''supercomputer'' located in or destined to the PRC; or

(ii) Incorporated into, or used in the ''development,'' or ''production,'' of any ''part,'' ''component,'' or ''equipment'' that will be used in a ''supercomputer'' located in or destined to the PRC.

■ 3. Effective on October 21, 2022, add supplement no. 1 to part 734 to read as follows:

Supplement No. 1 to Part 734—Model Certification for Purposes of Advanced Computing FDP Rule

(a) *General.* This supplement is included in the EAR to assist exporters, reexporters, and transferors in determining whether the items being exported, reexported, or transferred (in-country) are subject to the EAR based on the advanced computing FDP rule under § 734.9(h). The model certificate provided by BIS in this supplement is not required under the EAR, but through its provision, the certificate may assist exporters, reexporters, and transferors with the process of resolving potential red flags regarding whether an item is subject to the EAR based on § 734.9(h). The model certificate provided in this supplement by BIS contemplates signature by an official or designated employee of the certifying company and inclusion of all the information described in paragraph (b) of this supplement. Any certification relied on for this part must be retained pursuant to part 762 of the EAR.

Obtaining the certification set forth in this supplement does not relieve exporters, reexporters, and transferors of their obligation to exercise due diligence in determining whether items are subject to the EAR, including by following the ''Know Your Customer'' guidance in supplement no. 3 to part 732 of the EAR.

(b) *Model Criteria.* A certification meets the criteria described in this supplement if it contains at least the following information:

(1) The certification must be signed by an organization official specifically authorized to certify the document as being accurate and complete. The undersigned certifies that the information herein supplied in response to this paragraph is complete and correct to the best of his/her knowledge. By signing the certification below, I attest that:

(2) My organization is aware that the items, [INSERT A DESCRIPTION OF THE ITEMS], provided to this exporter, reexporter, or transferor, [INSERT NAME OF EXPORTER, REEXPORTER, OR TRANSFEROR], could be subject to the U.S. Export Administration Regulations (EAR) (15 CFR 730–774) if future transactions are within the destination scope of § 734.9(h)(2)(i) or (ii) and exported or reexported to or transferred within the People's Republic of China (China);

(3) My organization has reviewed the criteria for the advanced computing Foreign Direct Product (FDP) rule under § 734.9(h) and attests that from my organization's ''knowledge'' of the item, it would be subject to the EAR if the destination criteria are met in § 734.9(h)(2)(i) or (ii); and

(4) My organization affirms its commitment to apply with all applicable requirements under the EAR.

[INSERT NAME(S) OF CONSIGNEE(S)]
[INSERT DATE(S) SIGNED]

Note 1 to paragraph (b): *When multiple consignees who form a network engaged in a production process (or other type of collaborative activity, such as joint development) will be receiving items under the EAR, a single model certification statement for multiple consignees may be used for any export, reexport, or transfer (in-country) under the EAR.*

(c) *Additional Information.* Because this is only a model certification, exporters, reexporters, or transferors may add additional elements to the certification and/or use it for multiple purposes as part of their compliance program. For example, if a company has ten affiliated companies in a multi-step supply chain, instead of obtaining a model certification for each export, reexport, or transfer (in-country), the initial exporter, reexporter, or transferor may get all ten parties to sign the certification, which may further reduce the burden on parties participating in the supply chain.

PART 736—GENERAL PROHIBITIONS

■ 4. The authority citation for part 736 continues to read as follows:

Authority: 50 U.S.C. 4801–4852; 50 U.S.C. 4601 *et seq.;* 50 U.S.C. 1701 *et seq.;* E.O. 12938, 59 FR 59099, 3 CFR, 1994 Comp., p. 950; E.O. 13020, 61 FR 54079, 3 CFR, 1996 Comp., p. 219; E.O. 13026, 61 FR 58767, 3 CFR, 1996 Comp., p. 228; E.O. 13222, 66 FR 44025, 3 CFR, 2001 Comp., p. 783; E.O. 13338, 69 FR 26751, 3 CFR, 2004 Comp., p. 168; Notice of November 10, 2021, 86 FR

62891 (November 12, 2021); Notice of May 9, 2022, 87 FR 28749 (May 10, 2022).

■ 5. Effective on October 21, 2022, supplement no. 1 to part 736 is amended by adding paragraph (d) to read as follows:

Supplement No. 1 to Part 736—General Orders

* * * * *

(d) General Order No. 4: The purpose of this General Order is to avoid disruption of supply chains for items specified in paragraph (d)(1) of this supplement that are ultimately destined to customers outside of People's Republic of China (China).

(1) *Temporary General License (TGL).* BIS authorizes, from October 21, 2022, through April 7, 2023, exports, reexports, in-country transfers, and exports from abroad destined to or within China by companies not headquartered in Country Groups D:1 or D:5 or E (see supplement no. 1 to part 740 of the EAR) to continue or engage in integration, assembly (mounting), inspection, testing, quality assurance, and distribution of items covered by ECCN 3A090, 4A090, and associated software and technology in ECCN 3D001, 3E001, 4D090, or 4E001; or any item that is a computer, integrated circuit, ''electronic assembly'' or ''component'' and associated software and technology, specified elsewhere on Commerce Control List (supplement no. 1 to part 774 of the EAR), which meets or exceeds the performance parameters of ECCN 3A090 or 4A090. This does not authorize the export, reexport, in-country transfer, or export from abroad to ''end-users'' or ''ultimate consignees'' in China. This TGL does not overcome the license requirements of § 744.11 or § 744.21 of the EAR when an entity listed in supplements no. 4 or 7 to part 744 is a party to the transaction as described in § 748.5(c) through (f) of the EAR, or when there is knowledge of any other prohibited end use or end user. This TGL is only for companies that engage in the specific activities authorized under this TGL.

(2) *Recordkeeping requirement.* Prior to any export, reexport, or transfer (in-country) to China pursuant to this TGL, the exporter, reexporter, or transferor, must retain the name of the entity receiving the item and the complete physical address of where the item is destined in China and the location of that company's headquarters.

* * * * *

PART 740—LICENSE EXCEPTIONS

■ 6. The authority citation for part 740 continues to read as follows:

Authority: 50 U.S.C. 4801–4852; 50 U.S.C. 4601 *et seq.;* 50 U.S.C. 1701 *et seq.;* 22 U.S.C. 7201 *et seq.;* E.O. 13026, 61 FR 58767, 3 CFR, 1996 Comp., p. 228; E.O. 13222, 66 FR 44025, 3 CFR, 2001 Comp., p. 783.

■ 7. Effective on October 7, 2022, § 740.2 is amended by adding paragraph (a)(9) to read as follows:

§ 740.2 Restrictions on all License Exceptions.

* * * * *

(a) * * *

(9) The item is identified in paragraph (a)(9)(i) of this section, being exported, reexported, or transferred (in-country) to or within the People's Republic of China (PRC), and the license exception is other than: RPL (excluding 3B090, 3D001 (for 3B090), and 3E001 (for 3B090)), under the provisions of § 740.10, including § 740.10(a)(3)(v), which prohibits exports and reexports of replacement parts to countries in Country Group E:1 (see supplement no. 1 to this part)); GOV, restricted to eligibility under the provisions of § 740.11(b)(2)(ii); or TSU (excluding 3B090, 3D001 (for 3B090), and 3E001 (for 3B090)), under the provisions of § 740.13(a) and (c). Items restricted to eligibility only for the foregoing license exceptions are:

(i) Controlled under ECCNs 3B090, or associated software and technology in 3D001, or 3E001; or

(ii) [Reserved]

* * * * *

■ 8. Effective on October 21, 2022, § 740.2 is further amended by revising paragraph (a)(9) to read as follows:

§ 740.2 Restrictions on all License Exceptions.

* * * * *

(a) * * *

(9) The item is identified in paragraphs (a)(9)(i) and (ii) of this section, being exported, reexported, or transferred (in-country) to or within the People's Republic of China (PRC), and the license exception is other than: RPL (excluding 3B090, 3D001 (for 3B090), and 3E001 (for 3B090)), under the provisions of § 740.10, including § 740.10(a)(3)(v), which prohibits exports and reexports of replacement parts to countries in Country Group E:1 (see supplement no. 1 to this part)); GOV, restricted to eligibility under the provisions of § 740.11(b)(2)(ii); or TSU (excluding 3B090, 3D001 (for 3B090), and 3E001 (for 3B090)), under the provisions of § 740.13(a) and (c). Items restricted to eligibility only for the foregoing license exceptions are:

(i) Controlled under ECCNs 3A090, 3B090, 4A090, or associated software and technology in 3D001, 3E001, 4D090, and 4E001; or

(ii) A computer, integrated circuit, ''electronic assembly'' or ''component'' specified elsewhere on the CCL which meets or exceeds the performance parameters of ECCN 3A090 or 4A090.

* * * * *

■ 9. Effective on October 7, 2022, § 740.10 is amended by revising paragraph (c)(2) to read as follows:

§ 740.10 License Exception Servicing and replacement of parts and equipment (RPL).

* * * * *

(c) * * *

(2) Records maintained pursuant to this section may be requested at any time by an appropriate BIS official as set forth in § 762.7 of the EAR. Records that must be included in the annual or semi-annual reports of exports and reexports of ''600 Series'' items under the authority of License Exception RPL are described in §§ 743.4 and 762.2(b) of the EAR.

PART 742—CONTROL POLICY—CCL BASED CONTROLS

■ 10. The authority citation for part 742 continues to read as follows:

Authority: 50 U.S.C. 4801–4852; 50 U.S.C. 4601 *et seq.;* 50 U.S.C. 1701 *et seq.;* 22 U.S.C. 3201 *et seq.;* 42 U.S.C. 2139a; 22 U.S.C. 7201 *et seq.;* 22 U.S.C. 7210; Sec. 1503, Pub. L. 108–11, 117 Stat. 559; E.O. 12058, 43 FR 20947, 3 CFR, 1978 Comp., p. 179; E.O. 12851, 58 FR 33181, 3 CFR, 1993 Comp., p. 608; E.O. 12938, 59 FR 59099, 3 CFR, 1994 Comp., p. 950; E.O. 13026, 61 FR 58767, 3 CFR, 1996 Comp., p. 228; E.O. 13222, 66 FR 44025, 3 CFR, 2001 Comp., p. 783; Presidential Determination 2003–23, 68 FR 26459, 3 CFR, 2004 Comp., p. 320; Notice of November 10, 2021, 86 FR 62891 (November 12, 2021).

■ 11. Effective on October 7, 2022, § 742.6 is amended by adding paragraphs (a)(6) and (b)(10) to read as follows:

§ 742.6 Regional stability.

(a) * * *

(6) *RS requirement that applies to the People's Republic of China (China) for semiconductor manufacturing items*—(i) *Exports, reexports, transfers (in-country).* A license is required for items specified in ECCN 3B090 and associated software and technology in 3D001 (for 3B090), 3E001 (for 3B090)) being exported, reexported, or transferred (in-country) to or within the China.

(ii) *Deemed exports.* The license requirements in this paragraph (a)(6) do not apply to deemed exports or deemed reexports.

* * * * *

(b) * * *

(10) *Semiconductor manufacturing items when destined to China.* There is

a presumption of denial for applications for items specified in paragraph (a)(6) of this section being exported, reexported, or transferred (in-country) to or within the China. See § 744.11(a)(2)(ii) of the EAR for license requirements, license review policy, and license exceptions applicable to specific entities. License applications for semiconductor manufacturing items, such as semiconductor equipment, destined to end users in China that are headquartered in the United States or in a country in Country Group A:5 or A:6 will be considered on a case-by-case basis, taking into account factors including technology level, customers and compliance plans.

* * * * *

■ 12. Effective on October 21, 2022, § 742.6 is further amended by revising paragraphs (a)(6) and (b)(10) to read as follows:

§ 742.6 Regional stability.

(a) * * *

(6) *RS requirement that applies to the People's Republic of China (China) for advanced computing and semiconductor manufacturing items*—(i) *Exports, reexports, transfers (in-country).* A license is required for items specified in ECCNs 3A090, 3B090, 4A090, 5A992 (that meet or exceed the performance parameters of ECCNs 3A090 or 4A090) and associated software and technology in 3D001 (for 3A090 or 3B090), 3E001 (for 3A090 or 3B090), 3B090, or 3D001 (for 3A090 or 3B090), 4D090, 4E001 (for 4A090 and 4D090), and 5D992 (that meet or exceed the performance parameters of ECCNs 3A090 or 4A090) being exported, reexported, or transferred (in-country) to or within the China. A license is also required for the export from the China to any destination worldwide of 3E001 (for 3A090) technology developed by an entity headquartered in the China that is the direct product of software subject to the EAR and is for the "production" of commodities identified in ECCNs 3A090, 4A090, or identified elsewhere on the CCL that meet or exceed the performance parameters of ECCNs 3A090 or 4A090, consistent with § 734.9(h)(1)(i)(B)(*1*) and (h)(2)(ii) of the EAR.

(ii) *Deemed exports.* The license requirements in this paragraph (a)(6) do not apply to deemed exports or deemed reexports.

* * * * *

(b) * * *

(10) *Advanced computing and semiconductor manufacturing items when destined to China.* There is a presumption of denial for applications for items specified in paragraph (a)(6) of this section being exported, reexported, or transferred (in-country) to or within the China. See § 744.11(a)(2)(ii) of the EAR for license requirements, license review policy, and license exceptions applicable to specific entities. License applications for semiconductor manufacturing items, such as semiconductor equipment, destined to end users in China that are headquartered in the United States or in a country in Country Group A:5 or A:6 will be considered on a case-by-case basis, taking into account factors including technology level, customers and compliance plans.

* * * * *

PART 744—END–USE AND END–USER CONTROLS

■ 13. The authority citation for part 744 continues to read as follows:

Authority: 50 U.S.C. 4801–4852; 50 U.S.C. 4601 *et seq.;* 50 U.S.C. 1701 *et seq.;* 22 U.S.C. 3201 *et seq.;* 42 U.S.C. 2139a; 22 U.S.C. 7201 *et seq.;* 22 U.S.C. 7210; E.O. 12058, 43 FR 20947, 3 CFR, 1978 Comp., p. 179; E.O. 12851, 58 FR 33181, 3 CFR, 1993 Comp., p. 608; E.O. 12938, 59 FR 59099, 3 CFR, 1994 Comp., p. 950; E.O. 13026, 61 FR 58767, 3 CFR, 1996 Comp., p. 228; E.O. 13099, 63 FR 45167, 3 CFR, 1998 Comp., p. 208; E.O. 13222, 66 FR 44025, 3 CFR, 2001 Comp., p. 783; E.O. 13224, 66 FR 49079, 3 CFR, 2001 Comp., p. 786; Notice of November 10, 2021, 86 FR 62891 (November 12, 2021); Notice of September 19, 2022, 87 FR 57569 (September 19, 2022).

■ 14. Effective on October 21, 2022, § 744.1 is amended by adding a sentence at the end of paragraph (a)(1) to read as follows:

§ 744.1 General provisions.

(a)(1) * * * Section 744.23 sets forth restrictions on exports, reexports, and transfers (in-country) for certain "supercomputer" and semiconductor manufacturing end use.

* * * * *

■ 15. Effective on October 12, 2022, § 744.6 is amended by revising paragraphs (c) and (d) and adding paragraph (e)(3) to read as follows:

§ 744.6 Restrictions on specific activities of "U.S. persons."

* * * * *

(c) *Additional prohibitions on "U.S. persons" informed by BIS.* (1) BIS may inform "U.S. persons," either individually by specific notice, through amendment to the EAR published in the **Federal Register**, or through a separate notice published in the **Federal Register**, that a license is required because an activity could involve the types of 'support' (as defined in paragraph (b)(6) of this section) to the end uses or end users described in paragraphs (b)(1) through (5) of this section. Specific notice is to be given only by, or at the direction of, the Deputy Assistant Secretary for Export Administration. When such notice is provided orally, it will be followed by a written notice within two working days signed by the Deputy Assistant Secretary for Export Administration. However, the absence of any such notification does not excuse the "U.S. person" from compliance with the license requirements of paragraph (b) of this section.

(2) Consistent with paragraph (c)(1) of this section, BIS is hereby informing "U.S. persons" that a license is required for the following activities, which could involve 'support' for the weapons of mass destruction-related end uses set forth in paragraph (b) of this section.

(i) Shipping, transmitting, or transferring (in-country) to or within the PRC any item not subject to the EAR that you know will be used in the "development" or "production" of integrated circuits at a semiconductor fabrication "facility" located in the PRC that fabricates integrated circuits meeting any of the following criteria:

(A) Logic integrated circuits using a non-planar architecture or with a "production" technology node of 16/14 nanometers or less;

(B) NOT–AND (NAND) memory integrated circuits with 128 layers or more; or

(C) Dynamic random-access memory (DRAM) integrated circuits using a "production" technology node of 18 nanometer half-pitch or less; or

(ii) Facilitating the shipment, transmission, or transfer (in-country) of any item not subject to the EAR that you know will be used in the "development" or "production" of integrated circuits at a semiconductor fabrication "facility" located in the PRC that fabricates integrated circuits that meet any of the criteria in paragraphs (c)(2)(i)(A) through (C) of this section;

(iii) Servicing any item not subject to the EAR that you know will be used in the "development" or "production" of integrated circuits at a semiconductor fabrication "facility" located in the PRC that fabricates integrated circuits that meet any of the criteria in paragraphs (c)(2)(i)(A) through (C) of this section;

(iv) Shipping, transmitting, or transferring (in-country) to or within the PRC any item not subject to the EAR and meeting the parameters of any ECCN in Product Groups B, C, D, or E in Category 3 of the CCL that you know will be used in the "development" or "production" of integrated circuits at any semiconductor fabrication "facility" located in the PRC, but you do not know whether such semiconductor fabrication "facility" fabricates integrated circuits that meet any of the criteria in paragraphs (c)(2)(i)(A) through (C) of this section;

(v) Facilitating the shipment, transmission, or transfer (in-country) to or within the PRC of any item not subject to the EAR and meeting the parameters of any ECCN in Product Groups B, C, D, or E in Category 3 of the CCL that you know will be used in the "development" or "production," of integrated circuits at any semiconductor fabrication "facility" located in the PRC, but you do not know whether such semiconductor fabrication "facility" fabricates integrated circuits that meet any of the criteria in paragraphs (c)(2)(i)(A) through (C) of this section;

(vi) Servicing any item not subject to the EAR and meeting the parameters of any ECCN in Product Groups B, C, D, or E in Category 3 of the CCL that you know will be used in the "development" or "production" of integrated circuits at any semiconductor fabrication "facility" located in the PRC, but you do not know whether such semiconductor fabrication "facility" fabricates integrated circuits that meet any of the criteria in paragraphs (c)(2)(i)(A) through (C) of this section;

(vii) Shipping, transmitting, or transferring (in-country) to or within the PRC any item not subject to the EAR and meeting the parameters of ECCN 3B090, 3D001 (for 3B090), or 3E001 (for 3B090) regardless of end use or end user;

(viii) Facilitating the shipment, transmission, or transfer (in-country) to or within the PRC of any item not subject to the EAR and meeting the parameters of ECCN 3B090, 3D001 (for 3B090), or 3E001 (for 3B090), regardless of end use or end user; or

(ix) Servicing any item not subject to the EAR located in the PRC and meeting the parameters of ECCN 3B090, 3D001 (for 3B090), or 3E001 (for 3B090), regardless of end use or end user.

(d) *Exceptions.* (1) No License Exceptions apply to the prohibitions described in paragraphs (b)(1) through (4) and (c)(2)(i) through (vi) of this section.

(2) Notwithstanding the prohibitions in paragraphs (b)(5) and (c)(2)(vii) through (ix) of this section, "U.S. persons" who are employees of a department or agency of the U.S. Government may 'support' a 'military-intelligence end use' or a 'military-intelligence end user,' as described in paragraph (b)(5) of this section, or engage in the activities described in paragraphs (c)(2)(vii) through (ix) of this section, if the 'support' is provided in the performance of official duties in furtherance of a U.S. Government program that is authorized by law and subject to control by the President by other means. This paragraph (d)(2) does not authorize a department or agency of the U.S. Government to provide 'support' that is otherwise prohibited by other administrative provisions or by statute. 'Contractor support personnel' of a department or agency of the U.S. Government are eligible for this authorization when in the performance of their duties pursuant to the applicable contract or other official duties. 'Contractor support personnel' for the purposes of this paragraph (d)(2) has the same meaning given to that term in § 740.11(b)(2)(ii) of the EAR. This authorization is not available when a department or agency of the U.S. Government acts as an agent on behalf of a non-U.S. Government person.

(e) * * *

(3) Applications for licenses submitted pursuant to the notice of a license requirement set forth in paragraph (c)(2) of this section will be reviewed with a presumption of denial, except for end users in the PRC headquartered in the United States or a country in Country Group A:5 or A:6, which will be considered on a case-by-case basis taking into account factors including technology level, customers, and compliance plans.

■ 16. Effective on October 21, 2022, § 744.11 is amended by revising paragraph (a)(2) to read as follows:

§ 744.11 License requirements that apply to entities acting or at significant risk of acting contrary to the national security or foreign policy interests of the United States.

* * * * *

(a) * * *

(2) *Entity List foreign-"direct product" (FDP) license requirements, review policy, and license exceptions*—(i) *Footnote 1 entities.* You may not, without a license or license exception, reexport, export from abroad, or transfer (in-country) any foreign-produced item subject to the EAR pursuant to § 734.9(e)(1)(i) of the EAR when an entity designated with footnote 1 on the Entity List in supplement. no. 4 to this part is a party to the transaction. All license exceptions described in part 740 of the EAR are available for foreign-produced items that are subject to this license requirement if all terms and conditions of the applicable license exception are met and the restrictions in § 740.2 of this EAR do not apply. The sophistication and capabilities of technology in items is a factor in license application review; license applications for foreign-produced items subject to a license requirement by this paragraph (a)(2) that are capable of supporting the "development" or "production" of telecom systems, equipment, and devices below the 5G level (*e.g.,* 4G, 3G) will be reviewed on a case-by-case basis.

(ii) *Footnote 4 entities.* You may not, without a license, reexport, export from abroad, or transfer (in-country) any foreign-produced item subject to the EAR pursuant to § 734.9(e)(2) of the EAR when an entity designated with footnote 4 on the Entity List in supp. no. 4 to this part is a party to the transaction, or that will be used in the "development" or "production" of any "part," "component," or "equipment" produced, purchased, or ordered by any such entity. See § 744.23 for additional license requirements that may apply to these entities. The license review policy for foreign-produced items subject to this license requirement is set forth in the entry in supplement no. 4 to this part for each entity with a footnote 4 designation.

* * * * *

■ 17. Effective on October 7, 2022, add § 744.23 to read as follows:

§ 744.23 Semiconductor manufacturing end use.

(a) *General prohibition.* In addition to the license requirements for items specified on the CCL, you may not export, reexport, or transfer (in-country) without a license any item subject to the EAR meeting the product scope in paragraph (a)(1) of this section when you have "knowledge" at the time of export, reexport, or transfer (in-country) that the item is destined for the end-use described in paragraph (a)(2) of this section.

(1) *Product scope.* Any of the following items meet the product scope of the prohibition in this section:

(i)–(ii) [Reserved]

(iii) Any item subject to the EAR when you know the items will be used in an end use described in paragraphs (a)(2)(iii)(A) through (C) of this section;

(iv) Any item subject to the EAR and classified in an ECCN in Product Groups B, C, D, or E in Category 3 of the CCL when you know the items will be used in an end use described in paragraph (a)(2)(iv) of this section; or

(v) Any item subject to the EAR when you know the item will be used in an end use described in paragraph (a)(2)(v) of this section.

(2) *End-use scope.* The following activities meet the end-use scope of the prohibition in this section:

(i)–(ii) [Reserved]

(iii) The ''development'' or ''production'' of integrated circuits at a semiconductor fabrication ''facility'' located in the PRC that fabricates integrated circuits meeting any of the following criteria:

(A) Logic integrated circuits using a non-planar transistor architecture or with a ''production'' technology node of 16/14 nanometers or less;

(B) NOT AND (NAND) memory integrated circuits with 128 layers or more; or

(C) Dynamic random-access memory (DRAM) integrated circuits using a ''production'' technology node of 18 nanometer half-pitch or less; or

(iv) The ''development'' or ''production'' of integrated circuits at any semiconductor fabrication ''facility'' located in the PRC, but you do not know whether such semiconductor fabrication ''facility'' fabricates integrated circuits that meet any of the criteria in paragraphs (a)(2)(iii)(A) through (C) of this section.

(v) The ''development'' or ''production'' in the PRC of any ''parts,'' ''components'' or ''equipment'' specified under ECCN 3B001, 3B002, 3B090, 3B611, 3B991, or 3B992.

(b) *Additional prohibition on persons informed by BIS.* BIS may inform persons, either individually by specific notice or through amendment to the EAR published in the **Federal Register**, that a license is required for a specific export, reexport, or transfer (in-country) of any item subject to the EAR to a certain end-user, because there is an unacceptable risk of use in, or diversion to, the activities specified in paragraph (a)(1) of this section. Specific notice is to be given only by, or at the direction of, the Deputy Assistant Secretary for Export Administration. When such notice is provided orally, it will be followed by a written notice within two working days signed by the Deputy Assistant Secretary for Export Administration or the Deputy Assistant Secretary's designee. However, the absence of any such notification does not excuse persons from compliance with the license requirements of paragraph (a) of this section.

(c) *License exceptions.* No license exceptions may overcome the prohibition described in paragraph (a) of this section.

(d) *License review standards.* There is a presumption of denial for applications to export, reexport, or transfer (in-country) items described in paragraph (a)(1) of this section that are for end uses described in paragraph (a)(2) of this section, except for items controlled under paragraph (a)(2)(iii) of this section for end users in China that are headquartered in the United States or in a Country Group A:5 or A:6 country, which will be considered on a case-by-case basis taking into account factors including technology level, customers, and compliance plans.

■ 18. Effective on October 21, 2022, revise § 744.23 to read as follows:

§ 744.23 ''Supercomputer'' and semiconductor manufacturing end use.

(a) *General prohibition.* In addition to the license requirements for items specified on the CCL, you may not export, reexport, or transfer (in-country) without a license any item subject to the EAR meeting the product scope in paragraph (a)(1) of this section when you have ''knowledge'' at the time of export, reexport, or transfer (in-country) that the item is destined for the end-use described in paragraph (a)(2) of this section.

(1) *Product scope.* Any of the following items meet the product scope of the prohibition in this section:

(i) An integrated circuit (IC) subject to the EAR and specified in ECCN 3A001, 3A991, 4A994, 5A002, 5A004, or 5A992 when you know the item will be used in an end use described under paragraph (a)(2)(i) or (ii) of this section;

(ii) A computer, ''electronic assembly,'' or ''component'' subject to the EAR and specified in ECCN 4A003, 4A004, 4A994, 5A002, 5A004, or 5A992 when you know the item will be used in an end use described under paragraph (a)(2)(i) or (ii) of this section;

(iii) Any items subject to the EAR when you know the items will be used in an end use described in paragraphs (a)(2)(iii)(A) through (C) of this section;

(iv) Any items subject to the EAR and classified in an ECCN in Product Groups B, C, D, or E in Category 3 of the CCL when you know the items will be used in an end use described in paragraph (a)(2)(iv) of this section; or

(v) Any item subject to the EAR when you know the item will be used in an end use described in paragraph (a)(2)(v) of this section.

(2) *End-use scope.* The following activities meet the end-use scope of the prohibition in this section:

(i) The ''development,'' ''production,'' ''use,'' operation, installation (including on-site installation), maintenance (checking), repair, overhaul, or refurbishing of a ''supercomputer'' located in or destined to the PRC;

(ii) The incorporation into, or the ''development'' or ''production'' of any ''component'' or ''equipment'' that will be used in a ''supercomputer'' located in or destined to the PRC; or

(iii) The ''development'' or ''production,'' of integrated circuits at a semiconductor fabrication ''facility'' located in the PRC that fabricates integrated circuits meeting any of the following criteria:

(A) Logic integrated circuits using a non-planar transistor architecture or with a ''production'' technology node of 16/14 nanometers or less;

(B) NOT AND (NAND) memory integrated circuits with 128 layers or more; or

(C) Dynamic random-access memory (DRAM) integrated circuits using a ''production'' technology node of 18 nanometer half-pitch or less; or

(iv) The ''development'' or ''production'' of integrated circuits at any semiconductor fabrication ''facility'' located in the PRC, but you do not know whether such semiconductor fabrication ''facility'' fabricates integrated circuits that meet any of the criteria in paragraphs (a)(2)(iii)(A) through (C) of this section; or

(v) The ''development'' or ''production'' in the PRC of any ''parts,'' ''components,'' or ''equipment'' specified under ECCN 3B001, 3B002, 3B090, 3B611, 3B991, or 3B992.

(b) *Additional prohibition on persons informed by BIS.* BIS may inform persons, either individually by specific notice or through amendment to the EAR published in the **Federal Register**, that a license is required for a specific export, reexport, or transfer (in-country) of any item subject to the EAR to a certain end-user, because there is an unacceptable risk of use in, or diversion to, the activities specified in paragraph (a)(2) of this section. Specific notice is to be given only by, or at the direction of, the Deputy Assistant Secretary for Export Administration. When such notice is provided orally, it will be followed by a written notice within two working days signed by the Deputy Assistant Secretary for Export Administration or the Deputy Assistant Secretary's designee. However, the absence of any such notification does not excuse persons from compliance with the license requirements of paragraph (a) of this section.

(c) *License exceptions.* No license exceptions may overcome the prohibition described in paragraph (a) of this section.

(d) *License review standards.* There is a presumption of denial for applications to export, reexport, or transfer (in-country) items described in paragraph (a)(1) of this section that are for end uses described in paragraph (a)(2) of this section, except for items controlled under paragraph (a)(2)(iii) of this section for end users in China that are headquartered in the United States or in a Country Group A:5 or A:6 country, which will be considered on a case-by-case basis taking into account factors including technology level, customers and compliance plans.

■ 19. Effective on October 21, 2022, supplement no. 4 is amended by:

■ a. Revising Under CHINA the entries for ''Beijing Institute of Technology,'' ''Beijing Sensetime Technology Development Co., Ltd.,'' ''Changsha Jingjia Microelectronics Co., Ltd.,'' ''Chengdu Haiguang Integrated Circuit,'' ''Chengdu Haiguang Microelectronics Technology,'' ''China Aerospace Science and Technology Corporation (CASC) 9th Academy 772 Research Institute,'' ''Dahua Technology,'' ''Harbin institute of Technology,'' ''Higon,'' ''IFLYTEK,'' ''Intellifusion,'' ''Megvii Technology,'' ''National Supercomputing Center Changsha (NSCC–CS),'' ''National Supercomputing Center Guangzhou (NSCC–GZ),'' ''National Supercomputing Center Jinan,'' ''National Supercomputing Center Shenzhen,'' ''National Supercomputing Center Tianjin (NSCC–TJ),'' ''National Supercomputing Center Wuxi,'' ''National Supercomputer Center Zhengzhou,'' ''National University of Defense Technology (NUDT),'' ''New H3C Semiconductor Technologies Co., Ltd.,'' ''Northwestern Polytechnical University,'' ''Shanghai High-Performance Integrated Circuit Design Center,'' ''Sugon,'' ''Sunway Microelectronics,'' ''Tianjin Phytium Information Technology,'' ''Wuxi Jiangnan Institute of Computing Technology,'' and ''Yitu Technologies''; and

■ b. Revising footnote 1 and adding footnote 4.

The revisions and addition read as follows:

Supplement No. 4 to Part 744—Entity List

* * * * *

Country	Entity	License requirement	License review policy	Federal Register citation
* * * * * * *				
CHINA, PEOPLE'S REPUBLIC OF.	* * * * * *			
	Beijing Institute of Technology, No. 5 South Zhongguancun Street, Haidian District, Beijing, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Presumption of denial	85 FR 83420, 12/22/20. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Beijing Sensetime Technology Development Co., Ltd., a.k.a., the following two aliases: —Beijing Shangtang Technology Development Co., Ltd.; *and* —Sense Time. 5F Block B, Science and Technology Building, Tsing-hua Science Park, Haidian District, Beijing, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Case-by-case review for ECCNs 1A004.c, 1A004.d, 1A995, 1A999.a, 1D003, 2A983, 2D983, and 2E983, and for EAR99 items described in the Note to ECCN 1A995; case-by-case review for items necessary to detect, identify and treat infectious disease; and presumption of denial for all other items subject to the EAR.	84 FR 54004, 10/9/19. 85 FR 34505, 6/5/20. 85 FR 44159, 7/22/20. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Changsha Jingjia Microelectronics Co., Ltd.,902, Building B1, Lugu Science and Technology Innovation Pioneer Park, 1698 Yuelu West Ave., Changsha High-tech Development Zone; *and* Building 3, Changsha Productivity Promotion Center, No. 2, Lujing Rd., Yuelu District, Changsha City, Hunan Province; *and* No. 1, Meixihu Road, Yuelu District, Changsha City, Hunan Province, 410221; *and* Room 1501, Aipu Building, 395 Xinshi North Road, Shijiazhuang City, Hebei Province, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Presumption of denial	86 FR 71560, 12/17/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Chengdu Haiguang Integrated Circuit, a.k.a., the following two aliases: —Hygon; *and* —Chengdu Haiguang Jincheng Dianlu Sheji. China (Sichuan) Free Trade Zone, No. 22–31, 11th Floor, E5, Tianfu Software Park, No. 1366, Middle Section of Tianfu Avenue, Chengdu High-tech Zone, Chengdu, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Presumption of denial	84 FR 29373, 6/24/19. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.

Country	Entity	License requirement	License review policy	Federal Register citation
	Chengdu Haiguang Microelectronics Technology, a.k.a., the following two aliases: —HMC; *and* —Chengdu Haiguang Wei Dianzi Jishu. China (Sichuan) Free Trade Zone, No. 23–32, 12th Floor, E5, Tianfu Software Park, No. 1366, Middle Section of Tianfu Avenue, Chengdu High-tech Zone, Chengdu, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Presumption of denial	84 FR 29373, 6/24/19. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	China Aerospace Science and Technology Corporation (CASC) 9th Academy 772 Research Institute, a.k.a., the following four aliases: —772 Research Institute; —Beijing Institute of Microelectronics Technology; —Beijing Microelectronics Technology Institute; *and* —BMTI. No. 2, Siyingmen North Road, Donggaodi, Fengtai District, Beijing, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Presumption of denial	87 FR 51877, 8/24/22. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Dahua Technology, 807, Block A, Meike Building No. 506, Beijing South Road, New City, Urumqi, Xinjiang, China; 1199 Bin'an Road, Binjiang High-tech Zone, Hangzhou, China; *and* 6/F, Block A, Dacheng Erya, Huizhan Avenue, Urumqi, China; *and* No. 1187, Bin'an Road, Binjiang District, Hangzhou City, Zhejiang Province, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Presumption of denial	84 FR 54004, 10/9/19. 85 FR 44159, 7/22/20. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Harbin Institute of Technology, No. 92 Xidazhi Street, Nangang District, Harbin, Heilongjiang, China; *and* No. 92 West Dazhi Street, Nangang District, Harbin, Heilongjiang, China; *and* No. 2 West Wenhua Road, Weihai, Shandong, China; *and* Pingshan 1st Road, Shenzhen, Guangdong, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Presumption of denial	85 FR 34497, 6/5/20. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Higon, a.k.a., the following five aliases: —Higon Information Technology; —Haiguang Xinxi Jishu Youxian Gongsi; —THATIC; —Tianjing Haiguang Advanced Technology Investment; *and* —Tianjing Haiguang Xianjin Jishu Touzi Youxian Gongsi. Industrial Incubation-3–8, North 2–204, 18 Haitai West Road, Huayuan Industrial Zone, Tianjin, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR)[4].	Presumption of denial	84 FR 29373, 6/24/19. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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Country	Entity	License requirement	License review policy	**Federal Register** citation
	IFLYTEK, National Intelligent Speech High-tech Industrialization Base, No. 666, Wangjiang Road West, Hefei City, Anhui Province, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Case-by-case review for ECCNs 1A004.c, 1A004.d, 1A995, 1A999.a, 1D003, 2A983, 2D983, and 2E983, and for EAR99 items described in the Note to ECCN 1A995; case-by-case review for items necessary to detect, identify and treat infectious disease; and presumption of denial for all other items subject to the EAR.	84 FR 54004, 10/9/19. 85 FR 44159, 7/22/20. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Intellifusion, a.k.a., the following two aliases: —Shenzhen Yuntian Lifei Technology Co., Ltd.; —Yuntian Lifei. 1st Floor, Building 17, Shenzhen Dayun Software Town, 8288 Longgang Avenue, Yuanshan District, Longgang District, Shenzhen, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Case-by-case review for ECCNs 1A004.c, 1A004.d, 1A995, 1A999.a, 1D003, 2A983, 2D983, and 2E983, and for EAR99 items described in the Note to ECCN 1A995; case-by-case review for items necessary to detect, identify and treat infectious disease; and presumption of denial for all other items subject to the EAR.	85 FR 34505, 6/5/20. 85 FR 44159, 7/22/20. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Megvii Technology, 3rd Floor, Block A, Rongke Information Center, No. 2 South Road, Haidian District, Beijing, China; *and* Floor 3rd Unit A Raycom Infotech Park, No 2 Kexueyuan, Beijing, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Case-by-case review for ECCNs 1A004.c, 1A004.d, 1A995, 1A999.a, 1D003, 2A983, 2D983, and 2E983, and for EAR99 items described in the Note to ECCN 1A995; case-by-case review for items necessary to detect, identify and treat infectious disease; and presumption of denial for all other items subject to the EAR.	84 FR 54004, 10/9/19. 85 FR 44159, 7/22/20. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	National Supercomputing Center Changsha (NSCC–CS), Changsha City, Hunan Province, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	80 FR 8527, 2/18/15. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
	National Supercomputing Center Guangzhou (NSCC–GZ), Sun Yat-Sen University, University City, Guangzhou, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	80 FR 8527, 2/18/15. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
	National Supercomputing Center Jinan, a.k.a., the following two aliases: —Shandong Computing Center; *and* —NSCC–JN. No. 1768, Xinluo Street, High-tech Development Zone, Jinan City, Shandong Province, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	86 FR 18438, 4/9/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.

Country	Entity	License requirement	License review policy	Federal Register citation
	National Supercomputing Center Shenzhen, a.k.a., the following three aliases: —The National Supercomputing Shenzhen Center; —Shenzhen Cloud Computing Center; *and* —NSCC–SZ. No. 9 Duxue Road, University Town Community, Taoyuan Street, Nanshan District, Shenzhen, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	86 FR 18438, 4/9/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
	National Supercomputing Center Tianjin (NSCC–TJ), 7th Street, Binhai New Area, Tianjin, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	80 FR 8527, 2/18/15. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
	National Supercomputing Center Wuxi, a.k.a., the following one alias: —NSCC–WX. No. 1, Yinbai Road, Binhu District, Wuxi City, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	86 FR 18438, 4/9/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
	National Supercomputer Center Zhengzhou, a.k.a., the following one alias: —NSCC–ZZ. Southeast of the intersection of Fengyang Street and Changchun Road, Zhongyuan District, Zhengzhou City, China; *and* 1st Floor, Building 18, Zhengzhou University (South Campus), Zhengzhou City, China; *and* Room 213, Institute of Drug Research, Zhengzhou University, Changchun Road, High-tech Zone, Zhengzhou City, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	86 FR 18438, 4/9/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
	National University of Defense Technology (NUDT), a.k.a., the following three aliases: —Central South CAD Center; —CSCC; *and* —Hunan Guofang Keji University. Garden Road (Metro West), Changsha City, Kaifu District, Hunan Province, China; *and* 109 Deya Road, Kaifu District, Changsha City, Hunan Province, China; *and* 47 Deya Road, Kaifu District, Changsha City, Hunan Province, China; *and* 147 Deya Road, Kaifu District, Changsha City, Hunan Province, China; *and* 47 Yanwachi, Kaifu District, Changsha, Hunan, China; *and* Wonderful Plaza, Sanyi Avenue, Kaifu District, Changsha, China; *and* No. 54 Beiya Road, Changsha, China; *and* No. 54 Deya Road, Changsha, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	80 FR 8527, 2/18/15. 84 FR 29373, 6/24/19, 87 FR 38925, 6/30/22. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	New H3C Semiconductor Technologies Co., Ltd., No. 1, Floor 1, Unit 1, Building 4, No. 219, Tianhua 2nd Rd., Chengdu High-Tech Zone, China (Sichuan) Pilot Free Trade Zone, China; *and* Beijing Branch—Room 401, 4th Floor, Building 1, No. 8 Yard, Yongjia North Road, Haidian District, Beijing, China; *and* Shanghai Branch—No. 666 Shengxia Rd., 122 Yindong Rd., China (Shanghai) Pilot Free Trade Zone, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	86 FR 67319. 11/26/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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Country	Entity	License requirement	License review policy	Federal Register citation
	Northwestern Polytechnical University, a.k.a., the following three aliases: —Northwestern Polytechnic University; —Northwest Polytechnic University; *and* —Northwest Polytechnical University. 127 Yonyi Xilu, Xi'an 71002 Shaanxi, China; *and* Youyi Xi Lu, Xi'an, Shaanxi, China; *and* No. 1 Bianjia Cun, Xi'an; *and* West Friendship Rd. 59, Xi'an; *and* 3 10 W Apt 3, Xi'an.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	66 FR 24266, 5/14/01. 75 FR 78883, 12/17/10. 77 FR 58006, 9/19/12. 81 FR 64696, 9/20/16. 84 FR 40241, 8/14/19. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
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	Shanghai High-Performance Integrated Circuit Design Center, a.k.a., the following two aliases: —Shenwei Micro; *and* —Shanghai High-Performance IC Design Center. No. 399, Bi sheng Road, Zhangjiang Hi-Tech Park, Pudong New Area, Shanghai, China; *and* 428 Zhanghen Rd, Zhangjiang High Tech Park, Pudong District, Shanghai, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	86 FR 18438, 4/9/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
*	*	*	*	*
	Sugon, a.k.a., the following nine aliases: —Dawning; —Dawning Information Industry; —Sugon Information Industry; —Shuguang; —Shuguang Information Industry; —Zhongke Dawn; —Zhongke Shuguang; —Dawning Company; *and* —Tianjin Shuguang Computer Industry. Sugon Building, No. 36 Zhongguancun Software Park, No. 8 Dongbeiwang West Road, Haidian District, Beijing; *and* No. 15, Haitai Huake Street, Huayuan Industrial Zone, Tianjin; *and* Sugon Science and Technology Park, No. 64 Shuimo West Street, Haidian District, Beijing, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	84 FR 29373, 6/24/19. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
*	*	*	*	*
	Sunway Microelectronics, a.k.a., the following two aliases: —Chengdu Shenwei Technology; *and* —Chengdu Sunway Technology. Building D22, Electronic Science and Technology Park, Section 4, Huafu Avenue, Chengdu, China; *and* Shuangxing Avenue, Gongxing Street, Southwest Airport Economic Development Zone, Shuangliu District, Chengdu, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	86 FR 18438, 4/9/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
*	*	*	*	*

Country	Entity	License requirement	License review policy	Federal Register citation
	Tianjin Phytium Information Technology, a.k.a., the following three aliases: —Phytium; —Phytium Technology; *and* —Tianjin Feiteng Information Technology. Bldg 5 Xin'an Venture Plaza 1 Haiyuan M Rd Binhai New Area Tianjin, 300450 China; *and* Building 5, Xin'an Chuangye Plaza, No. 1, Haiyuan Middle Road, Binhai New District, Tianjin, China; *and* 8th Floor, Quantum Core Tower, No.27 Zhichun Road, Haidian District, Beijing, China; *and* 10th Floor, Office Building, Wangdefu Kaiyue International Building, No.526 Sanyi Avenue, Kaifu District, Changsha City, Hunan Province; China; *and* Room 101, No. 1012, Hulin Road, Huangpu District, Guangzhou, China; *and* 100 Waihuanxi Rd, 3F–326 Science Pavilion, Panyu District, Guangdong, Guangzhou, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	86 FR 18438, 4/9/21. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
*	*	*	*	*
	Wuxi Jiangnan Institute of Computing Technology, a.k.a., the following two aliases: —Jiangnan Institute of Computing Technology; *and* —JICT. No. 699, Shanshui East Road, Binhu District, Wuxi City, China, *and* No. 188, Shanshui East Road, Binhu District, Wuxi City, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Presumption of denial	84 FR 29373, 6/24/19. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
*	*	*	*	*
	Yitu Technologies, 23F, Shanghai Arch Tower I, 523 Loushanguan Rd, Changning District, Shanghai, China.	For all items subject to the EAR. (See §§ 734.9(e) and 744.11 of the EAR) [4].	Case-by-case review for ECCNs 1A004.c, 1A004.d, 1A995, 1A999.a, 1D003, 2A983, 2D983, and 2E983, and for EAR99 items described in the Note to ECCN 1A995; case-by-case review for items necessary to detect, identify and treat infectious disease; and presumption of denial for all other items subject to the EAR.	84 FR 54004, 10/9/19. 85 FR 44159, 7/22/20. 87 FR [INSERT FR PAGE NUMBER, 10/13/22.
*	*	*	*	*
*	*	*	*	*

[1] For this entity, "items subject to the EAR" includes foreign-produced items that are subject to the EAR under § 734.9(e)(1) of the EAR. See § 744.11(a)(2)(i) for related license requirements and license review policy for these items.

* * * * * * *

[4] For this entity, "items subject to the EAR" includes foreign-produced items that are subject to the EAR under § 734.9(e)(2) of the EAR. See § 744.11(a)(2)(ii) for related license requirements and license review policy.

PART 762—RECORDKEEPING

■ 20. The authority citation for part 762 continues to read as follows:

Authority: 50 U.S.C. 4801–4852; 50 U.S.C. 4601 *et seq.;* 50 U.S.C. 1701 *et seq.;* E.O. 13222, 66 FR 44025, 3 CFR, 2001 Comp., p. 783.

■ 21. Effective on October 21, 2022, § 762.2 is amended by redesignating paragraphs (b)(3) through (31) as paragraphs (b)(4) through (32) and adding new paragraph (b)(3) to read as follows:

§ 762.2 Records to be retained.

* * * * *

(b) * * *

(3) Section 734.9(h), Foreign Direct Product (FDP) supply chain certification;

* * * * *

PART 772—DEFINITIONS OF TERMS

■ 22. The authority citation for part 772 continues to read as follows:

Authority: 50 U.S.C. 4801–4852; 50 U.S.C. 4601 *et seq.;* 50 U.S.C. 1701 *et seq.;* E.O. 13222, 66 FR 44025, 3 CFR, 2001 Comp., p. 783.

■ 23. Effective on October 21, 2022, § 772.1 is amended by adding a definition for "Supercomputer" in alphabetical order to read as follows:

§ 772.1 Definitions of terms as used in the Export Administration Regulations (EAR).

* * * * *

Supercomputer. (734, 744) A computing "system" having a collective maximum theoretical compute capacity of 100 or more double-precision (64-bit) petaflops or 200 or more single-precision (32-bit) petaflops within a 41,600 ft^3 or smaller envelope.

Note 1 to "Supercomputer": The 41,600 ft^3 envelope corresponds, for example, to a 4x4x6.5 ft rack size and therefore 6,400 ft^2 of floor space. The envelope may include empty floor space between racks as well as adjacent floors for multi-floor systems.

Note 2 to "Supercomputer": Typically, a 'supercomputer' is a high-performance multi-rack system having thousands of closely coupled compute cores connected in parallel with networking technology and having a high peak power capacity requiring cooling elements. They are used for computationally intensive tasks including scientific and engineering work. Supercomputers may include shared memory, distributed memory, or a combination of both.

* * * * *

PART 774—THE COMMERCE CONTROL LIST

■ 24. The authority citation for part 774 continues to read as follows:

Authority: 50 U.S.C. 4801–4852; 50 U.S.C. 4601 *et seq.;* 50 U.S.C. 1701 *et seq.;* 10 U.S.C. 8720; 10 U.S.C. 8730(e); 22 U.S.C. 287c, 22 U.S.C. 3201 *et seq.;* 22 U.S.C. 6004; 42 U.S.C. 2139a; 15 U.S.C. 1824; 50 U.S.C. 4305; 22 U.S.C. 7201 *et seq.;* 22 U.S.C. 7210; E.O. 13026, 61 FR 58767, 3 CFR, 1996 Comp., p. 228; E.O. 13222, 66 FR 44025, 3 CFR, 2001 Comp., p. 783.

■ 25. Effective on October 7, 2022, supplement no. 1 to part 774 is amended by adding ECCN 3B090 after ECCN 3B002 and revising ECCNs 3B991, 3D001, and 3E001 to read as follows:

Supplement No. 1 to Part 774—The Commerce Control List

* * * * *

3B090 Semiconductor manufacturing equipment, not Controlled by 3B001, as follows (see List of Items Controlled) and "specially designed" "parts," "components," and "accessories" therefor.

License Requirements

Reason for Control: RS, AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
RS applies to entire entry.	China (see § 742.6(a)(6))
AT applies to entire entry.	AT Column 1

List Based License Exceptions (See Part 740 for a description of all license exceptions)

LVS: N/A
GBS: N/A

List of Items Controlled

Related Controls: N/A
Related Definitions: N/A *Items:*

a. Semiconductor manufacturing deposition equipment, as follows:

a.1. Equipment for depositing cobalt through electroplating processes.

a.2. Chemical vapor deposition equipment capable of deposition of cobalt or tungsten fill metal having a void/seam having a largest dimension less than or equal to 3 nm in the fill metal using a bottom-up fill process.

a.3 Equipment capable of fabricating a metal contact within one processing chamber by:

a.3.a. Depositing a layer using an organometallic tungsten compound while maintaining the wafer substrate temperature between 100 °C and 500 °C; and

a.3.b. Conducting a plasma process where the chemistries include hydrogen, including H_2+N_2 and NH_3.

a.4. Equipment capable of fabricating a metal contact in a vacuum environment by:

a.4.a. Using a surface treatment during a plasma process where the chemistries include hydrogen, including H_2, H_2+N_2, and NH_3, while maintaining the wafer substrate temperature between 100 °C and 500 °C;

a.4.b. Using a surface treatment consisting of a plasma process where the chemistries include oxygen (including O_2 and O_3) while maintaining the wafer substrate temperature between 40 °C and 500 °C; and

a.4.c. Depositing a tungsten layer while maintaining the wafer substrate temperature between 100 °C and 500 °C.

a.5. Equipment capable of depositing a cobalt metal layer selectively in a vacuum environment where the first step uses a remote plasma generator and an ion filter, and the second step is the deposition of the cobalt layer using an organometallic compound.

Note: *This control does not apply to equipment that is non-selective.*

a.6. Physical vapor deposition equipment capable of depositing a cobalt layer with a thickness of 10 nm or less on a top surface of a copper or cobalt metal interconnect.

a.7. Atomic layer deposition equipment capable of depositing a 'work function metal' for the purpose of adjusting transistor electrical parameters by delivering an organometallic aluminum compound and a titanium halide compound onto a wafer substrate.

Technical note: *'Work function metal' is a material that controls the threshold voltage of a transistor.*

a.8. Equipment capable of fabricating a metal contact in a vacuum environment by depositing all of the following:

a.8.a. A titanium nitride (TiN) or tungsten carbide (WC) layer using an organometallic compound while maintaining the wafer substrate temperature between 20 °C and 500 °C;

a.8.b. A cobalt layer using a physical sputter deposition technique where the process pressure is 1–100 mTorr while maintaining the wafer substrate temperature below 500 °C; and

a.8.c. A cobalt layer using an organometallic compound, where the process pressure is 1–100 Torr, and the wafer substrate temperature is maintained between 20 °C and 500 °C.

a.9. Equipment capable of fabricating copper metal interconnects in a vacuum environment that deposits all of the following:

a.9.a. A cobalt or ruthenium layer using organometallic compound where the process pressure is 1–100 Torr, and the wafer substrate temperature is maintained between 20 °C and 500 °C; and

a.9.b. A copper layer using a physical vapor deposition technique where the process pressure is 1–100m Torr and the wafer substrate temperature is maintained below 500 °C.

a.10. Equipment capable of area selective deposition of a barrier or liner using an organometallic compound.

Note: *3B090.a.10 includes equipment capable of area selective deposition of a barrier layer to enable fill metal contact to an underlying electrical conductor without a barrier layer at the fill metal via interface to an underlying electrical conductor.*

a.11. Atomic layer deposition equipment capable of producing a void/seam free fill of tungsten or cobalt in a structure having an aspect ratio greater than 5:1, with openings smaller than 40 nm, and at temperatures less than 500 °C.

* * * * *

3B991 Equipment, not controlled by 3B001 or 3B090, for the manufacture of electronic "parts," "components" and materials, and "specially designed" "parts," "components" and "accessories" therefor.

License Requirements

Reason for Control: AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
AT applies to entire entry.	AT Column 1

List Based License Exceptions (See Part 740 for a description of all license exceptions)

LVS: N/A
GBS: N/A

List of Items Controlled

Related Controls: N/A

Related Definitions: 'Sputtering' is an overlay coating process wherein positively charged ions are accelerated by an electric field towards the surface of a target (coating material). The kinetic energy of the impacting ions is sufficient to cause target surface atoms to be released and deposited on the substrate. (Note: Triode, magnetron or radio frequency sputtering to increase adhesion of coating and rate of deposition are ordinary modifications of the process.)

Items:

a. Equipment ''specially designed'' for the manufacture of electron tubes, optical elements and ''specially designed'' ''parts'' and ''components'' therefor controlled by 3A001 or 3A991;

b. Equipment ''specially designed'' for the manufacture of semiconductor devices, integrated circuits and ''electronic assemblies'', as follows, and systems incorporating or having the characteristics of such equipment:

Note: *3B991.b also controls equipment used or modified for use in the manufacture of other devices, such as imaging devices, electro-optical devices, acoustic-wave devices.*

b.1. Equipment for the processing of materials for the manufacture of devices, ''parts'' and ''components'' as specified in the heading of 3B991.b, as follows:

Note: *3B991 does not control quartz furnace tubes, furnace liners, paddles, boats (except ''specially designed'' caged boats), bubblers, cassettes or crucibles ''specially designed'' for the processing equipment controlled by 3B991.b.1.*

b.1.a. Equipment for producing polycrystalline silicon and materials controlled by 3C001;

b.1.b. Equipment ''specially designed'' for purifying or processing III/V and II/VI semiconductor materials controlled by 3C001, 3C002, 3C003, 3C004, or 3C005 except crystal pullers, for which see 3B991.b.1.c below;

b.1.c. Crystal pullers and furnaces, as follows:

Note: *3B991.b.1.c does not control diffusion and oxidation furnaces.*

b.1.c.1. Annealing or recrystallizing equipment other than constant temperature furnaces employing high rates of energy transfer capable of processing wafers at a rate exceeding 0.005 m^2 per minute;

b.1.c.2. ''Stored program controlled'' crystal pullers having any of the following characteristics:

b.1.c.2.a. Rechargeable without replacing the crucible container;

b.1.c.2.b. Capable of operation at pressures above 2.5×10^5 Pa; *or*

b.1.c.2.c. Capable of pulling crystals of a diameter exceeding 100 mm;

b.1.d. ''Stored program controlled'' equipment for epitaxial growth having any of the following characteristics:

b.1.d.1. Capable of producing silicon layer with a thickness uniform to less than ±2.5% across a distance of 200 mm or more;

b.1.d.2. Capable of producing a layer of any material other than silicon with a thickness uniformity across the wafer of equal to or better than ± 3.5%; *or*

b.1.d.3. Rotation of individual wafers during processing;

b.1.e. Molecular beam epitaxial growth equipment;

b.1.f. Magnetically enhanced 'sputtering' equipment with ''specially designed'' integral load locks capable of transferring wafers in an isolated vacuum environment;

b.1.g. Equipment ''specially designed'' for ion implantation, ion-enhanced or photo-enhanced diffusion, having any of the following characteristics:

b.1.g.1. Patterning capability;

b.1.g.2. Beam energy (accelerating voltage) exceeding 200 keV;

b.1.g.3 Optimized to operate at a beam energy (accelerating voltage) of less than 10 keV; *or*

b.1.g.4. Capable of high energy oxygen implant into a heated ''substrate'';

b.1.h. ''Stored program controlled'' equipment for the selective removal (etching) by means of anisotropic dry methods (*e.g.,* plasma), as follows:

b.1.h.1. Batch types having either of the following:

b.1.h.1.a. End-point detection, other than optical emission spectroscopy types; *or*

b.1.h.1.b. Reactor operational (etching) pressure of 26.66 Pa or less;

b.1.h.2. Single wafer types having any of the following:

b.1.h.2.a. End-point detection, other than optical emission spectroscopy types;

b.1.h.2.b. Reactor operational (etching) pressure of 26.66 Pa or less; *or*

b.1.h.2.c. Cassette-to-cassette and load locks wafer handling;

Notes: *1. ''Batch types'' refers to machines not ''specially designed'' for production processing of single wafers. Such machines can process two or more wafers simultaneously with common process parameters, e.g., RF power, temperature, etch gas species, flow rates.*

2. ''Single wafer types'' refers to machines ''specially designed'' for production processing of single wafers. These machines may use automatic wafer handling techniques to load a single wafer into the equipment for processing. The definition includes equipment that can load and process several wafers but where the etching parameters, e.g., RF power or end point, can be independently determined for each individual wafer.

b.1.i. ''Chemical vapor deposition'' (CVD) equipment, *e.g.,* plasma-enhanced CVD (PECVD) or photo-enhanced CVD, for semiconductor device manufacturing, having either of the following capabilities, for deposition of oxides, nitrides, metals or polysilicon:

b.1.i.1. ''Chemical vapor deposition'' equipment operating below 10^5 Pa; *or*

b.1.i.2. PECVD equipment operating either below 60 Pa (450 millitorr) or having automatic cassette-to-cassette and load lock wafer handling;

Note: *3B991.b.1.i does not control low pressure ''chemical vapor deposition'' (LPCVD) systems or reactive ''sputtering'' equipment.*

b.1.j. Electron beam systems ''specially designed'' or modified for mask making or semiconductor device processing having any of the following characteristics:

b.1.j.1. Electrostatic beam deflection;

b.1.j.2. Shaped, non-Gaussian beam profile;

b.1.j.3. Digital-to-analog conversion rate exceeding 3 MHz;

b.1.j.4. Digital-to-analog conversion accuracy exceeding 12 bit; *or*

b.1.j.5. Target-to-beam position feedback control precision of 1 micrometer or finer;

Note: *3B991.b.1.j does not control electron beam deposition systems or general purpose scanning electron microscopes.*

b.1.k. Surface finishing equipment for the processing of semiconductor wafers as follows:

b.1.k.1. ''Specially designed'' equipment for backside processing of wafers thinner than 100 micrometer and the subsequent separation thereof; *or*

b.1.k.2. ''Specially designed'' equipment for achieving a surface roughness of the active surface of a processed wafer with a two-sigma value of 2 micrometer or less, total indicator reading (TIR);

Note: *3B991.b.1.k does not control single-side lapping and polishing equipment for wafer surface finishing.*

b.1.l. Interconnection equipment which includes common single or multiple vacuum chambers ''specially designed'' to permit the integration of any equipment controlled by 3B991 into a complete system;

b.1.m. ''Stored program controlled'' equipment using ''lasers'' for the repair or trimming of ''monolithic integrated circuits'' with either of the following characteristics:

b.1.m.1. Positioning accuracy less than ± 1 micrometer; *or*

b.1.m.2. Spot size (kerf width) less than 3 micrometer.

b.2. Masks, mask ''substrates,'' mask-making equipment and image transfer equipment for the manufacture of devices, ''parts'' and ''components'' as specified in the heading of 3B991, as follows:

Note: *The term ''masks'' refers to those used in electron beam lithography, X-ray lithography, and ultraviolet lithography, as well as the usual ultraviolet and visible photo-lithography.*

b.2.a. Finished masks, reticles and designs therefor, except:

b.2.a.1. Finished masks or reticles for the production of unembargoed integrated circuits; *or*

b.2.a.2. Masks or reticles, having both of the following characteristics:

b.2.a.2.a. Their design is based on geometries of 2.5 micrometer or more; *and*

b.2.a.2.b. The design does not include special features to alter the intended use by means of production equipment or ''software'';

b.2.b. Mask ''substrates'' as follows:

b.2.b.1. Hard surface (*e.g.,* chromium, silicon, molybdenum) coated ''substrates'' (*e.g.,* glass, quartz, sapphire) for the preparation of masks having dimensions exceeding 125 mm x 125 mm; *or*

b.2.b.2. ''Substrates'' ''specially designed'' for X-ray masks;

b.2.c. Equipment, other than general purpose computers, ''specially designed'' for computer aided design (CAD) of semiconductor devices or integrated circuits;

b.2.d. Equipment or machines, as follows, for mask or reticle fabrication:

b.2.d.1. Photo-optical step and repeat cameras capable of producing arrays larger than 100 mm x 100 mm, or capable of producing a single exposure larger than 6 mm x 6 mm in the image (*i.e.,* focal) plane, or capable of producing line widths of less than 2.5 micrometer in the photoresist on the ''substrate'';

b.2.d.2. Mask or reticle fabrication equipment using ion or ''laser'' beam lithography capable of producing line widths of less than 2.5 micrometer; *or*

b.2.d.3. Equipment or holders for altering masks or reticles or adding pellicles to remove defects;

Note: *3B991.b.2.d.1 and b.2.d.2 do not control mask fabrication equipment using photo-optical methods which was either commercially available before the 1st January, 1980, or has a performance no better than such equipment.*

b.2.e. ''Stored program controlled'' equipment for the inspection of masks, reticles or pellicles with:

b.2.e.1. A resolution of 0.25 micrometer or finer; *and*

b.2.e.2. A precision of 0.75 micrometer or finer over a distance in one or two coordinates of 63.5 mm or more;

Note: *3B991.b.2.e does not control general purpose scanning electron microscopes except when ''specially designed'' and instrumented for automatic pattern inspection.*

b.2.f. Align and expose equipment for wafer production using photo-optical or X-ray methods, *e.g.,* lithography equipment, including both projection image transfer equipment and step and repeat (direct step on wafer) or step and scan (scanner) equipment, capable of performing any of the following functions:

Note: *3B991.b.2.f does not control photo-optical contact and proximity mask align and expose equipment or contact image transfer equipment.*

b.2.f.1. Production of a pattern size of less than 2.5 micrometer;

b.2.f.2. Alignment with a precision finer than ± 0.25 micrometer (3 sigma);

b.2.f.3. Machine-to-machine overlay no better than ± 0.3 micrometer; *or*

b.2.f.4. A light source wavelength shorter than 400 nm;

b.2.g. Electron beam, ion beam or X-ray equipment for projection image transfer capable of producing patterns less than 2.5 micrometer;

Note: *For focused, deflected-beam systems(direct write systems), see 3B991.b.1.j or b.10.*

b.2.h. Equipment using ''lasers'' for direct write on wafers capable of producing patterns less than 2.5 micrometer.

b.3. Equipment for the assembly of integrated circuits, as follows:

b.3.a. ''Stored program controlled'' die bonders having all of the following characteristics:

b.3.a.1. ''Specially designed'' for ''hybrid integrated circuits'';

b.3.a.2. X–Y stage positioning travel exceeding 37.5 x 37.5 mm; *and*

b.3.a.3. Placement accuracy in the X–Y plane of finer than ± 10 micrometer;

b.3.b. ''Stored program controlled'' equipment for producing multiple bonds in a single operation (*e.g.,* beam lead bonders, chip carrier bonders, tape bonders);

b.3.c. Semi-automatic or automatic hot cap sealers, in which the cap is heated locally to a higher temperature than the body of the package, ''specially designed'' for ceramic microcircuit packages controlled by 3A001 and that have a throughput equal to or more than one package per minute.

Note: *3B991.b.3 does not control general purpose resistance type spot welders.*

b.4. Filters for clean rooms capable of providing an air environment of 10 or less particles of 0.3 micrometer or smaller per 0.02832 m^3 and filter materials therefor.

* * * * *

3D001 ''Software'' ''specially designed'' for the ''development'' or ''production'' of commodities controlled by 3A001.b to 3A002.h, or 3B (except 3B991 and 3B992).

License Requirements

Reason for Control: NS, RS, AT

Control(s)	*Country chart (See Supp. No. 1 to part 738)*
NS applies to ''software'' for commodities controlled by 3A001.b to 3A001.h, 3A002, and 3B.	NS Column 1
RS applies to ''software'' for commodities controlled by 3B090.	China (see § 742.6(a)(6))
AT applies to entire entry.	AT Column 1

Reporting Requirements

See § 743.1 of the EAR for reporting requirements for exports under License Exceptions, Special Comprehensive Licenses, and Validated End-User authorizations.

List Based License Exceptions (See Part 740 for a description of all license exceptions)

TSR: Yes, except for ''software'' ''specially designed'' for the ''development'' or ''production'' of Traveling Wave Tube Amplifiers described in 3A001.b.8 having operating frequencies exceeding 18 GHz.

Special Conditions for STA

STA: License Exception STA may not be used to ship or transmit ''software'' ''specially designed'' for the ''development'' or ''production'' of equipment specified by 3A002.g.1 or 3B001.a.2 to any of the destinations listed in Country Group A:6 (See Supplement No.1 to part 740 of the EAR).

List of Items Controlled

Related Controls: N/A
Related Definitions: N/A
Items:

The list of items controlled is contained in the ECCN heading.

* * * * *

3E001 ''Technology'' according to the General Technology Note for the ''development'' or ''production'' of commodities controlled by 3A (except 3A980, 3A981, 3A991, 3A992, or 3A999), 3B (except 3B991 or 3B992) or 3C (except 3C992).

License Requirements

Reason for Control: NS, MT, NP, RS, AT

Control(s)	*Country chart (See Supp. No. 1 to part 738)*
NS applies to ''technology'' for commodities controlled by 3A001, 3A002, 3A003, 3B001, 3B002, or 3C001 to 3C006..	NS Column 1
MT applies to ''technology'' for commodities controlled by. 3A001 or 3A101 for MT reasons.	MT Column 1
NP applies to ''technology'' for commodities controlled by. 3A001, 3A201, or 3A225 to 3A234 for NP reasons.	NP Column 1
RS applies to ''technology'' for commodities controlled by 3B090 or ''software'' specified by 3D001 (for 3B090 commodities)..	China (See § 742.6(a)(6)).
AT applies to entire entry.	AT Column 1

License Requirements Note: *See § 744.17 of the EAR for additional license requirements for microprocessors having a processing speed of 5 GFLOPS or more and an arithmetic logic unit with an access width of 32 bit or more, including those incorporating ''information security'' functionality, and associated ''software'' and ''technology'' for the ''production'' or ''development'' of such microprocessors.*

Reporting Requirements

See § 743.1 of the EAR for reporting requirements for exports under License Exceptions, Special Comprehensive Licenses, and Validated End-User authorizations.

List Based License Exceptions (See Part 740 for a description of all license exceptions)

TSR: Yes, except N/A for MT, and ''technology'' for the ''development'' or ''production'' of: (a) vacuum electronic device amplifiers described in 3A001.b.8, having operating frequencies exceeding 19 GHz; (b) solar cells, coverglass-interconnect-cells or covered-interconnect-cells (CIC) ''assemblies'', solar arrays and/or solar panels described in 3A001.e.4; (c) ''Monolithic Microwave Integrated Circuit'' (''MMIC'') amplifiers in 3A001.b.2; and (d) discrete microwave transistors in 3A001.b.3.

Special Conditions for STA

STA: License Exception STA may not be used to ship or transmit ''technology'' according to the General Technology Note for the "development" or "production" of equipment specified by ECCNs 3A002.g.1 or 3B001.a.2 to any of the destinations listed in Country Group A:6 (See Supplement No.1 to part 740 of the EAR). License Exception STA may not be used to ship or transmit "technology" according to the General Technology Note for the "development" or "production" of components specified by ECCN 3A001.b.2 or b.3 to any of the destinations listed in Country Group A:5 or A:6 (See Supplement No.1 to part 740 of the EAR).

List of Items Controlled

Related Controls: (1)"Technology" according to the General Technology Note for the "development" or "production" of certain "space-qualified" atomic frequency standards described in Category XV(e)(9), MMICs described in Category XV(e)(14), and oscillators described in Category XV(e)(15) of the USML are "subject to the ITAR" (see 22 CFR parts 120 through 130). See also 3E101, 3E201 and 9E515. (2) "Technology" for "development" or "production" of "Microwave Monolithic Integrated Circuits" ("MMIC") amplifiers in 3A001.b.2 is controlled in this ECCN 3E001; 5E001.d refers only to that additional "technology" "required" for telecommunications.

Related Definition: N/A

Items:

The list of items controlled is contained in the ECCN heading.

Note 1: 3E001 does not control "technology" for equipment or "components" controlled by 3A003.

Note 2: 3E001 does not control "technology" for integrated circuits controlled by 3A001.a.3 to a.14, having all of the following:

(a) Using "technology" at or above 0.130 µm; and

(b) Incorporating multi-layer structures with three or fewer metal layers.

Note 3: 3E001 does not apply to 'Process Design Kits' ('PDKs') unless they include libraries implementing functions or technologies for items specified by 3A001.

Technical Note: A 'Process Design Kit' ('PDK') is a software tool provided by a semiconductor manufacturer to ensure that the required design practices and rules are taken into account in order to successfully produce a specific integrated circuit design in a specific semiconductor process, in accordance with technological and manufacturing constraints (each semiconductor manufacturing process has its particular 'PDK').

■ 26. Effective on October 21, 2022, supplement no. 1 to part 774 is further amended by:

■ a. Under Category 3, Product Group A, revising Note 3;

■ b. Adding ECCN 3A090 after ECCN 3A003;

■ c. Revising ECCNs 3A991, 3D001, and 3E001;

■ d. Adding ECCN 4A090 after ECCN 4A005;

■ e. Revising ECCN 4A994;

■ f. Adding ECCN 4D090 after ECCN 4D004; and

■ g. Revising ECCNs 4D994, 4E001, 5A992, and 5D992.

The additions and revisions read as follows:

Supplement No. 1 to Part 774—The Commerce Control List

* * * * *

Category 3—Electronics A. "End Items," "Equipment," "Accessories," "Attachments," "Parts," "Components," and "Systems"

* * * * *

Note 3: *The status of wafers (finished or unfinished), in which the function has been determined, is to be evaluated against the parameters of items in 3A.*

* * * * *

3A090 Integrated circuits as follows (see List of Items Controlled).

License Requirements

Reason for Control: RS, AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
RS applies to entire entry.	China (See § 742.6(a)(6))
AT applies to entire entry.	AT Column 1

List Based License Exceptions (See Part 740 for a description of all license exceptions)

LVS: N/A

GBS N/A

List of Items Controlled

Related Controls: See ECCNs 3D001 and 3E001 for associated technology and software controls.

Related Definitions: N/A

Items:

a. Integrated circuits that have or are programmable to have an aggregate bidirectional transfer rate over all inputs and outputs of 600 Gbyte/s or more to or from integrated circuits other than volatile memories, and any of the following:

a.1. One or more digital processor units executing machine instructions having a bit length per operation multiplied by processing performance measured in TOPS, aggregated over all processor units, of 4800 or more;

a.2. One or more digital 'primitive computational units,' excluding those units contributing to the execution of machine instructions relevant to the calculation of TOPS for 3A090.a.1, having a bit length per operation multiplied by processing performance measured in TOPS, aggregated over all computational units, of 4800 or more;

a.3. One or more analog, multi-value, or multi-level 'primitive computational units' having a processing performance measured in TOPS multiplied by 8, aggregated over all computational units, of 4800 or more; or

a.4. Any combination of digital processor units and 'primitive computational units' whose calculations according to 3A090.a.1, 3A090.a.2, and 3A090.a.3 sum to 4800 or more.

Note: *Integrated circuits specified by 3A090.a include graphical processing units (GPUs), tensor processing units (TPUs), neural processors, in-memory processors, vision processors, text processors, co-processors/accelerators, adaptive processors, field-programmable logic devices (FPLDs), and application-specific integrated circuits (ASICs). Examples of integrated circuits are in the Note to 3A001.a.*

Technical Notes:

1. A 'primitive computational unit' is defined as containing zero or more modifiable weights, receiving one or more inputs, and producing one or more outputs. A computational unit is said to perform 2N–1 operations whenever an output is updated based on N inputs, where each modifiable weight contained in the processing element counts as an input. Each input, weight, and output might be an analog signal level or a scalar digital value represented using one or more bits. Such units include:

—*Artificial neurons*
— *Multiply accumulate (MAC) units*
—*Floating-point units (FPUs)*
—*Analog multiplier units*
—*Processing units using memristors, spintronics, or magnonics*
—*Processing units using photonics or non-linear optics*
—*Processing units using analog or multi-level nonvolatile weights*
—*Processing units using multi-level memory or analog memory*
— *Multi-value units*
—*Spiking units*

2. Operations relevant to the calculation of TOPS for 3A090.a include both scalar operations and the scalar constituents of composite operations such as vector operations, matrix operations, and tensor operations. Scalar operations include integer operations, floating-point operations (often measured by FLOPS), fixed-point operations, bit-manipulation operations, and/or bitwise operations.

3. TOPS is Tera Operations Per Second or 10^{12} Operations per Second.

4. The rate of TOPS is to be calculated at its maximum value theoretically possible when all processing elements are operating simultaneously. The rate of TOPS and aggregate bidirectional transfer rate is assumed to be the highest value the manufacturer claims in a manual or brochure for the integrated circuit. For example, the threshold of 4800 bits x TOPS can be met with 600 tera integer operations at 8 bits or 300 tera FLOPS at 16 bits. The bit length of an operation is equal to the highest bit length of any input or output of that operation. Additionally, if an item specified by this entry is designed for operations that achieve different bits x TOPS value, the highest bits x TOPS value should be used for the purposes of 3A090.a.

5. For integrated circuits specified by 3A090.a that provide processing of both sparse and dense matrices, the TOPS values are the values for processing of dense matrices (*e.g.,* without sparsity).

b. [Reserved]

* * * * *

3A991 Electronic devices and "components," not controlled by 3A001.

License Requirements

Reason for Control: AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
AT applies to entire entry.	AT Column 1

License Requirements Note: *See § 744.17 of the EAR for additional license requirements for microprocessors having a processing speed of 5 GFLOPS or more and an arithmetic logic unit with an access width of 32 bit or more, including those incorporating "information security" functionality, and associated "software" and "technology" for the "production" or "development" of such microprocessors.*

List Based License Exceptions (See Part 740 for a description of all license exceptions)

LVS: N/A
GBS: N/A

List of Items Controlled

Related Controls: For associated "software" for commodities in this ECCN, see 3D991 and for associated "technology for commodities in this ECCN, see 3E991.
Related Definitions: N/A
Items:

a. "Microprocessor microcircuits", "microcomputer microcircuits", and microcontroller microcircuits having any of the following:

a.1. A performance speed of 5 GFLOPS or more and an arithmetic logic unit with an access width of 32 bit or more;

a.2. A clock frequency rate exceeding 25 MHz; *or*

a.3. More than one data or instruction bus or serial communication port that provides a direct external interconnection between parallel "microprocessor microcircuits" with a transfer rate of 2.5 Mbyte/s;

b. Storage integrated circuits, as follows:

b.1. Electrical erasable programmable read-only memories (EEPROMs) with a storage capacity;

b.1.a. Exceeding 16 Mbits per package for flash memory types; *or*

b.1.b. Exceeding either of the following limits for all other EEPROM types:

b.1.b.1. Exceeding 1 Mbit per package; *or*

b.1.b.2. Exceeding 256 kbit per package and a maximum access time of less than 80 ns;

b.2. Static random access memories (SRAMs) with a storage capacity:

b.2.a. Exceeding 1 Mbit per package; *or*

b.2.b. Exceeding 256 kbit per package and a maximum access time of less than 25 ns;

c. Analog-to-digital converters having any of the following:

c.1. A resolution of 8 bit or more, but less than 12 bit, with an output rate greater than 200 million words per second;

c.2. A resolution of 12 bit with an output rate greater than 105 million words per second;

c.3. A resolution of more than 12 bit but equal to or less than 14 bit with an output rate greater than 10 million words per second; *or*

c.4. A resolution of more than 14 bit with an output rate greater than 2.5 million words per second;

d. Field programmable logic devices having a maximum number of single-ended digital input/outputs between 200 and 700;

e. Fast Fourier Transform (FFT) processors having a rated execution time for a 1,024 point complex FFT of less than 1 ms;

f. Custom integrated circuits for which either the function is unknown, or the control status of the equipment in which the integrated circuits will be used is unknown to the manufacturer, having any of the following:

f.1. More than 144 terminals; *or*

f.2. A typical "basic propagation delay time" of less than 0.4 ns;

g. Traveling-wave "vacuum electronic devices," pulsed or continuous wave, as follows:

g.1. Coupled cavity devices, or derivatives thereof;

g.2. Helix devices based on helix, folded waveguide, or serpentine waveguide circuits, *or* derivatives thereof, with any of the following:

g.2.a. An "instantaneous bandwidth" of half an octave or more; *and*

g.2.b. The product of the rated average output power (expressed in kW) and the maximum operating frequency (expressed in GHz) of more than 0.2;

g.2.c. An "instantaneous bandwidth" of less than half an octave; *and*

g.2.d. The product of the rated average output power (expressed in kW) and the maximum operating frequency (expressed in GHz) of more than 0.4;

h. Flexible waveguides designed for use at frequencies exceeding 40 GHz;

i. Surface acoustic wave and surface skimming (shallow bulk) acoustic wave devices (*i.e.,* "signal processing" devices employing elastic waves in materials), having either of the following:

i.1. A carrier frequency exceeding 1 GHz; *or*

i.2. A carrier frequency of 1 GHz or less; *and*

i.2.a. A frequency side-lobe rejection exceeding 55 Db;

i.2.b. A product of the maximum delay time and bandwidth (time in microseconds and bandwidth in MHz) of more than 100; *or*

i.2.c. A dispersive delay of more than 10 microseconds;

j. Cells as follows:

j.1. Primary cells having an energy density of 550 Wh/kg or less at 293 K (20°C);

j.2. Secondary cells having an energy density of 350 Wh/kg or less at 293 K (20°C);

Note: 3A991.j does not control batteries, including single cell batteries.

Technical Notes:

1. For the purpose of 3A991.j energy density (Wh/kg) is calculated from the nominal voltage multiplied by the nominal capacity in ampere-hours divided by the mass in kilograms. If the nominal capacity is not stated, energy density is calculated from the nominal voltage squared then multiplied by the discharge duration in hours divided by the discharge load in Ohms and the mass in kilograms.

2. For the purpose of 3A991.j, a 'cell' is defined as an electrochemical device, which has positive and negative electrodes, and electrolyte, and is a source of electrical energy. It is the basic building block of a battery.

3. For the purpose of 3A991.j.1, a 'primary cell' is a 'cell' that is not designed to be charged by any other source.

4. For the purpose of 3A991.j.2, a 'secondary cell' is a 'cell' that is designed to be charged by an external electrical source.

k. "Superconductive" electromagnets or solenoids "specially designed" to be fully charged or discharged in less than one minute, having all of the following:

Note: 3A991.k does not control "superconductive" electromagnets or solenoids designed for Magnetic Resonance Imaging (MRI) medical equipment.

k.1. Maximum energy delivered during the discharge divided by the duration of the discharge of more than 500 kJ per minute;

k.2. Inner diameter of the current carrying windings of more than 250 mm; *and*

k.3. Rated for a magnetic induction of more than 8T or "overall current density" in the winding of more than 300 A/mm^2;

l. Circuits or systems for electromagnetic energy storage, containing "components" manufactured from "superconductive" materials "specially designed" for operation at temperatures below the "critical temperature" of at least one of their "superconductive" constituents, having all of the following:

l.1. Resonant operating frequencies exceeding 1 MHz;

l.2. A stored energy density of 1 MJ/M^3 or more; *and*

l.3. A discharge time of less than 1 ms;

m. Hydrogen/hydrogen-isotope thyratrons of ceramic-metal construction and rate for a peak current of 500 A or more;

n. Digital integrated circuits based on any compound semiconductor having an equivalent gate count of more than 300 (2 input gates);

o. Solar cells, cell-interconnect-coverglass (CIC) assemblies, solar panels, and solar arrays, which are "space qualified" and not controlled by 3A001.e.4.

p. Integrated circuits, n.e.s., having any of the following:

p.1. A processing performance of 8 TOPS or more; or

p.2. An aggregate bidirectional transfer rate over all inputs and outputs of 150 Gbyte/s or more to or from integrated circuits other than volatile memories.

Technical Notes: *For the purposes of 3A991.p:*

1. This ECCN includes but is not limited to central processing units (CPU), graphics processing units (GPU), tensor processing units (TPU), neural processors, in-memory processors, vision processors, text processors, co-processors/accelerators, adaptive processors, and field-programmable logic devices (FPLDs).

2. TOPS is Tera Operations Per Second or 10^{12} Operations per Second.

3. The rate of TOPS is to be calculated at its maximum value theoretically possible *when all processing elements are operating simultaneously. The rate of TOPS and aggregate bidirectional transfer rate is assumed to be the highest value the manufacturer claims in a manual or brochure for the integrated circuit. Operations include both scalar operations and the scalar constituents of composite operations such as vector operations, matrix operations, and tensor operations. Scalar operations include integer operations, floating-point operations (often measured by FLOPS), fixed-point operations, bit-manipulation operations, and/or bitwise operations.*

* * * * *

3D001 "Software""specially designed" for the "development" or "production" of commodities controlled by 3A001.b to 3A002.h, 3A090, or 3B (except 3B991 and 3B992).

License Requirements

Reason for Control: NS, RS, AT

Control(s)	*Country chart (See Supp. No. 1 to part 738)*
NS applies to "software" for commodities controlled by 3A001.b to 3A001.h, 3A002, and 3B.	NS Column 1
RS applies to "software" for commodities controlled by 3A090 or 3B090..	China (see § 742.6(a)(6))
AT applies to entire entry.	AT Column 1

Reporting Requirements

See § 743.1 of the EAR for reporting requirements for exports under License Exceptions, Special Comprehensive Licenses, and Validated End-User authorizations.

List Based License Exceptions (See Part 740 for a description of all license exceptions)

TSR: Yes, except for "software" "specially designed" for the "development" or "production" of Traveling Wave Tube Amplifiers described in 3A001.b.8 having operating frequencies exceeding 18 GHz.

Special Conditions for STA

STA: License Exception STA may not be used to ship or transmit "software" "specially designed" for the "development" or "production" of equipment specified by 3A002.g.1 or 3B001.a.2 to any of the destinations listed in Country Group A:6 (See Supplement No.1 to part 740 of the EAR).

List of Items Controlled

Related Controls: N/A
Related Definitions: N/A
Items:

The list of items controlled is contained in the ECCN heading.

* * * * *

3E001 "Technology" according to the General Technology Note for the "development" or "production" of commodities controlled by 3A (except 3A980, 3A981, 3A991, 3A992, or 3A999), 3B (except 3B991 or 3B992) or 3C (except 3C992).

License Requirements

Reason for Control: NS, MT, NP, RS, AT

Control(s)	*Country chart (See Supp. No. 1 to part 738)*
NS applies to "technology" for commodities controlled by 3A001, 3A002, 3A003, 3B001, 3B002, or 3C001 to 3C006.	NS Column 1.
MT applies to "technology" for commodities controlled by 3A001 or 3A101 for MT reasons.	MT Column 1.
NP applies to "technology" for commodities controlled by 3A001, 3A201, or 3A225 to 3A234 for NP reasons.	NP Column 1.
RS applies to "technology" for commodities controlled by 3A090 or 3B090 or "software" specified by 3D001 (for 3A090 or 3B090 commodities).	China (See § 742.6(a)(6)).
RS applies to "technology" for commodities controlled in 3A090, when exported from China.	Worldwide (See § 742.6(a)(6))
AT applies to entire entry.	AT Column 1

License Requirements Note: *See § 744.17 of the EAR for additional license requirements for microprocessors having a processing speed of 5 GFLOPS or more and an arithmetic logic unit with an access width of 32 bit or more, including those incorporating "information security" functionality, and associated "software" and "technology" for the "production" or "development" of such microprocessors.*

Reporting Requirements

See § 743.1 of the EAR for reporting requirements for exports under License Exceptions, Special Comprehensive Licenses, and Validated End-User authorizations.

List Based License Exceptions (See Part 740 for a description of all license exceptions)

TSR: Yes, except N/A for MT, and "technology" for the "development" or "production" of: (a) vacuum electronic device amplifiers described in 3A001.b.8, having operating frequencies exceeding 19 GHz; (b) solar cells, coverglass-interconnect-cells or covered-interconnect-cells (CIC) "assemblies", solar arrays and/or solar panels described in 3A001.e.4; (c) "Monolithic Microwave Integrated Circuit" ("MMIC") amplifiers in 3A001.b.2; and (d) discrete microwave transistors in 3A001.b.3.

Special Conditions for STA

STA: License Exception STA may not be used to ship or transmit "technology" according to the General Technology Note for the "development" or "production" of equipment specified by ECCNs 3A002.g.1 or 3B001.a.2 to any of the destinations listed in Country Group A:6 (See Supplement No.1 to part 740 of the EAR). License Exception STA may not be used to ship or transmit "technology" according to the General Technology Note for the "development" or "production" of components specified by ECCN 3A001.b.2 or b.3 to any of the destinations listed in Country Group A:5 or A:6 (See Supplement No.1 to part 740 of the EAR).

List of Items Controlled

Related Controls: (1) "Technology" according to the General Technology Note for the "development" or "production" of certain "space-qualified" atomic frequency standards described in Category XV(e)(9), MMICs described in Category XV(e)(14), and oscillators described in Category XV(e)(15) of the USML are "subject to the ITAR" (see 22 CFR parts 120 through 130). See also 3E101, 3E201 and 9E515. (2) "Technology" for "development" or "production" of "Microwave Monolithic Integrated Circuits" ("MMIC") amplifiers in 3A001.b.2 is controlled in this ECCN 3E001; 5E001.d refers only to that additional "technology" "required" for telecommunications.
Related Definition: N/A
Items:

The list of items controlled is contained in the ECCN heading.

Note 1: *3E001 does not control "technology" for equipment or "components" controlled by 3A003.*

Note 2: *3E001 does not control "technology" for integrated circuits controlled by 3A001.a.3 to a.14, having all of the following:*

(a) Using "technology" at or above 0.130 μm; and

(b) Incorporating multi-layer structures with three or fewer metal layers.

Note 3: *3E001 does not apply to 'Process Design Kits' ('PDKs') unless they include libraries implementing functions or technologies for items specified by 3A001.*

Technical Note: *A 'Process Design Kit' ('PDK') is a software tool provided by a semiconductor manufacturer to ensure that the required design practices and rules are taken into account in order to successfully produce a specific integrated circuit design in a specific semiconductor process, in accordance with technological and manufacturing constraints (each semiconductor manufacturing process has its particular 'PDK').*

* * * * *

4A090 Computers as follows (see List of Items Controlled) and related equipment, "electronic assemblies," and "components" therefor.

License Requirements

Reason for Control: RS, AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
RS applies to entire entry.	China (see § 742.6(a)(6))
AT applies to entire entry.	AT Column 1

List Based License Exceptions (See Part 740 for a description of all license exceptions)

LVS: N/A
GBS: N/A

List of Items Controlled

Related Controls: For associated "software" for commodities in this ECCN, see 4D090 and for associated "technology" for commodities in this ECCN, see 4E001.
Related Definitions: N/A
Items:

a. Computers, "electronic assemblies," and "components" containing integrated circuits, any of which exceeds the limit in 3A090.a.

Technical Note: *Computers include "digital computers," "hybrid computers," and analog computers.*

b. Reserved

* * * * *

4A994 Computers, "electronic assemblies" and related equipment, not controlled by 4A001 or 4A003, and "specially designed" "parts" and "components" therefor (see List of Items Controlled).

License Requirements

Reason for Control: AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
AT applies to entire entry.	AT Column 1

List Based License Exceptions (See Part 740 for a description of all license exceptions)

LVS: N/A
GBS: N/A

List of Items Controlled

Related Controls: For associated "software" for commodities in this ECCN, see 4D994 and for associated "technology" for commodities in this ECCN, see 4E992.
Related Definitions: N/A
Items:

Note 1: *The control status of the "digital computers" and related equipment described in 4A994 is determined by the control status of other equipment or systems provided:*

a. The "digital computers" or related equipment are essential for the operation of the other equipment or systems;

b. The "digital computers" or related equipment are not a "principal element" of the other equipment or systems; and

N.B. 1: *The control status of "signal processing" or "image enhancement" equipment "specially designed" for other equipment with functions limited to those required for the other equipment is determined by the control status of the other equipment even if it exceeds the "principal element" criterion.*

N.B. 2: *For the control status of "digital computers" or related equipment for telecommunications equipment, see Category 5, Part 1 (Telecommunications).*

c. The "technology" for the "digital computers" and related equipment is determined by 4E.

a. Electronic computers and related equipment, and "electronic assemblies" and "specially designed" "parts" and "components" therefor, rated for operation at an ambient temperature above 343 K (70 °C);

b. "Digital computers", including equipment of "signal processing" or image enhancement", having an "Adjusted Peak Performance" ("APP") equal to or greater than 0.0128 Weighted TeraFLOPS (WT);

c. "Electronic assemblies" that are "specially designed" or modified to enhance performance by aggregation of processors, as follows:

c.1. Designed to be capable of aggregation in configurations of 16 or more processors;

c.2. [Reserved];

Note 1: *4A994.c applies only to "electronic assemblies" and programmable interconnections with a "APP" not exceeding the limits in 4A994.b, when shipped as unintegrated "electronic assemblies". It does not apply to "electronic assemblies" inherently limited by nature of their design for use as related equipment controlled by 4A994.k.*

Note 2: *4A994.c does not control any "electronic assembly" "specially designed" for a product or family of products whose maximum configuration does not exceed the limits of 4A994.b.*

d. [Reserved];

e. [Reserved];

f. Equipment for "signal processing" or "image enhancement" having an "Adjusted Peak Performance" ("APP") equal to or greater than 0.0128 Weighted TeraFLOPS WT;

g. [Reserved];

h. [Reserved];

i. Equipment containing "terminal interface equipment" exceeding the limits in 5A991;

j. Equipment "specially designed" to provide external interconnection of "digital computers" or associated equipment that allows communications at data rates exceeding 80 Mbyte/s.

Note: *4A994.j does not control internal interconnection equipment (e.g., backplanes, buses) passive interconnection equipment, "network access controllers" or "communication channel controllers".*

k. "Hybrid computers" and "electronic assemblies" and "specially designed" "parts" and "components" therefor containing analog-to-digital converters having all of the following characteristics:

k.1. 32 channels or more; and

k.2. A resolution of 14 bit (plus sign bit) or more with a conversion rate of 200,000 conversions/s or more.

l. Computers, "electronic assemblies," and "components," n.e.s., containing integrated circuits, any of which exceeds the limit of ECCN 3A991.p.

Technical Note: *For the purposes of 4A994.l, computers include "digital computers," "hybrid computers," and analog computers.*

* * * * *

4D090 "Software" "specially designed" or modified for the "development" or "production," of computers and related equipment, "electronic assemblies," and "components" therefor specified in ECCN 4A090.

License Requirements

Reason for Control: RS, AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
RS applies to entire entry.	China (See § 742.6(a)(6)).
AT applies to entire entry.	AT Column 1.

List Based License Exceptions (See Part 740 for a description of all license exceptions)

TSR: N/A

List of Items Controlled

Related Controls: For associated "technology" for software in this ECCN, see 4E001.
Related Definitions: N/A
Items:

The list of items controlled is contained in the ECCN heading.

* * * * *

4D994 "Software" other than that controlled in 4D001 "specially designed" or modified for the "development," "production," or "use" of commodities controlled by 4A101 or 4A994.

License Requirements

Reason for Control: AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
AT applies to entire entry.	AT Column 1

List Based License Exceptions (See Part 740 for a description of all license Exceptions)

TSR: N/A

List of Items Controlled

Related Controls: N/A
Related Definitions: N/A
Items:

The list of items controlled is contained in the ECCN heading.

* * * * *

4E001 "Technology" as follows (see List of Items Controlled).

License Requirements

Reason for Control: NS, MT, RS, CC, AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
NS applies to entire entry.	NS Column 1.

Control(s)	Country chart (See Supp. No. 1 to part 738)
MT applies to "technology" for items controlled by 4A001.a and 4A101 for MT reasons.	MT Column 1.
RS applies to "technology" for commodities controlled by 4A090 or "software" specified by 4D090.	China (See § 742.6(a)(6)).
CC applies to "software" for computerized finger-print equipment controlled by 4A003 for CC reasons.	CC Column 1.
AT applies to entire entry.	AT Column 1.

Reporting Requirements

See § 743.1 of the EAR for reporting requirements for exports under License Exceptions, and Validated End-User authorizations.

List Based License Exceptions (See Part 740 for a description of all license exceptions)

TSR: Yes, except for the following:

(1) "Technology" for the "development" or "production" of commodities with an "Adjusted Peak Performance" ("APP") exceeding 29 WT or for the "development" or "production" of commodities controlled by 4A005 or "software" controlled by 4D004; or

(2) "Technology" for the "development" of "intrusion software".

APP: Yes to specific countries (see § 740.7 of the EAR for eligibility criteria).

ACE: Yes for 4E001.a (for the "development", "production" or "use" of equipment or "software" specified in ECCN 4A005 or 4D004) and for 4E001.c, except to Country Group E:1 or E:2. See § 740.22 of the EAR for eligibility criteria.

Special Conditions for STA

STA: License Exception STA may not be used to ship or transmit "technology" according to the General Technology Note for the "development" or "production" of any of the following equipment or "software": a. Equipment specified by ECCN 4A001.a.2; b. "Digital computers" having an 'Adjusted Peak Performance' ('APP') exceeding 29 Weighted TeraFLOPS (WT); or c. "software" specified in the License Exception STA paragraph found in the License Exception section of ECCN 4D001 to any of the destinations listed in Country Group A:6 (See Supplement No. 1 to part 740 of the EAR); and may not be used to ship or transmit "software" specified in 4E001.a (for the "development", "production" or "use" of equipment or "software" specified in ECCN 4A005 or 4D004) and 4E001.c to any of the destinations listed in Country Group A:5 or A:6.

List of Items Controlled

Related Controls: N/A
Related Definitions: N/A
Items:

a. "Technology" according to the General Technology Note, for the "development", "production", or "use" of equipment or "software" controlled by 4A (except 4A980 or 4A994) or 4D (except 4D980, 4D993, 4D994).

b. "Technology" according to the General Technology Note, other than that controlled by 4E001.a, for the "development" or "production" of equipment as follows:

b.1. "Digital computers" having an "Adjusted Peak Performance" ("APP") exceeding 15 Weighted TeraFLOPS (WT);

b.2. "Electronic assemblies" "specially designed" or modified for enhancing performance by aggregation of processors so that the "APP" of the aggregation exceeds the limit in 4E001.b.1.

c. "Technology" for the "development" of "intrusion software."

Note 1: *4E001.a and 4E001.c do not apply to "vulnerability disclosure" or "cyber incident response".*

Note 2: *Note 1 does not diminish national authorities' rights to ascertain compliance with 4E001.a and 4E001.c.*

* * * * *

5A992 Equipment not controlled by 5A002 (see List of Items Controlled)

License Requirements

Reason for Control: RS, AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
RS applies to items controlled by 5A992.c that meet or exceed the performance parameters of ECCN 3A090 or 4A090.	RS (see § 742.6(a)(6))
AT applies to entire entry.	AT Column 1

License Requirements Note: *See § 744.17 of the EAR for additional license requirements for microprocessors having a processing speed of 5 GFLOPS or more and an arithmetic logic unit with an access width of 32 bit or more, including those incorporating "information security" functionality, and associated "software" and "technology" for the "production" or "development" of such microprocessors.*

List Based License Exceptions (See Part 740 for a description of all license exceptions)

LVS: N/A
GBS: N/A

List of Items Controlled

Related Controls: N/A
Related Definitions: N/A
Items:

a. [Reserved]

b. [Reserved]

c. Commodities classified as mass market encryption commodities in accordance with § 740.17(b) of the EAR.

* * * * *

5D992 "Information Security" "software," not controlled by 5D002, as follows (see List of Items Controlled).

License Requirements

Reason for Control: RS, AT

Control(s)	Country chart (See Supp. No. 1 to part 738)
RS applies to items controlled by 5D992.c that meet or exceed the performance parameters of ECCN 3A090 or 4A090.	RS (see § 742.6(a)(6)).
AT applies to entire entry.	AT Column 1.

License Requirements Note: *See § 744.17 of the EAR for additional license requirements for microprocessors having a processing speed of 5 GFLOPS or more and an arithmetic logic unit with an access width of 32 bit or more, including those incorporating "information security" functionality, and associated "software" and "technology" for the "production" or "development" of such microprocessors.*

List Based License Exceptions (See Part 740 for a description of all license exceptions)

TSR: N/A

List of Items Controlled

Related Controls: This entry does not control "software" designed or modified to protect against malicious computer damage, *e.g.,* viruses, where the use of "cryptography" is limited to authentication, digital signature and/or the decryption of data or files.
Related Definitions: N/A
Items:

a. [Reserved]

b. [Reserved]

c. "Software" classified as mass market encryption software in accordance with § 740.17(b) of the EAR.

* * * * *

Thea D. Rozman Kendler,
Assistant Secretary for Export Administration.

[FR Doc. 2022–21658 Filed 10–7–22; 11:15 am]

BILLING CODE 3510–33–P

General

The Impact of a Non-Compete Clause on Patient Care and Orthopaedic Surgeons in the State of Louisiana: Afraid of a Little Competition?

William F. Sherman[1] [a], Akshar H. Patel[2], Bailey J. Ross[1], Olivia C. Lee[3], Claude S. Williams IV[4], Felix H. Savoie III[2]

[1] Orthopaedic Surgery, Tulane University School of Medicine, [2] Orthopedic Surgery, Tulane University School of Medicine, [3] Orthopedic Surgery, Louisiana State University Health Sciences Center New Orleans, [4] Southern Orthopaedic Specialists

Keywords: restrictive, covenant, non-compete, employed, law, survey

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Background

Non-compete clauses (NCC) are commonly required for physicians practicing in an employed model. With growing pressures driving surgeons to practice in an employed model instead of physician-led practices, the purpose of this survey was to determine the impact of NCCs on orthopaedic surgeons and their patients in Louisiana.

Methods

A voluntary, single-mode online survey containing 23 questions was created using the Qualtrics XM Platform (Qualtrics, Provo, UT) and distributed to 259 orthopaedic surgeons who are members of the Louisiana Orthopaedic Association. Survey questions assessed the prevalence and details of existing NCCs and perceptions of their impact on surgeons' practice, patients, and personal life.

Results

117 members responded (response rate: 45.2%), of which 91 (77.8%) finished the survey. Nearly half (44%) of respondents had an expired or active NCC in their contract. Most (84.3%) believed NCCs give employers unfair leverage during contract negotiations. NCCs have deterred or would deter 71.4% of respondents from accepting another job offer. Respondents believed NCCs negatively impact patients, including forcing patients to drive long distances to maintain continuity of care (64.4%) and forcing surgeons to abandon their patients if they seek new employment (76.7%). Many respondents reported NCCs also exert significant detrimental effects on their personal life, including mandatory relocation of their family (67.0%). Nearly all (97.8%) believed such clauses have become unreasonable over the last decade with the rise of large hospital conglomerates. Most surgeons (83.7%) believed that removal of NCCs from all orthopaedic surgeons' contracts would improve the overall healthcare of orthopaedic patients in Louisiana.

Conclusion

Perceptions of NCCs were overwhelmingly negative among orthopaedic surgeons in Louisiana. Such clauses give employers an unfair advantage during contract negotiations and exert a significant detrimental impact on surgeons and their patients. While NCCs may be reasonable in the business sector and other professions, it is unclear how such clauses benefit surgeons or improve patient care and may be detrimental to both.

a **Corresponding author:**
William Sherman MD, MBA
swilliam1@tulane.edu
+1-504-982-0252

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Study Design

Cross-sectional Survey

INTRODUCTION

Restrictive covenants, also known as non-compete clauses (NCC), have been a highly contested contractual agreement of the employed physician model, and the changing landscape of healthcare continues to bring this to the forefront.[1,2] Physician employment by large groups, hospitals, and hospital systems has grown such that up to 36.2% of specialty surgeons in 2020 were currently employed or worked in employed models compared to 25.1% in 2012 according to the American Medical Association.[3–5] Increased hospital employment of physicians may increase inappropriate referrals, unnecessary imaging, and hospital-physician integration potentially resulting in low-value patient care.[6]

Hospital employed models rise at the expense of private practices due to myriad reasons including disproportionate reimbursements via insurers, hospital-owned primary care driving referrals, and lack of governmental funding to private groups.[7–9] Analysis of the 2005 to 2014 trend of outpatient isolated arthroscopic partial meniscectomy charges by LaPrade et al. revealed hospital reimbursement increased steadily by 28.8% while surgeon payments declined by 15.5% over the same time period indicating a widening gap between hospital and surgeon reimbursement.[10,11] Additionally, in a 2021 study, Jeurissen et al. determined the growth of for-profit hospitals was largely due to subsidy access and favorable reimbursement plans from public health care payors, which aided the creation and expansion of new for-profit hospitals.[12] As the increased trend of independent orthopaedic practice acquisition by large healthcare entities in the U.S. continues, NCCs will become an even greater issue for both surgeons and their patients.[8]

NCCs in business were initially established to prevent turnover, and in many cases, to prevent an employee who received training regarding a specific technology from competing with the former employer.[13,14] In medicine, the services provided by the surgeon are learned and acquired prior to employment; the employer is not providing proprietary trade secrets, knowledge, or skills that would protect the employer from unfair competition. Instead, the purpose of the NCC is largely to deter a physician from leaving an employer by not allowing them to continue to practice in the same community, which can give an unfair leverage to employers/large hospital systems.[15,16]

With growing pressures driving surgeons into employed models instead of physician-led practices, the purpose of this survey was to determine the impact of NCCs on orthopaedic surgeons and their patients in a state where the law allows employers to place this restriction on their physicians.

MATERIALS AND METHODS

After obtaining exemption from our institution's Institutional Review Board (IRB#2021-1034), a link to an anonymous online survey was distributed via email to 259 board-eligible or board-certified orthopaedic surgeons who are current members of the Louisiana Orthopaedic Association (LOA). The total collection period for the survey data was from November 21, 2021 to February 12, 2022. Four follow-up emails were sent to non-respondents at three weeks, six weeks, nine weeks, and eleven weeks after initial communication in order to boost participation and maximize the response rate.

A voluntary, single-mode (online) survey containing 23 questions (**Appendix 1**) was created and distributed using Qualtrics XM Platform (Qualtrics, Provo, UT, USA). Objective questions asked about the prevalence of NCCs in surgeons' contracts (expired or active clause versus no such clause at any time), details of existing NCCs (e.g., duration and regional coverage), surgeons' status as a president or senior partner of a group, and requirements for NCCs for new employees. Subjective questions asked about rationales for NCCs and perceptions of their impact on surgeons (personally and professionally), patients, and practices. One of these questions included an optional text response component for respondents to elaborate on their answer. Six questions were in a multiple response format in which more than one option could be chosen by respondents. Therefore, percentages may not total 100% for those questions. Demographic data including years in practice, orthopaedic subspecialty, practice type, and practice area (i.e., rural or urban and population size) were also collected. Respondents who did not finish the survey were excluded from the analysis.

STATISTICAL ANALYSIS

Statistical analyses on deidentified survey data were performed using Microsoft Excel (Microsoft Corporation, Redmond, WA, USA) with the XLStat statistical package add-on (Addinsoft Inc., New York, NY, USA) with an α level set to 0.05. A survey sample power analysis with a finite population correction determined that 155 respondents were needed to achieve a 95% confidence interval (CI) with a 5% sampling error for the results. Univariate analyses were performed to compare survey responses for (A) surgeons with versus without a NCC in their contract, (B) surgeons in private practice versus other practice types, and (C) presidents/senior partners of groups versus junior partners/employees. Proportions of responses were compared with a chi-square test with Yate's continuity correction or Fischer's exact test when a count for a response was less than 5.

Table 1. Demographic data of survey respondents stratified by the presence or absence of an expired or active non-compete clause (NCC) in respondents' contracts.

Demographic Parameter	All Respondents (n = 91)	NCC (n = 40)	No NCC (n = 51)	p-value
Years in Practice, n (%)				
< 5 years	13 (14.3)	9 (22.5)	4 (7.8)	0.069
5—10 years	16 (17.6)	7 (17.5)	9 (17.6)	0.796
10—15 years	29 (31.9)	12 (33.0)	17 (33.3)	0.911
> 15 years	33 (36.3)	12 (33.0)	21 (41.2)	0.378
Subspecialty, n (%)				
Foot / Ankle	8 (8.8)	1 (2.5)	7 (13.7)	0.074
General Orthopaedics	16 (17.6)	7 (17.5)	9 (17.6)	0.796
Hand	9 (9.9)	5 (12.5)	4 (7.8)	0.499
Oncology	1 (1.1)	0 (0.0)	1 (2.0)	1
Other	3 (3.3)	1 (2.5)	2 (3.9)	1
Pediatrics	4 (4.4)	2 (5.0)	2 (3.9)	1
Shoulder / Elbow	7 (7.7)	3 (7.5)	4 (7.8)	1
Spine	4 (4.4)	1 (2.5)	3 (5.9)	0.628
Sports Medicine	19 (20.9)	12 (30.0)	7 (13.7)	0.102
Trauma	6 (6.6)	2 (5.0)	4 (7.8)	0.691
Total Joints	14 (15.4)	5 (12.5)	9 (17.6)	0.702
Practice Type, n (%)[1]				
Private Practice	56 (61.5)	17 (42.5)	39 (76.5)	**0.002**
Academics	17 (18.9)	6 (15.0)	11 (21.6)	0.598
Hospital-Based Practice	26 (28.6)	20 (50.0)	6 (11.8)	**< 0.001**
Veterans Affairs Center	2 (2.2)	0 (0.0)	2 (3.9)	1
State Employee	1 (1.1)	0 (0.0)	1 (2.0)	1
Not Specified	1 (1.1)	1 (2.5)	0 (0.0)	0.440
President / Senior Partner, n (%)	36 (39.6)	11 (27.5)	25 (49.0)	**0.037**
Practice Area, n (%)				
Rural, < 10k population size	2 (2.2)	1 (2.5)	1 (2.0)	1
Rural, 10k—50k population size	15 (16.5)	9 (22.5)	6 (11.8)	0.278
Urban, > 50k population size	74 (81.3)	30 (75.0)	44 (86.3)	0.272

[1]Respondents were instructed to select all applicable practice types; because 9 (9.9%) respondents reported practicing in multiple practice types, the percentages do not add up to 100%. Bolded p-values indicate statistically significant results.

RESULTS

RESPONDENT DEMOGRAPHICS

The survey was distributed to 259 orthopaedic surgeons who are active members of the LOA, of which 117 responded (response rate: 45.2%). Most respondents (n = 91, 77.8%) finished the survey (Table 1). With only 91 respondents, the study was underpowered to achieve a 95% CI with a 5% margin of error. Post-hoc calculations showed that the analysis was adequately powered to achieve a 95% CI with a 9% margin of error.

As determined by a multiple response set, most LOA members worked in a private group (n = 56, 61.5%) or in a hospital-based practice (n = 26, 28.6%). A substantial proportion of respondents were president or senior partners of a group (n = 36, 39.6%). Most respondents practiced in an urban area with a population density > 50,000 people (81.3%) and had been in practice for at least 10 years (68.2%). The most common subspecialties represented were sports medicine (20.9%), general orthopaedics (17.6%), and total joints (15.4%).

A slight majority (56.0%) of the 91 LOA members who completed the survey never had a NCC in their contract. As determined by a multiple response set, significantly more respondents without a NCC work in private practices (76.5% vs. 42.5%, $p = 0.002$) while significantly more respondents with a NCC work in hospital-based practices (50.0% vs. 11.8%, $p < 0.001$). Additionally, significantly more surgeons without a NCC are president or senior partner of their group (49.0% vs. 27.5%, $p = 0.037$).

Table 2. Details of expired or active non-compete clauses among LOA members.

Question / Answers	n (%)
Does your non-compete clause expire after a certain time of employment?)[1]	n = 35
Yes, after 1 year	4 (11.4)
Yes, after 2 years	17 (48.6)
Yes, after 3 year	1 (2.9)
Yes, after 4 year	0 (0.0)
Yes, after 5 year	1 (2.9)
It does not expire	12 (34.3)
How widespread was/is your non-compete clause?[1,2]	n = 35
It covers my city	10 (28.6)
It covers my region / zip code	24 (68.6)
It covers my state	3 (8.6)
It covers an area with any facility owned or operated by my employer / group	9 (25.7)
Did your non-compete clause change after your employer began expanding locations?	n = 40
Yes	9 (22.5)
No	24 (60.0)
N/A	7 (17.5)
Do you require non-compete clauses for your newly employed surgeons/junior partners?[3]	n = 36
Yes	9 (25.0)
No	21 (58.3)
N/A	6 (16.7)
Why do you primarily require non-compete clauses?[2,4]	n = 9
Reduce competition	1 (11.1)
Invested time/effort to employ partners	7 (77.8)
Deter partners from starting their own practice	3 (33.3)
Create a goodwill between practice and partners	2 (22.2)
Other (Paraphrased free text: "They are required at my practice but I am against them")	1 (11.1)

[1]Question not answered by 5 respondents with a non-compete clause. [2]Respondents were instructed to select all applicable responses; because some respondents selected multiple answers, the percentages do not add up to 100%. [3]Question answered by current presidents / senior partners of groups. [4]Question answered by current presidents / senior partners of groups who require non-compete clauses for all newly hired surgeons.

DETAILS OF NON-COMPETE CLAUSES

Many (48.6%) respondents with a NCC in their contract reported that their clause had or would expire after two years of employment (Table 2). As determined by a multiple response set, 68.6% (24/35) of respondents' NCCs cover their region / zip code. The terms of NCCs changed for 9 (22.5%) surgeons when their employer began expanding locations, while the clause did not change for 24 (60.0 %) surgeons. Among the 36 presidents or senior partners of a group, 21 (58.3%) do not require NCCs for newly hired surgeons. The 9 (25.0%) presidents or senior partners of groups who do mandate NCCs for all new hires most commonly cited the investment of time and effort it takes to employ partners (77.8%) as the reason for this requirement.

PERCEPTIONS OF NON-COMPETE CLAUSES

Perceptions of NCCs among LOA members were overwhelmingly negative: 86.7% of respondents supported removing NCCs from all orthopedic surgeons' contracts and 97.8% believed that such clauses have become increasingly unreasonable over the last decade with the rise of hospital conglomerates (Figure 1). Notably, a moderate proportion (17.8%) of LOA members would leave their current job if their contract did not have a NCC, and a majority (71.4%) reported that NCCs have previously deterred them from accepting another job offer or would do so in the future. Nearly all respondents (94.4%) believed that insertion of NCCs during annual contract renewals should not be allowed.

Perceptions and attitudes towards NCCs varied between different LOA member demographics (Table 3). Notably, 40% of LOA members with a NCC would leave their current job if there was no NCC, while 0% of respondents without a NCC expressed desire to seek new employment ($p < 0.001$). A significantly larger percentage of current presidents or senior partners of groups believed that NCCs are important for private groups to be able to recruit new surgeons (19.4% vs. 5.5%, $p = 0.046$) while significantly more junior partners

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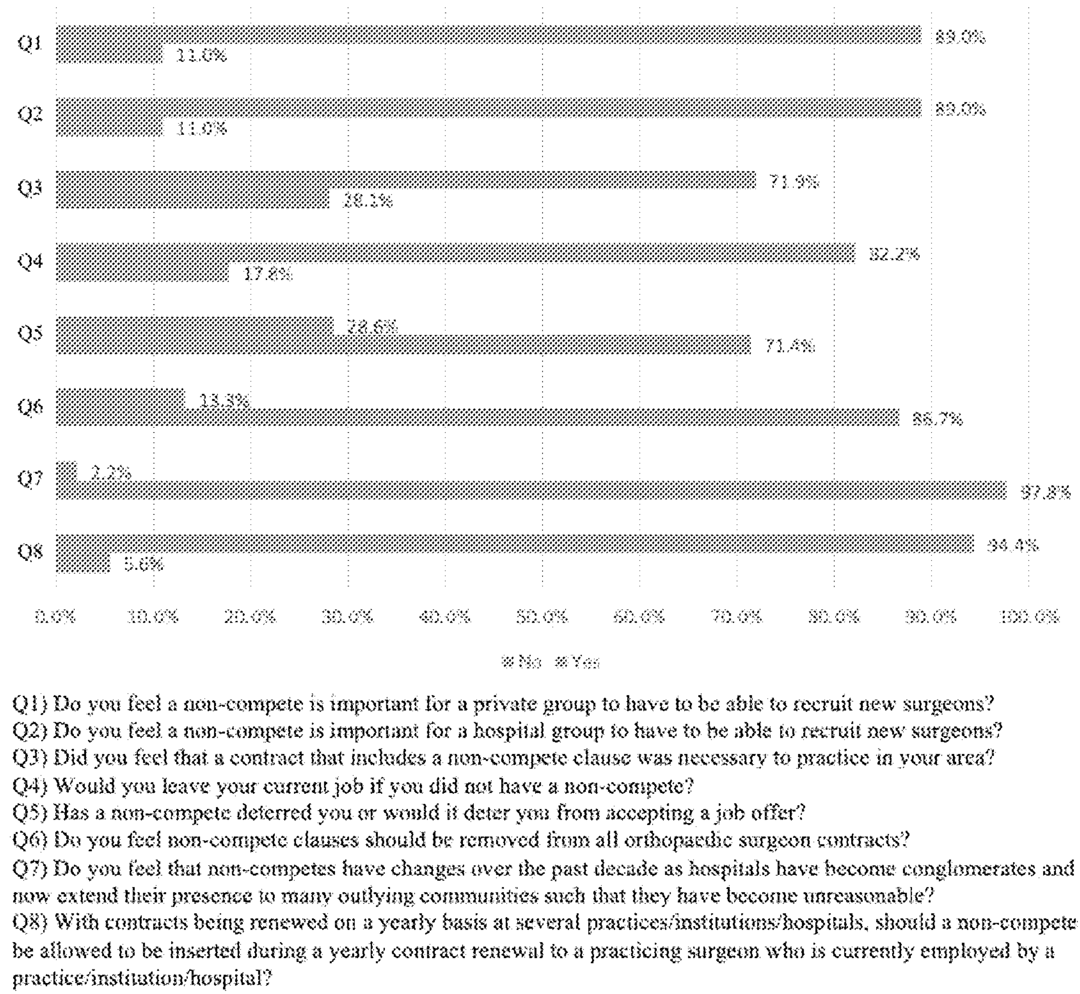

Figure 1. Perceptions of non-compete clauses among all survey respondents.

or employees supported removing NCCs from all orthopaedic surgeons' contracts (92.7% vs. 77.1%, p = 0.034).

IMPACT OF NON-COMPETE CLAUSES ON SURGEONS AND PATIENTS

Perceptions regarding the impact of NCCs on orthopaedic surgeons and patients were overwhelmingly negative (Figure 2). Most respondents (84.3%) believed that NCCs give employers unfair leverage during contract renegotiations and a substantial proportion believed that such clauses force surgeons to abandon their patients (76.7%). Additionally, 83.7% of surgeons felt that removal of all NCCs would improve the overall healthcare of orthopaedic patients in Louisiana (Table 4).

NCCs also exert several negative effects on respondents' personal lives. A majority of surgeons believed that such clauses would prevent maintenance of their current practice in their desired city (67%), forcing surgeons to relocate their family (67%). More than half of respondents (60.4%) would be unhappy in their current job if their contract included a NCC but would be unable to relocate due to personal reasons. Many surgeons reported that they would resent their partners (47.3%) or hospital (58.2%) for including a NCC in their contract.

Several notable differences were found regarding the impact of NCCs on surgeons and patients between different LOA member demographics (Tables 5–7). In terms of personal impact, significantly more surgeons with a NCC reported that they have had or would have to relocate their family due to the clause (80.0% vs. 56.9%, p = 0.035). Additionally, significantly more non-private practice surgeons felt they would have to relocate their family due to a NCC (84.9% vs. 58.9%, p = 0.021). As compared to current presidents or senior partners of groups, significantly more junior partners or employees believed that NCCs give employers unfair leverage during contract renegotiations (94.4% vs. 68.6%, p = 0.002). Conversely, a significantly higher percentage of current presidents or senior partners believed that NCCs have no impact on future contract renegotiations (20.0% vs. 3.7%, p = 0.026).

DISCUSSION

NCCs have been utilized in several health care fields such as counseling, social work, and medicine; enacting such

Table 3. Perceptions of NCCs for respondents with vs. without a NCC, private practice vs. other practice type, and president/senior partners vs. junior partners/employees.

	NCC (n = 40)	No NCC (n = 51)	p-value	Private Practice (n = 56)	Other Practice Types (n = 34)	p-value	President or Senior Partner (n = 36)	Junior Partner or Employee (n = 55)	p-value
Do you feel a non-compete is important for a private group to have to be able to recruit new surgeons? n (%)									
Yes	5 (12.5)	5 (9.8)	0.944	7 (12.5)	3 (8.8)	0.737	7 (19.4)	3 (5.5)	**0.046**
No	35 (87.5)	46 (90.2)		49 (87.5)	31 (91.2)		29 (80.6)	52 (94.5)	
Do you feel a non-compete is important for a hospital group to have to be able to recruit new surgeons? n (%)									
Yes	4 (10.0)	6 (11.7)	1	9 (16.1)	1 (2.9)	0.083	6 (16.7)	4 (7.3)	0.185
No	36 (90.0)	45 (88.3)		47 (83.9)	33 (97.1)		30 (83.3)	51 (92.7)	
Did you feel that a contract that includes a non-compete clause was necessary to practice in your area? n (%)									
Yes	19 (47.5)	7 (14.3)*	**0.001**	11 (20.4)*	14 (41.2)	**0.035**	10 (29.4)*	16 (29.1)	0.836
No	21 (52.5)	42 (85.7)		43 (79.6)	20 (58.8)		24 (70.6)	39 (70.9)	
Would you leave your current job if you did not have a non-compete? n (%)									
Yes	16 (40.0)	0 (0.0)*	**< 0.001**	6 (10.7)	9 (27.3)	0.085	4 (11.1)	12 (22.2)*	0.261
No	24 (60.0)	50 (100.0)		50 (89.3)	24 (72.7)		32 (88.9)	42 (77.8)	
Has a non-compete deterred you or would it deter you from accepting a job offer? n (%)									
Yes	31 (77.5)	34 (66.7)	0.367	37 (66.1)	27 (79.4)	0.265	25 (69.4)	40 (72.7)	0.919
No	9 (22.5)	17 (33.3)		19 (33.9)	7 (20.6)		11 (30.6)	15 (27.3)	
Do you feel non-compete clauses should be removed from all orthopaedic surgeon contracts? n (%)									
Yes	36 (90.0)	42 (84.0)*	0.537	44 (80.0)*	33 (97.1)	**0.026**	27 (77.1) *≈	51 (92.7)	**0.034**
No	4 (10.0)	8 (16.0)		11 (20.0)	1 (2.9)		8 (22.9)	4 (7.3)	
Do you feel that non-competes have changes over the past decade as hospitals have become conglomerates and now extend their presence to many outlying communities such that they have become unreasonable? n (%)									
Yes	39 (97.5)	50 (98.0)	1	55 (98.2)	33 (97.1)	1	35 (97.2)	54 (98.2)	1
No	1 (2.5)	1 (2.0)		1 (1.8)	1 (2.9)		1 (2.8)	1 (1.8)	
With contracts being renewed on a yearly basis at several practices/institutions/hospitals, should a non-compete be allowed to be inserted during a yearly contract renewal to a practicing surgeon who is currently employed? n (%)									
Yes	4 (10.0)	1 (2.0)	0.165	3 (5.5)*	2 (5.9)	1	3 (8.6)*	2 (3.7)*	0.378
No	36 (90.0)	50 (98.0)		52 (94.5)	32 (94.1)		32 (91.4)	52 (96.3)	

*Throughout the table, there are instances in which a few respondents did not provide an answer to the given question. In such cases, the percentages reported were calculated out of the total number of respondents from the cohort that answered the question. Bolded p-values indicate statistically significant results.

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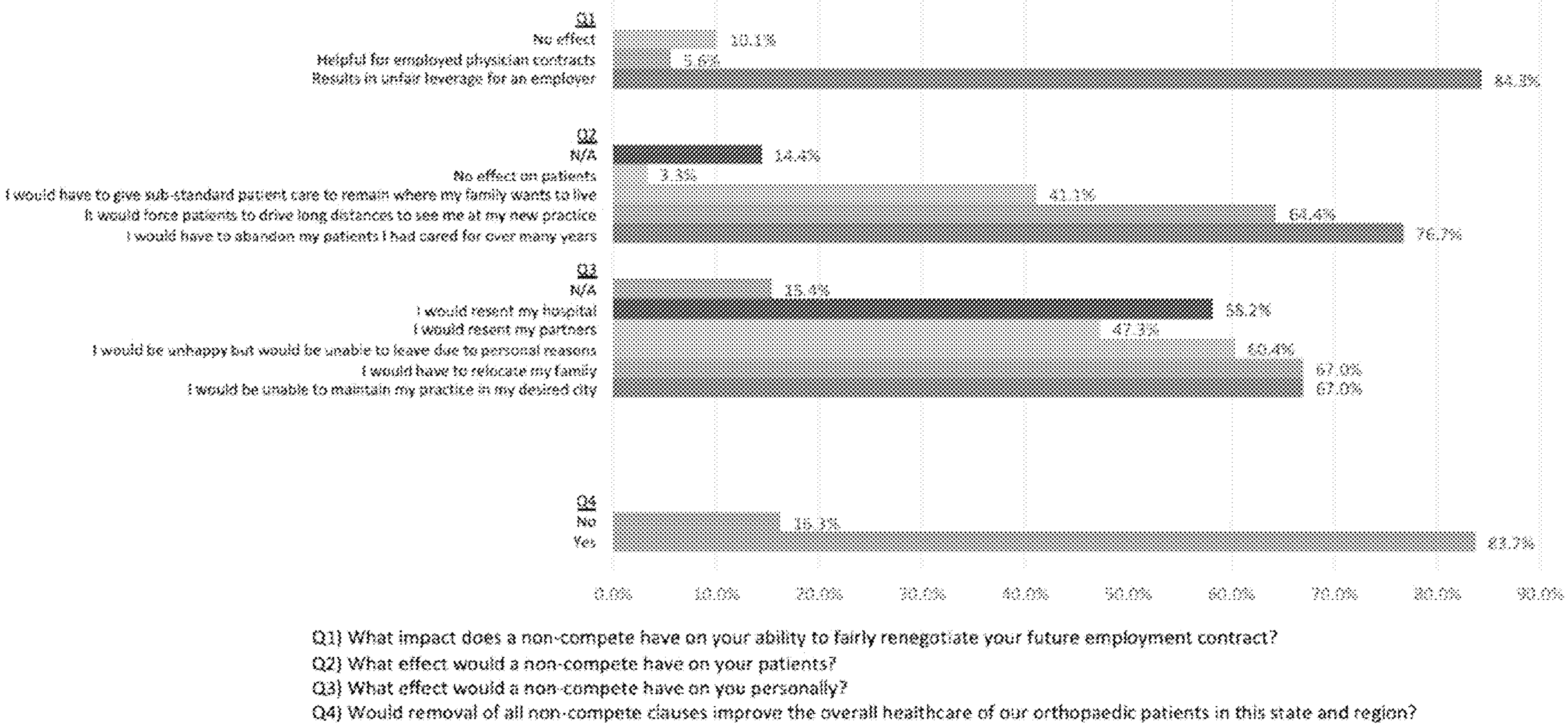

Figure 2. Perceived impact of non-compete clauses on surgeons and patients among all LOA members who completed the survey.

covenants can cause harmful disruption of the patient-physician relationship, which is the foundation of clinical care.[13] Physicians are integrally involved in the community. In the event of termination of a contract with a NCC, or if a position of employment becomes untenable, the surgeon-patient relationship is unnecessarily ended when a surgeon could otherwise continue to provide care in the same community.[15] Surgeons are often chosen by their patients after much research, and long-term care follows through the development of trust in the surgeon over time. Chapon et al. reported clarity of information and a surgeon's reputation are the most important factors influencing patients' surgeon selection, confirming that patients are motivated to choose their surgeon based on the core value of the fiduciary relationship.[17] Patients who are awaiting a surgical procedure or are in the post-operative phase are particularly vulnerable to a surgeon's departure. Compared to surgeons with no restrictive covenants, our survey demonstrated a significant majority (60%) of respondents with NCCs had concerns about providing sub-standard care due to their NCC preventing them from leaving their current job and remaining in the area where their family lives.

Currently, the state of Louisiana is ranked 46th in overall healthcare according to U.S. News & World Report.[18] This low ranking illustrates ample opportunity for improvement. However, restrictive covenants may impede recruitment of some of the brightest and best trained surgeons to practice in Louisiana. This notion was supported by our survey in which 71.4% of surgeons believed that a NCC had previously or would deter them from accepting a new job, with most respondents being subspecialized (82.4%) and having at least 10 years of practice experience (68.2%). As a result of NCCs being legal and relatively common in Louisiana, skilled surgeons with options may choose to practice in states with less contractual restrictions. For example, California, North Dakota, and Oklahoma have enacted statutes declaring non-competition agreements void, while Colorado, Massachusetts, and Delaware have passed statutes that severely limit the enforceability of NCCs.[19] Such measures grant significantly greater professional and personal autonomy and may entice talented physicians to relocate to these areas for practice. Notably, almost all non-private practice surgeons (96.9%) in this survey believed the overall healthcare of patients in Louisiana would improve by removing NCCs from the contracts of all orthopaedic surgeons. This result illustrates that NCCs exert a detrimental impact not only on surgeons in our state, but also their patients.

On April 2nd, 2021, House Bill 483 entitled "Prohibition of Noncompete Contract Clauses" was introduced by a state representative to the Louisiana State Legislature.[20] Although the proposed bill initially encompassed the same provisions for all physicians, new modifications in the engrossed bill and now re-engrossed bill will limit the scope of non-compete agreements for only certain types of physicians. Under the proposed law, NCCs will be prohibited for all primary care physicians in the state of Louisiana, while only being prohibited for physician specialists including orthopaedic surgeons who are not state employees and have worked for an employer for at least three years.[21–23] Although a reasonable buyout clause can be utilized in contracts with physician specialists, specific criteria remain. Egregiously, only non-state employed physician specialists will still be prohibited from practicing within a restrictive geographic area for a maximum of two years.[23] After passing in the Louisiana House of Representatives on May 11, 2021, the bill was sent to the State Senate where it is currently awaiting review by the Committee on Commerce, Consumer Protection, and International Affairs.[20] In its current form, the revised bill has striking disparities in the contractual limitations of NCCs based on whether a physician provides primary care or specialty services. The underlying motives for these differences are unclear. Although all physicians have taken an ethical oath to treat their patients impartially, a critical question must be asked: why should physician specialists such as orthopaedic surgeons be treated differently under law? This discrepancy is likely due to a monetary influence by employers rather than a strategy for improving the general welfare of patients. In the event a community is underserved by specialists, which is a growing concern in communities around the country, this policy can work directly against the mission to improve access to specialty healthcare.[24–26]

On July 9, 2021, Executive Order 14036, "Promoting Competition in the American Economy," was signed by the President of the United States to curtail unfair anti-competitive practices including non-compete agreements used by companies that restrict the ability of workers to change jobs.[27] However, the long-term effects of this directive may be restricted and less impactful for physicians as physician contracts are subject to the strictures of state laws.[28] As NCCs are frequently regulated by states, each state not only has the ability to ban non-compete covenants, but also to determine the scope, parameters, and situation for which NCCs can be banned. For example, certain states including Washington, Oregon, Nevada, Illinois, Virginia, Maryland, Delaware, Rhode Island, Connecticut, Massachusetts, Maine, and New Hampshire only ban NCCs for low-wage/hourly workers. It must be noted that these restrictive covenants affect not only healthcare workers of all wages, including surgeons, but also patients. Another principal concern revealed in this survey was a significant and overwhelming majority of respondents working in practice types other than private practice believed that NCCs would force them to abandon their patients if they left their job (91.2%). Furthermore, as a consequence of NCCs, a majority of respondents (52.9%) believed they have previously or would hypothetically have to provide sub-standard patient care in order to remain in their desired city compared to their private practice counterparts.

According to a 2020 physician survey assessing the impact of COVID-19 on the U.S. healthcare system, 50% of physicians believed that hospitals will exert stronger influence over the organization and delivery of healthcare as a result of the pandemic.[29] Some of the lasting effects of the COVID-19 pandemic have already become apparent.[30] In a 2021 Physician Advocacy Institute report conducted by Avalere Health, the COVID-19 pandemic was noted to

Table 4. Optional free text response for improvement to healthcare question.

Would removal of all non-compete clauses improve the overall healthcare of our orthopaedic patients in this state and region?
Yes
• Now that insurance companies can be bought by systems, they control the patients. Controlling the surgeons means they cannot leave if the care is substandard. Non-compete clauses need to go away.
• Doctors and patients would then be free to choose what is best for themselves.
• Competition in a marketplace only results in improved care for patients.
• Jobs & situations change. With healthcare systems that now cover huge areas, being outside of those areas is not realistic.
• Possibly attract more good surgeons to the area.
• Let the patients decide where their care is best. Do not allow systems to make doctors choose between where they want to practice and succumb to whatever rules the hospital system decides for them.
• The practices would better assist the clinicians to live productive lives while having better control over their practices.
• Non-compete clauses strictly keep surgeons from building a patient base and only allow the employers/hospitals the ability to control surgeon salary and patients.
• There would be better access to care.
• Surgeons who remain in unhealthy orthopaedic groups/practices cannot emotionally or psychologically be their best versions.
• There is no reason to restrict access to a physician. If your group/facility is good enough, they should be able to tolerate any loss of patients or income if an individual physician should decide to leave. If they are not good enough, they should get out of the business.
• It would allow physicians greater ability to align and collaborate to create quality programs.
• Physicians should choose where to practice regardless of healthcare entity presence.
• Non-competes in contracts are leverage of a large corporation or entity against a single unit or person. They are completely and totally unfair.
• Patients should be allowed to go with their surgeons. Period.
• Non-competes drive competitive surgeons out of the New Orleans area and sometimes out of the state. This leaves our patients in the region with substandard care.
• Removal of non-competes would require employers to compete for my service and allow me to better negotiate for patient care needs that I'm currently being denied.
• Removal of non-competes would force hospitals to provide better support to physicians in order to balance the demands of patient care.
• Your employer or group would have to improve your treatment or practice to keep you.
• Patient-doctor relationships are the basis of medicine, not patient-hospital or patient-practice relationships.

accelerate the decade-long trend of healthcare consolidation: 48,400 additional physicians left private practice to become employees of hospitals or other corporate entities, with these large systems now owning more than half of all U.S. medical practices.[31] As consolidation continues, nearly all respondents of this survey (97.8%) believed that NCCs have become unreasonable over the last decade with the rise of hospital conglomerates. This finding highlights the stark contrast between the beneficial impact of NCCs on large employers and the significant detrimental effects on surgeons professionally and personally.

With the changing landscape of healthcare, restrictive covenants have become an archaic tool for large hospital systems to leverage their power and monopolize healthcare. By controlling the surgeons' ability to seek innovative technologies with which to treat patients in the same region or expand their own ability to provide a higher-level of patient care by accepting another job, aggressive utilization of stringent NCCs is directly limiting patients' access to specialty healthcare. Additionally, as few employees have the resources required for prolonged litigation, these individuals face the unfair choice of remaining with their current employer or outright leaving their community.[27] In this survey, 67.0% of surgeons believed that a NCC would disrupt their current state of practice in their desired city and force them to relocate their families. Furthermore, more than half of respondents (60.4%) expressed that they would be unhappy in their current job if their contract included a NCC, but would be unable to relocate due to personal reasons such as having children in school or family in the area. This finding highlights how employers further limit surgeons' autonomy through NCCs as physicians' personal lives may already restrict their ability to seek new employment. Thus, NCCs may be used as leverage both during the hiring process and contract re-negotiations. Our survey illustrates how the restriction of surgeons' personal auton-

Table 5. Perceived impact of NCCs on surgeons and patients for respondents with vs. without a NCC.

	NCC (n = 40)	No NCC (n = 51)	p-value
What impact does a non-compete have on your ability to fairly renegotiate your future employment contract? n (%)	n = 39	n = 50	
Results in unfair leverage for an employer	33 (84.6)	42 (84.0)	0.830
Helpful for employed physician contracts	5 (12.8)	0 (0.0)	**0.014**
No effect	1 (2.6)	8 (16.0)	0.072
What effect would a non-compete have on your patients? n (%)	n = 39	n = 50	
I would have to abandon patients I had cared for over many years leaving their care to someone who did not know them or their surgical history as well	32 (82.1)	37 (72.6)	0.421
My patients would have to drive a long distance to see me at my new practice after I left due to my non-compete clause	28 (71.8)	30 (58.8)	0.293
I would have to give sub-standard patient care because my non-compete prevents me from leaving my job and remaining in the area my family wishes to live	23 (60.0)	14 (27.5)	**0.005**
A non-compete would have no effect on my patients	2 (5.1)	1 (2.0)	0.577
N/A	0 (0.0)	13 (25.5)	**< 0.001**
What effect would a non-compete have on you personally? n (%)	n = 40	n = 51	
I would be unable to maintain my practice in my desired city	30 (75.0)	31 (60.8)	0.227
I would have to relocate my family due to a non-compete	32 (80.0)	29 (56.9)	**0.035**
I would be unhappy with my job but would be unable to leave due to a personal situation (kids in school, family in the region, etc.)	28 (70.0)	27 (52.9)	0.151
I would resent my partners for mandating a non-compete clause in my contract	20 (50.0)	23 (45.1)	0.800
I would resent my hospital for mandated a non-compete clause in my contract	27 (67.5)	26 (60.0)	0.170
N/A	2 (5.1)	12 (23.5)	**0.019**
Would removal of non-compete clauses improve overall healthcare of orthopaedic patients in Louisiana? n (%)	n = 37	n = 49	
Yes	33 (89.2)	39 (79.6)	0.377
No	4 (10.8)	10 (20.4)	

Bolded p-values indicate statistically significant results.

omy by NCCs occurs not only in the short-term, but persists and may increase with time.

LIMITATIONS

There are several limitations to this study. Of the 259 orthopaedic surgeons to whom the survey was distributed, only 117 (45.2%) surgeons responded and only 91 (35.1%) completed the survey in its entirety. Therefore, the views expressed by respondents in this study may not reflect those of the entire LOA membership nor all orthopaedic surgeons in Louisiana. The response rate may have been improved with a longer period of data collection; however, the duration of the study and follow-up emails were limited purposefully to decrease survey fatigue. It is also possible that response bias is present given that this study relied on subjective responses to survey questions and similar individuals may have answered certain questions differently. Additionally, the possibility for selection bias exists with the low response rate. Post-hoc calculations showed that, based on the response rate, the survey was adequately powered to detect significant differences with a 95% CI and a 9% margin of error. Though the survey was better powered to detect significant differences with a 90% CI and 7% error margin, which are acceptable parameters and commonly used in social sciences, an α of 0.05 was used to maximize the validity of the significant findings. An additional limitation is that the LOA membership may not have been entirely consistent during the survey distribution time such that members who initially received the survey may have left the society and new members may have joined during data collection. These numbers have been explored, however, and the impact of this limitation on the results is negligible.

CONCLUSION

NCCs were initially established in business to reduce turnover and prevent employees from being trained on proprietary technology at an employer and then leaving to work for a competitor. In medicine, however, physicians are trained prior to employment and there are no tangible improvements in clinical knowledge or skill conferred solely by working for a single employer. This survey demonstrated that perceptions of NCCs are overwhelmingly negative among orthopaedic surgeons in Louisiana. Such clauses give employers an unfair advantage during contract negotiations and exert a significant detrimental impact on surgeons and their patients. While NCCs may be reasonable in the business sector and other professions, it is unclear how

Table 6. Perceived impact of NCCs on surgeons and patients for surgeons in private practice vs. other practice types.

	Private Practice (n = 56)	Other Practice Types* (n = 34)	p-value
What impact does a non-compete have on your ability to fairly renegotiate your future employment contract? n (%)	n = 55	n = 34	
Results in unfair leverage for an employer	43 (78.2)	32 (94.1)	0.070
Helpful for employed physician contracts	5 (9.1)	0 (0.0)	0.152
No effect	7 (12.7)	2 (5.9)	0.473
What effect would a non-compete have on your patients? n (%)	n = 55	n = 34	
I would have to abandon patients I had cared for over many years leaving their care to someone who did not know them or their surgical history as well	38 (69.1)	31 (91.2)	**0.019**
My patients would have to drive a long distance to see me at my new practice after I left due to my non-compete clause	33 (60.0)	25 (75.5)	0.283
I would have to give sub-standard patient care because my non-compete prevents me from leaving my job and remaining in the area my family wishes to live	19 (34.6)	18 (52.9)	0.136
A non-compete would have no effect on my patients	2 (3.6)	1 (2.9)	1
N/A	12 (21.8)	1 (2.9)	**0.014**
What effect would a non-compete have on you personally? n (%)	n = 56	n = 33	
I would be unable to maintain my practice in my desired city	35 (62.5)	26 (78.8)	0.173
I would have to relocate my family due to a non-compete	33 (58.9)	28 (84.9)	**0.021**
I would be unhappy with my job but would be unable to leave due to a personal situation (kids in school, family in the region, etc.)	33 (58.9)	28 (84.9)	**0.021**
I would resent my partners for mandating a non-compete clause in my contract	29 (51.8)	14 (42.4)	0.526
I would resent my hospital for mandated a non-compete clause in my contract	30 (53.6)	23 (69.7)	0.203
N/A	11 (19.6)	3 (9.1)	0.238
Would removal of non-compete clauses improve overall healthcare of orthopaedic patients in Louisiana? n (%)	n = 53	n = 32	
Yes	40 (75.5)	31 (96.9)	**0.014**
No	13 (24.5)	1 (3.1)	

*Includes physicians working in an academic practice, hospital-based practice, VA center, and state employees. Bolded p-values indicate statistically significant results.

such clauses benefit surgeons or improve patient care and may be detrimental to both.

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AUTHOR CONTRIBUTIONS

W.S.: Study design, Writing manuscript, Final manuscript approval

A.P.: Literature review, Data collection, Writing manuscript, Editing manuscript

B.R.: Data analysis, Writing manuscript, Editing manuscript

O.L.: Study design, Editing manuscript, Final manuscript approval

C.W.: Survey distribution, Editing manuscript, Final manuscript approval

F.H.: Study design, Editing manuscript, Final manuscript approval

DISCLOSURES

All conflicts of interest have been identified, and there has been no significant financial support or funding for this work that could have influenced its outcome.

Table 7. Perceived impact of NCCs on surgeons and patients for presidents / senior partners versus junior partners / employees.

	President / Senior Partner (n = 36)	Junior Partner / Employee (n = 55)	p-value
What impact does a non-compete have on your ability to fairly renegotiate your future employment contract? n (%)	n = 35	n = 54	
Results in unfair leverage for an employer	24 (68.6)	51 (94.4)	**0.002**
Helpful for employed physician contracts	4 (11.4)	1 (1.9)	0.076
No effect	7 (20.0)	2 (3.7)	**0.026**
What effect would a non-compete have on your patients? n (%)	n = 35	n = 55	
I would have to abandon patients I had cared for over many years leaving their care to someone who did not know them or their surgical history as well	26 (74.3)	43 (78.2)	0.865
My patients would have to drive a long distance to see me at my new practice after I left due to my non-compete clause	24 (68.6)	34 (61.8)	0.670
I would have to give sub-standard patient care because my non-compete prevents me from leaving my job and remaining in the area my family wishes to live	14 (40.0)	23 (41.8)	0.961
A non-compete would have no effect on my patients	0 (0.0)	3 (5.5)	0.279
N/A	7 (20.0)	6 (10.9)	0.374
What effect would a non-compete have on you personally? n (%)	n = 36	n = 55	
I would be unable to maintain my practice in my desired city	24 (66.7)	37 (67.3)	0.867
I would have to relocate my family due to a non-compete	24 (66.7)	37 (67.3)	0.867
I would be unhappy with my job but would be unable to leave due to a personal situation (kids in school, family in the region, etc.)	25 (69.4)	30 (54.6)	0.229
I would resent my partners for mandating a non-compete clause in my contract	16 (44.4)	27 (49.1)	0.826
I would resent my hospital for mandated a non-compete clause in my contract	20 (55.6)	33 (60.0)	0.839
N/A	4 (11.1)	10 (18.2)	0.554
Would removal of non-compete clauses improve overall healthcare of orthopaedic patients in Louisiana? n (%)	n = 35	n = 51	
Yes	27 (77.1)	45 (88.2)	0.284
No	8 (22.9)	6 (11.8)	

Bolded p-values indicate statistically significant results.

ADDITIONAL INFORMATION

IRB exemption was given by Tulane University Human Research Protection Office for Study Reference#: 2021-1034

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APPENDIX 1. NON-COMPETE CLAUSE SURVEY DISTRIBUTED TO LOA MEMBERS

Q1: DO YOU HAVE A NON-COMPETE CLAUSE IN YOUR CONTRACT?

a) Yes
b) No
c) I had one that is now expired

Q2: IF QUESTION 1 IS A OR C, THEN DOES YOUR NON-COMPETE EXPIRE AFTER A CERTAIN AMOUNT OF EMPLOYMENT?

a) Yes after 1 year
b) Yes after 2 years
c) Yes after 3 years
d) Yes after 4 years
e) Yes after 5+ years
f) It does not expire

Q3: IF QUESTION 1 IS A OR C, THEN HOW WIDESPREAD IS OR WAS YOUR NON-COMPETE CLAUSE? (SELECT ALL THAT APPLY)

☐ It covers my city
☐ It covers my region/zip code
☐ It covers statewide
☐ It covers an area within any facility owned or operated by my employer/group
☐ N/A

Q4: IF QUESTION 3 IS A-D, THEN DID YOUR NON-COMPETE CHANGE AFTER YOUR EMPLOYER BEGAN EXPANDING LOCATIONS? (I.E. WHEN YOU SIGNED YOUR CONTRACT, IT SAID "YOU CANNOT WORK WITHIN X MILES FROM YOUR EMPLOYER'S FACILITY," THEN THE FACILITY EXPANDED, AND NOW THE DISTANCE FROM YOUR NON-COMPETE HAS ALSO EXPANDED)

a) Yes
b) No
c) N/A

Q5: ARE YOU THE PRESIDENT OR A SENIOR PARTNER OF A GROUP?

a) Yes
b) No

Q6: IF YES TO QUESTION 5, DO YOU REQUIRE NON-COMPETE CLAUSES FOR YOUR NEW EMPLOYED SURGEONS/JUNIOR PARTNERS?

a) Yes
b) No
c) N/A

Q7: DO YOU FEEL A NON-COMPETE IS IMPORTANT FOR A **PRIVATE GROUP** TO HAVE TO BE ABLE TO RECRUIT NEW SURGEONS?

a) Yes
b) No

Q8: DO YOU FEEL A NON-COMPETE IS IMPORTANT FOR A **HOSPITAL GROUP** TO HAVE TO BE ABLE TO RECRUIT NEW SURGEONS?

a) Yes
b) No

Q9: IF YES TO QUESTION 6, WHY DO YOU PRIMARILY REQUIRE NON-COMPETE CLAUSES? (SELECT ALL THAT APPLY)

a) Reduce competition
b) Invested time/effort to employ partners
c) Deter partners from starting their own practice
d) Create a goodwill between practice and partners
e) Other ____

Q10: WHAT IMPACT DOES A NON-COMPETE HAVE ON YOUR ABILITY TO FAIRLY RENEGOTIATE YOUR FUTURE EMPLOYMENT CONTRACT:

a) No effect
b) Helpful for employed physician contracts
c) Results in unfair leverage for an employer

Q11: DID YOU FEEL THAT A CONTRACT THAT INCLUDES A NON-COMPETE CLAUSE WAS NECESSARY TO PRACTICE IN YOUR AREA? (SELECT ALL THAT APPLY)

☐ Yes, there was only one viable employer
☐ Yes, all employers required non-compete
☐ Yes, the employer had such a large market share the contract was non-negotiable
☐ No

Q12: WOULD YOU LEAVE YOUR CURRENT JOB IF YOU DID NOT HAVE A NON-COMPETE?

a) Yes
b) No

Q13: HAS A NON-COMPETE DETERRED YOU OR WOULD IT DETER YOU FROM ACCEPTING A JOB OFFER?

a) Yes
b) No

Q14: WHAT EFFECT WOULD A NON-COMPETE **HAVE ON YOUR PATIENTS?** (SELECT ALL THAT APPLY)

☐ I would have to abandon patients I had cared for over many years leaving their care to someone who did not know them or their surgical history as well
☐ My patients would have to drive a long distance to see

me at my new practice after leaving the previous practice due to my non-compete

☐ I would have to give them care I felt was sub-standard or continue to do so because my non-compete does not allow for me to leave my current job and remain in the area my family wishes to live

☐ A non-compete would have no effect on my patients

☐ N/A

Q15: WHAT EFFECT WOULD A NON-COMPETE **HAVE ON YOU PERSONALLY**? (SELECT ALL THAT APPLY)

☐ I would be unable to maintain my practice in my desired city due to a non-compete

☐ I would have to relocate my family due to a non-compete

☐ I would be unhappy with my job due to a non-compete and would not be able to leave due to my personal situation (kids in school, family in the region, etc.)

☐ I would resent my partners for mandating a non-compete clause in my contract

☐ I would resent my hospital for mandating a non-compete clause in my contract

☐ N/A

Q16: DO YOU FEEL NON-COMPETE CLAUSES SHOULD BE REMOVED FROM ALL ORTHOPAEDIC SURGEON CONTRACTS?

a) Yes
b) No

Q17: DO YOU FEEL THAT NON-COMPETES HAVE CHANGED OVER THE PAST DECADE AS HOSPITALS HAVE BECOME CONGLOMERATES AND NOW EXTEND THEIR PRESENCE TO MANY OUTLYING COMMUNITIES SUCH THAT THEY HAVE BECOME UNREASONABLE?

a) Yes
b) No

Q18: WOULD REMOVAL OF ALL NON-COMPETE CLAUSES IMPROVE THE OVERALL HEALTHCARE OF OUR ORTHOPAEDIC PATIENTS IN THIS STATE AND REGION?

a) Yes (if yes, please explain why) ____________________
b) No (if no, please explain why not) ____________________

Q19: WITH CONTRACTS BEING RENEWED ON A YEARLY BASIS AT SEVERAL PRACTICES/INSTITUTIONS/ HOSPITALS, SHOULD A NON-COMPETE BE ALLOWED TO BE INSERTED DURING A YEARLY CONTRACT RENEWAL TO A PRACTICING SURGEON WHO IS CURRENTLY EMPLOYED BY A PRACTICE/INSTITUTION/HOSPITAL?

a) Yes
b) No

Q20: HOW MANY YEARS HAVE YOU BEEN IN PRACTICE?

☐ Less than 5 years (1)

☐ Between 5-10 years (2)

☐ Between 10-15 years (3)

☐ Greater than 15 years (4)

Q21: WHAT IS YOUR SUB-SPECIALTY?

a) General
b) Hand
c) Shoulder/elbow
d) Foot/ankle
e) Total Joints
f) Orthopaedic Trauma
g) Sports Medicine
h) Spine
i) Pediatric Orthopaedics
j) Oncology
k) Other (please specify) _________________________

Q22: WHICH OF THE FOLLOWING BEST DESCRIBES YOUR PRACTICE SETTING? (SELECT ALL THAT APPLY)

☐ Private practice-community base

☐ Academic

☐ Hospital based

☐ Veterans administration

☐ Military

☐ State employee

Q23: WHAT SETTING BEST DESCRIBES YOUR PRACTICE AREA?

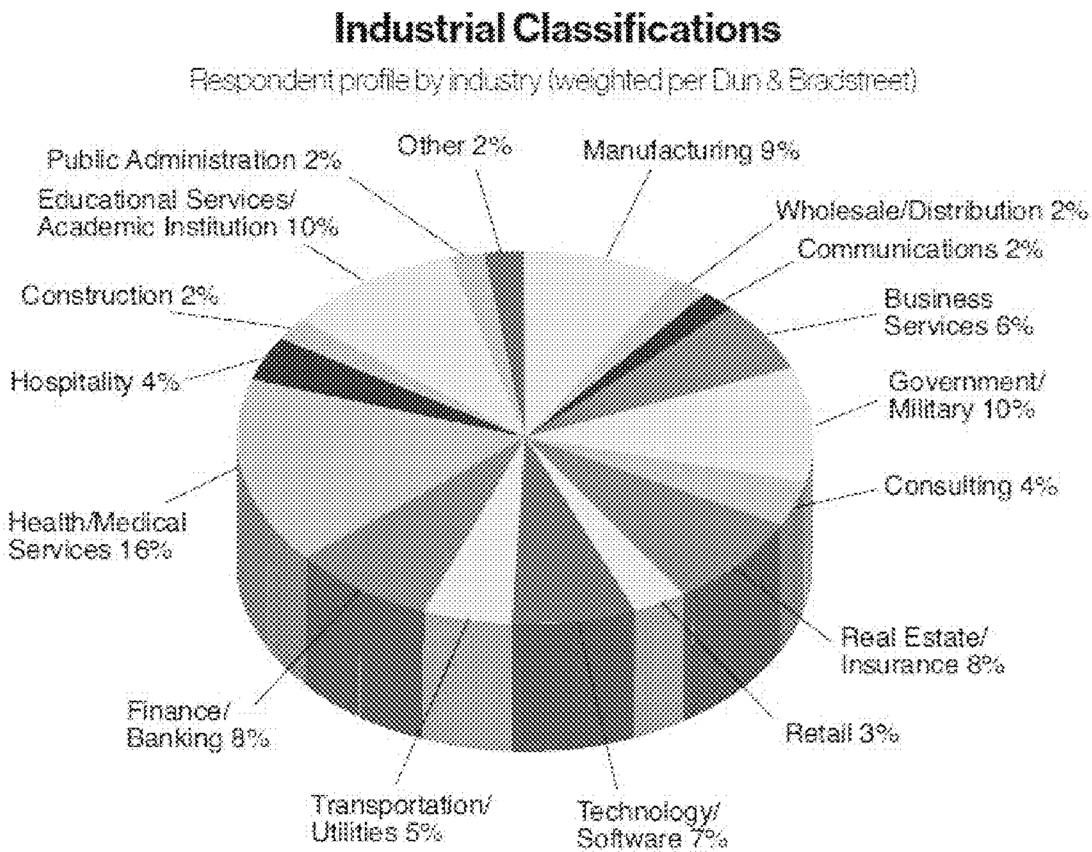
a) Urban area with a population ⩾ 50,000 people
b) Large rural area with a population between 10,000 to 49,999 people
c) Small rural area with a population <10,000 people

2022 Training Industry Report

U.S. training expenditures passed the $100 billion-mark for the first time in 2021-2022, according to Training magazine's 2022 Training Industry Report.

By **Lorri Freifeld** - November 16, 2022

ABOUT THIS STUDY



Now in its 41st year, The Industry Report is recognized as the training industry's most trusted source of data on budgets, staffing, and programs. This year, the study was conducted by an outside research firm April-July 2022, when members from the *Training* magazine database were e-mailed an invitation to participate in an online survey. Only U.S.- based corporations and educational institutions with 100 or more employees were included in the analysis.

The data represents a cross-section of industries and company sizes.

SURVEY RESPONDENTS

Small companies 36% (100-999 employees)

Midsize 43% (1,000-9,999 employees)

Large 21% (10,000 or more employees)

Total respondents 260

Note that the figures in this report are weighted by company size and industry according to a Dun & Bradstreet database available through Hoovers of U.S. companies. Since small companies dominate the U.S. market, in terms of sheer numbers, these organizations receive a heavier weighting, so that the data accurately reflects the U.S. market.

About Survey Respondents:

- 57% are managers or above in the organization
- 20% are developers or instructional designers
- 20% are mid- to low-level (based on title selection) associates
- 64% determine the need for purchasing products and services
- 23% set the budget
- 33% manage requests for proposals/bids
- 69% recommend the purchase
- 21% have the final purchase decision

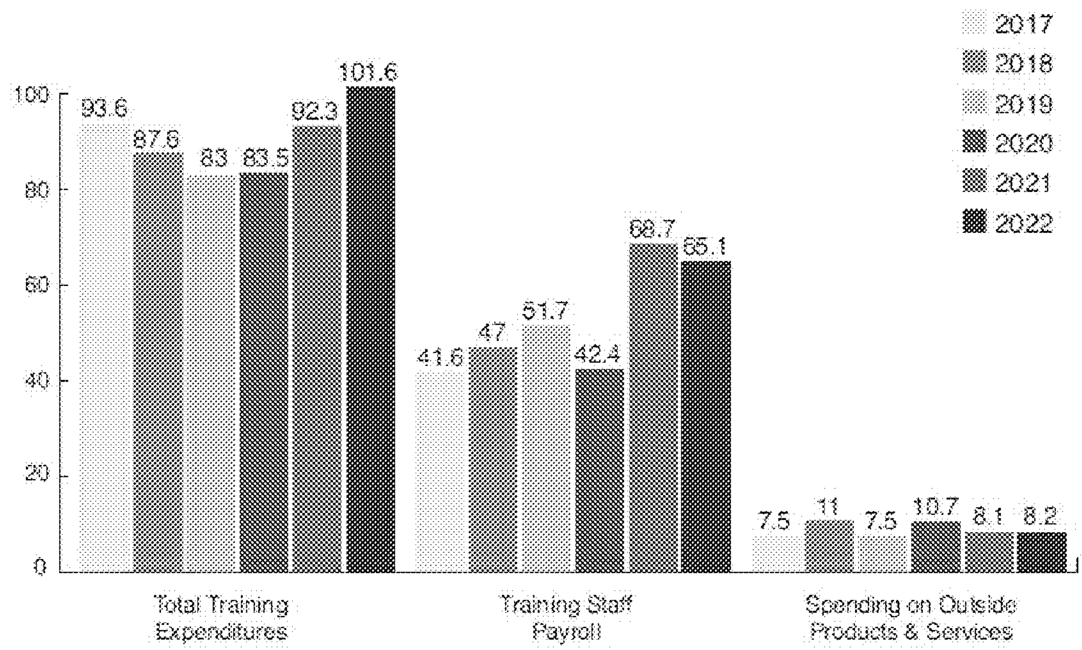
TRAINING EXPENDITURES

U.S. training expenditures passed the $100 billion-mark for the first time in 2021-2022. Rising 10 percent to $101.6 billion, the jump was fueled, in part, by a significant increase in large companies' budgets, inflation, and organizations continuing to invest in virtual training technologies amid the ongoing COVID-19 pandemic but also starting to go back to some in-person training and allowing travel. Payroll decreased, but spending on outside products and services rose 1 percent to $8.2 billion. And other training expenditures (i.e., travel, facilities, equipment) rebounded to nearly 2020 levels at $28.3 billion from $15.5 billion in 2021.

The training expenditure figures were calculated by projecting the average training budget to a weighted universe of 142,283 companies, using a Dun & Bradstreet database available through Hoovers of U.S. organizations with more than 100 employees.

Note: Although small companies have the smallest annual budgets, there are so many of them (123,495) that they account for almost one-third of the total budget for training expenditures.

Training Expenditures 2017-2022
In $ Billions



DEFINITIONS

Total training spending: All training-related expenditures for the year, including training budgets, technology spending, and staff salaries.

Training staff payroll: The annual payroll for all staff personnel assigned to the training function.

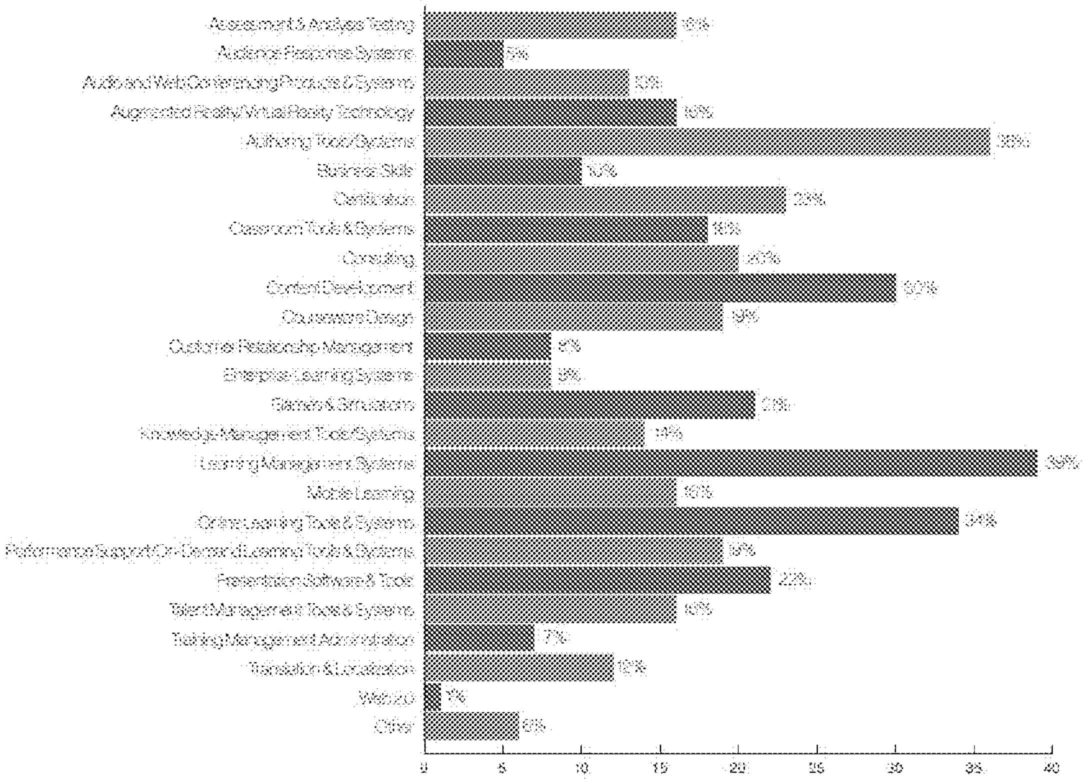
Outside products and services: Annual spending on external vendors and consultants, including all products, services, technologies, off-the-shelf and custom content, and consulting services.

Average of Total Annual Budget

Organization Type	Large	Midsize	Small	Average
Education	$1,285,714	$1,680,000	$103,333	$1,069,000
Government/Military	$98,420,000	$1,643,774	$410,921	$14,660,700
Manufacturer/Distributor	$8,047,264	$1,211,538	$389,917	$3,528,449
Nonprofit	$1,037,500	$648,636	$214,300	$537,120
Association	$8,900,000	$875,000	$100,000	$2,687,500
Retail/Wholesale	$5,000,000	$2,238,779	$519,033	$2,054,315
Services	$15,032,500	$1,491,489	$418,718	$3,418,755
Avg. Across Sizes	$19,239,425	$1,473,427	$368,891	$4,806,664

Average training expenditures for large companies increased from $17.5 million in 2021 to $19.2 million in 2022. The number for midsize companies increased from $1.3 million in 2021 to $1.5 million in 2022. Small companies rose from $341,505 to $368,891 in 2022.

Types of Training Products and Services Intended to Purchase Next Year



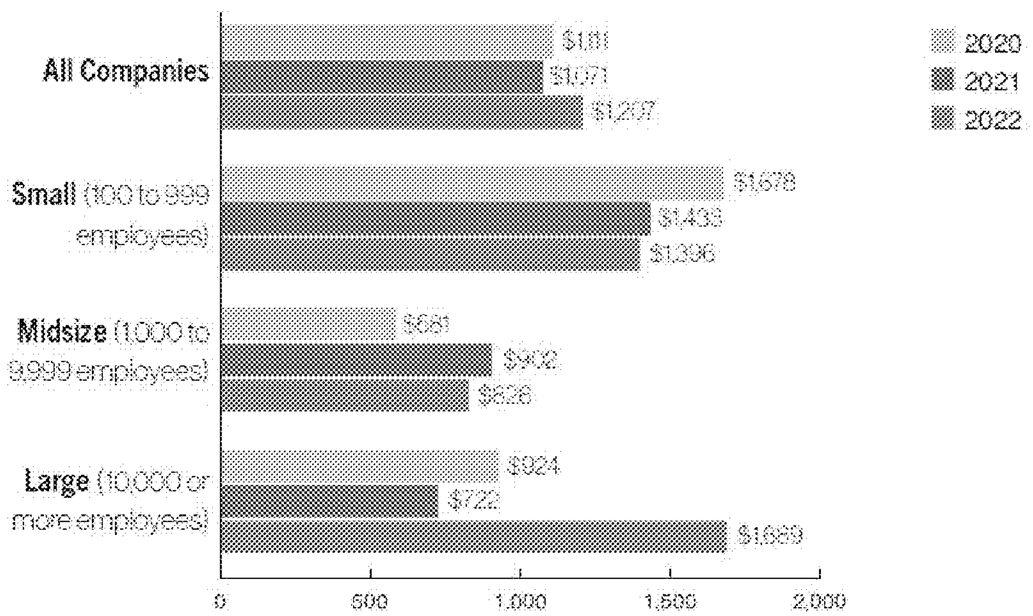
Some 38 percent of organizations said they increased staff from the year before (up from 23 percent), while 45 percent said the level remained the same (vs. 59 percent last year). Some 17 percent said it was lower. Large services and government/ military organizations had the biggest personnel costs ($5 million-plus). This year, midsize companies spent less than half as much as large companies, while small companies spent about one-third as much as midsize ones. The average payroll figure for large companies was $3.5 million; for midsize organizations, it was $1.4 million; for small companies, it was $443,731.

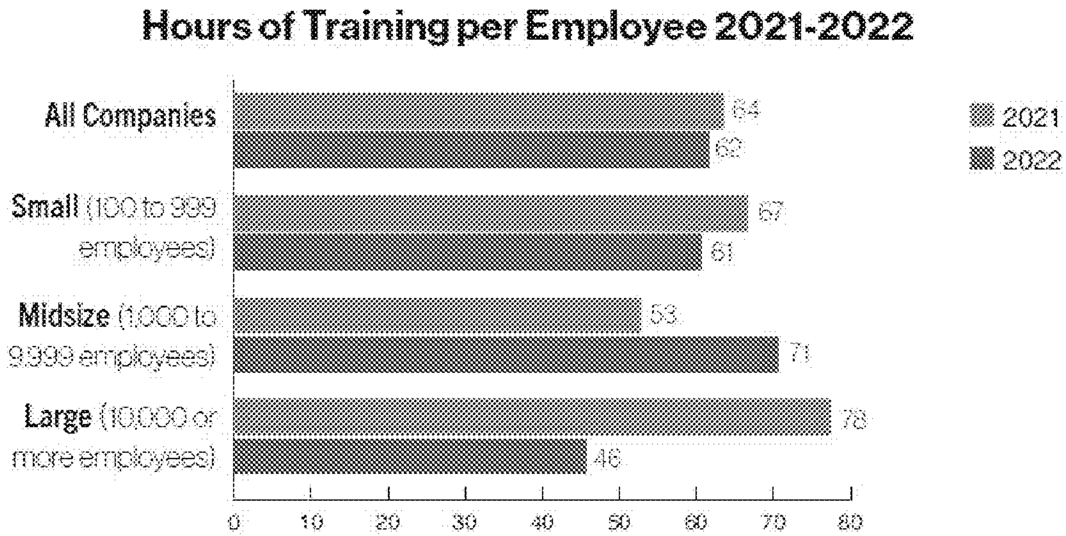
For those who reported an increase in their training staff, the average increase was 6 people, down from 15 in 2021. For those who reported a decrease in their staff, the average decrease was 8 people—down from 43 last year.

Other training expenditures increased this year to $28.3 billion from $15.5 billion in 2021. Such expenditures can include travel, training facilities, in-house training development, and equipment. On average, organizations spent 16 percent of their budget or $382,729 (up from $337,190 last year) on learning tools and technologies. Large government/military organizations had the largest budgets for learning tools ($7 million). Midsize education organizations had the largest tool budget in their size range ($550,500).

Looking ahead, the most frequently anticipated purchases are learning management systems (39 percent vs. 35 percent last year); authoring tools/systems at 36 percent vs. 39 percent last year; online learning tools and systems at 34 percent both years; and content development (30 percent in 2022 and 33 percent in 2021). This is followed by certification at 23 percent both years; presentation software and tools (22 percent vs. 25 percent last year); games and simulations at 21 percent both years; consulting (20 percent this year vs. 21 percent last year); and courseware design (19 percent vs. 20 percent last year). Augmented/virtual reality tech comes in at 16 percent. Categories receiving less than 10 percent of hits include audience response systems, customer relationship management, enterprise learning systems, training management administration, and Web 2.0.

Training Expenditures per Learner 2020-2022

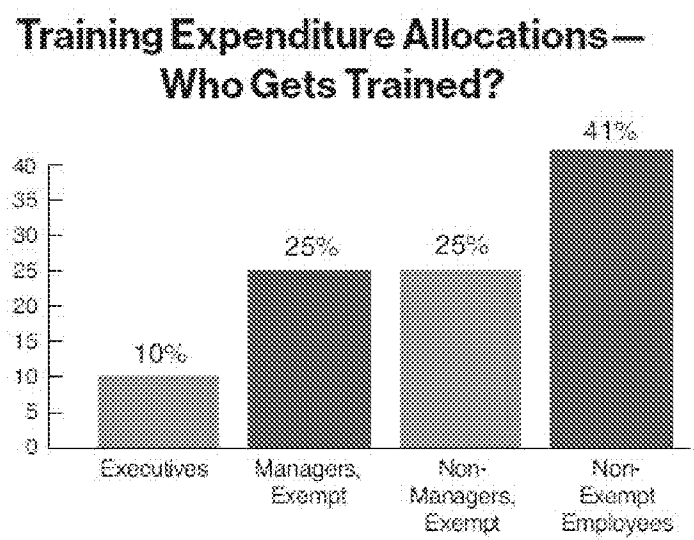




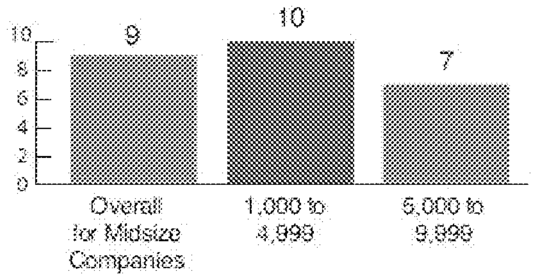
Overall, on average, companies spent $1,207 per learner this year compared with $1,071 per learner in 2021. Services organizations spent the most per learner this year ($1,512), followed by retailers/wholesalers ($1,299). Large companies spent more ($1,689) than midsize ($826) and small ($1,396) companies.

While spending a bit more per learner, companies provided slightly fewer hours of training than last year. On average, employees received 62.4 hours of training per year, compared to nearly 64 hours last year. Midsize companies provided the most hours of training this year (71). Small education organizations had the highest average number of hours overall (nearly 360), followed by midsize government military organizations (nearly 210).

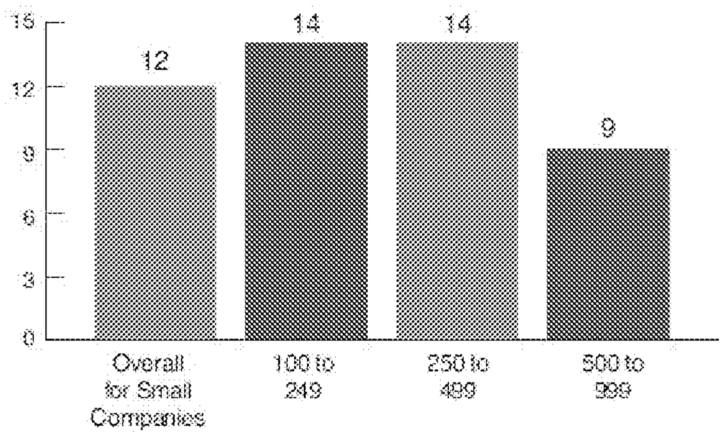
Companies continued to devote the bulk of their training expenditures to training non-exempt employees (41 percent in 2021 and 2022).



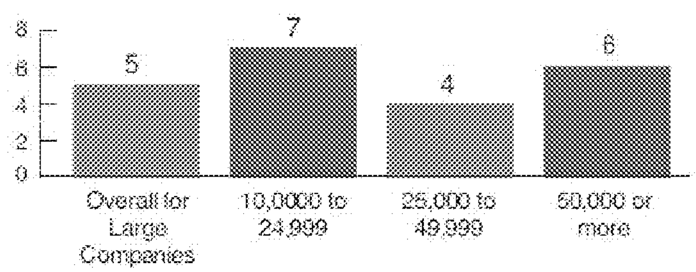
Staff per 1,000 Learners
Midsize Companies

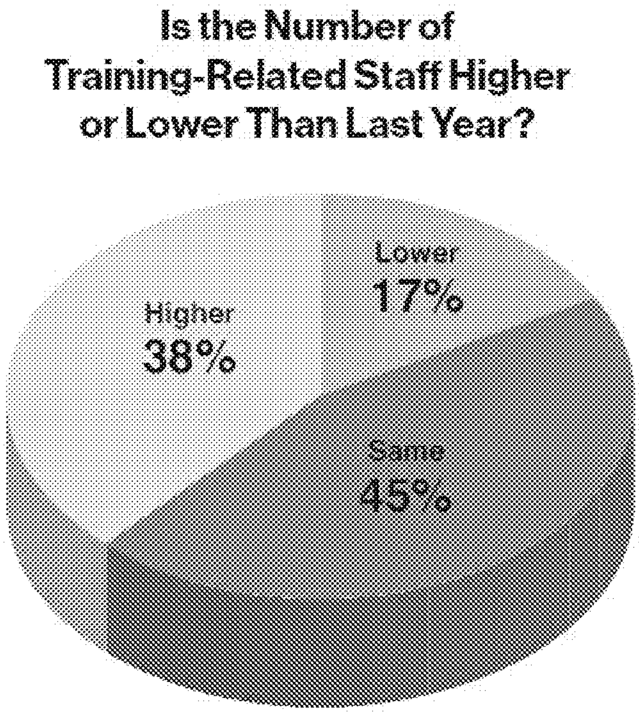


Staff per 1,000 Learners
Small Companies



Staff per 1,000 Learners
Large Companies



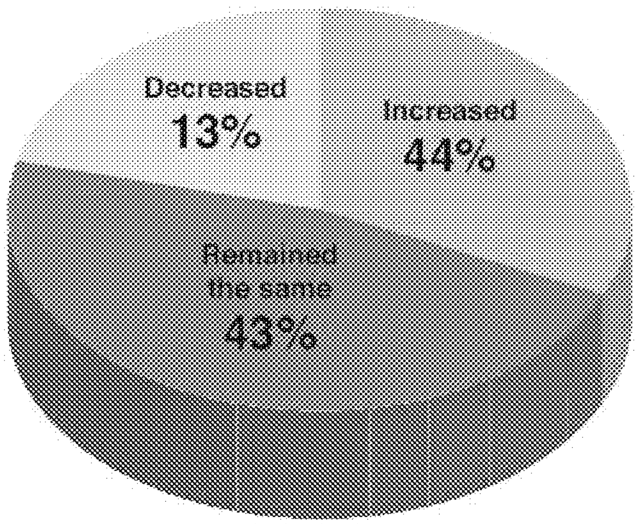


The average training budget for large companies was $19.2 million, while midsize companies allocated an average of $1.5 million, and small companies dedicated an average of $368,891.

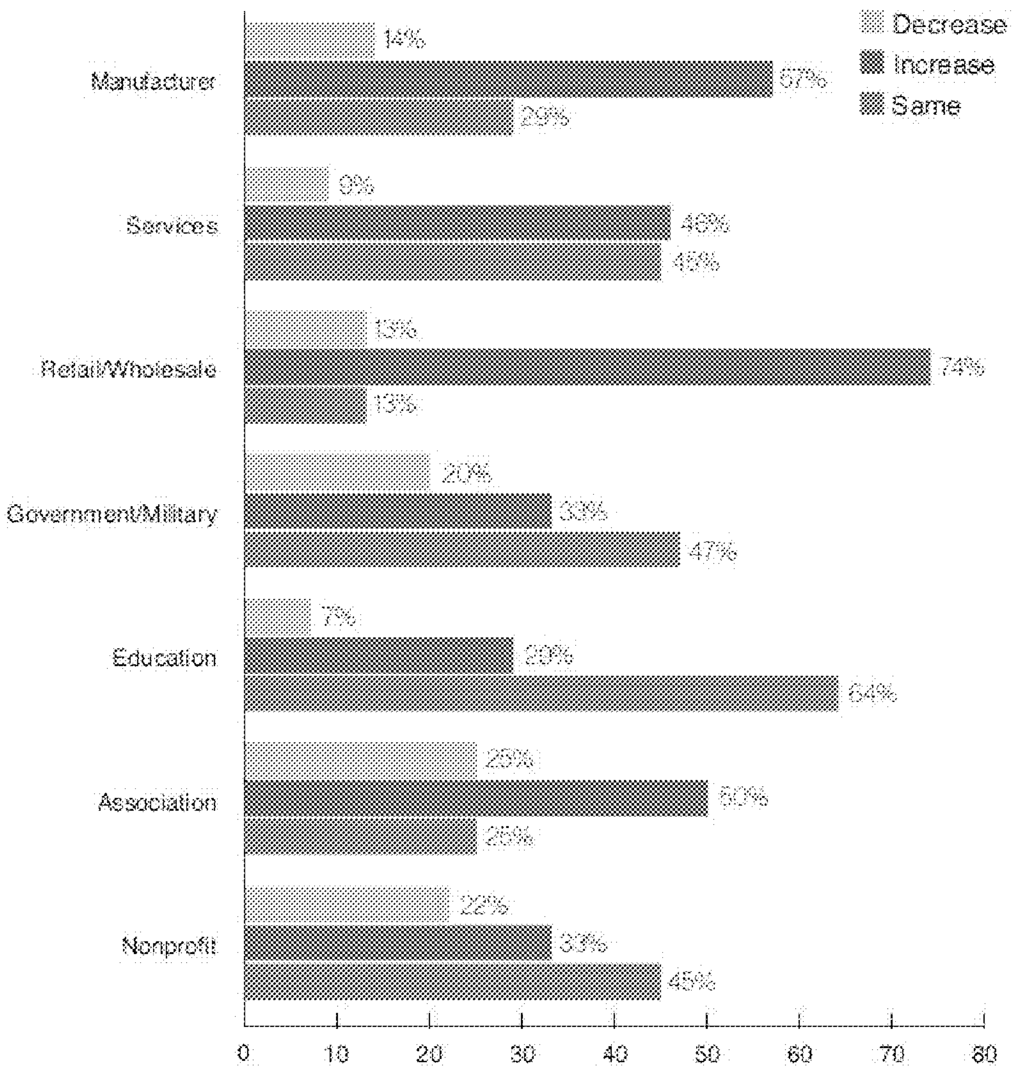
TRAINING BUDGET

This year, the number of companies reporting that their budgets increased rose 12 percent to 44 percent. Those indicating their budgets decreased fell to 13 percent from 21 percent in 2021. Some 43 percent said their budget remained the same vs. 47 percent in 2021. Associations showed the greatest tendency for budget cuts, while retailers/ wholesalers showed a greater tendency for gains. Increases were not evenly distributed across organization sizes. Small companies showed the greatest number of increased budgets (49 percent vs. 44 percent for midsize companies and 35 percent for large ones).

What Happened to Your Training Budget This Year?



Budget Change by Industry

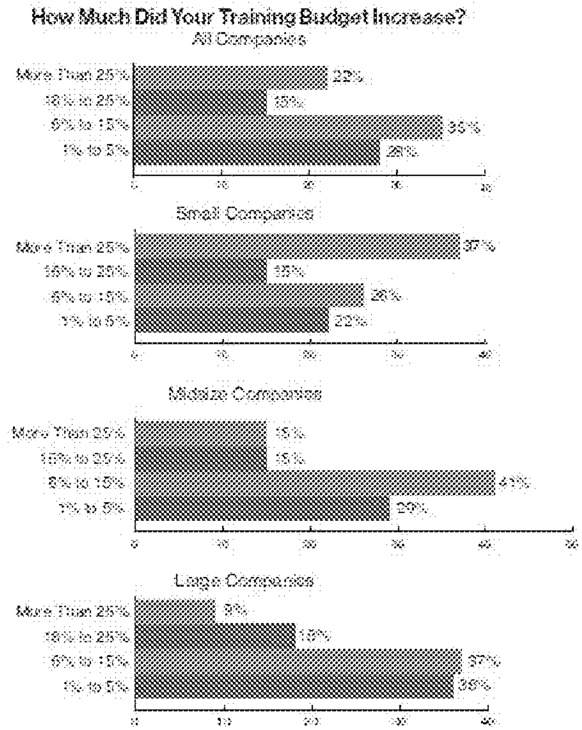


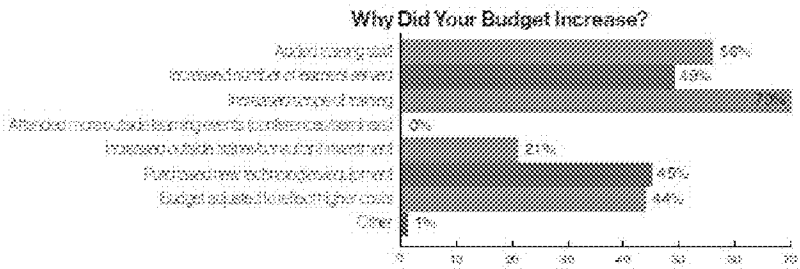
Most of the budget increases were modest—less than 16 percent. Some 35 percent saw increases in the 6 to 15 percent range (vs. 51 percent last year), while 28 percent of organizations reported increases in the 1 to 5 percent range compared with 21 percent last year. Some 37 percent reported increases in the 16-plus percent range (vs. 29 percent in 2021). Most respondents who reported an increase in their training budgets attributed it to the following reasons:

- Increased scope of training programs (70 percent vs. 59 percent last year)
- Added training staff (56 percent vs. 45 percent last year)
- Increased number of learners served (49 percent vs. 38 percent last year)
- Purchased new technologies/equipment (45 percent vs. 50 percent in 2021)

This year, a quarter of the respondents who reported budget decreases cited a drop of more than 16 percent. Some 40 percent reported budget decreases between 6 and 15 percent (vs. 28 percent last year), and 35 percent cited 1 to 5 percent decreases vs. 23 percent in 2021. Some 50 percent cited budget cuts due to COVID-19 for the decrease compared with 76 percent last year. Some 35 percent noted reduced training staff vs. 18 percent last year. This was followed by:

- Attended fewer outside learning events or decreased number of learners served (25 percent for both vs. 39 percent and 18 percent, respectively, last year)
- Decreased outside trainer/consultant investment or decreased scope of training (both at 10 percent vs. 22 percent and 10 percent, respectively, last year)
- Other reasons such as market conditions reducing profit, reduced business need, and budget cuts as part of corporate support reduction due to Congressional action or from state/federal levels (18 percent vs. 16 percent in 2021)



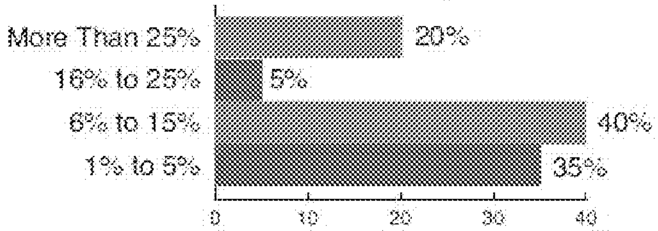


Like the last 10 years, the highest percentage of organizations (32 percent) said management/supervisory training will receive more funding than the year before, but all the other categories followed closely behind, including: onboarding (29 percent); interpersonal skills (25 percent); profession/ industry-specific training (20 percent); executive development, IT/systems training, and customer service training (all at 19 percent). On average, organizations plan to allocate the most funding to profession/industry-specific training ($1.4 million); mandatory compliance training ($846,207); and management/supervisory training ($591,992).

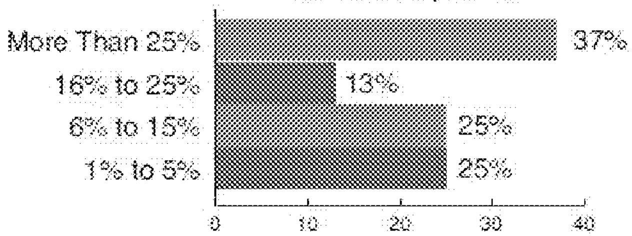
The highest priorities for training in terms of allocating resources in 2023 are: increasing the effectiveness of training programs (32 percent vs. 31 percent last year); increasing learner usage of training programs (21 percent vs. 19 percent); and measuring the impact of training programs (21 percent vs. 17 percent).

How Much Did Your Training Budget Decrease?

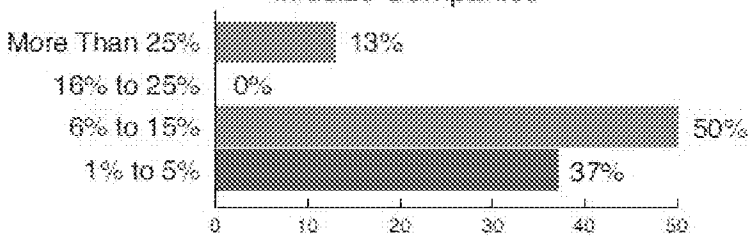
All Companies



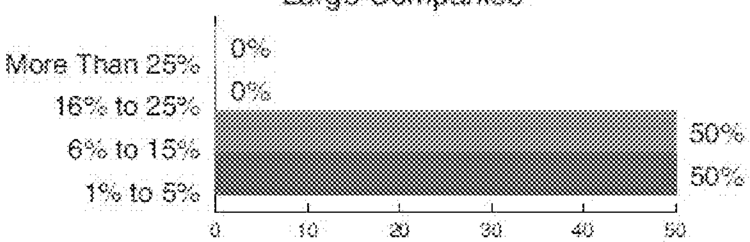
Small Companies



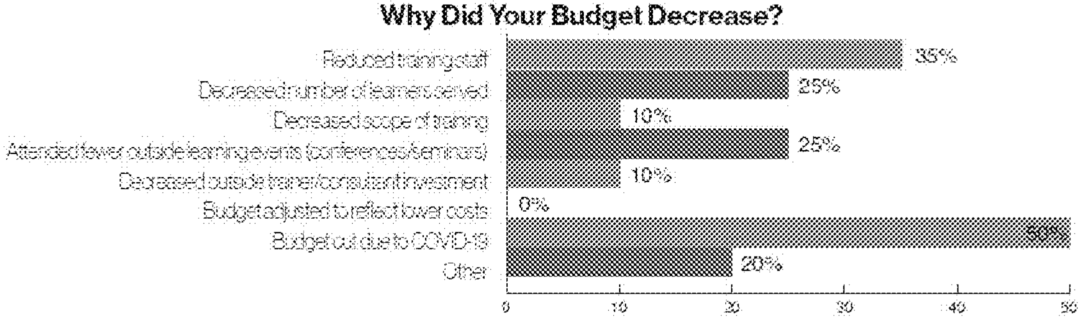
Midsize Companies



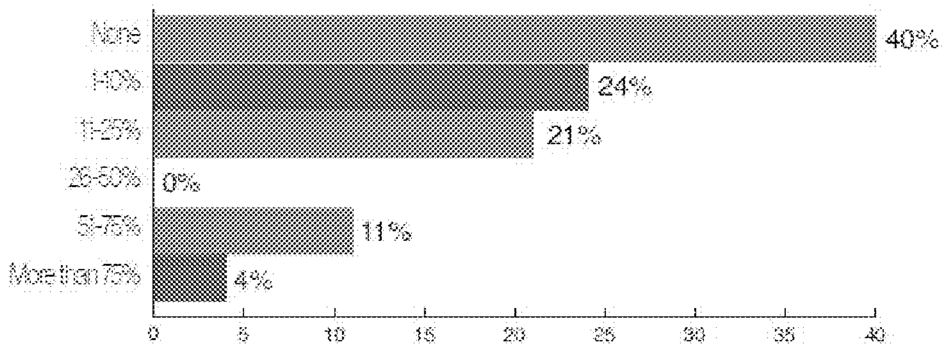
Large Companies



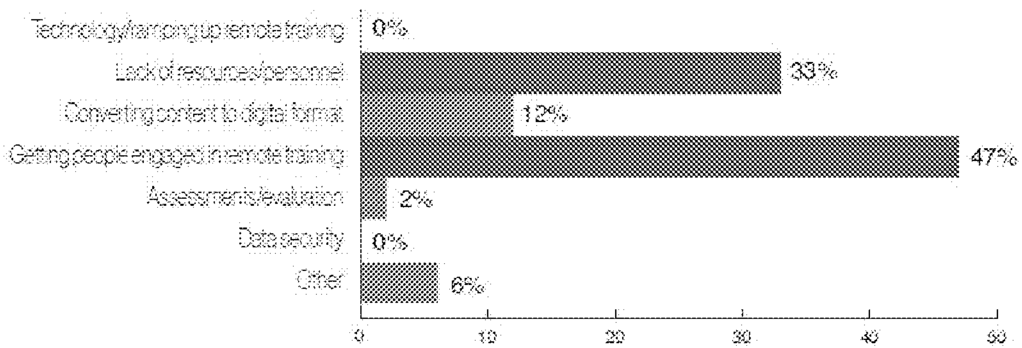
Why Did Your Budget Decrease?



How much of your organizational training was put on hold last year due to the ongoing COVID-19 pandemic?"



What have been your biggest training challenges during the pandemic?



In terms of training delivery post-pandemic, the majority of respondents (47 percent) indicated they plan to return to some classroom training while maintaining some of the remote learning instituted during the crisis.

This year's survey once again included three questions to help understand the effects of the COVID-19 pandemic on training delivery. The highest percentage—40 percent—said no training was put on hold due to the pandemic vs. 33 percent last year. Some 24 percent said 1 to 10 percent of training was put on hold vs. 25 percent last year. This was followed closely by 11 to 25 percent of training (21 percent vs. 23 percent last year). Some 11 percent said 51 to 75 percent was put on hold (vs. 13 percent last year), while 4 percent of respondents indicated more than 75 percent of training was put on hold (vs. 6 percent in 2021).

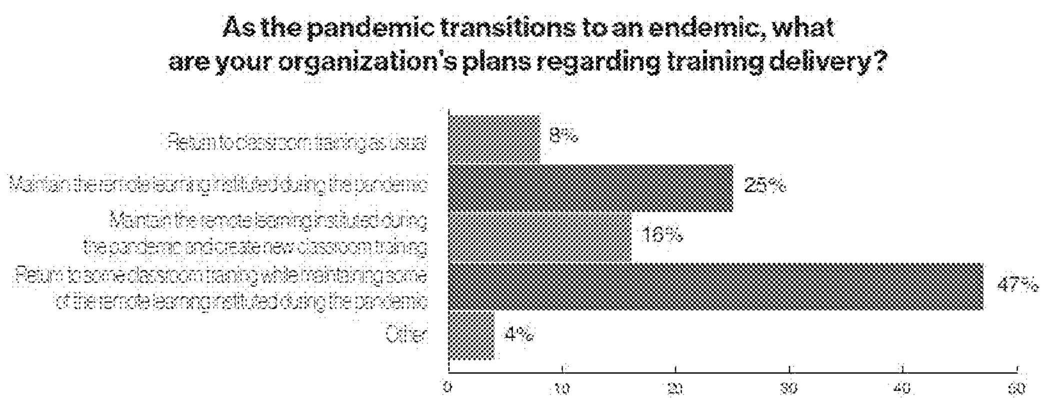
In terms of the biggest training challenges during the pandemic, the top choice was getting people engaged in remote training at 47 percent (up from 31 percent last year), and lack of resources/personnel at 33 percent (compared to 24 percent in 2021). This was followed by converting content to digital format (12 percent, down a bit from 16 percent last year). Technology/ramping up remote training was no longer a factor at all (it was noted by 15 percent last year), nor was data security (vs. 2 percent last year). Like last year, organizations did not seem very concerned about assessments/evaluation (2 percent vs. 5 percent last year).

Some 6 percent of respondents chose "Other" in answer to the challenge question, with answers such as:

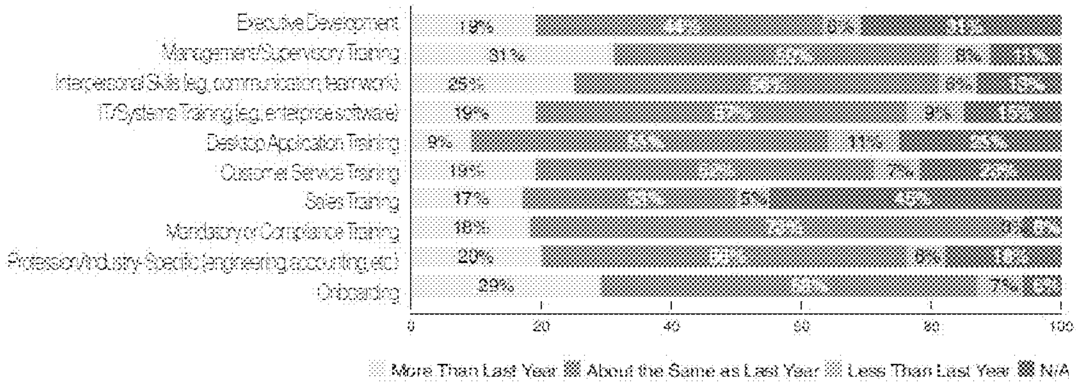
- Not completing instructor-mandated training.
- Reducing Zoom fatigue.

Looking ahead at organizations' plans regarding training delivery as the pandemic evolves into an endemic, the majority (47 percent, down from 56 percent last year) indicated they plan to return to some classroom training while maintaining some of the remote learning instituted during the crisis. Some 8 percent said they plan to return to classroom training as usual (same as last year), while 25 percent said they would maintain the remote learning instituted during the pandemic (up from 15 percent in 2021). Another 16 percent indicated they would stay the current course and maintain the remote learning instituted during the pandemic and create new classroom training (down slightly from 17 percent last year). Four percent indicated "other" answers, including:

- We will define and execute a blended learning strategy.
- We will generate higher-quality and engaging content.
- Nothing is changing.
- We will continue doing what we have always done. We've been 100 percent remote since 2017.
- Aside from having smaller class sizes, we did not change anything due to the pandemic.



Projected Funding for Learning Areas Next Year

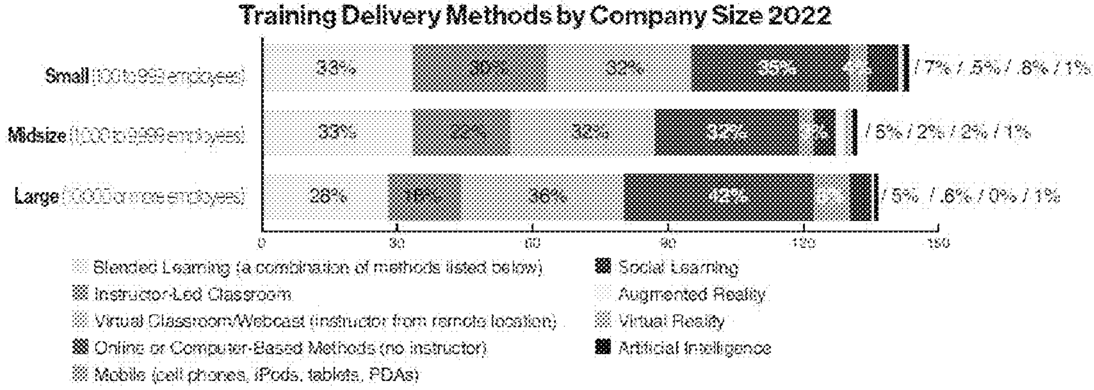


TRAINING DELIVERY

Some 32 percent of hours were delivered with blended learning techniques, down from 43 percent last year.

- Virtual classroom/Webcasting accounted for 33 percent of hours delivered, down from 37 percent in 2021. Some 35 percent of hours were delivered via online or computer-based technologies, up slightly from 34 percent last year.
- Some 24 percent of training hours were delivered by a stand-and-deliver instructor in a classroom setting—down from 30 percent last year as the pandemic continued.
- 4 percent of training hours were delivered via mobile devices, the same as in 2021. This year, 6 percent of training hours were delivered via social learning (vs. 9 percent last year). New technologies such as augmented reality (1 percent), virtual reality (1 percent), and artificial intelligence (1 percent) were not widely used and stayed roughly the same in terms of usage from 2021.

Training Delivery Methods by Company Size 2022



Blended learning is used exclusively or mostly (90 to 100 percent of the time) by 11 percent of the organizations. More companies (39 percent) use it for 10 to 29 percent of their training. There was a jump in usage of social learning methods this year, with 28 percent of organizations using it for 10 to 29 percent of their training.

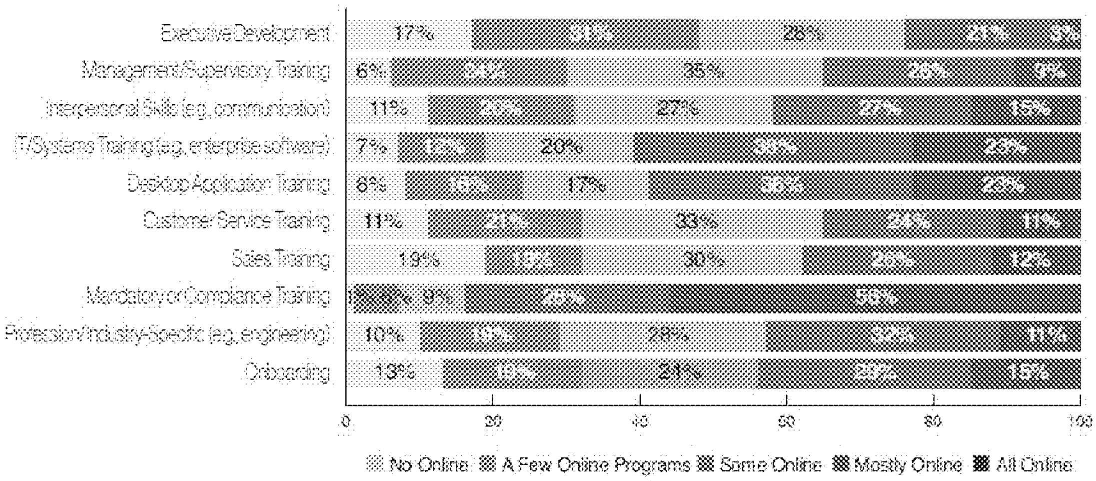
Mandatory or compliance training continued to be done mostly online, with 93 percent of organizations doing at least some of it online and 56 percent entirely online (up from 50 percent last year). Online training also often is used for IT/ systems training (82 percent), desktop application training (77 percent), profession/industry-specific training (72 percent), management/supervisory training (71 percent), customer service and interpersonal skills training (both at 70 percent), and onboarding and sales training (both at 69 percent). Online training was least used for executive development (52 percent).

In terms of technology usage, of the 12 learning technologies presented, the most often used included:

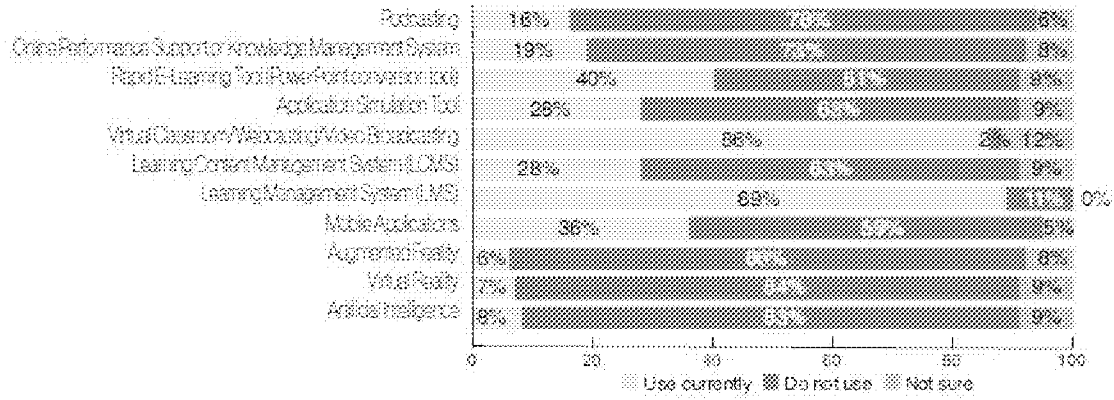
- Learning management systems (LMSs) at 89 percent, down just a bit from 90 percent last year, followed by virtual classroom/Webcasting/video broadcasting at 86 percent (down from 88 percent last year). One hundred percent of large companies and 95 percent of midsize ones currently use LMSs vs. 76 percent of small companies.
- Rapid e-learning tools (40 percent, down from 43 percent last year)
- Mobile applications at 36 percent (up from 30 percent in 2021)
- Application simulation tools (28 percent, up from 25 percent last year)
- Learning content management systems (LCMSs) at 28 percent (up from 20 percent last year)
- Online performance support (EPSS) or knowledge management systems at 19 percent (down slightly from 20 percent last year)
- Podcasting at 16 percent (down from 22 percent last year)
- The delivery methods least often used for training remained the same as last year:
- Virtual reality at 7 percent (up a bit from 6 percent last year)
- Augmented reality at 6 percent (up from 5 percent in 2021)
- Artificial intelligence at 8 percent (up from 6 percent last year)

Large companies appear more inclined to experiment with some of the newer technologies than small or midsize organizations: Some 14 percent of large companies currently are using artificial intelligence vs. 7 percent of midsize companies and 6 percent of small ones. However, 11 percent of midsize companies are incorporating augmented and virtual reality into their training compared to roughly 5 percent of large and small companies.

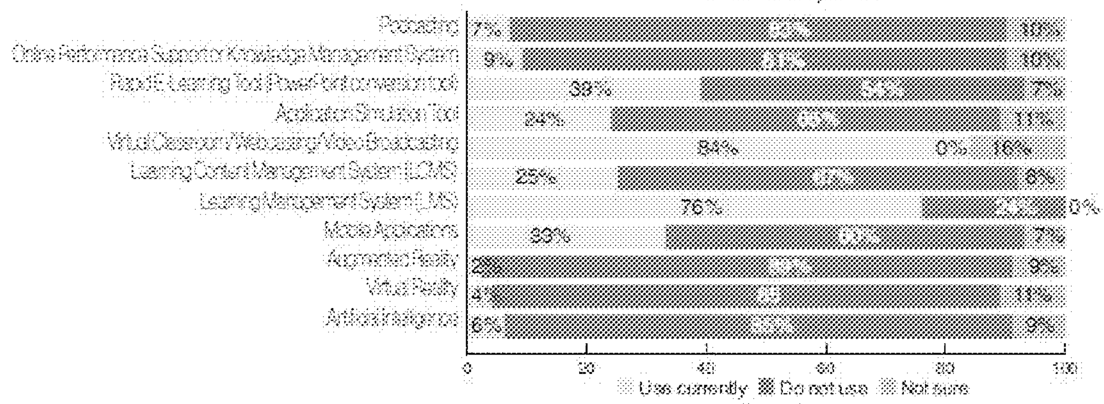
Online Method Use for Types of Training



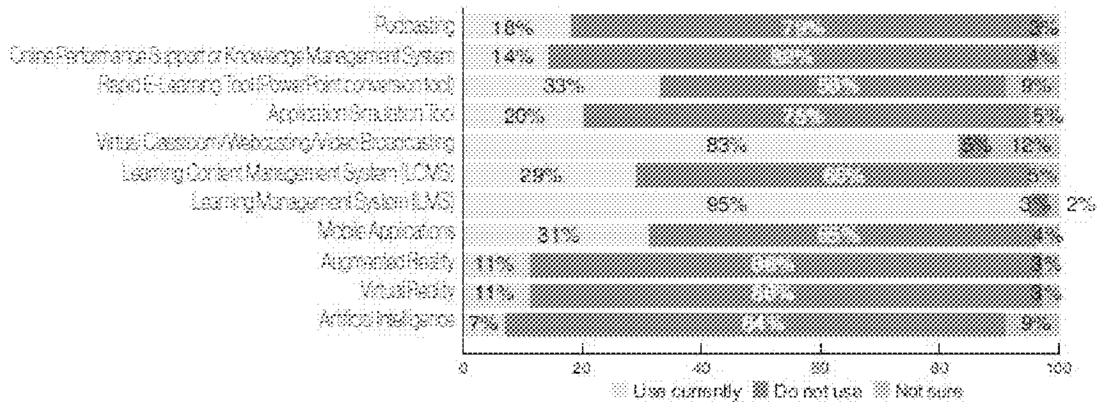
Learning Technologies Current Usage All Companies



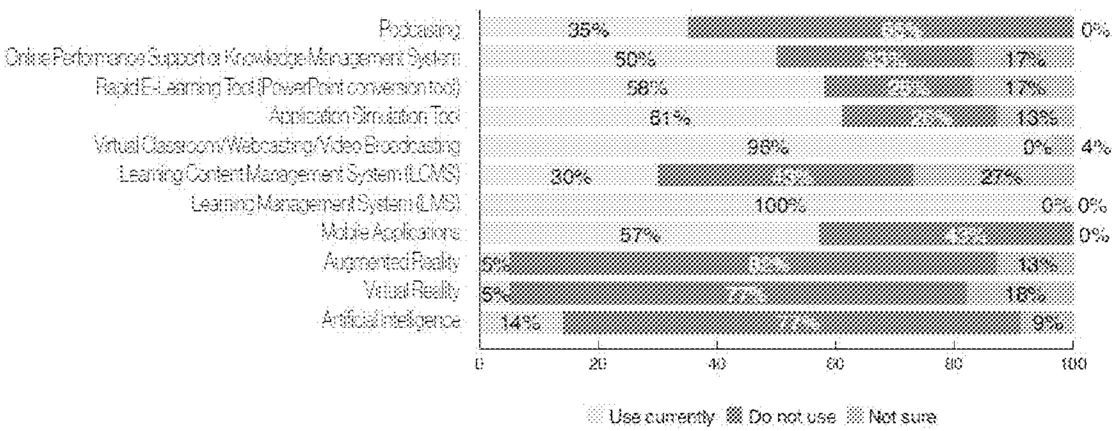
Small Companies



Midsize Companies



Learning Technologies Current Usage Large Companies



TRAINING OUTSOURCING

2022 saw a significant decrease in the average expenditure for training outsourcing: $197,519, down from $379,038 in 2021. Large companies on average spent $760,882 vs. $163,333 for midsize companies and $31,367 for small ones. An average of 4 percent of the total training budget was spent on outsourcing in 2022 vs. 7 percent in 2021.

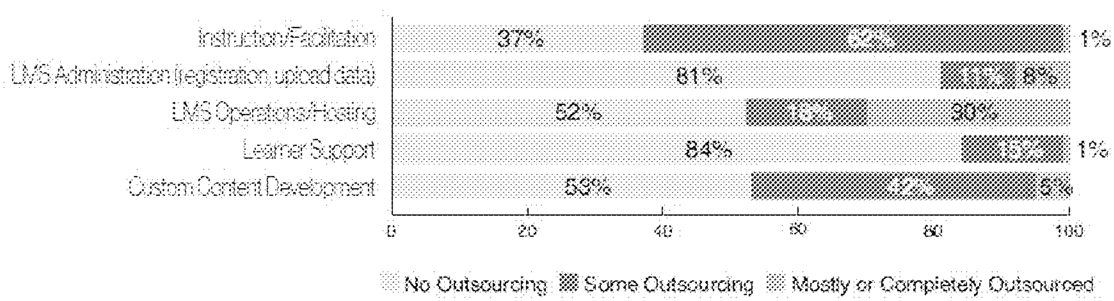
On average, 30 percent of companies mostly or completely outsourced LMS operations/hosting (up from 23 percent last year), while learner support and LMS administration largely were handled in-house (84 percent and 81 percent, respectively).

More instruction/facilitation is outsourced than handled in-house (63 percent vs. 37 percent). Across all the topic areas, small and midsize companies outsourced about the same, and large companies somewhat more. In the areas of custom content development and LMS operations/hosting, the larger the company, the greater the outsourcing.

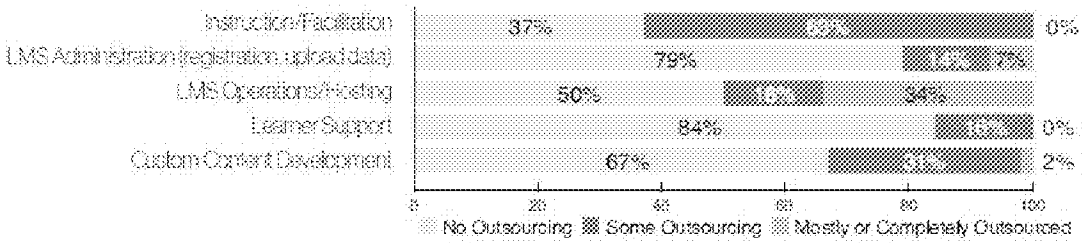
The level of outsourcing is expected to stay relatively steady in 2023—some 85 percent of organizations said they expect to stay the same in the outsourcing area. The percentage of companies expecting to increase outsourcing (7 percent) is slightly lower than those expecting to use outsourcing less (9 percent). Just about half of respondents said they don't plan to outsource learner support (51 percent) or LMS administration (49 percent) in the next 12 months.

With respect to company size, large companies expect a bigger decrease in outsourcing than either small or midsize companies. Midsize and small companies are more likely to report that they don't and won't outsource.

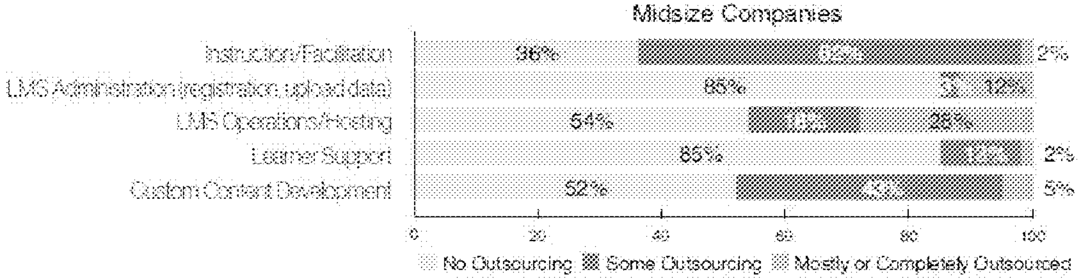
Extent of Outsourcing All Companies



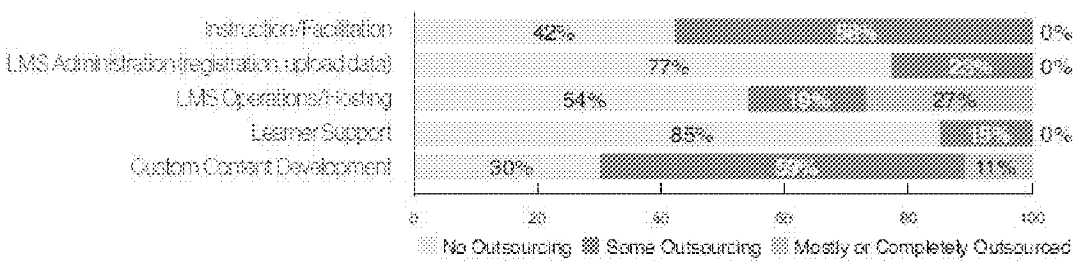
Extent of Outsourcing Small Companies



Midsize Companies

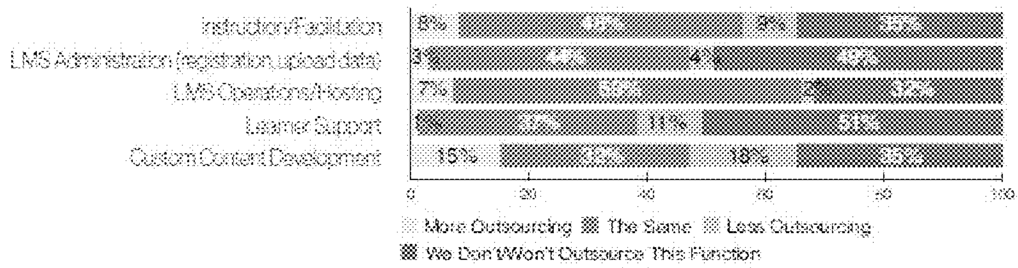


Large Companies

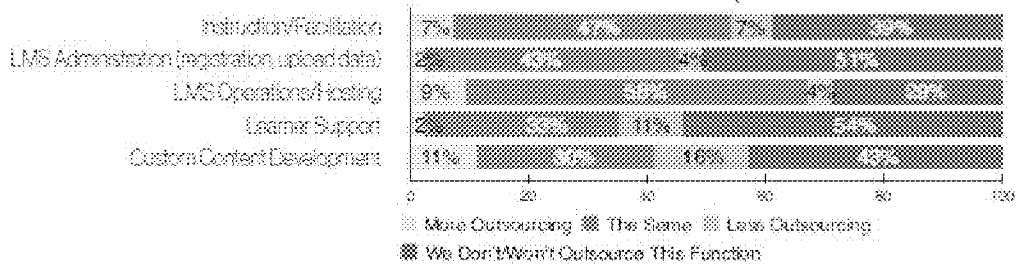


For 2023, large companies expect a bigger decrease in outsourcing than either small or midsize companies. But small and midsize companies are more likely to report that they don't and won't outsource.

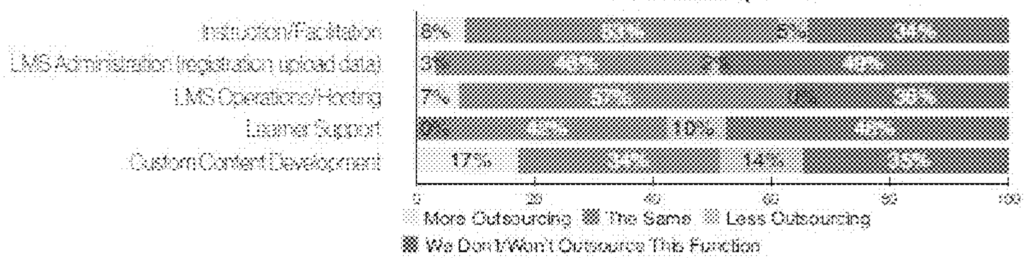
Projected Use of Outsourcing All Companies



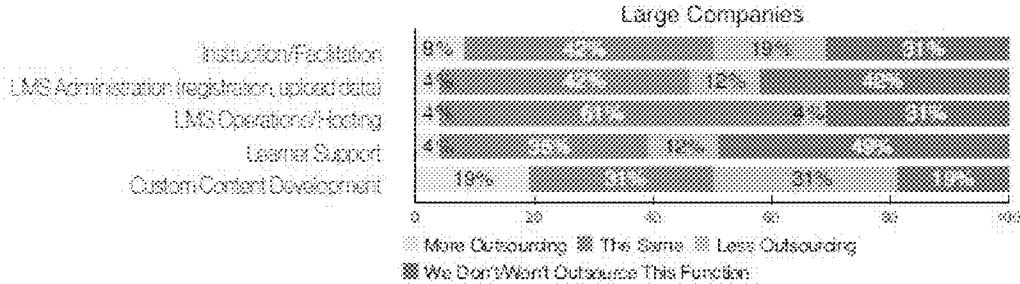
Small Companies



Midsize Companies



Large Companies



Lorri Freifeld

http://www.trainingmag.com

Lorri Freifeld is the editor/publisher of Training magazine. She writes on a number of topics, including talent management, training technology, and leadership development. She spearheads two awards programs: the Training APEX Awards and Emerging Training Leaders. A writer/editor for the last 30 years, she has held editing positions at a variety of publications and holds a Master's degree in journalism from New York University.

What Languages Do We Speak in the United States?

Nearly 68 Million People Spoke a Language Other Than English at Home in 2019

December 06, 2022

Written by: Sandy Dietrich and Erik Hernandez

The number of people in the United States who spoke a language other than English at home nearly tripled from 23.1 million (about 1 in 10) in 1980 to 67.8 million (almost 1 in 5) in 2019, according to a recent U.S. Census Bureau report.

At the same time, the number of people who spoke only English also increased, growing by approximately one-fourth from 187.2 million in 1980 to 241 million in 2019 (Figure 1).

The report, Language Use in the United States: 2019 [https://www.census.gov/library/publications/2022/acs/acs-50.html] , uses American Community Survey (ACS) [/programs-surveys/acs.html] data to highlight trends and characteristics of the different languages spoken in the United States over the past four decades.

> **Chinese, Vietnamese, Tagalog and Arabic speakers were *more* likely to be naturalized U.S. citizens than not U.S. citizens. Spanish speakers were *less* likely to be naturalized U.S. citizens (18%) than not U.S. citizens (28%).**

In this article we refer to foreign-language "speakers" as those who report speaking a language other than English (LOTE) at home, not necessarily all those who can speak that language.

Related America Counts Stories

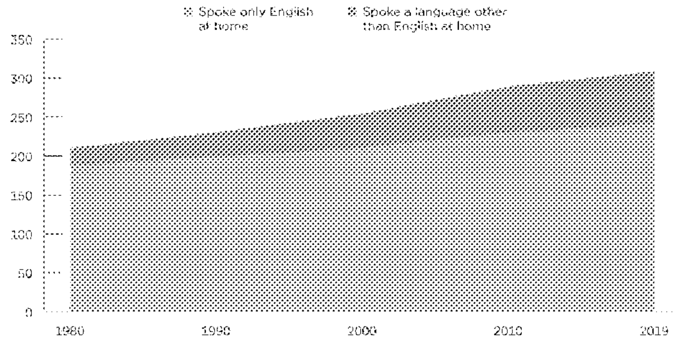
America Counts Story

Broad Diversity of Asian, Native Hawaiian, Pacific Islander Population

During Asian and Pacific Islander Heritage Month, we explore the broad diversity of this population in the United States.

[/library/stories/2022/05/aanhpi-population-diverse-geographically-dispersed.html]

Figure 1.
Languages Spoken at Home for the Population 5 Years and Older: 1980-2019
(In millions)



Source: U.S. Census Bureau, 1980, 1990, and 2000 Censuses; 2010 and 2019 American Community Survey, 1-year estimates.

[/content/dam/Census/library/stories/2022/12/languages-we-speak-in-united-states-figure-1.jpg]

The Hispanic population is the largest minority group [https://www.nytimes.com/2003/01/22/us/hispanics-now-largest-minority-census-shows.html] in the United States. So it is not surprising Spanish was the most common non-English language spoken in U.S. homes (62%) in 2019 – 12 times greater than the next four most common languages.

Table 1.
Five Most Frequently Spoken Languages Other Than English (LOTE) in U.S. Homes: 2019

Language	Estimate	Percent of LOTE population
Spanish or Spanish Creole	41,757,391	61.6
Chinese	3,494,544	5.2
Tagalog	1,763,585	2.6
Vietnamese	1,570,526	2.3
Arabic	1,260,437	1.9

Source: U.S. Census Bureau, 2019 American Community Survey, 1-year estimates.

[/content/dam/Census/library/stories/2022/12/languages-we-speak-in-united-states-table.jpg]

Age and Nativity by Language

Figure 2 displays the breakdown of age and nativity for the five most commonly spoken languages other than English in 2019. Speakers of Spanish and Arabic, the first and fifth most common foreign languages spoken, had similar age compositions.

Both had the greatest share (16%) of speakers ages 5 to 14 years and a small share of older speakers – 14% of Spanish speakers and 13% of Arabic speakers were ages 60 and over.

In contrast, only 4% of Tagalog speakers were ages 5 to 14 but a third (33%) were 60 or older.

More than half (55%) of Spanish speakers were U.S.-born, four times the share (13%) of Tagalog speakers.

Chinese, Vietnamese, Tagalog and Arabic speakers were *more* likely to be naturalized U.S. citizens than not U.S. citizens. Spanish speakers were *less* likely to be naturalized U.S. citizens (18%) than not U.S. citizens (28%).

America Counts Story

2020 U.S. Population More Racially, Ethnically Diverse Than in 2010

2020 Census results released today allow us to measure the nation's racial and ethnic diversity and how it varies at different geographic levels.

[/library/stories/2021/08/2020-united-states-population-more-racially-ethnically-diverse-than-2010.html]

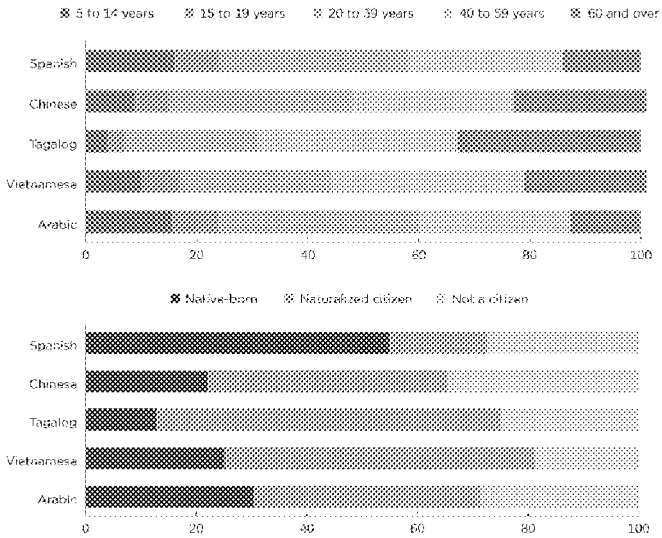
America Counts Story

Improved Race, Ethnicity Measures Show U.S. is More Multiracial

Today's release of 2020 Census data provides a new snapshot of the racial and ethnic composition of the country.

[/library/stories/2021/08/improved-race-ethnicity-measures-reveal-united-states-population-much-more-multiracial.html]

Figure 2.
Most Frequently Spoken Languages at Home by Age, Nativity and Citizenship: 2019
(In percent)



Source: U.S. Census Bureau, 2019 American Community Survey, 1-year estimates.

[/content/dam/Census/library/stories/2022/12/languages-we-speak-in-united-states-figure-2.jpg]

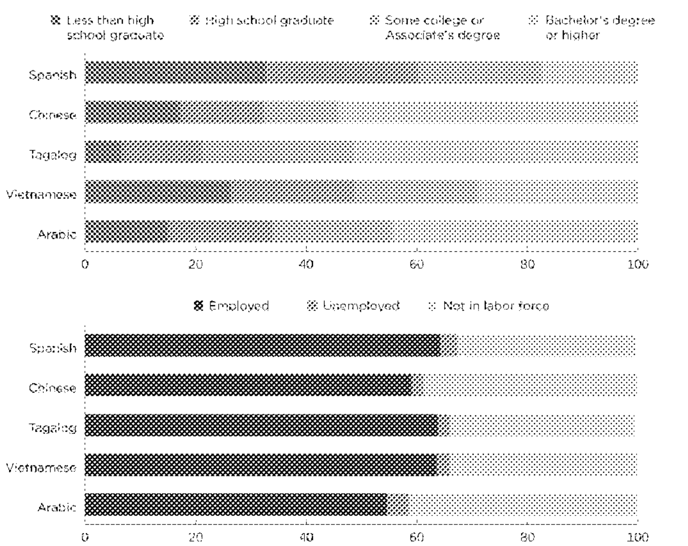
Educational Attainment and Employment

In 2019, 51% of Tagalog and 54% of Chinese speakers had a bachelor's degree or higher (these two groups were not statistically different from each other) compared to only 17% of Spanish speakers. Figure 3 shows educational attainment for the U.S. population ages 25 years and older by language spoken at home.

About a third (33%) of Spanish speakers did not graduate from high school, the largest share of speakers of the five most common languages other than English.

Employment status of speakers ages 16 and over did not vary much across the five languages (Figure 3). Less than 4% were unemployed in 2019 – not significantly different than the national average.

Figure 3.
Most Frequently Spoken Languages at Home by Education Attainment and Employment Status: 2019
(In percent)



Source: U.S. Census Bureau, 2019 American Community Survey, 1-year estimates.

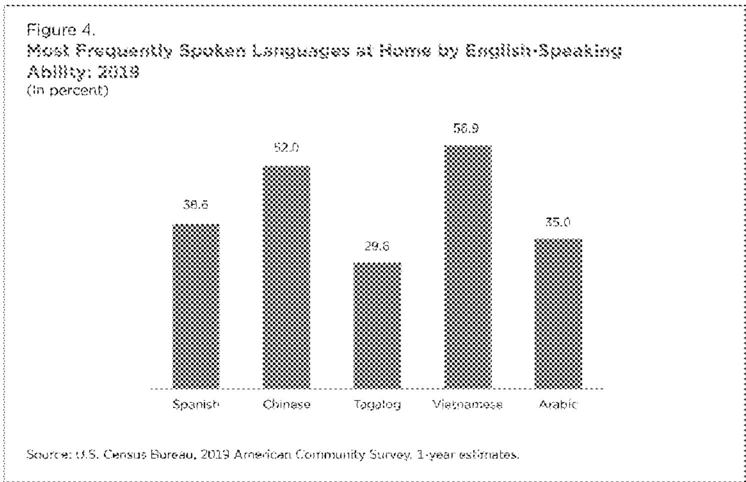
[/content/dam/Census/library/stories/2022/12/languages-we-speak-in-united-states-figure-3.jpg]

English Proficiency by Language

The federal government relies on data on language use and English proficiency to provide language services under the Voting Rights Act, as well as to allocate educational funds to state English as a Second Language

(ESL) programs.

Based on the 2019 data, 52% of people who spoke Chinese and 57% of those who spoke Vietnamese at home in the United States spoke English "less than very well," compared to the other three common languages: Spanish 39%, Tagalog 30%, and Arabic 35% (Figure 4). This may have resulted from a recent increase in immigration from Asia [https://www.census.gov/library/working-papers/2012/demo/POP-twps0096.html] and newcomers who have not had enough time to assimilate and master English yet.



[/content/dam/Census/library/stories/2022/12/languages-we-speak-in-united-states-figure-4.jpg]

Household Characteristics by Language

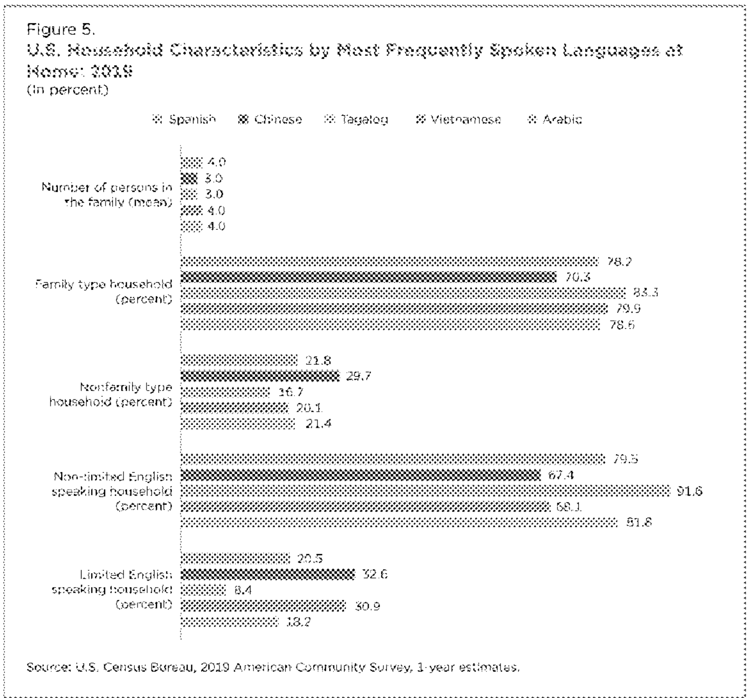
In addition to individual differences, there were also differences in the U.S. households that spoke the five most frequently spoken non-English languages (Figure 5).

A limited English-speaking household is one in which no members ages14 and over speak only English or speak English "very well." About a third of Chinese (33%) and Vietnamese (31%) households were limited English-speaking households – four times greater than Tagalog households.

In contrast, Tagalog-speaking households were more likely to be "non-limited" English speaking. About 92% of Tagalog-speaking households were non-limited English speaking and 8% were limited English speaking.

The majority of households across all five languages were family households, defined as having at least two members (including the householder) related by birth, marriage or adoption. On average, these households each had zero to one child under age 18 and three to four persons in the family.

Among nonfamily households, defined either as a person living alone or one who shares the housing unit with nonrelatives such as boarders or roommates, a greater proportion (30%) of Chinese-speaking households were nonfamily compared to households speaking the other four languages. Half as many Tagalog-speaking households (17%) were nonfamily households.



[/content/dam/Census/library/stories/2022/12/languages-we-speak-in-united-states-figure-5.jpg]

About the Data

The American Community Survey is a nationally representative survey of households in the United States administered annually to a sample of approximately 3.5 million housing unit addresses (obtaining information about every household member). In addition to language information, the ACS collects data on demographic and socioeconomic characteristics.

For a comprehensive review at the individual languages and languages groups spoken in the United States, refer to the Language Use in the United States: 2019 [https://www.census.gov/library/publications/2022/acs/acs-50.html] report.

Sandy Dietrich is a survey statistician in the Census Bureau's Survey Improvement Research Branch.

Erik Hernandez is a survey statistician in the Census Bureau's Education and Social Stratification Branch.

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Race [/library/stories.html?tagfilter_List_1688678669=Census:Topic/ThePopulation/race#List_1688678669]

Related Statistics

InfoBrief

U.S. R&D Increased by $51 Billion in 2020 to $717 Billion; Estimate for 2021 Indicates Further Increase to $792 Billion

Gary Anderson, John Jankowski, and Mark Boroush

New data from the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation indicate that research and experimental development (R&D)[1] performed in the United States totaled $717.0 billion in 2020 (table 1). The estimated total for 2021, based on performer-reported expectations, is $791.9 billion. U.S. R&D totals were $494.5 billion in 2015 and $406.6 billion in 2010. (All amounts and calculations are reported in current dollars, unless otherwise noted.)

The U.S. R&D system consists of the activities of a diverse group of R&D performers and sources of funding. Included here are private businesses, the federal government, nonfederal governments, higher education institutions, and other nonprofit organizations. The organizations that perform R&D often receive significant levels of outside funding, and organizations that fund R&D may also themselves be performers. The data for this InfoBrief derive mainly from NCSES surveys of the annual R&D expenditures of these performers and funders.

Table 1

U.S. R&D expenditures, by performing sector and source of funds: 2010–21

(Millions of current and constant 2012 dollars)

Performing sector and source of funds	2010	2011	2012	2013	2014	2015	2016
					Current $millions		
All performers	406,600	426,215	433,716	454,271	475,969	494,499	521,700

Performing sector and source of funds	2010	2011	2012	2013	2014	2015	2016
Business	278,977	294,092	302,251	322,528	340,728	355,821	379,529
Federal government	50,798	53,524	52,144	51,086	52,687	52,847	51,187
Federal intramural[c]	31,970	34,950	34,017	33,406	34,783	34,199	31,762
FFRDCs	18,828	18,574	18,128	17,680	17,903	18,649	19,424
Nonfederal government	691	694	665	620	583	595	620
Higher education	56,084	60,088	60,895	61,548	62,351	64,635	67,792
Nonprofit organizations[d]	18,050	17,817	17,762	18,489	19,620	20,601	22,573
All funding sources	406,600	426,215	433,716	454,271	475,969	494,499	521,700
Business	248,126	266,427	275,728	297,188	318,410	333,243	360,291
Federal government	126,617	127,014	123,837	120,132	118,367	119,532	118,175
Nonfederal government	4,303	4,387	4,158	4,243	4,213	4,277	4,995

FFRDC = federally funded research and development center.

[a] Some data for 2020 are preliminary and may be revised later.
[b] The data for 2021 include estimates and are likely to be revised later.
[c] Includes expenditures of federal intramural R&D as well as costs associated with

[d] Some components of the R&D performed by nonprofit organizations are estimated and may be revised later.

Note(s):
Data are based on annual reports by performers. Expenditure levels for higher education, federal government, and nonfederal government performers are calendar year approximations based on fiscal year data.

Source(s):
National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).

The "Data Sources, Limitations, and Availability" section at the end of this InfoBrief summarizes the main data sources and methodology and provides further details on the data. Data cited in this report that do not appear in one of this InfoBrief's tables or figures come from the companion data tables, *National Patterns of R&D Resources: 2020–21 Data Update,* found at https://ncses.nsf.gov/pubs/nsf23321.

Preliminary 2021 Estimates and Current Trends in U.S. R&D Totals and National R&D Intensity

U.S. Total R&D

Year-over-year increases in U.S. total R&D expenditures averaged $17.6 billion (4.0% Compound Average Growth Rate [CAGR]) over the 2010–15 period. Subsequent yearly increases have been more notable. The three years leading to 2020 saw increases of $50.6 billion (2017–18), $61.8 billion (2018–19) and $50.8 billion (2019–20), averaging a 7.7% rate for 2015–20. For 2021, business R&D and total R&D performance are estimated to increase by $69.2 and $74.9 billion, respectively (table 2).

Table 2

Annual change in U.S. R&D expenditures and gross domestic product, by performing sector: 1990–2021

(Percent)

Expenditures and gross domestic product	Longer term trends			Most recent					
	1990–2000	2000–10	2010–20	2010–11	2011–12	2012–13	2013–14	2014–15	2015–16
					Current $				
Total R&D, all performers	5.8	4.3	5.8	4.8	1.8	4.7	4.8	3.9	5.5
Business	6.4	3.4	6.9	5.4	2.8	6.7	5.6	4.4	6.7
Federal government	1.9	5.9	2.4	5.4	-2.6	-2.0	3.1	0.3	-3.1
Federal intramural	2.1	5.2	2.4	9.3	-2.7	-1.8	4.1	-1.7	-7.1
FFRDCs	1.7	7.3	2.4	-1.4	-2.4	-2.5	1.3	4.2	4.2
Nonfederal government[c]	NA	NA	-0.1	0.4	-4.2	-6.8	-5.9	2.0	4.3
Higher education	5.9	6.9	3.4	3.4	1.3	1.1	1.3	3.7	4.9
Nonprofit organizations[d]	8.8	6.6	4.5	-1.3	-0.3	4.1	6.1	5.0	9.6
Gross domestic product	5.6	3.9	3.4	3.7	4.2	3.6	4.2	3.7	2.7
					Constant 2012 $				
Total R&D, all performers	3.7	2.1	4.1	2.7	-0.1	2.9	2.9	2.9	4.5
Business	4.3	1.2	5.1	3.3	0.9	4.9	3.7	3.4	5.6
Federal government	-0.1	3.8	0.7	3.2	-4.4	-3.7	1.2	-0.7	-4.1
Federal [illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

NA = not available.

FFRDCs = federally funded research and development centers.

[a] Some data for 2020 are preliminary and may be revised later.
[b] The R&D data for 2021 include estimates and are likely to be revised later.
[c] Survey data on state internal R&D performance were not available prior to 2006; data for 2008 were not collected.
[d] Some components of the R&D performed by nonprofit organizations are estimated and may later be revised.

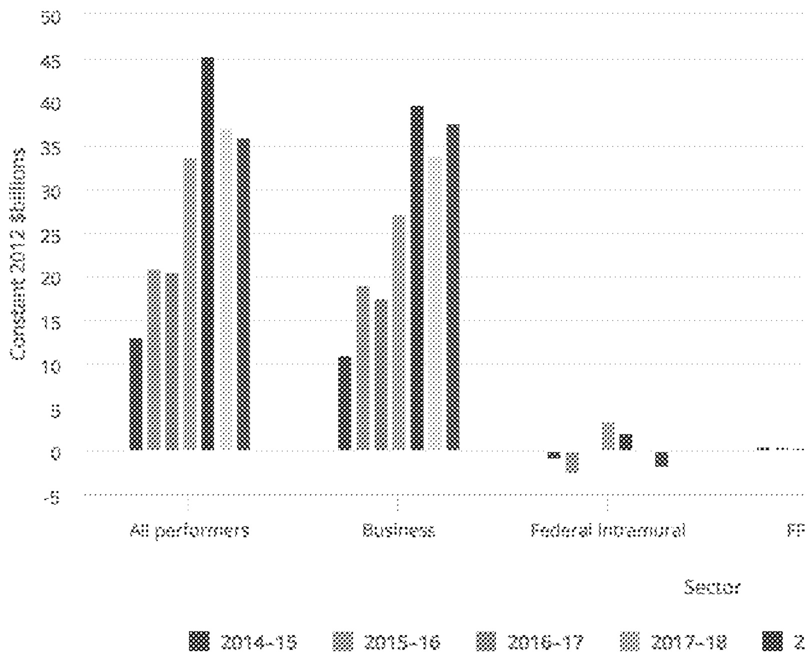
Note(s):
The longer term trend rates are calculated as compound annual growth rates.

Source(s):
National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).

Adjusting for inflation,[2] growth in U.S. total R&D averaged 4.1% annually over the 2010–20 period. By comparison, average annual growth of U.S. total R&D in the prior decade (2000–10) was lower at 2.1%. The estimate for 2021 shows inflation-adjusted R&D growing at 5.7% from the 2020 level. Comparisons in constant dollars demonstrate the effect of recent increased inflation[3] on real R&D performance. In constant dollar terms, business R&D performance is estimated to increase by $37.7 billion over the 2020 level, while performance in the government and higher education sectors is estimated to decline (table 2, figure 1).

Figure 1

Year-over-year changes in U.S. R&D expenditures, by performer: 2014–21



Data View

FFRDC = federally funded research and development center.

Note(s):
Some data for 2020 are preliminary and may be revised later. The data for 2021 include estimates and are likely to be revised later.

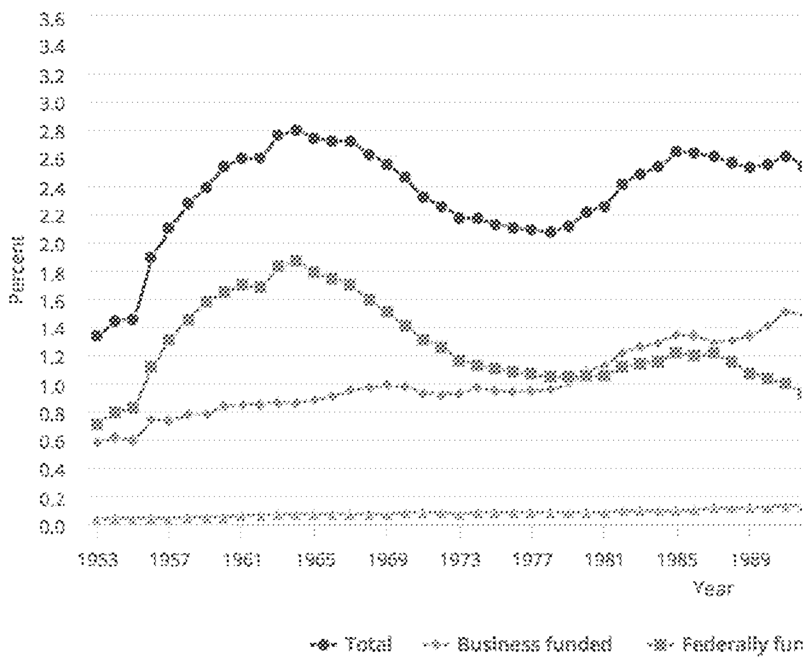
Source(s):
National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).

R&D-to-GDP Ratio

The ratio of total national R&D expenditures to gross domestic product (GDP) (i.e., R&D intensity) is widely used by national statistical offices and other policy analysts as an overall gauge of the relative priority of a nation's R&D effort among multiple investment and consumption options. In this edition of the *National Patterns* series, the ratio of U.S. R&D to GDP was 3.40% in 2020 and is estimated to remain at 3.40% in 2021 (figure 2). Prior to 2019 when R&D intensity reached 3.12%, the highest U.S. ratios recorded were 2.79% in 1964, 2.78% in 2009, 2.79% again in 2016, 2.84% in 2017, and 2.94% in 2018.[4] Reaching an R&D intensity level above 3.0% is widely regarded in the R&D policy community as a notable national achievement. U.S. R&D to GDP exceeded the Organisation for Economic Co-operation and Development average (2.67%). The U.S. ratio also exceeded that of other key R&D performing nations, such as China (2.40%), France (2.35%), and the United Kingdom (1.71% [2019]). Israel (5.44%) and South Korea (4.81%) had higher ratios than the United States, whereas Germany (3.13%) and Japan (3.27%) had similar ratios to the United States.[5]

Figure 2

Ratio of U.S. R&D to gross domestic product, by source of funds for R&D: 1953–2021



Data View

GDP = gross domestic product.

Note(s):
Some data for 2020 are preliminary and may be revised later. The data for 2021 include estimates and are likely to be revised later. The federally funded data represent the federal government as a funder of R&D by all performers; similarly the business funded data cover the business sector as a funder of R&D by all performers. The "other" category includes the R&D funded by all other sources—mainly, by higher education, nonfederal government, and nonprofit organizations. The GDP data used reflect the U.S. Bureau of Economic Analysis statistics of late October 2022.

Source(s):
National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).

The extent to which the rising ratio of U.S. R&D to GDP is attributable to increased business funding of R&D is clear. In the decade leading up to 2020, business funding grew at a 7.7% (CAGR) rate in 2010–20, while federal funding grew at a 1.5% rate and GDP grew at a 3.4% rate. Notably, the higher education sector's funding of R&D grew at 6.6% over the same period.

Federally funded R&D as a percentage of GDP peaked in the 1960s at 1.86% in 1964 and generally has declined since. Even with the infusion of the American Recovery and Reinvestment Act (ARRA) funds, federally funded R&D did not rise higher than 0.87% of GDP in 2009. For the latter half of the past decade, federal funding for R&D remained at or below 0.70% of GDP. By contrast, business R&D funding in 2010 was 1.65% of GDP and increased to 2.47% by 2020.

Performers of R&D

Business

The business sector is by far the largest performer of U.S. R&D. In 2020, domestically performed business R&D accounted for $543.2 billion, or 76% of the $717.0 billion national R&D total (table 1 and table 3). The business sector's predominance in national R&D performance has long been the case, with its annual share ranging between 69% and 76% since 2000.

R&D performed in the domestic United States by businesses occurs widely in manufacturing and nonmanufacturing. In 2020, companies in manufacturing industries performed 57% of business R&D. Among nonmanufacturing industries, information (including software publishing) and professional and scientific services accounted for 80% of the remainder.[6]

Table 3

U.S. R&D expenditures, by performing sector, source of funds, and type of R&D: 2020

(Millions of dollars and percent distribution)

Performing sector and type of R&D	Source of funds ($ millions)					
	Total	Business	Federal government	Nonfederal government	Higher education	Nonpr organiza
R&D	716,955	520,363	147,657	5,670	23,191	2(
Business	543,220	512,224	29,772	241	**	
Federal government	64,237	179	63,848	44	**	
Federal intramural	40,371	0	40,371	0	0	
FFRDCs	23,866	179	23,478	44	**	
Nonfederal government	683	20	298	348	3	
Higher education	80,842	4,837	41,462	4,464	22,252	7
Nonprofit organizations	27,973	3,103	12,278	572	935	1'
Percent distribution by funding source	100.0	72.6	20.6	0.8	3.2	
Basic research	111,883	38,239	46,205	2,963	14,450	1(
Business	36,371	34,053	2,191	24	**	
Federal government	12,099	35	12,024	9	**	
Federal intramural	7,310	0	7,310	0	0	

Performing sector	Source of funds ($ millions)					
			Federal	Nonfederal	Higher	Nonpr

* = amount < $0.5 million; ** = small to negligible amount, included as part of the funding provided by nonprofit organizations.

FFRDC = federally funded research and development center.

Note(s):
Some data for 2020 are preliminary and may be revised later. Some components of R&D performance and funding by other nonprofit organizations are projected and may later be revised.

Source(s):
National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).

Higher Education

R&D performed in the United States by the higher education sector totaled $80.8 billion in 2020, or 11% of U.S. total R&D (table 1 and table 3).[7] In the period 2000–20, the higher education share of U.S. total R&D ranged between 11% and 14%.

Adjusted for inflation, growth in this sector's R&D performance averaged 1.6% annually during 2010–20, well behind U.S. total R&D (4.1%). For the preceding decade, growth in higher education R&D performance was a robust 4.6%. The annual percent change in 2010–20 varied; there was low growth or contraction in 2010–14 with a return to modest increases in 2015–20. The estimate for 2021 indicates a slight contraction (-0.5%) when measured in constant dollars as inflation outpaces a slight increase in the level of higher education R&D performance (table 2).

Federal Agencies and Federally Funded Research and Development Centers

The federal government performed $64.2 billion of the U.S. R&D total in 2020 (table 1 and table 3). This amount included $40.4 billion (6% of the U.S. total) performed by the intramural R&D facilities of federal agencies and $23.9 billion (3%) performed by the 43[8] federally funded research and development centers (FFRDCs). The federal share of U.S. R&D performance ranged between 11% and 13% in 2000–10. Subsequently, the federal share declines to 8% in 2021. Much like recent R&D trends in the education sector, a modest 1.5% year-over-year increase in nominal federal R&D performance estimated for 2021 results in a 2.9% decline when measured in constant dollars (table 2).

State Government

State agency intramural R&D performance in 2020 totaled $683 million—a small share (about 0.1%) of the U.S. total (table 1 and table 3). This includes all 50 states and the District of Columbia.

Nonprofit Organizations

R&D performed in the United States by nonprofit organizations (excluding higher education institutions and federal and nonfederal government) was $28.0 billion in 2020, based on a new annual survey of this sector (table 1 and table 3).[9] This was 4% of U.S. total R&D, a share that has changed little since the early 2000s.

R&D by Type of R&D

In 2020, basic research activities in all sectors accounted for $111.9 billion, or 16% of U.S. total R&D expenditures (table 4). Applied research was $133.3 billion, or 19% of the total. Most of the total of U.S. R&D expenditures was experimental development at $471.7 billion, or 66%.

The higher education sector accounted for just under half (45%) of basic research performance in 2020 (table 4). The business sector was the second-largest basic research performer (33%). Business was the majority performer (59%) of the $133.3 billion of applied research in 2020. Higher education was second at 17%; federal intramural performers plus FFRDCs accounted for 16% of the applied research total. Business continued to dominate development performance, accounting for 91% of the U.S. total $471.7 billion of that category in 2020.

Federal funding accounted for 41% of the $111.9 billion of basic research in 2020 (table 3). But federal funds were less prominent for applied research (33% of $133.3 billion) and experimental development (12% of $471.7 billion). The business sector provided the greatest share of funding for applied research (56%) and the predominant share for experimental development (86%). Interestingly, it also accounted for a sizable share (34%) of funding for basic research.

Over the 2010–20 period, the split of U.S. total R&D expenditures among the three types of R&D did not largely change. The share of applied research ranged between 19% and 21% throughout the period (table 4). Similarly, except for 2010 (possibly impacted by ARRA funds), the share of basic research remained in the 16%–17% range. Experimental development's share was 62% in 2010 and remained at or below 66% through 2020. Adjusting for inflation, about $19 billion more in basic research was performed in 2020 than in 2010, $35 billion more in applied research, and $153 billion more in experimental development.

Table 4

U.S. R&D expenditures, by type of R&D: Selected years, 1970–2021

(Billions of current and constant 2012 dollars and percent)

Type of R&D	1970	1980	1990	2000	2010	2011	2012	2013	2014
					Current $billions				
All R&D	26.3	63.2	152.0	267.9	406.6	426.2	433.7	454.3	476.
Basic research	3.6	8.7	23.0	42.0	76.4	73.6	73.8	79.1	82.
Applied research	5.8	13.7	34.9	56.5	79.0	81.9	86.8	88.2	91.
Experimental development	16.9	40.7	94.1	169.4	251.2	270.8	273.1	287.0	301.
					Constant 2012 $billions				
All R&D	121.2	149.6	238.7	343.4	422.8	434.2	433.7	446.5	459.
Basic research	16.6	20.7	36.2	53.9	79.4	74.9	73.8	77.8	79.
Applied research	26.5	32.5	54.8	72.4	82.2	83.4	86.8	86.6	88.
Experimental development	78.1	96.4	147.7	217.1	261.2	275.8	273.1	282.0	290.
					Percent distribution				
R&D performance									
All R&D	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.
Basic research	13.7	13.8	15.2	15.7	18.8	17.3	17.0	17.4	17.
Applied research	21.9	21.7	23.0	21.1	19.4	19.2	20.0	19.4	19.
Experimental development	64.4	64.5	61.9	63.2	61.8	63.5	63.0	63.2	63.
R&D performance by performer									
Basic research	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.
Business	15.7	13.8	20.1	16.7	21.4	17.7	18.0	24.7	26.

NA = not available.

FFRDC = federally funded research and development center.

[a] Some data for 2020 are preliminary and may be revised later.
[b] The data for 2021 include estimates and are likely to be revised later.

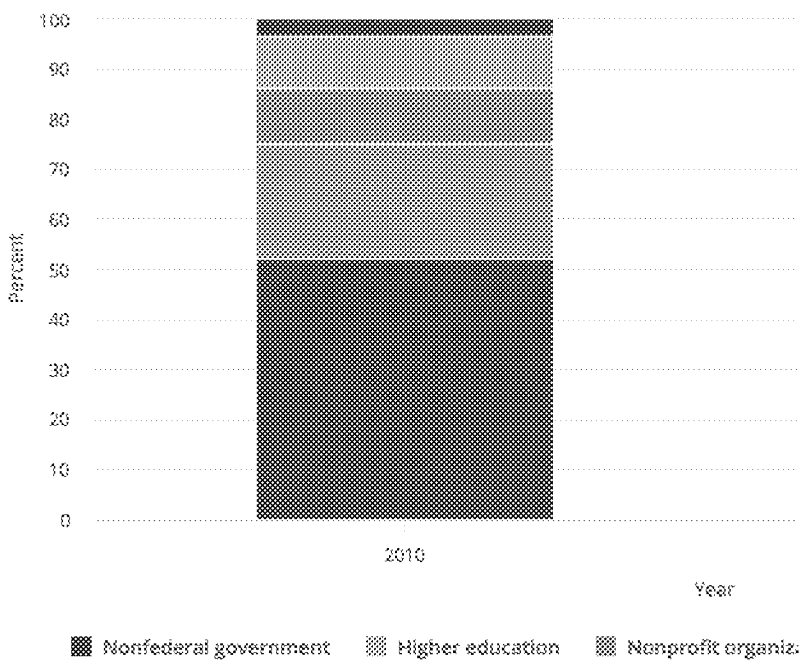
Note(s):
Data throughout the span of time reported here are consistently based on Organisation for Economic Co-operation and Development *Frascati Manual* definitions for basic research, applied research, and experimental development. Prior to 2010, however, some changes had been introduced in the questionnaires of the sectoral expenditure surveys to improve the accuracy of respondents' classification of their R&D by type. Accordingly, small percentage changes in the historical data may not be meaningful.

Source(s):
National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).

The shifting in the relative roles of performers and funders by sector—particularly among business, government, and higher education—are of great interest (table 4, figure 3). In 2010, businesses performed 21% of U.S. basic research, but the sector's share of basic research rose to 33% by 2020. The share of U.S. basic research performed by higher education institutions—historically, the nation's largest basic research performer—declined from 51% in 2010 to 45% in 2020, although in absolute terms higher education basic research performance increased from $39 billion to $51 billion during this period. Further, businesses funded 23% of U.S. basic research in 2010, rising to 34% in 2020 (figure 3). Over the same period, the federally funded share declined from 52% in 2010 to 41% in 2020. The increased relative performance of the business sector as a performer and funder of basic research is remarkable.

Figure 3

Basic research, by source of funds 2010 and 2020



Data View

Note(s):
Some data for 2020 are preliminary and may be revised later.

Source(s):
National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).

Data Sources, Limitations, and Availability

The statistics on U.S. R&D presented in this report derive mainly from integrating the data on R&D expenditures and funding collected by NCSES's annual national surveys of the organizations that perform and fund the vast majority of U.S. R&D. These surveys cover each of four sectors of the economy: higher education, government, business enterprise, and nonprofit organizations.[10] In some cases, the primary data from these surveys are adjusted to enable consistent integration of the statistics across these separately conducted surveys. In addition, preliminary or otherwise estimated values may be used where final data from one or more of the surveys are not yet available but can reasonably be calculated. Estimates in this InfoBrief are based on census and sample survey data which are subject to nonsampling error. Sample-survey–based estimates are also subject to sampling error. All comparative statements in this InfoBrief have undergone statistical testing and are significant at the 90% confidence level except statements reliant on modeled estimates.

The R&D surveys include NCSES's annual surveys of business R&D (the Business Enterprise Research and Development Survey for 2019–20, the preceding Business Research and Development Survey for 2017–18, the Business R&D and Innovation Survey for 2008–16, and the Survey of Industrial R&D for 2007 and earlier years). In addition, the business R&D totals include the R&D expenditures reported by "micro" companies (defined as companies with fewer than 10 employees) through NCSES surveys fielded for 2016 and forward (the 2016 Business R&D and Innovation Survey—Microbusiness and the Annual Business Survey (ABS) since 2017).[11] Other NCSES survey data sources are the Higher Education Research and Development Survey (for FYs 2010–20), and the preceding Survey of R&D Expenditures at Universities and Colleges (FY 2009 and earlier years), the Survey of Federal Funds for Research and Development (FYs 2020–21 and earlier years), and the FFRDC Research and Development Survey (FY 2020 and earlier years). Amounts for the R&D performed by nonprofit organizations with funding from the nonprofit sector and from business sources are estimated based on data and parameters from the FY 2020 Nonprofit Research Activities (NPRA) module of the ABS, the 2016 NPRA Survey, and the 1996–97 Survey of R&D Funding and Performance by Nonprofit Organizations.

A full set of detailed statistical tables associated with the National Patterns data is available in the companion report: *National Patterns of R&D Resources: 2020–21 Data Update*, at https://ncses.nsf.gov/pubs/nsf23321. This supplementary report also provides further details on the nature of the data and the *National Patterns* methodologies. For further information and questions, contact the author.

Notes

1 *Research and experimental development* (R&D) comprise creative and systematic work undertaken in order to increase the stock of knowledge—including knowledge of humankind, culture,

and society—and to devise new applications of available knowledge. *Basic research* is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundations of phenomena and observable facts, without any particular application or use in view. *Applied research* is original investigation undertaken in order to acquire new knowledge; directed primarily toward a specific, practical aim or objective. *Experimental development* is systematic work, drawing on knowledge gained from research and practical experience and producing additional knowledge, which is directed to producing new products or processes or to improving existing products or processes. See Organisation for Economic Co-Operation and Development (OECD). 2015. *Frascati Manual 2015: Guidelines for Collecting and Reporting Data on Research and Experimental Development.* The Measurement of Scientific, Technological and Innovation Activities, OECD Publishing: Paris. Available at https://doi.org/10.1787/9789264239012-en.

2 In this report, dollars adjusted for inflation (i.e., constant dollars) are based on the gross domestic product (GDP) implicit price deflator (currently in 2012 dollars) as published by the Bureau of Economic Analysis (BEA) at https://www.bea.gov/iTable/index_nipa.cfm. Note that GDP deflators are calculated on an economy-wide scale and do not explicitly focus on R&D.

3 Inflation measured by the Consumer Price Index (CPI) for 2014–20 ranged between 0.1% and 2.4%. In 2021, inflation was 4.7% (https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1913-).

4 Due to sample variability in the data for the business R&D component, the calculated R&D-to-GDP ratios for 1964, 2009, and 2017 are not significantly different from one another at a 90% confidence level.

5 See Organisation for Economic Co-Operation and Development, *Main Science and Technology Indicators, 2022*, Paris. Available at https://www.oecd.org/sti/msti.htm.

6 Additional statistics on R&D performed in the United States by the business sector are available at https://www.nsf.gov/statistics/srvyberd/. See also Wolfe R; National Center for Science and Engineering Statistics (NCSES). 2022. *Businesses Spent Over a Half Trillion Dollars for R&D Performance in the United States During 2020, a 9.1% Increase*

Over 2019. NSF 22-343. Alexandria, VA: National Science Foundation. Available at http://ncses.nsf.gov/pubs/nsf22343.

7 The data on higher education R&D reported by *National Patterns* differ from the underlying survey data in several respects. First, *National Patterns* translates the Higher Education R&D (HERD) Survey's primary data in academic fiscal years to calendar year equivalents. Second, *National Patterns* reports higher education R&D expenditures that are adjusted to remove the double-counting of pass-through funding that are included in HERD Survey source data. For further details on this topic, see "Technical Notes" in the companion report National Center for Science and Engineering Statistics (NCSES). 2023. *National Patterns of R&D Resources: 2020–21 Data Update*. NSF 23-321. Alexandria, VA: National Science Foundation. Available at https://ncses.nsf.gov/pubs/nsf23321.

8 The number of FFRDCs reflects that NCSES was informed in June 2021 that the Green Bank Observatory separated from the National Radio Astronomy Observatory in October 2016 to become an independent institution; both retained FFRDC status. The Master Government List of FFRDCs was subsequently updated to reflect this change.

9 The most recent data on nonprofit organization R&D come from the FY 2020 Nonprofit Research Activities (NPRA) module of the ABS and the 2016 NPRA Survey. Data for nonprofit organization R&D, 2017–19 are estimated based on the 2016 and 2020 data. The availability of 2020 survey data allowed for improved measurement of nonprofit R&D performance over 2017–21 period, resulting in minor changes to previously published estimates. For 1998–2015, data for nonprofit organization R&D funded by the federal government come from the NCSES annual Survey of Federal Funds for Research and Development; data for that funded by businesses and by the nonprofit sector itself are estimated, based on parameters from the 1996–97 Survey of Research and Development Funding and Performance by Nonprofit Organizations.

10 For further details on the correspondence between sectors used to measure R&D and those used in the System of National Accounts, please see the *Frascati Manual 2015: Guidelines for Collecting and Reporting Data on Research and Experimental Development*.

11 Estimates from the NCSES business R&D surveys mentioned are all derived from sample data and thereby contain sampling error. Consequently, estimates of total U.S. R&D also contain sampling error. For more information on this topic and other surveys used in the *National Patterns* tabulations, see the "Technical Notes" in the companion report available at https://ncses.nsf.gov/pubs/nsf23321.

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Contact Us

Report Authors

Gary Anderson
Acting Program Director
NCSES
Tel: (703) 292-9092
E-mail: ganderso@nsf.gov

John Jankowski
Senior Economic Advisor (retired)
NCSES

Mark Boroush
Senior Analyst (retired)
NCSES

NCSES

National Center for Science and Engineering Statistics
Directorate for Social, Behavioral and Economic Sciences
National Science Foundation
2415 Eisenhower Avenue, Suite W14200
Alexandria, VA 22314
Tel: (703) 292-8780
FIRS: (800) 877-8339
TDD: (800) 281-8749
E-mail: ncsesweb@nsf.gov

National Center for Science and Engineering Statistics
2415 Eisenhower Avenue, Suite W14200, Alexandria, VA 22314
Tel: (703) 292-8780 FIRS: (800) 877-8339 TDD: (800) 281-8749

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FTC's Non-Compete Law Could Propel Rise in Trade Secrets Lawsuits

Published: Feb 08, 2023 | By Rosemary Scott

Courtesy Getty Images

Trade secrets litigations and disputes have been on the rise in recent years, especially in fields with increased competition and sensitive data like the biopharma industry.

Given the Federal Trade Commission's **recent proposal** to ban all non-compete agreements nationwide, the trend is likely to continue. If passed, the rule would force biotech companies to find another way to protect themselves against the unlawful sharing of confidential information.

In the past year alone, trade secrets lawsuits involving industry leaders like **Roche** and **Pfizer** have graced headlines, but million-dollar suits filed by large pharma companies are only the tip of the proverbial iceberg.

What is - and isn't - a Trade Secret

A **report** published by investment bank and advisory firm Stout showed that in 2020, federal cases pertaining to trade secret disputes yielded $3 billion in damages.

The authors of the report predicted litigation activity will continue to expand in the coming years due in part to an increase in technological advancement and the digitization of information. They also cited the Defend Trade Secrets Act of 2016 (DTSA) as a cause.

Gregory Bombard, legal expert and trial lawyer at Greenberg Traurig, called the DTSA "the most significant change in trade secret law in the last 10 years."

He told *BioSpace* that previously, trade secrets cases were litigated in state courts under state law. The act brought a **uniform definition** and protection for trade secrets across the U.S.

The United States Patent and Trademark Office (USPTO) states that under federal law, a trade secret:

- is information that has either actual or potential independent economic value by virtue of not being generally known,
- has value to others who cannot legitimately obtain the information, and
- is subject to reasonable efforts to maintain its secrecy.

Bombard said the phrase "reasonable efforts," meant to describe an employer's actions to protect their confidential information, is one of the primary points contested in a trade secrets lawsuit.

"That definition is relatively malleable," he said. "As long as the court finds that a plaintiff has taken reasonable measures to keep the information secret, that information can qualify as a trade secret."

Nicholson Price, a professor of law at the University of Michigan law school, told *BioSpace* that one of the most common reasonable measures employers take is requiring employees to sign non-compete agreements, effectively stopping the sharing of information before it can begin.

"Non-competes are another way of achieving that goal by saying that you can't even put yourself in a position to use our secret information, because for some period of time, you can't work for a company where that information would be useful," Nicholson said.

However, if the FTC's ban on non-competes goes into effect, companies will have to rely on other measures, such as non-disclosure agreements and restricting access to sensitive information altogether.

The Burden of Proof

Once the information has met all the requirements to be protected under trade secret law, the plaintiff must then prove the defendant is guilty of misappropriation.

In some cases, of course, there is hard evidence, like a hard drive or computer filled with sensitive information that a former employee gave to their new employer.

But in others, the case must be built based on circumstantial evidence, often presented in the form of a product or research that the plaintiff believes the company in question could not have produced on its own.

These cases include myriad challenges for the court, especially when life sciences companies are involved.

By nature, a trade secret is meant to be just that - secret. But when a plaintiff is presenting their case in court, they walk a tightrope between proving sensitive information has been shared and not revealing said information to the public.

For example, in 2021, Oakwood Laboratories **brought its case** against Dr. Bagavathikanun Thanoo to the Third Circuit Court of Appeals after a district court had dismissed the company's complaint four separate times.

The information in question was related to a microsphere technology, which cost Oakwood $130 million dollars and took over 20 years to develop. In contrast, it took Aurobindo Pharma, the company that employed Thanoo, only a few years, much less money and a much smaller pool of resources to develop the same technology.

The district court argued that even though Oakwood submitted over **16 exhibits** describing the information that was misappropriated, it did not adequately define the trade secrets in question.

The Third Circuit overturned this ruling. It wrote that the district court's demand for further precision in the pleading was "misplaced," and "ignore[d] the challenges a trade secret plaintiff commonly faces when only discovery will reveal exactly what the defendants are up to."

Shades of Gray

Bombard called these types of cases "gray in nature." They often contain multiple shades, as even after a plaintiff shows the court that confidential information was, in fact, shared, they then have to prove exactly who shared it.

This is difficult for life sciences companies, as there is often an overlap between the skills and knowledge that researchers and scientists gain throughout their careers and the sensitive information they acquire in their time in a specific role.

"The court has to try to distinguish between what information in that person's head is confidential or secret information belonging to their old employer and what comes from their own general skill and knowledge as a scientist," Bombard said. "Those can be very challenging questions to work out."

Still, the same **report** that added up the billions in damages from trade secrets cases also showed that well over half (68%) of the cases studied were ruled in favor of the plaintiffs.

This shows that though the burden of proof is heavy, as long as pharma companies take reasonable precautions, the court is likely to rule in their favor.

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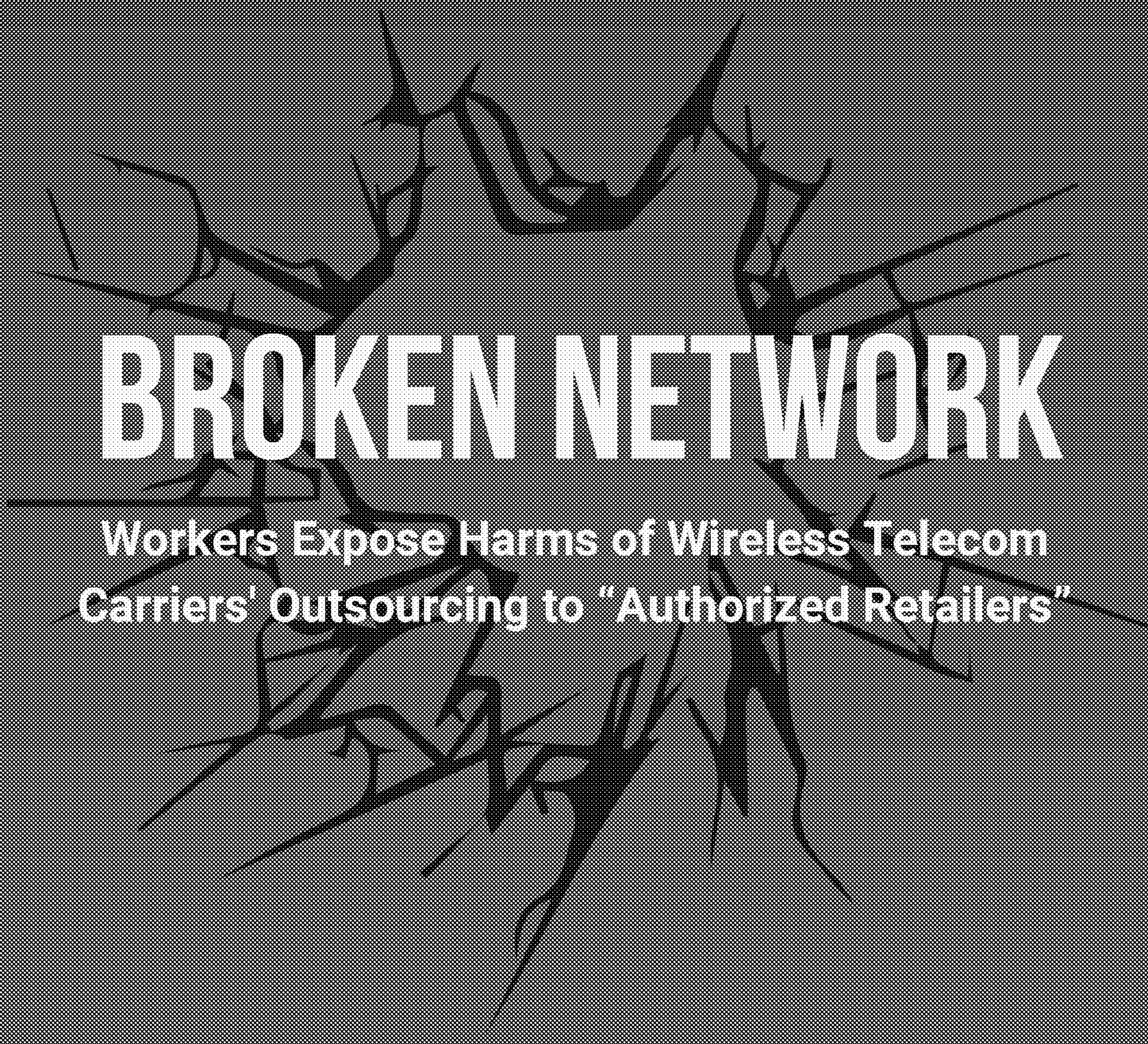

Workers Expose Harms of Wireless Telecom Carriers' Outsourcing to "Authorized Retailers"

FEBRUARY 2023

COMMUNICATIONS WORKERS OF AMERICA AND NATIONAL EMPLOYMENT LAW PROJECT

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Findings from a new worker survey and worker interviews reveal that AT&T, T-Mobile, and Verizon outsourcing of retail work to "authorized retailers" is associated with unstable wages, inadequate training, fraudulent sales practices, among other job and customer service issues, and often comes with various forms of carrier control over store operations.

INTRODUCTION

In 2022, Verizon Wireless employees in Washington, Oregon, and Illinois joined the wave of U.S. retail workers unionizing to demand better pay and working conditions.[1] Overcoming illegal union busting tactics by management, workers voted to form a union with the Communications Workers of America (CWA), uniting with fellow Verizon Wireless retail workers in New York who had unionized in 2014, and joining counterparts at AT&T Mobility who have unionized corporate stores nationwide.[2] Organizing and contract wins by Verizon and AT&T employees are turning tens of thousands of retail jobs in the wireless telecommunications industry into good jobs and ensuring that a well-trained workforce provides good quality service to customers in numerous communities across the country.

However, not all retail workers in the wireless telecommunications industry have the ability to form a union and bargain directly with the company that holds power over their wages and working conditions. The industry's three dominant carriers—AT&T, T-Mobile, and Verizon—outsource most of their retail operations to third parties, referred to as "authorized retailers" or "authorized dealers."[3]

Outsourcing in the wireless telecom industry is far from unusual in today's economy. Millions of workers across industries and occupations, from workers at McDonald's franchises to ride-hail drivers mislabeled as independent contractors by Uber to workers at AT&T authorized retailers, have been placed in work arrangements that shield their employers from liability for job quality and make union organizing and collective bargaining difficult to impossible. This pervasive "workplace fissuring" has played a central role in denying workers legal protections, undercutting wages and working conditions, and shielding large corporations from accountability for the treatment of the workers integral to the success of their businesses.[4]

What does the outsourcing of retail operations in the wireless telecom industry mean for workers and customers?

To learn about job and service quality issues at carrier-licensed retailers, CWA and the National Employment Law Project reached out to workers at AT&T Mobility, Verizon Wireless, and T-Mobile authorized retailers using online advertisements. Sharing their experiences through an online survey and a series of telephone interviews, 204 authorized retailer workers from 43 states provided a first-of-its-kind look at the effects of outsourcing in the wireless telecom industry.

KEY FINDINGS:

- **Unstable wages:** Almost 3 in 4 authorized retail workers surveyed reported that 25 percent or more of their pay was derived from commissions tied to sales, and about 4 in 5 workers worried about meeting basic financial responsibilities as a result of receiving less than their expected levels of commissions or bonuses.

- **Wage theft:** More than 9 in 10 authorized retail workers surveyed reported that an employer had stolen wages from them in at least one of four ways—paid them below the minimum wage rate, denied them overtime premiums, denied them due commissions or bonuses or incentive payments, or required them to work off the clock.

- **Exhausting schedules:** Nearly 2 in 3 authorized retail workers surveyed reported that they were unable to take meal or rest breaks during their shift. Nearly half of authorized retail workers surveyed reported that they were required to work overtime.

- **Inadequate job training:** More than half of authorized retail workers surveyed reported that they did not receive the training they needed to do their jobs effectively.

- **Retaliatory work environments:** More than half of authorized retail workers surveyed reported that they had experienced negative treatment from their employer for raising workplace issues.

- **Curtailed job mobility due to non-competes:** Almost 1 in 3 authorized retail workers surveyed reported that they were subject to a non-compete agreement preventing them from taking a job at a competing firm for a period of time. Another third were not sure whether they had signed such an agreement.

- **Fraudulent sale practices:** Workers at authorized retailers in survey comments and interviews described witnessing dishonest sales practices in their workplace and reported that these practices were acknowledged or encouraged by management.

- **Poor customer service quality:** Just over 4 in 10 authorized retail workers surveyed rated customer service provided by their store as somewhere between awful and adequate.

- **Carrier control:** About 9 in 10 authorized retail workers surveyed reported that the wireless carrier that licensed their direct employer played a role in setting policies and practices at their workplace, raising doubts about authorized retailers' status as independent employers.

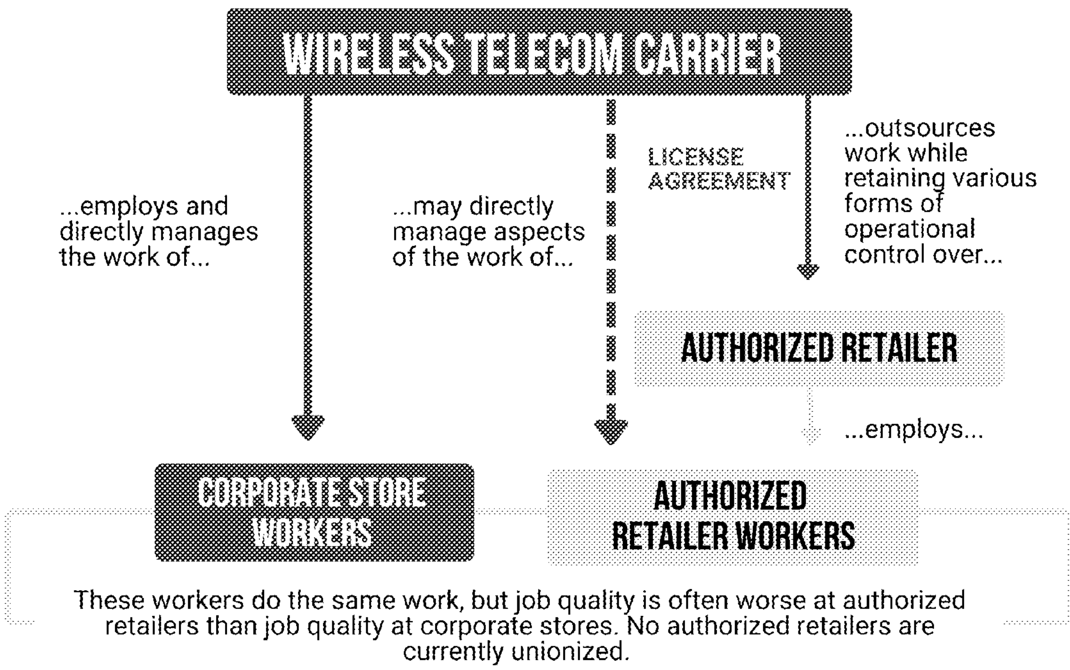
These findings point to the need for worker organizing, federal policies to expand organizing rights and other worker protections, and more resources for enforcement of labor and employment laws on the books.

THE WIRELESS TELECOMMUNICATIONS INDUSTRY AND AUTHORIZED RETAILERS

Smartphones have become an integral part of modern life, and just about everybody owns one.[5] Indeed, smartphone sales and servicing is big business; the three carriers—AT&T, T-Mobile, and Verizon—that dominate the wireless telecommunications industry together took in $337.1 billion in revenue in 2022.[6]

The workforce retailing smartphones and providing technical assistance to customers is large, numbering around 200,000, and is spread across 36,500 brick-and-mortar stores located in every corner of the country.[7] While tens of thousands of these workers have unionized, carriers are increasingly outsourcing retail work in the wireless telecom industry, eliminating good union jobs and negatively impacting customer service quality.

As the diagram below illustrates, wireless telecom carriers sell products and services via both corporate stores and authorized retailers.



Carriers formalize their relationship with authorized retailers using license agreements. Unlike a franchise agreement, a license agreement does not require the payment of upfront fees by the licensee to the licensor.[8] This legal difference enables licensors (the carriers) to avoid disclosures required under franchise laws.

Wireless carriers currently outsource the operation of between 60 to 80 percent of their branded retail locations to authorized retailers. AT&T's escalated use of authorized retailers in the last five years—from 61 percent of stores in January 2018 to 73 percent in December 2022—coincided with a loss of 10,000 union-represented jobs.

Authorized retailers range in size from mom-and-pop operations running a single store to large companies that operate thousands of stores—for example, AT&T's largest authorized retailer, Prime Communications, operates nearly 2,000 AT&T-branded stores nationwide.[9]

Stores run by third parties may look identical to corporate stores, aside from a small "Authorized Retailer" label on the storefront window. However, differences in job quality and customer service quality between corporate stores and authorized retailers can be stark.

In a telephone interview, one worker explained that she had recently been transitioned out of a unionized corporate store job by a carrier when her store was closed and converted to an authorized retailer. She noticed differences in job quality just weeks after the transition. She described differences in pay structure: "The commission structure is different. They don't have six month raises." About the transition, she said, "The company kind of threw us to the wolves. That's how I feel."

T-Mobile and Verizon, through trade group affiliation, support public policy change that facilitates "workplace fissuring." The carriers are members (Verizon via a trade group called TechNet and T-Mobile via the Retail Industry Leaders Association) of a mega-lobby group called the Coalition for Workforce Innovation that is aimed at changing federal policy to lock workers across occupations, industries, and work arrangements into "independent contractor" or nonemployee status, stripping workers of fundamental labor rights and protections.[10] To this end, the group backed legislation called the Worker Flexibility and Choice Act, which was introduced in the U.S. House of Representatives in July of 2022.[11] The Coalition for Workforce Innovation has also been a fierce opponent of the Protecting the Right to Organize (PRO) Act, which strengthens organizing and collective bargaining rights.[12]

COMMISSION-DRIVEN PAY AT AUTHORIZED RETAILERS CREATES UNSTABLE WAGES

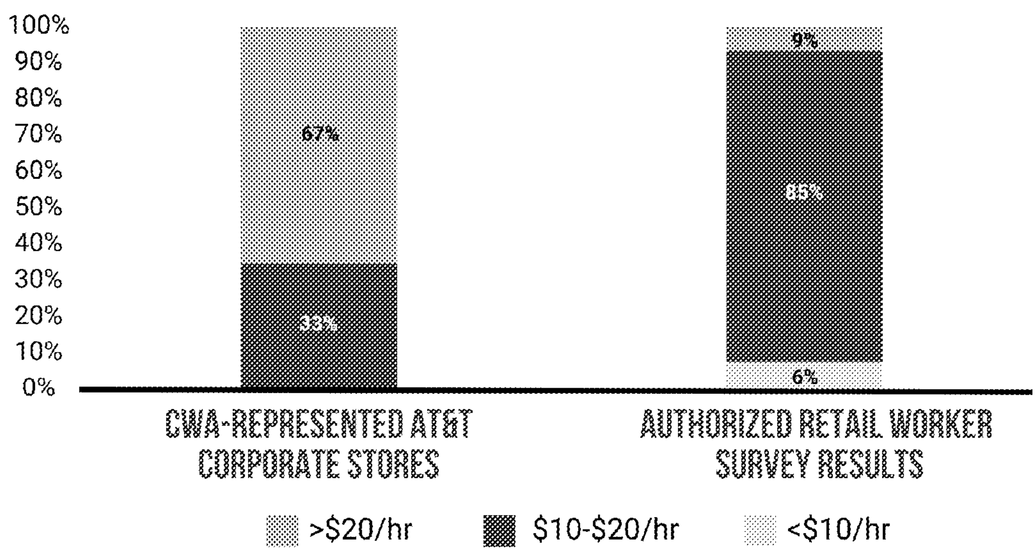
Wireless authorized retail workers in the survey were asked about their hourly base pay rates, excluding any commissions or bonuses that are "at-risk," meaning they are dependent on successfully hitting individual or team sales goals.

Low Levels of Base Pay: Nearly three-quarters (150 of 204) of authorized retail workers surveyed reported making less than $16 per hour in base pay. Nearly one-quarter (44 of 204) of workers surveyed reported making less than $12 per hour. Less than 1 in 10 (18 of 204) workers surveyed reported making more than $20 per hour.

THE UNION DIFFERENCE REGARDING HOURLY WAGES

Base pay rates for surveyed workers at authorized retailers are lower than the rates of union-represented retail store employees working directly for AT&T. CWA-represented Retail Sales Consultants across AT&T received an average hourly base wage of $19.77 in December 2022. Approximately 67 percent of CWA-represented AT&T corporate store workers make more than $20 per hour in base pay and only 11 percent make less than $16 per hour.

Comparing the distribution of base pay rates between surveyed authorized retail workers and CWA-represented Retail Sales Consultants at AT&T corporate stores across the country shows that union bargaining significantly improves worker pay.



The carriers pay authorized retailers a commission on each sale and this business model is reflected in how workers are paid. We asked workers at authorized retailers about commission pay.

Receive Commissions: More than 9 in 10 authorized retail workers surveyed (192 of 204) reported receiving commissions or bonus payments in addition to hourly base pay.

Share of Pay in Commissions: Nearly 3 in 4 (142 of 192) authorized retail workers surveyed who responded that they receive commissions or bonus payments reported that commissions or bonus payments comprised more than a quarter of their take-home pay, and more than 2 in 5 (84 of 192) reported that such pay made up over half of their take-home pay.

The reliance on commission pay for workers at authorized retailers creates financial instability. They are vulnerable to fluctuations in the business and also changes in their employer's sales quotas.

Financial Insecurity: About 4 in 5 authorized retail workers surveyed (159 of 204) reported worrying about meeting basic financial responsibilities (for example, paying mortgage, rent, groceries) as a result of receiving less than their expected levels of bonuses, incentive payments, or commission.

One T-Mobile authorized retail employee in Kansas reported struggling with sales targets: "You can't get commissions if you can't make sales...There were sometimes times when we would get maybe three people in the door. Maybe. [Management's] solution for us not hitting the sales goal was that we should have pushed everything on those three people."

A worker at an AT&T authorized retailer in New Jersey reported that the company made "constant additions to sales quotas to decrease pay." This was an experience reported by other authorized retail workers as well. A worker at a T-mobile authorized retailer in Texas reported that monthly changes to the commission structure "made it nearly impossible to get paid out."

THE UNION DIFFERENCE REGARDING COMMISSIONS

Under labor agreements for retail store employees working directly for AT&T, minimum commission payments at 100% of sales targets make up just over 20% of the total compensation package. Union workers have bargained for more stable take-home pay, shifting a greater share of earnings into base pay rather than at-risk commissions. In 2017, AT&T members negotiated a new agreement that moved 25% of their at-risk commission payment into base hourly pay.

THE CARRIER ROLE IN SETTING PAY FOR WORKERS AT AUTHORIZED RETAILERS

More than 3 in 5 (124 of 204) authorized retail workers surveyed reported that carriers were involved in setting performance benchmarks, which determine payments from commission plans.

MANY WORKERS AT AUTHORIZED RETAIL STORES DO NOT RECEIVE ESSENTIAL WORKPLACE BENEFITS

Access to employment benefits is an important issue for retail workers. Workers in this survey were asked whether they received basic benefits from their employer: health insurance, retirement, paid vacation, and paid sick leave. Access to these benefits was not universal. In particular, less than half of respondents reported access to retirement benefits and paid sick leave.

Health Insurance: About 1 in 4 (56 of 204) authorized retail workers surveyed reported that they did not receive health insurance from their employer.

Retirement Benefits: More than half (108 of 204) of authorized retail workers surveyed reported that they did not receive a retirement benefit from their employer.

Paid Sick Leave: More than half of authorized retail workers surveyed (112 of 204) reported that they did not receive paid sick leave from their employer.

Paid vacation: About 1 in 3 (63 of 204) authorized retail workers surveyed reported that they did not receive paid vacation from their employer.

THE UNION DIFFERENCE REGARDING EMPLOYMENT BENEFITS

Union-represented AT&T retail workers have collectively bargained agreements guaranteeing each of the benefits above, as well as vision, dental, disability, and life insurance.

EMPLOYMENT BENEFIT	AUTHORIZED RETAIL WORKER SURVEY RESULTS	CWA-REPRESENTED AT&T CORPORATE STORES
Employer-subsidized health insurance	Fewer than 3 in 4 workers (148 of 204)	All workers
Retirement benefit	Fewer than 1 in 2 workers (96 of 204)	All workers - 401k match and Cash Balance Pension Plan[13]
Paid sick leave	Fewer than 1 in 2 workers (92 of 204)	All workers - Up to 10 days per year based on service
Paid vacation	About 2 in 3 workers (141 of 204)	All workers - Up to 5 weeks per year based on service

WORKERS AT AUTHORIZED RETAILERS REPORT WIDESPREAD WAGE THEFT

Authorized retailers have come under legal fire for various forms of wage theft. A lawsuit involving 4,600 workers at Verizon retailer Cellular Connection and alleging unpaid off-the-clock work in violation of the Fair Labor Standards Act was settled for $2.4 million in November 2020.[14] The Verizon authorized retailer Victra settled a class action lawsuit involving 20,000 employees and alleging failure to pay overtime for $1.86 million in December 2020.[15] In January 2020, Prime Communications, an AT&T authorized retailer paid $660,000 to settle a class action lawsuit alleging theft of commissions and overtime pay.[16]

"This company will steal your money and your time."

-T-Mobile Authorized Retail Employee in Louisiana

Workers at authorized retailers were asked whether they had experienced various forms of wage theft in the three months prior to the survey. Reports of wage theft were widespread.

Any form of wage theft: More than 9 in 10 (186 of 204) authorized retail workers surveyed reported that an employer had stolen wages from them in at least one of four ways—paid them below the minimum wage rate, denied them overtime premiums, denied them due commissions or bonuses or incentive payments, or required them to work off the clock.

Required off-the-clock work time: More than 2 in 5 (86 of 204) authorized retail workers surveyed reported that they had been required to work off the clock.

Unpaid commissions: While commissions comprise a large share of workers' overall pay (as described above), more than a third (72 of 204) of authorized retail workers surveyed reported not being paid commissions, bonuses, or incentive payments owed to them.

Unpaid overtime premiums: Nearly a third (62 of 204) of authorized retail workers surveyed reported not receiving overtime pay owed to them.

A worker at a T-Mobile authorized retailer in Louisiana reported experiencing multiple forms of wage theft. With an hourly base pay rate of less than $12, she relied heavily on commissions to make ends meet. However, she was regularly denied commission payments due to her. "They cheat you out of your commission," she said of the T-Mobile licensee employing her. Furthermore, she reported that her employer denied her overtime pay and required her to work off the clock. "This company will steal your money and your time," she said.

A Verizon authorized retailer worker in Alabama described how a faulty performance tracking system led to unpaid commissions daily, and no repair was offered. "Everyday [there] are system issues that are out of our control that goes against our metrics that they refuse to fix and our pay is affected."

THE CARRIER ROLE IN CREATING WAGE AND HOUR ISSUES FOR WORKERS AT AUTHORIZED RETAILERS

More than a third (76 of 204) of workers surveys reported that carriers were involved in setting employee work schedules.

More than 3 in 5 (124 of 204) workers reported that carriers were involved in setting performance benchmarks. These performance benchmarks are informed by carrier-determined commission structures designed to drive sales and generate profits for authorized dealers and for carriers.

SCHEDULING ISSUES AT AUTHORIZED RETAILERS OFTEN LEAD TO OVERWORK AND UNPREDICTABLE SCHEDULES

Unstable and abusive scheduling practices are common across the retail and service industry.[17] Workers at authorized retailers were asked about their work schedules. Most workers reported that the days and hours they were scheduled to work changed from week to week. Overwork was a common complaint, and a large share of workers also reported experiencing unexpected cuts to their work hours.

Fluctuating schedules: 4 in 5 (163 of 204) authorized retail workers surveyed reported that their hours or work days changed from one week to the next.

Working without breaks: Nearly 2 in 3 (134 of 204) authorized retail workers surveyed reported that they were unable to take meal or rest breaks during their shift. While meal and rest breaks are not required under federal law, many states require both.[18]

Forced overtime: Nearly half (96 of 204) of authorized retail workers surveyed reported that they were required to work overtime.

Unpaid on-call time: 1 in 3 (67 of 204) authorized retail workers surveyed reported that they were forced to remain on call without pay and without guaranteed hours. On-call hours hinder the ability of workers to balance work and life, and to do other paid work.

Last-minute cuts to scheduled work time: 1 in 4 (51 of 204) authorized retail workers surveyed reported that they had been sent home from work early without pay.

THE UNION DIFFERENCE REGARDING WORK SCHEDULES

Union-represented AT&T store employees have bargained protections around their work schedule that give them flexibility and predictability while keeping their income consistent, including:

1. Scheduling based on seniority
2. Two weeks advance notice of monthly schedules
3. Paid leave, including vacation, holidays, illness, and short notice "excused with pay" time
4. Quota relief which ensures that days off don't come at the expense of sales goals and commissions.

In addition, before requiring overtime hours, AT&T must provide an explanation of emergency business needs to the local union and provide the expected duration of the temporary overtime schedules.

INADEQUATE JOB TRAINING CONTRIBUTES TO POOR CUSTOMER SERVICE AND HIGH TURNOVER

Employee training is an essential element of good customer service. Customers expect knowledgeable staff prepared to help them address technical issues and navigate complicated company policies and sales promotions. Workplace training has also been found to be correlated with reductions in workplace stress for customer service workers.[19]

Authorized retail workers were asked about the job training they received and about the level of customer service provided by their store.

> "No one in this company has been properly trained or know[s] what they are doing."
>
> -AT&T Authorized Retail Employee in Alabama

Inadequate training: More than half (105 of 204) of authorized retail workers surveyed reported that they did not receive the training they needed to do their jobs effectively.

Customer service: Just over 4 in 10 (67 of 204) authorized retail workers surveyed rated customer service provided by their store as somewhere between awful and adequate.

An AT&T Mobility authorized retailer worker in Alabama who said that AT&T had a hand in providing training to workers said, "No one in this company has been properly trained or know[s] what they are doing." She rated the customer service in her store as "awful."

A worker at a T-Mobile authorized retailer in Texas said that there was "little to no training for new employees," and attributed poor training to high turnover rates.

THE CARRIER ROLE IN TRAINING AUTHORIZED RETAILER WORKERS

More than half (108 of 204) of workers surveyed reported that carriers were involved in the job training they received.

WORKERS REPORT RETALIATORY WORKPLACES AND UNFAIR TERMINATIONS

Workers were asked whether they had experienced employer retaliation for raising workplace issues. And several workers reported being fired without just cause.

Retaliation for speaking up about workplace issues: More than half (108 of 204) of authorized retail workers surveyed reported that they had experienced negative treatment from their employer for raising workplace issues.

A worker at a T-Mobile authorized retailer in Oklahoma reported that her employment was imperiled when she raised concerns about cutbacks to her hours following a raise in her pay rate. "Since my hourly pay rate was raised, I have lost hours on my schedule. When I raised this issue to my boss, he threatened to fire me."

Unfair termination: Several workers shared stories of being fired without warning or just cause.

An AT&T authorized retailer worker in Michigan described being terminated following a long bout of COVID-19. "I had COVID for 2 months and they fired me for it."

A worker at a T-Mobile authorized retailer in Missouri described how he was fired "with ZERO write ups or verbal warnings," his manager attributing his termination to his failure to meet "numbers."

THE UNION DIFFERENCE REGARDING DISCIPLINE AND TERMINATIONS

Unionized retail workers have just cause protection under their contract from arbitrary or unfair discipline and dismissal. CWA agreements covering retail workers at Verizon and AT&T also have grievance and arbitration procedures designed to resolve workplace issues in a fair and equitable manner.

THE CARRIER ROLE IN DISCIPLINING AND TERMINATING AUTHORIZED RETAILER WORKERS

More than 4 in 10 (90 of 204) workers surveyed reported that carriers were involved in disciplining or terminating workers.

OBSTRUCTION OF JOB MOBILITY THROUGH NON-COMPETE AGREEMENTS IN EMPLOYMENT CONTRACTS

Nearly one in five U.S. workers is subject to "non-compete" agreements that prevent them from taking a job at a rival firm (which may be very broadly defined) for what may be an extended period of time.[20] Non-compete agreements can lock workers into bad jobs, weaken workers' labor market and bargaining power, and force workers into underemployment and unemployment.

Workers were asked whether they had signed a non-compete agreement with their employer barring them from taking a job at another authorized retailer or at a carrier-run store during or after their current job.

Non-compete agreements: Almost a third (63 of 204) of authorized retail workers surveyed reported that, as a condition of employment, they were required to sign a non-compete agreement that would prevent them from taking a job at a store run directly by a wireless carrier or another competing outlet. Another third (66 of 204) of authorized retail workers surveyed were unsure if they had signed such an agreement.

INTENSE FOCUS ON UPSELLING LEADS TO FRAUDULENT SALES PRACTICES

The authorized retail business model is focused on sales and creates an environment that can incentivize store managers to engage in dishonest sales practices. A 2017 survey of more than 1,300 AT&T employees found widespread reports of customer issues related to fraudulent sales practices at third-party authorized retailers. Nearly two thirds of AT&T customer service employees (64%) had experiences of customers reporting

> "[I was] forced to cram account… adding lines to unsuspecting victims in the guise of 'bundling.'"
>
> -AT&T Authorized Retail Employee in Oklahoma

third-party retailers who enrolled them in services that were not requested by the customer.[23]

This practice of adding additional services to a customer's account without their knowledge to hit sales goals is known as "cramming." Workers at authorized retailers in our survey and interviews described witnessing this practice in their workplace and reported that the practice was acknowledged or encouraged by management.

One AT&T authorized retail worker in Oklahoma reported that he was "forced to cram accounts...adding lines to unsuspecting victims in the guise of 'bundling'" and was subject to "insane sales metrics that only fraud can achieve." He reported that management e-mails containing references to "increases of zero usage activations" amounted to an admission that the authorized retailer was aware that the practice was occurring.

Another worker at an AT&T authorized retailer in New York reported that her district manager "tells us to take advantage of people's incompetence to make sales or hit quotas." A T-Mobile authorized retail worker in Kansas reported that "because of our low traffic, our manager was telling us just to put lines on people's accounts" and that the manager would "credit the account $30 immediately so that way they wouldn't even see it on their bill."

CARRIER ROLE IN DETERMINING EMPLOYMENT AND WORKPLACE POLICIES AND PRACTICES AT AUTHORIZED RETAILERS

Workers at AT&T Mobility, T-Mobile, and Verizon Wireless authorized retailers we asked about carrier involvement in determining employment and workplace policies and practices.

More than 9 in 10 (184 of 204) authorized retail workers surveyed reported carrier involvement in some aspect of their employment or workplace policies or practices, such as hiring and promoting workers, setting performance benchmarks or metrics, setting work schedules, and training workers.

The control that carriers exert over authorized retailers is related to the job quality and customer service issues workers identified in our survey and interviews.

RECOMMENDATIONS

Fixes to corporate labor policy and to public policy can ensure that workers are empowered through collective bargaining rights and that the wireless telecommunications industry provides good jobs to workers and honest, high-quality service to communities.

AT&T Mobility, T-Mobile, Verizon Wireless, and other carriers should end their practice of outsourcing work to authorized retailers, which produces negative outcomes for both workers and consumers. The proliferation of outsourcing creates a barrier to unionizing and a race to the bottom in wages and working conditions, and it promotes upselling and fraudulent sales practices that harm consumers. Carriers should directly employ workforces of well-trained, career technicians and customer service professionals to ensure high quality service, and insource work they have contracted out to authorized retailers.

> "I would rather just not work for someone who is not held to the same standard as a corporate store."
>
> -T-Mobile Authorized Retail Employee in Kansas

Congress should pass the Protecting the Right to Organize (PRO) Act so that more workers in the U.S. have real negotiating power over the terms and conditions of their work. The PRO Act expands and strengthens organizing and collective bargaining rights under the National Labor Relations Act (NLRA) (1935). It also establishes a clear joint employer standard under the NLRA that will ensure all employers that exert control over workers are seated at the bargaining table and are held accountable for violations of organizing rights. Key provisions include new monetary penalties for violations of the NLRA, anti-retaliation protections for unionizing workers, and expanded protections against union-busting by employers.

Unionized wireless retail workers have shown that collective bargaining can be an effective tool to halt workplace fissuring in retail. In 2022, CWA-represented members at AT&T Mobility bargained a new agreement that included groundbreaking limits on AT&T's ability to outsource corporate retail stores to authorized retailers.[22]

> "When the COVID-19 pandemic hit, corporate retail locations closed and the employees got hazard pay... [My employer] did not pay us extra for hazard pay and did not close locations besides Mall locations... Corporate retail gets paid more than authorized retail, why did they get to close and get a paid leave? When they get paid more and can do more. We worked throughout the entire pandemic risking our lives and still had metrics that had to be met."
>
> -AT&T Authorized Retail Employee in Georgia

The National Labor Relations Board should finalize a more expansive standard to determine joint-employer status under the NLRA, replacing a narrow standard established in 2020. The Board initiated a rulemaking process in 2022. In determining joint-employer status under the NLRA, a new rule should consider both direct and indirect forms of control exercised by employers and reserved authority employers hold. Workers employed by labor-only subcontractors, especially those exclusively serving a single corporation, should be presumed to be jointly employed.

Congress must address decades-long disinvestment in federal agencies to improve enforcement of labor and employment laws, building on the 2023 Omnibus Appropriations bill that provided funding increases to the Department of Labor and the National Labor Relations Board. The chronic underfunding of regulatory agencies hampers workers' ability to seek recourse when their rights are violated. Congress should prioritize additional appropriations that are urgently needed to equip agencies with the resources they need to adequately protect workers' rights. In addition, interagency cooperation should be institutionalized to review and evaluate enforcement efforts, recommend rescission of harmful regulations and sub-regulatory guidance, and ensure that agencies are pooling resources where possible.

Congress should pass the Workforce Mobility Act, which prohibits the use of non-compete agreements by employers, except in the dissolution of a partnership or the sale of a business. The bill also provides a private right of action and grants enforcement power to the Federal Trade Commission (FTC) and the Department of Labor (DOL). Further, it would require employers to make their employees aware of the limitation on non-competes, as studies have found that non-competes are often used even when they are illegal or unenforceable. The law would also give the DOL authority to make the public aware of the limitation, and require the FTC and the DOL to submit a report to Congress on any enforcement actions taken.[23]

The Federal Trade Commission should use its regulatory authority to ban non-compete agreements. President Biden's "Executive Order on Promoting Competition in the American Economy" in July 2021 directed the FTC to pursue federal rulemaking in this area to curtail the usage of agreements and clauses that may unfairly limit worker mobility.[24] The FTC is seeking public comment through March 10, 2023, on a proposed rule that would ban the use of non-competes by employers and entities engaging independent contractors, and nullify all existing non-compete agreements. **Worker groups and advocates should weigh in in support of the proposed rule.** The FTC's proposal is based on the agency's preliminary finding that non-compete clauses in employment contracts "constitute an unfair method of competition" in violation of Section 5 of the Federal Trade Commission Act, which the FTC is charged with implementing.[25]

Congress should pass the Schedules That Work Act to ensure that workers have stable and predictable schedules and pay, the right to request scheduling changes, and anti-retaliation protections for making such requests for flexibility.[26]

Congress should pass legislation to establish a just cause standard for employment termination to prevent unfair and retaliatory firings. Such legislation would prevent arbitrary terminations and prevent retaliatory firings of whistleblowers.[27] The U.S. lags behind many other wealthy democracies around the world, including the United Kingdom, Australia, and Japan, which require that employers provide workers with evidence-based just cause for termination, and a fair process surrounding termination that includes notice.[28]

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NATIONAL EMPLOYMENT LAW PROJECT

90 Broad Street, Suite 1100,
New York, NY 10004
NELP.org

COMMUNICATIONS WORKERS OF AMERICA

501 3rd Street NW
Washington, DC 20001
(202) 434-1100
CWA.org

Executive Summary

The National Association of Manufacturers conducted a survey on the effects that a ban of noncompete agreements would have on manufacturers. Prior to this survey, manufacturers had previously stated that the Federal Trade Commission's proposed ban would significantly affect their business models, employees and operations. The survey ran from Thursday, Feb. 16, until Monday, Feb. 27, and received significant feedback with 150 respondents completing the survey.

Background

On Jan. 19, the FTC formally proposed a novel rulemaking to ban noncompete agreements in the workplace. While the rule does not directly apply to all types of employment restrictions, some restrictions, like non-disclosure agreements, could be subject to the rule if they are broad enough in scope. The proposed rule's blanket ban on the use of noncompete agreements goes far beyond the intended use of these agreements. Many manufacturers use noncompete agreements to ensure that their intellectual property and investment in their senior leadership are protected should that employee seek a new position at a different company.

Summary of Findings

- **70% of Manufacturers Use Noncompetes:** Approximately 70% of respondents use noncompete agreements, and 75% use non-disclosure agreements. The FTC's proposed rule would ban noncompetes and any non-disclosure that they interpret as a de-facto noncompete. (See Question 1.)

- **Noncompetes Are Vital to Protecting Manufacturers' Intellectual Property:** Respondents stated that their top priorities that they protect under noncompete agreements are intellectual property (~93%), sales information (~87%), industrial processes (~72%) and business strategy (~52%). (See Question 5.)

- **Key Personnel Exist at All Levels:** The top positions covered under noncompete agreements are senior managers (~85%), sales employees (~75%) and engineers (~65%). (See Question 2.)

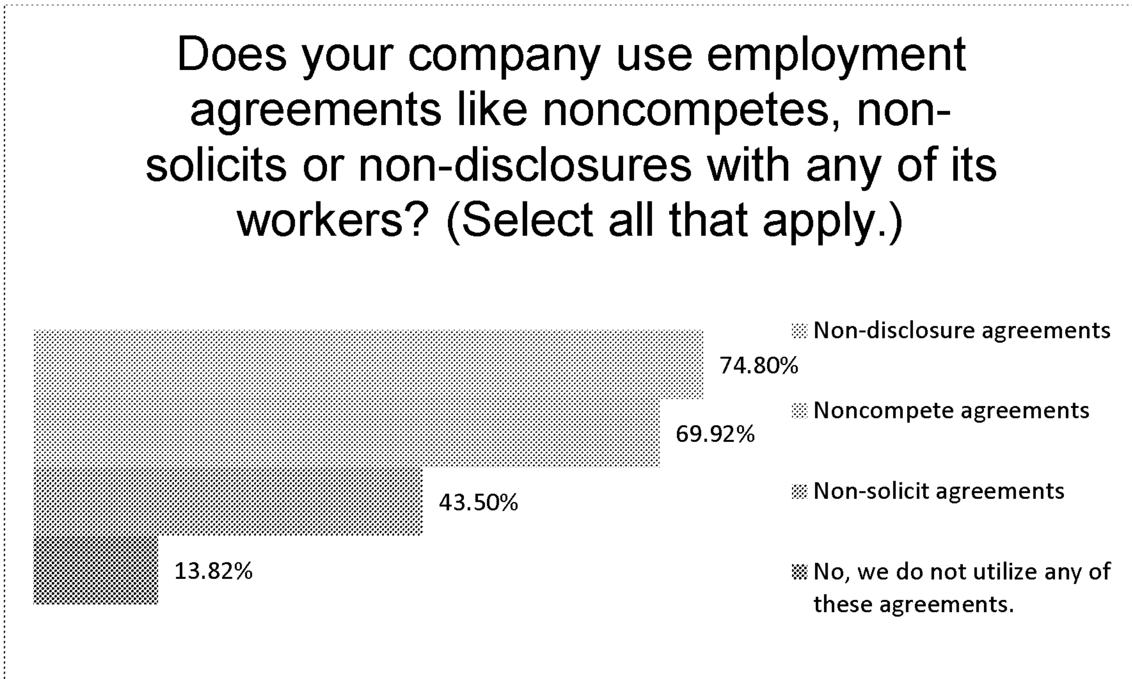
- **Banning Noncompetes Will Hurt Manufacturers:** The FTC's ban of noncompete agreements would cause a disruption to approximately 66% of manufacturers. That breakdown shows that 29% of respondents would experience "moderate" effects, with another 22% and approximately 15% seeing significant and very significant effects, respectively. (See Question 4.)

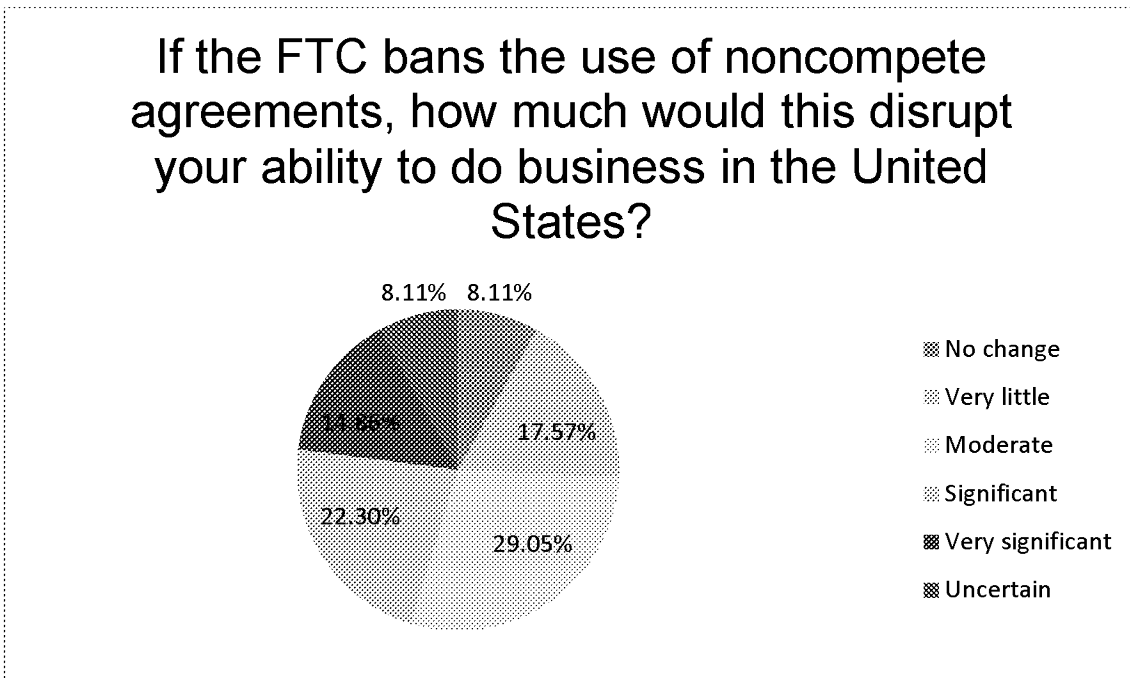
- **Noncompetes Are Used Responsibly and as Needed:** Approximately 89% of respondents tailor their noncompete agreements to last from six months to two years. Around 51% of respondents stated that they use them for more than one year and no more than two years. Another 38% stated that they use them for six months to one year. (See Question 3.)

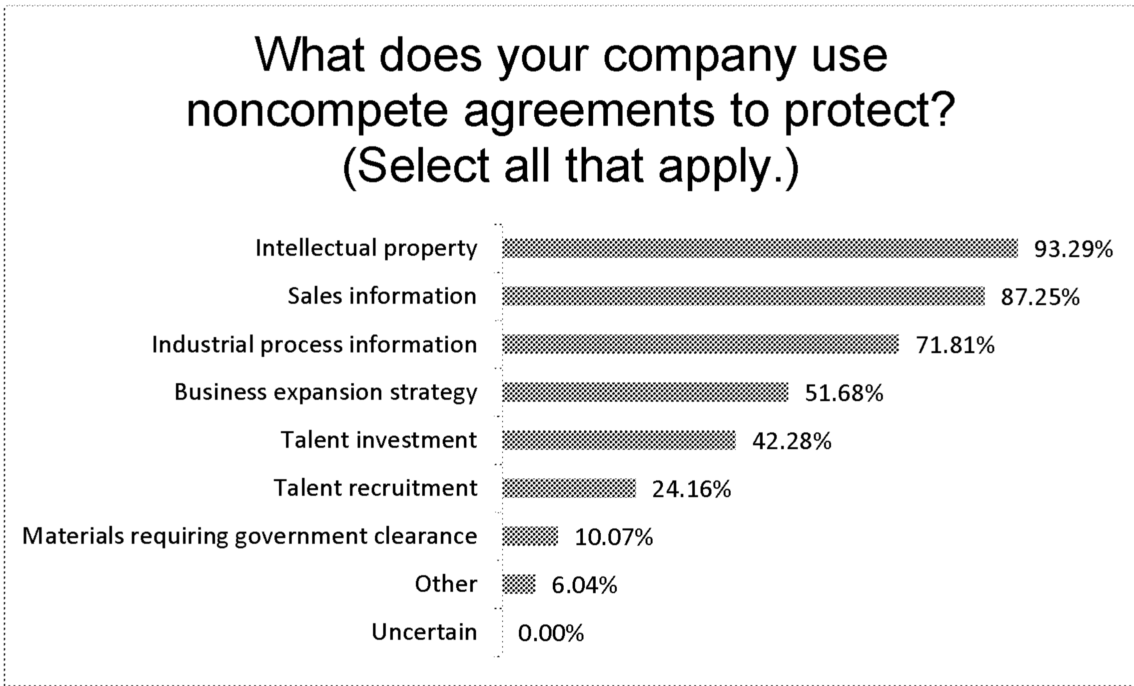
- **A Ban Will Affect All Manufacturers:** This issue affects large manufacturers and small and medium-sized manufacturers alike, with 51% of respondents representing large manufacturers and 49% representing SMMs. (See Question 10.)

- **A Noncompete Ban Would Harm Future Training and Investment in Employees:** Around half of manufacturers said that noncompete agreements affect their investment in training or related programs. (See Question 6.)

Charts







Survey Data

1) Does your company use employment agreements like noncompetes, non-solicits or non-disclosures with any of its workers? (Select all that apply.)
    a. Noncompete agreements – 69.92%
    b. Non-solicit agreements – 43.5%
    c. Non-disclosure agreements – 74.8%
    d. No, we do not utilize any of these agreements. – 13.82%

70% of Manufacturers use noncompete agreements and 75% use non-disclosures.

2) If so, what occupations are covered? (Select all that apply.)
    a. Senior managers – 84.77%
    b. Engineers – 64.9%
    c. Customer service employees – 24.5%
    d. Sales employees – 74.83%
    e. Parts production – 14.57%
    f. Administrative services (accounting, HR, etc.) – 34.44%
    g. Information technology – 37.09%
    h. Construction or repair – 11.26%
    i. Uncertain – 2.65%
    j. Other (please specify) – 19.21%

3) How long is the noncompete agreement in effect following the employee's departure?
    a. 6 months or less – 2.68%
    b. Above 6 months to 1 year – 38.26%
    c. More than 1 year and no more than 2 years – 51.01%

d. Other (please explain) – 8.05%

4) If the FTC bans the use of noncompete agreements, how much would this disrupt your ability to do business in the United States?
    a. No change – 8.11%
    b. Very little – 17.57%
    c. Moderate – 29.05%
    d. Significant – 22.3%
    e. Very significant – 14.86%
    f. Uncertain – 8.11%

5) What does your company use noncompete agreements to protect? (Select all that apply.)
    a. Intellectual property – 93.29%
    b. Industrial process information – 71.81%
    c. Sales information – 87.25%
    d. Business expansion strategy – 51.68%
    e. Talent investment – 42.28%
    f. Talent recruitment – 24.16%
    g. Materials requiring a government clearance – 10.07%
    h. Uncertain – 0%
    i. Other (please specify) – 6.04%

6) Is your company more likely to invest in training or related programs for employees who have noncompete agreements? (Select all that apply.)
    a. Yes, we are more likely to invest in training or related programs *for senior executives* who have a noncompete. – 35.62%
    b. Yes, we are more likely to invest in training or related programs *for employees with intrinsic knowledge of our business* who have a noncompete. – 37.67%
    c. Yes, we are more likely to invest in training or related programs for *all employees* who have a noncompete. – 29.45%
    d. No, noncompete agreements do not affect our investment in training or related programs for employees. – 49.32%
    e. Other (please specify) – 2.05%

7) If the FTC bans noncompete agreements, would you face a loss of talent? (Select all that apply.)
    a. Yes, we would face a loss of talent to domestic competitors. – 43.24%
    b. Yes, we would face a loss of talent to foreign competitors. – 14.86%
    c. No, we would not face any loss of talent. – 18.92%
    d. Uncertain – 37.84%

8) Is there any other information that you would like us to know about your use of noncompete agreements?

    Summary of Answers:

    The FTC's proposed rule will significantly harm many manufacturers. Manufacturers routinely face poaching activity from competitors in certain sectors such as life sciences that puts confidential information at risk. The ability to enforce confidentiality obligations is extremely difficult absent contractual agreements not to compete or solicit. Companies rarely have the means to investigate even well-founded confidential information theft concerns, and litigation on a hunch of such theft is inefficient and unlikely to survive an early motion to dismiss.

Noncompete provisions offer value in the protection of trade secrets and industrial processes. A ban on noncompetes will suppress manufacturers' collaborative, team approach to production and innovation by forcing companies to compartmentalize employees to reduce leaks of proprietary processes and confidential information. This will also lead to an increased risk of losing employees to competitors that will hire individuals to access their valuable knowledge of products, markets and customers that the competitors did not develop on their own. As turnover increases, efficiency will be reduced and litigation costs will soar as companies seek to prevent this knowledge from being shared with their competitors. Additionally, the deterrent and preventive effect of noncompetes is powerful and preferable to other types of agreements that are difficult to enforce and only become legally actionable once confidential or proprietary information has been compromised.

State laws already require that noncompete agreements are limited in scope and purpose. The FTC's proposal misunderstands the fundamental differences between a retail employee and an advanced manufacturing employee. This proposal will only discourage manufacturers from hiring more workers at a time when manufacturers are averaging more than 800,000 open jobs a month.

9) What is your company's primary industrial classification?
   a. Chemicals – 8.05%
   b. Computer and electronic products – 4.03%
   c. Electrical equipment and appliances – 6.04%
   d. Fabricated metal products – 20.81%
   e. Food manufacturing – 7.38%
   f. Furniture and related products – 2.01%
   g. Machinery – 10.07%
   h. Nonmetallic mineral products – 0.67%
   i. Paper and paper products – 6.71%
   j. Petroleum and coal products – 0.00%
   k. Plastics and rubber products – 8.05%
   l. Primary metals – 2.68%
   m. Transportation equipment – 5.37%
   n. Wood products – 0.67%
   o. Other (please specify) – 17.45%

10) What is your firm size (e.g., the parent company, not your establishment)?
   a. Fewer than 50 employees – 10.74%
   b. 50 to 499 employees – 38.26%
   c. 500 or more employees – 51.01%
   d. Uncertain – 0%

Opinion Poll

Small business owners support banning non-compete agreements

April 13, 2023

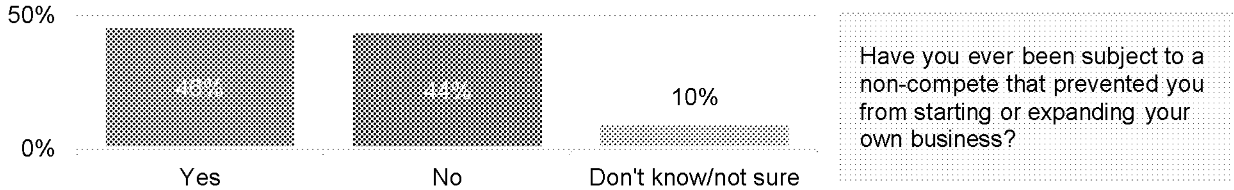
Small Business Majority
1015 15th Street, NW, Suite 450
Washington, DC 20005
(202) 828-8357
www.smallbusinessmajority.org

Findings

President Biden called on the Federal Trade Commission (FTC) to ban non-compete agreements in his second State of the Union address. In response, the FTC recently proposed a rule to ban non-compete agreements, sparking a debate about the impact this rule would have on the business community. A new opinion poll of small business owners nationwide reveals that our nation's entrepreneurs are being harmed by non-compete agreements, and they strongly support the Federal Trade Commission's proposed rule to ban them in most instances.

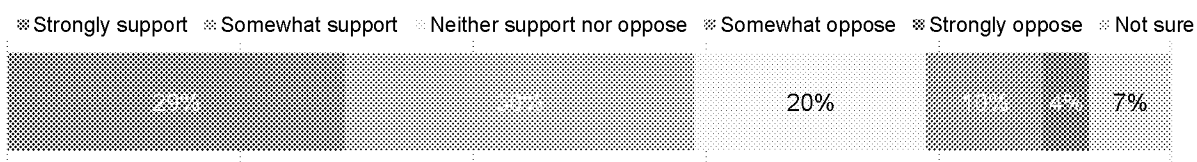
The poll reveals that nearly half of small businesses (46%) report that they were subject to a non-compete agreement that prevented them from starting or expanding their business. More than a third (35%) have been prevented from hiring an employee due to a non-compete agreement.

Figure 1: Small businesses harmed by non-compete agreements



While some have argued that non-compete agreements will harm the small business community, the survey finds that the proposal has strong support among small businesses. Nearly 6 in 10 (59%) support the FTC's proposed rule, with only 14% opposing the ban. Notably, those who currently use non-competes in their business are even more supportive of the ban (67%) compared to those who don't (51%).

Figure 2: Small business owners support banning of non-compete agreements



Importantly, a number of small businesses are using non-disclosure agreements to protect their confidential information or trade agreements (42%). What's more, 69% believe that non-disclosure agreements can protect their confidential information or trade secrets as effectively as a non-compete agreement.

This poll comes on the heels of a recent Federal Reserve working paper noting the important role entrepreneurs who leave a company to start new ventures have in creating dynamic, successful firms.[1] The data highlights how non-compete agreements can stifle free, fair and open competition and hamper entrepreneurs' ability to start their own endeavors as well as attract and retain a quality workforce.

Methodology

This poll reflects a national survey of 312 small business owners and decision-makers in the United States. The poll was an online survey conducted on SurveyMonkey on April 2, 2023. The margin of error is +/- 6%.

[1] "Entrepreneurship through Employee Mobility, Innovation, and Growth", Federal Reserve Bank of Atlanta, September 2022, https://www.atlantafed.org/-/media/documents/research/publications/wp/2022/09/26/10--entrepreneurship-and-employee-mobility.pdf

Survey Toplines

1. **Before this survey, were you familiar with non-compete agreements?**

   Yes....82%

   No....18%

2. **Do you use non-compete agreements in your business?**

   Yes....48%

   No....52%

3. **Have you ever been subject to a non-compete that prevented you from starting or expanding your own business?**

   Yes....46%

   No....44%

   Don't know/not sure....10%

4. **Have you ever been prevented from hiring a worker because they were subject to a non-compete agreement?**

   Yes....35%

   No....56%

   I don't know....9%

5. **The FTC is considering prohibiting the use of most non-compete agreements. Do you support or oppose such a ban?**

   Strongly support....29%

   Somewhat support....30%

   Neither support nor oppose....20%

   Somewhat oppose....10%

   Strongly oppose....4%

   Don't know/not sure....7%

6. **Have you ever asked employees to sign a non-disclosure agreement to protect confidential information or trade secrets?**

   Yes....42%

   No....53%

   I don't....5%

7. **Do you believe that such a non-disclosure agreement can protect your confidential information or trade secrets as effectively as a non-compete agreement?**

   Strongly agree....24%

   Somewhat agree....35%

   Neither agree nor disagree....24%

   Somewhat disagree....7%

   Strongly disagree....3%

   Don't know/not sure....7%

8. Business Size

Self-employed	35%
Fewer than 10 employees	21%
10-24 employees	12%
25-49 employees	6%
50-74 employees	7%
75-100 employees	7%
More than 100 employees	12%

9. Ethnicity

Asian or Asian American	13%
Black, African or African American	9%
Hispanic, Latinx or Spanish Origin	10%
Middle Eastern or North African	5%
American Indian or Alaska Native	2%
Native Hawaiian or other Pacific Islander	1%
White or Caucasian	52%
Some other race, ethnicity or ethnic origin	1%
Prefer not to answer	7%

10. Age

< 18	0%
18-29	19%
30-44	31%
45-60	38%
> 60	12%

11. Gender

Male	43%
Female	57%

12. Region

East North Central	16%
East South Central	4%
Middle Atlantic	16%
Mountain	6%
New England	3%
Pacific	21%
South Atlantic	19%
West North Central	6%
West South Central	10%

United States Government Accountability Office

Testimony
Before the Subcommittee on Oversight, Committee on Ways and Means, House of Representatives

For Release on Delivery
Expected at 2 p.m. ET
Wednesday, April 26, 2023

TAX ADMINISTRATION

IRS Oversight of Hospitals' Tax-Exempt Status

Statement of Jessica Lucas-Judy, Director, Strategic Issues

GAO-23-106777

GAO Highlights

Highlights of GAO-23-106777, a testimony before the Subcommittee on Oversight, Committee on Ways and Means, House of Representatives

April 26, 2023

TAX ADMINISTRATION

IRS Oversight of Hospitals' Tax-Exempt Status

Why GAO Did This Study

Slightly more than half of the approximately 5,000 community hospitals in the United States are private, nonprofit organizations. IRS and the Department of the Treasury have recognized the promotion of health as a charitable purpose and have specified that nonprofit hospitals are eligible for a tax exemption. IRS has further stated that these hospitals can demonstrate their charitable purpose by providing services that benefit their communities as a whole.

In 2010, Congress and the President enacted PPACA, which established additional requirements for tax-exempt hospitals to maintain a tax exemption.

This testimony discusses the requirements for a nonprofit hospital to qualify for tax-exempt status and challenges with verifying compliance with some of those requirements, and is based on a report that GAO issued in September 2020. This testimony reflects updated information GAO obtained from IRS regarding its implementation of the recommendations made in that report.

What GAO Recommends

In September 2020, GAO recommended Congress consider specifying what services and activities demonstrate sufficient community benefit. As of April 2023, Congress had not enacted such legislation. GAO also recommended IRS update tax forms to increase transparency about hospitals' community benefits. IRS agreed and made minor adjustments to the form's instructions, but the form still relies on a narrative description of community benefits that hospitals provide.

View GAO-23-106777. For more information, contact Jessica Lucas-Judy at (202) 512-6806 or lucasjudyj@gao.gov.

What GAO Found:

Hospitals must satisfy three sets of requirements for a nonprofit tax exemption (see figure) but hospital community benefits are not defined in law.

Requirements for Nonprofit Hospitals to Obtain and Maintain a Tax Exemption

ORGANIZATIONAL AND OPERATIONAL REQUIREMENTS
A hospital must be organized and operate to achieve a charitable purpose—the promotion of health for the benefit of the community.

COMMUNITY BENEFITS
Internal Revenue Service has identified six factors that demonstrate community benefit:
- Operate an emergency room open to all, regardless of ability to pay
- Maintain a board of directors drawn from the community
- Maintain an open medical staff policy that is not limited to certain physicians
- Provide care to all patients able to pay, including those who do so through Medicare and Medicaid
- Use surplus funds to improve facilities, equipment, and patient care
- Use surplus funds to advance medical training, education, and research

PATIENT PROTECTION AND AFFORDABLE CARE ACT (PPACA) REQUIREMENTS
Hospitals must:
- Conduct a community health needs assessment
- Maintain a written financial assistance policy
- Set a limit on charges
- Set billing and collection limits

IRS must review each tax-exempt hospital's community benefit activities at least once every 3 years.

Source: GAO review of relevant laws and regulations. | GAO-23-106777

In 1969, the Internal Revenue Service (IRS) identified factors that can demonstrate community benefits, but they are not requirements. IRS does not have authority to specify activities hospitals must undertake and makes determinations based on facts and circumstances. As a result, tax-exempt hospitals have broad latitude to determine the community benefits they provide, but the lack of clarity creates challenges for IRS in administering tax law.

Additionally, the form on which hospitals report community benefits solicits that information inconsistently, resulting in a lack of transparency. For example, hospitals may describe the use of surplus funds to improve facilities, equipment, and patient care narratively. This qualitative reporting format does not require tax-exempt hospitals to specify the amount of surplus funds used to improve facilities, equipment, and patient care. It could also result in incomplete information on how hospitals are providing community benefits.

GAO's 2020 analysis of IRS data identified 30 hospitals that reported no spending on community benefits in 2016. According to IRS officials, hospitals with little to no community benefit expenses would indicate potential noncompliance. IRS is required to review hospitals' community benefit activities at least once every 3 years, but was unable to provide evidence that it did so because it did not have a well-documented process to ensure those activities were being reviewed. Consistent with GAO's September 2020 recommendations, in 2021 IRS updated its overall guidance instructing its employees to document whether a hospital organization satisfies the community benefit standard and established an audit code to track that review.

Chairman Schweikert, Ranking Member Pascrell, and Members of the Subcommittee:

I am pleased to be here today to discuss our work on the Internal Revenue Service's (IRS) oversight of hospitals' tax-exempt status. Slightly more than half of the approximately 5,000 community hospitals in the United States are private, nonprofit organizations.[1] Nonprofit organizations can obtain and maintain a federal tax exemption if they are organized for one or more purposes specified in the Internal Revenue Code section 501(c)(3). The Joint Committee on Taxation estimated the total revenue loss from the tax exemption of hospitals at $12.6 billion in 2002.[2] Hospitals reported that they provided $76 billion in community benefits in 2016—the most recent data available when we reviewed this issue in 2020.[3]

Nonprofit hospitals can be tax-exempt if they provide certain community benefits, such as an emergency room open to all.[4] They must also meet legal requirements in the Patient Protection and Affordable Care Act (PPACA), such as maintaining a written financial assistance policy.

My remarks today are based on our September 2020 report on IRS oversight of tax-exempt hospitals.[5] I will focus on three aspects of this report—(1) the requirements that must be met for a nonprofit hospital to qualify for tax-exempt status, (2) challenges with verifying compliance with some of those requirements, and (3) IRS's oversight of the community benefit standard and PPACA requirements.

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[1]American Hospital Association, Fast Facts, accessed April 17, 2023, https://www.aha.org/statistics/fast-facts-us-hospitals. Community hospitals exclude nonfederal psychiatric hospitals and other hospitals, including long-term care hospitals and those within an institution.

[2]Congressional Budget Office, *Nonprofit Hospitals and the Provision of Community Benefits* (Washington, D.C: December 2006) reports the Joint Committee on Taxation estimate.

[3]GAO, *Tax Administration: Opportunities Exist to Improve Oversight of Hospitals' Tax-Exempt Status,* GAO-20-679 (Washington, D.C.: Sept. 17, 2020). For the purposes of this statement, we use the term "tax-exempt hospitals" to refer to nongovernmental, nonprofit, and tax-exempt hospitals. Government hospitals—including those at the federal, state, tribal, and local levels—are also exempt from federal taxation.

[4]IRS defines a hospital organization as an entity that operated at least one hospital facility during a tax year. A hospital facility is an entity that is required to be licensed, registered, or similarly recognized by a state as a hospital. Nonhospital health care facilities may include, but are not limited to, rehabilitation and other outpatient clinics, mobile clinics, and skilled nursing facilities.

[5]GAO-20-679.

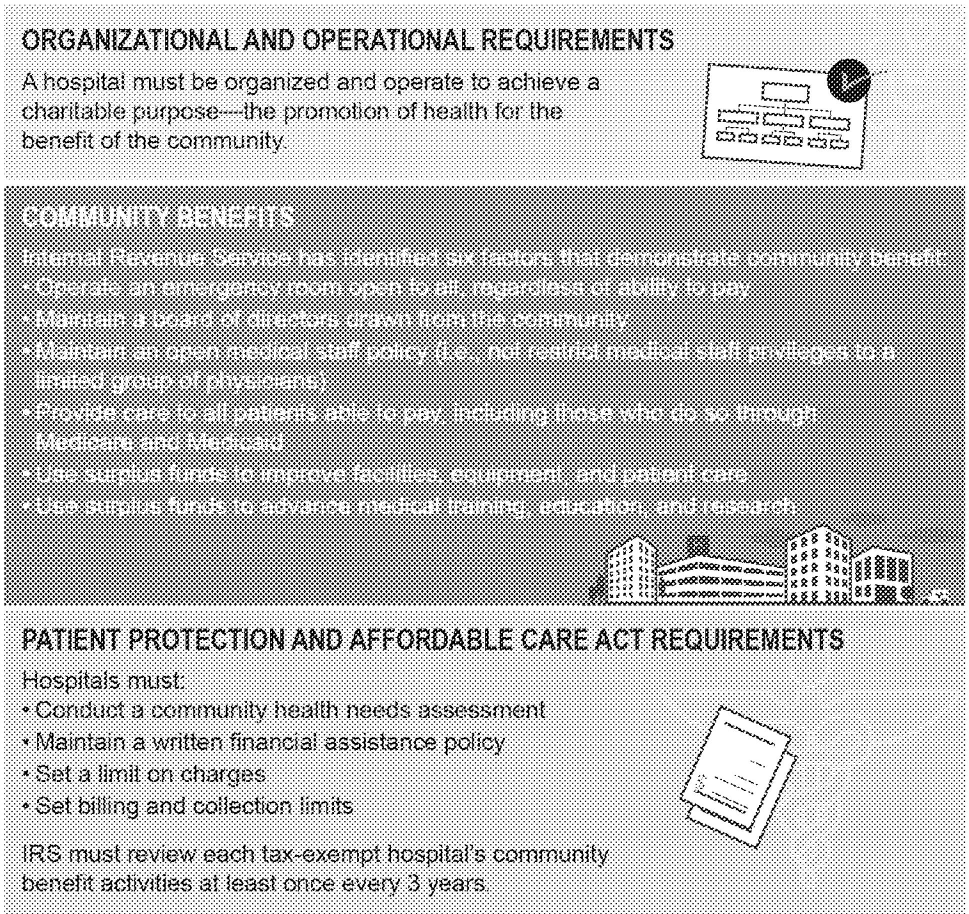
To conduct our prior work, we reviewed relevant provisions of the Internal Revenue Code, Department of the Treasury regulations, revenue rulings, and guidance. We also reviewed IRS policies, procedures, audit plans, and determining factors for reviewing tax-exempt hospitals, and we interviewed IRS officials. We examined the most recent data available at the time of that report (tax year 2016) from forms hospitals are required to file with IRS documenting the community benefits they provide and their compliance with PPACA. More detailed information on our objectives, scope, and methodology can be found in the 2020 report. Since the issuance of that report, we received and reviewed information from IRS on actions taken in response to our recommendations.

We conducted the work on which this statement is based in accordance with generally accepted government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives.

Requirements for Hospitals' Tax-Exempt Status

Nonprofit hospitals must satisfy three sets of requirements to obtain and maintain federal tax-exempt status (see fig. 1).

Figure 1: Requirements for Nonprofit Hospitals to Obtain Federal Tax-Exempt Status



Source: GAO review of relevant laws and regulations. | GAO-23-106777

The Internal Revenue Code requires that all organizations seeking a tax exemption under section 501(c)(3) be organized and operated for one or more purposes, which can be charitable, religious, or educational, among others.[6] The code does not specifically identify hospitals as being eligible for a tax exemption. However, IRS and federal courts have recognized

[6]Section 501 of the Internal Revenue Code covers the majority of these organizations, which include public charities, social welfare organizations, business leagues, and private foundations. Other types of organizations, such as education-oriented programs, farmers' cooperatives, and political organizations, are also wholly or partially tax exempt. 26 U.S.C. §§ 501(c)(3), 521, 527, 529-530.

that the promotion of health for a community's benefit is a charitable purpose.[7]

IRS has also identified factors—referred to as the community benefit standard—for how hospitals could demonstrate that they provide benefits to the community. As described below, the types of benefits they could provide are not detailed in the Internal Revenue Code and are not mandatory by law.

Lastly, as shown in figure 1, PPACA established four additional requirements that tax-exempt hospitals must meet to maintain a tax exemption.[8]

Development of the Community Benefit Standard

In a 1956 revenue ruling, IRS required tax-exempt hospitals to provide charity care to the extent of their financial abilities.[9] IRS determined in the ruling that only hospitals that operated for the benefit of those not able to pay, and not exclusively for the benefit of those who were able and expected to pay, could qualify for a tax exemption.

In 1959, Treasury updated its regulations to establish that organizations can receive tax-exempt status by demonstrating a charitable purpose, such as the promotion of health.

In 1969, 4 years after Congress and the President created Medicare and Medicaid, IRS removed the requirement for tax-exempt hospitals to provide charity care—patient care without charge or at rates below cost—when it issued Revenue Ruling 69-545.[10] The ruling compares the extent to which two hypothetical hospitals satisfy the Internal Revenue Code's requirements for a tax exemption. In making that comparison, the ruling identifies six factors that distinguish how one hospital satisfies the requirements and how the second does not. IRS says that although a hospital is no longer required to provide charity care, it considers doing so to be a significant factor indicating community benefit.

There is no specific definition of community benefit. These six factors currently serve as the primary examples of community benefits that

[7]See Geisinger Health Plan v. Comm'r, 985 F.2d 1210, 1216 (3d Cir. 1993) (discussing IRS policy and cases construing exemption provisions for hospitals).

[8]Pub. L. No. 111-148, tit. IX, § 9007, 129 Stat. 119, 855 (2010), *codified at* 26 U.S.C. § 501(r).

[9]Rev. Rul. 56-185, 1956-1 C.B. 202. Charity care is generally defined as care provided to patients whom the hospital deems unable to pay all or a portion of their bills.

[10]Rev. Rul. 69-545, 1969-2 C.B. 117.

hospitals can provide to obtain and maintain a tax exemption. The factors are commonly referred to as the community benefit standard. IRS describes the six factors on its website:

- **Operate an emergency room open to all, regardless of ability to pay.** A hospital that does not operate a full-time emergency room may not be fulfilling the community's need for emergency health care. If that emergency room is not open to everyone regardless of ability to pay, the hospital may not be serving a significant segment of the community.[11]
- **Maintain a board of directors drawn from the community.** A hospital board of directors comprised of independent civic leaders helps to ensure that the hospital serves public, rather than private, interests, and therefore operates for the benefit of the community.
- **Maintain an open medical staff policy (i.e., not restrict medical staff privileges to a limited group of physicians).** A hospital that restricts its medical staff privileges to a limited group of physicians is likely to be operating for the private benefit of the staff physicians rather than for the public interest.
- **Provide care to all patients able to pay, including those who do so through Medicare and Medicaid.** A hospital that restricts admissions to patients of staff members, or otherwise discriminates against patients with the ability to pay for nonemergency services, is not operating for the benefit of the community.
- **Use surplus funds to (1) improve facilities, equipment, and patient care; and (2) advance medical training, education, and research.** The use of surplus funds for these purposes demonstrates that a hospital is promoting the health of the community.[12]

The standard states that a hospital need not meet all of the factors to qualify for a tax exemption. The absence of any one factor, or the presence of others, may not necessarily be conclusive of the hospital's

[11]IRS Revenue Ruling 83-157 established that if a state health planning agency determined that additional emergency facilities would be unnecessary and duplicative, or if the hospital offers medical care limited to special conditions unlikely to necessitate emergency care, such as eye or cancer hospitals, then the fact that a hospital organization does not operate an emergency room will not, by itself, disqualify it from a tax exemption. Rev. Rul. 83-157, 1983-2 C.B. 94.

[12]IRS, *Charitable Hospitals — General Requirements for Tax-Exemption Under Section 501(c)(3)*, accessed April 30, 2020. https://www.irs.gov/charities-non-profits/charitable-hospitals-general-requirements-for-tax-exemption-under-section-501c3.

community benefits. Furthermore, IRS considers all of a hospital's facts and circumstances relevant when determining whether a hospital's community benefits are sufficient to warrant a tax exemption.

Patient Protection and Affordable Care Act Requirements

PPACA established four additional requirements that tax-exempt hospitals must meet to maintain a tax exemption.[13]

- **Conduct a community health needs assessment.** Every 3 years, each tax-exempt hospital must identify the community's health needs and develop an implementation plan for how it will address those needs.[14]
- **Maintain a written financial assistance policy.** Each tax-exempt hospital must publish a written policy that identifies who can qualify for financial assistance for medical services, how the hospital calculates costs for those services, and the actions the hospital will take in the event of nonpayment.
- **Set a limit on charges.** A tax-exempt hospital cannot charge individuals eligible for financial assistance more for medical services than they do patients with insurance.
- **Set billing and collection limits.** A tax-exempt hospital may not take extraordinary collection actions against an individual, such as filing a lawsuit, before the hospital determines whether that individual is eligible for financial assistance.

In addition, the law established a new requirement for IRS to review the community benefit activities of each tax-exempt hospital at least once every 3 years.[15]

Congress Could Clarify the Law to Improve Oversight of Tax-Exempt Hospitals

Congress has taken actions that convey an expectation that hospitals, in exchange for a tax exemption, should provide services and activities that benefit the immediate communities in which they operate. Specifically, in PPACA, Congress required tax-exempt hospitals to identify each hospital's community's health needs, indicating an expectation that hospitals provide benefits to the immediate community.

However, a broad range of activities fall within the Internal Revenue Code's requirement for a tax exemption for charitable organizations,

[13]Pub. L. No. 111-148, tit. IX, § 9007, 129 Stat. 119, 855 (2010), *codified at* 26 U.S.C. § 501(r).

[14]PPACA establishes that a tax-exempt hospital that does not meet the community health needs assessment requirement must pay an excise tax. See 26 U.S.C. § 4959.

[15]PPACA, Pub. L. No. 111-148, tit. IX, § 9007(c), 129 Stat. 119, 857 (2010).

making it challenging to ensure that the community benefits that hospitals provide justify their tax exemption.

IRS does not have authority to define specific types of services and activities that a hospital must undertake to qualify for a tax exemption. Instead, it provides guidance on the types of activities that can demonstrate community benefits. In this regard, the Internal Revenue Code does not identify explicit community benefit activities required for tax-exempt status, and the factors IRS identified in its 1969 ruling are examples and not requirements.

Furthermore, some of the factors may have lost relevance. For example, in 2005, the Commissioner of Internal Revenue told Congress that some community benefit factors, such as maintaining an open medical staff policy and accepting patients on Medicare and Medicaid, are now common features of all hospitals.[16] Additionally, the Emergency Medical Treatment and Active Labor Act, signed into law in 1986, requires that all hospitals that operate emergency rooms provide emergency treatment to all, regardless of ability to pay.[17] As a result, these standards may be a less useful gauge for measuring community benefit than they once were.

The Internal Revenue Code and IRS's implementation of it gives tax-exempt hospitals broad latitude to determine the nature and amount of community benefits they provide. Representatives of tax-exempt hospitals told us that current law and the community benefit standard offer hospitals needed flexibility in demonstrating community benefits. For example, a hospital located in a remote rural community may be the only hospital within hundreds of miles, making its existence the primary benefit to the community.

However, that lack of clarity also creates challenges for IRS in administering tax law. For example, given this ambiguity, a hospital could, in theory, maintain a tax exemption by operating an emergency room open to all and accepting patients on Medicare or Medicaid, which are common among hospitals, while spending little to no money on charity care or other community benefit activities. In our September 2020 report, we identified 30 hospitals that reported no spending on community benefits in 2016, and other hospitals that could have been at risk for

[16] *The Tax-exempt Hospitals Sector before the Committee on Ways and Means U.S. House of Representatives*, 109th Cong. 8-18, (2005) (statement of Mark W. Everson, Commissioner of Internal Revenue).

[17] Emergency Medical Treatment and Active Labor Act, Pub. L. No. 99-272, tit. IX, § 9121(b), 100 Stat 164 (1986).

noncompliance with the community benefit standard during a similar period (see table 1).[18]

Table 1: Number of Hospital Organizations with Little to No Community Benefit Spending, Tax Years 2014-2016

	2014	2015	2016
No financial assistance	64	68	48
No community benefit spending	48	45	30
Less than 1 percent community benefit spending	142	137	108

Source: GAO analysis of Internal Revenue Service data. | GAO-23-106777

Note: Financial assistance includes financial aid (i.e., charity care), Medicaid, and other means-tested government programs. The calculation of community benefit corrects for hospitals that reported negative spending values due to excess off-setting revenues, such as grants or Medicaid reimbursements.

IRS officials told us that the agency had not revoked a hospital's tax-exempt status for failing to provide sufficient community benefits in the previous 10 years.

We recommended that Congress consider amending the Internal Revenue Code to specify services and activities Congress believes would provide sufficient community benefits, which could improve IRS's ability to oversee tax-exempt hospitals. As of April 2023, Congress has not enacted such legislation.

IRS Could Improve Transparency of Community Benefit Information but Has Taken Action to Improve Its Oversight Ability

[18]We examined data on community benefit information that hospitals report from Forms 990, Schedule H, which hospitals are required to file with IRS. Those data were obtained from IRS Statistics of Income (SOI) public microdata files that covered the entire population of tax-exempt hospitals for tax year up to 2016, the most recent year available at the time of our review.

Reporting on Community Benefits

IRS requires a tax-exempt hospital to file Schedule H with its Form 990 annually to provide the public with information on its policies and activities and the community benefits that its facilities provide. IRS has stated a tax-exempt organization's Form 990, along with its schedules, can be the primary or sole source of information the public uses to understand a tax-exempt organization's operations, such as the community benefits a hospital provides.

However, Form 990, Schedule H solicits information inconsistently, resulting in a lack of clarity about the community benefits hospitals provide. The schedule includes questions intended to capture information on each of the six factors of the community benefit standard. However, these questions are located on different parts of the schedule and hospitals are instructed to address them in different ways.

For three of the six factors, IRS explicitly directs tax-exempt hospitals to report the extent to which they have addressed them. For the other three factors, IRS provides a space for hospitals to describe in a narrative the community benefits they provide, noting those factors as examples of community benefits.

For example, IRS directs hospitals to identify the specific costs they incur by providing health education and medical research. However, hospitals may describe the use of surplus funds to improve facilities, equipment, and patient care in a narrative format.

This qualitative reporting format does not require tax-exempt hospitals to specify the amount of surplus funds used to improve facilities, equipment, and patient care. It could also result in potentially incomplete information on how hospitals are providing community benefits.

In our analysis of hospitals' Form 990, Schedule H filings for tax years 2015 through 2018, we found inconsistencies in what hospitals reported in the narrative description. Some provided numerous examples of how they used surplus funds to improve their facilities and patient care, while others did not address any of the suggested factors.

Furthermore, the quantitative, machine-readable publicly available data IRS releases on the community benefits reported by tax-exempt hospitals on Form 990, Schedule H do not contain information that hospitals describe narratively.[19] Therefore, this reporting results in information on half of the factors that is inconsistent and difficult to obtain.

[19]Forms 990 are disclosable to the public and can be requested by submitting Form 4506-A.

We recommended IRS update Form 990, including Schedule H and instructions where appropriate, to ensure that the information demonstrating the community benefits a hospital is providing is clear and can be easily identified by Congress and the public, including the community benefit factors. IRS agreed with this recommendation.

In response to our recommendation, IRS made minor adjustments to Form 990, Schedule H instructions to indicate that responses should include all of the community benefit factors. However, IRS still asks hospitals to describe narratively additional information important to understanding the full scope of the community benefits they provide. IRS could fully implement our recommendation through further updates to its forms. This would help ensure that community benefit information is clear and can be easily identified by Congress and the public.

Reporting by Facility

Form 990, Schedule H directs tax-exempt hospitals to report their community benefit expenses at the hospital organization level rather than at the facility level. Therefore, hospital organizations that operate multiple facilities report community benefits in the aggregate for all of their facilities.

For example, a hospital organization reports the amount of charity care it provides and its costs for medical training, education, and research for all of its facilities as a whole, not for each facility. In doing so, it is not transparent how much each facility contributes to the total. A few facilities could contribute the majority of community benefit expenses, while others contribute little to none. In tax year 2016, 46 percent of hospital facilities were part of a hospital organization, and therefore those facilities' community benefit expenses were reported as part of the organization as a whole.

We recommended IRS assess the benefits and costs, including the tax law implications, of requiring tax-exempt hospital organizations to report community benefit expenses on Schedule H by individual facility rather than by collective organization and take action, as appropriate.

In response to our 2020 recommendation, IRS qualitatively assessed the benefits and costs of requiring community benefit reporting on a facility-by-facility basis. According to IRS's assessment, such reporting would impose greater burdens on tax-exempt hospitals and IRS with no tax administration benefit. Specifically, IRS determined that because the tax exemption is granted at the organization level, reporting community benefits at the facility level would provide no additional tax administration benefit. While reporting at the facility level would increase transparency, we closed our recommendation as implemented, recognizing the tradeoffs between the burdens and benefits of more detailed reporting.

Improvements in IRS Review of Hospitals' Community Benefits

IRS verifies many aspects of hospitals' reports during its triennial Community Benefit Activity Reviews (CBAR), but it did not have a well-documented process to identify hospitals at risk for noncompliance with the community benefit standard. IRS requires hospitals to self-report compliance with all four PPACA requirements on Form 990, Schedule H, Part V. Hospitals must answer a series of yes or no questions for each of the four PPACA requirements. In addition PPACA required IRS to review information about hospitals' community benefit activities at least every 3 years.

IRS referred almost 1,000 hospitals to its audit division for potential PPACA violations from fiscal years 2015 through 2019. However, IRS could not identify whether any of these referrals related to community benefits.

IRS stated that it sends back forms that are materially incomplete and requests that hospitals complete the missing information; however, we found that some of the hospitals left the required community benefit section of Form 990, Schedule H blank. These hospitals may have actually spent funds on community benefit activities, but did not complete the form. Other hospitals reported spending amounts that were approximately 0 percent of expenses.[20]

IRS's guidance contained specific questions that address the community benefit factors, but there was no direction on when a hospital should be referred for audit if the revenue agent is unable to verify the factor.

According to IRS officials, hospitals with little to no community benefit expenses may warrant an audit. However, IRS was unable to provide evidence that it conducted reviews specifically related to hospitals' community benefits.

[20]IRS agents in the Statistics of Income group in the Research Applied Analytics and Statistics Division correct some of the Form 990, Schedule H data for obvious errors before posting the public files onto IRS's website. However, those changes do not extend to the forms themselves that IRS officials would review in a CBAR.

For example, according to IRS officials, of the 37 hospitals that reported zero or negative community benefit spending in tax year 2016:

- 21 were referred for examination or compliance check as a result of their CBAR reviews.[21]
- Six of these hospitals were referred for audit based on CBAR review of the 2016 Form 990.
- The other 15 referrals were made based on other tax years.

However, in all these cases, the referrals were made as a result of possible issues with the financial assistance policy or community health needs assessment but not issues with the community benefit standard. IRS officials said the other 16 hospitals that reported no spending on community benefits were not referred for audit because they met the PPACA requirements.

Furthermore, IRS did not have a way to determine if hospitals were being selected for audit for potential noncompliance related to community benefits during a CBAR. While it used audit issue codes that differentiate between PPACA-related noncompliance and other noncompliance, there were no codes related to potential noncompliance with the community benefit standard. According to IRS, from 2016 through 2019, fewer than 10 cases each year were referred to its audit division during the CBAR for an issue not related to PPACA.

We recommended IRS establish a well-documented process to identify hospitals at risk for noncompliance with the community benefit standard that would ensure hospitals' community benefit activities are being consistently reviewed. We also recommended IRS establish specific audit codes for identifying potential noncompliance with the community benefit standard.

In response, in 2021 IRS updated the guidance for CBAR reviews to include instructions for employees to document case files with relevant facts and circumstances considered during their review that determine whether the hospital organization satisfies the community benefit standard for exemption. IRS also established an audit code in its Case Management System under Healthcare Issues 18010.000 for "Healthcare - Community Benefit Standard for Exemption." These actions will help

[21]We provided IRS with a list of 37 hospitals that, based on our review of Form 990, Schedule H data, reported zero or negative net community benefit spending for tax year 2016. This number is larger than the amount reported in table 1, because the values in table 1 correct for the cases for which hospitals reported negative spending in Medicaid.

IRS ensure it is effectively reviewing hospitals' community benefit activities.

In summary, IRS can easily verify whether the legal requirements in PPACA are met. However, it is harder for IRS to verify community benefits because IRS does not have the authority to define specific services and activities hospitals must undertake to qualify for a tax exemption. Additional clarity about specific services and activities Congress believes would provide sufficient community benefits could improve IRS's ability to oversee tax-exempt hospitals.

In addition, IRS action to update and revise Form 990, Schedule H that enables tax-exempt hospitals to present community benefit information clearly, consistently, and comprehensively could help IRS, Congress, and the broader public better understand the full scope of the community benefits a hospital provides and whether they justify a tax exemption.

Chairman Schweikert, Ranking Member Pascrell, and Members of the Subcommittee, this concludes my prepared remarks. I look forward to answering any questions that you may have.

GAO Contact and Staff Acknowledgments

If you or your staff have any questions about this testimony, please contact me at (202) 512-6806 or lucasjudyj@gao.gov. Contact points for our Offices of Congressional Relations and Public Affairs may be found on the last page of this statement. GAO staff who made key contributions to this testimony are Sonya Phillips (Assistant Director), Jennifer G. Stratton (Analyst-in-Charge), Caitlin Cusati, Steven Flint, Robert Gebhart, James A. Howard, Matthew Levie, Ed Nannenhorn, Sonya Vartivarian, Peter Verchinski, Daniel Webb, and Alicia White.

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Federal Preemption: A Legal Primer

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May 18, 2023

Bryan L. Adkins
Legislative Attorney

Alexander H. Pepper
Legislative Attorney

Jay B. Sykes
Legislative Attorney

The Constitution's Supremacy Clause provides that federal law is "the supreme Law of the Land" notwithstanding any state law to the contrary. This language is the foundation for the doctrine of federal preemption, according to which federal law supersedes conflicting state laws. The Supreme Court has identified two general ways in which federal law can preempt state law. First, federal law can *expressly* preempt state law when a federal statute or regulation contains explicit preemptive language. Second, federal law can *impliedly* preempt state law when Congress's preemptive intent is implicit in the relevant federal law's structure and purpose.

In both express and implied preemption cases, the Supreme Court has made clear that Congress's purpose is the "ultimate touchstone" of its statutory analysis. In analyzing congressional purpose, the Court has at times applied a canon of statutory construction known as the "presumption against preemption," which instructs that federal law should not be read as superseding states' historic police powers "unless that was the clear and manifest purpose of Congress."

In cases involving express preemption, the Supreme Court's decisions have depended heavily on the details of particular statutory schemes, but the Court has assigned some phrases specific meanings even when they have appeared in different statutory contexts. The Court also must sometimes interpret savings clauses—statutory provisions designed to insulate certain categories of state law from federal preemption.

In implied preemption cases, the Court has identified two subcategories of implied preemption: field preemption and conflict preemption.

Field preemption occurs when a pervasive scheme of federal regulation implicitly precludes supplementary state regulation or when states attempt to regulate a field where there is a sufficiently dominant federal interest. Applying these principles, the Court has held that federal law occupies a number of regulatory fields, including alien registration, nuclear safety regulation, and the regulation of locomotive equipment.

Conflict preemption, in contrast, occurs when simultaneous compliance with both federal and state regulations is impossible (impossibility preemption) or when state law poses an obstacle to the accomplishment of federal goals (obstacle preemption).

The Court's cases recognizing impossibility preemption are not limited to instances in which compliance with federal and state law is impossible in a literal sense. Rather, the Court has held that compliance with both federal and state law can be "impossible" even when a regulated party can petition the federal government for permission to comply with state law or avoid violations of the law by refraining from selling a regulated product altogether.

In its obstacle preemption decisions, the Court has concluded that state law can interfere with federal goals by frustrating Congress's intent to adopt a uniform system of federal regulation; conflicting with Congress's goal of establishing a regulatory ceiling for certain products or activities; or by impeding the vindication of a federal right.

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The Constitution's Supremacy Clause provides that "the Laws of the United States . . . shall be the supreme Law of the Land; and the Judges in every State shall be bound thereby, any Thing in the Constitution or Laws of any State to the Contrary notwithstanding."[1] This language is the foundation for the doctrine of federal preemption, under which federal law supersedes conflicting state laws.[2]

Federal preemption of state law is a ubiquitous feature of the modern regulatory state and "almost certainly the most frequently used doctrine of constitutional law in practice."[3] Preemptive federal statutes shape the regulatory environment for most major industries, including drugs and medical devices, banking, air transportation, securities, automobile safety, and tobacco.[4]

As a result, disputes over preemption "rage in the courts, in Congress, before agencies, and in the world of scholarship."[5] These debates implicate many of the themes that recur throughout both the Supreme Court's preemption case law and the federalism literature. Proponents of broad federal preemption often cite the benefits of uniform national regulations[6] and the concentration of expertise in federal agencies.[7] Opponents typically appeal to the importance of policy experimentation,[8] the greater democratic accountability that they believe accompanies state and

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[1] U.S. CONST. art. VI, cl. 2.

[2] Murphy v. Nat'l Collegiate Athletic Ass'n, 138 S. Ct. 1461, 1479 (2018); Gade v. Nat'l Solid Wastes Mgmt. Ass'n, 505 U.S. 88, 108 (1992).

[3] Stephen A. Gardbaum, *The Nature of Preemption*, 79 CORNELL L. REV. 767, 768 (1994). *See also* Jamelle C. Sharpe, *Toward (a) Faithful Agency in the Supreme Court's Preemption Jurisprudence*, 18 GEO. MASON L. REV. 367, 367 (2011) ("Preemption has become one of the most frequently recurring and perplexing public law issues facing the federal courts today."); Garrick B. Pursley, *Preemption in Congress*, 71 OHIO ST. L. J. 511, 514 (2010) (describing preemption as "the issue of constitutional law that most directly impacts everyday life"); Thomas W. Merrill, *Preemption and Institutional Choice*, 102 NW. U. L. REV. 727, 730 (2008) (noting that "[p]reemption is one of the most widely applied doctrines in public law").

[4] Pursley, *supra* note 3, at 513.

[5] William W. Buzbee, *Introduction*, *in* PREEMPTION CHOICE: THE THEORY, LAW, AND REALITY OF FEDERALISM'S CORE QUESTION 1, 1 (William W. Buzbee ed., 2009).

[6] *See* Alan Untereiner, *The Defense of Preemption: A View From the Trenches*, 84 TUL. L. REV. 1257, 1262 (2010) (arguing that the "multiplicity of government actors below the federal level virtually ensures that, in the absence of federal preemption, businesses with national operations that serve national markets will be subject to complicated, overlapping, and sometimes even conflicting legal regimes"); Brief for the Chamber of Commerce of the United States of America as Amicus Curiae at 20, Geier v. Am. Honda Motor Co., No. 98-1811 (U.S. Nov. 19, 1999), 1999 WL 1049891 (arguing that "common-law decisionmaking is notoriously ill-suited to the establishment of nationwide standards that strike the proper balance among the multitude of societal interests at stake in a particular regulatory setting").

[7] *See* Untereiner, *supra* note 6, at 1262 ("In many cases, Congress's adoption of a preemptive scheme . . . ensures that the legal rules governing complex areas of the economy or products are formulated by expert regulators with a broad national perspective and needed scientific or technical expertise, rather than by decision makers—such as municipal officials, elected state judges, and lay juries—who may have a far more parochial perspective and limited set of information.").

[8] *See* Charles W. Tyler & Heather K. Gerken, *The Myth of the Laboratories of Democracy*, 122 COLUM. L. REV. 2187, 2230 (2022) ("[W]herever [preemption] exists, federal law displaces state law, thereby 'stifling state-by-state diversity and experimentation' . . . ."); Ernest A. Young, *Making Federalism Doctrine: Fidelity, Institutional Competence, and Compensating Adjustments*, 46 WM. & MARY L. REV. 1733, 1850 (2004) ("Preemption doctrine . . . goes to whether state governments actually have the opportunity to provide beneficial regulation for their citizens; there can be no experimentation or policy diversity, and little point to citizen participation, if such opportunities are supplanted by federal policy.").

local regulation,[9] and the gap-filling role of state common law in deterring harmful conduct and compensating injured plaintiffs.[10]

In addition to these general normative disputes, preemption decisions also raise narrower interpretive issues.

As **Figure 1** illustrates, the Supreme Court has identified two general types of preemption. First, federal law can *expressly* preempt state law when a federal statute or regulation contains explicit preemptive language. Second, federal law can *impliedly* preempt state law when its structure and purpose implicitly reflect Congress's preemptive intent.[11]

The Court has identified two subcategories of implied preemption: field preemption and conflict preemption.

Field preemption occurs when a pervasive scheme of federal regulation implicitly precludes supplementary state regulation or when states attempt to regulate a field where the federal interest is sufficiently dominant.[12]

In contrast, conflict preemption occurs when compliance with both federal and state regulations is impossible (impossibility preemption)[13] or when state law poses an "obstacle" to the accomplishment of the "full purposes and objectives" of Congress (obstacle preemption).[14]

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[9] *See* Robert R.M. Verchick & Nina Mendelson, *Preemption and Theories of Federalism*, *in* PREEMPTION CHOICE: THE THEORY, LAW, AND REALITY OF FEDERALISM'S CORE QUESTION 13, 17 (William W. Buzbee ed., 2009) ("Citizens are often presumed to be able to participate more directly in policy making at the state level. Greater state autonomy to regulate will mean more opportunities for citizens to participate in governance and seek responsive government."); Roderick M. Hills, Jr., *Against Preemption: How Federalism Can Improve the National Legislative Process*, 82 N.Y.U. L. REV. 1, 4 (2007) ("Federalism's value, if there is any, lies in the often competitive interaction between the levels of government. In particular, a presumption against federal preemption of state law makes sense not because states are necessarily good regulators of conduct within their borders, but rather because state regulation makes Congress a more honest and democratically accountable regulator of conduct throughout the nation.").

[10] Thomas O. McGarity, THE PREEMPTION WAR: WHEN FEDERAL BUREAUCRACIES TRUMP LOCAL JURIES 237 (2008) ("The common law provides an effective vehicle for filling the regulatory gaps that inevitably arise at the implementation stage because agencies can never anticipate and regulate every potentially socially undesirable aspect of an ongoing business and cannot possibly envision all of the possible ways that regulatees will react to regulatory programs.").

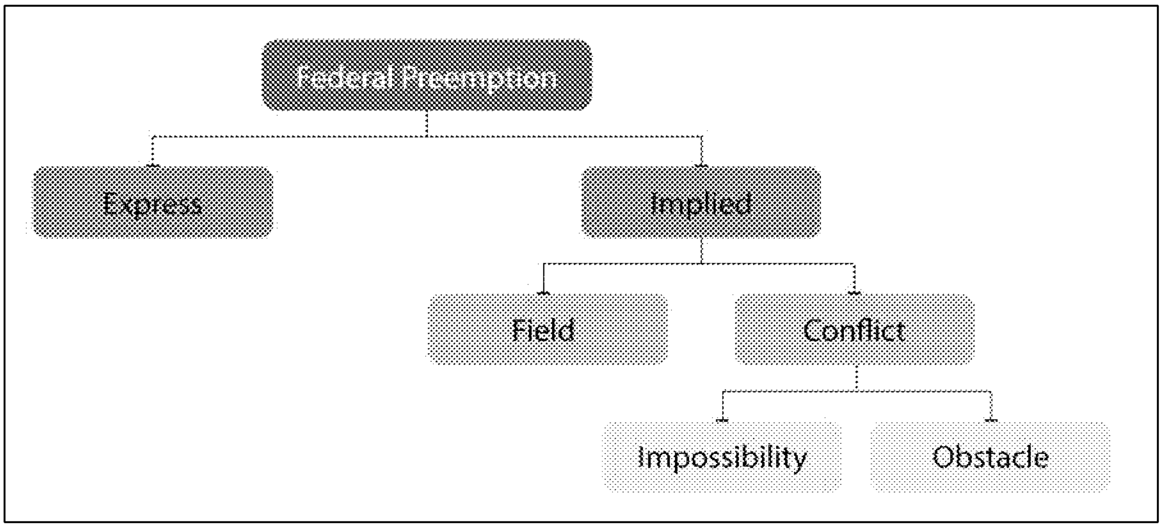
[11] Gade v. Nat'l Solid Wastes Mgmt. Ass'n, 505 U.S. 88, 98 (1992).

[12] Arizona v. United States, 567 U.S. 387, 399 (2012) ("[Congress's] intent to displace state law altogether can be inferred from a framework of regulation 'so pervasive . . . that Congress left no room for the States to supplement it' or where there is a 'federal interest . . . so dominant that the federal system will be assumed to preclude enforcement of state laws on the same subject.'") (quoting Rice v. Santa Fe Elevator Corp., 331 U.S. 218, 230 (1947)).

[13] Fla. Lime & Avocado Growers, Inc. v. Paul, 373 U.S. 132, 142–43 (1963).

[14] Hines v. Davidowitz, 312 U.S. 52, 67 (1941).

Figure 1. Preemption Taxonomy



Source: CRS.

While the Supreme Court has repeatedly distinguished these preemption categories, it has also explained that the presence of a preemption clause in a federal statute does not preclude the possibility of implied preemption.[15] Congress must therefore consider the possibility that courts may construe statutes as impliedly preempting certain categories of state law even if such laws do not fall within the explicit terms of a preemption clause.

This report provides a general overview of federal preemption to inform Congress as it crafts laws implicating overlapping federal and state interests. The report begins by reviewing two general principles that have shaped the Court's preemption jurisprudence: the primacy of congressional intent and the presumption against preemption.

The report then examines how courts have interpreted certain language that is commonly used in preemption clauses. Next, the report reviews judicial interpretations of statutory savings clauses—provisions that insulate certain categories of state law from federal preemption. Finally, the report discusses the Court's implied preemption case law by examining illustrative examples of its field preemption, impossibility preemption, and obstacle preemption decisions.

General Preemption Principles

The Primacy of Congressional Intent

The Supreme Court has explained that in determining whether—and to what extent—federal law preempts state law, the purpose of Congress is the "ultimate touchstone" of its statutory analysis.[16] The Court has further instructed that Congress's intent is discerned "primarily" from a statute's text.[17] The Court has also noted, however, the importance of statutory structure and purpose in determining how Congress intended a federal regulatory scheme to interact with

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[15] Geier v. Am. Honda Motor Co., 529 U.S. 861, 881–82 (2000) (holding that a federal regulatory scheme impliedly preempted state common law claims involving automobile safety, even though a preemption clause in the relevant statute did not expressly encompass those claims).

[16] Wyeth v. Levine, 555 U.S. 555, 565 (2009) (quoting Medtronic, Inc. v. Lohr, 518 U.S. 470, 485 (1996)).

[17] *Medtronic*, 518 U.S. at 486.

related state laws.[18] Like many of its statutory interpretation cases, then, the Court's preemption decisions often involve disputes over the appropriateness of consulting extratextual evidence to determine Congress's intent.[19]

The Presumption Against Preemption

In evaluating congressional purpose, the Supreme Court has at times employed a canon of construction called the "presumption against preemption," which instructs that federal law should not be read to preempt laws involving the states' historic police powers[20] "unless that was the clear and manifest purpose of Congress."[21] The presumption is rooted in principles of federalism and respect for state sovereignty.[22] While the Court has described the presumption against preemption as one of the "cornerstones" of its preemption jurisprudence, it has invoked the presumption inconsistently.[23]

[18] *Id.* ("Congress' intent, of course, primarily is discerned from the language of the pre-emption statute and the statutory framework surrounding it. Also relevant, however, is the structure and purpose of the statute as a whole, as revealed not only in the text, but through the reviewing court's reasoned understanding of the way in which Congress intended the statute and its surrounding regulatory scheme to affect business, consumers, and the law.") (citations and internal quotation marks omitted).

[19] *See, e.g.*, *Wyeth*, 555 U.S. at 583 (Thomas, J., concurring in the judgment) (rejecting the Court's obstacle preemption jurisprudence as "inconsistent with the Constitution," while noting that the Court "routinely invalidates state laws based on perceived conflicts with broad federal policy objectives, legislative history, or generalized notions of congressional purposes that are not embodied within the text of federal law"). For further background on the legal debate over using legislative history and other extratextual evidence to interpret statutes, *see* CRS Report R45153, *Statutory Interpretation: Theories, Tools, and Trends*, by Valerie C. Brannon.

[20] The Supreme Court uses the term "police power" to refer to the states' general power of governing, such as regulating to promote public health, safety, and welfare. *See, e.g.*, Nat'l Fed'n of Indep. Bus. v. Sebelius, 567 U.S. 519, 536 (2012) ("Our cases refer to this general power of governing, possessed by the States but not by the Federal Government, as the 'police power.'").

[21] Rice v. Santa Fe Elevator Corp., 331 U.S. 218, 230 (1947); *see also, e.g.*, *Wyeth*, 555 U.S. at 565 ("[I]n all pre-emption cases, and particularly in those in which Congress has legislated . . . in a field which the States have traditionally occupied, . . . we start with the assumption that the historic police powers of the States were not to be superseded by the Federal Act unless that was the clear and manifest purpose of Congress.'") (citations and internal quotation marks omitted); N.Y. State Conf. of Blue Cross & Blue Shield Plans v. Travelers Ins. Co., 514 U.S. 645, 654 (1995) ("[W]e have never assumed lightly that Congress has derogated state regulation, but instead have addressed claims of pre-emption with the starting presumption that Congress does not intend to supplant state law."); Puerto Rico Dep't of Consumer Affs. v. Isla Petroleum Corp., 485 U.S. 495, 500 (1988) ("As we have repeatedly stated, we start with the assumption that the historic police powers of the States were not to be superseded by the Federal Act unless that was the clear and manifest purpose of Congress.") (citations and internal quotation marks omitted).

[22] *See* Tarrant Reg'l Water Dist. v. Herrmann, 569 U.S. 614, 631 n.10 (2013); Cipollone v. Liggett Grp., Inc., 505 U.S. 504, 533 (1992) (Blackmun, J., concurring in part, concurring in the judgment in part, and dissenting in part).

[23] *See, e.g.*, Mut. Pharm. Co. v. Bartlett, 570 U.S. 472 (2013) (holding that federal law preempted state law without mentioning the presumption against preemption); Kurns v. R.R. Friction Prods. Corp., 565 U.S. 625 (2012) (similar); PLIVA, Inc. v. Mensing, 564 U.S. 604, 622 (2011) (similar); Bruesewitz v. Wyeth LLC, 562 U.S. 223 (2011) (similar); Rowe v. New Hampshire Motor Transport Ass'n, 552 U.S. 364 (2008) (similar); Geier v. Am. Honda Motor Co., 529 U.S. 861 (2000) (similar); United States v. Locke, 529 U.S. 89, 108 (2000) (similar). *See also, e.g.*, Charles W. Tyler & Heather K. Gerken, *The Myth of the Laboratories of Democracy*, 122 Colum. L. Rev. 2187, 2240 (2022) ("The Court has recognized the presumption since its 1947 decision in *Rice v. Santa Fe Elevator Corp.*, but it has applied the presumption only episodically—sometimes calling it a 'cornerstone[]' of preemption jurisprudence, other times ignoring it entirely."); Thomas W. Merrill, *Preemption and Institutional Choice*, 102 Nw. U. L. Rev. 727, 741 (2008) ("[T]he presumption against preemption is honored as much in the breach as in observance.").

In a 2016 decision, the Court also appeared to depart from prior case law[24] when it suggested that the presumption did not apply in express preemption cases.[25] Since that decision, lower courts have disagreed over the presumption's application to interpretations of preemption clauses.[26] Although several federal circuit courts have held that the presumption no longer applies in express preemption cases,[27] one circuit court has concluded that the presumption remains valid in cases involving areas historically regulated by states.[28]

The Supreme Court has also appeared to endorse a narrower exception to the presumption against preemption involving areas in which the federal government has traditionally had a "significant" regulatory presence.[29] In *United States v. Locke*, the Court held that the federal Ports and Waterways Safety Act preempted state regulations involving maritime commerce—an area in which there was a "history of significant federal presence."[30] When a state regulates in such an area, the Court explained, "there is no beginning assumption that concurrent regulation by the State is a valid exercise of its police powers."[31]

In a subsequent decision, however, the Court appeared to retreat from its reasoning in *Locke*. In its 2009 decision in *Wyeth v. Levine*, the Court invoked the presumption when it held that federal law did not preempt certain state law claims concerning drug labeling.[32] In allowing the claims to proceed, the Court acknowledged that the federal government had regulated drug labeling for more than a century, but explained that the presumption can apply even when the federal government has long regulated a subject.[33]

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[24] *See, e.g.*, CTS Corp. v. Waldburger, 573 U.S. 1, 19 (2014) ("[W]hen the text of a pre-emption clause is susceptible of more than one plausible reading, courts ordinarily accept the reading that disfavors preemption.") (citations and internal quotation marks omitted); Wyeth, 555 U.S. at 565 (explaining that the presumption against preemption applies "[i]n all pre-emption cases"); Altria Grp., Inc. v. Good, 555 U.S. 70, 77 (2008) (explaining that the Court "begin[s its] analysis" with a presumption against preemption "[w]hen addressing questions of *express or implied* pre-emption") (emphasis added); Bates v. Dow Agrosciences LLC, 544 U.S. 431, 449 (2005) ("Even if [the defendant] had offered us a plausible alternative reading of [the relevant preemption clause]—indeed, even if its alternative were just as plausible as our reading of the text—we would nevertheless have a duty to accept the reading that disfavors pre-emption."); Egelhoff v. Egelhoff *ex rel.* Breiner, 532 U.S. 141, 151 (2001) (invoking the presumption against preemption in interpreting ERISA's preemption clause); Medtronic, Inc. v. Lohr, 518 U.S. 470, 485 (1996) (explaining that the presumption against preemption applies "[i]n all pre-emption cases"); De Buono v. NYSA-ILA Med. & Clinical Servs. Fund, 520 U.S. 806, 814 (1997) (invoking the presumption against preemption in interpreting ERISA's preemption clause); *Travelers*, 514 U.S. at 654 (same); *Cipollone*, 505 U.S. at 518 (invoking the presumption against preemption in interpreting the Federal Cigarette Labeling and Advertising Act's preemption clause).

[25] Puerto Rico v. Franklin Cal. Tax-Free Tr., 579 U.S. 115, 125 (2016).

[26] *See, e.g.*, Cal. Rest. Ass'n v. City of Berkeley, No. 21-16278, 2023 WL 2962921, at *9 (9th Cir. Apr. 17, 2023) (O'Scannlain, J., concurring) (collecting cases and observing that "[t]here is much confusion over how broadly to read *Franklin*[]").

[27] *See* Dialysis Newco, Inc. v. Cmty. Health Sys. Grp. Health Plan, 938 F.3d 246, 259 (5th Cir. 2019); Watson v. Air Methods Corp., 870 F.3d 812, 817 (8th Cir. 2017); EagleMed LLC v. Cox, 868 F.3d 893, 903 (10th Cir. 2017); Atay v. Cnty. of Maui, 842 F.3d 688, 699 (9th Cir. 2016).

[28] *See* Lupian v. Joseph Cory Holdings LLC, 905 F.3d 127, 131 n.5 (3d Cir. 2018) ("[W]e have determined that, because [*Franklin*] . . . did not address claims involving areas historically regulated by states, we would continue to apply the presumption against preemption to express preemption claims.").

[29] United States v. Locke, 529 U.S. 89, 108 (2000).

[30] *Id.*

[31] *Id.*

[32] Wyeth v. Levine, 555 U.S. 555, 565 n.3 (2009).

[33] *Id.* (explaining that the presumption's application "accounts for the historic presence of state law but does not rely on the absence of federal regulation").

Whether the presumption continues to apply in fields traditionally regulated by the federal government thus remains unclear.

Language Commonly Used in Express Preemption Clauses

Congress often relies on the language of existing preemption clauses in drafting new legislation.[34] This type of reliance can have important consequences, as courts often look to the settled meaning of statutory language to discern Congress's intent.[35]

This section of the report discusses how the Supreme Court has interpreted federal statutes that expressly preempt (1) state laws "related to" certain subjects, (2) state laws concerning certain subjects "covered" by federal laws and regulations, (3) state requirements that are "in addition to, or different than" federal requirements, and (4) state "requirements," "laws," "regulations," and "standards."[36]

While preemption decisions depend heavily on the details of particular statutory schemes, the Court has assigned some of these phrases specific meanings even when they have appeared in different statutory contexts.

"Related to"

Some preemption clauses provide that a federal statute supersedes all state laws that are "related to" a specific matter of federal regulatory concern. The Supreme Court has characterized such provisions as "deliberatively expansive"[37] and "conspicuous for [their] breadth."[38]

At the same time, the Court has cautioned against strictly literal interpretations of "related to" preemption clauses. Instead of reading such clauses "to the furthest stretch of [their]

[34] ALAN UNTEREINER, THE PREEMPTION DEFENSE IN TORT ACTIONS: LAW, STRATEGY AND PRACTICE 77 (2008) ("Although express preemption provisions cover a wide range of subjects, they also follow certain familiar patterns. They often contain similar if not identical words or phrases, including limitations on or exceptions to the scope of preemption.").

[35] *See* Bragdon v. Abbott, 524 U.S. 624, 645 (1998) ("When administrative and judicial interpretations have settled the meaning of an existing statutory provision, repetition of the same language in a new statute indicates, as a general matter, the intent to incorporate its administrative and judicial interpretations as well."); *see also* Morales v. Trans World Airlines, Inc., 504 U.S. 374, 383–84 (1992) (relying on the Court's earlier interpretation of a preemption clause in the Employee Retirement Income Security Act to interpret a similarly worded preemption clause in the Airline Deregulation Act).

[36] Although some preemption clauses might appear to issue commands directly to states, the Supreme Court has explained that all forms of preemption are based on federal laws that regulate private actors. Murphy v. Nat'l Collegiate Athletic Ass'n, 138 S. Ct. 1461, 1475, 1479–80 (2018). The Constitution authorizes Congress to "regulate individuals, not States," and the Court therefore requires that preemption clauses must be "best read" as conferring rights or imposing restrictions on private actors. *Id.* at 1479. For example, the preemption clause in the Airline Deregulation Act of 1978 provides that "no State . . . shall enact or enforce any law" related to prices, routes, or services of a covered air carrier. 49 U.S.C. § 41713(b)(1) (as amended). The Court has explained that, while this clause "might appear to operate directly on States," it instead regulates private actors by conferring on covered carriers "a federal right to engage in certain conduct subject only to certain (federal) constraints." *Murphy*, 138 S. Ct. at 1480. For a more in-depth discussion of the relationship between preemption principles and the prohibition on issuing direct commands to states (the "anticommandeering" doctrine), see CRS Report R45323, *Federalism-Based Limitations on Congressional Power: An Overview*, coordinated by Kevin J. Hickey.

[37] Pilot Life Ins. Co. v. Dedeaux, 481 U.S. 41, 46 (1987).

[38] FMC Corp. v. Holliday, 498 U.S. 52, 58 (1990).

indeterminacy,"[39] the Court has looked to Congress's statutory objectives to cabin the clauses' scope.[40]

The following subsections discuss the Court's interpretation of three statutes that contain "related to" preemption clauses: the Employee Retirement Income Security Act, the Airline Deregulation Act, and the Federal Aviation Administration Authorization Act.

Employee Retirement Income Security Act

The Employee Retirement Income Security Act (ERISA) contains perhaps the most prominent example of a preemption clause that uses "related to" language.[41] ERISA imposes comprehensive federal regulations on private employee benefit plans.[42] The statute also contains a preemption clause providing that its requirements preempt all state laws that "relate to" regulated benefit plans.[43]

In interpreting this provision, the Supreme Court has held that ERISA preempts two categories of state law: (1) state laws that have a "connection with" ERISA plans, and (2) state laws that contain a "reference to" ERISA plans.[44]

The Court has held that state laws have an impermissible "connection with" ERISA plans if they govern "a central matter of plan administration" or interfere with "nationally uniform plan administration."[45] In contrast, state laws that indirectly affect ERISA plans are not preempted unless the relevant effects are particularly "acute."[46]

Applying these standards, the Court has ruled that ERISA preempts state laws governing areas of "core ERISA concern," like the designation of ERISA plan beneficiaries[47] and the disclosure of information regarding health plan benefits.[48]

In contrast, the Supreme Court has held that ERISA does not preempt state laws imposing surcharges on certain types of insurers[49] and mandating wage levels for specific categories of employees who work on public projects.[50] The Court has explained that these state laws are

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[39] N.Y. State Conference of Blue Cross & Blue Shield Plans v. Travelers Ins. Co., 514 U.S. 645, 655 (1995).

[40] *See, e.g.*, *id.* at 656 ("We simply must . . . look instead to the objectives of the . . . statute as a guide to the scope of the state law that Congress understood would survive."); Dan's City Used Cars, Inc. v. Pelkey, 569 U.S. 251, 263–64 (2013); *Travelers*, 514 U.S. at 661. *See also* Cal. Div. of Labor Standards Enf't v. Dillingham Constr., N.A., Inc., 519 U.S. 316, 335 (1997) (Scalia, J., concurring) ("[A]pplying the 'relate to' provision [in the Employee Retirement Income Security Act (ERISA)] according to its terms was a project doomed to failure, since, as many a curbstone philosopher has observed, everything is related to everything else.").

[41] Daniel J. Meltzer, *Preemption and Textualism*, 112 MICH. L. REV. 1, 20 (2013) ("The most frequently litigated 'related to' preemption clause is found in [ERISA].").

[42] *See* 29 U.S.C. §§ 1001–1461.

[43] *Id.* § 1144(a).

[44] Rutledge v. Pharm. Care Mgmt. Ass'n, 141 S. Ct. 474, 479–81 (2020); Shaw v. Delta Air Lines, Inc., 463 U.S. 85, 96–97 (1983).

[45] *Rutledge*, 141 S. Ct. at 480; Egelhoff v. Egelhoff *ex rel.* Breiner, 532 U.S. 141, 148 (2001).

[46] *Travelers*, 514 U.S. at 668. *See also Rutledge*, 141 S. Ct. at 480–81.

[47] *Egelhoff*, 532 U.S. at 147.

[48] Gobeille v. Liberty Mut. Ins. Co., 577 U.S. 312, 323 (2016).

[49] *Travelers*, 514 U.S. at 651–52.

[50] Cal. Div. of Labor Standards Enf't v. Dillingham Constr., N.A., Inc., 519 U.S. 316, 334 (1997).

permissible because they affect ERISA plans only indirectly and that ERISA preempts such laws only if the relevant indirect effects are particularly strong.[51]

The Court has also held that ERISA preempts state laws that contain an impermissible "reference to" ERISA plans. Under the Court's case law, a state law will contain an impermissible "reference to" ERISA plans where it "acts immediately and exclusively upon ERISA plans," or where the existence of an ERISA plan is "essential" to the state law's operation.[52]

In *Mackey v. Lanier Collection Agency & Service, Inc.*, for example, the Supreme Court concluded that ERISA preempted a state statute that prohibited the garnishment of funds in plans "subject to . . . [ERISA]."[53] Because the challenged state statute expressly referenced ERISA plans, the Court held that it fell within the scope of ERISA's preemption clause even if it was enacted "to help effectuate ERISA's underlying purposes."[54]

Similarly, in *Ingersoll-Rand Company v. McClendon*, the Court held that ERISA preempted an employee's state law claim alleging that he was terminated in order to prevent his regulated pension from vesting.[55] The Court reasoned that ERISA preempted this state law claim because the action made specific reference to and was premised on the existence of an ERISA-regulated pension plan.[56]

The Supreme Court's decision in *District of Columbia v. Greater Washington Board of Trade* offers a third example of preemption based on a state law's "reference to" ERISA plans.[57] There, the Court held that ERISA preempted a state statute requiring employers that provided health insurance to their employees to continue providing coverage at existing benefit levels while employees received workers' compensation benefits.[58] This state law was preempted, the Court concluded, because ERISA regulates employee health insurance, meaning that the state law specifically referred to ERISA-regulated plans.[59]

Airline Deregulation Act

The Airline Deregulation Act (ADA) is another example of a statute that employs "related to" preemption language.[60] Enacted in 1978, the ADA largely deregulated domestic air transportation.[61]

To ensure that state governments did not interfere with this deregulatory effort, the ADA prohibits states from enacting laws "related to a price, route, or service of an air carrier."[62]

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[51] *Travelers*, 514 U.S. at 668. *See also Rutledge*, 141 S. Ct. at 480 ("A state law may . . . be subject to pre-emption if acute, albeit indirect, economic effects of the state law force an ERISA plan to adopt a certain scheme of substantive coverage.") (internal quotation marks omitted).

[52] *Dillingham*, 519 U.S. at 325.

[53] 486 U.S. 825, 828 (1988) (quoting Ga. Code Ann. § 18-4-22.1 (1982)).

[54] *Id.* at 829–30.

[55] 498 U.S. 133, 139–41 (1990).

[56] *Id.* at 140.

[57] 506 U.S. 125 (1992).

[58] *Id.* at 130.

[59] *Id.*

[60] 49 U.S.C. § 1371 (1979).

[61] Am. Airlines, Inc. v. Wolens, 513 U.S. 219, 222 (1995).

[62] 49 U.S.C. § 41713(b)(1) (as amended) (emphasis added).

In interpreting this language, the Supreme Court has relied upon similar reasoning as used in its ERISA decisions, concluding that the ADA preempts state laws that have a "connection with" or "reference to" airline prices, routes, or services.[63]

In *Morales v. Trans World Airlines, Inc*., for example, the Court relied in part on its ERISA case law to hold that the ADA preempted a state's effort to enforce guidelines regarding the content and format of airline fare advertising.[64] The Court reached this conclusion on the grounds that the guidelines expressly referenced airfares and were likely to have a significant impact on airfares.[65]

Federal Aviation Administration Authorization Act

The Federal Aviation Administration Authorization Act of 1994 (FAAA) is a third example of a statute that utilizes "related to" preemption language.[66] While the FAAA is (as its title suggests) principally concerned with aviation regulation, it also supplemented Congress's deregulation of the trucking industry. The statute pursued this objective with a preemption clause prohibiting states from enacting laws "related to a price, route, or service of any motor carrier . . . with respect to the transportation of property."[67]

In *Rowe v. New Hampshire Motor Transport Association*, the Supreme Court relied in part on its ERISA and ADA case law to hold that the FAAA preempted certain state laws regulating the delivery of tobacco, including a law that required retailers shipping tobacco to employ motor carriers that utilized certain kinds of recipient-verification services.[68]

The Court reached this conclusion for two principal reasons. First, the Court reasoned that the requirement had an impermissible "connection with" motor carrier services because it "focuse[d] on" such services.[69] Second, the Court concluded that the FAAA preempted the state law because of the state law's significant adverse effects on the federal statute's deregulatory objectives. Specifically, the Court reasoned that the state law had a "connection with" these objectives because it dictated that motor carriers use certain types of recipient-verification services, thereby substituting the state's commands for competitive market forces.[70]

Although the Supreme Court has thus relied on its ERISA and ADA case law in interpreting the FAAA's preemption clause, the Court has also explained that the clause's "with respect to" qualifying language significantly narrows the statute's preemptive scope.

In *Dan's City Used Cars, Inc. v. Pelkey*, the Court relied on this language to hold that the FAAA did not preempt state law claims involving the storage and disposal of a towed car.[71] In allowing the claims to proceed, the Court observed that the FAAA's preemption clause mirrored the ADA's preemption clause with "one conspicuous alteration"—the addition of the phrase "with respect to

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[63] Morales v. Trans World Airlines, Inc., 504 U.S. 374, 384 (1992) ("Since the relevant language of the ADA is identical, we think it appropriate to adopt the same standard here: State enforcement actions having a connection with or reference to airline 'rates, routes, or services' are pre-empted . . . .").

[64] *Id.* at 388–89.

[65] *Id.* at 390; *see id.* at 388 ("[B]eyond the guidelines' express reference to fares, it is clear as an economic matter that state restrictions on fare advertising have the forbidden significant effect upon fares.").

[66] 49 U.S.C. § 14501.

[67] *Id.* § 14501(c)(1) (emphasis added).

[68] 552 U.S. 364, 368 (2008).

[69] *Id.* at 371.

[70] *Id.* at 372.

[71] 569 U.S. 251, 265 (2013).

the transportation of property."[72] According to the Court, this phrase "massively" limited the scope of FAAA preemption.[73] Because the relevant state law claims involved the storage and disposal of towed vehicles rather than their transportation, the Court held that they did not qualify as state laws that "related to" motor carrier services "with respect to the transportation of property."[74]

Takeaways

The Supreme Court's case law concerning "related to" preemption clauses reflects a number of general principles. The Court has consistently held that state laws "relate to" matters of federal regulatory concern when they have a "connection with" or contain a "reference to" such matters.[75]

Generally, state laws have an impermissible "connection with" matters of federal concern when they:

- prescribe rules governing an issue central to the relevant federal regulatory scheme;[76]
- interfere with uniform national policies regarding a matter of federal concern;[77] or
- have indirect effects on the federal scheme that are particularly "acute"[78] or "significant."[79]

As a corollary to the latter principle, the Court has made clear that state laws having only "tenuous, remote, or peripheral" effects on an issue of federal concern are not sufficiently "related to" the issue to warrant preemption.[80]

The Court has concluded that state laws contain a "reference to" a matter of federal regulatory interest if they "act[] immediately and exclusively upon" the matter or if the existence of a federal regulatory scheme is "essential" to the state law's operation.[81]

The inclusion of qualifying language can narrow the scope of "related to" preemption clauses. As the Court made clear in *Dan's City*, the scope of "related to" preemption clauses can be significantly limited by the addition of "with respect to" qualifying language.[82]

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[72] *Id.* at 261.

[73] *Id.* (citation and internal quotation marks omitted).

[74] *Id.* (emphasis added).

[75] *See, e.g.*, Rutledge v. Pharm. Care Mgmt. Ass'n, 141 S. Ct. 474, 479 (2020); Rowe v. N.H. Motor Transport Ass'n, 552 U.S. 364, 370 (2008); Morales v. Trans World Airlines, Inc., 504 U.S. 374, 383 (1992); Shaw v. Delta Air Lines, Inc., 463 U.S. 85, 96 (1983).

[76] Egelhoff v. Egelhoff *ex rel.* Breiner, 532 U.S. 141, 148 (2001).

[77] *Rutledge*, 141 S. Ct. at 479–81.

[78] N.Y. State Conf. of Blue Cross & Blue Shield Plans v. Travelers Ins. Co., 514 U.S. 645, 668 (1995).

[79] *Morales*, 504 U.S. at 388.

[80] *Shaw*, 463 U.S. at 100 n.21.

[81] Cal. Div. of Labor Standards Enf't v. Dillingham Constr., N.A., Inc., 519 U.S. 316, 325 (1997).

[82] Dan's City Used Cars, Inc. v. Pelkey, 569 U.S. 251, 261 (2013).

"Covering"

The Federal Railroad Safety Act contains a preemption clause allowing states to regulate railroad safety until the federal government prescribes a regulation or issues an order "covering the subject matter" of the relevant state requirement.[83]

In *CSX Transportation, Inc. v. Easterwood*, the Supreme Court interpreted this language as having a narrower effect than "related to" preemption clauses.[84] The Court explained that "covering" is a more restrictive term than "related to," and that federal law will accordingly cover the subject of a state law only if it "substantially subsume[s]" that subject.[85]

Applying this standard, the Court held that federal regulations of grade crossing safety did not preempt state law claims alleging that a train operator failed to maintain adequate warning devices at a crossing where a collision had occurred.[86] The Court allowed these claims to proceed because the relevant federal regulations did not "substantially subsume" the subject of warning device adequacy.[87]

At the same time, the *Easterwood* Court held that federal regulations preempted other state law claims alleging that a train traveled at an unsafe speed. In holding that these claims were preempted, the Court reasoned that federal maximum-speed regulations "substantially subsumed"—and therefore "covered"—the subject of train speeds.[88]

"In addition to, or different than"

A number of federal statutes preempt state requirements that are "in addition to, or different than" federal requirements.[89] The Supreme Court has explained that these statutes preempt state law even in cases where a regulated entity can comply with both federal and state requirements.

The Court adopted this position in *National Meat Association v. Harris*, where it interpreted a preemption clause in the Federal Meat Inspection Act (FMIA) prohibiting states from imposing

[83] 49 U.S.C. § 20106(a)(2).

[84] 507 U.S. 658, 664 (1993).

[85] *Id.*

[86] *Id.* at 665–73.

[87] *Id.* at 667. The Court held that related regulations concerning warning devices installed with federal funds did not apply to the facts in *Easterwood*. *Id.* at 670–73. The Court later held that federal law and these regulations preempted state law claims against a train operator for the alleged inadequacy of warning devices installed using federal funds. Norfolk S. Ry. Co. v. Shanklin, 529 U.S. 344, 358–59 (2000).

[88] 507 U.S. at 673–76.

[89] *See, e.g.*, 7 U.S.C. § 136v(b) (providing that states "shall not impose or continue in effect any requirements for labeling and packaging [pesticides] *in addition to or different from* those required under this subchapter") (emphasis added); 21 U.S.C. § 467e ("Marking, labeling, packaging, or ingredient requirements . . . *in addition to, or different than*, those made under this chapter may not be imposed by any State . . . .") (emphasis added); 7 U.S.C. § 4817(b) ("The regulation of [promotion and consumer education involving pork and pork products] . . . that is *in addition to or different from* this chapter may not be imposed by a State.") (emphasis added); 21 U.S.C. § 360k(a) ("[N]o state . . . may establish or continue in effect with respect to a device intended for human use any requirement . . . which is *different from, or in addition to*, any requirement applicable under this chapter to the device, and . . . which relates to the safety or effectiveness of the device or to any other matter included in a requirement applicable to the device under this chapter.") (emphasis added); 21 U.S.C. § 1052(b) ("Requirements within the scope of this chapter with respect to premises, facilities, and operations of any official plant which are *in addition to or different than* those made under this chapter may not be imposed by any State . . . .") (emphasis added).

requirements on meatpackers and slaughterhouses that are "in addition to, or different than" federal requirements.[90]

In *Harris*, the Court held that certain California slaughterhouse regulations were "in addition to, or different than" federal regulations because they imposed a distinct set of requirements that went beyond those imposed by federal law.[91] Because the California requirements differed from federal requirements, the Court explained, they fell within the plain meaning of the FMIA's preemption clause, even though slaughterhouses were able to comply with both sets of restrictions.[92]

Preemption clauses that employ "in addition to, or different than" language often raise a second interpretive issue involving the status of state requirements that are identical to federal requirements.

The Supreme Court has interpreted two statutes employing this language to not preempt parallel state law requirements.[93] In instructing lower courts on how to assess whether state requirements in fact parallel federal requirements, the Court has explained that state law need not explicitly incorporate federal standards in order to avoid qualifying as "in addition to, or different than" federal requirements.[94] Instead, the relevant inquiry looks to the substance of state requirements to determine whether they mirror federal law.

The Court has also explained that state requirements do not qualify as "in addition to, or different than" federal requirements simply because state law provides injured plaintiffs with different remedies than federal law.[95] Accordingly, absent contextual evidence to the contrary, preemption clauses that employ "in addition to, or different than" language will allow states to give plaintiffs a damages remedy for violations of state requirements even where federal law does not offer such a remedy for violations of parallel federal requirements.[96]

"Requirements," "Laws," "Regulations," and "Standards"

Federal statutes frequently preempt state "requirements," "laws," "regulations," and/or "standards" concerning subjects of federal regulatory concern.[97] These preemption clauses have raised the question of whether they encompass state common law actions.

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90 565 U.S. 452, 455 (2012).

91 *Id.* at 459 (citation and internal quotation marks omitted).

92 *Id.* at 459–60.

93 Bates v. Dow Agrosciences LLC, 544 U.S. 431, 446 (2005); Medtronic, Inc. v. Lohr, 518 U.S. 470, 494–97 (1996).

94 *Bates*, 544 U.S. at 447.

95 *See id.* at 447–48.

96 *See id.*

97 *See, e.g.*, 7 U.S.C. § 136v(b) (providing that no state "shall . . . impose or continue in effect any *requirements* for labeling or packaging in addition to or different from those required under this subchapter") (emphasis added); 21 U.S.C. § 360k(a) (providing that no state "may establish or continue in effect with respect to a device intended for human use any *requirement* . . . which is different from, or in addition to, any requirement applicable under this chapter to the device") (emphasis added); 46 U.S.C. § 4306 ("[A] State . . . may not establish, continue in effect, or enforce a *law or regulation* establishing a recreational vessel or associated equipment performance or other safety standard or imposing a requirement for associated equipment . . . that is not identical to a regulation prescribed under . . . this title.") (emphasis added); 49 U.S.C. § 30103(b)(1) ("When a motor vehicle safety standard is in effect under this chapter, a State . . . may prescribe or continue in effect a *standard* applicable to the same aspect of performance of a motor vehicle or motor vehicle equipment only if the *standard* is identical to the standard prescribed under this chapter.") (emphases added).

The Supreme Court has explained that, absent evidence to the contrary, a preemption clause's reference to state "requirements" includes state common law duties.[98]

In contrast, the Court has interpreted one preemption clause's reference to state "law[s] or regulation[s]" as encompassing only "positive enactments" and not common law actions.[99] The Court reached this conclusion in *Sprietsma v. Mercury Marine*, where it held that the Federal Boat Safety Act of 1971 (FBSA) did not preempt common law claims involving boat safety.[100] The FBSA contains a preemption clause prohibiting states from enforcing "a law or regulation" concerning boat safety that is not identical to federal laws and regulations.[101] The statute also includes a savings clause providing that compliance with federal requirements does not "relieve a person from liability at common law or under State law."[102]

In *Sprietsma*, the Court held that the phrase "law or regulation" in the FBSA's preemption clause did not encompass state common law claims for three reasons.[103] First, the Court reasoned that the inclusion of the article "a" before "law or regulation" implied a "discreteness" that is reflected in statutes and regulations, but not in common law.[104] Second, the Court concluded that the pairing of the terms "law" and "regulation" indicated that Congress intended to preempt only positive enactments. In particular, the Court reasoned that if the term "law" were given an expansive interpretation that included common law claims, it would also encompass "regulations" and thereby render the inclusion of that latter term superfluous.[105] Third, the Court reasoned that the FBSA's savings clause provided additional support for the conclusion that the phrase "law or regulation" did not encompass common law actions.[106]

With respect to federal statutes that preempt state "standards," the Supreme Court has explained that it is possible to interpret "standards" as encompassing common law actions, but it has interpreted the term more narrowly where the specific statutory context suggested that Congress did not intend to preempt common-law tort actions.[107]

Savings Clauses

Many federal statutes contain provisions that purport to restrict their preemptive effect. These savings clauses make clear that federal law does not preempt certain categories of state law, reflecting Congress's recognition of the need for states to "fill a regulatory void" or "enhance protection for affected communities" through supplementary regulation.[108]

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[98] Riegel v. Medtronic, Inc., 552 U.S. 312, 324 (2008); *see also* Medtronic, Inc. v. Lohr, 518 U.S. 470 (1996); Cipollone v. Liggett Grp., Inc., 505 U.S. 504, 521 (1992).

[99] Sprietsma v. Mercury Marine, 537 U.S. 51, 63 (2002).

[100] *Id.*

[101] 46 U.S.C. § 4306.

[102] *Id.* § 4311(h).

[103] *Sprietsma*, 537 U.S. at 63.

[104] *Id.*

[105] *Id.*

[106] *Id.*

[107] Geier v. Am. Honda Motor Co., 529 U.S. 861, 868 (2000). For a further discussion of the Court's holding in *Geier*, see *infra* "Compliance Savings Clauses."

[108] Sandi Zellmer, *When Congress Goes Unheard: Savings Clauses' Rocky Judicial Reception*, *in* PREEMPTION CHOICE: THE THEORY, LAW, AND REALITY OF FEDERALISM'S CORE QUESTION 144, 146 (William W. Buzbee ed., 2009).

The law regarding savings clauses "is not especially well developed," and cases involving such clauses "turn very much on the precise wording of the statutes at issue."[109]

With these caveats in mind, this section discusses three general categories of savings clauses: (1) "anti-preemption provisions," (2) "compliance savings clauses," and (3) "remedies savings clauses."

Anti-Preemption Provisions

Some savings clauses contain language indicating that "nothing in" the relevant federal statute "may be construed to preempt or supersede" certain categories of state law.[110] Others say that the relevant federal statute "does not annul, alter, or affect" state laws "except to the extent that those laws are inconsistent" with the federal statute.[111] Certain statutes containing this "inconsistency" language further provide that state laws are not "inconsistent" with the relevant federal statute if they provide greater protection to consumers than federal law.[112] Some courts and commentators have labeled these clauses "anti-preemption provisions."[113]

Courts have given effect to the plain language of these provisions, concluding that they evince Congress's intent to allow states to adopt regulations that are consistent with federal law.[114]

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[109] UNTEREINER, *supra* note 34, at 204–05.

[110] *See, e.g.*, 7 U.S.C. § 2910(a) ("Nothing in this chapter may be construed to preempt or supersede any other program relating to beef promotion organized and operated under the laws of the United States or any State."); *id.* § 6812(c) ("Nothing in this chapter may be construed to preempt or supersede any other program relating to cut flowers or cut greens promotion and consumer information organized and operated under the laws of the United States or a State."); *id.* § 7811(c) ("Nothing in this chapter may be construed to preempt or supersede any other program relating to Hass avocado promotion, research, industry information, and consumer information organized and operated under the laws of the United States or of a State.").

[111] *See, e.g.*, 12 U.S.C. § 2616 ("This chapter does not annul, alter, or affect, or exempt any person subject to the provisions of this chapter from complying with, the laws of any State with respect to [real estate] settlement practices, except to the extent that those laws are inconsistent with any provision of this chapter, and then only to the extent of the inconsistency."); 15 U.S.C. § 1693q ("This subchapter does not annul, alter, or affect the laws of any State relating to electronic fund transfers, dormancy fees, inactivity charges or fees, service fees, or expiration dates of gift certificates, store gift cards, or general-use prepaid cards, except to the extent that those laws are inconsistent with the provisions of this subchapter, and then only to the extent of the inconsistency."); 15 U.S.C. § 5722(a) ("This subchapter does not annul, alter, or affect, or exempt any person subject to the provisions of this subchapter from complying with, the laws of any State with respect to telephone billing practices, except to the extent that those laws are inconsistent with any provision of this subchapter, and then only to the extent of the inconsistency.").

[112] 12 U.S.C. § 2616 (authorizing the Consumer Financial Protection Bureau (CFPB) to determine whether state laws are "inconsistent with" the relevant federal statute, and providing that the CFPB "may not determine that any State law is inconsistent with" the federal statute "if the [CFPB] determines that such law gives greater protection to the consumer."); 15 U.S.C. § 1693q ("A State law is not inconsistent with this subchapter if the protection such law affords any consumer is greater than the protection afforded by this subchapter."); 15 U.S.C. § 5722(a) (authorizing the Federal Trade Commission (FTC) to determine whether state laws are "inconsistent with" the relevant federal statute, and providing that the FTC "may not determine that any State law is inconsistent with" the federal statute "if the [FTC] determines that such law gives greater protection to the consumer.").

[113] *See* Gobeille v. Liberty Mut. Ins. Co., 577 U.S. 312, 326 (2016); Bank of Am. v. City & Cnty. of S.F., 309 F.3d 551, 565 (9th Cir. 2002); Bank One v. Guttau, 190 F.3d 844, 850 (8th Cir. 1999); UNTEREINER, *supra* note 34, at 20.

[114] *See, e.g.*, Perkins v. Johnson, 551 F. Supp. 2d 1246, 1255 (D. Colo. 2008).

Compliance Savings Clauses

Some savings clauses provide that compliance with federal law does not relieve a person from liability under state law.[115] The principal interpretive issue with such clauses is whether they limit a statute's preemptive effect (a question of federal law) or are instead intended to discourage the conclusion that compliance with federal regulations necessarily renders a product nondefective as a matter of state tort law.[116]

While the Supreme Court has not adopted a generally applicable rule concerning the meaning of compliance savings clauses, it has concluded that such clauses can support a narrow interpretation of a statute's preemptive effect.

In *Geier v. American Honda Motor Co.*, the Court relied in part on a compliance savings clause in the National Traffic and Motor Vehicle Safety Act (NTMVSA) to hold that the statute did not expressly preempt state common law claims against an automobile manufacturer.[117] The NTMVSA contains a preemption clause prohibiting states from enforcing safety standards for motor vehicles that are not identical to federal standards.[118] The statute also includes a savings clause providing that compliance with federal safety standards does not "exempt any person from any liability under common law."[119]

In *Geier*, the Court explained that, although it was "possible" to read the NTMVSA's preemption clause standing alone as encompassing the state law claims, that reading of the statute would leave the Act's savings clause without effect.[120] The Court thus held that the NTMVSA did not expressly preempt state common law claims based in part on the Act's savings clause.[121]

Similarly, as discussed, the Court's decision in *Sprietsma v. Mercury Marine* indicated that a compliance savings clause in the FBSA "buttresse[d]" the conclusion that state common law claims did not qualify as "law[s] or regulation[s]" within the meaning of the statute's preemption clause.[122]

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[115] *See, e.g.*, 15 U.S.C. § 2074(a) ("Compliance with consumer product safety rules or other rules or orders under this chapter shall not relieve any person from liability at common law or under State statutory law to any other person."); 21 U.S.C. § 360pp(e) ("Except as provided in the first sentence of section 360ss of this title, compliance with this part or any regulations issued thereunder shall not relieve any person from liability at common law or under statutory law."); 42 U.S.C. § 5409(c) ("Compliance with any Federal manufactured home construction or safety standard issued under this chapter does not exempt any person from any liability under common law."); 46 U.S.C. § 4311(h) (providing that compliance with federal boat regulations "does not relieve a person from liability at common law or under State law.").

[116] *See* UNTEREINER, *supra* note 34, at 194–96. In many jurisdictions, a defendant's compliance with government regulations can serve as relevant evidence in products liability litigation, and some courts have further held that compliance with government regulations renders a product nondefective as a matter of law. *See* RESTATEMENT (THIRD) OF TORTS: PRODUCTS LIABILITY § 4 cmt. e (1998).

[117] 529 U.S. 861, 868 (2000).

[118] 49 U.S.C. § 30103(b). The NTMVSA was recodified without substantive change in 1994, but in *Geier* the Court referred to the pre-1994 version of the statute. 529 U.S. at 865; 15 U.S.C. § 1392(d) (1988).

[119] 49 U.S.C. § 30103(e); 15 U.S.C. § 1397(k) (1988).

[120] *Geier*, 529 U.S. at 868. As discussed in "Automobile Safety Regulations," the *Geier* Court held that the NTMVSA *impliedly* preempted the relevant common law claims even though it did not *expressly* preempt those claims. Notably, the Court appeared to consider the NTMVSA's savings clause to be relevant only to its interpretation of the statute's express preemption clause, reasoning that the savings clause did not create any sort of "special burden" disfavoring *implied* preemption. *Geier*, 529 U.S. at 870–71.

[121] *Id.* at 868.

[122] 537 U.S. 51, 63 (2002).

The Court has thus relied on compliance savings clauses to inform its interpretation of preemption clauses, but has not held that such clauses automatically insulate state laws from preemption.

Remedies Savings Clauses

Some savings clauses provide that "nothing in" a federal statute "shall in any way abridge or alter the remedies now existing at common law or by statute."[123] While the case law on these "remedies savings clauses" is limited, the Supreme Court has interpreted one such clause as evincing Congress's intent to disavow field preemption, but not as preserving state laws that conflict with federal objectives.[124]

"State" vs. "State or Political Subdivision Thereof"

Some savings clauses limit a federal statute's preemptive effect with respect to certain laws enacted by "State[s] or political subdivisions thereof,"[125] while others by their terms insulate only "State" laws.[126]

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[123] 47 U.S.C. § 414. *See also* 7 U.S.C. § 209(b) ("[T]his section shall not in any way abridge or alter the remedies now existing at common law or by statute, but the provisions of this chapter are in addition to such remedies."); *id.* § 499e(b) ("[T]his section shall not in any way abridge or alter the remedies now existing at common law or by statute, and the provisions of this chapter are in addition to such remedies.").

[124] *See* Pennsylvania R.R. v. Puritan Coal Mining Co., 237 U.S. 121, 129–30 (1915) ("The [savings clause] was added . . . not to nullify other parts of the act, or to defeat rights or remedies given by preceding sections, but to preserve all existing rights which were not inconsistent with those created by the statute . . . But for this proviso . . . , it might have been claimed that, Congress having entered the field, the whole subject of liability of carrier to shippers in interstate commerce had been withdrawn from the jurisdiction of the state courts, and this clause was added to indicate that the commerce act, in giving rights of action in Federal courts, was not intended to deprive the state courts of their general and concurrent jurisdiction."); *see also* Am. Tel. & Tel. Co. v. Cent. Off. Tel., Inc., 524 U.S. 214, 226 (1998) (holding that a remedies savings clause in the Communications Act of 1934 did not save state laws that were inconsistent with federal law).

[125] *See, e.g.*, 33 U.S.C. § 1370 ("[N]othing in this chapter shall . . . preclude or deny the right of any *State or political subdivision thereof* . . . to adopt or enforce . . . any standard or limitation respecting discharges of pollutants. . . .") (emphasis added); 42 U.S.C. § 2018 ("Nothing in this chapter shall be construed to affect the authority or regulations of any Federal, *State, or local agency* with respect to the generation, sale, or transmission of electric power produced through the use of nuclear facilities licensed by the Commission.") (emphasis added); 42 U.S.C. § 6929 ("Nothing in this chapter shall be construed to prohibit any *State or political subdivision* thereof from imposing any requirements, including those for site selection, which are more stringent than those imposed by such regulations.") (emphasis added).

[126] *See, e.g.*, 7 U.S.C. § 136v(a) ("A *State* may regulate the sale or use of any federally registered pesticide or device in the State, but only if and to the extent that the regulation does not permit any sale or use prohibited by this subchapter.") (emphasis added); 42 U.S.C. § 9614(a) ("Nothing in this chapter shall be construed or interpreted as preempting any *State* from imposing additional liability or requirements with respect to the release of hazardous substances within such State.") (emphasis added); 49 U.S.C. § 14501(c)(2)(A) (providing that the Interstate Commerce Act "shall not restrict the safety regulatory authority of a *State* with respect to motor vehicles . . . .") (emphasis added).

Similarly, some preemption clauses bar any "State or . . . political subdivision thereof" from regulating a certain subject matter, while others by their terms preempt only "State" laws. *Compare* 42 U.S.C. § 7543(a) ("No *State or any political subdivision thereof* shall adopt or attempt to enforce any standard relating to the control of emissions from new motor vehicles or new motor vehicle engines subject to this part.") (emphasis added); 49 U.S.C. § 5125(a) (providing that "a requirement of a *State, political subdivision of a State*, or Indian tribe is preempted" under certain circumstances) (emphasis added); 49 U.S.C. § 14501(a)(1) ("No *State or political subdivision thereof* . . . shall enact or enforce any law, rule, regulation, standard, or other provision having the force and effect of law relating to" certain subjects) (emphasis added), *with* 7 U.S.C. § 136v(b) ("Such *State* shall not impose or continue in effect any requirements for labeling or packaging in addition to or different from those required under this subchapter.") (emphasis added); 21 (continued...)

The Supreme Court has twice held that savings clauses that by their terms applied only to "State" laws also insulated local laws from preemption.

In *Wisconsin Public Intervenor v. Mortier*, the Court held that the Federal Insecticide, Fungicide, and Rodenticide Act did not preempt local ordinances regulating pesticides based in part on a savings clause providing that "State[s]" may regulate federally registered pesticides in certain circumstances.[127] In concluding that the term "State" included political subdivisions of states, the Court relied on the principle that local governments are "convenient agencies" by which state governments can exercise their powers.[128]

Similarly, in *City of Columbus v. Ours Garage & Wrecker Service, Inc.*, the Court held that the Interstate Commerce Act (ICA) did not preempt municipal safety regulations governing tow-truck operators based in part on a savings clause providing that the ICA "shall not restrict the safety regulatory authority of a State with respect to motor vehicles."[129] Relying in part on its reasoning in *Mortier*, the Court explained that, absent a clear statement to the contrary, Congress's reference to the regulatory authority of a "State" should be read to preserve "the traditional prerogative of the States to delegate their authority to their constituent parts."[130]

Implied Preemption

As discussed, federal law can impliedly preempt state law even when it does not do so expressly.[131] Like its express preemption decisions, the Supreme Court's implied preemption cases focus on Congress's intent.[132]

The Supreme Court has recognized two general forms of implied preemption: field preemption and conflict preemption. Field preemption occurs when a pervasive scheme of federal regulation implicitly precludes supplementary state regulation or when states attempt to regulate a field where there is a sufficiently dominant federal interest.[133] Conflict preemption occurs when state law interferes with federal goals.[134]

U.S.C. § 360eee-4(b)(2) ("No *State* shall regulate third-party logistics providers as wholesale distributors.") (emphasis added); 42 U.S.C. § 7543(a) ("No *State* shall require certification, inspection, or any other approval relating to the control of emissions from any new motor vehicle or new motor vehicle engine as condition precedent to the initial retail sale, titling (if any), or registration of such motor vehicle, motor vehicle engine, or equipment.") (emphasis added).

[127] 501 U.S. 597, 607–08 (1991); 7 U.S.C. § 136v(a).

[128] *Mortier*, 501 U.S. at 607–08 (citation and internal quotation marks omitted).

[129] 536 U.S. 424, 428–29 (2002); 49 U.S.C. § 14501(c)(2)(A).

[130] *Ours Garage*, 536 U.S. at 429.

[131] *See* Crosby v. Nat'l Foreign Trade Council, 530 U.S. 363, 372 (2000).

[132] *See* Wyeth v. Levine, 555 U.S. 555, 565 (2009) ("[T]he purpose of Congress is the ultimate touchstone in every pre-emption case.") (quoting Medtronic, Inc. v. Lohr, 518 U.S. 470, 485 (1996)); Retail Clerks Int'l Ass'n v. Schermerhorn, 375 U.S. 96, 103 (1963)); Barnett Bank of Marion Cnty., N.A. v. Nelson, 517 U.S. 25, 31 (1996) (explaining that where "explicit pre-emption language does not appear, or does not directly answer the question . . . courts must consider whether the federal statute's 'structure and purpose,' or nonspecific statutory language, nonetheless reveal a clear, but implicit, pre-emptive intent.").

[133] *See* Arizona v. United States, 567 U.S. 387, 399 (2012); Gade v. Nat'l Solid Wastes Mgmt. Ass'n, 505 U.S. 88, 98 (1992).

[134] *Arizona*, 567 U.S. at 399; *Gade*, 505 U.S. at 98. The Court has explained that these subcategories of implied preemption are not "rigidly distinct," and that "field preemption may be understood as a species of conflict preemption" because "[a] state law that falls within a pre-empted field conflicts with Congress' intent . . . to exclude state regulation." English v. Gen. Elec. Co., 496 U.S. 72, 79 n.5 (1990); *see also* LAURENCE TRIBE, AMERICAN
(continued...)

Field Preemption

The Supreme Court has held that federal law preempts state law where Congress has manifested an intention that the federal government occupy an entire field of regulation.[135] Federal law may reflect such an intent through a scheme of federal regulation that is "so pervasive as to make reasonable the inference that Congress left no room for States to supplement it," or where federal law concerns "a field in which the federal interest is so dominant that the federal system will be assumed to preclude enforcement of state laws on the same subject."[136]

Applying these principles, the Court has held that federal law occupies a variety of regulatory fields, including alien registration;[137] nuclear safety;[138] aircraft noise;[139] the "design, construction, alteration, repair, maintenance, operation, equipping, personnel qualification, and manning" of tanker vessels;[140] wholesales of natural gas in interstate commerce;[141] and locomotive equipment.[142]

Examples

Grain Warehousing

In its 1947 decision in *Rice v. Santa Fe Elevator Corp.*, the Supreme Court held that federal law preempted a number of fields related to grain warehousing, precluding even complementary state regulations of those fields.[143] In that case, the Court held that the federal Warehouse Act and associated regulations preempted a variety of state law claims brought against a grain warehouse, including allegations that the warehouse had engaged in unfair pricing, maintained unsafe elevators, and impermissibly mixed different qualities of grain.[144]

The Court discerned Congress's intent to occupy the relevant fields from an amendment to the Warehouse Act that made the Secretary of Agriculture's authorities "exclusive" vis-à-vis federally licensed warehouses.[145] Because the text and legislative history of this amendment reflected Congress's intent to eliminate overlapping federal and state warehouse regulations, the Court held that federal law occupied a number of fields involving grain warehousing. As a result, the Court

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CONSTITUTIONAL LAW § 6-29, at 1185 (3d ed. 2000) (noting that when state law "undermines a congressional decision in favor of national uniformity of standards," it presents "a situation similar in practical effect to that of federal occupation of a field").

135 *Arizona*, 567 U.S. at 399; Rice v. Santa Fe Elevator Corp., 331 U.S. 218, 230 (1947).

136 *Rice*, 331 U.S. at 230.

137 *See* Arizona v. United States, 567 U.S. 387, 401 (2012).

138 *See, e.g.*, English v. Gen. Elec. Co., 496 U.S. 72, 82–85 (1990).

139 City of Burbank v. Lockheed Air Terminal Inc., 411 U.S. 624, 633 (1973).

140 United States v. Locke, 529 U.S. 89, 111 (2000) (quoting 46 U.S.C. § 3703(a)); *see* Ray v. Atl. Richfield Co., 435 U.S. 151, 163–65 (1978).

141 Schneidewind v. ANR Pipeline Co., 485 U.S. 293, 300, 305 (1988); Exxon Corp. v. Eagerton, 462 U.S. 176, 184 (1983).

142 Kurns v. R.R. Friction Prods. Corp., 565 U.S. 625, 636 (2012).

143 331 U.S. 218 (1947). The Supreme Court's mid-century decisions did not always clearly distinguish between field preemption and conflict preemption. *See, e.g.*, Pennsylvania v. Nelson, 350 U.S. 497, 501–02 (1956) (noting that "different criteria have furnished touchstones" for the Court's implied preemption decisions, and that the Court had used a variety of expressions in those decisions, including "conflicting; contrary to; occupying the field; repugnance; difference; irreconcilability; inconsistency; violation; curtailment; and interference").

144 *Rice*, 331 U.S. at 221–22.

145 *Id.* at 232–33.

concluded that the Warehouse Act preempted certain state law claims that intruded into those federally regulated fields, even if federal law established standards that were less strict than those imposed by state law.[146]

Immigration: Alien Registration

The Court has also held that federal law preempts the field of alien registration.[147] In its 1941 decision in *Hines v. Davidowitz*, the Court held that federal immigration law—which required aliens to register with the federal government—preempted a Pennsylvania law that required aliens to register with the state, pay a registration fee, and carry an identification card.[148] The Court explained that alien regulation is "intimately blended and intertwined" with the federal government's core responsibilities and that Congress had enacted a "complete" regulatory scheme involving that field, meaning federal law preempted the additional state requirements.[149]

The Court reaffirmed these general principles in its 2012 decision in *Arizona v. United States*.[150] In *Arizona*, the Court held that the Immigration and Nationality Act (INA), which requires aliens to carry an alien registration document,[151] preempted an Arizona statute that made violations of that federal requirement a crime under state law.[152]

In holding that federal law preempted this Arizona requirement, the Court explained that—like the statutory framework at issue in *Hines*—the INA represented a "comprehensive" regulatory regime that occupied the field of alien registration.[153] The Court inferred Congress's intent to occupy this field from the INA's "full set of standards" governing alien registration, which included specific penalties for noncompliance.[154] The Court thus held that federal law preempted even complementary state laws regulating alien registration, like the challenged Arizona requirement.[155]

The Court has also made clear, however, that other types of state laws concerning aliens do not necessarily fall within the preempted field of alien registration. In its 1976 decision in *De Canas v. Bica*, for example, the Court held that federal law did not preempt a California law prohibiting

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[146] *Id.* at 236. The *Rice* Court also held that certain state law claims—for example, an allegation that the warehouse had violated state law by failing to secure state approval for certain construction contracts—survived preemption because they involved fields that the Warehouse Act did not address. *Id.* at 236-37.

[147] *See* Arizona v. United States, 567 U.S. 387 (2012). Under the Immigration and Nationality Act, the term "alien" refers to "any person not a citizen or national of the United States." 8 U.S.C. § 1101(a)(3).

[148] 312 U.S. 52, 72–74 (1941).

[149] *Id.* at 66–67. While *Hines* did not hold that federal power over alien regulation was "exclusive," subsequent Supreme Court cases have characterized it as a field preemption decision. *See Arizona*, 567 U.S. at 401.

[150] *Arizona*, 567 U.S. at 401–02 ("Federal law makes a single sovereign responsible for maintaining a comprehensive and unified system to keep track of aliens within the Nation's borders.").

[151] 8 U.S.C. § 1304(e).

[152] *Arizona*, 567 U.S. at 400–03. Even though a violation of the identification card requirement was already punishable as a misdemeanor under federal law, the Arizona statute made violation of the requirement a state misdemeanor. *Id.*

[153] *Id.*

[154] *Id.*

[155] *Id.* at 401–03. In *Arizona*, the Court also invalidated two other provisions of the relevant Arizona law because they conflicted with federal law. First, the Court held that federal law preempted an Arizona provision that prohibited unauthorized aliens from seeking work. *Id.* at 406–07. Second, the Court held that federal law preempted a provision in the Arizona statute that allowed state police to arrest without a warrant persons whom they had probable cause to believe committed a removable offense. *Id.* at 410. The Court reasoned that this provision conflicted with federal objectives by allowing state police to perform the functions of an immigration officer in circumstances not authorized by federal law. *Id.* at 408–09.

the employment of aliens not entitled to lawful residence in the United States.[156] The Court based this conclusion on the absence of provisions regulating employment eligibility in the INA at the time.[157]

The Court has also upheld several state laws regulating the activities of aliens since *De Canas*. In *Chamber of Commerce v. Whiting*, for example, the Court held that federal law did not preempt an Arizona statute allowing the state to revoke an employer's business license for hiring aliens who did not possess work authorization.[158]

Nuclear Energy: Safety Regulation

The Supreme Court has also held that federal law preempts the field of nuclear safety regulation. The Court has explained, however, that this field does not encompass all state laws that affect safety decisions made by nuclear power plants. Instead, the Court has concluded that state laws fall within the preempted field of nuclear safety regulation if they (1) are motivated by safety concerns and implicate a "core federal power," or (2) have a "direct and substantial" effect on safety decisions made by nuclear facilities.[159]

This division of authority is the result of a regulatory regime that has changed significantly over the course of the 20th century. The federal government initially maintained a monopoly over the use, control, and ownership of nuclear technology.[160] Beginning in 1954, however, the Atomic Energy Act (AEA) allowed private entities to own, construct, and operate nuclear power plants subject to a "strict" licensing and regulatory regime administered by the Atomic Energy Commission (AEC).[161]

In 1959, Congress amended the AEA to give the states greater authority over nuclear energy regulation. The 1959 Amendments allowed states to assume responsibility over certain nuclear materials as long as their regulations were "coordinated and compatible" with federal requirements.[162] While the 1959 Amendments reserved certain key authorities to the federal government, they also affirmed the states' authority to regulate "activities for purposes other than protection against radiation hazards."[163] Congress reorganized the administrative framework surrounding these regulations in 1974, when it replaced the AEC with the Nuclear Regulatory Commission (NRC).[164]

The Supreme Court has held that, although this regulatory scheme preempts the field of nuclear safety regulation, certain state regulations of nuclear power plants that have a non-safety rationale fall outside this preempted field.

The Court identified this distinction in *Pacific Gas & Electric Co. v. State Energy Resources Conservation & Development Commission*, where it held that federal law did not preempt a

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[156] 424 U.S. 351 (1976).

[157] *Id.* at 359. *De Canas* pre-dated the current federal work authorization rules for aliens. *See* 8 U.S.C. § 1324a(a)(1)(A).

[158] 563 U.S. 582, 587 (2011). In *Whiting*, the Court also upheld a provision of the Arizona law that required employers to use the "E-Verify" program, which allows users to verify a person's work authorization status. *See id.* at 608–09.

[159] *See* Va. Uranium, Inc. v. Warren, 139 S. Ct. 1894, 1904 (2019) (Gorsuch, J, lead opinion); English v. Gen. Elec. Co., 496 U.S. 72, 84–85 (1990).

[160] *English*, 496 U.S. at 80.

[161] *Id.* at 81–82; 42 U.S.C. § 2011.

[162] 42 U.S.C. § 2021(g).

[163] *Id.* § 2021(k).

[164] *Id.* §§ 5814, 5841.

California statute regulating the construction of new nuclear power plants.[165] The California statute conditioned the construction of new nuclear power plants on a state agency's determination concerning the availability of adequate storage facilities and means of disposal for spent nuclear fuel.[166] In challenging this statute, two public utilities contended that federal law made the federal government the "sole regulator of all matters nuclear."[167]

The Supreme Court rejected this argument, reasoning that the relevant statutes reflected Congress's intent to allow states to regulate nuclear power plants for non-safety purposes.[168] The Court then concluded that the California law was not preempted because it was motivated by concerns over electricity generation and the economic viability of new nuclear power plants—not a desire to intrude into the preempted field of nuclear safety regulation.[169]

In addition to holding that the AEA does not preempt all state statutes and regulations concerning nuclear power plants, the Court has upheld the availability of certain state tort claims related to injuries sustained by power plant employees.

In *Silkwood v. Kerr-McGee Corp.*, the Court upheld a punitive damages award against a nuclear laboratory arising from an employee's injuries from plutonium contamination.[170] The Court rejected the laboratory's argument that the damages award impermissibly punished and deterred conduct related to the preempted field of nuclear safety.[171] In rejecting this argument, the Court observed that Congress had not provided alternative federal remedies for persons injured in nuclear accidents.[172] This omission was significant, the Court reasoned, because it was "difficult to believe" that Congress would have removed all judicial recourse from plaintiffs injured in nuclear accidents without an explicit statement to that effect.[173]

The Court also reasoned that Congress had assumed the continued availability of state tort remedies when it adopted a 1957 amendment to the AEA.[174] Under the relevant amendment, the federal government partially indemnified power plants for certain liabilities for nuclear accidents.

165 461 U.S. 190, 216 (1983).

166 *Id.* at 194.

167 *Id.* at 205.

168 *Id.*

169 *Id.* at 213–16. In its 2019 decision in *Virginia Uranium, Inc. v. Warren*, the Court clarified that AEA preemption will depend on this type of inquiry into the motivations of a challenged state law only when the state law implicates a "core federal power" reserved to the NRC. 139 S. Ct. 1894, 1904 (2019) (Gorsuch, J., lead opinion); *id.* at 1909 (Ginsburg, J., concurring in the judgment). In that case, the Court held that federal law did not preempt a Virginia statute banning the mining of uranium—a radioactive metal used in the production of nuclear fuel. *See id.* at 1900 (Gorsuch, J., lead opinion); *id.* at 1912 (Ginsburg, J., concurring in the judgment). Under the AEA and its subsequent amendments, the NRC has the authority to regulate the milling, transfer, use, and disposal of uranium, but not uranium *mining* conducted on private lands. *See id.* at 1900 (Gorsuch, J., lead opinion). In upholding the Virginia mining ban, a majority of the Court declined to evaluate the state's underlying motivation, explaining that such an inquiry is appropriate (if at all) only when state law regulates an activity related to the NRC's "core federal powers" under the AEA. *See id.* at 1904 (Gorsuch, J., lead opinion); *id.* at 1912–14 (Ginsburg, J., concurring in the judgment). While the Court interpreted *Pacific Gas* as recognizing that the construction of nuclear power plants involves one of these "core federal powers," a majority of the Justices agreed that uranium mining does not implicate similar federal authorities because it falls outside the NRC's jurisdiction. *See id.* at 1904 (Gorsuch, J, lead opinion); *id.* at 1912 (Ginsburg, J., concurring in the judgment). The Court accordingly relied on this distinction to uphold the Virginia law without evaluating its underlying purpose.

170 464 U.S. 238, 241–42 (1984).

171 *Id.* at 249.

172 *Id.*

173 *Id.*

174 *Id.* at 251–52.

According to the Court, this scheme reflected an assumption that plaintiffs injured in such accidents retained the ability to bring tort claims against the power plants.[175]

The Supreme Court applied this reasoning from *Silkwood* six years later in *English v. General Electric Co.*, where it held that federal law did not preempt state tort claims alleging that a nuclear laboratory had retaliated against a whistleblower for reporting safety concerns.[176]

In allowing the claims to proceed, the Court rejected the argument that federal law preempts all state laws that affect plants' nuclear safety decisions. Rather, the Court explained that a state law must have a "direct and substantial" effect on such decisions in order to fall within the federally preempted field of nuclear safety regulation.[177] While the Court acknowledged that the relevant tort claims may have had "some effect" on safety decisions by making retaliation against whistleblowers more costly than safety improvements, it concluded that such an effect was not sufficiently "direct and substantial" to render the claims preempted.[178]

In making this assessment, the Court relied on *Silkwood*, where it held that the relevant punitive damages award fell outside the field of nuclear safety regulation despite its likely impact on safety decisions.[179] Because the Court concluded that the type of damages award at issue in *Silkwood* affected safety decisions more directly and "far more substantially" than the whistleblower's retaliation claims, it held that the retaliation claims were not preempted.[180]

Takeaways

A determination that federal law preempts a field has powerful consequences, displacing even state laws and regulations that are consistent with or complementary to federal law.[181] Because of these effects, the Supreme Court has cautioned against overly hasty inferences that Congress has occupied a field.[182] The Court has rejected the argument that the comprehensiveness of a federal regulatory scheme is sufficient to conclude that federal law occupies a field, explaining that Congress and federal agencies often adopt "intricate and complex" laws and regulations without intending to assume exclusive regulatory authority over the relevant subjects.[183]

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175 *Id.* at 250–52.

176 496 U.S. 72, 90 (1990).

177 *Id.* at 85.

178 *Id.*

179 *Id.* at 85–86.

180 *Id.* at 86.

181 *See* Arizona v. United States, 567 U.S. 387, 401–02 (2012); Rice v. Santa Fe Elevator Corp., 331 U.S. 218, 230 (1947).

182 *See* O'Melveny & Myers v. FDIC, 512 U.S. 79, 85 (1994) ("Nor would we adopt a court-made rule to supplement federal statutory regulation that is comprehensive and detailed; matters left unaddressed in such a scheme are presumably left subject to the disposition provided by state law."); *see also* Southland Corp. v. Keating, 465 U.S. 1, 18 (1984) (Stevens, J., concurring in part and dissenting in part) ("[E]ven where a federal statute does displace State authority, it rarely occupies a legal field completely, totally excluding all participation by the legal systems of the states.") (citation and internal quotation marks omitted).

183 *See* N.Y. State Dep't of Social Servs. v. Dublino, 413 U.S. 405, 415 (1973). *See also* Hillsborough Cnty. v. Automated Med. Lab'ys, Inc., 471 U.S. 707, 716–17 (1985) (explaining that courts should not infer field preemption "whenever an agency deals with a problem comprehensively," because such an inference would be inconsistent with "the federal-state balance embodied in [the Court's] Supremacy Clause jurisprudence").

The Court has sometimes relied on legislative history and statutory structure—in addition to the comprehensiveness of federal regulations—in assessing field preemption arguments.[184] It is unclear, however, to what extent the Court might rely on even these sources in future cases.[185]

The Court has also adopted a narrow view of the scope of certain preempted fields. For example, the Court has rejected the proposition that federal nuclear energy regulations preempt all state laws that affect the preempted field of nuclear safety regulation. Rather, the Court has explained that, when a core federal power is not at issue, state laws fall within that field only if they have a "direct and substantial" effect on it.[186]

As a corollary to this principle, the Supreme Court has held that—in certain contexts—generally applicable state laws are more likely to fall outside a federally preempted field than state laws that "target" entities or issues within the field. In *Oneok, Inc. v. Learjet, Inc.*, for example, the Court held that state antitrust claims against natural gas pipelines fell outside the preempted field of interstate natural gas wholesaling because the relevant state antitrust law was not "aimed" at natural gas companies and instead applied broadly to all businesses.[187]

Finally, the Court's case law underscores that Congress can narrow the scope of a preempted field with explicit statutory language. In *Pacific Gas*, for example, the Court held that the preempted field of nuclear safety regulation did not encompass state laws motivated by non-safety concerns based in part on a statutory provision disavowing such an intent.[188] While the Court has subsequently narrowed the circumstances in which it will apply *Pacific Gas*'s purpose-centric inquiry to state laws affecting nuclear energy,[189] it has reaffirmed the general principle that Congress can circumscribe a preempted field's scope with non-preemption clauses.[190]

Conflict Preemption

Federal law also impliedly preempts conflicting state laws.[191] The Supreme Court has identified two subcategories of conflict preemption. First, federal law impliedly preempts state law when it is impossible for regulated parties to comply with both sets of laws (impossibility preemption).[192] Second, federal law impliedly preempts state laws that pose an obstacle to the "full purposes and objectives" of Congress (obstacle preemption).[193] The two subsections below discuss these subcategories of conflict preemption.

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[184] *See, e.g.*, Rice v. Santa Fe Elevator Corp., 331 U.S. 218, 232–36 (1947); De Canas v. Bica, 424 U.S. 351, 359–60 (1976).

[185] *See* Bates v. Dow Agrosciences LLC, 544 U.S. 431, 459 (2005) (Thomas, J., concurring in part and dissenting in part) (noting "this Court's increasing reluctance to expand federal statutes beyond their terms through doctrines of implied pre-emption"); Camps Newfound/Owatonna, Inc. v. Town of Harrison, 520 U.S. 564, 617 (1997) (Thomas, J., dissenting) ("[O]ur recent cases have frequently rejected field pre-emption in the absence of statutory language expressly requiring it."); Kurns v. R.R. Friction Prods. Corp., 565 U.S. 625, 640–41 (2012) (Sotomayor, J., concurring in part and dissent in part) (quoting Justice Thomas's language from *Camps Newfound*).

[186] English v. Gen. Elec. Co., 496 U.S. 72, 85 (1990).

[187] 575 U.S. 373, 384–88 (2015); *see also English*, 496 U.S. at 83 (explaining in dicta that generally applicable criminal laws are not likely to fall within the preempted field of nuclear safety regulation).

[188] Pac. Gas & Elec. Co. v. State Energy Res. Conservation & Dev. Comm'n, 461 U.S. 190, 209–10, 213–14 (1983).

[189] *See supra* note 169.

[190] *See* Va. Uranium, Inc. v. Warren, 139 S. Ct. 1894, 1902–3 (2019) (Gorsuch, J., lead opinion); *id.* at 1912–13 (Ginsburg, J., concurring in the judgment).

[191] *See* Gade v. Nat'l Solid Wastes Mgmt. Ass'n, 505 U.S. 88, 108 (1992).

[192] Fla. Lime & Avocado Growers, Inc. v. Paul, 373 U.S. 132, 142–43 (1963).

[193] Hines v. Davidowitz, 312 U.S. 52, 67 (1941).

Impossibility Preemption

The Supreme Court has held that federal law preempts state law when it is impossible to comply with both sets of laws.[194] To illustrate this principle, the Court has explained that a hypothetical federal law forbidding the sale of avocados with more than 7% oil content would preempt a state law forbidding the sale of avocados with less than 8% oil content, because avocado sellers could not sell their products and comply with both laws.[195]

The Court has characterized impossibility preemption as a "demanding defense,"[196] and its case law on the issue is not as well developed as other areas of its preemption jurisprudence.[197] Even so, the Court has addressed impossibility preemption in two decisions concerning prescription drug labeling.

Generic Drug Labeling

In *PLIVA, Inc. v. Mensing* and *Mutual Pharmaceutical Co. v. Bartlett*, the Supreme Court held that federal regulations of generic drug labels preempted certain state law claims brought against generic drug manufacturers because it was impossible for the manufacturers to comply with both federal and state law.[198]

In both cases, plaintiffs alleged that they suffered adverse effects from certain generic drugs and argued that the drugs' labels should have included additional warnings.[199] In response, the drug manufacturers argued that the Hatch-Waxman Amendments (Hatch-Waxman) to the Food, Drug, and Cosmetic Act preempted the state law claims.[200]

Under Hatch-Waxman, drug manufacturers can secure Food and Drug Administration (FDA) approval for generic drugs by demonstrating that they are equivalent to a brand-name drug already approved by the FDA.[201] In doing so, the generic drug manufacturers need not comply with the FDA's standard preapproval process, which requires extensive clinical testing and the development of FDA-approved labeling.[202] They must, however, ensure that the labels for their drugs are the same as the labels for corresponding brand-name drugs, meaning that generic manufacturers cannot unilaterally change their labels.[203]

In both *PLIVA* and *Bartlett*, the Court held that the Hatch-Waxman Amendments preempted the relevant state law claims because it was impossible for the generic drug manufacturers to comply with both federal and state law.[204] The Court reached this conclusion because federal law

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[194] *Fla. Lime*, 373 U.S. at 142–43.

[195] *Id.*

[196] Wyeth v. Levine, 555 U.S. 555, 573 (2009).

[197] *See* Meltzer, *supra* note 41, at 8 (describing situations in which it is impossible to comply with both state and federal requirements as "rare").

[198] 564 U.S. 604, 618 (2011); 570 U.S. 472, 493 (2013).

[199] *PLIVA*, 564 U.S. at 610; *Bartlett*, 570 U.S. at 475.

[200] *PLIVA*, 564 U.S. at 610; *Bartlett*, 570 U.S. at 475.

[201] *See PLIVA*, 564 U.S. at 612.

[202] *Id.* at 612–13; *Bartlett*, 570 U.S. at 476–77.

[203] *PLIVA*, 564 U.S. at 612–13; *Bartlett*, 570 U.S. at 477. For further information on the approval and labeling process for generic drugs under Hatch-Waxman and related laws, see CRS Report R46778, *The Generic Drug User Fee Amendments (GDUFA): Background and Reauthorization*, by Agata Bodie.

[204] *PLIVA*, 564 U.S. at 617–18; *Bartlett*, 570 U.S. at 486–87.

prohibited generic manufacturers from unilaterally altering their labels, while the state law claims depended on the existence of a duty to make such alterations.[205]

In reaching this conclusion in *PLIVA*, the Court rejected the argument that it was possible for manufacturers to comply with both federal and state law by petitioning the FDA to impose new labeling requirements on the corresponding brand-name drugs.[206] The Court rejected this argument on the grounds that impossibility preemption occurs whenever a party cannot independently comply with both federal and state law without seeking "special permission and assistance" from the federal government.[207]

Similarly, in *Bartlett*, the Court rejected the argument that it was possible for generic drug makers to comply with both federal and state law by refraining from selling the relevant drugs. The Court rejected this "stop-selling" argument on the grounds that it would render impossibility preemption "all but meaningless."[208] As a result, an evaluation of whether it is possible to comply with both federal and state law must presuppose some affirmative conduct by the regulated party.

Despite its decisions in *PLIVA* and *Bartlett*, the Supreme Court has rejected impossibility preemption arguments made by brand-name drug manufacturers, who are entitled to unilaterally strengthen the warning labels for their drugs. In *Wyeth v. Levine*, the Court held that federal law did not preempt a state law failure-to-warn claim brought against a branded drug manufacturer, reasoning that it was possible for the manufacturer to strengthen its label for the drug without FDA approval.[209]

Obstacle Preemption

Federal law also impliedly preempts state laws that pose an "obstacle" to the "full purposes and objectives" of Congress.[210] In its obstacle preemption cases, the Supreme Court has held that state law can interfere with federal goals by frustrating Congress's intent to adopt a uniform system of federal regulation; conflicting with Congress's goal of establishing a regulatory "ceiling" for certain products or activities; or by impeding the vindication of a federal right.[211]

The Court has also cautioned, however, that obstacle preemption does not justify a "freewheeling judicial inquiry" into whether state laws are "in tension" with federal objectives, as such a standard would undermine the principle that "it is Congress rather than the courts that preempts state law."[212]

[205] *PLIVA*, 564 U.S. at 617–18; *Bartlett*, 570 U.S. at 486–87.

[206] *PLIVA*, 564 U.S. at 616.

[207] *Id.* at 623–24.

[208] *Bartlett*, 570 U.S. at 488–89.

[209] 555 U.S. 555, 573 (2009). The *Wyeth* Court indicated, however, that an impossibility preemption defense may be available to brand-name drug manufacturers when there is "clear evidence" that the FDA would have rejected a proposed change to a brand-name drug's label. *Id.* at 571. The Court further clarified this standard in its 2019 decision in *Merck Sharp & Dohme Corp. v. Albrecht*, explaining that "clear evidence" requires drug manufacturers to demonstrate that they "fully informed" the FDA of the justifications for the warning required by the relevant state law and that the FDA nevertheless rejected the proposed change. 139 S. Ct. 1668, 1672 (2019).

[210] *See* Hines v. Davidowitz, 312 U.S. 52, 67 (1941).

[211] *See id.*; Geier v. American Honda Motor Co., Inc., 529 U.S. 861, 875 (2000); Felder v. Casey, 487 U.S. 131, 153 (1988).

[212] Chamber of Commerce v. Whiting, 563 U.S. 582, 607 (2011) (quoting Gade v. Nat'l Solid Wastes Mgmt. Ass'n, 505 U.S. 88, 111 (1992) (Kennedy, J., concurring in part and concurring in judgment)).

The subsections below discuss a number of cases in which the Court has held that state law poses an obstacle to the accomplishment of federal goals.

Foreign Sanctions

The Supreme Court has concluded that state laws can pose an obstacle to the accomplishment of federal objectives by interfering with Congress's choice to concentrate decisionmaking in federal authorities.

The Court's decision in *Crosby v. National Foreign Trade Council* illustrates this type of conflict between state law and federal policy goals.[213] In *Crosby*, the Court held that a federal statute imposing sanctions on Burma preempted a Massachusetts statute that restricted state agencies' ability to purchase goods or services from companies doing business with Burma.[214]

The Court identified several ways in which the Massachusetts law interfered with the federal statute's objectives. First, the Court reasoned that the Massachusetts law interfered with Congress's decision to provide the President with the flexibility to add or waive sanctions in response to ongoing developments.[215]

Second, the Court explained that, by penalizing certain individuals and conduct that Congress explicitly excluded from federal sanctions, the Massachusetts statute interfered with the federal statute's goal of limiting the economic pressure imposed by the sanctions to "a specific range."[216] In identifying this conflict, the Court rejected the state's argument that its law shared the same goals as the federal statute. Instead, the Court reasoned that the additional sanctions imposed by the state law would undermine Congress's intended "calibration of force."[217]

Third, the Court concluded that the Massachusetts law undermined the President's capacity for effective diplomacy by compromising his ability "to speak for the Nation with one voice."[218]

Automobile Safety Regulations

The Supreme Court has concluded that some federal laws and regulations evince an intent to establish both a regulatory floor and ceiling for certain products and activities. The Court has interpreted certain federal automobile safety regulations, for example, as not only imposing minimum safety standards on carmakers, but as insulating manufacturers from certain forms of stricter state regulation as well.

In *Geier v. American Honda Motor Co.*, the Court held that the National Traffic and Motor Vehicle Safety Act (NTMVSA) and associated regulations impliedly preempted state tort claims alleging that an automobile manufacturer had negligently designed a car without a driver's side airbag.[219] While the Court rejected the argument that the NTMVSA expressly preempted the state

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213 530 U.S. 363, 366–67 (2000).

214 *Id.* at 366–67, 373–74. As the Court noted in *Crosby*, Burma changed its name to Myanmar in 1989. *See id.* at 366 n.1. However, because the parties in *Crosby* referred to the country as Burma, the Court followed suit. *Id.*

215 *Id.* at 376.

216 *Id.* at 377–79.

217 *Id.* at 379–80. After *Crosby*, Congress has included specific language in certain sanctions statutes that explicitly allows states to pass sanctions laws of their own. *See, e.g.*, Comprehensive Iran Sanctions, Accountability, and Divestment Act of 2010, P.L. 111-195, § 202, 124 Stat. 1312, 1342–43.

218 *Crosby*, 530 U.S. at 380–81.

219 529 U.S. 861, 865 (2000).

law claims,[220] it reasoned that the claims interfered with the federal objective of giving car manufacturers the option of installing a "variety and mix" of passive restraints.[221]

The Court discerned this goal from, among other things, the history of the relevant regulations and Department of Transportation (DOT) comments indicating that the regulations were intended to lower costs, incentivize technological development, and encourage gradual consumer acceptance of airbags, rather than impose an immediate requirement.[222] The Court thus held that the NTMVSA impliedly preempted the state law claims because they conflicted with these federal goals.[223]

The Court has rejected, however, the argument that federal automobile safety standards impliedly preempt all state tort claims concerning automobile safety. In *Williamson v. Mazda Motor of America, Inc.*, the Court held that a different federal safety standard did not preempt a state law claim alleging that a carmaker should have installed a certain type of seatbelt in a car's rear seat.[224]

While the regulation at issue in *Williamson* allowed manufacturers to choose between two seatbelt options, the Court distinguished the case from *Geier* on the grounds that the DOT's decision to offer carmakers a choice was not a "significant" regulatory objective.[225] Specifically, the Court reasoned that the state tort action did not conflict with the purpose of the relevant federal regulation, because the DOT's decision to offer manufacturers an option was based on relatively minor design and cost-effectiveness concerns.[226]

Federal Civil Rights

The Supreme Court has also held that state law can pose an obstacle to federal goals where it impedes the vindication of federal rights.

In *Felder v. Casey*, the Court held that 42 U.S.C. § 1983 (Section 1983)—which provides individuals with the right to sue state officials for federal civil rights violations—preempted a state statute adopting certain procedural rules for bringing Section 1983 claims in state court.[227] The state statute required Section 1983 plaintiffs to provide government defendants 120 days' written notice of the circumstances giving rise to their claims, the amount of their claims, and their intent to bring suit.[228]

The Court held that federal law preempted these requirements because their purpose and effect conflicted with Section 1983's remedial objectives.[229] Specifically, the Court reasoned that the requirements' purpose of minimizing the state's liability conflicted with Section 1983's goal of providing relief to individuals whose constitutional rights are violated by state officials.[230] The Court also concluded that the state statute's effects interfered with federal objectives because the

[220] *See supra* "Compliance Savings Clauses."

[221] *Geier*, 529 U.S. at 881.

[222] *Id.* at 874–75.

[223] *Id.* at 881.

[224] 562 U.S. 323 (2011).

[225] *Id.* at 332.

[226] *Id.* at 335.

[227] 487 U.S. 131, 153 (1988).

[228] *Id.* at 134.

[229] *Id.* at 138.

[230] *Id.* at 141–42.

statute's enforcement would result in different outcomes in Section 1983 litigation based on whether a claim was brought in state or federal court.[231]

Takeaways

The Supreme Court has held that state law can conflict with federal law in a number of ways. State law can conflict with federal law when it is impossible to comply with both sets of laws. While the Court has characterized this type of impossibility preemption argument as a "demanding defense,"[232] its decisions in *PLIVA* and *Bartlett* arguably extended the doctrine's scope.[233] In those cases, the Court made clear that impossibility preemption remains a viable defense even in instances in which a regulated party can petition the federal government for permission to comply with state law[234] or stop selling a regulated product altogether.[235]

State law can also conflict with federal law when it poses an obstacle to federal goals. In evaluating congressional intent in obstacle preemption cases, the Court has relied upon statutory text,[236] structure,[237] and legislative history[238] to determine a statute's preemptive scope.

Relying on these indicia of legislative purpose, the Court has held that state laws can pose an obstacle to federal goals by interfering with a uniform system of federal regulation,[239] imposing stricter requirements than federal law (where federal law evinces an intent to establish a regulatory ceiling),[240] or by impeding the vindication of a federal right.[241]

While obstacle preemption has played an important role in the Court's preemption jurisprudence since the mid-20th century, recent developments have called the scope of the doctrine into question. Commentators have noted the tension between increasingly popular textualist theories of statutory interpretation (which generally reject extratextual evidence as a possible source of statutory meaning) and obstacle preemption doctrine (which potentially requires courts to consult such evidence).[242]

Identifying this possible inconsistency, Justice Thomas has categorically rejected the Court's obstacle preemption jurisprudence, criticizing the Court for "routinely invalidat[ing] state laws based on perceived conflicts with broad federal policy objectives, legislative history, or generalized notions of congressional purposes that are not embodied within the text of federal law."[243]

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[231] *Id.* at 138.

[232] Wyeth v. Levine, 555 U.S. 555, 573 (2009).

[233] *See* Ernest A. Young, *"The Ordinary Diet of the Law": The Presumption Against Preemption in the Roberts Court*, 2011 SUP. CT. REV. 253, 327–28 (2011) (characterizing *PLIVA* as an "expansion" of impossibility preemption).

[234] PLIVA, Inc. v. Mensing, 564 U.S. 604, 623–24 (2011).

[235] Mutual Pharm. Co. v. Bartlett, 570 U.S. 472, 488 (2013).

[236] *See* Crosby v. Nat'l Foreign Trade Council, 530 U.S. 363, 380 (2000).

[237] *See id.* at 377–80.

[238] *See id.* at 375 n.9.

[239] *Id.* at 374–77.

[240] *Geier*, 529 U.S. at 875.

[241] Felder v. Casey, 487 U.S. 131, 153 (1988).

[242] Note, *Preemption as Purposivism's Last Refuge*, 126 HARV. L. REV. 1056, 1065 (2013). *See also* Meltzer, *supra* note 41, at 35–43 (considering whether obstacle preemption is consistent with textualism).

[243] Wyeth v. Levine, 555 U.S. 555, 583 (2009) (Thomas, J., concurring in the judgment).

Justice Thomas's skepticism toward obstacle preemption arguments has drawn additional support in recent cases, especially from Justice Gorsuch. In the Court's decision in *Virginia Uranium, Inc. v. Warren*, Justice Gorsuch authored an opinion joined by Justices Thomas and Kavanaugh in which he rejected the proposition that implied preemption analysis should appeal to "abstract and unenacted legislative desires" not reflected in a statute's text.[244]

While Justice Gorsuch did not there explicitly endorse a wholesale repudiation of obstacle preemption, he later joined Justice Thomas's call for the Court to abandon its "purposes and objectives" preemption jurisprudence in a 2020 concurring opinion.[245] Although skepticism toward obstacle preemption arguments has drawn additional support in recent Supreme Court cases, to date it has remained a minority view.

Author Information

Bryan L. Adkins
Legislative Attorney

Jay B. Sykes
Legislative Attorney

Alexander H. Pepper
Legislative Attorney

Disclaimer

244 Va. Uranium, Inc. v. Warren, 139 S. Ct. 1894, 1907 (2019).

245 Kansas v. Garcia, 140 S. Ct. 791, 807 (2020) (Thomas, J., concurring). Justice Gorsuch also joined Justice Thomas's concurrence with the denial of certiorari in *Lipschultz v. Charter Advanced Servs. (MN), LLC*, 140 S. Ct. 6 (2019), in which Justice Thomas expressed doubt that a federal agency policy can serve as the basis for preemption of state law. *Id.* at 7.

Innovation through Labor Mobility: Evidence from Non-Compete Agreements

Kate Reinmuth* and Emma Rockall†

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Abstract

A large share of the United States workforce is subject to non-compete agreements, which have recently become the topic of intense policy debate. Proponents argue that high enforceability provides innovation incentives that outweigh negative worker outcomes like suppressed wages. However, we argue that the effect of non-compete agreements on innovation is actually an open empirical question. To answer it, we leverage state-level judicial rulings and statutory changes to estimate the impact of non-compete enforceability on patenting, entry, and inventor mobility. We find that non-compete agreements have a statistically and economically significant *negative* impact on innovation. For an increase of the mean size in our sample, patenting would be expected to decrease by 13%. This effect manifests primarily for incumbents rather than entrants. Moreover, our work suggests a central role for labor mobility as a channel of idea diffusion that increases overall innovation, with inventor mobility expected to decrease by 22% for an increase in enforceability of the mean size in our sample.

Keywords: Non-Compete Agreements, Innovation, Labor Mobility, Knowledge Diffusion

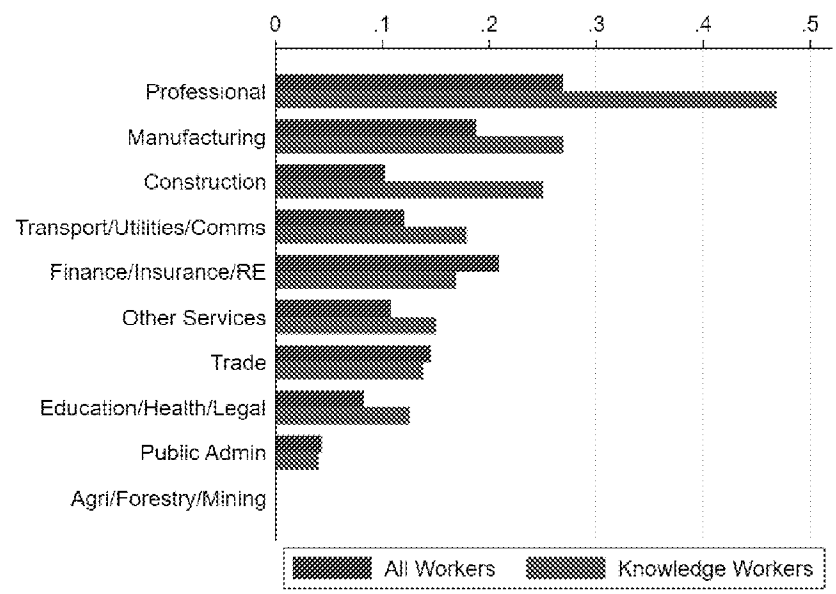
JEL Codes: O31, O33, J21, E24, K31

*Stanford University (Dept. of Economics) and Stanford Law School – email: reinmuth@stanford.edu
†Stanford University (Dept. of Economics) – email: erockall@stanford.edu

1 Introduction

A large share of the United States workforce is currently subject to non-compete agreements (NCAs). These restrictive covenants in employment contracts prevent employees from joining a rival firm or starting a new firm within the same industry for some duration post-separation (as specified in the clause). A 2017 survey of firms (Colvin and Shierholz (2019)) suggests that 30-45% of the US private sector workforce is subject to an NCA. And recent data from the US Bureau of Labor Statistics (BLS) National Longitudinal Survey of Youth 1997 Cohort (NLSY97) suggests that these agreements are especially prevalent among professional sector "knowledge workers" – the executives, managers, computer specialists, engineers, researchers, and scientists whom we might expect to be the most involved in innovative work. As **Figure 1** shows, early 50% of professional sector knowledge workers report being subject to an NCA.

Figure 1: NCA Prevalence Across Industries and Worker Type



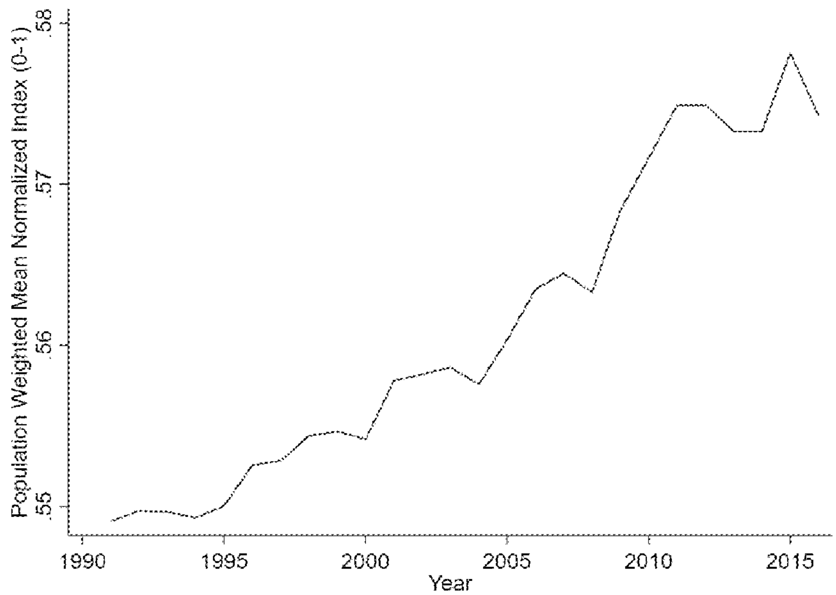
Share of workers from the NLSY 1997 cohort subject to NCAs by industry and worker type from 2017-2019. Knowledge workers refer to workers who serve in roles such as executives, managers, computer specialists, engineers, architects, scientists and researchers (CPS occupation codes 0010-2000). Data source: NLSY97.

This statistic is particularly striking because it is likely underestimated. A 2014 survey of private sector workers indicates that employees have very little scope to negotiate these clauses, with many of them reporting they were not even *informed* about the clause until after their employment commenced (Starr et al. (2021)). Thus, employee self-reporting of NCAs is likely to understate the true prevalence of NCAs.[1]

Over the last few decades, both the use and enforcement of NCAs have grown in the US. For example, between 2002 and 2013, there was a near-doubling in the number of legal cases decided where an employer sued a former employee to enforce an NCA – from 390 to 760 lawsuits (Simon and Loten (2013)). This trend unsurprisingly coincides with an increase in the legal enforceability of NCAs in many states. **Figure 2** shows a population-weighted national average of an index measuring NCA enforceability, which we discuss in additional detail below. The index shows that enforceability increased consistently (i.e., was more favorable to employers than employees) over the same time period.

[1]This is consistent with the fact that higher rates of NCA use are reported by firms in surveys like Colvin and Shierholz (2019).

Figure 2: Trends in NCA Enforceability



Weighted average state-level NCA enforceability by year. For consistency with the empirical results presented below, states are weighted by share of population in the previous year. Data sources: Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the index are available in Section 2.1 and Appendix Section D.

More recently, however, some states have begun to restrict the enforceability of NCAs, and NCAs have become a hotly contested public policy topic relevant to economists interested in a number of different sectors of the economy. States have begun to roll back the use of NCAs over the last five years in particular.[2] And, taking this recent trend to a potential extreme, the Federal Trade Commission (FTC) recently proposed a rule to ban NCAs at the federal level, citing concerns about harm to workers and competition.

In this paper, we focus on one of the most oft-touted benefits of NCAs: their effect on innovation. As Kitch (1980) summarizes, if "the courts leave employees free to leave the firm and exploit the information in competition with the firm[,] this competition eliminates the return that would otherwise generate the incentive for investment in the production of

[2]See **Appendix Figure 38** for a trend that includes additional recent years.

that information." There has come to be a common presumption in the legal literature and related policy discussions that it is this benefit to innovation that must be traded off against distributional impacts on workers – e.g., their wages and mobility as standalone outcomes. However, there are reasons to think that NCAs might *harm* innovation. For example, NCAs could have a negative effect on entry when new firms cannot hire the workers they need because those workers are covered by incumbent NCAs. NCAs may also negatively affect productivity and innovation by reducing the flow of new ideas and technologies between firms. Therefore, we argue here that the net impact of NCAs on innovation is *a priori* theoretically ambiguous and ultimately an empirical question. Accordingly, we tackle two research questions as follows. First, what is the net (local) impact of a change in NCA enforceability on innovation? And second, what channel(s) explain the direction and magnitude of this effect?

In order to estimate the local effect of NCAs on innovation, we leverage judicial rulings and legislative policy changes as sources of plausibly exogenous variation in the state-level enforceability, and therefore use, of NCAs.[3] To measure innovation, we use US Patent and Trademark Office (USPTO) data on patent filings in each state as a proxy for state-level innovation.[4] Additionally, we use the patent data to measure the frequency with which inventors move and patent at different firms from year-to-year. Our analysis begins with a case study to investigate the effects of a single change in NCA enforceability on innovation and inventor mobility. This case study helps provide the intuition behind our more comprehensive analysis and allows us to show granular descriptive statistics about the patterns at play in this setting. We then turn to a state-year difference-in-differences approach to estimate the effect of state-level changes in NCA enforceability on innovation using all of the variation in our data.

[3] See, e.g., Garmaise (2009); Marx et al. (2009); Chen et al. (2018); Hausman and Lavetti (2021); and Johnson et al. (WPb).

[4] Here, we follow the innovation economics literature and focus on patents for our headline empirical results. However, we recognize the standard limitations of patent data – e.g., that we will skew towards capturing industries that patent their intellectual property, causing us to miss some fields where patenting is more rare, such as software.

The case study considers the effect of one plausibly exogenous point of variation in NCA enforceability: a decision handed down by the Supreme Court of Ohio in March 2004 that suddenly and significantly expanded the circumstances under which NCAs were enforceable in the state of Ohio. We find that both in-state inventor moves and Ohio patenting fall significantly following this decision.

Our headline results build upon this case study to consider the average impact of all 26 changes in NCA enforceability from our baseline sample, rather than just one. Using staggered difference-in-differences estimation, this more comprehensive analysis again identifies an economically and statistically significant decline in patenting due to increases in NCA enforceability. For an increase of the mean size in our sample, for example, in-state patenting would be expected to decrease by 13%. Thus, contrary to the hypothesis laid out by NCA proponents in typical policy debates, the net effect of NCAs on innovation appears to be negative.[5]

By focusing on NCA *enforceability* rather than observed use, we avoid the issue of highly innovative firms' endogenous choice to use NCAs. We also avoid the issue of endogenous firm location choice (i.e., that highly innovative firms choose to locate in states with high NCA enforceability) by focusing on *intertemporal variation* in the most restrictive terms that firms could use (i.e., that are legally enforceable in their state). These state-level changes in NCA enforceability are also plausibly exogenous – primarily reflecting sudden judicial rulings that change the case law of what is and is not legally enforceable in an individual state. Our empirical approach robustly handles the non-absorbing treatments of this setting by including "clean control" and "clean treatment" conditions to ensure that we are estimating a true treatment effect in an apples-to-apples comparison and not, for example, including previously-treated observations in the control group or attributing the patenting effects of multiple close-in-time changes in enforceability to a single treatment.

We also provide a number of robustness checks on the results throughout our paper. For

[5]Concurrent work by Johnson et al. (WPa) affirms this result.

example, we show that our results appear to be driven by true changes in patenting, not simply changes in the propensity of firms to patent a given innovation (i.e., to substitute between patents and trade secrets). Moreover, we show that cross-state spillovers are minimal in this setting and, as a result, neither threaten the validity of our estimated treatment effect nor limit us from using our results to think about the effect of a national policy. We also provide a number of checks in the appendix to show that our results are robust to alternative sample definitions, econometric specifications, and outcome measures.

To understand the mechanisms behind the overall effect of NCAs on innovation, we then turn to consider three specific channels through which NCAs may affect innovation. First, we consider incumbent innovation incentives, whereby NCAs increase innovation when firms can better appropriate the returns to their R&D. Second, we consider firm entry, which could have either a positive or a negative effect of NCAs on innovation, depending on whether improved R&D appropriability outweighs potential barriers to entry (e.g., difficulty recruiting talent), or vice versa. Third, we consider a knowledge diffusion channel, whereby NCAs decrease innovation when the flow of new ideas and technologies is hampered because inventors have a harder time moving between firms. The estimated negative net effect of NCA enforceability on patenting indicates that incumbent innovation incentives are outweighed by one or both of the other channels.

Therefore, we further assess the entry and knowledge diffusion channels individually to disentangle the mechanism(s) behind the overall net effect. The entry channel does not appear to be driving these results. We find no statistically significant effect of changes in NCA enforceability on state-level business applications from the Census Business Formation Statistics (BFS). In contrast, we observe a statistically significant decline in inventor mobility that parallels the overall impact on innovation, suggesting that knowledge diffusion may be a key driver of patenting effects in this setting.

This paper contributes directly to a growing literature on NCAs. Although NCAs have been a popular topic in legal scholarship and policy discussions historically, the relevant economic literature is narrower. A number of papers address specific NCA-related labor market outcomes. For example, Lipsitz and Starr (2022) and Young (2024) look at the effect on wages of banning non-compete agreements for low-wage workers in Oregon and Austria, respectively. Balasubramanian et al. (2020) examines the impact of NCA restrictions in Hawaii in 2015 on the careers of technology workers. And Johnson et al. (WPb) uses changes in enforceability to look at the impact on earnings and job mobility. Relatively few papers consider the net impact of NCAs on innovation, and those that do have a narrower focus than this paper. For example, Conti (2014) suggests that, from 1990 to 2000, firms in states where NCAs were more enforceable pursued "riskier" R&D paths, but the author is not able to identify the *causal effect* of NCAs because he relies on existing state-level differences in the cross-section. Carlino (2021) and Starr et al. (2018) both consider the entry dimension, looking at state-level startup activity and within-industry spin-outs, respectively. Jeffers (WP) also uses matched employee-employer data from LinkedIn to examine how labor market frictions, induced by NCAs, affect firm capital investment decisions and new firm entry. This paper contributes a novel estimate of the causal effect of NCAs on total innovative output as well as new evidence on the channels through which that effect operates.[6]

In this regard, our work is also more broadly related to the literatures on innovation incentives and innovation spillovers. There are a variety of papers focusing on the impact of other policies such as patenting (Acemoglu and Akcigit (2012); Boldrin and Levine (2013); Budish et al. (2015)), taxes (Akcigit et al. (2016); Akcigit et al. (2022)), and other R&D incentives on innovation outcomes (Bloom et al. (2019); Autor et al. (2020)). Several papers have also considered how these policies may operate (or be amplified) via innovation spillovers, which many studies have found to be large (Cohen et al. (2002); Keller (2004); Bloom et al. (2013); Akcigit and Kerr (2018); Akcigit et al. (WP); Matray (2021)). In this paper, we contribute to this broader literature by highlighting the potential role of labor

[6]Although not directly related to NCAs, we note that some other literatures discuss themes related to the effect of labor mobility on innovation. For example, Krueger and Ashenfelter (2018) discuss the implications of "no-poach" agreements in franchises, and the occupational licensing literature addresses similar questions of market power in labor markets (e.g., Shapiro (1986); Kleiner (2000)).

mobility as a channel through which innovation spillovers may occur, and therefore how NCAs may ultimately dampen rather than increase aggregate innovation.

This paper proceeds as follows. In Section 2, we describe the data used in this paper, including how we quantify changes in the enforceability of NCAs by extending a state-level annual index capturing judicial rulings and legislative policy changes over time. In Section 3, we introduce a case study to fix ideas before outlining our empirical approach for the all-state analysis that uses staggered difference-in-differences estimation. In Section 4, we present our all-state results that document the negative local average treatment effect of an increase in NCA enforceability on innovation. In Section 5, we discuss our conceptual framework for the mechanisms through which NCA enforceability might affect innovation and examine the empirical evidence on the possible drivers of the observed overall effect. This analysis suggests that inventor mobility, rather than entry, appears to be driving a substantial part of the observed decline in patenting. In Section 6, we consider other potential factors at play in this setting, such as spillovers across states, and find that our baseline estimates are unaffected. Finally, in Section 7, we briefly consider national policy counterfactuals.

2 Key Data

2.1 Index of State-Level Changes

In order to estimate the impact of NCAs on innovation, we track and quantify state-level changes in the enforceability of NCAs by following Bishara (2011) and utilizing an index of state-level enforcement of NCAs. Bishara (2011) developed a set of seven questions about NCA enforceability, each of which is scored each question out of ten and then weighted by importance to create an index of state-level NCA enforceability over time out of a total possible score of 600.[7] Overall, a score of 600 would mean NCAs are highly enforceable, and a score of 0 would mean NCAs are hardly enforceable at all.

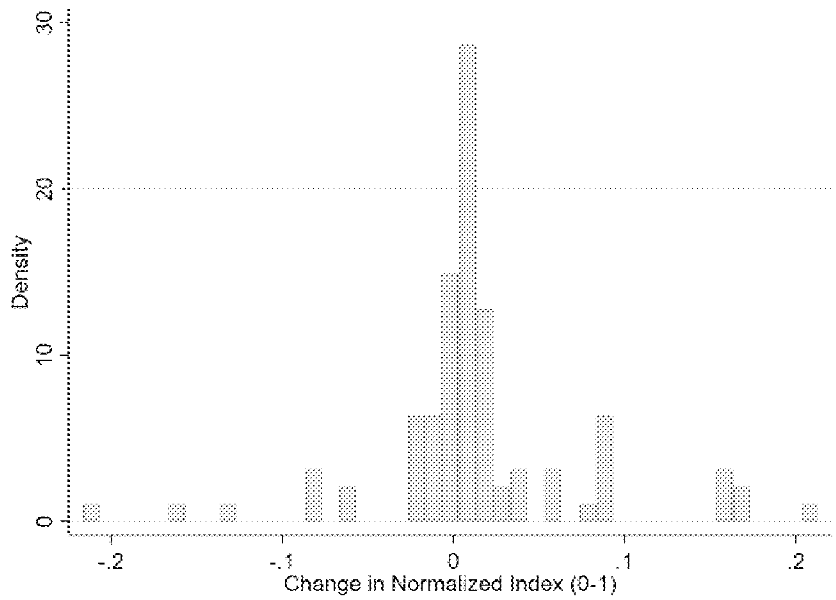
[7] The questions are detailed in Appendix D.

Bishara (2011) calculates this index for the years 1991 and 2011, and Marx (2022) extends the index to cover the years between 1991 and 2011 and up until 2014. However, in recent years, there have been major changes to enforceability. Therefore, this paper newly extends the annual index through 2022. To accomplish this, we use a catalog of NCA enforceability changes broken down by state[8] to identify all changes in enforceability (e.g., due to state supreme court rulings or statutory changes). A number of these changes do not fit neatly within the Bishara framework – e.g., recent changes in many states that restrict the use of NCAs only for low-wage workers. As a result, for our baseline index we use only those changes that affect all workers, as opposed to only a subset of low-paid workers or those in specific occupations. This is also consistent with the goal of this paper, as limits on NCA enforceability with respect to low-wage workers are less likely to affect professional knowledge workers involved in innovation. We then normalize the index on a 0 to 1 scale (rather than 0 to 600). Below, we limit our results to years from 1991 up to and including 2016 in order to observe a reasonable horizon of post-treatment effects. This also allows us to account for lags in the patent system (and the time necessary for forward citations to accrue) that would render recent data less complete and subject to greater mismeasurement. **Figure 3** shows the distribution of non-zero changes to enforceability that we observe in the normalized index during this period.[9]

[8] Provided by Beck Reed Riden LLP.

[9] **Appendix Figure 39** shows the distribution of changes for the wider time period.

Figure 3: Distribution of Non-Zero Changes in NCA Enforceability



State-level changes in NCA enforceability, as measured by the normalized index, across years. Data sources: Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Additional details on the index are available in Appendix Section D.

Note that we observe both large and small changes on either side of zero. However, the majority of our changes in this period are "strengthenings" in NCA enforceability – i.e., changes greater than zero – which are consistent with the general trend we observed above toward greater NCA enforceability during this period. The average change in this time period is 0.09 points in our baseline sample (as defined below), which approximately corresponds to a 9 percentage point change in enforceability.

2.2 US Patent Filings

As our main measure of innovation, we use patent filings from the USPTO's PatentsView project. Although patents are not a perfect measure of innovation – e.g., there are innovations that firms do not patent, either because they are not eligible to be patented or because the firm would prefer to keep the technology as a trade secret – like much of the innovation literature, we contend that patents are a useful proxy for broader innovation, and one for which we have detailed disambiguated data for the universe of filings in the US since 1976. Although NCAs may not be directly relevant to protecting ideas already under patent, they have a material effect on firms' abilities to protect "tacit knowledge" – e.g., work-in-progress research (e.g., follow-on innovations), research methods, negative knowledge, unpatentable byproducts of research, etc., which are generated alongside patent disclosures – as well as trade secrets.

For the analysis discussed below, we restrict our sample to granted patents, with an identified filing location within the US, and we take each granted patent's date of application to construct our panel of patents by year. We also restrict our baseline analysis to focus only on patents filed by US corporations.[10] For our baseline analysis, we restrict our sample to 1991-2016, as lags in patent granting mean that the data available post-2016 are likely to be incomplete for the reasons discussed above.[11] In addition to information about each inventor, information about assignees (typically inventors' affiliated companies), inventor and assignee locations, technology fields, and citations are available from the USPTO. For our baseline estimates, we take the location of the assignee as the location of the patent.[12] This approach avoids any concerns that the firm may shift some of its research to locations with stronger non-compete laws in response to a change. Nonetheless, in the appendix we also replicate our analysis using inventor location as the patent location, and restricting our sample to only those patents where assignee and inventor locations align, and find our results are robust to all specifications.

In the appendix we also use different citation measures to weight patents by approximations of their value rather than assuming (as we would when focusing on patent counts alone)

[10]We focus on corporate patenting – and exclude, e.g., government and academic patenting – to align with our interest in how NCAs affect firm incentives and innovative productivity.

[11]That is to say that data after 2016 are likely to be incomplete at least in terms of forward citations if not also in terms of conversion from application to granted patent in the most recent years.

[12]It does not appear to be the case that assignee locations are simply each assignee's headquarters. Rather, it appears as though assignees list patent-specific locations (e.g., the office where the work was done) as their location on patent applications. See **Appendix Figure 42** for an example of this.

that all patents are equally valuable or innovative. We find that our results are robust to this type of value-weighting. Forward citations are a common proxy for impact in the existing patent literature; they measure how many subsequent patents cite the patent in question and therefore are thought to approximate the extent to which a given patent has led to follow-on inventions.[13] Backward citations are a slightly less common measure, but recent research suggests that they may actually capture technological "value" more effectively;[14] they measure how many *previous* patents were cited by the patent in question, with the intuition that having fewer backward citations indicates a more original invention. For our novelty weighting, we weight patents by 1/(backward cites + 1). At the patent level, backward and forward citations are also winsorized to keep a single (either true or mismeasured) outlier patent from driving the results.

Using these data, we construct a panel for the entire sample period on inventors and assignees linked to their patents (and each patent's citations) as well as inventors linked to their assignee firms across years. We see this inventor-specific mobility data, which looks at when a given inventor switches from patenting with one firm to patenting instead with a different firm, as close to our primary object of interest when it comes to mobility and as a unique contribution to this literature.[15]

2.3 Business Formation Statistics

As discussed above, we also utilize data on firm entry from the Census BFS, which reports information on new business applications and formations. We observe the total applications for an Employer Identification Number (EIN) submitted by entrepreneurs and corporations

[13]Although forward-weighted citations are a popular measure in the innovation literature, we de-prioritize them in the analysis here because of the potential for NCAs to affect not only innovative activity but also subsequent citation networks. For example, a patent by a firm whose inventors are less likely to move may have a lower propensity to be cited, all else equal. Therefore, we prioritize the patent count results as our baseline specification instead and would caution against over-indexing on citation-weighted results.

[14]E.g., see the discussion in Jaffe and de Rassenfosse (2017).

[15]Note that the outside option to such a move would include staying at the initial firm as well as moving to a non-patenting firm or to a patenting firm but in a non-patenting role.

for each state.[16] In addition to applications, the BFS data also report information on business conversion/formations. Specifically, for quarter t, it reports how many applications are converted to formed businesses by period $t + 4$ quarters or $t + 8$ quarters. BFS data are reported at a quarterly frequency from 2004 to the present. For purposes of the data analysis discussed below, we aggregate applications to the yearly level to match the index of state-level enforcement of NCAs.

3 Empirical Approach

3.1 Identification

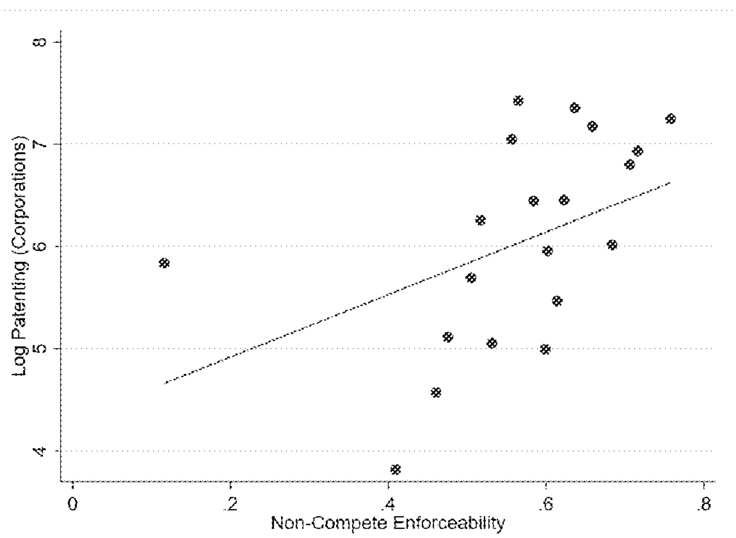
There are a number of challenges to estimating the causal impact of NCAs on innovation directly. For example, the use of NCAs by firms is very likely to be endogenous to their future innovation. For example, if a firm anticipates that they are likely to have valuable innovations in the future, they may be more incentivized to include NCAs in their employment contracts. Ignoring this endogeneity could bias any estimates of the impact of NCAs on innovation, as it would spuriously suggest a positive relationship between the two due to the reverse causality of anticipated innovations on NCA use. For this reason, even where direct information on NCA use and terms is available (for example, for the executives of listed firms), this information is not helpful for identifying the causal effect of NCAs on innovation.

To deal with this endogeneity, we instead focus on NCA *enforceability*. Rather than focusing on the actual employment contract terms that firms do use, this allows us to focus on variation in the most restrictive terms that they *could* use (i.e., that are legally enforceable in their state). Even enforceability may not be exogenous to firms in the cross-section, though, given that a firm's location choice is likely endogenous. It may be that highly innovative

[16] The data exclude applications for tax liens, estates, trusts, or certain financial filings, applications with no state-county geocodes, applications with certain NAICS codes in sector 11 (agriculture, forestry, fishing and hunting) or 92 (public administration) that have low transition rates, and applications in certain industries (e.g. private households, civic and social organizations).

firms choose to locate in states with high NCA enforceability, for example, but that does not necessarily imply the high degree of NCA enforceability *causes* their innovation. **Figure 4** shows the naive correlation between NCA enforceability and patenting across states. The type of spurious positive correlation shown there might have contributed to the popular narrative that NCAs support innovation. However, our results below show that the direction of this relationship is actually *reversed* when we account for this type of endogeneity.

Figure 4: Bin-Scatter of Log Patenting on NCA Enforceability



Bin scatter plot that groups states into bins by NCA enforceability and then plots the mean of log corporate patenting in each bin along the y-axis. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

Instead, we use state-level *changes* in NCA enforceability as our independent variable, which we argue are plausibly exogenous. These changes largely reflect judicial rulings that change the case law of what is and is not legally enforceable. Some changes also result from state legislation, which directly alter a state's statutes on NCA enforceability, overriding past legislation as well as past case law. Even in cases where we might worry that legislatures may change NCA policy in response to state-level conditions, Johnson et al. (WPb) shows that these changes are not predictable using a range of state-level characteristics.

3.2 Case Study: *Lake Land v. Columber* Decision

To fix ideas and provide intuition on the setting, we first consider a case study before jumping into a broader analysis of the effects of non-compete enforceability on innovation across all states. In March 2004, the Supreme Court of Ohio expanded the circumstances under which an NCA would be enforceable. In *Lake Land Employment Group of Akron, LLC v. Columber*, the court overturned the previous Ohio rule that an employee who signed an NCA after the commencement of employment had to be compensated for the agreement to be enforceable, ruling instead continued employment would constitute adequate consideration to enforce an NCA going forward. This represented a sudden and substantial increase in the enforceability of Ohio NCAs.[17] This change in enforceability was both unanticipated and would have meant that Ohio firms could relatively costlessly distribute NCAs to their employees the next day (whereas they would have previously needed to compensate those employees in order for the agreements to be enforceable).

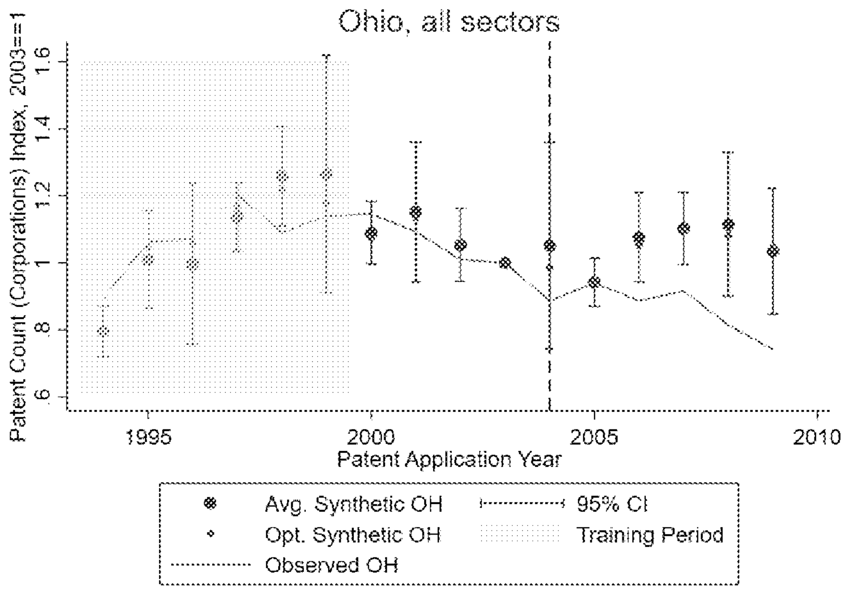
Turning now to how this change might have affected inventors and corporations' patenting, **Figure 5** compares Ohio patenting before and after the change to that of a synthetic control for Ohio constructed from states in our sample that never had a change in their NCA enforceability.[18] The green line in the figure documents observed Ohio patenting each year. The red dots represent the optimal synthetic control when we include all control states in the set of potential controls. The blue dots represent the average optimal synthetic control from 500 permutations where we randomly omit control states from the set of potential controls; from this, we can also construct standard errors and the 95% confidence intervals shown in the blue bars. This comparison suggets that Ohio patenting fell relative to the synthetic

[17]This judicial ruling relates to the Bishara index question: "Will a change in the terms and conditions of employment provide sufficient consideration to support a covenant not to compete entered into after the employment relationship has begun? Will continued employment provide sufficient consideration after the employment relationship has begun?"

[18]This figure normalizes patenting to a state's patenting to its 2003 level for visibility.

control after the *Lake Land* decision in 2004.

Figure 5: Ohio Patenting – Synthetic Control Comparison



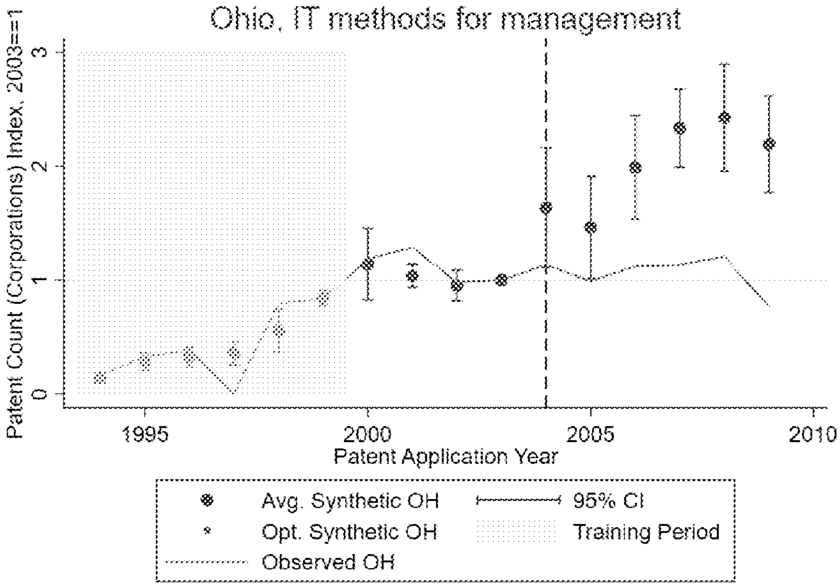
Comparison of observed Ohio patenting to synthetic Ohio patenting. The green line visualizes the trend in observed Ohio patenting. The red dots show the optimal synthetic control when all never-treated states are included as potential controls. The *synth* command in Stata constructs optimal weighted combination of untreated units in the training period as: 18% DC, 5% Mississippi, 5% West Virginia, 5% South Dakota, 5% Indiana, 4% New Jersey, 4% Tennessee, 4% New York, 4% Alabama, 4% Missouri, 3% Pennsylvania, 3% Colorado, 3% Virginia, 3% Oklahoma, 3% North Dakota, 3% Rhode Island, 3% Nebraska, 3% Utah, 3% Wyoming, 3% North Carolina, 3% New Hampshire, 3% Minnesota, 2% Montana, 2% New Mexico, 2% Washington, and 2% Nevada. The blue dots show the average synthetic control when we run 500 permutations of the analysis while randomly omitting various potential controls from the set under consideration. This approach also allows us to calculate the 95% confidence intervals show in the blue bars by bootstrapping the standard errors. All state-level patenting trends are indexed to 2003 levels. Data source: PatentsView. Details on the patent data are available in Section 2.2.

We can verify that this observed drop in Ohio patenting is not driven by industry compositional effects by also examining industry-level impacts.[19] By focusing on a high-tech industry, we can also rule out that the effect in **Figure 5** is simply driven by Ohio's exposure to the transport industry during the Great Recession. For example, **Figure 6** shows that there is also a sharp negative effect on Ohio patenting in information technology (IT)

[19]The World Intellectual Property Organization (WIPO) provides granular technology field information.

methods for management following the *Lake Land* ruling.

Figure 6: Ohio IT Methods Patenting – Synthetic Control Comparison



Comparison of observed Ohio patenting to synthetic Ohio patenting, now limited to the IT methods for management field defined by WIPO. The green line visualizes the trend in observed Ohio patenting. The red dots show the optimal synthetic control when all never-treated states are included as potential controls. The *synth* command in Stata constructs optimal weighted combination of untreated units in the training period as: 8% Indiana, 8% New Hampshire, 7% Minnesota, 7% Tennessee, 6% Missouri, 6% North Carolina, 6% New Jersey, 6% Pennsylvania, 6% New York, 6% District of Columbia, 5% Utah, 5% Virginia, 5% Washington, 5% Oklahoma, 5% Colorado, 5% Nevada, and 5% Nebraska. The blue dots show the average synthetic control when we run 500 permutations of the analysis while randomly omitting various potential controls from the set under consideration. This approach also allows us to calculate the 95% confidence intervals show in the blue bars by bootstrapping the standard errors. All state-level patenting trends are indexed to 2003 levels. Data source: PatentsView. Details on the patent data are available in Section 2.2.

The IT methods for management WIPO field relates to the International Patent Classification for "data processing methods, specifically adapted for administrative, commercial, financial, managerial, supervisory, or forecasting purposes." That is, this field represents software for these special purposes.[20] It is intuitive that experience with and tacit knowl-

[20]Although many believe that software is never patentable, this is not actually the state of patent law today. The key inquiry in determining software patentability is whether the claim is directed to an abstract idea. If not, then the software is eligible. However, if it is directed to an abstract idea, then the technology

edge around software would be valuable in a fast-moving and frontier field.[21]

To further confirm that it is the *Lake Land* decision driving these effects and not just some other event that happened around the same time, we can look directly at in-state inventor mobility in Ohio during this same time period.[22] **Figure 7** shows the number of moves by IT methods inventors (i) within Ohio; (ii) out of Ohio; and (iii) into Ohio. Although the three series move together in the pre-period, the number of within-state moves drops sharply below the number of across-state moves in 2004 and afterwards. This is precisely what one would expect an increase in NCA enforceability to accomplish, as NCAs generally have limited within-state geographic scope.

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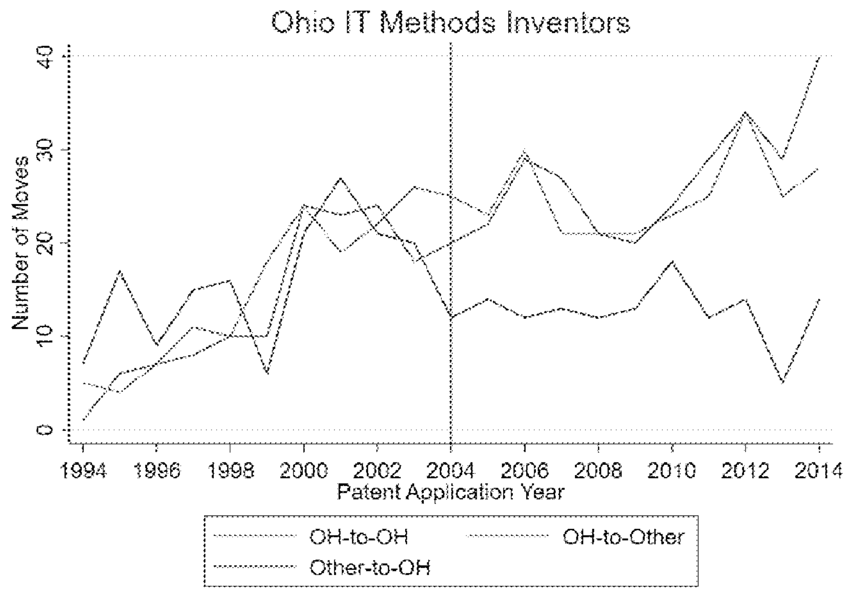
is ineligible without additional elements that "transform the abstract idea to a new and useful end" (Alice v. CLS Bank, 2014). For example, simply adding a computer to an abstract idea is not transformative (Alice v. CLS Bank, 2014). However, "an improvement to computer functionality" is not directed to an abstract idea (Enfish v. Microsoft, 2016). Moreover, the "non-conventional and non-generic arrangement of known, conventional pieces" constituting "a technical improvement over prior art ways" may transform the abstract idea (BASCOM v. AT&T, 2016).

[21]These statistics also likely understate the amount of innovative activity going on, as only a subset of software is patentable.

[22]As described above, we define inventor mobility here as how many times we observe an inventor patenting historically at one firm and then switching to patenting at a new firm in year t. Inventor mobility thus captures *moves between patenting-related jobs at innovative firms.* Even a decline in moves driven by inventors who move to non-patenting jobs and thus out of our sample would be relevant to our analysis because this such a response would still take the inventor out of the innovative ecosystem. Nonetheless, in our all-state analysis below, we consider the *share of inventors in the sample* who move and continue to see a proportional and statistically significant decline in inventor moves.

Figure 7: Moves by Ohio IT Methods Inventors – by Origin and Destination



Comparison of the number of moves each year by Ohio IT methods for management inventors who either moved within, out of, or into Ohio. A move is counted in this figure whenever we observe an inventor patenting historically at one firm and then switching to patenting at a new firm in year t. Data sources: PatentsView; clean organization lookup created by this paper. Details on the patent data are available in Section 2.2. The clean organization lookup is discussed in additional detail in Footnote 33.

These coincident drops in in-state inventor mobility and in-state patenting suggest that *Lake Land* played a significant role in changing the innovative landscape of Ohio by restricting worker mobility.

3.3 All-State Estimation

For our main results, we adopt a staggered difference-in-differences estimation approach: local projections difference-in-differences (LP-DiD) developed by Dube et al. (WP). This estimator is similar to other popular estimators like Callaway and Sant'Anna (2021) and Borusyak et al. (2021b) and shares their desirable features of, for example, avoiding the negative weights bias under staggered heterogeneous treatments of two-way fixed effects models; however, it also uniquely permits non-absorbing and non-binary treatments like we have in our setting here. Our estimating equation is the following:

$$
\begin{aligned}
y_{i,t+h} - y_{i,t-1} = \beta_h \cdot \mathbb{I}_{it} \cdot \Delta X_{it} & \qquad \text{treatment (change in index)} \\
+ \delta_{t+h} - \delta_{t-1} & \qquad \text{time effects} \\
+ \epsilon_{it+h} & \qquad \text{for } h = -H, ..., H,
\end{aligned}
\tag{1}
$$

where we restrict the sample to observations that are either (i) clean controls – i.e., not-yet or never treated states; or (ii) clean treatments – i.e., state-years with only one treatment in the past H years and with treatments greater than a threshold c.[23] In this specification, $y_{i,t+h} - y_{i,t-1}$ is the difference in the relevant outcome variable (log patents, log business applications, etc.). ΔX_{it} is the change in our continuous treatment variable – the normalized state-level index of NCA enforceability. Dube et al. (WP) allows for outcome lags to be included on the right-hand side of the estimating equation.[24] Although not part of our baseline specification, we include a version of our results with these lags in the appendix to show robustness. Finally, we also control for time-fixed effects, δ. For our baseline specification we use: $H = 5$ years and $c = 15/600$.[25] We cluster standard errors at state-level, and for our baseline results we weight each state by its population share in the previous year. In the appendix, we also present our results unweighted, and weighted by their patent share in the previous year, and show our findings are robust to either alternative weighting scheme.

The primary assumption necessary for the validity of the LP-DiD estimator is captured in the clean treatment and control conditions noted above, which requires that in order to be included as either a treatment or control observation, a state must be either newly

[23]For additional information on which states have strengthenings, weakenings, or neither in our baseline sample, see **Appendix Figure 30**.

[24]This is the local projections piece of the LP-DiD estimating equation. Controlling for pre-treatment values of time-varying covariates, including outcome dynamics, on the right-hand side allows a weaker parallel trends assumption than is standard to the typical DiD approach.

[25]This low $c = 15/600$ threshold is conservative, as we show that setting a higher threshold further strengthens our estimated effects, supporting the generalizability of our conclusions to other potential policy changes.

or not-yet treated such that it is not experiencing some previous dynamic treatment effect from a previous change.[26] With these restrictions, we have 26 total treatments for our baseline 1991-2016 sample, of which 17 are instances in which NCA enforceability increased ("strengthenings"), and 9 are instances where enforceability decreased ("weakenings"). We also include a number of other checks in the appendix to show that our results are robust to different permutations of this analysis.[27]

4 All-State Results

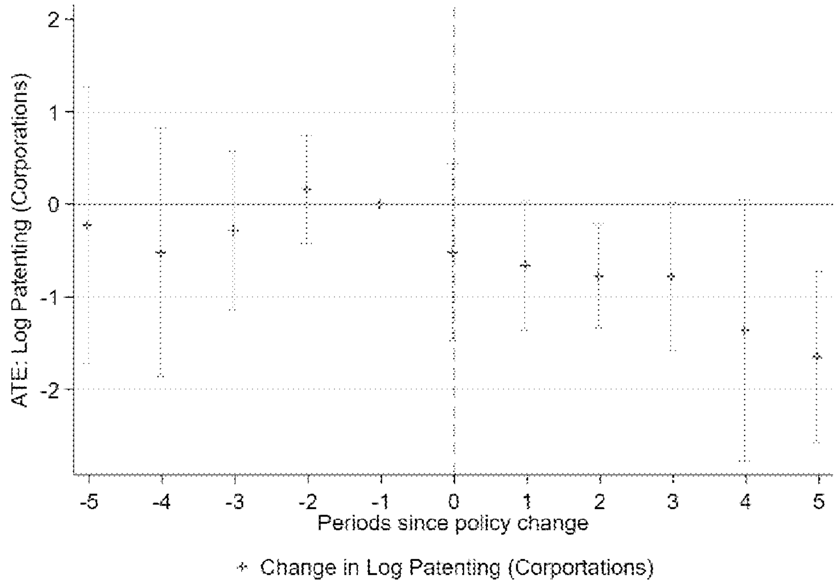
Figures 8 and 9 present our headline results of the impact of all 26 changes in NCA enforceability in our baseline sample. The peak decline in patenting that we observe occurs after 5 years. These coefficients imply an economically significant decline in patenting due to increases in NCA enforceability. For example, they suggest that a strengthening of NCA enforceability from the median enforcement level observed in our sample to the maximum enforcement level observed in our sample (i.e., a move on the normalized index from 0.59 to 0.80) would decrease patenting by about 28% after 5 years.[28] For a more modest change in enforcement (e.g., of the average size observed in our sample), our estimates suggest that an increase of 0.09 points in our normalized index would decrease patenting by about 13%.

[26]Using a previously treated unit that is still experiencing lagged time-varying and heterogeneous treatment effects as a control would introduce bias. The LP-DiD methodology avoids this by restricting the sample so that "unclean" observations are not included.

[27]In particular, we additionally restrict our sample such that we have a balanced panel of 13 treatments, of which 10 are strengthening and 3 are weakening. Under this specification our estimates are very similar in magnitude and more tightly estimated than in our baseline, suggesting the broader sample is conservative. However, we maintain the unbalanced as our baseline to ensure consistent and sufficient samples for the BFS results, for which we have a reduced time period of data availability. Below, we also show results from the analysis when using a higher threshold of $c = 50/600$. This reduces our sample to 10 strengthenings and 4 weakenings, and again results in a similar and more precisely estimated effect than in our baseline specification.

[28]Note: predicted change is equal to $\exp(\beta_5 * \Delta X) - 1$.

Figure 8: Estimated Effect of Changes in NCA Enforceability on Log Patent Count



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

We estimate Equation 1 by first regressing the outcome measure on the year effects and then regressing the residual on the treatment. This implementation allows us to estimate calendar year fixed effects that are constant across ts and hs rather than estimating these effects specific to time horizons and treatment years. As a result, the R-squared terms shown in the tables below reflect only the share of the variation in the residual that is explained by the treatment variable, and not the share of the variation in the outcome that is explained by the year fixed effects.

Figure 9: Estimated Effect of Changes in NCA Enforceability on Log Patent Count

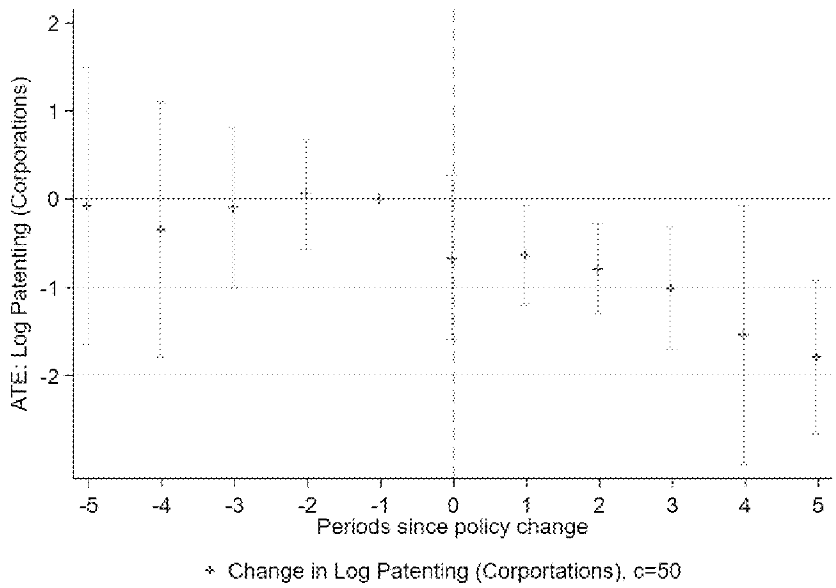
Year Relative to Treatment:	-5	-4	-3	-2	-1	0	1	2	3	4	5
Treatment: Change in Index	-0.209	-0.445	-0.253	0.127	.	-0.419	-0.659*	-0.722***	-0.784 *	-1.368*	-1.60***
	(0.763)	(0.651)	(0.450)	(0.302)	.	(0.459)	(0.355)	(0.269)	(0.405)	(0.721)	(0.471)
Year FE	X	X	X	X	X	X	X	X	X	X	X
Constant	X	X	X	X	X	X	X	X	X	X	X
Observations	541	584	629	668	719	712	712	710	708	704	689
R-squared	0.000	0.002	0.001	0.000	.	0.004	0.004	0.004	0.003	0.007	0.006

Standard errors clustered by state are shown in parentheses.
Note: States are weighted in year *t* by their population share in year *t-1*.
*** p<0.01, ** p<0.05, * p<0.1.

See **Appendix Figures 23 and 24** for analogous impact and novelty-weighted results.

Specifying a higher minimum threshold (c) for clean treatments results in marginally larger treatment effect estimates and smaller standard errors. See **Figure 10**.

Figure 10: Estimated Effect of Changes in NCA Enforceability on Log Patent Count (C=50/600)



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 50/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

That is, the estimated treatment effect is even more statistically significant when we focus on larger (and therefore likely better measured and more salient changes). These results (and the robustness checks included in the appendices) suggest that there is an economically and statistically significant negative impact on patenting following an increase in NCA enforceability.

4.1 Product Patents versus Process Patents

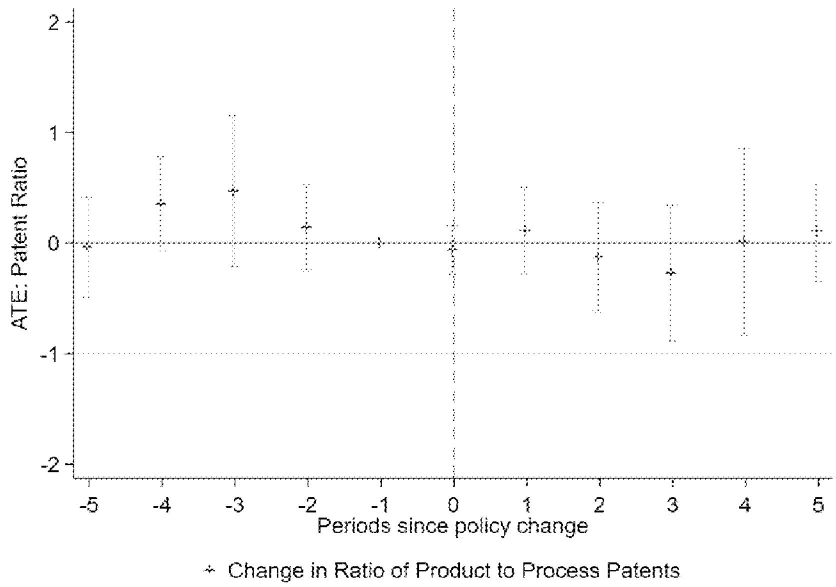
An additional challenge in identifying the relationship between NCAs and innovation is that NCAs may affect not only innovation directly, but also the propensity of firms to patent a given innovation. That is, if firms view NCAs and patents as substitutes in protecting their inventions and ideas, we might pick up substitution effects alongside innovation effects. Such substitution is unlikely to be an issue here, though. Discussions with legal scholars have revealed that the risk of not patenting an eligible invention is generally too large for firms to adopt such a strategy, even under fully enforceable NCAs – e.g., if a competitor independently invents and patents your same invention, it obtains the right to exclude you from use of the invention. And, even short of a competitor *patenting* your invention, independent discovery and reverse engineering would destroy any right you have to exclude others.

As empirical evidence, we can consider the treatment effect separately for 'product' and 'process' patents to confirm that our estimates reflect the true impact of NCAs on *innovation* rather than substitution.[29] To the extent that product innovations are hard to protect through trade secrets alone due to the potential for reverse-engineering, firms are unlikely to choose not to patent eligible product innovations even in the face of high NCA enforceability. Substitution between trade secrets (protected by NCAs) and patents may be more of a concern for process innovations. Our results in **Figure 11** show, however, that the mix of product and process patents granted within a state does not change in response to changes in NCA enforceability, such that it does not seem to be substitution away from (process) patenting that generates our results. If firms are simply using patents as a substitute for trade secrets that become harder to protect in the presence of weaker NCA enforcement, rather than actually conducting additional R&D and innovation, then we should see most (if not all) of our effect operating through the process-only patents channel such that the relative frequency of product- and process-only patents changes too. However, we can see

[29]Patents are categorized as process or product patents based on an index by Heinrich et al. (2022). We do not take a stance here on the appropriate classification of mixed patents.

that the relative frequencies are unaffected and that it does not appear as though process patents are driving our baseline results discussed above. Moreover, we observe real simultaneous changes in inventor moves in the channel-specific results discussed below, suggesting that more fundamental changes are happening in innovative industries in response to NCA enforceability.

Figure 11: Estimated Effect of Changes in NCA Enforceability on the Ratio of Product-Only Patents to Process-Only Patents



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the ratio of product-only patents to process-only patents in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; Heinrich et al. (2022) patent categorizations. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

5 Channels Analysis

We consider three specific channels through which NCAs may affect innovation. First, the most common explanation for why NCAs might increase innovation is **incumbent innovation incentives**. Just as patents are thought to encourage innovation by allowing firms to better appropriate the returns on R&D expenditures (e.g., by allowing them to charge higher markups on innovative products for a period of time following a novel invention), NCAs may also incentivize incumbent innovation by helping firms protect their confidential information (e.g., trade secrets, tacit knowledge, negative knowledge, etc.) and maintain a competitive advantage over rivals by restricting the flow of information.

However, incumbent firms are not the only source of innovation. Our second channel, **firm entry**, is important as well. Garcia-Macia et al. (2019) estimates, for example, that firm entry accounts for approximately 20% of total innovation in the US. But, without empirical analysis, the effect of NCAs on entry is theoretically ambiguous. On the one hand, NCAs might have a positive effect on firm entry to the extent that they increase the expected profits of a successful entrant (e.g., as with incumbents: by allowing firms to earn supra-normal profits on their innovations or by reducing the wages and bargaining power of workers). However, NCAs could also have a negative effect on entry, as they directly impose barriers to entry. For example, a worker covered by an NCA is legally prohibited from entering the market as a rival firm. Moreover, even if a would-be entrepreneur is not themselves covered by an NCA, they may still find it difficult to enter the market if most workers in the industry are covered by NCAs such that it proves difficult to recruit talent. Among other things, this paper assesses the net impact of NCAs on this entry channel, which is otherwise uncertain.

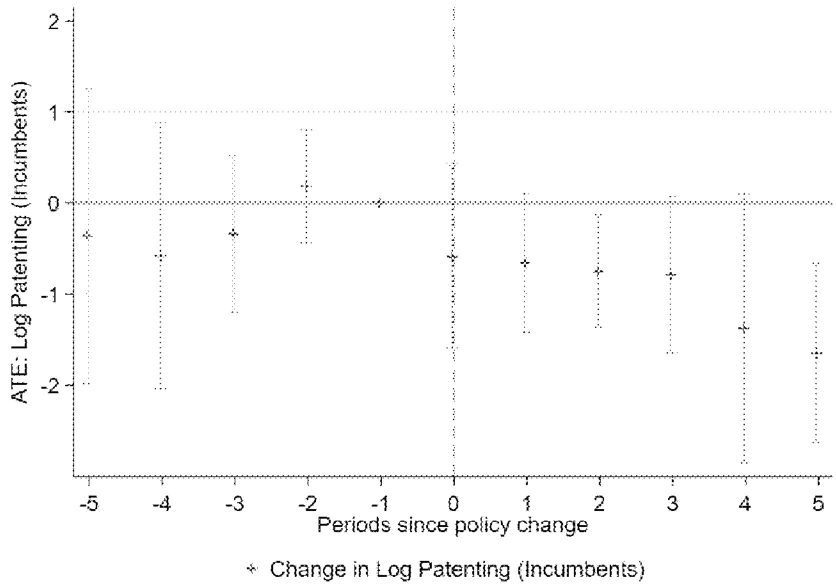
Third, NCAs may negatively affect productivity and innovation by reducing **knowledge diffusion** – i.e., the flow of new ideas and technologies between firms. This channel impacts the ability of other firms to learn about and improve upon the new technologies produced by rivals.[30] As discussed above, if workers moving between firms is an important mechanism through which innovations spread and diffuse, then direct limits on employee mobility will hamper this channel of knowledge flows.

The estimated negative net effect of NCA enforceability on patenting discussed above indicates that incumbent innovation incentives are outweighed by one or both of the other channels. Therefore, to start untangling which channel/mechanism is driving these results, we first split our headline results to look at the patenting of firms who have previously patented ("incumbents") – i.e., excluding first-time entrants. **Figures 12 and 13**[31] show the estimated effect of NCA enforceability on the patenting of incumbents. Incumbents see a decline in patenting similar to that of our headline estimates, suggesting that, at the very least, not all of the observed decline in overall patenting can be explained by reduced entry. Rather, these results show that *incumbent* firms themselves are innovating significantly less following an increase in NCA enforceability.

[30] This channel has been pointed to as a potential explanation behind Silicon Valley's growth, for example.

[31] As discussed above, the R-squared terms shown in the table below reflect only the share of the variation in the residual that is explained by the treatment variable, and not the share of the variation in the outcome that is explained by the year fixed effects.

Figure 12: Estimated Effect of Changes in NCA Enforceability on Log Patent Count - Incumbents (Firms Who Have Previously Patented) Only



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by incumbents in year h relative to the time of the policy change ($h = 0$). Incumbents are defined as corporations with previous observed patenting. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 13: Estimated Effect of Changes in NCA Enforceability on Log Patent Count - Incumbents (Firms Who Have Previously Patented) Only

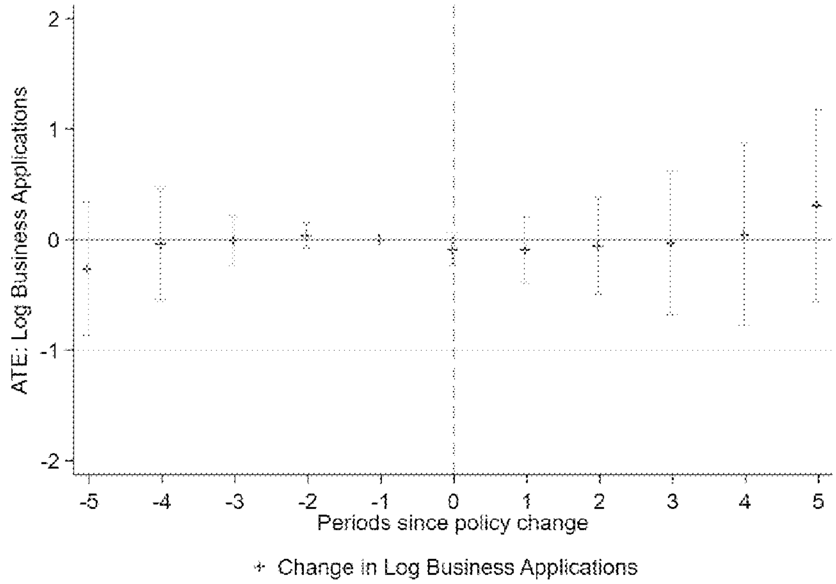
Year Relative to Treatment:	-5	-4	-3	-2	-1	0	1	2	3	4	5
Treatment: Change in Index	-0.345	-0.497	-0.315	0.157	.	-0.489	-0.654*	-0.691**	-0.791*	-1.371*	-1.598***
	(0.825)	(0.707)	(0.449)	(0.319)	.	(0.473)	(0.391)	(0.298)	(0.438)	(0.755)	(0.495)
Year FE	X	X	X	X	X	X	X	X	X	X	X
Constant	X	X	X	X	X	X	X	X	X	X	X
Observations	541	584	629	668	719	712	712	710	708	704	689
R-squared	0.001	0.002	0.001	0.000	.	0.004	0.003	0.003	0.003	0.006	0.006

Standard errors clustered by state are shown in parentheses.
Note: States are weighted in year *t* by their population share in year *t-1*.
*** p<0.01, ** p<0.05, * p<0.1.

We can further assess the magnitude of the entry channel by using the Census BFS data discussed above. **Figures 14 and 15**[32] show the estimated effect of changes in NCA enforceability on business applications. These results again show no statistically significant effect of changes in NCA enforceability on entry – and certainly not a *decline* of the magnitude we see for patenting overall. This could be consistent with the negative barriers to entry channel being cancelled out (at least partially) by the positive profitability channel from our theoretical framework outlined above.

[32]As discussed above, the R-squared terms shown in the table below reflect only the share of the variation in the residual that is explained by the treatment variable, and not the share of the variation in the outcome that is explained by the year fixed effects.

Figure 14: Estimated Effect of Changes in NCA Enforceability on Log Entry (Business Applications)



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log state-level count of business applications in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: Census BFS; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the business applications data are available in Section 2.3. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 15: Estimated Effect of Changes in NCA Enforceability on Log Entry (Business Applications)

Year Relative to Treatment:	-5	-4	-3	-2	-1	0	1	2	3	4	5
Treatment: Change in Index	-0.265	-0.039	-0.004	0.034	.	-0.089	-0.090	-0.059	-0.029	0.041	0.309
	(0.308)	(0.259)	(0.112)	(0.057)	.	(0.073)	(0.152)	(0.222)	(0.333)	(0.421)	(0.442)
Year FE	X	X	X	X	X	X	X	X	X	X	X
Constant	X	X	X	X	X	X	X	X	X	X	X
Observations	110	144	175	210	244	244	240	238	238	238	236
R-squared	0.010	0.000	0.000	0.001	.	0.003	0.002	0.001	0.000	0.000	0.007

Standard errors clustered by state are shown in parentheses.
Note: States are weighted in year *t* by their patent share in year *t-1*.
*** p<0.01, ** p<0.05, * p<0.1.

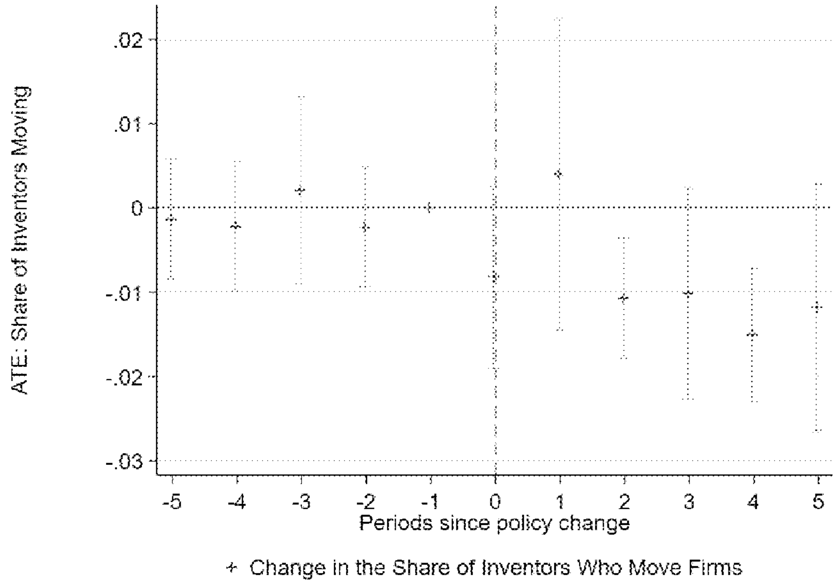
These results are unchanged when considering either four-quarter business formations or eight-quarter business formations, as shown in the appendix. In summary, firm entry does not seem to explain the estimated negative effect of NCAs on innovation.

In contrast, the observed impact on patenting is paralleled by a real impact on inventor mobility. We measure inventor moves from the patent data using disambiguated inventor and assignee names.[33] An example mover is included for reference in **Appendix Figure 40**. See **Figures 16 and 17**[34] for inventor mobility results that suggest a strengthening from median to max enforceability (i.e., 0.59 → 0.80) would cause a 0.2pp (from a base rate of 0.5pp, or 51%) decrease in the share of inventors moving firms after 5 years. A strengthening of average size in our data (i.e., 0.09) corresponds to a 0.1pp (or 22%) decrease in inventor moves after 5 years.

[33] To ensure that we are accurately measuring inventors who move across firms, we also contribute a novel clean organization lookup that further disambiguates firm names from the USPTO data. For example, USPTO's disambiguated assignee organizations include organization names like: DARTMOUNTH COLLEGE, TRUSTEES OF DARTMOUTH COLLEGE, THE TRUSTEES OF DARTMOUGH COLLEGE, THE TRUSTEES OF DARTMOUTH COLLEGE AND DARTMOUTH-HITCHCOCK CLINIC, TRUSTEES OF DARTMOUTH, and TRUSTEES OF DARTMOUTH UNIVERSITY. It would be incorrect to consider an inventor we see attached to multiple of these organization names as moving. Therefore, through work involving ChatGPT, Gemini, and manual effort, we have assembled a clean lookup that consolidates these firm names into a clean ID from which we can accurately measure inventor moves.

[34] As discussed above, the R-squared terms shown in the table below reflect only the share of the variation in the residual that is explained by the treatment variable, and not the share of the variation in the outcome that is explained by the year fixed effects.

Figure 16: Estimated Effect of Changes in NCA Enforceability on Share of Inventors Moving



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the share of inventors moving firms in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. Inventor moves are defined as above and now also within state and industry given that these are the types of moves targeted by NCAs. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D. The clean organization lookup is discussed in additional detail in Footnote 33.

Figure 17: Estimated Effect of Changes in NCA Enforceability on Share of Inventors Moving

Year Relative to Treatment:	-5	-4	-3	-2	-1	0	1	2	3	4	5
Treatment: Change in Index	-0.001	-0.002	0.002	-0.002	.	-0.008	0.004	-0.011***	-0.010	-0.015***	-0.012
	(0.004)	(0.004)	(0.006)	(0.004)	.	(0.006)	(0.009)	(0.004)	(0.006)	(0.004)	(0.007)
Year FE	X	X	X	X	X	X	X	X	X	X	X
Constant	X	X	X	X	X	X	X	X	X	X	X
Observations	552	595	639	683	727	727	723	721	721	721	719
R-squared	0.000	0.000	0.000	0.000	.	0.005	0.001	0.006	0.004	0.009	0.005

Standard errors clustered by state are shown in parentheses.
Note: States are weighted in year *t* by their population share in year *t-1*.
*** p<0.01, ** p<0.05, * p<0.1.

That inventors are strongly affected alongside patenting supports the role of labor mobility as a channel of knowledge diffusion.[35]

6 Other Considerations

6.1 Accounting for Spillovers

So far, we have estimated the impact of state-level changes in NCA enforceabiliity. To extrapolate to the expected effects of a national policy (e.g., the FTC's proposed ban), we additionally need to account for the potential impact of cross-state spillover effects.[36] Accounting for certain spillover effects could intensify our estimated net effect. For example, accounting for how declines in patenting in Ohio would inhibit follow-on innovation in other states would increase our estimated magnitudes. However, accounting for other spillover effects could dampen our net effect. For example, if workers move states to escape NCAs (following an increase in enforceability in their initial state of residence), they may increase innovation in their destination state. To ensure that our estimated effect is conservative, we now also control for out-of-state migration effects, which may dampen our baseline estimated treatment effect.

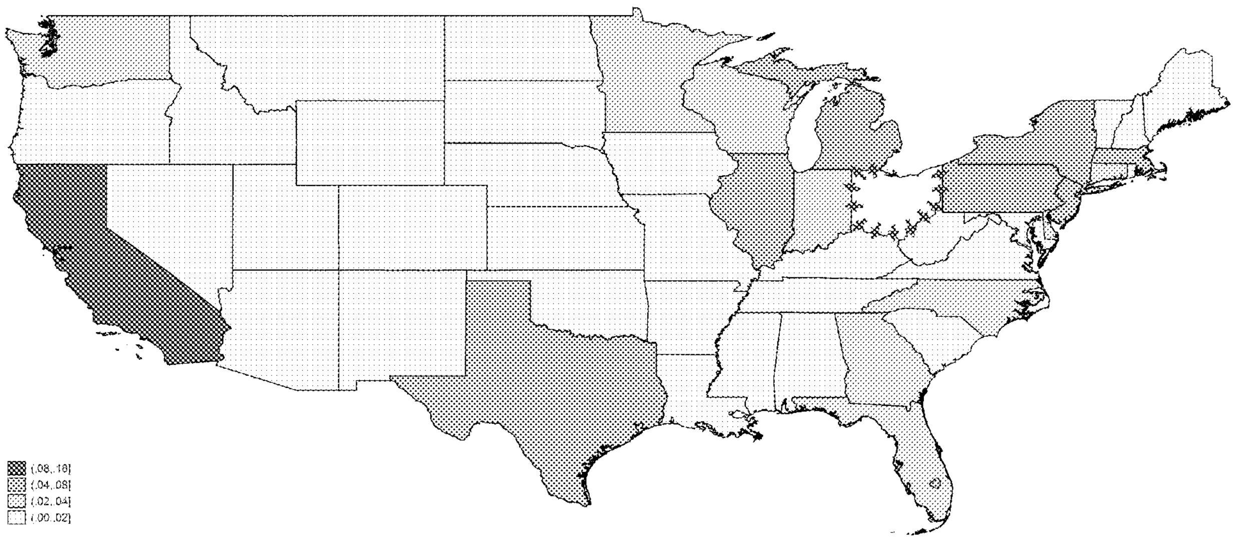
To do so, we control for the relative exposure of one state to all other states' movers. Helpful in this step is the fact that inventor migration patterns have stable determinants (e.g., distance, industry mix, demographics, and relative economy size). For example, **Figure 18** shows the relative shares with which inventors moving out of Ohio end up in other states. California is the most common, as might be expected based on factors like the relative size of its inventive economy. However, states like Wisconsin, Illinois, Indiana, and Pennsylvania are also well-represented, as might be expected based on factors like distance of migration.

[35]It also helps us understand the timing of the patenting effects, which is fairly immediate and growing over time. The immediacy of the initial effect is less surprising given these equally immediate impacts on mobility and the fact that existing research shows a "strong *contemporaneous* relationship between R&D expenditures and patenting" (emphasis added) (Hall et al. (1986); Pakes and Griliches (WP)).

[36]Doing so will also allow us to confirm the validity of SUTVA in our baseline estimates above.

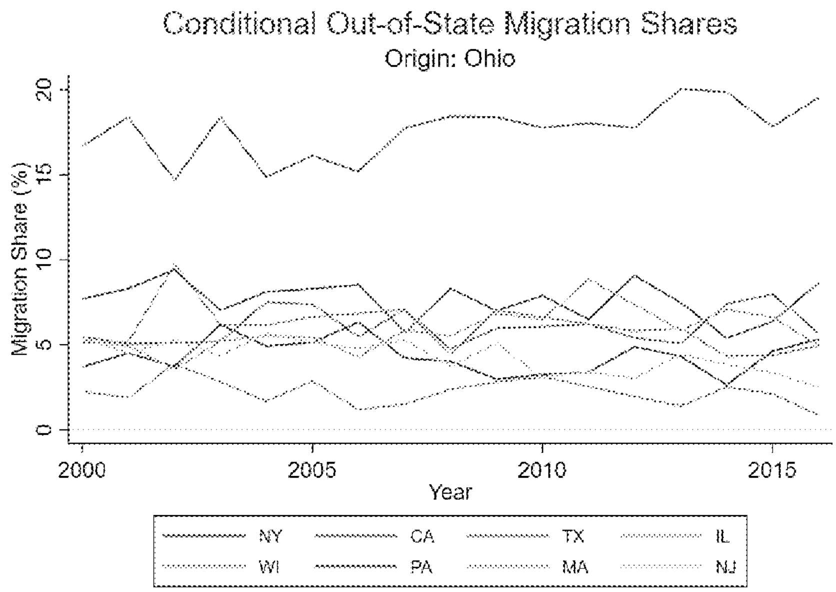
Figure 19 shows that these migration shares (conditional on out-of-state migration) are relatively constant over time.

Figure 18: Example Mover Destinations (Ohio)



Map of destination states for Ohio inventors who move out of the state. Darker colors indicate states that are more frequent recipients of Ohio inventors, as detailed in the legend. Inventor moves are defined as above. Data sources: PatentsView; clean organization lookup. Details on the patent data are available in Section 2.2. The clean organization lookup is discussed in additional detail in Footnote 33.

Figure 19: Mover Destination Stability (Ohio)



Plot of the annual share of Ohio inventors who move out of state who end up in the destination states denoted in the legend. For visibility, only the 8 most common destination states are plotted. Inventor moves are defined as above. Data sources: PatentsView; clean organization lookup. Details on the patent data are available in Section 2.2. The clean organization lookup is discussed in additional detail in Footnote 33.

Given this, we can define a gravity-style control for the cumulative exposure of state i to all other states' changes in enforceability.[37] Specifically, we can specify the following term to capture state i's exposure to movers out of other states due to other states' changes in enforceability as a percentage of i's initial inventor population:

$$\lambda_{i,t+h} := 100 \cdot \left(\sum_{\forall o \neq i} \underbrace{wm_{oi,t-1}}_{i\text{'s exp. to } o} \cdot \underbrace{\mathbb{I}_{o,t} \cdot m_{o,t-1} \cdot [M_{o,t+h} - M_{o,t-1}]}_{\text{change in \# movers out of } o} \right) / \underbrace{P_{i,t-1}}_{\text{\# inventors in } i}, \tag{2}$$

where $wm_{oi,t}$ is the share of inventors who move out of state o in year t that end up in state i; $m_{o,t}$ is the level count of inventors moving out of state o in year t; $M_{o,t}$ is the log count of

[37] This control is in the style of existing work such as Dubé et al. (2017); Borusyak and Hull (2023); Borusyak et al. (2021a); Peri et al. (2015); Kerr and Lincoln (2010); and Card (2001). However, it is somewhat novel in that it captures exposure to multiple events rather than a singular event.

inventors moving out of state o in year t; and $P_{i,t}$ is the level inventor population in state i in year t.

With this term in mind, we can predict the change in the number of inventors moving out of state that is induced by a change in NCA policy in the first stage of the following two-stage regression, and then use that predicted change to include a predicted $\hat{\lambda}$ as a covariate in the second stage (which is a version of our baseline specification):[38]

$$1. \quad M_{o,t+h} - M_{o,t-1} = \theta_h \cdot \mathbb{I}_{o,t} \cdot \Delta X_{o,t} + \gamma_{t+h} - \gamma_{t-1} + \varepsilon^1_{o,t+h} \tag{3}$$

$$2. \quad Y_{i,t+h} - Y_{i,t-1} = \beta_h \cdot \mathbb{I}_{i,t} \cdot \Delta X_{i,t} + \delta_{t+h} - \delta_{t-1} + \rho_h \cdot \hat{\lambda}_{i,t+h} + \varepsilon^2_{i,t+h} \tag{4}$$

Here, ρ is a parameter to test for the presence of spillovers through inventor moves.

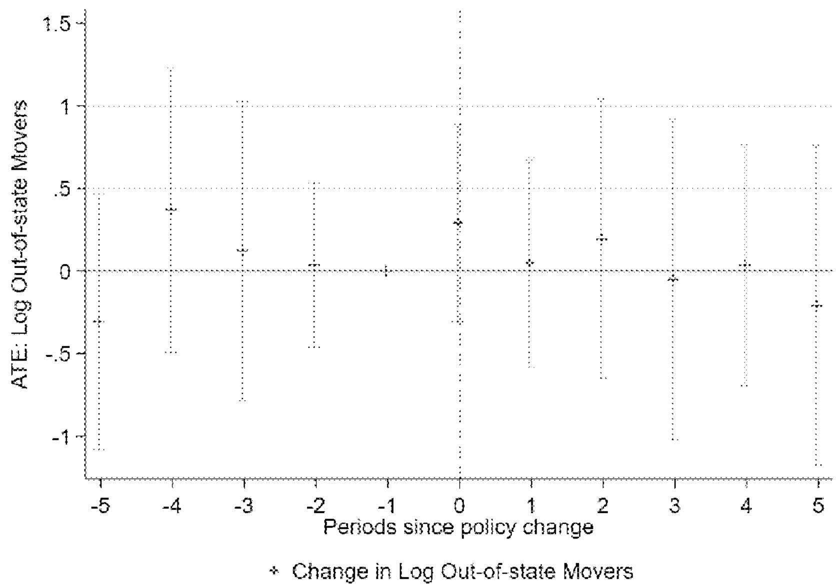
This analysis suggests that there are no statistically significant spillover effects from migration. See **Figure 20**.[39] This result is consistent with existing literature that finds that accounting for individual workers' out-of-state migration does not change optimal state-level policies, such as optimal state-level income taxation (Mazerov (2023)). Accordingly, the estimated net effect of a change in NCA enforceability on patenting is unchanged from our baseline specification shown above. See **Figure 21**. Details on the first stage results of this regression analysis can be found **Appendix Figure 41**.[40]

[38]The two identifying assumptions necessary for this approach are: (i) treatment in state i affects state j patenting only proportionally to historical migration flows; and (ii) treatment in state i is exogenous to things happening in state j.

[39]Note that the effect of the spillovers is insensitive to state i's treatment period, which makes sense because the spillovers are timed according to *other* states' treatment periods.

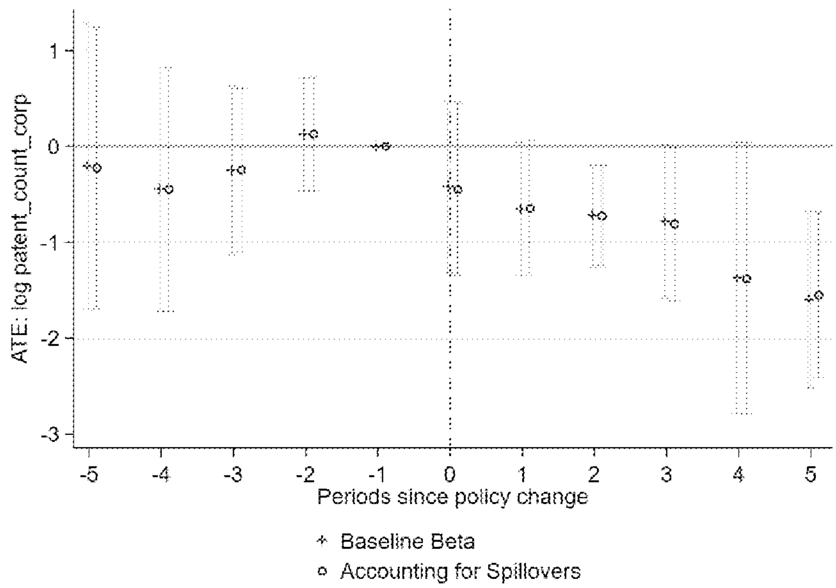
[40]There, we see no statistically significant impact of change in NCA enforceability on out-of-state moves, with F-stat of the treatment indicators $\in [0, 3]$ for all $h \in [-5, 5]$.

Figure 20: Estimated ρ



Plot of the estimated average treatment effect of a 1 percent increase in the number of inventors in a destination state because of changes in NCA enforceability in other origin states on the log of destination state-level corporate patenting in year h relative to the time of the destination state's policy change ($h = 0$). Details on the econometric specification can be found in Equations 2, 3, and 4. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D. The clean organization lookup is discussed in additional detail in Footnote 33.

Figure 21: Updated Estimated Effect of Changes in NCA Enforceability on Log Patent Count



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$) before accounting for spillovers (in red) and after accounting for spillovers (in blue). Details on the econometric specification can be found in Equation 1 (for the red "baseline" series) and in Equations 2, 3, and 4 (for the blue "accounting for spillovers" series). Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D. The clean organization lookup is discussed in additional detail in Footnote 33.

6.2 Limitations

The preceding analysis raises a number of additional considerations that are beyond the scope of this paper due to data limitations, but which we hope to explore in future work. Firstly, another potential mechanism that we do not include in our channels analysis is any potential discouragement effect of increased NCA enforceability on incumbent innovations. It is possible that more enforcement of NCAs could discourage inventors from working as hard as before (either directly when inventors are forced to stay in a job that they would like to leave or indirectly due to the lower pay from stronger NCAs that has been identified by others in the existing literature). However, in the patent data we cannot observe, for example, compensation or hours worked, so it is hard to speak to this channel directly.

As previewed above, our focus on patented inventions necessarily excludes a potentially significant portion of innovative activity. Many innovations may not be patented for various reasons such as eligibility, and if the drivers of patented versus non-patented innovations differ, our conclusions may not fully capture the impact of NCA enforceability on overall innovation. Future work that explores non-patent measures of innovation would be a valuable addition to this area of research.

Additionally, an important caveat when extrapolating our results to policy changes that would be larger than those considered in our analysis (recall: the average change in our sample is $\sim$0.09 points on the normalized index) is that the reduced-form nature of our approach limits our ability to assess potential non-linearities in the relationship between NCA enforceability and innovation. The treatment effect may depend both on the starting level of enforceability and the magnitude of the change. Indeed our results find a larger treatment effect for larger changes (possibly suggesting a role for salience), but it could also be true that, while NCAs dampen innovation locally, the sign of the treatment effect reverses as enforceability approaches zero. This could happen, for example, if the strength of the various channels changes across the range of enforceability. For this reason, extrapolating our local estimates to broader contexts requires caution. We do not claim in this paper that the optimal level of NCA enforceability is zero; rather, we only claim that, on average, the current level of enforceability appears to be too high to maximize innovation. Future research that employs structural models and richer data would allow for a more robust understanding of these trends.

Finally, this study examines the effects of NCA enforcement largely at the state and national level. This is likely to mask significant heterogeneity between different workers, firms, and industries, all of which may be insightful into how these channels operate and what the key determinants of knowledge diffusion are. Although we do not explore this potential heterogeneity in this paper, this would likely be a valuable area of future research.

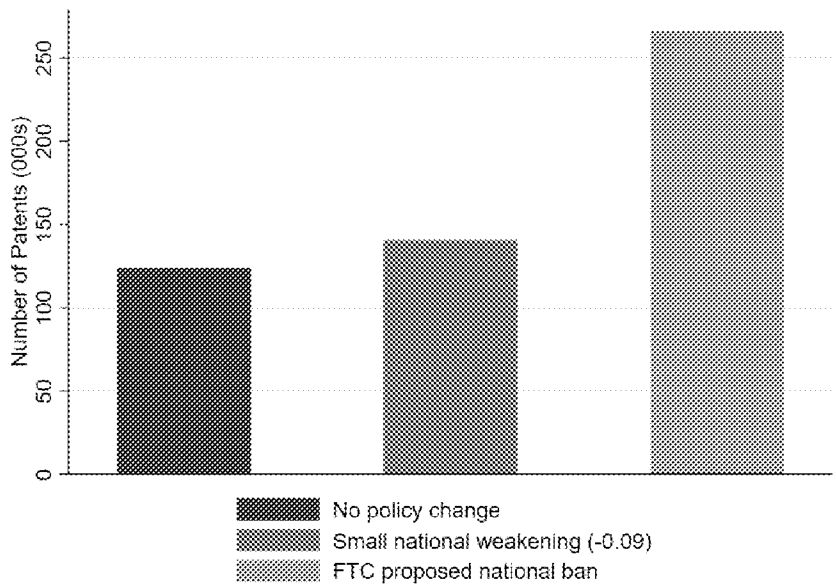
7 Discussion

Given these results, we can turn to think next about the effect of a federal policy that weakens NCA enforceability nationwide. Our preferred policy counterfactual is one that matches up well with the average treatments observed in our data. Therefore, we consider what the effect of a 0.09 point weakening in our normalized index would do to patenting in every state across the country.[41] Given the lack of significant spillovers in the other direction above, we use our baseline β estimate from 5 years after a hypothetical change for this exercise. The second bar of **Figure 22** shows what the effect of this federal decrease in national enforceability would do to patenting based on our point estimates – predicting a 14% increase in patenting nationwide.

One could take our results a step farther and extrapolate linearly to think about what these results might imply for the effect of the FTC's proposed ban on NCAs. For the reasons discussed above, we heavily caveat such extrapolation. However, the sign and economically significant magnitude of the predicted effect should encourage policymakers to seriously consider the potential upside to innovation of such a ban. The third bar of **Figure 22** shows what the effect of this federal ban would do to patenting based on our point estimates. Extrapolating linearly, our results predict a 115% increase in patenting nationwide.

[41] In the case that a state's 2022 enforceability is already less than 0.09, we take that state to zero enforceability for this counterfactual.

Figure 22: Back-of-the-Envelope Calculation of the National Effect of Federal Rules that Decrease NCA Enforceability



The first (navy) bar shows the number of patent applications filed in 2016. The second (green) bar shows the predicted effect of a nationwide decrease of NCA enforceability equivalent to a 0.09 point change in the normalized enforceability index using our baseline estimated β when $h = 5$ (or five years after a change in enforceability). The third (teal) bar shows the analogous predicted effect of a nationwide ban of NCAs. For these counterfactual policy changes, we take a state's 2022 score on the normalized enforceability index as its initial condition. In the case that a state's 2022 enforceability is already less than 0.09, we take that state to zero enforceability for the second counterfactual prediction. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

8 Conclusion

This paper suggests that NCAs have a significant negative net impact on innovation, in contrast to what is often assumed in policy discussions. The impact is not only statistically significant but also economically significant: a strengthening from the median to maximum observed enforceability in our sample (i.e., 0.59 to 0.80 on our normalized index) is associated with a 28% decrease in patenting after five years. Even for a more modest change in enforceability, our estimates suggest that an increase of 0.09 points in our normalized index (the mean observed change) would decrease patenting by 13%.

This effect is not simply driven by NCAs restricting entry. In fact, our results find no statistically significant impact on entry from changes in NCA enforcement. This result is consistent with the idea that more enforceable NCAs might simultaneously introduce positive profitability incentives for entry and negative barriers to entry that cancel each other out overall. Our work here suggests that much of the effect may instead be coming from the knowledge diffusion channel, which implies an important role for labor mobility in innovation.

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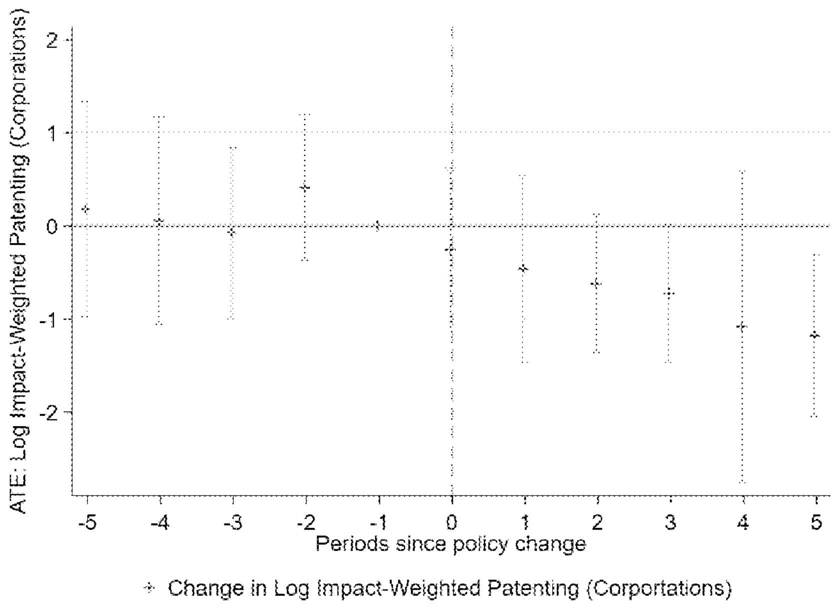
A Additional Results

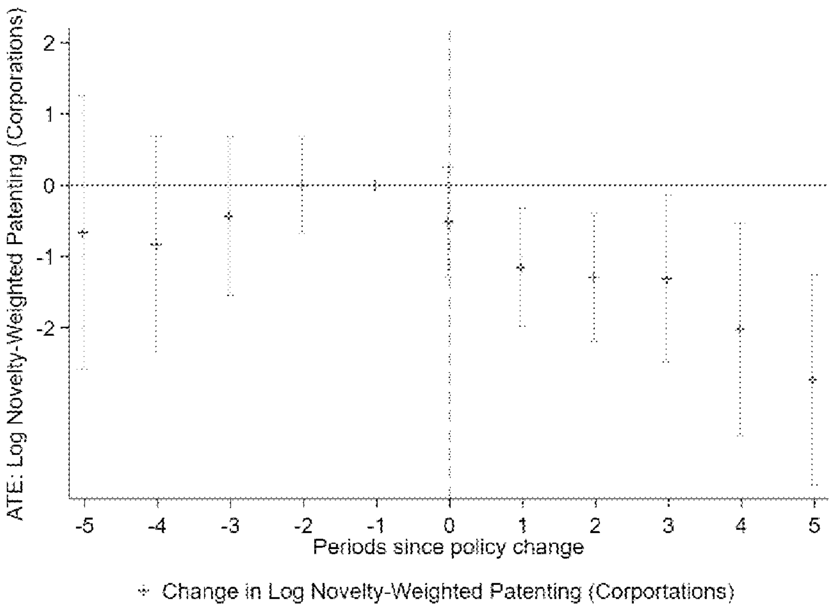
A.1 Impact and Novelty-Weighted Patent Outcomes

Figure 23: LP-DiD Coefficient Estimates: Log Impact-Weighted Patent Count



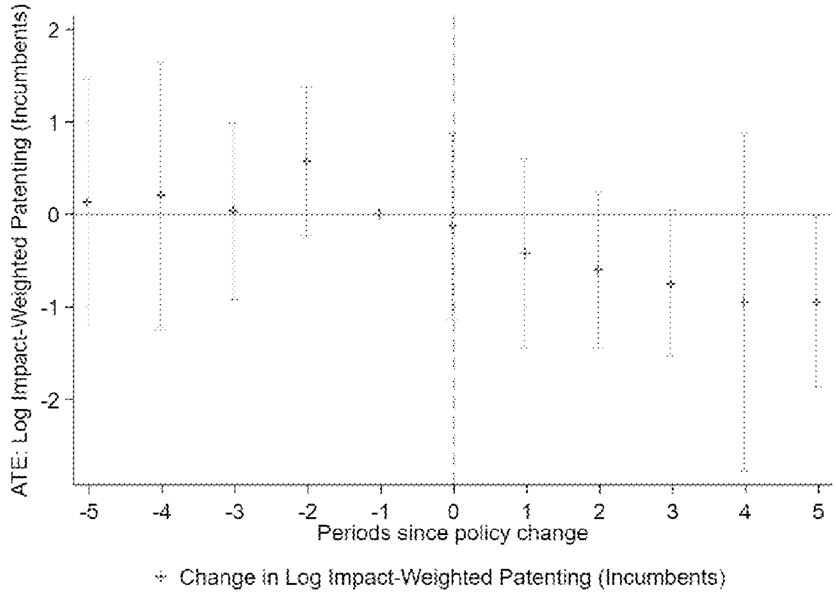
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting weighted by forward citations in year h relative to the time of the policy change ($h = 0$). Forward citations measure how many subsequent patents cite the patent in question and therefore are thought to approximate the extent to which a given patent has led to follow-on inventions. However, we de-prioritize them in this analysis because of the potential for NCAs to affect not only patenting but also citation networks. Forward citations are windsorized at the 1st and 99th percentiles. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 24: LP-DiD Coefficient Estimates: Log Novelty-Weighted Patent Count



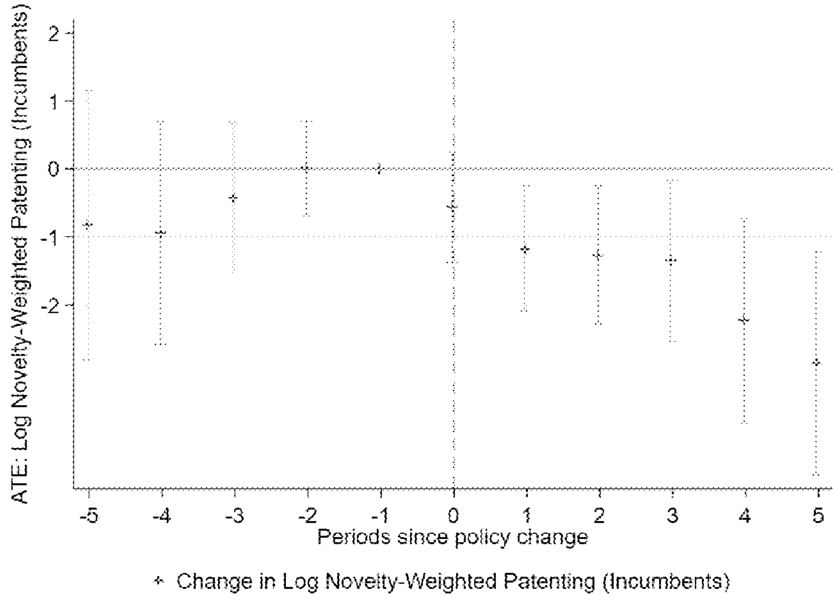
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting weighted by inverse backward citations in year h relative to the time of the policy change ($h = 0$). Backward citations measure how many previous patents were cited by the patent in question, with the intuition that having fewer backward citations indicates a more original invention. Inverse backward citations are defined to be equal to $1/(\text{backward cites} + 1)$. Backward citations are windsorized at the 1st and 99th percentiles. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 25: LP-DiD Coefficient Estimates: Log Impact-Weighted Patent Count - Incumbents Only



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by incumbents weighted by forward citations in year h relative to the time of the policy change ($h = 0$). Incumbents are defined as corporations with previous observed patenting. Forward citations measure how many subsequent patents cite the patent in question and therefore are thought to approximate the extent to which a given patent has led to follow-on inventions. However, we de-prioritize them in this analysis because of the potential for NCAs to affect not only patenting but also citation networks. Forward citations are windsorized at the 1st and 99th percentiles. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 26: LP-DiD Coefficient Estimates: Log Novelty-Weighted Patent Count - Incumbents Only

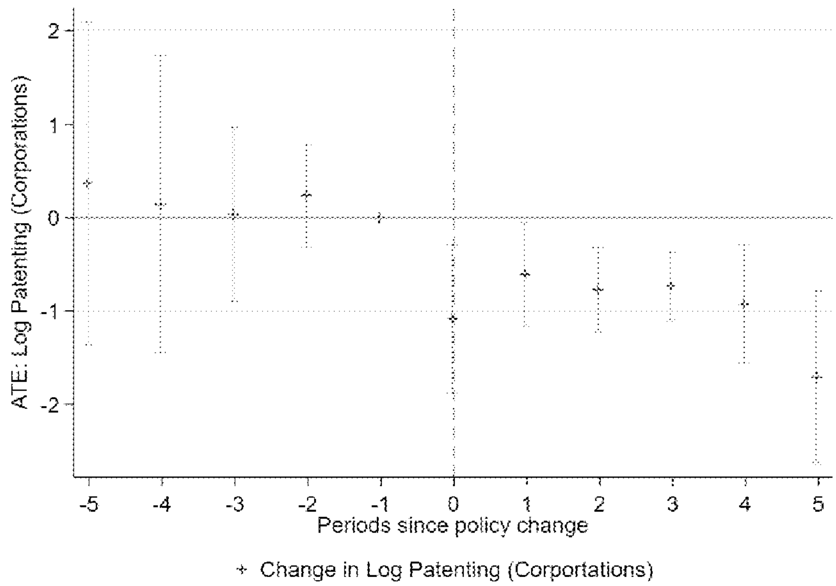


Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by incumbents weighted by inverse backward citations in year h relative to the time of the policy change ($h = 0$). Incumbents are defined as corporations with previous observed patenting. Backward citations measure how many previous patents were cited by the patent in question, with the intuition that having fewer backward citations indicates a more original invention. Inverse backward citations are defined to be equal to 1/(backward cites + 1). Backward citations are windsorized at the 1st and 99th percentiles. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

B Robustness Checks

B.1 Results with Balanced Panel

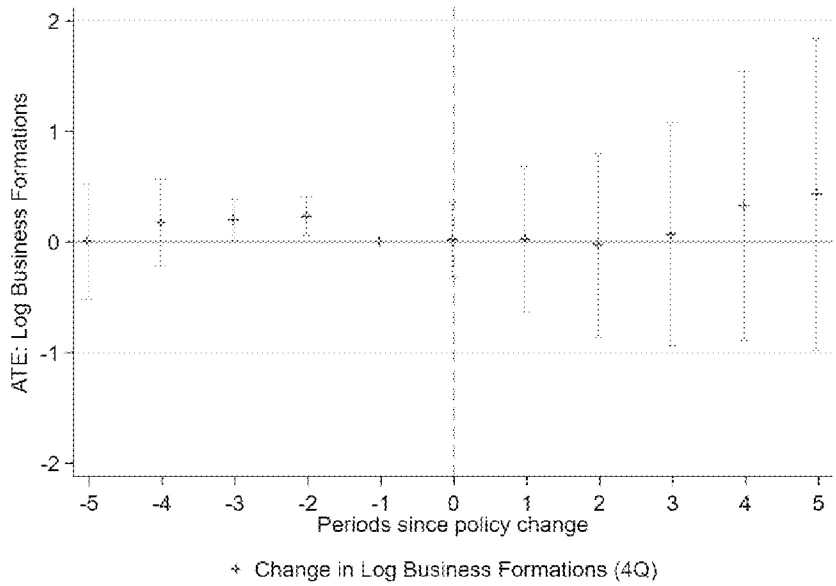
Figure 27: LP-DiD Coefficient Estimates: Balanced Panel



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Limited to a balanced panel where we can observe a full clean 5 years of outcomes on either side of t. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

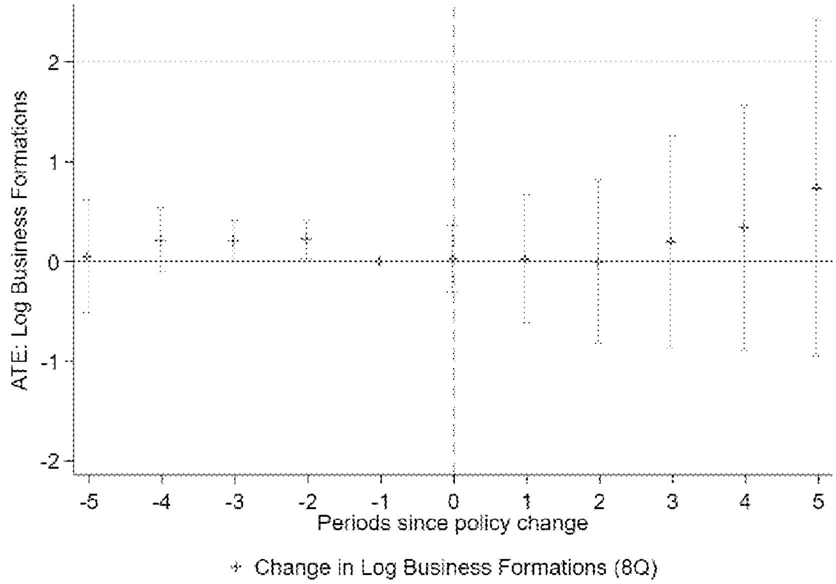
B.2 Entry Robustness Checks

Figure 28: LP-DiD Coefficient Estimates: Log Entry (Four-Quarter Business Formations)



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log state-level count of business formations within four quarters of the year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: Census BFS; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the business formations data are available in Section 2.3. Details on the index are available in Section 2.1 and Appendix Section D.

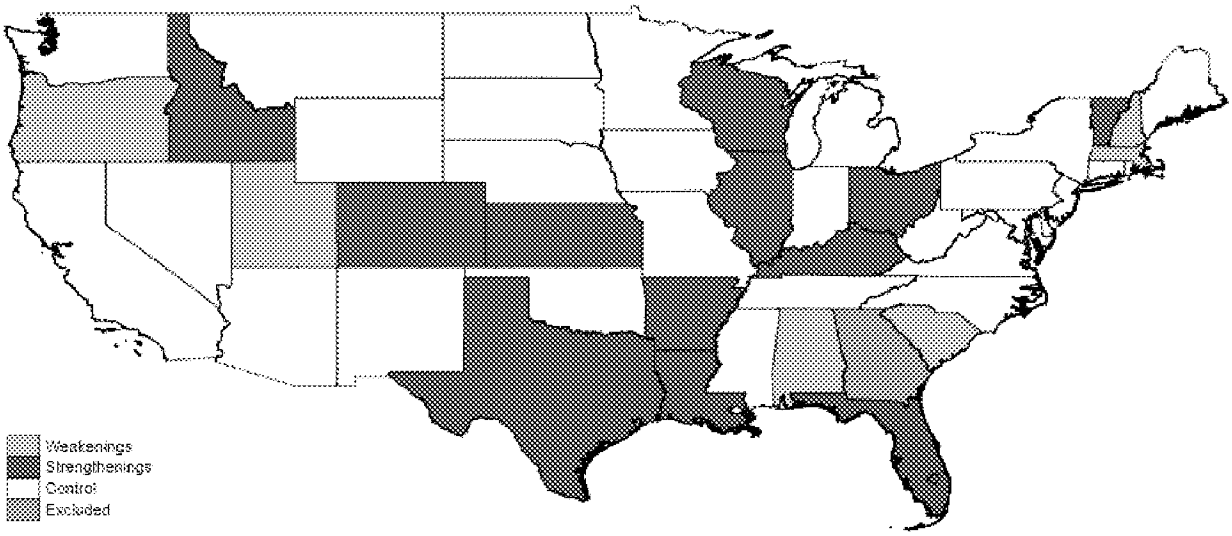
Figure 29: LP-DiD Coefficient Estimates: Log Entry (Eight-Quarter Business Formations)



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log state-level count of business formations within eight quarters of the year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: Census BFS; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the business formations data are available in Section 2.3. Details on the index are available in Section 2.1 and Appendix Section D.

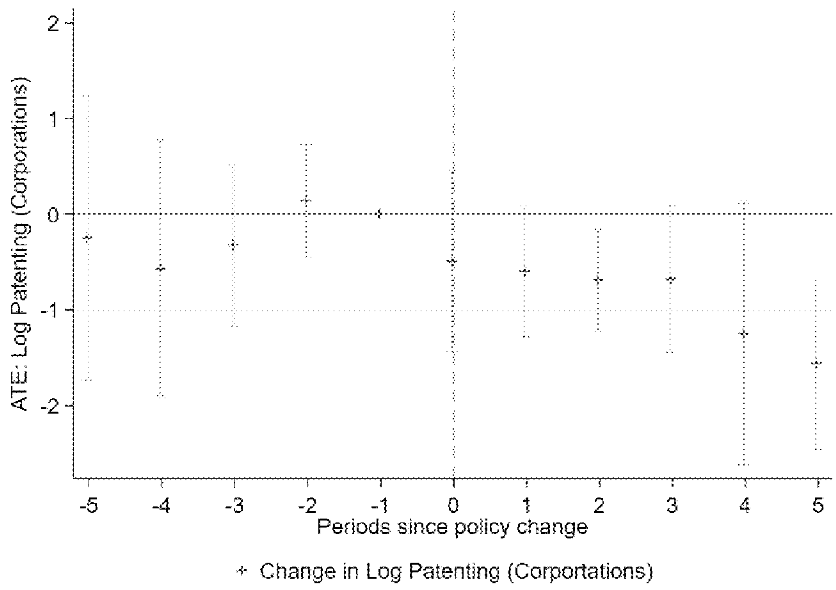
B.3 Alternative Sample Definitions

Figure 30: Map of Baseline Sample



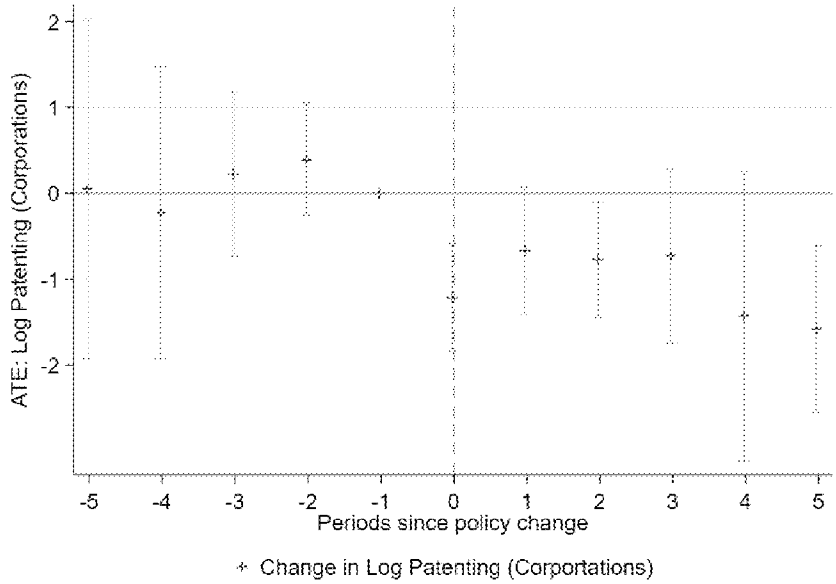
Map of state assignments to treatment and control groups. Note that states listed as treated may also be controls during their not-yet treated period or excluded in subsequent periods (e.g., if another treatment occurs). Data source: Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 31: LP-DiD Coefficient Estimates: Log Patent Count - Excluding California



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Excludes California from the analysis. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

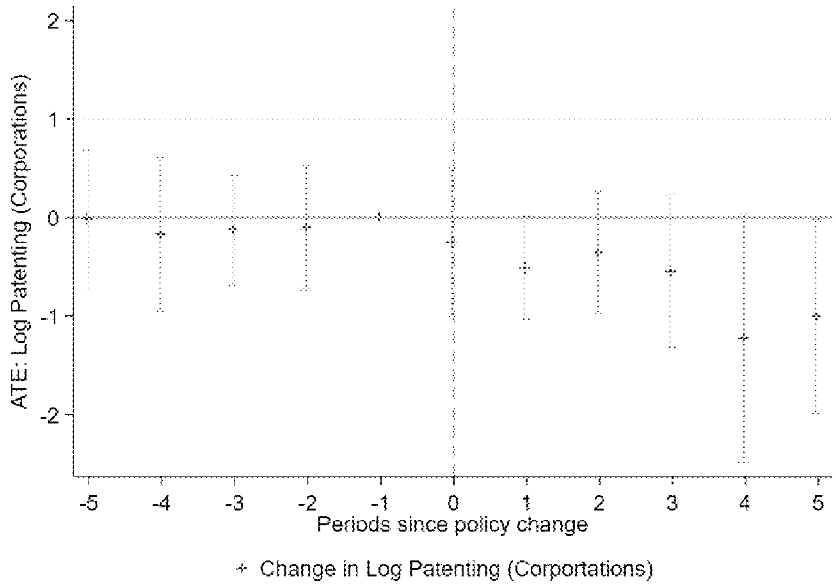
Figure 32: LP-DiD Coefficient Estimates: Log Patent Count - Strengthenings Only



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Excludes treatments that are weakenings (i.e., decreases in enforceability) from the analysis. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

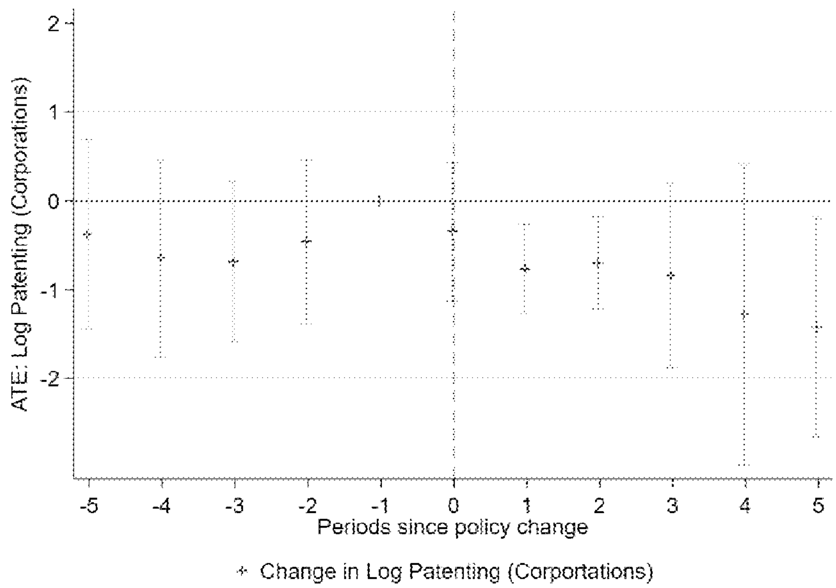
B.4 Alternate Patent Location Definition

Figure 33: LP-DiD Coefficient Estimates: Log Patent Count - Inventor Location



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Uses the location of the first-listed inventor rather than the location of the assignee as the location of the patent. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

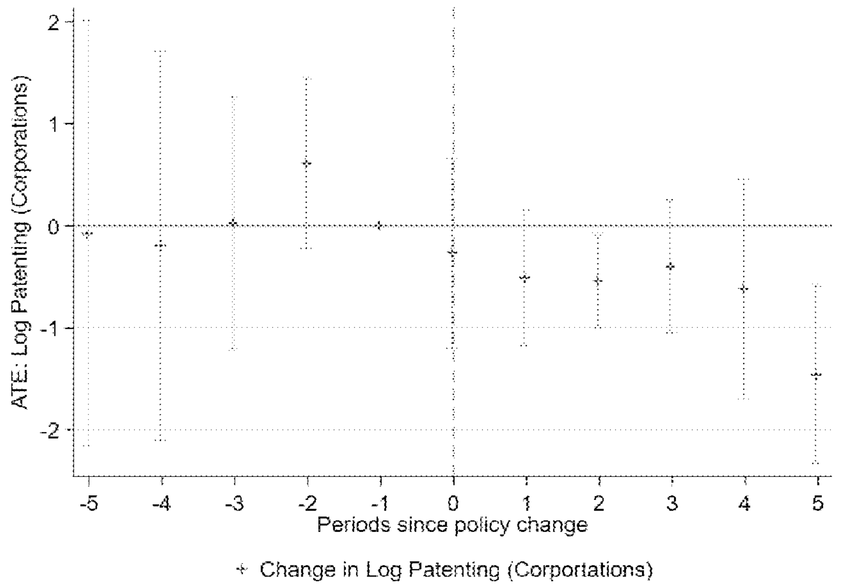
Figure 34: LP-DiD Coefficient Estimates: Log Patent Count - Shared Location



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Uses the shared location of the first-listed inventor and assignee as the location of the patent. Excludes patents with different author and assignee locations. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

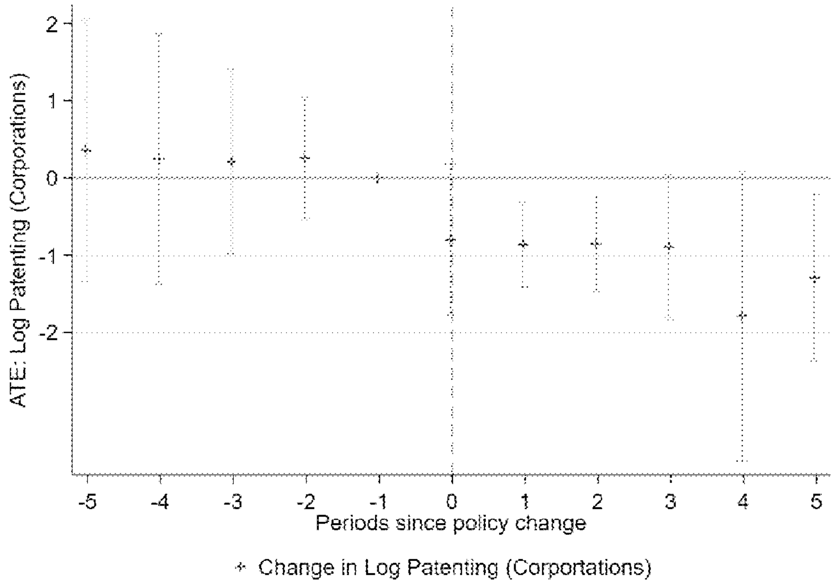
B.5 Example Results with Alternate Weighting

Figure 35: LP-DiD Coefficient Estimates: Log Patent Count - Unweighted



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are not weighted. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 36: LP-DiD Coefficient Estimates: Log Patent Count - Weighted by Share of Patents



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of patent applications filed in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

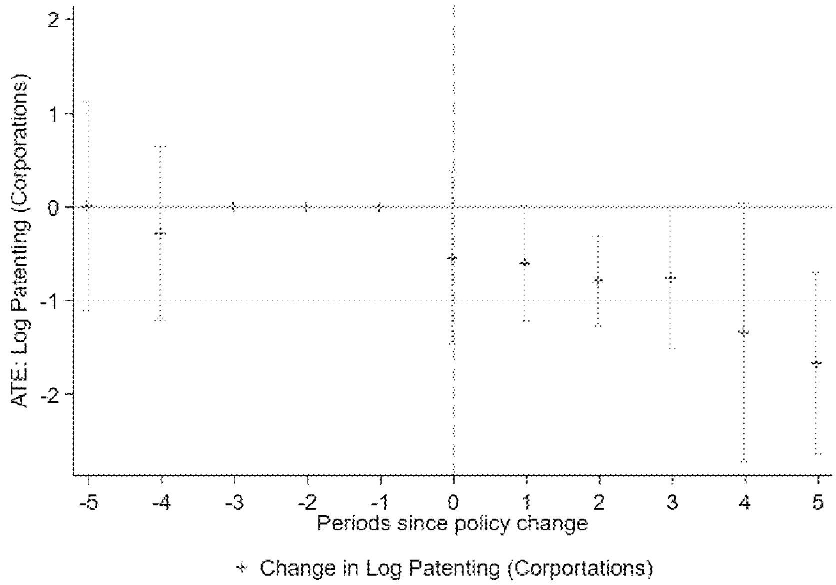
B.6 Example Results with Outcome Lags in LP-DiD

As discussed in Dube et al. (WP), we can also include outcome lags on the right-hand side of the estimating equation to control for pre-treatment values of time-varying covariates:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = \beta_h \cdot \mathbb{I}_{it} \cdot \Delta X_{it} \quad & \text{treatment (change in index)} \\ + \sum_{k=1}^{K} \gamma_k^h \cdot y_{i,t-k} \quad & \text{outcome lags} \\ + \delta_{t+h} - \delta_{t-1} \quad & \text{time effects} \\ + \epsilon_{it+h} \quad & \text{for } h = -H, ..., H, \end{aligned} \tag{5}$$

where we include K lags of the outcome variable, which helps control for any concerns about patenting predicting changes in enforceability. Doing so gives very similar results for our patent outcomes (see below).

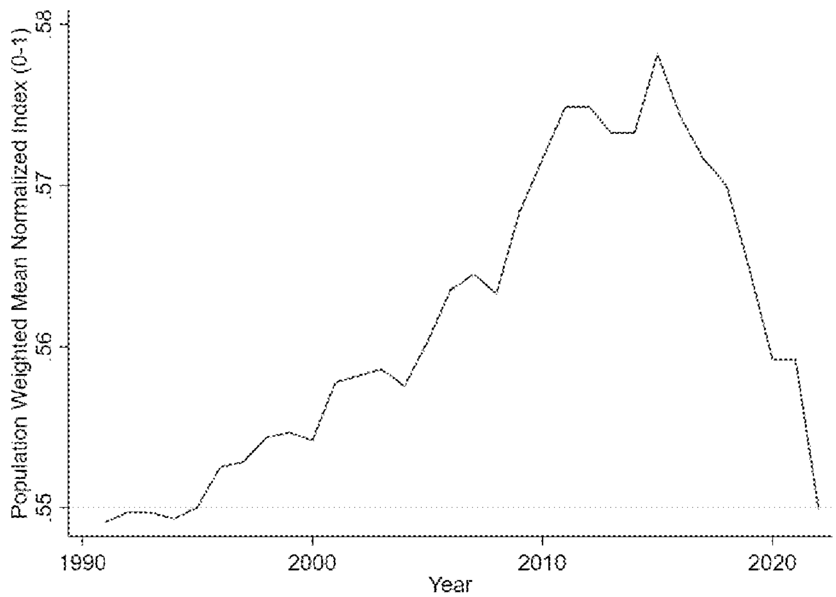
Figure 37: LP-DiD Coefficient Estimates: Log Patent Count - Conditioning on Lagged Outcomes



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 5. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D.

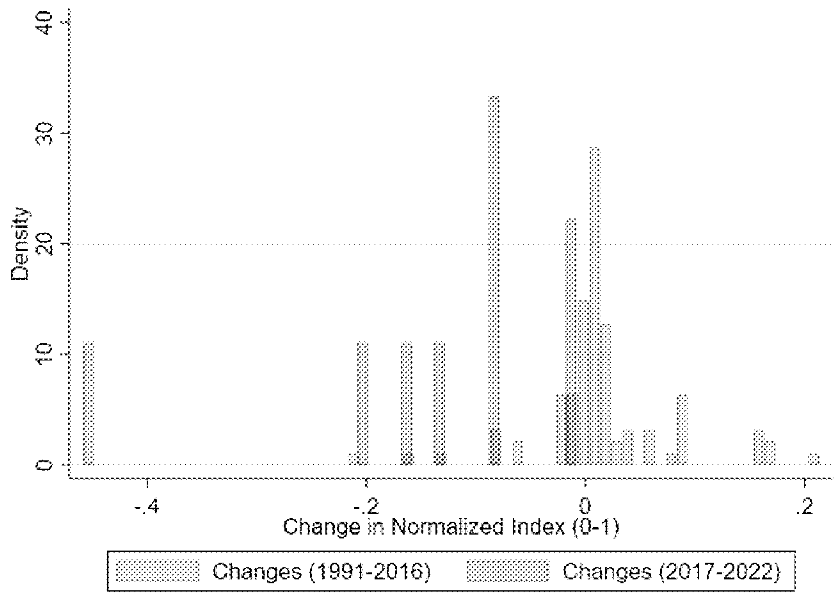
C Supplementary Figures

Figure 38: Trends in NCA Enforceability



Population-weighted average state-level NCA enforceability by year. Data sources: Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 39: Distribution of Non-Zero Changes in NCA Enforceability



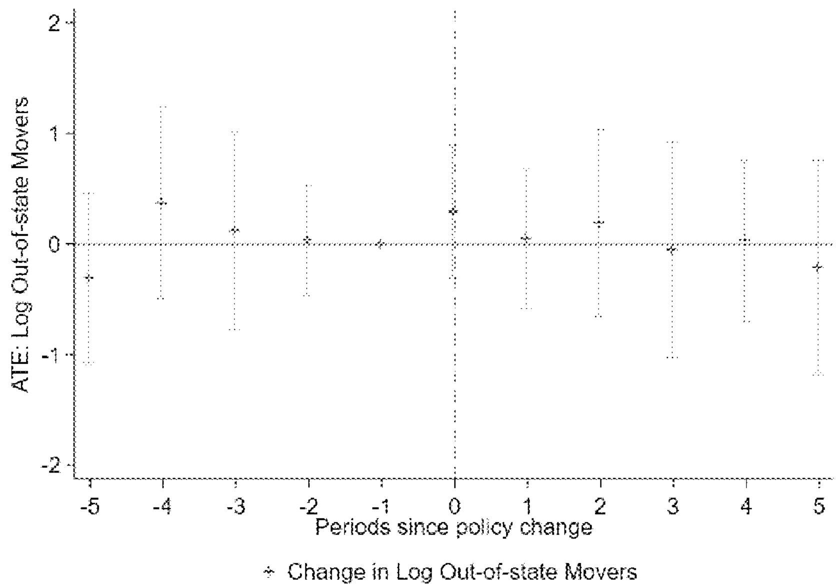
State-level changes in NCA enforceability, as measured by the normalized index, across years. Data sources: Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the index are available in Section 2.1 and Appendix Section D.

Figure 40: Example Moving Inventor

Year	Inventor ID	Assignee #1	Assignee #2	Assignee #3	Assignee #4
1991	fl:ja_ln:hughett-1	X			
1992	fl:ja_ln:hughett-1	X			
1993	fl:ja_ln:hughett-1	X {Exit}			
1999	fl:ja_ln:hughett-1		X [illegible]		
2000	fl:ja_ln:hughett-1		X		
2003	fl:ja_ln:hughett-1		X {Exit}	X [illegible]/Exit}	
2005	fl:ja_ln:hughett-1				X [illegible]
2008	fl:ja_ln:hughett-1				
2009	fl:ja_ln:hughett-1				X
2010	fl:ja_ln:hughett-1				X
2011	fl:ja_ln:hughett-1				X
2012	fl:ja_ln:hughett-1				X
2013	fl:ja_ln:hughett-1				X
2014	fl:ja_ln:hughett-1				X
2016	fl:ja_ln:hughett-1				X

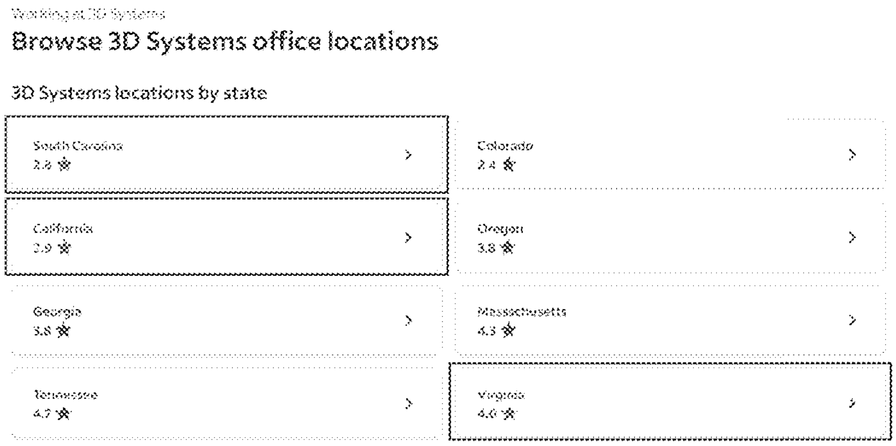
Example of an inventor switching between patenting at different firms over time. Data source: PatentsView. Details on the patent data are available in Section 2.2.

Figure 41: First Stage Results of Spillovers Regression



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of out-of-state movers in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 3. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section D. The clean organization lookup is discussed in additional detail in Footnote 33.

Figure 42: Example Assignee Locations



assignee_ste	organization	new_id	patent_count
CA	3D System, Inc.	383	11
CA	3D Systems, Inc.	383	540
SC	3D Systems, Inc.	383	488
SC	3D Systems, Incorporated	383	7
VA	3D Systems, Incorporated	383	4

Example of a firm with multiple office locations also assigning patents to multiple locations in the patent data both within the same raw organization name(s) and after receiving a clean organization ID from the lookup created by this paper. Data sources: Indeed.com (link); PatentsView; clean organization lookup created by this paper. Details on the patent data are available in Section 2.2. The clean organization lookup is discussed in additional detail in Footnote 33.

D Bishara (2011) Index Questions

1. Is there a state statute of general application that governs the enforceability of covenants not to compete? (Weight = 10)

    - Score = 0: statute that disfavors enforcement
    - Score = 5: no statute or statute that is neutral in its approach to enforcement
    - Score = 10: statute that favors strong enforcement

2. What is an employer's protectable interest and how is that defined? (Weight = 10)

    - Score = 0: strictly defined limited protectable interest
    - Score = 5: balanced approach to defining a protectable interest
    - Score = 10: broadly defined protectable interest

3. What must plaintiff be able to show to prove the existence of an enforceable covenant not to compete? (Weight = 5)

    - Score = 0: strong burden of proof on the employer
    - Score = 5: balanced approach to the burden placed on the employer
    - Score = 10: weak burden of proof on the plaintiff employer

4. Does the signing of a covenant not to compete at the inception of the employment relationship provide sufficient consideration to support the covenant? (Weight = 10)

    - Score = 0: start of employment is never sufficient
    - Score = 5: start of employment is sometimes sufficient
    - Score = 10: start of employment is always sufficient

5. Will a change in the terms and conditions of employment provide sufficient consideration to support a covenant not to compete entered into after the employment relationship has begun? Will continued employment provide sufficient consideration after the employment relationship has begun? (Weight = 5)

    - Score = 0: neither continued employment nor a beneficial change in terms would be sufficient consideration
    - Score = 5: only a beneficial change in terms was sufficient to support a covenant not to compete
    - Score = 10: continued employment is always sufficient

6. If the restrictions in the covenant not to compete are unenforceable because they are overbroad, are the courts permitted to modify the covenant to make the restrictions more narrow and to make the covenant enforceable? If so, under what circumstances will the courts allow reduction and in what form? (Weight = 10)

    - Score = 0: strictly defined limited protectable interest
    - Score = 5: balanced approach to defining a protectable interest
    - Score = 10: broadly defined protectable interest

7. If the employer terminates the employment relationship, is the covenant enforceable? (Weight = 10)

- Score = 0: not enforceable if the employer terminates
- Score = 5: enforceable only in some circumstances
- Score = 10: always enforceable if the employer terminates

AMA backs effort to ban many physician noncompete provisions

JUN 13, 2023

Andis Robeznieks
Senior News Writer

To protect physicians and boost patient access, the House of Delegates took action to ban noncompete contracts for physicians in clinical practice who are employed by for-profit or nonprofit hospitals, hospital systems or staffing company employers.

Unfair noncompete clauses are extensive in health care, affecting between 37% and 45% of physicians. They can be especially problematic for residents, fellows and young physicians by limiting their opportunities for career advancement and restricting their ability to provide care in economically or socially marginalized communities.

Concerns about noncompetes became especially acute when, during the COVID-19 pandemic, physicians advocating for health care worker safety were threatened with termination. Because of noncompete clauses, this could have meant months or years of unemployment or geographic relocation.

Removing noncompete clauses is also seen as a way to improve patient access, enhance the availability of specialist coverage in a community and reduce health inequities by allowing physicians to work for multiple hospitals.

The AMA *Code of Medical Ethics* says: “Covenants not-to-compete restrict competition, can disrupt continuity of care, and may limit access to care.”

To protect physicians and help improve patient access, delegates adopted policies to:

- Support policies, regulations and legislation that prohibits covenants not-to-compete for all physicians in clinical practice who hold employment contracts with for-profit or non-profit hospital, hospital system, or staffing company employers.

- Oppose the use of restrictive covenants not-to-compete as a contingency of employment for any physician-in-training, regardless of the Accreditation Council for Graduate Medical Education accreditation status of the residency or fellowship training program.

Delegates also directed the AMA to "study and report back on current physician employment contract terms and trends with recommendations to address balancing legitimate business interests of physician employers while also protecting physician employment mobility and advancement, competition and patient access to care."

The study, the policy says, should include the appropriate regulation or restriction of:

- Covenants not to compete in physician contracts with independent physician groups that include time, scope, and geographic restrictions.
- De facto noncompete restrictions that allow employers to recoup recruiting incentives upon contract termination.

"Allowing physicians to work for multiple hospitals can enhance the availability of specialist coverage in a community, improving patient access to care and reducing health care disparities," said AMA Trustee Ilse Levin, DO, MPH & TM.

"We must keep in mind," Dr. Levin added, "that owners of private practices often invest heavily when hiring and training physicians, and those owners may believe that they need to use reasonable noncompete agreements to compete with large hospital systems or other dominant institutional employers. Preserving and fostering independent physicians and other physician-led organizations is crucial to a healthy nation."

Read about the other highlights from the 2023 AMA Annual Meeting.

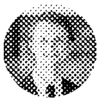
FEDERAL RESERVE BANK
OF MINNEAPOLIS

New data on non-compete contracts and what they mean for workers

Federal Reserve survey data open up new avenues for research

June 21, 2023

AUTHORS



Tyler Boesch

Data Scientist, Community Development and Engagement

Jacob Lockwood

Board of Governors of the Federal Reserve System

Ryan Nunn

Assistant Vice President, Community Development and Engagement

Mike Zabek

Board of Governors of the Federal Reserve System

Article Highlights

- In new Fed data, about one in nine workers reports having a non-compete
- Workers on West Coast less likely to have non-competes, while those in South Atlantic states more likely
- Data allow researchers to see how non-competes relate to financial well-being, other outcomes

Non-compete contracts, which limit the job options workers have when they leave their current employers, have been much in the news over the last few years. Policymakers at the federal and state levels have taken action to restrict the use of non-competes or their enforceability in court. However, our knowledge of who has these contracts has been limited, with relatively little survey evidence available. Fortunately, the Survey of Household Economics and Decisionmaking (SHED)—a key Federal Reserve survey conducted annually since 2013—newly includes a question on non-competes.[1] We analyzed the latest release of SHED data, from 2022, and found that about one in nine adult workers currently has a non-compete, but this rate varies considerably by geographic region and worker age.

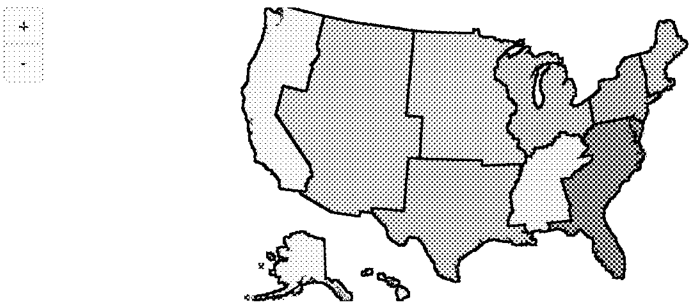
The SHED is not the first survey to ask about non-competes.[2] However, the SHED data are valuable because they are broadly representative of the U.S. workforce and collected annually. The new data allow analysts to explore many topics, whether linked to a famous SHED question about financial resilience, questions about job search, or a host of other worker and household decisions. We explore some of these connections here, but note that others can also make use of SHED data to better understand non-competes and their effects on the labor market.

Who has non-competes

Consistent with original survey work by researchers Evan Starr, J.J. Prescott, and Norman Bishara (SPB) and a 2021 Federal Reserve Bank of Minneapolis analysis of U.S. Bureau of Labor Statistics (BLS) data, we find that non-competes can be found throughout the labor force, including for workers with less education and lower wages. The SHED data show that overall, 11.4 percent of adult workers currently have non-competes. However, the SHED data extend our understanding in key ways. For example, we find that workers on the West Coast are substantially less likely to have non-competes than workers in the South Atlantic, at rates of 9.0 percent and 13.3 percent, respectively. See Figure 1, which shows estimates for census regions rather than individual states.

1

Non-compete rates are lowest in the Pacific region and highest in the South Atlantic region



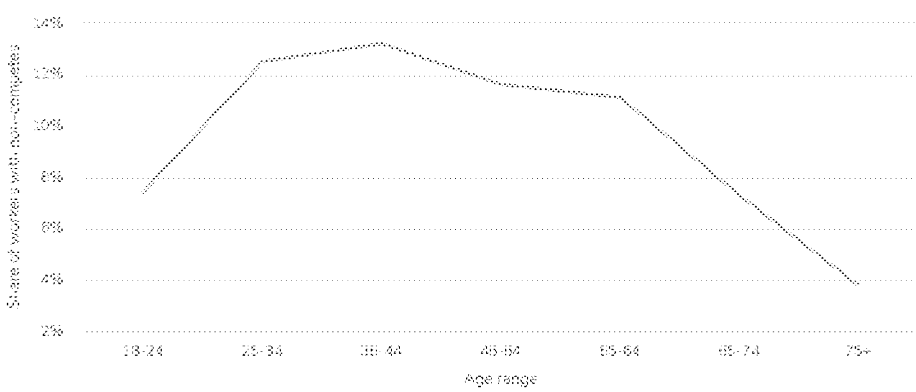
Note: Sample includes individuals ages 18 and older who work for someone else. We exclude those who answered "Don't know" to a question about whether they have a non-compete
Source: Authors' calculations using data from the Federal Reserve Board's Survey of Household Economics and Decisionmaking, 2022

Relatedly, we also find that workers are less likely to have non-competes in the three states that do not enforce them (California, North Dakota, and Oklahoma), where the overall rate is 7.0 percent, than in the other 47 states, where the overall rate is 12.0 percent. These patterns are somewhat different from earlier survey evidence showing similar rates of non-competes in states that do and do not enforce them (SPB 2021, page 68). Still, 7.0 percent is a significant share. The pattern suggests that, while some employers may avoid using non-competes in states where they are unenforceable, some employers use them regardless—perhaps because of limited understanding of how enforceability varies across states (Prescott and Starr 2021).

We also find that non-competes are much more common among mid-career workers (35- to 44-year-olds) than among younger and older workers. As shown in Figure 2, 13.2 percent of 35- to 44-year-olds report having non-competes, while only 7.3 percent of 65- to 74-year-olds have them. By contrast, the BLS data used in the 2021 Minneapolis Fed analysis included only workers aged 32–38 at the time, and the SPB survey indicated proportionally less variation across age groups. Both the BLS and SHED data indicate lower rates of overall non-compete holding than in the SPB survey.[3]

2

Non-competes are most common for mid-career workers



Note: Sample includes individuals ages 18 and older who work for someone else. We exclude those who answered "Don't know" to a question about whether they have a non-compete
Source: Authors' calculations using data from the Federal Reserve Board's Survey of Household Economics and Decisionmaking, 2022

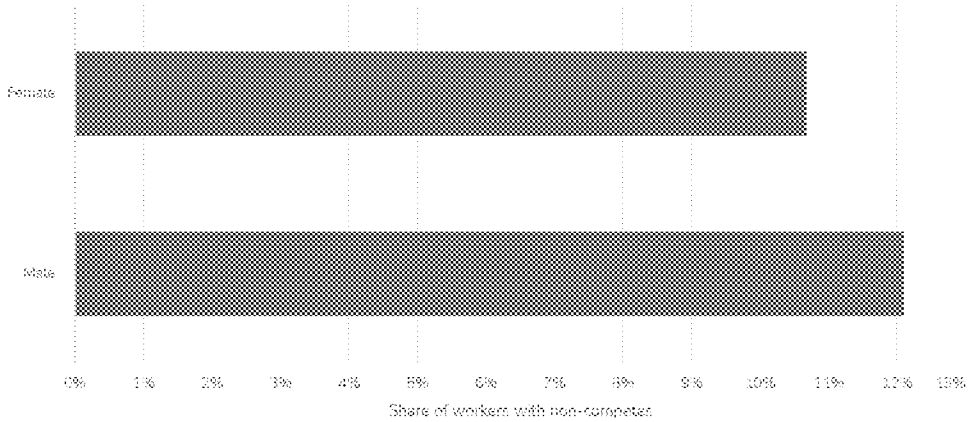
The SHED data allow us to break out the incidence of non-competes by gender, race/ethnicity, educational attainment, industry, and income. We find that men are somewhat more likely to report having non-competes, as are workers with four-year college degrees. Industries vary widely in their use of non-competes: workers in professional services (19.2 percent) and finance (18.2 percent) are more likely to have non-competes than workers in construction (7.1 percent), education (7.8 percent), or public administration (4.7

percent). In line with previous analysis, we also find that workers with higher family incomes are more likely to have non-competes than those with lower incomes. These findings are shown in Figure 3, which enables users to select from a drop-down menu to explore various data cuts.4

3

Non-compete rates vary by worker characteristics

Gender



Note: Sample includes individuals ages 18 and older who work for someone else. We exclude those who answered "Don't know" to a question about whether they have a non-compete.
Source: Authors' calculations using data from the Federal Reserve Board's Survey of Household Economics and Decisionmaking, 2022

Implications for workers

New data on non-competes in the SHED are also valuable because of other aspects of the survey that can help researchers understand how non-competes affect workers. In addition to questions on non-competes, the SHED contains questions about personal finances, income, employment, higher education, migration, and housing. The SHED also has a panel dimension that can allow researchers to see how outcomes change over time among workers with non-competes.

Relative to previous surveys that asked about non-competes, the SHED contains much more detail about personal finances among people earning lower incomes. For example, the SHED asks a) whether people have an emergency fund of savings built up in case of a job loss and b) if people would pay an unexpected $400 expense with cash or its equivalent. These questions about people's liquid savings are relevant for understanding the possible effects of non-compete contracts that can restrict workers' ability to accept new jobs. This connects with a burgeoning research literature that has found negative effects of non-competes (particularly non-competes that are stringently enforced) on wages of lower-paid workers (Balasubramanian et al. 2022, Lipsitz and Starr 2022) and increases in likelihood of career detours (Marx 2011; Marx, Singh, and Fleming 2015). And it is particularly relevant for those workers whose non-competes are enforceable even when they are fired without cause, as is the case in many states.

The SHED's question about emergency savings is especially relevant: "Have you set aside emergency or rainy day funds that would cover your expenses for 3 months in case of sickness, job loss, economic downturn, or other emergencies?" A rainy-day fund is particularly important for someone with a non-compete because the non-compete makes it more difficult for them to find a new job.

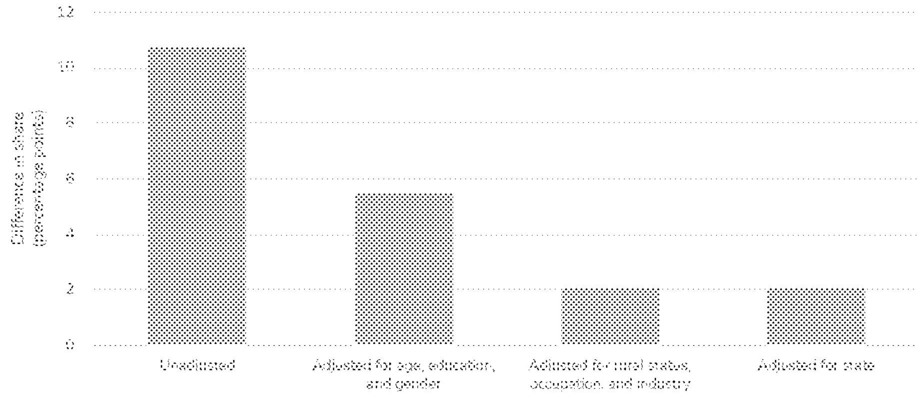
Looking strictly at the association between non-competes and having an emergency fund, we find that workers with non-competes are 10.8 percent more likely to have an emergency fund. However, the association is complicated by the fact that, as shown in Figure 3, non-competes are more common among mid-career, highly educated workers who tend to have more savings. We therefore present unadjusted estimates as well as estimates adjusted for differences in worker characteristics.

When we adjust for those differences in Figure 4, we find much smaller and statistically insignificant associations between non-competes and savings. While workers with non-competes are more likely to have emergency funds than are workers in general, they appear to have emergency funds at similar rates to workers with similar backgrounds and jobs.

Another important dimension of personal finances is how easily someone could handle a relatively modest expense. The SHED's "$400 question" asks how respondents would cover an unanticipated $400 expense; we distinguish those who would pay the expense using cash (or a credit card they would pay off in full at the next statement) from those who would pay it in some other way, including with a loan or sale of property.

4

Workers with non-competes are more likely to have emergency savings, but the gap is much smaller among comparable workers

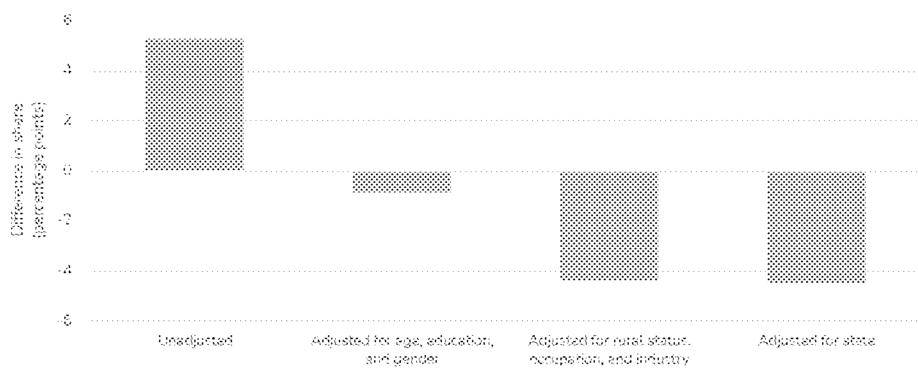


Note: Sample includes individuals ages 18 and older who work for someone else. We exclude those who answered "Don't know" to a question about whether they have a non-compete. Moving across the columns from left to right, each new set of adjustments includes the previous columns' adjustments.
Source: Authors' calculations using data from the Federal Reserve Board's Survey of Household Economics and Decisionmaking, 2022

Overall, people with non-competes are more likely to handle a $400 expense with cash or its equivalent, despite a substantial share still reporting that they would use something else. However, the gap closes and even reverses when we adjust for differences in worker and job characteristics. After adjusting for differences in age, education, and gender, that gap is eliminated. After further adjustments for rural location, occupation, industry, and state—in addition to age, education, and gender—those with non-competes are actually 4.4 percentage points less likely to say they would use cash or its equivalent to meet the emergency expense.

5

Workers with non-competes are more likely to use cash to pay an unanticipated $400 expense, but the gap reverses among comparable workers



Note: Sample includes individuals ages 18 and older who work for someone else. We exclude those who answered "Don't know" to a question about whether they have a non-compete. Moving across the columns from left to right, each new set of adjustments includes the previous columns' adjustments.
Source: Authors' calculations using data from the Federal Reserve Board's Survey of Household Economics and Decisionmaking, 2022

We also conduct the same exercise with several questions about job search and negotiations to show some of the possibilities the survey opens for researchers interested in career outcomes. We find that workers with non-competes are 10 percentage points more likely to ask for a raise or promotion and 7 percentage points more likely to apply for new jobs. These differences persist, in large part, after adjusting for the worker characteristics described above.[5] The results are somewhat in contrast to findings that non-competes (and/or their stringent enforcement) tend to reduce workers' job-search activity (Prescott and Starr 2021), wages (Lipsitz and Starr 2019), and mobility (Balasubramanian et al. 2022). As before, however, we do not have reason to believe these estimates reflect a causal effect of non-competes, but they suggest avenues for deeper investigation.

Informing the policy discussion

The recent explosion of public discussion about non-competes has made clear the need for better and more systematic data collection. The BLS and now the Federal Reserve have invested in this effort through the introduction of questions in their long-running survey initiatives. These investments are all the more timely because of the numerous state and federal policy actions now underway—actions whose effects will be difficult to measure without ongoing data collection.

We encourage other researchers and policy analysts to explore the SHED data, which offer new avenues for investigating non-compete contracts and their implications for workers. Particular strengths of the SHED include its focuses on personal finances, job search behavior, and a number of other topics relevant for people earning low incomes. Non-competes matter for reasons that go beyond what the SHED and other worker surveys can speak to, but the surveys do provide an important factual basis for the decisions policymakers are grappling with.

We thank Matt Marx and Evan Starr for insightful feedback on an earlier draft. Any errors remain the authors' own.

Endnotes

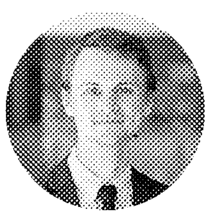
1 The 2022 SHED yielded a final sample of 11,667 respondents. See Board of Governors of the Federal Reserve System (2023) for more details.

2 Notably, researchers Evan Starr, J.J. Prescott, and Norman Bishara conducted their own groundbreaking survey in 2014 on non-compete contracts. Later, in its long-running study of Americans born in the early 1980s, the U.S. Bureau of Labor Statistics followed up with questions about non-competes, which researchers from the Federal Reserve Bank of Minneapolis analyzed in a 2021 article.

3 Our overall estimate, from the SHED, is 11.4 percent, by contrast to 18 percent overall in the SPB survey. Differences between them may be due in part to differences in handling of "Don't know" responses; see SPB (2021) for details of their imputation procedure. In the 2021 Minneapolis Fed analysis and here, these responses are omitted. (However, in the appendix of the 2022 SHED report, "Don't know" responses are not omitted, leading to a slightly lower estimate.) In the sample used in this article, 9.5 percent of respondents were not sure whether they currently have a non-compete. Another difference between the SHED and the SPB survey is the time they were conducted; in the years between the surveys, considerable policy action and public attention have focused on non-compete contracts.

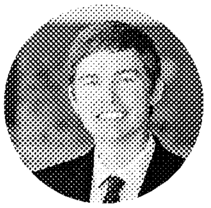
4 Because the sample of American Indian or Alaska Native respondents is small and the estimate is correspondingly imprecise, Figure 3 does not show an estimate for the group. The share of American Indian or Alaska Native workers with a non-compete is not statistically significantly different than the overall share.

5 Relatedly, Rothstein and Starr (2022) find a positive association between having a non-compete and being likely to bargain. However, their data included task-level controls, the inclusion of which nearly eliminated the association. In other words, when comparing workers who are assigned similar tasks, the difference disappeared.



Tyler Boesch
Data Scientist, Community Development and Engagement

Tyler Boesch analyzes data, develops visualizations, and creates statistical models to help the Community Development and Engagement team understand issues affecting low- and moderate-income communities. Before joining the Bank, he was a graduate research assistant with the University of Minnesota Center for Urban and Regional Affairs.



REQUEST AS A SPEAKER

Ryan Nunn

Assistant Vice President, Community Development and Engagement

Ryan Nunn is an assistant vice president in the Minneapolis Fed's Community Development and Engagement Department. Leading the Bank's applied research function, Ryan works to improve outcomes for low- and moderate-income communities with the help of better evidence and analysis.

Motivating Inventors: Non-Competes, Innovation Value and Efficacy

Zhaozhao He

2021, 2023

The F.T.C. considered the 2023 and 2021 versions of Motivating Inventors: Non-Competes, Innovation Value and Efficacy by Zhaozhao He as part of the rulemaking process. Both versions are attached.

Motivating Inventors:
Non-competes, Innovation Value and Efficiency

Zhaozhao He†

ABSTRACT

Non-compete agreements help protect business investments by restricting worker mobility, thereby increasing firm incentives to invest. Yet, they could damage the efficacy of innovation investments that crucially rest on employee incentives. Exploiting staggered reforms of state non-compete enforcement, I find that patents filed after an increased enforceability are less valuable and exploratory despite no less R&D spending. Inventors whose job prospects are more jeopardized, in a weaker bargaining position, and having greater incentives to switch firms produce patents experiencing greater value losses. These results imply that labor allocative inefficiency owing to mobility restrictions could compromise value creation from real investments.

Keywords: Allocative Inefficiency, Innovation Motivation, Inventor Mobility, Non-competes, Patent Value

JEL Classifications: D61, G30, J24, J31, J41, J61, K31, O34

This version: May 15, 2021
† Peter T. Paul College of Business and Economics, University of New Hampshire. Zhaozhao He can be reached at phone: (603)-862-2233, email: zhaozhao.he@unh.edu, and mailing address: 10 Garrison Ave, Durham, NH 03824

1. INTRODUCTION

Regulatory concerns over anticompetitive business practices in the U.S. are now at the culmination.[1] Not only in product markets, anticompetitive behavior has also been prominent in labor markets, facilitating labor market "monopsony"—a key contributor to the stagnation of wage growth and economic dynamism in decades (Council of Economic Advisor 2016; Krueger 2017).[2] The primary vertical restraints that firms regularly use are non-compete agreements (non-competes)—clauses that restrict post-employment mobility by prohibiting employees from leaving to join or establish a competing venture. A 2014 national survey reports nearly a fifth of U.S. workers (about 30 million) having a non-compete (Treasury 2016; Starr et al. 2019). Yet, growing evidence has shown deleterious effects of these clauses, most notably, on labor market churn—a pivotal element to the nation's long-run growth and prosperity. Consequently, non-compete practices have become increasingly controversial: federal lawmakers are urged to reform the policies and reexamine the legality of these contracts under antitrust frameworks; and President-elect Joe Biden recently proposed a national partial ban on non-competes.[3]

Given these harms, why are non-competes lawful? The typical legal justification is that by limiting workers' ability to join competitors, non-competes can help protect business interests, thereby encouraging investments in innovation and worker training. Previous studies, however, have shown mixed findings on firm investments (Garmaise 2011; Samila and Sorenson 2011; Starr 2019; Jeffers 2019).[4] An equally important and unexplored question is how non-competes affect return on investments. This lack of evidence is surprising because in principle non-competes allow firms to extract greater monopoly rents by preventing

[1] In July 2020, for the first time, chief executive officers of Amazon, Apple, Facebook, Alphabet testified before the House Judiciary antitrust subcommittee to address inquiries about whether these firms are abusing their power to suppress competition. See, e.g., "Amazon, Apple, Facebook and Google grilled on Capitol Hill over their market power," *The Washington Post*, July 29, 2020

[2] See, e.g., https://www.justice.gov/opa/pr/justice-department-requires-six-high-tech-companies-stop-entering-anticompetitive-employee

[3] See, e.g., the Mobility and Opportunity for Vulnerable Employees Act (https://www.congress.gov/bill/114th-congress/senate-bill/1504/text), the 2018 Workforce Mobility Act (https://www.congress.gov/bill/115th-congress/senate-bill/2782/text), a 2019 petition to the Federal Trade Commission (https://www.bloomberg.com/news/articles/2019-03-20/labor-groups-petition-u-s-ftc-to-prohibit-non-compete-clauses), and Biden's proposal (https://www.faircompetitionlaw.com/2020/12/02/president-bidens-proposed-ban-of-most-noncompetes-protection-strategy-and-steps-to-take-now/).

[4] Analyzing non-compete policy reforms across U.S. states, Garmaise (2011) finds that stricter enforcement results in lower capital expenditures but does not affect R&D, while Jeffers (2019) finds the opposite for capital expenditures. Samila and Sorenson (2011) document that increased supply of venture capital leads to larger increases in innovation and entrepreneurship in weak-enforcing states. Starr (2019) shows that firms in states with stronger non-compete enforcement are more likely to provide worker training.

misappropriation, which predicts greater investment returns than otherwise would. Nevertheless, truth is not always so straightforward. This paper investigates whether non-competes foster efficient investments through the lens of value created by innovation.

Innovation is a long process of experimentation involving exploration of unknown and untested ideas with highly uncertain payoffs (Holmstrom 1989). Developing successful innovations requires a considerable amount of effort from well-motivated employees. Manso (2011) suggests that one essential ingredient in contracts to best motivate innovation is the reward for innovation success over the long run. With a non-compete clause, however, workers face fewer career opportunities and are less able to capitalize on their gained expertise. Non-competes create barriers to exit for skilled workers (Marx and Fleming 2012), facilitating wage suppression and deteriorating employer-employee match quality (Garmaise 2011; Balasubramanian et al. 2020). Furthermore, workers could suffer prolonged unemployment spells or even "career detours" (Marx 2011). These perceived long-term "rewards" can undermine employees' incentives to innovate.[5] Since efforts are not verifiable ex ante, this introduces contract incompleteness that exposes the employer to ex post inefficiencies in innovation investments because workers may reduce efforts once the investment is made. Consequently, non-competes could impair ex post value creation, even though they help firms secure rents ex ante.

Empirically testing these ideas has proven challenging in several aspects. One of the major hurdles is that data on firm-level use of non-competes are not readily available. Yet, even if such data are ready to use, analysis with this choice variable is susceptible to endogeneity concerns. The use of non-competes could be correlated with unobserved firm characteristics that also affect innovation activity (the omitted variable concern). Or, firms with declining innovation potential may be more likely to have employees sign non-competes (the reverse causality concern). To overcome these challenges, I adopt a difference-in-differences identification strategy by exploiting staggered reforms of state non-compete legislation to

[5] An important question that may arise here is whether signing workers negotiate over their non-competes in order to receive some benefits. Evidence from the 2014 national survey suggests that only 10% of employees negotiate (Starr et al. 2019). So why would a worker agree to sign the contract? In practice, firms often strategically present a non-compete after the worker just accepts the job offer, which cripples the worker's ability to bargain. This happens in 70% of the cases among engineers as indicated from a 2009 industry survey (Marx 2011), and 33% among labor force participants in the 2014 national survey (Starr et al. 2019).

capture source of exogenous variation in firms' ability to enforce the contracts. This empirical setting relies on two premises that have already been validated. First, firms in states with a higher non-compete enforceability are more prone to use non-competes (Garmaise 2011; Kini et al. 2019). Second, increased enforceability particularly hampers the mobility of skilled workers (Fallick et al. 2006; Marx et al. 2009).

Using stock market reactions to new patent grants as a proxy for economic value of innovation following Kogan, Papanikolaou, Seru, Stoffman (2017), my firm-level analysis shows that during the period of 1992-2009 patents filed after a stronger enforcement of non-competes in the state create less value—they receive less positive stock market reactions when subsequently granted. Specifically, an increase in the enforceability of non-competes leads to a 32.5% reduction in patent value as a fraction of firm assets, after controlling for firm characteristics correlated with innovation, local economic conditions, and fixed effects at firm, state and industry-year levels. By contrast, a weaker non-compete enforceability in the state results in a 38.8% increase in patent value over assets. These results provide initial evidence that higher enforceability of non-competes hinders value creation from innovation.

Building on the concept of efficiency as value per input, I compute patent value over past R&D stock—inspired by Hirshleifer et al. (2013)—and patent value per inventor to assess innovation efficiency. I find negative effects of higher non-compete enforceability on firms' R&D efficiency and inventor value creation. To further explore sources of the inefficiency, I investigate capital allocation decisions and inventor turnover. Interestingly, the results show that firms increase R&D spending after a non-compete enforceability shock, regardless of the direction of the change. I then perform cross-sectional analyses and find that higher enforceability leads to a larger increase in R&D in industries with more knowledge workers, consistent with non-competes mitigating hold-up problems, whereas lower enforceability stimulates R&D more for firms exposed to greater technology spillovers, suggesting that non-competes inhibit knowledge spillovers. These findings help reconcile previously inconclusive evidence on firm investments.

A stronger enforceability also reduces numbers of newly hired inventors and inventor departures in the firm, indicating that non-competes hinder talent reallocation across firms. Thus, the value-reducing effect of increased enforceability on innovation is driven, to a significant extent, by the intensive margin because more inventors stay with the firm. Collectively, these results raise the possibility that allocative inefficiency in labor market due to mobility restrictions can lead to inefficient investments and that this channel manifests itself during the value generation of innovation investments.

The firm-level analyses rely on state of firm headquarters (HQ state) to assign treatment status, which can be noisy if a firm's geographic footprint is across multiple states. To enhance precision in estimates, I utilize patent-level data on assignee state to pinpoint the location where the innovation production takes place. I find consistent results for patent value at the patent level, after additionally controlling for technology class-year fixed effects. The value-destroying effect of increased enforceability is stronger for patents produced within HQ states but is negligible for those filed outside of HQ states.[6]

As innovation is a process of exploring unknowns, if non-competes disincentivize inventors, they may also affect inventors' exploratory efforts and search strategies. Employing measures of innovation search from Balsmeier et al. (2017), I find that when non-competes are more strictly enforced, patents tend to score lower on exploratory measures, have a higher fraction of backward self-citations—implying that inventors rely more on previous knowledge inside the firm, and have a higher fraction of forward self-citations—meaning that these patents are cited more heavily from patents produced by the same firm. These results indicate that more enforceable non-competes lead inventors to explore less toward new areas and rely more on previously known areas of expertise inside the firm.

To investigate potential mechanisms for lower patent value, I explore heterogeneity in this effect by analyzing inventor characteristics—specialization, ability and tenure—that are pertinent to their outside options and bargaining positions. My overall prediction is that inventors more vulnerable to non-competes should be discouraged more by a higher enforceability, resulting in larger value losses. Specifically, inventors specializing in narrow technology fields suffer more from a stronger enforcement because their outside options and mobility are more sharply reduced (Marx et al. 2009). Inventors having lower

[6] This is expected because out-of-state inventors are least likely to be affected by changes in labor laws passed in the HQ states. However, they may still be affected through a teamwork effect (i.e., if they collaborate with inventors residing in the HQ state) or a spillover effect within the organization.

innovation ability tend to be in a weaker bargaining position, making non-competes more binding. Lastly, inventors in early patenting careers may be discouraged more because "young" inventors often have greater incentives to switch firms (Trajtenberg 2006) but tend to have little leverage. Focusing on inventors residing in the same state as firm headquarters, I show that higher enforceability reduces patent value more among inventors with higher skill specialization, lower innovation ability and in early patenting careers.[7] These results explain non-competes inhibit value creation by impairing worker outside options and bargaining power, providing support for the theoretical prediction in Fulghieri and Sevilir (2011).[8]

Additional analyses and robustness checks corroborate the main results. Using non-executive stock and option grants as a proxy for firm's reliance on employee incentives to create value, I find firms with greater such reliance experience larger reductions in patent value and R&D efficiency following a stronger enforcement. I also find suggestive evidence that firms respond to non-compete reforms by locating their innovation labs to states with lower enforceability. Several identification tests confirm the validity of the DID approach.[9] These policy shocks are unlikely to be coincided with, or predicted by, changes in the state's economic conditions, political climate, and legal institutions on intellectual property protection.

There is little empirical evidence on how restricting labor mobility to protect knowledge affects value creation from innovation, and thereby investment efficiency, from a behavioral perspective—the behavioral aspect concerning the effect of inventor mobility on innovation motivation. After all, successful innovations are developed by well-motivated inventors. I expect and find that higher enforceability of non-competes leads to larger declines in patent value among inventors more vulnerable to non-competes. These findings echo Lobel and Amir (2011) who argue that the widespread use of non-competes may have

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[7] These regressions include measures to control for inventor past productivity, innovation experience and co-inventor networks, and incorporate a host of high-dimensional fixed effects at the inventor, firm, state and technology class-year levels.

[8] Fulghieri and Sevilir (2011) theorize that legal restrictions on labor mobility such as enforcing non-competes have a negative impact on employees' effort to innovate, and therefore on innovation value, by weakening employee outside options.

[9] First, there are no pre-existing trends in patent value between affected and un-affected patents, confirming the parallel trends assumption crucial to this empirical design. Second, to address the concern that innovative firms might sort into states based on varying non-compete enforcement regime, I exclude firms that have relocated their headquarters and find results robust to this exclusion. Third, I perform a matched sample analysis in which treated and control firms are similar in size and in the same industry. Fourth, I follow Ewen and Marx (2018) to exclude firms affected by a law-based weakening of the enforcement in Oregon due to its potentially limited effectiveness. In unreported analyses, I exclude firms in California from the sample to address the concern that California's non-compete ban and innovation hub might have a dominant effect on the results, which is not the case.

inadvertent counterproductive effect of lowering employee performance. As firms often claim that the most powerful resource is their people, using non-competes to retain talent, however, may backfire.[10]

This study joins the empirical literature on non-competes and innovation. Indirectly studying the role of non-competes in fostering innovation, Samila and Sorenson (2011) find a more positive effect of venture capital financing on patent counts in states weakly enforcing non-competes than those strongly doing so. However, an alternative explanation is that increased patents might just be a manifestation of higher propensity to patent innovations. Another two related studies are Jeffers (2019) who shows that increased enforceability stimulates capital expenditures in incumbents but reduces new firm entry, and Conti (2014) who finds that Florida's stronger enforcement leads to more highly cited patents. My paper differs in several aspects. First, I make use of data on patent value to directly examine how non-compete policies affect innovation value creation, which helps rule out the alternative explanation. Second, I study a much longer sample period, employ newly developed measures of innovation search, and provide further insights on investment efficiency. Third, I explore underlying mechanisms for value losses and inefficiency from a behavior perspective by focusing on inventors, offering a behavioral implication of non-competes.[11]

This paper adds to the concurrent debate on reforming non-compete laws that aims to strike a balance between benefits and costs from using the restrictive covenants. The primary benefit of non-competes is to protect business interests, which comes with a variety of costs to workers and the broader economy. By limiting outside options, non-competes disincentivize workers to invest in themselves and to innovate, leading to lower quality of human capital that is crucial to long-run economic growth.[12] Although

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[10] In a similar vein, Contigiani et al. (2018) show an adverse effect of trade secrecy protection on inventor-level patent counts and suggest that firms who advocate for stronger trade secrecy protection may find innovation outcomes against their original interests. My paper is different from theirs. First, I focus on employee signed restrictive clauses to examine the implications of mobility on innovation value and search strategy, which provide further insights on investment efficiency. Second, by using newer measures, I am able to circumvent the potential issues of using patents and citations to measure innovation activities, as discussed later.

[11] I also find that Florida's stronger enforcement leads to a substantial increase in self-citations among Florida's firms. The effect on highly cited patents disappears once I control the number of self-citations. Another differentiation from Jeffers (2019) is my finding on R&D investment, in contrast with the effect on capital expenditures. This is consistent with recent studies suggesting that economic factors can influence fixed investment and innovation very differently (e.g., He and Tian (2013)), which might be because innovation investment entails much different risk and return profile from capital investment (Holmstrom 1989).

[12] As mentioned, non-competes also weaken workers' bargaining power and facilitate labor market monopsony, slowing down wage growth and labor dynamism (e.g., Arnow-Richman (2006); Marx (2011); Treasury (2016)). By restraining mobility, non-competes further hinder entrepreneurship and knowledge diffusion (e.g., Gilson (1999); Fallick et al. (2006); Marx et al. (2009)).

existing evidence suggests that firms accrue most of the benefits provided by non-competes, this is the first paper that unveils a potential cost to firms—lowering the efficacy of innovation investments. So why do firms still use non-competes? Plausibly, firms might fear that they will be outcompeted by rivals if they don't, because non-competes reduce uncertainty of labor turnover and any repercussions from employee loss to competitors, allowing to maintain competitive edges. Also, firms might be short-sighted on saving labor costs as they are under no pressure to offer competitive wages to retain employees.

Overall, my findings suggest that labor allocative inefficiency as a result of mobility restrictions could further compromise value creation from innovation investments. On the surface, non-competes create deadweight loss only to the constrained employees. This loss ultimately passes on to the employers who depend heavily on high-quality human capital for their fundamentals. My findings resonate with the view of Landes and Posner (2003, p.371) that "it is not even clear that enforcing employee covenants not to compete generates social benefits in excess of its social costs," and speak to the tenet of antitrust that anticompetitive forces tend to reduce efficiency, lower output and undermine social welfare.[13]

2. NON-COMPETE LAWS

2.1 Institutional Background

Non-competes, also known as covenants-not-to-compete or CNCs, are contracts that preclude workers from joining or starting a competing firm within a geographic area for a certain period (typically one to two years) after leaving their jobs. The agreements usually specify a list of competitors or fields where employees cannot work upon separation (Valiulis 1985). The geographic scope is often a state, a county, a city or a 10- or 50-mile radius around the business location (Malsberger 2004). Thus, non-competes are most effective when workers are in the same state as the business corporation. Firms use non-competes to prevent misappropriation of intellectual property, reduce labor turnover, and improve their

[13] Council of Economic Advisors (2016) explains that non-competes imposed by employers "can lead to inefficient reductions in employment and output, where some workers who would have been willing to work at the competitive market wage are never hired, and the output they would have produced is produced less efficiently by other firms if at all."

bargaining position relative to workers (White House 2016; Treasury 2016). These benefits to firms are at the expense of workers, social welfare and economic dynamism, as discussed earlier.

Systematic data on the use of non-competes among U.S. workers are not available. However, survey evidence suggests that non-competes are pervasive, and they are concentrated among knowledge-intensive occupations such as technical professions and managerial positions (see, e.g., Starr et al. 2019). This is because knowledge workers are most likely to possess proprietary information that firms seek to protect. Non-competes are effective in retaining those workers: empirical evidence has shown that a stronger enforcement restrains the mobility of top executives (Garmaise 2011), scientists and engineers (Marx 2011) and inventors (Marx et al. 2009). In fact, they are deemed as one of the most powerful mechanisms that bind workers to a firm (Garmaise 2011), and may be the only means by which the firm can ban workers from using their skills in competitors (Marx 2011).[14]

This follows the key aspect that distinguishes a non-compete from other types of intellectual property protection: it targets the knowledge embodied in a person and restricts the flow of the input, namely talent, rather than the output of innovation. Unlike outputs (e.g., information), people have desires and motivations. After signing non-competes, workers essentially transfer the property rights over their expertise to their employer (Gilson 1999; Marx 2011), which means that non-competes impose restrictions on the use of knowledge. These restrictions "were characterized in quasi-slavery terms, as if they deprived the employee of his freedom and independence" (Fisk 2009, p.6). Indeed, scientists and engineers bound by non-competes often "involuntarily leave their technical field to avoid a potential lawsuit" and take "career detours" (Marx 2011), forgoing accumulated specialties.[15] Consequently, excessive constraints by

[14] Firms also use alternative mechanisms to influence employee mobility such as patenting, relying on trade secrets laws, and applying other restrictive covenants (i.e., a non-disclosure agreement or a non-solicitation agreement). The effectiveness of these tools is less clear. For instance, most knowledge remains unpatented because of high fixed costs arising from lengthy examination processes and legal issues and costs of disclosure. Secrecy laws are somewhat ineffective because misappropriation of trade secrets is often difficult to prove (Decker 1993). Although the non-disclosure agreement restricts an employee from disseminating trade secrets, the worker can still work for a competitor using acquired skills and know-how without revealing any proprietary information of the ex-employer, even if this is happening (Marx 2011). Non-competes help mitigate these issues by prohibiting workers from joining rival companies at the first place.

[15] It is worth mentioning that litigation over non-competes is on the rise. Beck Reed Riden LLP, a law firm, found a 61% increase in the number of employees getting sued by ex-employers for the violation of non-competes over 2002–2013 (White House 2016).

non-competes demoralize workers who perceive less ownership and control over the skills to be developed. This behavioral effect on innovation motivation, initially proposed by Lobel and Amir (2011), illustrates another negative externality of non-competes that has received minimal attention thus far.

As states have jurisdiction over labor laws, there is a wide variance in the manner and degree to which non-compete clauses are enforced. In some states, non-compete enforcement is governed by statute, while in others it is determined by case law precedents. Each state has its own set of rules to judge whether a non-compete is reasonable in its scope. The common law rule of reason allows the state courts to void those contracts with more negative consequences to the worker or society than needed to protect the employer's legitimate business interests. While weighing employer interest against employee hardship and public welfare, the courts consider the reasonableness of the actual restriction with respect to its duration, geographic scope, and limitation on professional activities (Lester and Ryan 2009). In California and North Dakota, however, no aspects of non-competes are enforceable (Gilson 1999).[16] At the opposite extreme, Florida (from 1997 onwards) has the strongest enforcement regime that prohibits courts from considering employee hardship and permits the employer to obtain an injunction upon non-compete violation.

Employers often write non-competes that are overly broad/unreasonable, and they frequently ask workers to sign non-competes that are entirely or partly unenforceable in certain jurisdictions. For instance, California workers are bound by non-competes at a rate of 22 percent, slightly higher than the national average of 19 percent. Doing so could exert a "chilling effect" on worker behavior (e.g., by imposing a threat to deter job searches (Jeffers 2019) or to prevent workers from accepting outside offers) even if these agreements are unenforceable under state law (Marx and Fleming 2012; White House 2016).[17] As the barrier to access talent rises and competition diminishes, the "chilling effect" spills over to those who have not signed. This illustrates how non-competes may have brought about negative externalities in the broader labor market—another distinction from intellectual property laws that only protect outputs.

[16] See CAL. BUS. & PROF. CODE §§ 16600-16602.5 (Cal. 2008)
[17] Such misuse of non-competes has attracted regulatory attention. The White House Call for Action in 2016 urged states to improve transparency by requiring employers to give advance notice to prospective employees if a job offer contains a non-compete clause. The Mobility and Opportunity for Vulnerable Employees Act (the MOVE Act) is a new bill that proposes a similar requirement.

States adopt different approaches to address such unenforceable non-competes (see, e.g., Treasury 2016). States like Nebraska and Virginia implement a "red-pencil" doctrine, under which courts will refuse to enforce unreasonable non-competes, or contracts containing any unenforceable provisions. Many other states permit certain degree of judicial modification on overbroad non-competes in an effort to generate enforceable contracts, under the "blue-pencil" or "equitable reform" doctrines. While the "blue-pencil" doctrine (in Montana and North Carolina) entails striking offensive clauses from the agreements, the "equitable reform" approach, currently prevailing in about 30 states, allows employers to redraft the contracts. The latter empowers employers and may encourage them to take risks of writing unreasonable provisions, further amplifying the "chilling effect" across the labor markets (Lester and Ryan 2009).

These differences in non-compete enforcement across states usually have deep historical roots, and states rarely changed the enforcement policies up until 2000s. Motivated by the growing concerns over non-competes, several states have proposed new bills to limit the enforcement.[18] So, owing to the lack of variation in these laws and limited data on the use of non-competes, estimating the impacts of non-competes has proven challenging. Recent studies start to exploit exogenous reforms of non-compete laws in a set of U.S. states (Marx et al. 2009; Garmaise 2011; Ewens and Marx 2018). I follow Garmaise (2011) and Ewens and Marx (2018) to formulate research design by exploiting these regulatory changes.

2.2 Time-Series Changes in Non-compete Enforceability

Garmaise (2011) identifies three states that experienced major changes in non-compete enforcement at different times over 1992–2004. He also develops an enforceability index that measures the strength of the enforcement for each U.S. state by analyzing twelve questions proposed by Malsberger (2004). Following Garmaise (2011), Ewens and Marx (2018) extend the policy changes to 2016 by

[18] For example, Oregon passed a new law in 2008 to restrict the enforcement of non-competes, expressing concern about "a dangerous expansion in the sue of noncompetition agreements in Oregon." Other states like Missouri, New Jersey, Maryland, Massachusetts, Michigan and Washington have proposed bills to ban non-competes on some or even all workers (Treasury 2016).

reviewing Malsberger, Brock, and Pedowitz (2016), which provides definitive reference regarding legislative and judicial changes to state-by-state policy of non-compete enforcement.

It is important to note that reasons for these legal shifts were unrelated to corporate innovation, thus mitigating the potential endogeneity concerns over these laws.[19] Moreover, to the extent that judicial decisions are mainly driven by merits of the case in question, court rulings are unlikely to be expected by individuals, are independent of both state and federal governments, and are less likely to be influenced by firm lobbying. Therefore, the policy reforms as a result of judicial changes can represent truly exogenous shocks of the legal environment. With regard to legislative changes, even if the enactment of the new laws was anticipated, firms could have changed their innovation policies before these laws became effective, which will bias against finding any treatment effect of the new laws.

To understand the economic and political motivations behind the passage of non-compete reforms, Table 1 investigates whether a state's macroeconomic conditions, political climate, or intellectual property laws predict the change in non-compete legislation during my sample period of 1992-2009. The dependent variable in columns (1)-(2) is *CNC Enf. Down*, an indicator equal to one if a state has decreased non-compete enforceability in the year, which includes Texas (1994), Louisiana (2001) and Oregon (2008). In columns (3)-(4), *CNC Enf. Up* is an indicator equal to one if a state has increased enforceability in the year, which includes Florida (1996), Louisiana (2003), Vermont (2005) and Idaho (2008). Observations for states that change the enforcement are dropped from the sample after the law is passed. All predicting variables are lagged by one year. I include year fixed effect to control for changes in macroeconomic environment and state fixed effects to control for unobserved state heterogeneity that is time-invariant.

Columns (1) and (3) of Table 1 show that changes in the enforceability, regardless of the direction, were unrelated to preexisting changes in state-level economic and political conditions. None of the variables (a state's GDP Growth, unemployment rate, population, income per capita, labor force participation and

[19] During my sample period of 1992-2009, Texas (1994), Louisiana (2001) and Vermont (2005) reformed their non-compete laws as a result of court decisions, while the enforcement changes in Florida (1996), Louisiana (2003), Oregon (2008) and Idaho (2008) were made by state legislators, according to Garmaise (2011) and Ewens and Marx (2018).

percent of republican legislators in the state legislatures and government) loads significantly. Columns (2) and (4) additionally include two most relevant intellectual protection laws—the Inevitable Disclosure Doctrine and UTSA (Trade Secrecy) laws.[20] The adoptions of these laws do not appear to be correlated with the state's reform of non-compete laws, after accounting for state fixed factors. In columns (5)-(6), the dependent variable is a categorical variable, *Increased CNC Enf.*, which equals one if a state has increased non-compete enforceability in the year, equals negative one if a state has decreased the enforceability in the year, and is zero otherwise. The results appear similar. Hence, the timing of non-compete policy reform is unlikely to be a function of changing political, economic, or related legal conditions, alleviating the potential omitted variable concern that poses a threat to this identification strategy.

3 THEORY AND HYPOTHESES

A stronger enforcement of non-competes reduces the possibility of knowledge leakage to competing firms by prohibiting employees from working for these rivals, enabling the firm to appropriate higher returns on its innovation investments. This enhanced protection would increase the firm's incentives to invest. Indeed, traditional economic models view non-competes necessary to prevent underinvestment in innovation by solving a "hold-up" problem (e.g., Rubin and Shedd 1981).[21] However, innovation is a long process of exploration and experimentation on untested ideas with unpredictable outcomes (Holmstrom 1989). Developing successful innovation requires a considerable amount of effort and persistence from motivated employees. As innovative endeavors are observable but not verifiable ex ante, details of effort are unlikely to be specified in employment contracts (Acharya et al. 2014). Once the investment is made and innovation process begins, workers may reduce efforts, recognizing that the costs

[20] *Inevitable Disclosure Doctrine* is an indicator equal to one for firms headquartered in states after the recognition of Inevitable Disclosure Doctrine in the year (Klasa et al. 2018). *State UTSA (Trade Secrecy)* is an index that measures the strength of legal protection of trade secrets based on the effective UTSA and case law precedents (Png 2017).

[21] According to the property rights theory (Grossman and Hart 1986; Hart and Moore 1990, 1994), bilateral relationships suffer from holdup problems when contracts are incomplete, which could dampen the willingness of economic actors to make investments ex ante. Without mobility restrictions, the firm must worry that it might not be able to recoup the returns on its innovation investment if the employee leaves or threatens to leave after the investment is made. Having a non-compete in place helps limit the employee's ability to hold up the employer ex post.

are sunk. This nonverifiability of employee effort is one indescribable contingency that makes labor contracts never complete, which can be a cause of ex post inefficiency in innovation investments.

Theoretical evidence suggests that non-competes discourage workers from investing in their own human capital (Garmaise 2011) by weakening their outside options and bargaining power. As discussed earlier, workers bound by non-competes perceive fewer external opportunities and are less able to bargain for better contractual terms. Current employers also feel a less need to pay competitive wages to retain talent (Marx et al. 2009). The role of non-competes in holding down wages is supported by Garmaise (2011) for executives and Balasubramanian et al. (2020) for technology workers. Both find lower worker earnings in states with stronger enforceability, confirming that non-competes weaken worker bargaining power.[22]

In addition to monetary costs, workers under a non-compete are confronted with prolonged unemployment spells or "career detours" after job termination. As mentioned briefly, scientists and engineers, especially those with specialized skills, often wait until their non-competes expire or change to a different industry after leaving their jobs to avoid non-compete infringement (Marx 2011), forgoing the skills accumulated over their careers. If workers could not capitalize on their skills and innovations by exploring better careers or being rewarded internally, they would perceive lower expected payoff from developing those skills and innovations, leading to lower incentives and human capital quality over time.

Consequently, higher enforceability of non-competes raises barriers to exit for skilled workers as well as barriers to access human capital inputs for prospective employers, generating allocative inefficiency in the labor market. Over the long term, employees tend to be stuck in jobs where they earn lower wages than would prevail in a competitive labor market and cannot be matched to workplaces where they would be more productive, known as the "job lock" (Council of Economic Advisor 2016; Krueger 2017).

Manso (2011) suggests that contract design to motivate innovation features tolerance for early failure and reward for long-term success. Yet, having a non-compete in place would entail lower long-term

[22] Kini et al. (2019) look into CEO employment contracts and find that CEOs who have more enforceable non-competes earn higher total pay and incentive pay. This is not surprising because unlike rank-and-file employees, a firm's CEO has significant bargaining power relative to the firm.

wage growth, a potential job lock, or even a career detour. But why cannot workers demand some sort of compensation, such as a bonus, when asked to sign a non-compete? A 2009 survey of Institute of Electrical and Electronics Engineers (IEEE) uncovers that in 70% of cases, firms ask for a non-compete after the engineer has just accepted the offer–a point at which the worker has little leverage to further negotiate (Marx 2011). The 2014 national survey to 11,505 labor force participants reports that 33% of employees have had similar experience and that only 10% of employees negotiated (Starr et al. 2019).

Therefore, enforceable non-competes could reduce ex post value of innovation, undermining the efficacy of investments. Indeed, Fulghieri and Sevilir (2011) theorize that mobility restrictions through enforcing non-competes negatively affect employee effort to innovate, and thereby value of innovation. Using experiments, Amir and Lobel (2014) observe that non-competes worsen worker performance. They argue that such disincentive effect on workers might hurt firm performance more than the actual employee loss would. Both studies allude that the disincentive effect of non-competes on workers outweighs any stimulus effect on firms in producing valuable innovations, which leads to the main hypothesis:

Hypothesis 1: *An increase in non-compete enforceability leads to a decrease in the value of innovation.*

I then examine inventors' characteristics pertinent to their outside options and bargaining positions to pin down the potential mechanisms. After all, inventors are the ones who have developed the innovations. I expect that inventors whose job prospects are weakened more, who are in a weaker bargaining position, and who have greater ex ante incentives to move should be discouraged more by a stronger non-compete enforcement such that their innovations create even less value, as elaborated below.

First, for inventors specializing in narrow technology fields (specialists), a higher non-compete enforceability weakens their outside options more because firms might enforce non-competes more aggressively against them since their job opportunities are most likely to be in direct competitors. In contrast, generalists may switch industries as they can transfer their skills to firms in different industries. Marx et al. (2009) show a larger decline in mobility for specialists than generalists (by 8%) after a stronger enforcement. Also faced with a potential "career detour," specialists are more jeopardized by the reform.

Second, inventors with lower innovation ability tend to be in a weaker bargaining position vis-à-vis their firm, compared with high-achievers, suggesting that non-competes are more binding for low-ability inventors. Supporting this conjecture, Fulghieri and Sevilir (2011) predict that the effect of outside options on employees' effort is larger when their bargaining power is lower because of greater marginal benefit of outside options on their effort. So, if a stronger enforcement disincentivizes inventors by weakening worker bargaining power, the effect should be stronger among low-ability inventors.

Third, inventors in early careers ("young" inventors) are more likely to switch firms in order to find a better match or capitalize on acquired skills, but they have little leverage due to limited experience. Such incentives to move diminish over time either because match quality improves or because moving constraints increase (e.g., costs of foregoing firm-specific human capital and family obligations).[23] Trajtenberg (2006) show that "younger" inventors exhibit higher mobility than seniors, suggesting that they are motivated more by outside options. Thus, "young" inventors might be discouraged more by higher enforceability.

Hypothesis 2: *An increase in non-compete enforceability leads to a larger decrease in innovation value for inventors with higher skill specialization, having lower innovation ability, and in early patenting careers.*

4. DATA AND METHOD

4.1 Data and Sample Construction

Sample construction starts with all publicly traded non-financial and non-utility U.S. industrial firms covered in Compustat North America Fundamentals Annual files. Industrial firms are defined as companies with SIC codes outside the ranges 4900-4949 (utilities) and 6000-6999 (financials). To be retained in the sample, firm-year observations are required to have positive values for book assets and sales,

[23] Parsons (1972) indicates that economic cost of worker-job separation increases by the amount of investments in firm-specific human capital, either by the firm or the worker, suggesting that firm-specific human capital leads to lower mobility. Marx et al. (2009) show an additional drop in mobility for inventors with greater firm-specific skills following higher non-compete enforceability. But if these workers also have lower ex ante incentives to leave due to higher separation cost, then the effect of higher enforceability on their incentives to innovate is ambiguous. Consistent with this, I do not find that inventors with greater firm-specific skills produce less valuable innovation than others after a stronger enforcement.

non-negative values for common equity, and non-missing values for R&D expenditures.[24] This sample is then merged with data on patent market value from Kogan, Papanikolaou, Seru, Stoffman (2017)—KPSS. Accordingly, the market value of a new patent is calculated as the three-day market-adjusted cumulative abnormal returns surrounding patent approval date multiplied by the firm's market capitalization prior to the announcement. Firm-years not in KPSS dataset are excluded because assigning zero to missing patent value would falsely assume that these patents do not create any value. So my sample consists of publicly traded industrial firms engaging in R&D with at least one patent grant and with needed stock price data.

I obtain data on changes in state non-compete enforceability from Garmaise (2011) over 1992-2004 and Ewens and Marx (2018) from 2005 onwards. As data for both patent value and inventors end in 2010, my sample period spans from 1992 to 2009, during which seven major reforms of non-compete legislation took place in six "treatment" states, allowing for a difference-in-differences framework to estimate the effects of changes in non-compete enforcement regime on patent value. Specifically, Texas (1994), Louisiana (2001) and Oregon (2008) decreased non-compete enforceability, whereas Florida (1996), Louisiana (2003), Vermont (2005) and Idaho (2008) increased the enforceability.

Since the enforcement of non-competes is governed by employment law, not corporate law, the relevant jurisdiction is the state where the employee works (Malsberger 2004). In the firm-level analysis, I map non-compete laws to the state where each firm is headquartered based on the rationale that non-compete signers are mostly high-skilled employees, who typically work at headquarters (Garmaise 2011). As Compustat only reports current headquarters location, I extract information on firm historical headquarters location in 10-K filings from Securities and Exchange Commission (SEC) Edgar database.

Importantly, I also leverage data on patent assignee location and inventor residence state to minimize errors in treatment assignment. With the location data, I can identify patents produced in HQ states and inventors most likely work at headquarters to enhance precision in estimations.

[24] The conventional approach in the literature is to replace missing values of R&D expense with zero, since firms who do not report R&D often have trivial R&D spending (see e.g., Brown and Petersen 2011). For the purposes of this study, only firms that engage heavily in internal development of innovations are more appropriate to study. Firms that obtain patents externally via mergers and acquisitions without R&D investments offer little implication for innovation efficiency.

I collect detailed information on patent assignee and technology classes from National Bureau of Economic Research (NBER) and Harvard Business School (HBS) patent files, patent inventor information from Harvard Patent Network Dataverse (Li et al. 2014), state-level data on GDP growth rates, total population, per capita personal income, and labor force from the Bureau of Economic Analysis, state unemployment rates from Bureau of Labor Statistics, state partisan composition from the National Conference of State Legislatures, industry occupation profiles from the Occupational Employment Statistics (OES) survey, and measures of technology spillovers developed by Bloom et al. (2013). The final sample consists of 14,585 firm-year observations for 2,644 unique firms over 1992-2009. These firms combined have applied for and been granted 537,021 patents during this period, which involve 86,592 inventors living in the state of firm headquarters at the time of innovation production.

4.2 Measurement of Key Variables

Empirical research on innovation has primarily relied on patent data, since patents are widely recognized as the major form of innovation outputs. I use market value of new patents as a proxy for innovation value to infer the return on innovation investment. An advantage of this measure over patent or citation counts is that it directly quantifies the *economic value* generated by a patent. This is also a standardized measure, allowing to analyze innovation quality across firms and over time while alleviating the truncation problem of citation-based measures. Also, Balsmeier et al. (2017) point out that increases in patents or citations do not necessarily imply increases in creative activities.[25] Finally, another issue is that higher mobility of scientists is associated with a higher propensity for firms to patent (Kim and Marschke 2005), which means that patents and citations could increase without creating real value after non-compete enforceability declines.[26] I analyze patent value at both firm and patent levels to address this concern.

[25] This is because the increases could simply be an artifact of changes in search strategy towards more crowded areas or familiar areas. They suggest that using simple patent or citation counts is insufficient and might lead to inaccurate inferences on innovation.
[26] Despite these concerns, I also test the impact of non-compete policy reforms on patent and citation counts. These results are reported in the Internet Appendix Table IA1 and discussed in Section 5.

To construct firm-level measures, I aggregate market value of new patents by firm and application year. *Patent Value* is the future market value of patents that a firm applied for in a year. By this way of construction, *Patent Value* is a forward measure because the time lag between filing and receiving an approval is often one to two years. Following KPSS (2017), I also calculate *Patent Value/Assets* as the market value of patents that a firm applied for in the year scaled by the firm's book assets. Motivated by Hirshleifer et al. (2013), *Patent Value/ R&D stock* is computed as total market value of patents that a firm applied in the year divided by past R&D stock from years $t-2$ to $t-6$ with a 20% depreciation rate. This variable helps evaluate how efficient the firm is in turning R&D dollars into realized value from innovation. To gauge average value creation of an inventor, *Patent Value Per Inventor* is calculated as total market value of patents that a firm applied in the year divided by the total number of inventors filing these patents.

In the patent-level analysis, I zero in on patents produced in the firm's state of headquarters to tease out noises due to treatment misassignment. In addition, I employ several new measures of innovation search (Balsmeier et al. 2017; He and Hirshleifer Forthcoming) to examine inventors' exploratory efforts. *Exploratory 90%* is an indicator equal to one if at least 90% of the patent's backward citations are based on new knowledge coming outside of the firm's existing knowledge base, which consists of all patents granted to the firm and patents cited by the firm in the past five years. *Exploratory Ratio*, a continuous variable, is the fraction of the patent's backward citations based on new knowledge. *Purely Exploratory* is a dummy equal to one if the patent does not cite any patents owned by the same firm. *Backward self-cites* is the ratio of citations made to patents owned by the same firm over total citations made. *Forward self-cites* is the ratio of self-citations received by the patent over total citations received. Higher values on the last two measures indicate more search within known areas and less exploratory effort toward areas new to the firm.

Lastly, using a sample of inventors residing in HQ states, I measure inventor characteristics in terms of skill, ability and experience. Following Marx et al. (2009), *Inventor Skill Specialization* is a Herfindahl concentration measure based on the share of patents in each three-digit technology class among all the patents that the inventor has filed in the past five years. Inspired by Balsmeier et al. (2017) that uncited patents are more likely to be failed innovations, I use the cumulative share of uncited patents in an inventor's patent portfolio (i.e., the cumulative number of uncited patents over the total number of patents produced up to the year) as an inverse proxy for the inventor's innovation ability. An inventor's patenting experience or career stage is proxied by number of years since the inventor's first granted patent application.

Table 2 reports descriptive statistics of the samples. All continuous variables are winsorized at their 1^{st} and 99^{th} percentiles. Dollar values are CPI-adjusted in 2016 dollars. Panel A presents summary statistics for the firm-level sample. On average, new patents that a firm applied in a year generate $1,778 million shareholder value, which accounts for 17.8% of the firm's assets. Patent value over R&D stock has a mean value of 1.9, and patent value created by each inventor is estimated to be $11.3 million. The average firm has a book value of assets of $3.9 billion and a leverage ratio of 16.1%. It is 18.6 years old. It has a Market-to-book ratio of 2.5, a cash flow ratio of -1.1%, a tangibility of 20.8% and a R&D-to-assets ratio of 10.2%. In Panel B on patent characteristics, the market value of an average patent is 0.78% of the firm's assets. 27.6% of the patents have an exploratory ratio over 90%. The average patent has an exploratory ratio of 57.7%, has made 15.1% backward self-citations and receives 13.9% forward self-citations. On the inventor characteristics displayed in Panel C, an average inventor has a skill specialization ratio of 49.7%, 8.5% uncited patents in the portfolio and 7.3 years of patenting experience. The Appendix provides detailed definitions for all variables.

4.3 Empirical Methodology

I adopt a difference-in-differences (DID) test design to analyze how changes in non-compete legislation affect innovation value. To capture the individual treatment effect of a strengthening or weakening enforcement, I define two indicators—*CNC Enf. Up* equal to one for firms headquartered in states after experiencing an increase in the enforceability, and zero otherwise, and *CNC Enf. Down* equal to one for firms in states after a reduced enforceability, and zero otherwise. Table 2 Panel A reports that 1.8% and 4.0% of firm-years are affected by, respectively, a stronger and weaker non-compete enforcement. I then estimate the following DID specification:

$$Y_{i,s,t} = \alpha + \beta_1\, CNC\ Enf.\ Up_{s,t} + \beta_2\, CNC\ Enf.\ Down_{s,t} + \beta'\, X_{i,s,t-1} + \mu_i + \omega_s + \gamma_j \times d_t + \varepsilon_{i,s,t}\ , \tag{1}$$

where $Y_{i,s,t}$ is one of the aforementioned measures of innovation value and efficiency of firm *i* headquartered in state *s* in year *t*. The key independent variables are *CNC Enf. Up*$_{s,t}$ and *CNC Enf. Down*$_{s,t}$. as defined above. β_1 and β_2 are DID estimates assessing how changes in non-compete enforceability affect subsequent innovation performance of treated firms relative to that of all other firms. I also follow prior literature to define *Increased CNC Enf.*, which equals one for firms in states after experiencing a higher enforceability, equals negative one for those in states after a lower enforceability, and is set to zero otherwise.

$X_{i,s,t-1}$ is a set of firm- and state-level controls measured in year $t-1$. It includes well-known determinants of innovation performance such as firm *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility* and *R&D/Assets*. To ensure local market conditions not driving the results, I include *State Industry HHI* (a proxy for in-state competition)*, State GDP Growth* and *ln(State Unemployment)* (proxies for economic environment). Lastly, I control *IDD* (an indicator for whether the state has adopted the Inevitable Disclosure Doctrine) to mitigate concern that states with stronger enforcement of non-competes also provide greater protection on trade secrets by adopting the IDD.

Equation (1) incorporates firm fixed effects (μ_i), HQ state fixed effects (ω_s), and industry × year fixed effects ($\gamma_j \times d_t$), where industry is defined at the two-digit SIC code level. The firm and HQ state fixed effects control for any unobserved time-invariant heterogeneity across firms and states, respectively. Incorporating industry × year fixed effects allows to account for intertemporal technological shocks across industries and for the possibility that unobserved time-varying industry factors might be driving the results. Since changes in non-compete regulation affect all firms headquartered in the state, I cluster standard errors at the HQ state level—the level of treatment—to correct for possible autocorrelations of the error terms for firms within the same state (Bertrand, Duflo, and Mullainathan 2004).

I next test the treatment effects at the patent level using Equation (2) specified below. The benefits of this unit-level analysis come from more accurate treatment assignment—by focusing on patents produced in the firm's state of headquarters—and mitigating the concern that the effects on innovation are driven more by quantity rather than the quality side of innovation activities.[27]

$$Y_{i,j,s,t} = \alpha + \beta_1\, CNC\ Enf.\ Up_{s,t} + \beta_2\, CNC\ Enf.\ Down_{s,t} + \beta'\, X_{i,s,t-1} + \mu_i + \gamma_k \times d_t$$

$$+\ \omega_s + \varepsilon_{i,j,s,t}\,, \qquad (2)$$

where $Y_{i,j,s,t}$ is the market value of patent j scaled by the assets of firm i (*Patent Value/Assets*) headquartered in state s in application year t. β_1 and β_2 are the DID estimates measuring the impact of changes in non-compete enforceability on subsequent market value of new patents filed after the law changes. This specification includes firm (μ_i) and HQ state (ω_s) fixed effects and incorporates technology class × year ($\gamma_k \times d_t$) fixed effects to account for time-varying technology shocks that might be correlated with both the legal changes and patent value. $X_{i,s,t-1}$ is a set of controls including *Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD.* Standard errors are clustered by firm HQ state.

5. EMPIRICAL RESULTS

5.1 Non-competes, Innovation Value and Efficiency

Table 3 presents the baseline results using Equation (1) that examine the effect of changes in non-compete enforceability on patent value at the firm level. The dependent variable in columns (1)-(2) is *ln(Patent Value)*, the natural logarithm of one plus subsequent market value of new patents that a firm applied in the year, and in columns (3)-(4) is *Patent Value/Assets*, the ratio of market value of new patents that a firm applied in the year over its book assets.

In column (1), the estimated coefficients of *CNC Enf. Up* and *CNC Enf. Down* are −0.383 (t = −3.59) and 0.272 (t = 3.22), respectively. These results suggest that new patents filed after a stronger enforcement of non-competes in the state receive less positive stock market reactions when subsequently granted, whereas those applied after a weaker enforcement are valued higher by equity investors.

[27] Information on assignee state is obtained from NBER patent database supplemented by HBS patent files, as Kogan et al. (2017) do not have this information.

Alternatively, using the categorical variable, column (2) reports a significant and negative coefficient estimate on *Increased CNC Enf.* ($t = -4.63$), indicating that on average an increase in non-compete enforceability leads to a 26.6% reduction in subsequent patent value.

The next two columns for *Patent Value/Assets* show consistent results. The estimated coefficients of *CNC Enf. Up* and *CNC Enf. Down* in column (3) are −0.058 ($t = -1.76$) and 0.069 ($t = 5.75$), respectively, indicating a 32.6% decline in patent value as a fraction of assets (relative to its sample mean of 0.178) following an increase in the enforceability and a 38.8% increase in patent value after enforceability weakens. In column (4), *Increased CNC Enf.* again has a negative and significant coefficient estimate indicating a treatment effect of similar size. These regressions include a set of firm-level determinants of innovation, local economic conditions, firm and state fixed effects to control for time-invariant heterogeneity across firms and states, and industry-year fixed effects to absorb time-varying industry shocks. Overall, the results in Table 3 provide support for *Hypothesis 1*.[28]

To investigate how changes in non-compete enforceability affect investment efficiency, I measure R&D efficiency based on the market value of patents, which has an intuitive interpretation: how efficient a firm is when turning R&D dollars into realized value from innovation outputs. Table 4 reports the results using Equation (1). The dependent variable in columns (1)-(2) is *Patent Value/R&D Stock*, computed as the total market value of patents that a firm applied in the year divided by past R&D stock from years $t - 2$ to $t - 6$ with a 20% depreciation rate. The results show a negative coefficient on *CNC Enf. Up* ($t = -3.75$) and a positive coefficient on *CNC Enf. Down* ($t = 4.39$), suggesting that a stronger enforcement undermines the efficacy of R&D expenditures to generate value whereas a weaker enforcement boosts value created from R&D. Column (2) shows that the result using *Increased CNC Enf.* has similar inference.

Another related question is how efficient the firm is in using labor inputs to create valuable outputs after the law changes. To show this, I calculate *ln(Patent Value per Inventor)*, the natural logarithm of one

[28] Table IA1 in the Internet Appendix reports the results for the number of patents, citation-weighted patents and raw citations. In calculating citation-weighted patents, the weight for each patent is calculated as the number of future citations divided by the average number of citations received by patents in the same technology class and year. The results are largely consistent with those for patent value. An increase in non-compete enforceability has a negative and significant effect on the numbers of patents and citation-weighted patents; the effect on the number of raw citations is also negative but not significant ($t = -1.56$).

plus the total market value of patents that a firm applied in the year divided by the number of inventors filing these patents.[29] The results presented in columns (3)-(4) of Table 4 closely mirror those for R&D efficiency—patent value created by each inventor on average drops significantly after a stronger enforcement but increases significantly after non-competes become less enforceable. These results also imply that weaker enforcement might stimulate greater inventor effort to create value.

5.2 Non-competes and Allocative Inefficiency

The results so far provide supportive evidence that higher enforceability of non-competes generates inefficiency in creating value from innovation for a given amount of R&D expenditures or innovative labor. To explore sources of inefficiency, I further investigate firms' allocation decisions on capital and labor by analyzing how they invest in R&D projects and manage innovative workforce.

5.2.1 Capital Allocation—R&D Investment

Table 5 panel A shows the results examining firms' investment in R&D projects. The dependent variable is a firm's *R&D-to-assets* ratio. Based on the specification of Equation (1) without including any controls, the results in column (1) show positive and significant coefficient estimates on both treatment indicators. These results remain similar after including full set of controls as reported in column (2)—the estimates of *CNC Enf. Up* and *CNC Enf. Down* are 0.023 ($t = 3.56$) and 0.019 ($t = 9.53$), respectively. These estimates suggest that compared with firms in unaffected states, a higher enforceability of non-competes leads to a 22.5% increase in R&D spending (relative to the sample mean) among treated firms, and a weaker enforceability increases R&D of affected firms by 18.6%. Given this, it is not surprising to see an insignificant coefficient estimate on *Increased CNC Enf.* in column (3) as found in previous research.

Indeed, economic theories offer ambiguous predictions on how enforcing/using non-competes could affect innovation investments such as R&D. As mentioned, a stronger enforcement may foster more

[29] Alternatively, I use the number of employees to scale patent value and find consistent results in unreported tests.

R&D investment by solving the hold-up problem. On the other hand, less enforceable non-competes might encourage more R&D owing to greater knowledge spillovers in a more fluid labor market. As such, if both of these mechanisms are at work, I expect that firms invest more in R&D if they benefit more from knowledge spillovers after a weaker enforcement and that higher enforceability stimulates more R&D for those facing a higher hold-up risk from their employees.

To capture the extent of knowledge spillovers that a firm is exposed to, I obtain the spillover measure from Bloom et al. (2013) that is based on a firm's position in technology space, and create *Closer Tech Space*, which is an indicator equal to one for firms with above-median technology spillovers every year. I then interact the treatment indicators (*CNC Enf. Up* and *CNC Enf. Down*) with *Closer Tech Space* and estimate Equation (1) with the interaction terms included. Column (4) in Table 5 reports the results. The coefficient estimate on *CNC Enf. Down* × *Closer Tech Space* is positive and significant at a 10% level, supporting the theory that weakening non-compete enforcement fosters more R&D when firms can benefit from greater knowledge spillovers via mobile workers.

Turning to the theory on hold-up problem, I use a firm's reliance on knowledge workers to proxy for the potential hold-up risk faced by the firm. Using data from Occupational Employment Statistics (OES) survey, I compute the fraction of managers and professional workers employed in a given industry every year to measure the intensity of knowledge workers. *More Knowledge Workers* is an indicator equal to one for firms in industries with the fraction of managers and professional workers above the median level across all industries every year, which is then interacted with the two treatment indicators. Column (5) reports the results based on Equation (1) while including the interaction terms. The estimate on *CNC Enf. Up* × *More Knowledge Workers* is positive and significant at a 1% level, suggesting that increased enforceability spurs more R&D among firms relying more on highly skilled workers. This result supports the theory that stronger non-compete enforcement fosters R&D by mitigating the hold-up problem.

Combined with previous findings on patent value, these results provide corroborative evidence that more enforceable non-competes bring about inefficiency in turning R&D dollars into valuable outputs.

5.2.2 Labor (Re)allocation—Inventor Turnover

I next investigate how firms manage innovative labor (i.e., net expanding or downsizing) after non-compete policy shocks by analyzing their ability to attract and retain inventors. Following the approach of Brav, Jiang, Ma, and Tian (2018), I use information of patent assignee for two successive patents filed by the same inventor to identify new hires and departing inventors. I then calculate *ln(New Hires)*, defined as the natural logarithm of one plus the number of newly joined inventors in the firm, and *ln(Leavers)*, defined as the natural logarithm of one plus the number of inventors leaving the firm. Using one of these two variables as the dependent variable, I estimate Equation (1) and report the results in Panel B of Table 5.

Column (1) shows the results for *ln(New Hires)* and column (2) for *ln(Leavers)*. The coefficient on *CNC Enf. Up* is negative and significant at a 1% level in both regressions, suggesting that higher enforceability reduces the numbers of newly hired inventors and inventor departures in the firm. The coefficient on *CNC Enf. Down* is positive but only significant (at a 1% level) in the regression of *ln(New Hires)*, indicating that a weaker enforcement increases firm access to new talent. These results provide evidence for the role of non-competes in hindering talent reallocation across firms. Noteworthy, these findings also imply that the negative impact of stronger non-compete enforcement on patent value mainly occurs at the intensive margin as more inventors stay with the firm, raising the possibility that allocative inefficiency of innovative labor could further lead to inefficiency in innovation investments.

5.3 Patent-level Analysis

I now analyze the treatment effects at the patent level using Equation (2). Doing so allows me to focus on patents produced in the firm's state of headquarters—the level of treatment in previous analysis, thereby minimizing errors in treatment assignment.[30] This unit level analysis also mitigates the concern that the observed effects on innovation are driven mainly by quantity rather than quality of innovation activities.

[30] In unreported tests, I find results to be similar when using assignee state as the level of treatment.

Table 6 presents the estimation results. The dependent variable is *Patent Value/Assets,* the ratio of the market value of a patent over the firm's book assets (multiplied by 100).

In column (1) in which I include all patents, *CNC Enf. Up* has a negative coefficient estimate significant at a 5% level and *CNC Enf. Down* has a positive coefficient significant at a 1% level. The results become stronger when only including patents produced within HQ states, as shown in column (2). These results consistently suggest that patents applied after increased non-compete enforceability create less value when eventually granted, whereas those filed after decreased enforceability are valued higher at the time of approval, reinforcing previous findings in the firm-level analysis. I then replicate these results with the categorical variable *Increased CNC Enf.* and obtain similar inference as conveyed in columns (3)-(4).

Lastly, column (5) shows that the value-destroying effect of a stronger enforcement is negligible for patents filed outside of HQ states after additionally controlling for assignee state fixed effects. This is expected since out-of-state inventors are least likely to be affected by changes in labor laws passed in the HQ states. But still, these inventors may be affected via spillover effects from firm headquarters, which explains why a lower enforceability enhances the value of out-of-state patents to a lesser degree than that of in-state patents.

5.3.1 Timing of the Treatment Effects

Having established robust average treatment effects of these laws on patent value, another important question is when the effects start to materialize. To show this, I replace *CNC Enf. Up* in Equation (2) with *CNC Enf. Up* $^{-2}$, *CNC Enf. Up* $^{-1}$, *CNC Enf. Up* ^{0}, *CNC Enf. Up* $^{+1}$, *CNC Enf. Up* $^{+2}$, and *CNC Enf. Up* $^{3+}$, which are dummy variables equal to one during two-year prior to, one-year prior to, current year, one-year post to, two-year post to, and three-year after, respectively, the increase of the enforceability in the state, and zero otherwise. I then run regressions using the sample of HQ patents while excluding patents affected by a weaker enforcement. I also create *CNC Enf. Down* $^{-2}$, *CNC Enf. Down* $^{-1}$, *CNC Enf. Down* ^{0}, *CNC Enf. Down* $^{+1}$, *CNC Enf. Down* $^{+2}$ and *CNC Enf. Down* $^{3+}$ in a similar fashion and carry out similar analysis. Figure 1 plots the coefficient estimates of these variables along with the 95% confidence intervals.

Panel A displays that the coefficient estimates on *CNC Enf. Up* $^{-2}$ and *CNC Enf. Up* $^{-1}$ are both small and indistinguishable from zero, confirming that there was no pre-existing trend before the increased enforceability. The coefficient estimates on *CNC Enf. Up* $^{+2}$ and *CNC Enf. Up* $^{3+}$ are negative and significant, suggesting that the decline in innovation value materializes two years after the policy change. Panel B shows that the positive effect of decreased non-compete enforceability on patent value gradually increases during this window but the estimated coefficients on *CNC Enf. Down* $^{-2}$ and *CNC Enf. Down* $^{-1}$ are insignificant, reaffirming the identification assumption of no pre-existing trends.

5.3.2 Innovation Exploration

If higher enforceability of non-competes undermines innovation value by disincentivizing inventors, it may also discourage search and exploratory efforts. To test this, I use recently developed measures of innovation search from Balsmeier et al. (2017) as dependent variables when estimating Equation (2). Table 7 reports the regression results. The dependent variables in the first three columns are *Exploratory 90%*, *Exploratory Ratio*, and *Purely Exploratory*. The results show that after non-compete enforceability increases, patents score lower on these exploratory measures, whereas a weaker enforceability leads patents to attach higher levels of these metrics. For example, in column (2), the coefficient estimates on the two treatment indicators, both significant at a 1% level, indicate that higher enforceability leads to an 11.8% reduction in exploratory ratio whereas lower enforceability results in a 9.5% increase in the ratio.

The next two columns examine citation patterns to infer direction of innovation search. Column (4) shows that following increased enforceability, patents have a higher fraction of backward self-citations—an 18.5% increase (t = 2.17), indicating that inventors rely more on previous knowledge inside the firm to develop innovation. These patents also receive a higher fraction of forward self-citations, which increases by 55.4% (t = 9.63) as column (5) shows, suggesting that they are cited more heavily from patents owned by the same firm, presumably by colleagues. Taken together, the results in Table 7 imply that enforcing non-competes more strictly might change inventors' innovative behavior to explore less toward areas new to the firm and rely more on previously known areas of expertise inside the firm.

5.4 Inventor Outside Options and Incentives to Innovate

The evidence documented thus far supports the first hypothesis that increased non-compete enforceability reduces innovation value and efficiency. To investigate potential explanations for this valuation loss, I now test *Hypothesis 2*, which involves analyzing heterogeneous treatment effects across inventors likely to be affected more negatively by the legal changes. I estimate the following specification at patent-inventor level and only include inventors residing in HQ states in these tests as they are most likely working at firm headquarters.

$$
\begin{aligned}
Y_{i,j,l,s,t} = \alpha &+ \beta_1 \, CNC\ Enf.\ Up_{s,t} \times Z_{l,s,t} + \beta_2 \, CNC\ Enf.\ Down_{s,t} \times Z_{l,s,t} + \beta_3 \, Z_{l,s,t} \\
&+ \beta_4 \, CNC\ Enf.\ Up_{s,t} + \beta_5 \, CNC\ Enf.\ Down_{s,t} + \beta' X_{i,s,t-1} + \Phi' L_{l,s,t} + \delta_l \\
&+ \mu_i + \gamma_k \times d_t + \omega_s + \varepsilon_{i,j,l,s,t} \,, \qquad (3)
\end{aligned}
$$

where $Y_{i,j,l,s,t}$ is the market value of patent j scaled by the assets of firm i (*Patent Value/Assets*), which is produced by inventor l residing in HQ state s and filed in year t. $Z_{l,s,t}$ is a vector containing dummy variables for inventors with higher skill specialization, having lower innovation ability and in early career stages. Thus, β_1—the coefficient on the interaction term of *CNC Enf. Up* and *Z*—tests how the detrimental effect of higher enforceability on patent value varies with inventors' outside options, bargaining power, and ex ante incentives to move across firms.

Equation (3) includes inventor (δ_l) fixed effects to account for any fixed unobserved inventor characteristics (such as innate talent), in addition to firm (μ_i) and HQ state (ω_s) fixed effects and technology class × year ($\gamma_k \times d_t$) fixed effects. $X_{i,s,t-1}$ is the same set of controls as in Equation (2). $L_{l,s,t}$ contains inventor-level controls including the inventor's past productivity (the natural logarithm of total number of patent grants in the past five years), number of inventors on the patent, inventor's patent experience, and the inventor's network size (the natural logarithm of one plus the cumulative number of unique coinventors on all patents previously filed by the inventor). δ_l and L are included to mitigate the concern that unobserved and observed inventor characteristics (i.e., productivity and network) that might be correlated with Z also affect patent value. Standard errors are again clustered by HQ state.

Table 8 reports the results. I first test whether inventors with higher skill specialization, whose job prospects are more jeopardized, produce less valuable innovation than other inventors after a stronger enforcement. The key variable is the interaction term of *CNC Enf. Up* and *Specialized Inventor*, which is an indicator equal to one if the inventor's skill specialization is above the sample median every year. Column (1) shows a negative and significant coefficient on this variable, after controlling for firm and inventor characteristics and a set of fixed effects at the inventor, firm, HQ state and technology class-year levels. Column (2) replicates the result by using *Increased CNC Enf.* to interact with *Specialized Inventor* and continues to show a negative and significant coefficient estimate. These results support the hypothesis that more enforceable non-competes dampen incentives to innovate by weakening inventor outside options.

The second test analyzes whether the value-decreasing effect on patent value is stronger among inventors with lower innovation ability who tend to be in a weaker bargaining position. I use the cumulative share of uncited patents in the inventor's portfolio as a proxy for failure rate and define *More Uncited Patents* as a dummy equal to one if the failure rate is above sample median every year. Using the two specifications as described above, columns (3) and (4) show negative and significant coefficient estimates on *CNC Enf. Up* × *More Uncited Patents* and *Increased CNC Enf.* × *More Uncited Patents*, respectively, supporting my hypothesis that higher non-compete enforceability disincentivizes inventors more if they are in a weaker bargaining position so that non-competes are more binding.

The third test examines whether the negative treatment effect on patent value is more pronounced among inventors in early patenting careers who often have stronger incentives to switch employers. This is done by including an interaction of *CNC Enf. Up* and *Young Inventor*, which is an indicator equal to one if the number of years since the inventor's first patent is in the bottom quartile of the sample every year. Column (5) reports a negative and significant coefficient estimate on this interaction term. In column (6), the coefficient of *Increased CNC Enf.* × *Young Inventor* is also negative but not significant. These results largely support the idea that stronger enforcement of non-competes discourages inventors who are more motivated by outside options but have little leverage to bargain (due to limited experience).

Noteworthy, an alternative mechanism is that reduced mobility after a stronger enforcement limits idea circulation among inventors across firms, thereby impeding idea recombination that is important for innovation. This view, however, is hard to explain directly why specialists or "young" inventors are affected more negatively than other inventors. My results are consistent with the interpretation that enforceable non-competes reduce incentives to innovate by weakening inventors' outside options and bargaining power.

5.5 Additional Analyses and Robustness Checks

5.5.1 On the Role of Employee Incentives

The findings documented here reflect the overarching theme that highlights the importance of (non-executive) employee incentives in fostering corporate innovation (e.g., Chang et al. 2015). If employee incentives indeed drive these results, I expect changes in non-compete enforceability to have a stronger effect on innovation value and efficiency in firms where incentives of rank-and-file employees are more important. To test this, I follow Chang et al. (2015) to calculate the Black-Scholes value of outstanding options held by non-executive employees (using data from IRRC and ExecuComp databases) as a proxy for the firm's reliance on employee incentives. *High Employee Options* is an indicator equal to one if the per-employee value of non-executive stock options is above the sample median every year. I then interact the two treatment indicators with *High Employee Options* and estimate the baseline Equation (1).

Table 9 shows the results. The dependent variables in columns (1)-(4) are *ln(Patent Value)*, *Patent Value/Assets*, *Patent Value/R&D Stock*, and *ln(Patent Value Per Inventor)*, respectively. The results support my prediction as the coefficient estimates on *CNC Enf. Up × High Employee Options* are all negative and significant at a 1% level and the coefficient estimates on *CNC Enf. Down × High Employee Options* are all positive and significant (*t*-stats ranging from 1.89 to 6.13) for the four outcome measures, suggesting that firms in which employee incentives are of greater importance experience larger reductions in patent value and innovation efficiency after non-compete enforceability increases, whereas a lower enforceability leads to larger gains for such firms in terms of these measured outcomes. The results also show positive associations between *High Employee Options* and innovation outcomes, consistent with Chang et al. (2015).

5.5.2 Identification Tests

Selection of Headquarters Location: One potential endogeneity concern here is that firms might choose their headquarters location (often proximate to research labs) based on state non-compete enforcement policies. If firms with better innovation potential are more likely to move to states weakly enforcing non-competes (for better access to talent from incumbents), then the estimated treatment effect would be biased upward due to this sorting. However, it could also be the case that these firms prefer stronger enforcement regime that provides greater protection on intellectual property. To mitigate the impact from sorting on the results, I exclude firms that have changed headquarters and rerun the firm-level regressions. Panel A of Table IA2 in the Internet Appendix shows that the results of this test remain similar as previously discussed, suggesting that firm sorting has little bearing on the estimated treatment effects.

Matched Sample Analysis: Another potential concern is that firms affected by changes in non-compete enforceability (treated firms) might be different enough from other firms in unaffected states (control firms) such that this control group may not provide the best counterfactual. To alleviate this concern, I replicate the firm-level analyses using a matched sample based on industry and firm size. Specifically, for each treated firm, I select five control firms that are closest in size and in the same industry from unaffected firms one year prior to the policy change taking place to the treated firm. Panel B of Table IA2 reports similar results using this matched sample as those from the full sample. Thus, the estimated effects are unlikely to be confounded by the differences between treated and control firms.

Law-based Weakening of the Enforcement: Ewens and Marx (2018) point out one concern over the identification from new laws that weakened the enforceability of non-competes. Due to the forward-looking nature of laws, if these laws were applied only to prospective contracts, firms might be unwilling to update their agreements with existing employees, leaving the previous provisions unchanged and rendering a limited effect of these new laws.[31] There is only one such case during my sample period, which took place in Oregon. Though a small representation in the sample, I exclude firms in Oregon and find that results after this exclusion, reported in Table IA2 Panel C, remain quantitatively and qualitatively similar.

5.5.3 Alternative CNC Enforceability Indexes

I also use alternative indexes that measure the strength of state non-compete enforceability from Kini et al. (2019) and Ertimur et al. (2018) as a robustness check. Both studies follow Garmaise's approach closely to extend the data on enforceability scores for each state (see more detailed description of variable definitions in the Internet Appendix Table IA6). I rescale these scores to generate values ranging from 0 to 1 and estimate a specification similar to Equation (1). Table IA3 in the Internet Appendix shows negative coefficient estimates on the two enforceability indexes significant mostly at 1% level for all the outcome measures of patent value and efficiency. Thus, in the cross-section, firms in states with a higher non-compete enforceability are associated with lower patent value and value per input (i.e., capital and labor).[32]

5.5.4 Potential Firm Response

Do firms react to non-compete policy reforms by changing the locations of their innovation activities so that they can circumvent the value-destroying effect of a stronger enforcement? To investigate this possibility, I follow Bradley, Kim, and Tian (2017) to consider the locality of patents. Specifically, I ask whether a firm is more likely to produce patents out of state of headquarters after non-compete enforceability increases. The dependent variable is *Out-of-HQ patent*, an indicator equal to one if the patent is applied outside of the firm's HQ state. I then estimate Equation (2) to test the treatment effects at the patent level. Table IA5 in the Internet Appendix reports the results. In column (1), *CNC Enf. Up* has a positive estimated coefficient, which is insignificant, and *CNC Enf. Down* has a negative coefficient

[31] This is less of a concern for new laws that aim to strengthen the enforceability because firms have incentives to revise employee contracts in order to take advantage of the new law, especially in states where continued employment is the only consideration for a valid non-compete (Ewens and Marx 2018).

[32] I also replicate the results analyzed at the patent level with the two enforceability indexes and continue to find a robust negative relationship between non-compete enforceability and patent value. These results are reported in the Internet Appendix Table IA4.

significant at a 1% level. Column (2) reports a positive and significant coefficient on *Increased CNC Enf.* These results largely support the conjecture. Moreover, cross-sectional analysis in columns (3)-(4) shows positive and significant coefficients on non-compete enforceability indexes, suggesting that firms in states strongly enforcing non-competes are more likely to produce out-of-state patents. Overall, these results imply that firms may respond to non-compete policy reforms by shifting their innovation activities to states with a lower enforceability where workers have stronger innovation incentives.

6. CONCLUSION

Motivated by the contrasting effects of non-competes on firm incentives to invest and worker incentives to innovate, this paper investigates how changes in non-compete laws affect value creation in innovation, which further sheds light on investment efficiency. Exploiting staggered changes in state non-compete enforceability, I find that patents filed subsequent to a stronger enforcement create significantly less economic value, as they receive less positive stock market reactions when granted. Measures of innovation efficiency also exhibit deterioration after enforceability increases. Moreover, patents tend to be less exploratory, indicating that inventors explore less toward new areas and rely more on known areas of expertise inside their firm following a higher non-compete enforceability.

I attempt to explain this valuation loss from a behavioral perspective by analyzing inventor characteristics. I expect that inventors whose external opportunities are more weakened, who are in a weaker bargaining position, and who have greater incentives to move across firms are discouraged more by a stronger enforcement. Indeed, I find that higher enforceability reduces patent value more among inventors with higher skill specialization, lower innovation ability and in early patenting career, supporting the notion that non-competes dampen incentives to innovate by weakening worker outside options and bargaining power. These results also indicate that this disincentive effect dominates the incentive effect on firm investments, which implies that labor allocative inefficiency owing to mobility restrictions could compromise value creation from real investments.

Much has been discussed on the benefits of non-competes to firms. This paper is among one of the few studies that discover the costs on employers, which is underexplored in the extant literature. The only study that offers similar implications is Samila and Sorenson (2011), who find inefficiency in venture capital investment in states that strongly enforce non-competes. They suggest that non-compete laws matter for the effectiveness of government programs that attempt to stimulate such investment. In a broader view, stricter protection on intellectual property via constraining labor mobility may reduce efficiency by undermining the worker incentives and power that are vital to value creation.

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Table 1. Predictive Regressions

This table presents results examining whether a state's macroeconomic, political, and legal institutional conditions predict the reform of non-compete laws. The dependent variable is *CNC Enf. Down* in columns (1) and (2), *CNC Enf. Up* in columns (3) and (4), and *Increased CNC Enf.* in columns (5) and (6). *CNC Enf. Down* is an indicator equal to one if a state has decreased non-compete enforceability in the year. *CNC Enf. Up* is an indicator equal to one if a state has increased non-compete enforceability in the year. *Increased CNC Enf.* is a categorical variable that takes the value of one if a state has increased non-compete enforceability in the year, takes the value of negative one if a state has decreased non-compete enforceability in the year, and is set to zero otherwise. All predicting variables are lagged by one year. *State GDP Growth* is the annual state GDP growth rate. *Ln(State Unemployment)* is the natural logarithm of state's unemployment rate. *ln(State Population)* is the natural logarithm of total population in the state. *ln(Per Capita Personal Income)* is the natural logarithm of per capita personal income in the state. *State Labor Force (Pct.)* is the ratio of labor force over total population in the state. *State Republicans (Pct.)* is the ratio of Republican to Democrat legislators in state legislatures and government. *Inevitable Disclosure Doctrine* is an indicator equal to one for firms headquartered in states after the recognition of IDD in the year. *State UTSA (Trade Secrecy)* is an index that measures the strength of legal protection of trade secrets based on the effective UTSA and case law precedents. Details on variable construction are described in the Appendix. All regressions control for state and year fixed effects. The *t*-statistics in parentheses are based on robust standard errors clustered by state. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	CNC Enf. Down		CNC Enf. Up		Increased CNC Enf.	
State GDP Growth	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.999)	(0.984)	(0.109)	(0.124)	(-0.267)	(-0.249)
ln(State Unemployment)	-0.008	-0.008	-0.005	-0.007	0.002	0.002
	(-0.870)	(-0.992)	(-0.211)	(-0.274)	(0.095)	(0.066)
ln(Per Capita Personal Income)	-0.075	-0.079	-0.129	-0.132	-0.055	-0.053
	(-1.211)	(-1.295)	(-1.547)	(-1.512)	(-0.538)	(-0.500)
State Labor Force (Pct.)	-0.080	-0.076	0.051	0.061	0.132	0.138
	(-1.148)	(-1.053)	(0.141)	(0.168)	(0.365)	(0.380)
ln(State Population)	-0.007	-0.009	-0.006	-0.007	0.001	0.002
	(-0.242)	(-0.319)	(-0.081)	(-0.088)	(0.013)	(0.032)
State Republicans (Pct.)	-0.015	-0.015	-0.048	-0.057	-0.033	-0.042
	(-0.261)	(-0.253)	(-0.937)	(-1.062)	(-0.429)	(-0.530)
Inevitable Disclosure Doctrine		0.004		0.009		0.004
		(0.467)		(0.575)		(0.245)
State UTSA (Trade Secrecy)		-0.010		0.047		0.058
		(-1.031)		(0.902)		(1.131)
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	833	833	833	833	833	833
Adjusted R^2	0.1031	0.1011	0.0260	0.0259	0.0515	0.0508

Table 2. Summary Statistics

Panel A reports descriptive statistics of firm-level variables of interest for the main sample over 1992–2009. This sample comprises publicly traded U.S. industrial firms having at least one patent grant in any given year, having non-missing R&D expenditures in Compustat and with identifiable historical headquarters location information in SEC 10-K filings, a total of 14,585 firm-year observations. Panel B reports summary statistics for patent-level sample containing 537,021 observations, and Panel C for inventor characteristics at the patent-inventor level with 567,867 observations. *Patent Value* is the total market value of patents ($ millions) that a firm applied for in a given year. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *Patent Value per Inventor* is the total market value of patents applied for in the year divided by the number of inventors in the firm. *Noncompetition (CNC) Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *Noncompetition (CNC) Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that equals one for firms headquartered in states after an increase in non-compete enforceability, equals negative one for firms headquartered in states after a reduction in the enforceability, and is set to zero otherwise. All other variables are defined in the Appendix. All continuous variables are winsorized at their 1st and 99th percentiles. Dollar values are CPI-adjusted in 2016 dollars.

Variable	Mean	S.D.	25th Percentile	Median	75th Percentile
A. Firm Level					
Patent Value ($mil)	1741.035	10162.000	4.481	23.590	199.301
Patent Value/Assets	0.178	0.267	0.026	0.073	0.203
Patent Value/R&D stock	1.935	3.413	0.207	0.661	1.962
Patent Value per Inventor	11.317	24.142	1.056	3.337	10.165
Noncompetition (CNC) Enf. Up	0.018	0.132	0.000	0.000	0.000
Noncompetition (CNC) Enf. Down	0.040	0.197	0.000	0.000	0.000
Increased CNC Enf.	-0.023	0.227	0.000	0.000	0.000
Assets ($mil)	3891.670	25771.000	54.838	212.312	1119.518
Leverage	0.161	0.165	0.007	0.117	0.268
Age	18.575	14.548	7.000	13.000	26.000
MktBk	2.538	2.219	1.234	1.763	2.923
Cash Flow	-0.011	0.245	-0.037	0.071	0.121
Tangibility	0.208	0.162	0.084	0.170	0.290
R&D/Assets	0.102	0.123	0.019	0.058	0.132
State Industry HHI	0.390	0.266	0.185	0.300	0.532
State GDP Growth	0.053	0.032	0.037	0.053	0.072
State Unemployment	5.651	1.650	4.575	5.375	6.417
Inevitable Disclosure Doctrine (IDD)	0.517	0.500	0.000	1.000	1.000
B. Patent Level					
Patent Value/Assets (%)	0.784	1.921	0.037	0.149	0.581
Exploratory 90%	0.276	0.447	0.000	0.000	1.000
Exploratory Ratio	0.577	0.351	0.250	0.619	0.933
Backward Self-cites	0.151	0.220	0.000	0.048	0.226
Forward Self-cites	0.139	0.242	0.000	0.000	0.188
C. Inventor Patent Level					
Patent Value/Assets (%)	1.032	2.252	0.053	0.223	0.837
Inventor Specialization	0.497	0.323	0.240	0.444	0.755
Fraction of Uncited Patents	0.085	0.170	0.000	0.000	0.100
Inventor Past Productivity	11.299	26.279	1.000	4.000	11.000
Inventors of the Patent	3.621	3.035	2.000	3.000	5.000
Inventor Patent Experience (years)	7.317	7.243	2.000	5.000	11.000
Inventor Network Size	17.170	20.387	5.000	11.000	22.000
Firm Knowledge Specialization	0.231	0.249	0.063	0.126	0.285

Table 3. Noncompete Enforceability and Patent Value

This table presents the regression results examining the effect of changes in CNC enforceability on patent market value at the firm level. The dependent variable is *ln(Patent Value)* in columns (1)-(2) and is *Patent Value/Assets* in columns (3)-(4). *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that takes the value of one for firms headquartered in states after an increase in non-compete enforceability, takes the value of negative one for firms headquartered in states after a reduction in non-compete enforceability, and is set to zero otherwise. All control variables are measured in year $t - 1$ and defined in the Appendix. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The sample includes firms granted at least one patent during a given year. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ln(Patent Value)		Patent Value/Assets	
CNC Enf. Up	**-0.383*** **		**-0.058***	
	(-3.587)		**(-1.759)**	
CNC Enf. Down	**0.272*** **		**0.069*** **	
	(3.215)		**(5.753)**	
Increased CNC Enf.		**-0.309*** **		**-0.065*** **
		(-4.625)		**(-5.689)**
Size	0.872***	0.872***	0.045***	0.045***
	(32.434)	(32.431)	(5.757)	(5.829)
Leverage	-0.591***	-0.590***	-0.077***	-0.077***
	(-4.959)	(-4.932)	(-2.833)	(-2.823)
ln(age)	0.077	0.077	0.031**	0.031**
	(1.267)	(1.263)	(2.253)	(2.267)
MktBk	0.166***	0.166***	0.032***	0.032***
	(20.694)	(20.700)	(14.247)	(14.230)
Cash Flow	0.026	0.026	-0.047*	-0.047*
	(0.327)	(0.326)	(-1.946)	(-1.944)
Tangibility	0.184	0.185	0.053	0.053
	(1.187)	(1.194)	(1.298)	(1.295)
R&D/Assets	1.311***	1.308***	0.214***	0.214***
	(10.070)	(10.046)	(5.134)	(5.131)
State Industry HHI	0.032	0.034	0.015	0.015
	(0.278)	(0.295)	(0.581)	(0.578)
State GDP Growth	1.980**	1.988**	0.498***	0.498***
	(2.122)	(2.104)	(2.731)	(2.698)
ln(State Unemployment)	0.008	0.008	-0.001	-0.001
	(0.081)	(0.092)	(-0.037)	(-0.041)
IDD	-0.051	-0.049	-0.001	-0.001
	(-1.100)	(-1.102)	(-0.108)	(-0.130)
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	14585	14585	14585	14585
Adjusted R^2	0.9335	0.9335	0.6514	0.6514

Table 4. R&D Efficiency and Inventor Value Creation

This table presents the regression results examining the effect of changes in CNC enforceability on productivity of R&D investment and inventors based on subsequent patent market value. The dependent variable is *Patent Value/R&D Stock* in columns (1)-(2) and is *ln(Patent Value per Inventor)* in columns (3)-(4). *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that takes the value of one for firms headquartered in states after an increase in non-compete enforceability, takes the value of negative one for firms headquartered in states after a reduction in non-compete enforceability, and is set to zero otherwise. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, R&D/Assets* (not in columns 1-2), *State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* which are measured in year $t-1$. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The sample includes firms granted at least one patent during a given year. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	Patent Value/R&D Stock		ln(Patent Value per Inventor)	
CNC Enf. Up	**-2.037*****		**-0.162*****	
	(-3.749)		**(-3.080)**	
CNC Enf. Down	**1.563*****		**0.232*****	
	(4.386)		**(4.442)**	
Increased CNC Enf.		**-1.721*****		**-0.209*****
		(-7.962)		**(-4.733)**
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	9751	9751	9631	9631
Adjusted R^2	0.7028	0.7028	0.7174	0.7174

Table 5. Decomposing Inefficiency

This table presents the regression results examining the effect of changes in CNC enforceability on R&D investment and inventor turnover. The dependent variable in Panel A is a firm's *R&D-to-assets* ratio. In Panel B, the dependent variables are *ln(New Hires)* and *ln(Leavers)*. *ln(New Hires)* is the natural logarithm of one plus the number of newly joined inventors in the firm. *ln(Leavers)* is the natural logarithm of one plus the number of inventors leaving the firm. *CNC Enf. Up* is an indicator equal to one for firms in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms in states after a lower enforceability. *Increased CNC Enf.* is a variable equal to one for firms in states after increased enforceability, equal to negative one for firms in states after decreased enforceability, and is set to zero otherwise. *Closer Tech Space* is an indicator equal to one for firms with above-median technology spillovers every year. *More Knowledge Workers* is an indicator equal to one for firms in knowledge worker intensive industries. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, R&D/Assets* (not in Panel A), *State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* all measured in year $t-1$. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Capital Allocation—R&D Investment

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	R&D/Assets				
CNC Enf. Up	**0.026*** **	**0.023*** **		0.009	-0.007
	(3.538)	**(3.556)**		(0.692)	(-0.734)
CNC Enf. Down	**0.014*** **	**0.019*** **		0.013***	0.019***
	(5.550)	**(9.528)**		(3.594)	(3.188)
Increased CNC Enf.			-0.005		
			(-0.388)		
CNC Enf. Down				**0.007***	
× Closer Tech Space				**(1.713)**	
CNC Enf. Up				0.018	
× Closer Tech Space				(1.569)	
Closer Tech Space				-0.002	
				(-0.796)	
CNC Enf. Down					-0.004
× More Knowledge Workers					(-0.699)
CNC Enf. Up					**0.021*** **
× More Knowledge Workers					**(3.601)**
More Knowledge Workers					0.002
					(0.974)
Controls	No	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes	Yes
N	14583	14583	14583	14455	14583
Adjusted R^2	0.7769	0.7933	0.7931	0.7938	0.8089

Panel B. Labor Reallocation--Inventor Turnover

	(1)	(2)
Dependent Variable:	ln(New Hires)	ln(Leavers)
CNC Enf. Up	**-0.129*** **	**-0.126*** **
	(-4.961)	**(-2.767)**
CNC Enf. Down	**0.107*** **	0.006
	(3.277)	(0.060)
Controls	Yes	Yes
Firm FEs	Yes	Yes
State FEs	Yes	Yes
Industry × Year FEs	Yes	Yes
N	9630	9630
Adjusted R^2	0.6348	0.6924

Table 6. Evidence from Patent Location at the Patent Level

This table presents the regression results examining the effect of changes in CNC enforceability on subsequent patent value at the patent level. The dependent variable is the market value of a new patent scaled by the firm's book assets, multiplied by 100. Columns (1) and (3) report results for the full sample, columns (2) and (4) for a subsample including patents filed in the firm's state of headquarters, column (5) for patents filed outside of the firm's headquarters state. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that takes the value of one for firms headquartered in states after an increase in non-compete enforceability, takes the value of negative one for firms headquartered in states after a reduction in non-compete enforceability, and is set to zero otherwise. Control variables include *Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* which are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, technology class × year, and state of headquarters fixed effects. Column (5) additionally includes assignee state fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	(Patent Value/Assets) × 100				
Sample	All Patents	HQ Patents	All Patents	HQ Patents	Out-of-HQ Patents
CNC Enf. Up	**-0.367****	**-0.410****			-0.351
	(-2.358)	**(-2.205)**			(-1.251)
CNC Enf. Down	**0.538*****	**0.654*****			0.136**
	(5.492)	**(5.868)**			(2.104)
Increased CNC Enf.			**-0.511*****	**-0.606*****	
			(-5.990)	**(-6.489)**	
Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
HQ State FEs	Yes	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes	Yes
Assignee State FEs	No	No	No	No	Yes
N	537021	447598	537021	447598	73639
Adjusted R^2	0.6317	0.6388	0.6316	0.6387	0.7238

Table 7. Exploratory Innovations

This table presents the regression results examining the effect of changes in CNC enforceability on the exploratory nature of innovation at the patent level. The dependent variables across the columns are *Exploratory 90%, Exploratory Ratio, Purely Exploratory, Backward Self-cites*, and *Forward Self-cites*, respectively. *Exploratory 90%* is an indicator equal to one if at least 90% of the patent's backward citations are based on new knowledge coming outside of the firm's existing knowledge base, which consists of all patents granted to the firm and patents cited by the firm in the past five years. *Exploratory Ratio* is the fraction of the patent's backward citations based on new knowledge coming outside of the firm's existing knowledge base. *Purely Exploratory* is an indicator equal to one if the patent does not cite any previous patents owned by the same assignee. *Backward Self-cites* is the ratio of citations made to patents owned by the same assignee over total citations made by the patent. *Forward Self-cites* is the ratio of self-citations received by the patent over total citations received. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. Control variables include *Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* which are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, technology class × year, and state of headquarters fixed effects. The sample includes patents filed in the firm's state of headquarters. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Exploratory 90%	Exploratory Ratio	Purely Exploratory	Backward Self-cites	Forward Self-cites
CNC Enf. Up	**-0.123*** **	**-0.068*** **	**-0.146*** **	**0.028** **	**0.077*** **
	(-4.983)	**(-2.925)**	**(-4.763)**	**(2.171)**	**(9.629)**
CNC Enf. Down	**0.041*** **	**0.055*** **	**0.054*** **	**-0.022*** **	-0.000
	(3.412)	**(3.893)**	**(3.054)**	**(-4.422)**	(-0.023)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes	Yes
N	421525	421525	424393	424393	355555
Adjusted R^2	0.1617	0.2200	0.1497	0.1629	0.1608

Table 8. Channel Tests: Evidence from Inventors

This table presents the regression results examining the differential effect of changes in CNC enforceability on patent value produced by inventors with greater skill specialization (columns 1-2), inventors with lower innovation ability (columns 3-4), and inventors who are relatively young in their innovation careers (columns 5-6). The dependent variable is the market value of a new patent scaled by the firm's book assets, multiplied by 100. *Specialized Inventor* is an indicator equal to one if the inventor's *skill specialization* is ranked above the sample median every year. *Inventor Skill Specialization* is an Herfindahl-Hirschman concentration measure based on the share of patents in each three-digit technology class among all the patents that the inventor has filed in the past five years. *More Uncited Patents* is an indicator equal to one if the cumulative fraction of uncited patents in the inventor's patent portfolio is greater than the sample median every year. *Young Inventor* is an indicator equal to one if number of years since the inventor's first patent application is in the bottom quartile of the sample every year. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms in states after a reduction in the enforceability. *Increased CNC Enf.* is a categorical variable equal to one for firms in states after an increase in the enforceability, equal to negative one for firms in states after a reduction in the enforceability, and zero otherwise. All regressions include controls—*Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD*. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	(Patent Value/Assets) × 100					
CNC Enf. Up	**-0.282*** **					
× Specialized Inventor	**(-4.966)**					
CNC Enf. Down	0.024*					
× Specialized Inventor	(1.956)					
Increased CNC Enf.		**-0.033** **				
× Specialized Inventor		**(-2.134)**				
CNC Enf. Up			**-0.241*** **			
× More Uncited Patents			**(-3.872)**			
CNC Enf. Down			0.088			
× More Uncited Patents			(1.566)			
Increased CNC Enf.				**-0.098***		
× More Uncited Patents				**(-1.750)**		
CNC Enf. Up					**-0.759*** **	
× Young Inventor					**(-9.600)**	
CNC Enf. Down					-0.023	
× Young Inventor					(-0.316)	
Increased CNC Enf.						-0.037
× Young Inventor						(-0.407)
Firm Knowledge Specialization	0.324	0.326	0.325	0.327	0.321	0.325
	(1.365)	(1.378)	(1.373)	(1.382)	(1.357)	(1.384)
ln(Inventor past productivity)	0.011	0.011	0.013	0.013	0.012	0.012
	(0.461)	(0.467)	(0.527)	(0.530)	(0.485)	(0.496)
ln(Inventors of the Patent)	0.026***	0.026***	0.026***	0.026***	0.026***	0.026***
	(3.085)	(3.078)	(2.946)	(2.941)	(3.056)	(3.059)
ln(Inventor Patent Experience)	-0.040	-0.040	-0.036	-0.037	-0.034	-0.035
	(-1.421)	(-1.423)	(-1.332)	(-1.333)	(-1.532)	(-1.594)
ln(Inventor Network Size)	-0.030	-0.030	-0.029	-0.029	-0.028	-0.029
	(-1.060)	(-1.068)	(-0.998)	(-1.000)	(-0.991)	(-1.012)
All other controls	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	567808	567808	567808	567808	567808	567808
Adjusted R^2	0.6587	0.6590	0.6915	0.6915	0.6915	0.6914

Table 9. The Role of Employee Incentives

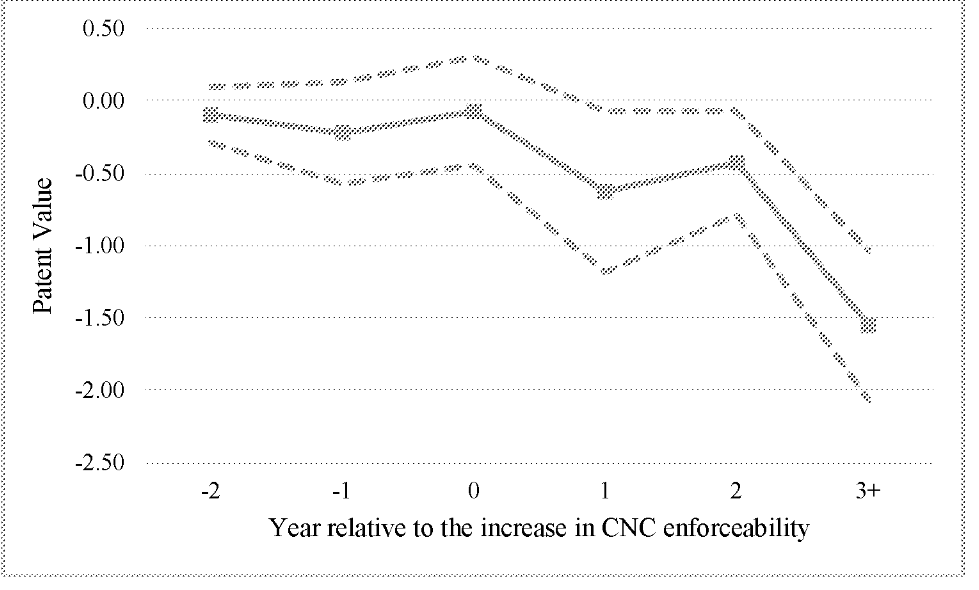
This table presents the regression results examining the differential effect of changes in CNC enforceability on patent value and innovation efficiency when employee incentives are more important to the firm. The dependent variables across columns are *ln(Patent Value), Patent Value/Assets, Patent Value/R&D Stock*, and *ln(Patent Value per Inventor)*, respectively. *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. *High Employee Options* is an indicator equal to one if the per-employee Black-Scholes value of non-executive stock options is above the sample median every year. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. All control variables are measured in year $t-1$ and are included in the regressions but not reported. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The sample includes firms granted at least one patent during a given year. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	(1) ln(Patent Value)	(2) Patent Value/Assets	(3) Patent Value/R&D Stock	(4) ln(Patent Value per Inventor)
CNC Enf. Up	**-0.314*** **	**-0.098*** **	**-1.389*** **	**-0.448*** **
× High Employee Options	**(-3.939)**	**(-6.395)**	**(-3.904)**	**(-5.547)**
CNC Enf. Down	**0.203***	**0.054*** **	**1.029*** **	**0.511*** **
× High Employee Options	**(1.892)**	**(3.641)**	**(3.285)**	**(6.127)**
High Employee Options	0.165***	0.031***	0.437***	0.135***
	(5.363)	(4.636)	(3.380)	(3.327)
CNC Enf. Up	-0.039	-0.015	-0.757**	0.128
	(-0.297)	(-0.493)	(-2.146)	(1.591)
CNC Enf. Down	0.136	0.064***	1.314**	-0.141
	(1.124)	(5.425)	(2.507)	(-1.036)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	5328	5328	4218	4874
Adjusted R^2	0.9342	0.7541	0.7428	0.6898

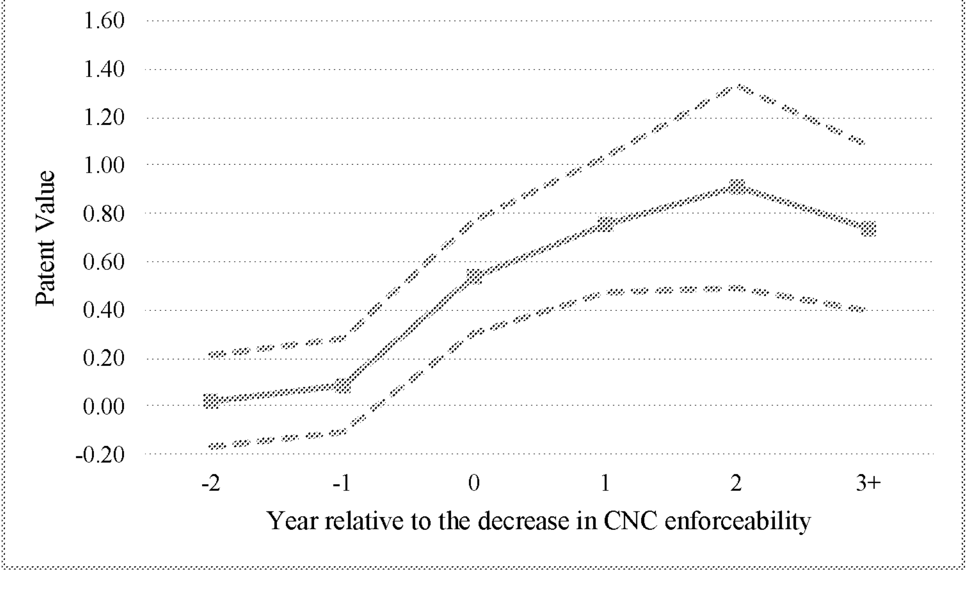
Figure 1. Dynamic Effects of Changes in CNC Enforceability on Patent Value

This figure shows the timing of the effect of changes in CNC enforceability on patent value at the patent level by estimating a dynamic DID regression. The dependent variable is the market value of a new patent over the firm's book assets, multiplied by 100. Panel A examines the dynamic effects of strengthening enforceability by estimating a DID specification in which *CNC Enf. Up* is replaced with *CNC Enf. Up* $^{-2}$, *CNC Enf. Up* $^{-1}$, *CNC Enf. Up* ^{0}, *CNC Enf. Up* $^{+1}$, *CNC Enf. Up* $^{+2}$, and *CNC Enf. Up* $^{3+}$, which takes the value of one during two-year prior to, one-year prior to, current year, one-year post to, two-year post to, and three-year after, respectively, the increase of CNC enforceability in the state of the firm's headquarters, and is zero otherwise. This sample excludes patents affected by a decrease in the enforceability. Similarly, Panel B presents the estimation results of replacing *CNC Enf. Down* with *CNC Enf. Down* $^{-2}$, *CNC Enf. Down* $^{-1}$, *CNC Enf. Down* ^{0}, *CNC Enf. Down* $^{+1}$, *CNC Enf. Down* $^{+2}$, and *CNC Enf. Down* $^{3+}$, which takes the value of one during two-year prior to, one-year prior to, current year, one-year post to, two-year post to, and three-year after, respectively, the reduction of CNC enforceability in the state of the firm's headquarters, and is zero otherwise. This sample excludes patents affected by an increase in the enforceability. Dash lines represent the 95% confidence intervals based on robust standard errors clustered by the firm's state of headquarters.

Panel A. CNC Enforceability Up



Panel B. CNC Enforceability Down



Appendix A. Variable Definitions

Variable	Description
A. Firm-level	
Patent Value	Total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date, converted into 2016 dollars; source: Kogan, Papanikolaou, Seru, and Stoffman (2017)
Patent Value/Assets	Total market value of patents applied for by a firm in the year scaled by the firm's book assets (AT).
Patent Value/R&D stock	Total market value of patents applied for by a firm in the year divided by past R&D stock from years $t-2$ to $t-6$ with a 20% depreciation rate, akin to the innovation efficiency measures developed by Hirshleifer, Hsu, and Li (2013).
Patent Value Per Inventor	Total market value of patents applied for by a firm in the year divided by the number of inventors in the firm. Data on inventor are obtained from Harvard Patent Network Dataverse (Li et al. 2014) available at https://dataverse.harvard.edu/dataverse/patent
R&D/Assets	The ratio of R&D expenditures (XRD) to book assets (AT) of the firm
Noncompetition (CNC) Enf. Down	An indicator equal to one for firms headquartered in states after a reduction in Noncompetition enforceability, and zero otherwise; source: Garmaise (2011) and Ewens and Marx (2018). Information on firm historical headquarters location is extracted from Securities and Exchange Commission (SEC) 10-K filings in the EDGAR database.
Noncompetition (CNC) Enf. Up	An indicator equal to one for firms headquartered in states after an increase in Noncompetition enforceability, and zero otherwise; source: Garmaise (2011) and Ewens and Marx (2018).
Increased CNC Enf.	A categorical variable that takes the value of one for firms headquartered in states after an increase in Noncompetition enforceability, takes the value of negative one for firms headquartered in states after a reduction in Noncompetition enforceability, and is set to zero otherwise.
Size	Natural Logarithm of the firm's book assets (AT), converted into 2016 dollars.
Leverage	The ratio of long-term debt (DLTT) plus debt in current liabilities (DLC) to total assets (AT).
Age	Number of years the firm is listed with a non-missing stock price on COMPUSTAT.
MktBk	The ratio of total assets (AT) minus book value of common equity (CEQ) plus the market value of common equity (PRCC_F × CSHO) over total assets (AT).
Cash Flow	Operating income before depreciation (OIBDP), less interest (XINT) and taxes (TXT), scaled by total assets (AT).
Cash Holdings	The ratio of cash plus marketable securities (CHE) over book assets (AT).
Tangibility	The ratio of total net property, plant, and equipment (PPENT) over total assets (AT).
State Industry HHI	Sales-based Herfindahl-Hirschman Index within firms in the same two-digit SIC industry and headquartered in the same state.
State GDP Growth	Annual state GDP growth rate; source: Bureau of Economic Analysis (BEA)
ln(State Unemployment)	Natural logarithm of state unemployment rate; source: US Bureau of Labor Statistics.

Inevitable Disclosure Doctrine (IDD)	An indicator equal to one for firms headquartered in states after a recognition of Inevitable Disclosure Doctrine (IDD); source: Klasa et al. (2018)
ln(Per Capita Personal Income)	Natural logarithm of per capita personal income (dollars) in the state; source: Bureau of Economic Analysis (BEA)
State Labor Force (Pct.)	the ratio of labor force over total population in the state; source: Bureau of Economic Analysis (BEA)
Ln(State Population)	the natural logarithm of total population in the state; source: Bureau of Economic Analysis (BEA)
State Republicans (Pct.)	the ratio of Republican to Democrat legislators in state legislatures and government. Nebraska is not included because members are elected on a nonpartisan basis. Data are obtained from the National Conference of State Legislatures and Book of the States.
State UTSA (Trade Secrecy)	an index that measures the strength of legal protection of trade secrets based on the effective UTSA and case law precedents; source: Png (2017)
Closer Tech Space	an indicator equal to one for firms with above-median technology spillovers every year using the measure based on a firm's position in technology space from Bloom et al. (2013).
Industry-level Knowledge Workers	the fraction of managers and professional workers employed in an industry at the 3-digit SIC code level before 2001 and at the 4-digit NAICS code level afterwards. Data on employment estimates are obtained from the Occupational Employment Statistics (OES) survey from the Bureau of Labor Statistics. The OES provides detailed breakdown of the total number of people employed in each industry by the occupational code. Because OES used its own taxonomy (with 258 broad occupations) before 1998, managerial occupations take codes from 10,000 to 19,999, and professional workers are assigned with occupational codes under the major group of 20,000, which includes scientists, engineers, technologists, heath practitioners, accountants, editors, computer programmers, and so forth. In 1999, the OES changed the occupation definitions to Standard Occupational Classification (SOC) system (with 444 broad occupations). Thus, from 1999 onward, managerial occupations are in the major group of 11-0000; professional workers are in the major groups with the first two digits of 13, 15, 17, 19, 21, 23, 25, 27, 29, followed by 0000. The OES data is available at https://www.bls.gov/oes/tables.htm.
More Knowledge Workers	An indicator equal to one for firms in knowledge worker intensive industries, defined as industries with the fraction of managers and professional workers above the median level across all industries every year.
ln(New Hires)	Natural logarithm of one plus the number of newly joined inventors in the firm
ln(Leavers)	Natural logarithm of one plus the number of inventors leaving the firm
High Employee Options	An indicator equal to one if the firm's option value per employee is above sample median every year. Option value per employee is the value of options granted to nonexecutive employees divided by the number of employees. Option value is estimated by Black-Scholes option pricing model. source: ExecuComp and IRRC
B. Patent Level	
Patent Value/Assets (%)	Market value of the patent scaled by the firm's book assets (AT), multiplied by 100.
Exploratory 90%	An indicator equal to one if at least 90% of the patent's backward citations are based on new knowledge coming outside of the firm's existing knowledge base, which consists of all patents granted to the firm and patents cited by the firm in the past five years.

Exploratory Ratio	Fraction of the patent's backward citations based on new knowledge coming outside of the firm's existing knowledge base.
Purely Exploratory	An indicator equal to one if the patent does not cite any previous patents owned by the same assignee.
Backward self-cites	the ratio of citations made to patents owned by the same assignee over total citations made by the patent
Forward self-cites	the ratio of self-citations received by the patent over total citations received
C. Inventor-patent Level	
Inventor Skill Specialization	Herfindahl-Hirschman concentration measure based on the share of patents in each three-digit technology class among all the patents that the inventor has filed in the past five years, following Marx, Strumsky, and Fleming (2009).
Specialized Inventor	An indicator equal to one if the inventor's skill specialization is above the sample median every year.
Fraction of Uncited Patents	Share of uncited patents in the inventor's patent portfolio, calculated as the cumulative number of uncited patents divided by the total number of patents that the inventor has produced up to a given year.
More Uncited Patents	An indicator equal to one if the inventor's cumulative share of uncited patents is above the sample median every year.
Young Inventor	An indicator equal to one if the number of years since the inventor's first applied patent (and eventually granted) is in the bottom quartile of the sample every year
Inventor past productivity	Total number of patents applied by the inventor (and eventually granted) in the past five years.
Inventors of the Patent	Number of coinventors on the patent
Inventor Patent Experience (years)	Number of years since the inventor's first filed and granted patent
Inventor Network Size	Cumulative number of unique coinventors on all prior patents filed by (and eventually granted to) the inventor.
Firm Knowledge Specialization	Herfindahl-Hirschman Index sum of squared percentages of patents within three-digit technology classes filed by the firm over the past five years. Information on primary technology classes for all patents is obtained from National Bureau of Economic Research (NBER) and Harvard Business School (HBS) Patent files.

Internet Appendix for

“Motivating Inventors: Non-competes, Innovation Value and Efficiency”

Table IA1. Patent and Citation Counts

This table presents the regression results examining the effect of changes in CNC enforceability on patent and citation counts at the firm level. The dependent variables across columns are *ln(patents)*, *ln(cite-weighted patents),* and *ln(cites)*, respectively. *ln(patents)* is the natural logarithm of one plus total number of patents applied for by the firm during the year. *ln(cite-weighted patents)* is the natural logarithm of one plus total number of citation weighted patent counts during the year; weight for each patent is calculated as the number of future citations divided by the average number of citations received by patents in the same technology class and year. *ln(cites)* is the natural logarithm of one plus total number of citations received by the patents applied for by the firm in the year. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. All control variables are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, industry × year, and state of headquarters fixed effects. The sample includes firms granted at least one patent during a given year. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) ln(patents)	(2) ln(cite-weighted patents)	(3) ln(cites)
CNC Enf. Up	-0.311***	-0.202**	-0.156
	(-2.845)	(-2.119)	(-1.555)
CNC Enf. Down	0.110	0.076	0.006
	(0.930)	(0.639)	(0.048)
Size	0.370***	0.388***	0.410***
	(10.869)	(11.541)	(9.353)
Leverage	-0.089	-0.112	-0.156
	(-1.191)	(-1.248)	(-1.601)
ln(age)	0.050	-0.087	-0.103
	(0.732)	(-0.953)	(-0.987)
MktBk	0.010***	0.019***	0.023**
	(3.037)	(3.299)	(2.584)
Cash Flow	-0.175**	-0.131*	-0.137
	(-2.523)	(-1.804)	(-1.198)
Tangibility	0.400**	0.286	0.164
	(2.323)	(1.517)	(0.734)
R&D/Assets	0.952***	1.178***	1.370***
	(6.926)	(7.402)	(6.225)
State Industry HHI	0.003	0.041	0.022
	(0.034)	(0.393)	(0.176)
State GDP Growth	0.516	0.265	0.576
	(0.847)	(0.381)	(0.499)
ln(State Unemployment)	-0.162	-0.177	-0.180
	(-1.366)	(-1.443)	(-1.203)
IDD	0.003	0.017	0.057
	(0.061)	(0.285)	(0.825)
Firm FEs	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes
N	14585	14585	14585
Adjusted R^2	0.8616	0.8142	0.7955

Table IA2. Identification Tests

This table presents the regression results examining the effect of changes in CNC enforceability on innovation value and efficiency. Panel A displays results after excluding firms that relocated their headquarters during the sample period. Panel B reports results using a matched sample in which treated and control firms are required to be in the same industry and close in firm size. Panel C shows results after excluding firms experiencing law-based weakening of non-compete enforceability in Oregon. In each panel, the dependent variables across columns are *ln(Patent Value), Patent Value/Assets, Patent Value/R&D Stock*, and *ln(Patent Value per Inventor)*, respectively. *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, State Industry HHI, State GDP Growth, ln(State Unemployment), IDD* and *R&D/Assets*. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Exclude Headquarters Relocations

Dependent Variable:	(1) ln(Patent Value)	(2) Patent Value/Assets	(3) Patent Value/R&D Stock	(4) ln(Patent Value per Inventor)
CNC Enf. Up	-0.434***	-0.059*	-1.976***	-0.244***
	(-4.189)	(-1.685)	(-3.567)	(-4.924)
CNC Enf. Down	0.235***	0.071***	1.724***	0.243***
	(3.354)	(4.518)	(5.540)	(5.153)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	12915	12915	8619	8441
Adjusted R^2	0.9337	0.6542	0.7066	0.7122

Panel B. Matched Sample

Dependent Variable:	(1) ln(Patent Value)	(2) Patent Value/Assets	(3) Patent Value/R&D Stock	(4) ln(Patent Value per Inventor)
CNC Enf. Up	-0.322***	-0.058**	-2.104***	-0.232***
	(-3.256)	(-2.137)	(-4.137)	(-4.058)
CNC Enf. Down	0.230***	0.076***	1.940***	0.263***
	(3.338)	(4.637)	(8.740)	(5.131)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	4051	4051	3151	2828
Adjusted R^2	0.9428	0.6745	0.7410	0.7567

Panel C. Exclude Oregon

Dependent Variable:	(1) ln(Patent Value)	(2) Patent Value/Assets	(3) Patent Value/R&D Stock	(4) ln(Patent Value per Inventor)
CNC Enf. Up	-0.376***	-0.058*	-2.044***	-0.164***
	(-3.501)	(-1.767)	(-3.753)	(-3.187)
CNC Enf. Down	0.229***	0.067***	1.744***	0.227***
	(3.807)	(4.801)	(7.472)	(4.333)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	14374	14374	9602	9490
Adjusted R^2	0.9339	0.6511	0.7025	0.7184

Table IA3. Alternative CNC Enforceability Indexes

This table presents robustness checks using alternative CNC enforceability indexes. Panel A displays results using enforceability scores from Kini et al. (2019). Panel B shows results employing enforceability index of Ertimur et al. (2018). In each panel, the dependent variables across columns are *ln(Patent Value), Patent Value/Assets, Patent Value/R&D Stock*, and *ln(Patent Value per Inventor)*, respectively. *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, State Industry HHI, State GDP Growth, ln(State Unemployment), IDD* and *R&D/Assets*. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Kini et al. (2019) CNC index

	(1)	(2)	(3)	(4)
Dependent Variable:	ln(Patent Value)	Patent Value/Assets	Patent Value/R&D Stock	ln(Patent Value per Inventor)
CNC Enf. Index	-1.051***	-0.307***	-6.866***	-0.933***
	(-3.055)	(-4.280)	(-8.429)	(-4.593)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	14585	14585	9750	9630
Adjusted R^2	0.9335	0.6515	0.7025	0.7174

Panel B. Ertimur et al. (2018) CNC index

	(1)	(2)	(3)	(4)
Dependent Variable:	ln(Patent Value)	Patent Value/Assets	Patent Value/R&D Stock	ln(Patent Value per Inventor)
CNC Enf. Index'	-1.085***	-0.203**	-6.228***	-0.852***
	(-4.289)	(-2.269)	(-3.403)	(-3.652)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	14584	14584	9749	9630
Adjusted R^2	0.9335	0.6515	0.7028	0.7174

Table IA4. Alternative CNC Enforceability Indexes (Patent Level)

This table presents the regression results examining the effect of changes in CNC enforceability on patent market value at the patent level using alternative CNC enforceability indexes. The dependent variable is the market value of a new patent scaled by the firm's book assets, multiplied by 100. Columns (1) and (4) report results for the full sample, columns (2) and (5) for the subsample including patents filed in the firm's state of headquarters, columns (3) and (6) for patents filed outside of the firm's headquarters state. *CNC Enf Index* is the enforceability scores from Kini et al. (2019). *CNC Enf Index'* is the enforceability index of Ertimur et al. (2018). All control variables are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, technology class × year, and state of headquarters fixed effects. Columns (3) and (6) additionally include assignee state fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	(Patent Value/Assets) × 100					
Sample	All Patents	HQ Patents	Out of HQ	All Patents	HQ Patents	Out of HQ
CNC Enf Index	-2.412***	-2.847***	-0.646**			
	(-7.366)	(-7.960)	(-2.331)			
CNC Enf Index'				-2.405***	-2.885***	-0.668**
				(-6.455)	(-7.684)	(-2.317)
Size	-1.608***	-1.772***	-0.792***	-1.608***	-1.773***	-0.792***
	(-8.084)	(-8.892)	(-4.495)	(-8.115)	(-8.932)	(-4.498)
MktBk	0.104***	0.087***	0.135***	0.105***	0.087***	0.135***
	(5.056)	(3.595)	(3.323)	(5.065)	(3.596)	(3.320)
R&D/Assets	2.325***	2.306***	1.496**	2.303***	2.278***	1.498**
	(3.326)	(3.755)	(2.113)	(3.311)	(3.708)	(2.120)
State Industry HHI	0.882*	0.565	0.459	0.885*	0.567	0.458
	(1.699)	(1.579)	(1.493)	(1.692)	(1.568)	(1.487)
State GDP Growth	0.165	-0.533	0.977	0.120	-0.588	0.979
	(0.160)	(-0.453)	(1.522)	(0.116)	(-0.498)	(1.526)
ln(State Unemployment)	-0.349	-0.341	-0.163	-0.335	-0.325	-0.160
	(-1.350)	(-1.049)	(-1.094)	(-1.299)	(-1.002)	(-1.080)
IDD	0.144***	0.104	0.173**	0.156***	0.118	0.176***
	(2.734)	(1.057)	(2.667)	(3.045)	(1.216)	(2.707)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
HQ State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Assignee State FEs	No	No	Yes	No	No	Yes
N	537021	447598	73639	536962	447540	73639
Adjusted R^2	0.6317	0.6388	0.7238	0.6317	0.6388	0.7238

Table IA5. Potential Firm Responses to Changes in Enforceability

This table presents the regression results examining the effect of changes in CNC enforceability on the likelihood of developing innovations outside of the firm's headquarters. The dependent variable is an indicator equal to one if the patent is filed outside of the firm's state of headquarters. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that takes the value of one for firms headquartered in states after an increase in non-compete enforceability, takes the value of negative one for firms headquartered in states after a reduction in non-compete enforceability, and is set to zero otherwise. *CNC Enf Index* is the enforceability scores from Kini et al. (2019). *CNC Enf Index'* is the enforceability index of Ertimur et al. (2018). Control variables include *Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* which are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, technology class × year, and state of headquarters fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	Out-of-HQ Patent			
CNC Enf. Up	0.038			
	(0.987)			
CNC Enf. Down	**-0.073*** **			
	(-3.257)			
Increased CNC Enf.		**0.067*** **		
		(4.422)		
CNC Enf Index			**0.280*** **	
			(4.989)	
CNC Enf Index'				**0.296*** **
				(4.387)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes
N	546919	546919	546919	546860
Adjusted R^2	0.6030	0.6030	0.6030	0.6030

Appendix IA6. Variable Definitions

Variable	Description
CNC Enf. Index	CNC enforceability scores from Kini et al. (2019), who follow Garmaise's methodology and updated the index based on his thresholds by using annual state-by-state survey of employee non-competes from a law firm, Beck Reed Riden LLP, for the period of 2005-2014. The scores are rescaled to range from 0 to 1.
CNC Enf. Index'	CNC enforceability scores from Ertimur et al. (2018), who also extend the enforceability index following Garmaise (2011). They obtained Garmaise's answers to the individual twelve questions analyzed in Malsberger (2004), which served as the basis for the index. They appointed three law students with experience in analyzing employment contracts to perform this task. As described in their Internet Appendix, these law students first need to replicate the index for 2004 using information in Malsberger (2004) and following the detailed process outlined by Garmaise (2011). After learning the construction process and correcting errors if they have made during the replication, the students were provided with Malsberger (2013) to extend the index to 2013. The scores are rescaled to range from 0 to 1.
Out-of-HQ Patent	an indicator equal to one if the patent is applied outside of the firm's state of headquarters.

Motivating Inventors:
Non-competes, Innovation Value and Efficiency

Zhaozhao He†

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ABSTRACT

Non-compete agreements help protect business investments by restricting worker mobility, thereby increasing firm incentives to invest. Yet, they could damage the efficacy of innovation investments that crucially rest on employee incentives. Exploiting staggered reforms of state non-compete enforcement, I find that patents filed after an increased enforceability are less valuable and exploratory despite no less R&D spending. Inventors whose job prospects are more jeopardized, in a weaker bargaining position, and having greater incentives to switch firms produce patents with greater value losses. These results imply that labor allocative inefficiency owing to mobility restrictions could compromise value creation from real investments.

Keywords: Allocative Inefficiency, Innovation Motivation, Inventor Mobility, Non-competes, Patent Value

JEL Classifications: D61, G30, J24, J31, J41, J61, K31, O34

† Peter T. Paul College of Business and Economics, University of New Hampshire. Zhaozhao He can be reached at phone: (603)-862-2233, email: zhaozhao.he@unh.edu, and mailing address: 10 Garrison Ave, Durham, NH 03824
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1. INTRODUCTION

Regulatory concerns over anticompetitive business practices in the U.S. are now at the culmination. Not only in product markets, anticompetitive behavior has also been prominent in labor markets, facilitating labor market "monopsony"—a key contributor to the stagnation of wage growth and economic dynamism in past few decades (Council of Economic Advisor 2016; Krueger 2017).[1] The primary vertical restraints that firms regularly use are non-compete agreements (non-competes)—clauses that restrict post-employment mobility by prohibiting employees from leaving to join or establish a competing venture. A 2014 national survey reports nearly a fifth of U.S. workers (about 30 million) having a non-compete (Starr et al. 2021). Yet, growing evidence has shown deleterious effects of these clauses, most notably, on labor market churn—a pivotal element to the nation's long-run growth and prosperity. Consequently, non-compete practices have become increasingly controversial: federal lawmakers are urged to reform the policies and reexamine the legality of these contracts under antitrust frameworks; in January 2023 the Federal Trade Commission has proposed new rules to ban noncompete clauses.[2]

Given these harms, why are non-competes lawful? The typical legal justification is that by limiting workers' ability to join competitors, non-competes can help protect business interests, thereby encouraging investments in innovation and worker training. Previous studies, however, have shown mixed findings on firm investments (Garmaise 2011; Samila and Sorenson 2011; Starr 2019; Jeffers 2024).[3] An equally important and unexplored question is how non-competes affect return on investments. This lack of evidence is surprising because in theory non-competes allow firms to extract greater monopoly rents by preventing misappropriation, which predicts greater investment returns than otherwise would. This paper investigates

[1] See, e.g., https://www.justice.gov/opa/pr/justice-department-requires-six-high-tech-companies-stop-entering-anticompetitive-employee

[2] See, e.g., the Mobility and Opportunity for Vulnerable Employees Act (https://www.congress.gov/bill/114th-congress/senate-bill/1504/text), the 2018 Workforce Mobility Act (https://www.congress.gov/bill/115th-congress/senate-bill/2782/text), a 2019 petition to the Federal Trade Commission (https://www.bloomberg.com/news/articles/2019-03-20/labor-groups-petition-u-s-ftc-to-prohibit-non-compete-clauses), Biden's proposal (https://www.faircompetitionlaw.com/2020/12/02/president-bidens-proposed-ban-of-most-noncompetes-protection-strategy-and-steps-to-take-now/), and FTC's proposed new rules (https://www.ftc.gov/legal-library/browse/federal-register-notices/non-compete-clause-rulemaking)

[3] Analyzing non-compete policy reforms across U.S. states, Garmaise (2011) finds that stricter enforcement results in lower capital expenditures but does not affect R&D, while Jeffers (2024) finds the opposite for capital expenditures. Samila and Sorenson (2011) document that increased supply of venture capital leads to larger increases in innovation and entrepreneurship in weak-enforcing states. Starr (2019) shows that firms in states with stronger non-compete enforcement are more likely to provide worker training.

whether non-competes foster efficient investments through the lens of value created by innovation and finds evidence contradicting to what theory predicts.

Innovation is a long process of experimentation involving exploration of unknown and untested ideas with highly uncertain payoffs (Holmstrom 1989). Developing successful innovations requires a considerable amount of effort from well-motivated employees. Manso (2011) suggests that to best motivate innovation, reward for innovation success over the long run is the key. With a non-compete clause, however, workers face fewer career opportunities and are less able to capitalize on their gained expertise. Non-competes create barriers to exit for skilled workers (Marx and Fleming 2012), facilitating wage suppression and deteriorating employer-employee match quality (Garmaise 2011). Furthermore, workers could suffer prolonged unemployment spells or even "career detours" (Marx 2011). These perceived long-term "rewards" could undermine employees' incentives to innovate.[4] Since efforts are not verifiable ex ante, this introduces contract incompleteness that could expose the employer to ex post inefficiencies in innovation investments because workers may reduce efforts once the investment is made. Consequently, non-competes could impair ex post value creation, even though they help firms secure rents ex ante.

Empirically testing these ideas has proven challenging in several aspects. One of the major hurdles is that data on firm-level use of non-competes are not readily available. Yet, even if such data are ready to use, analysis with this choice variable is susceptible to endogeneity concerns. The use of non-competes could be correlated with unobserved firm characteristics that also affect innovation activity (the omitted variable concern). Or, firms with declining innovation potential may be more likely to have employees sign non-competes (the reverse causality concern). To overcome these challenges, I adopt a difference-in-differences identification strategy by exploiting staggered reforms of state non-compete legislation to capture source of exogenous variation in firms' ability to enforce the contracts. This empirical setting relies on two premises that have already been validated. First, firms in states with a higher non-compete

[4] An important question that may arise here is whether signing workers negotiate over their non-competes in order to receive some benefits. Evidence from the 2014 national survey suggests that only 10% of employees negotiate (Starr et al. 2019). So why would a worker agree to sign the contract? In practice, firms often strategically present a non-compete after the worker just accepts the job offer, which cripples the worker's ability to bargain. This happens in 70% of the cases among engineers as indicated from a 2009 industry survey (Marx 2011), and 33% among labor force participants in the 2014 national survey (Starr et al. 2019).

enforceability are more prone to use non-competes (Garmaise 2011; Kini et al. 2021). Second, increased enforceability particularly hampers the mobility of skilled workers (Fallick et al. 2006; Marx et al. 2009).

Using stock market reactions to new patent grants as a proxy for economic value of innovation following Kogan, Papanikolaou, Seru, Stoffman (2017), firm-level analysis shows that patents filed after a stronger enforcement of non-competes in the state create less value—they receive less positive stock market reactions when subsequently granted. Specifically, an increased enforceability of non-competes leads to a 32.5% reduction in patent value as a fraction of firm assets, after controlling for firm characteristics, local economic conditions, and fixed effects at firm, state and industry-year levels. By contrast, a weaker enforceability in the state results in a 38.8% increase in patent value over assets. These results provide initial evidence that higher enforceability of non-competes hinders value creation from innovation.

Building on the concept of efficiency as value per input, I compute patent value over past R&D stock (Hirshleifer et al. 2013) and patent value per inventor to assess innovation efficiency. I find negative effects of higher non-compete enforceability on firms' R&D efficiency and inventor value creation. To further explore sources of the inefficiency, I investigate capital allocation decisions and inventor turnover. Interestingly, the results show that firms increase R&D spending after a non-compete enforceability shock, regardless of the direction of the change. Cross-sectional analyses show that higher enforceability leads to a larger increase in R&D in industries with more knowledge workers, consistent with non-competes mitigating hold-up problems, whereas lower enforceability stimulates R&D more for firms exposed to greater technology spillovers, suggesting that non-competes inhibit knowledge spillovers. These findings help reconcile previously inconclusive evidence on firm investments.

A stronger enforceability also reduces numbers of newly hired inventors and inventor departures within the firm, indicating that non-competes hinder talent reallocation across firms. Thus, the value-reducing effect of increased enforceability on innovation is driven, to a significant extent, by the intensive margin because more inventors stay with the firm. Collectively, these results raise the possibility that allocative inefficiency in labor market due to mobility restrictions can lead to inefficient investments and that this channel manifests itself during the value generation of innovation investments.

The firm-level analyses rely on state of firm headquarters (HQ state) to assign treatment status, which can be noisy if a firm's geographic footprint is across multiple states. To enhance precision in estimates, I utilize patent-level data to pinpoint the location where the innovation production takes place. I find consistent results for patent value at the patent level, after additionally controlling for technology class-year fixed effects. The value-destroying effect of increased enforceability is stronger for patents produced within HQ states but is negligible for those filed outside of HQ states.[5]

As innovation is a process of exploring unknowns, if non-competes disincentivize inventors, they may also affect inventors' exploratory efforts and search strategies. Employing measures of innovation search from Balsmeier et al. (2017), I find that when non-competes are more strictly enforced, patents tend to score lower on exploratory measures, have a higher fraction of backward self-citations—implying that inventors rely more on previous knowledge inside the firm, and have a higher fraction of forward self-citations—meaning that these patents are cited more heavily from patents produced by the same firm. Thus, more enforceable non-competes lead inventors to explore less toward new areas and rely more on previously known areas of expertise inside the firm.

To investigate potential mechanisms for lower patent value, I explore heterogeneity in this effect by analyzing inventor characteristics—specialization, ability and tenure—that are pertinent to their outside options and bargaining positions. My overall prediction is that inventors more vulnerable to non-competes should be discouraged more by a higher enforceability, resulting in larger value losses. Specifically, inventors specializing in narrow technology fields suffer more from a stronger enforcement because their outside options and mobility are more sharply reduced (Marx et al. 2009). Inventors having lower innovation ability tend to be in a weaker bargaining position, making non-competes more binding. Lastly, inventors in early patenting careers may be discouraged more because "young" inventors often have greater incentives to switch firms (Trajtenberg 2006) but tend to have little leverage. Focusing on inventors residing

[5] This is expected because out-of-state inventors are least likely to be affected by changes in labor laws passed in the HQ states. However, they may still be affected through a teamwork effect (i.e., if they collaborate with inventors residing in the HQ state) or a spillover effect within the organization.

in firm HQ state, I show that higher enforceability reduces patent value more among inventors with higher skill specialization, lower innovation ability and in early patenting careers.[6] These results explain non-competes inhibit value creation by impairing worker outside options and bargaining power, providing support for the theoretical prediction in Fulghieri and Sevilir (2011).[7]

Additional analyses and robustness checks corroborate the main results. Using non-executive stock and option grants as a proxy for firm's reliance on employee incentives to create value, I find firms with greater such reliance experience larger reductions in patent value and R&D efficiency following a stronger enforcement. I also find suggestive evidence that firms respond to non-compete reforms by locating their innovation labs to states with lower enforceability. Several identification tests confirm the validity of the DID approach.[8] These policy shocks are unlikely to be coincided with, or predicted by, changes in the state's economic conditions, political climate, and legal institutions on intellectual property protection.

There is little empirical evidence on how restricting labor mobility to protect knowledge affects value creation from innovation, and thereby investment efficiency, from a behavioral perspective—the behavioral aspect concerning the effect of inventor mobility on innovation motivation. After all, successful innovations are developed by well-motivated inventors. I expect and find that higher enforceability of non-competes leads to larger declines in patent value among inventors more vulnerable to non-competes. These findings echo Lobel and Amir (2011) who argue that the widespread use of non-competes may have inadvertent counterproductive effect of lowering employee performance. As firms often claim that the most powerful resource is their people, using non-competes to retain talent, however, may backfire.[9]

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[6] These regressions include measures to control for inventor past productivity, innovation experience and co-inventor networks, and incorporate a host of high-dimensional fixed effects at the inventor, firm, state and technology class-year levels.
[7] Fulghieri and Sevilir (2011) theorize that legal restrictions on labor mobility such as enforcing non-competes have a negative impact on employees' effort to innovate, and therefore on innovation value, by weakening employee outside options.
[8] First, there are no pre-existing trends in patent value between affected and un-affected patents, confirming the parallel trends assumption. Second, the results continue to hold under a stacked-event study approach. Third, to address the concern that innovative firms might sort into states based on varying non-compete enforcement regime, I exclude firms that have relocated their headquarters and find results robust. Third, I perform a matched sample analysis in which treated and control firms are similar in size and in the same industry. Fourth, I exclude firms affected by a law-based weakening of the enforcement in Oregon due to its potentially limited effectiveness. In unreported analyses, I exclude firms in California from the sample to address the concern that California's non-compete ban and innovation hub might have a dominant effect on the results, which is not the case.
[9] In a similar vein, Contigiani et al. (2018) show an adverse effect of trade secrecy protection on inventor-level patent counts and suggest that firms who advocate for stronger trade secrecy protection may find innovation outcomes against their original interests.

This study joins the empirical literature on non-competes and innovation. Indirectly studying the role of non-competes in fostering innovation, Samila and Sorenson (2011) find a more positive effect of venture capital financing on patent counts in states weakly enforcing non-competes than those strongly doing so. However, an alternative explanation is that increased patents might just be a manifestation of higher propensity to patent innovations. Conti (2014) finds that Florida's stronger enforcement leads to more highly cited patents, whereas Johnson et al. (2023) shows that increased enforceability reduces state-level citation-weighted patents by slowing down knowledge spillovers.[10] My paper differs from these studies in several aspects. First, I make use of data on patent value to examine how non-compete policies affect value creation from innovations. This allows me to circumvent the potential issues of using patents and citations, thereby helping rule out the alternative explanation mentioned above. Second, I employ measures of innovation search and provide further insights on firm investment efficiency. Third, I explore underlying mechanisms for the results from a behavior perspective by focusing on inventors, offering a behavioral implication of non-competes. This paper, therefore, provides first piece of evidence on how non-competes impede innovation and value creation at the intensive margin.

This paper adds to the concurrent debate on reforming non-compete laws that aims to strike a balance between benefits and costs from using the restrictive covenants. The primary benefit of non-competes is to protect business interests, which comes with a variety of costs to workers and the broader economy. By limiting outside options, non-competes disincentivize workers to invest in themselves, leading to lower quality of human capital that is crucial to long-run economic growth.[11] Although existing evidence suggests that firms accrue most of the benefits provided by non-competes, this is the first paper that unveils a potential cost to firms—lowering the efficacy of innovation investments. So why do firms still use non-competes? Plausibly, firms might fear that they will be outcompeted by rivals if they don't,

My paper focuses on employee signed restrictive clauses to examine the implications of mobility on innovation value and search strategy, which provide further insights on investment efficiency.

[10] I also find that Florida's stronger enforcement leads to a substantial increase in self-citations among Florida's firms. The effect on highly cited patents disappears once I control the number of self-citations.

[11] As mentioned, non-competes also weaken workers' bargaining power and facilitate labor market monopsony, slowing down wage growth and labor dynamism (e.g., Arnow-Richman (2006); Marx (2011); Treasury (2016)). By restraining mobility, non-competes further hinder entrepreneurship and knowledge diffusion (e.g., Gilson (1999); Fallick et al. (2006); Marx et al. (2009)).

because non-competes reduce uncertainty of labor turnover and any repercussions from employee loss, allowing to maintain competitive edges. Also, firms might be short-sighted on saving labor costs as they are under no pressure to offer competitive wages to retain employees.

Overall, my findings suggest that labor allocative inefficiency as a result of mobility restrictions could further compromise value creation from innovation investments. On the surface, non-competes create deadweight loss only to the constrained employees. This loss ultimately passes on to the employers who depend heavily on high-quality human capital for their fundamentals. My findings resonate with the view of Landes and Posner (2003, p.371) that "it is not even clear that enforcing employee covenants not to compete generates social benefits in excess of its social costs," and speak to the tenet of antitrust that anticompetitive forces tend to reduce efficiency, lower output and undermine social welfare.[12]

2. NON-COMPETE LAWS

2.1 Institutional Background

Non-competes, also known as covenants-not-to-compete or CNCs, are contracts that preclude workers from joining or starting a competing firm within a geographic area for a certain period (typically one to two years) after leaving their jobs. The agreements usually specify a list of competitors or fields where employees cannot work upon separation (Valiulis 1985). The geographic scope is often a state, a county, a city or a 10- or 50-mile radius around the business location (Malsberger 2004). Thus, non-competes are most effective when workers are in the same state as the business corporation. Firms use non-competes to prevent misappropriation of intellectual property, reduce labor turnover, and improve their bargaining position relative to workers. These benefits to firms are at the expense of workers, social welfare and economic dynamism, as discussed earlier.

[12] Council of Economic Advisors (2016) explains that non-competes imposed by employers "can lead to inefficient reductions in employment and output, where some workers who would have been willing to work at the competitive market wage are never hired, and the output they would have produced is produced less efficiently by other firms if at all."

Systematic data on the use of non-competes among U.S. workers are not available. However, survey evidence suggests that non-competes are pervasive, and they are concentrated among knowledge-intensive occupations such as technical professions and managerial positions (see, e.g., Starr et al. 2019). This is because knowledge workers are most likely to possess proprietary information that firms seek to protect. Non-competes are effective in retaining those workers: empirical evidence has shown that a stronger enforcement restrains the mobility of top executives (Garmaise 2011), scientists and engineers (Marx 2011) and inventors (Marx et al. 2009). In fact, they are deemed as one of the most powerful mechanisms that bind workers to a firm, and may be the only means by which the firm can ban workers from using their skills in competitors.[13]

This follows the key aspect that distinguishes a non-compete from other types of intellectual property protection: it targets the knowledge embodied in a person and restricts the flow of the input, namely talent, rather than the output of innovation. Unlike outputs (e.g., information), people have desires and motivations. After signing non-competes, workers essentially transfer the property rights over their expertise to their employer, which means that non-competes impose restrictions on the use of knowledge. These restrictions "were characterized in quasi-slavery terms, as if they deprived the employee of his freedom and independence" (Fisk 2009, p.6). Indeed, scientists and engineers bound by non-competes often "involuntarily leave their technical field to avoid a potential lawsuit" and take "career detours" (Marx 2011), forgoing accumulated specialties.[14] Consequently, excessive constraints by non-competes demoralize workers who perceive less ownership and control over the skills to be developed. This behavioral effect on

[13] Firms also use alternative mechanisms to influence employee mobility such as patenting, relying on trade secrets laws, and applying other restrictive covenants (i.e., a non-disclosure agreement or a non-solicitation agreement). The effectiveness of these tools is less clear. For instance, most knowledge remains unpatented because of high fixed costs arising from lengthy examination processes and legal issues and costs of disclosure. Secrecy laws are somewhat ineffective because misappropriation of trade secrets is often difficult to prove (Decker 1993). Although the non-disclosure agreement restricts an employee from disseminating trade secrets, the worker can still work for a competitor using acquired skills and know-how without revealing any proprietary information of the ex-employer, even if this is happening (Marx 2011). Non-competes help mitigate these issues by prohibiting workers from joining rival companies at the first place.

[14] It is worth mentioning that litigation over non-competes is on the rise. Beck Reed Riden LLP, a law firm, found a 61% increase in the number of employees getting sued by ex-employers for the violation of non-competes over 2002–2013 (White House 2016).

innovation motivation, initially proposed by Lobel and Amir (2011), illustrates another negative externality of non-competes that has received minimal attention thus far.

As states have jurisdiction over labor laws, there is a wide variance in the manner and degree to which non-compete clauses are enforced. In some states, non-compete enforcement is governed by statute, while in others it is determined by case law precedents. Each state has its own set of rules to judge whether a non-compete is reasonable in its scope. The common law rule of reason allows the state courts to void those contracts with more negative consequences to the worker or society than needed to protect the employer's legitimate business interests. While weighing employer interest against employee hardship and public welfare, the courts consider the reasonableness of the actual restriction with respect to its duration, geographic scope, and limitation on professional activities (Lester and Ryan 2009). In California and North Dakota, however, no aspects of non-competes are enforceable.[15] At the opposite extreme, Florida (from 1997 onwards) has the strongest enforcement regime that prohibits courts from considering employee hardship and permits the employer to obtain an injunction upon non-compete violation.

Employers often write non-competes that are overly broad/unreasonable, and they frequently ask workers to sign non-competes that are entirely or partly unenforceable in certain jurisdictions. For instance, California workers are bound by non-competes at a rate of 22 percent, slightly higher than the national average of 19 percent. Doing so could exert a "chilling effect" on worker behavior (e.g., by imposing a threat to deter job searches or to prevent workers from accepting outside offers) even if these agreements are unenforceable under state law.[16] As the barrier to access talent rises and competition diminishes, the "chilling effect" spills over to those who have not signed. This illustrates how non-competes may have brought about negative externalities in the broader labor market—another distinction from intellectual property laws that only protect outputs.

[15] See CAL. BUS. & PROF. CODE §§ 16600-16602.5 (Cal. 2008)
[16] Such misuse of non-competes has attracted regulatory attention. The White House Call for Action in 2016 urged states to improve transparency by requiring employers to give advance notice to prospective employees if a job offer contains a non-compete clause. The Mobility and Opportunity for Vulnerable Employees Act (the MOVE Act) is a new bill that proposes a similar requirement.

States adopt different approaches to address such unenforceable non-competes. States like Nebraska and Virginia implement a "red-pencil" doctrine, under which courts will refuse to enforce unreasonable non-competes, or contracts containing any unenforceable provisions. Many other states permit certain degree of judicial modification on overbroad non-competes in an effort to generate enforceable contracts, under the "blue-pencil" or "equitable reform" doctrines. While the "blue-pencil" doctrine (in Montana and North Carolina) entails striking offensive clauses from the agreements, the "equitable reform" approach, currently prevailing in about 30 states, allows employers to redraft the contracts. The latter empowers employers and may encourage them to take risks of writing unreasonable provisions, further amplifying the "chilling effect" across the labor markets (Lester and Ryan 2009).

These differences in non-compete enforcement across states usually have deep historical roots, and states rarely changed the enforcement policies up until 2000s. Motivated by the growing concerns over non-competes, several states have proposed new bills to limit the enforcement.[17] So, owing to the lack of variation in these laws and limited data on the use of non-competes, estimating the impacts of non-competes has proven challenging. Recent studies start to exploit exogenous reforms of non-compete laws in a set of U.S. states (Marx et al. 2009; Garmaise 2011; Ewens and Marx 2018). I follow Garmaise (2011) and Ewens and Marx (2018) to formulate research design by exploiting these regulatory changes.

2.2 Time-Series Changes in Non-compete Enforceability

Garmaise (2011) identifies three states that experienced major changes in non-compete enforcement at different times over 1992–2004. He also develops an enforceability index that measures the strength of the enforcement for each U.S. state by analyzing twelve questions proposed by Malsberger (2004). Following Garmaise (2011), Ewens and Marx (2018) extend the policy changes to 2016 by

[17] For example, Oregon passed a new law in 2008 to restrict the enforcement of non-competes, expressing concern about "a dangerous expansion in the sue of noncompetition agreements in Oregon." Other states like Missouri, New Jersey, Maryland, Massachusetts, Michigan and Washington have proposed bills to ban non-competes on some or even all workers (Treasury 2016).

reviewing Malsberger, Brock, and Pedowitz (2016), which provides definitive reference regarding legislative and judicial changes to state-by-state policy of non-compete enforcement.

It is important to note that reasons for these legal shifts were unrelated to corporate innovation, thus mitigating the potential endogeneity concerns over these laws.[18] Moreover, to the extent that judicial decisions are mainly driven by merits of the case in question, court rulings are unlikely to be expected by individuals, are independent of both state and federal governments, and are less likely to be influenced by firm lobbying. Therefore, the policy reforms as a result of judicial changes can represent truly exogenous shocks of the legal environment. With regard to legislative changes, even if the enactment of the new laws was anticipated, firms could have changed their innovation policies before these laws became effective, which will bias against finding any treatment effect of the new laws.

To understand the economic and political motivations behind the passage of non-compete reforms, Table 1 investigates whether a state's macroeconomic conditions, political climate, or intellectual property laws predict the change in non-compete legislation during my sample period of 1992-2009. The dependent variable in columns (1)-(2) is *CNC Enf. Down*, an indicator equal to one if a state has decreased non-compete enforceability in the year, which includes Texas (1994), Louisiana (2001) and Oregon (2008). In columns (3)-(4), *CNC Enf. Up* is an indicator equal to one if a state has increased enforceability in the year, which includes Florida (1996), Louisiana (2003), Vermont (2005) and Idaho (2008). Observations for states that change the enforcement are dropped from the sample after the law is passed. All predicting variables are lagged by one year. I include year fixed effect to control for changes in macroeconomic environment and state fixed effects to control for unobserved state heterogeneity that is time-invariant.

Columns (1) and (3) of Table 1 show that changes in the enforceability, regardless of the direction, were unrelated to preexisting changes in state-level economic and political conditions. None of the variables (a state's GDP Growth, unemployment rate, population, income per capita, labor force participation and

[18] During my sample period of 1992-2009, Texas (1994), Louisiana (2001) and Vermont (2005) reformed their non-compete laws as a result of court decisions, while the enforcement changes in Florida (1996), Louisiana (2003), Oregon (2008) and Idaho (2008) were made by state legislators, according to Garmaise (2011) and Ewens and Marx (2018).

percent of republican legislators in the state legislatures and government) loads significantly. Columns (2) and (4) additionally include two most relevant intellectual protection laws—the Inevitable Disclosure Doctrine and UTSA (Trade Secrecy) laws.[19] The adoptions of these laws do not appear to be correlated with the state's reform of non-compete laws, after accounting for state fixed factors. In columns (5)-(6), the dependent variable is a categorical variable, *Increased CNC Enf.*, which equals one if a state has increased non-compete enforceability in the year, equals negative one if a state has decreased the enforceability in the year, and is zero otherwise. The results appear similar. Hence, the timing of non-compete policy reform is unlikely to be a function of changing political, economic, or related legal conditions, alleviating the potential omitted variable concern that poses a threat to this identification strategy.

3 THEORY AND HYPOTHESES

A stronger enforcement of non-competes reduces the possibility of knowledge leakage to competing firms by prohibiting employees from working for these rivals, enabling the firm to appropriate higher returns on its innovation investments. This enhanced protection would increase the firm's incentives to invest. Indeed, traditional economic models view non-competes necessary to prevent underinvestment in innovation by solving a "hold-up" problem (e.g., Rubin and Shedd 1981).[20] However, innovation is a long process of exploration and experimentation on untested ideas with unpredictable outcomes (Holmstrom 1989). Developing successful innovation requires a considerable amount of effort and persistence from motivated employees. As innovative endeavors are observable but not verifiable ex ante, details of effort are unlikely to be specified in employment contracts (Acharya et al. 2014). Once the investment is made and innovation process begins, workers may reduce efforts, recognizing that the costs

[19] *Inevitable Disclosure Doctrine* is an indicator equal to one for firms headquartered in states after the recognition of Inevitable Disclosure Doctrine in the year (Klasa et al. 2018). *State UTSA (Trade Secrecy)* is an index that measures the strength of legal protection of trade secrets based on the effective UTSA and case law precedents (Png 2017).

[20] According to the property rights theory (Grossman and Hart 1986; Hart and Moore 1990, 1994), bilateral relationships suffer from holdup problems when contracts are incomplete, which could dampen the willingness of economic actors to make investments ex ante. Without mobility restrictions, the firm must worry that it might not be able to recoup the returns on its innovation investment if the employee leaves or threatens to leave after the investment is made. Having a non-compete in place helps limit the employee's ability to hold up the employer ex post.

are sunk. This nonverifiability of employee effort is one indescribable contingency that makes labor contracts never complete, which can be a cause of ex post inefficiency in innovation investments.

Theoretical evidence suggests that non-competes discourage workers from investing in their own human capital (Garmaise 2011) by weakening their outside options and bargaining power. As discussed, workers bound by non-competes perceive fewer external opportunities and are less able to bargain for better contractual terms. Current employers also feel a less need to pay competitive wages to retain talent (Marx et al. 2009). The role of non-competes in holding down wages is supported by Garmaise (2011) for executives and Balasubramanian et al. (2020) for technology workers. Both find lower worker earnings in states with stronger enforceability, confirming that non-competes weaken worker bargaining power.[21]

In addition to monetary costs, workers under a non-compete are confronted with prolonged unemployment spells or "career detours" after job termination. Scientists and engineers, especially those with specialized skills, often wait until their non-competes expire or change to a different industry after leaving their jobs to avoid non-compete infringement, forgoing the skills accumulated over their careers. If workers could not capitalize on their skills and innovations by exploring better opportunities, they would perceive lower expected payoff from developing those skills and innovations, leading to lower incentives and human capital quality over time.

Consequently, higher enforceability of non-competes raises barriers to exit for skilled workers as well as barriers to access human capital inputs for prospective employers, generating allocative inefficiency in the labor market. Over the long term, employees tend to be stuck in jobs where they earn lower wages than would prevail in a competitive labor market and cannot be matched to workplaces where they would be more productive, known as the "job lock" (Council of Economic Advisor 2016; Krueger 2017).

Manso (2011) suggests that contract design to motivate innovation features tolerance for early failure and reward for long-term success. Yet, having a non-compete in place would entail lower long-term

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[21] Kini et al. (2021) look into CEO employment contracts and find that CEOs who have more enforceable non-competes earn higher total pay and incentive pay. This is not surprising because unlike rank-and-file employees, a firm's CEO has significant bargaining power relative to the firm.

wage growth, a potential job lock, or even a career detour. But why cannot workers demand some sort of compensation, such as a bonus, when asked to sign a non-compete? A 2009 survey of Institute of Electrical and Electronics Engineers (IEEE) uncovers that in 70% of cases, firms ask for a non-compete after the engineer has just accepted the offer–a point at which the worker has little leverage to further negotiate (Marx 2011). The 2014 national survey to 11,505 labor force participants reports that 33% of employees have had similar experience and that only 10% of employees negotiated (Starr et al. 2019).

Therefore, enforceable non-competes could reduce ex post value of innovation, undermining the efficacy of investments. Indeed, Fulghieri and Sevilir (2011) theorize that mobility restrictions through enforcing non-competes negatively affect employee effort to innovate, and thereby value of innovation. Using experiments, Amir and Lobel (2014) observe that non-competes worsen worker performance. They argue that such disincentive effect on workers might hurt firm performance more than the actual employee loss would. Both studies allude that the disincentive effect of non-competes on workers outweighs any stimulus effect on firms in producing valuable innovations, which leads to the main hypothesis:

Hypothesis 1: *An increase in non-compete enforceability leads to a decrease in the value of innovation.*

I then examine inventors' characteristics pertinent to their outside options and bargaining positions to explore the potential mechanisms. After all, innovations are developed by inventors. I expect that inventors whose job prospects are weakened more, who are in a weaker bargaining position, and who have greater ex ante incentives to move should be discouraged more by a stronger non-compete enforcement such that their innovations create even less value, as elaborated below.

First, for inventors specializing in narrow technology fields (specialists), a higher non-compete enforceability weakens their outside options more because firms might enforce non-competes more aggressively against them since their job opportunities are most likely to be in direct competitors. In contrast, generalists may switch industries as they can transfer their skills to firms in different industries. Marx et al. (2009) show a larger decline in mobility for specialists than generalists (by 8%) after a stronger enforcement. Also faced with a potential "career detour," specialists are more jeopardized by the reform.

Second, inventors with lower innovation ability tend to be in a weaker bargaining position vis-à-vis their firm, compared with high-achievers, suggesting that non-competes are more binding for low-ability inventors. Supporting this conjecture, Fulghieri and Sevilir (2011) predict that the effect of outside options on employees' effort is larger when their bargaining power is lower because of greater marginal benefit of outside options on their effort. So, if a stronger enforcement disincentivizes inventors by weakening worker bargaining power, the effect should be stronger among low-ability inventors.

Third, inventors in early careers ("young" inventors) are more likely to switch firms in order to find a better match or capitalize on acquired skills, but they have little leverage due to limited experience. Such incentives to move diminish over time either because match quality improves or because moving constraints increase (e.g., costs of foregoing firm-specific human capital and family obligations).[22] Trajtenberg (2006) show that "younger" inventors exhibit higher mobility than seniors, suggesting that they are motivated more by outside options. Thus, "young" inventors might be discouraged more by higher enforceability.

Hypothesis 2: *An increase in non-compete enforceability leads to a larger decrease in innovation value for inventors with higher skill specialization, having lower innovation ability, and in early patenting careers.*

4. DATA AND METHOD

4.1 Data and Sample Construction

Sample construction starts with all publicly traded non-financial and non-utility U.S. industrial firms covered in Compustat North America Fundamentals Annual files. Industrial firms are defined as companies with SIC codes outside the ranges 4900-4949 (utilities) and 6000-6999 (financials). To be retained in the sample, firm-year observations are required to have positive values for book assets and sales,

[22] Parsons (1972) indicates that economic cost of worker-job separation increases by the amount of investments in firm-specific human capital, either by the firm or the worker, suggesting that firm-specific human capital leads to lower mobility. Marx et al. (2009) show an additional drop in mobility for inventors with greater firm-specific skills following higher non-compete enforceability. But if these workers also have lower ex ante incentives to leave due to higher separation cost, then the effect of higher enforceability on their incentives to innovate is ambiguous. Consistent with this, I do not find that inventors with greater firm-specific skills produce less valuable innovation than others after a stronger enforcement.

non-negative values for common equity, and non-missing values for R&D expenditures.[23] This sample is then merged with data on patent market value from Kogan, Papanikolaou, Seru, Stoffman (2017)—KPSS 2015 version. The market value of a new patent is calculated as the three-day market-adjusted cumulative abnormal returns surrounding patent approval date multiplied by the firm's market capitalization prior to the announcement. Firm-years not in KPSS dataset are excluded because assigning zero to missing patent value would falsely assume that these patents do not create any value. So my sample consists of publicly traded industrial firms engaging in R&D with at least one patent grant and stock price data.

I obtain data on changes in state non-compete enforceability from Garmaise (2011) over 1992-2004 and Ewens and Marx (2018) from 2005 onwards. Patent inventor information is drawn from Harvard Patent Network Dataverse (Li et al. 2014), which provides dis-ambiguous inventor identifiers and ends in 2010. The sample period thus goes from 1992 to 2009, during which seven major reforms of non-compete legislation took place in six "treatment" states, allowing for a difference-in-differences framework to estimate the effects of changes in non-compete enforcement. Specifically, Texas (1994), Louisiana (2001) and Oregon (2008) decreased non-compete enforceability, whereas Florida (1996), Louisiana (2003), Vermont (2005) and Idaho (2008) increased the enforceability.

Since the enforcement of non-competes is governed by employment law, not corporate law, the relevant jurisdiction is the state where the employee works (Malsberger 2004). In the firm-level analysis, I map non-compete laws to the state where each firm is headquartered based on the rationale that non-compete signers are mostly high-skilled employees, who typically work at headquarters (Garmaise 2011). As Compustat only reports current headquarters location, I extract information on firm historical headquarters location in 10-K filings from Securities and Exchange Commission (SEC) Edgar database.

[23] The conventional approach in the literature is to replace missing values of R&D expense with zero, since firms who do not report R&D often have trivial R&D spending (see e.g., Brown and Petersen 2011). For the purposes of this study, only firms that engage heavily in internal development of innovations are more appropriate to study. Firms that obtain patents externally via mergers and acquisitions without R&D investments offer little implication for innovation efficiency.

Importantly, I also leverage data on patent assignee location and inventor residence state to minimize errors in treatment assignment. With the location data, I can identify patents produced in HQ states and inventors most likely work at headquarters to enhance precision in estimates.

I collect detailed information on patent assignee and technology classes from National Bureau of Economic Research (NBER) and Harvard Business School (HBS) patent files, state-level data on GDP growth rates, total population, per capita personal income, and labor force from the Bureau of Economic Analysis, state unemployment rates from Bureau of Labor Statistics, state partisan composition from the National Conference of State Legislatures, industry occupation profiles from the Occupational Employment Statistics (OES) survey, and measures of technology spillovers developed by Bloom et al. (2013). The final sample consists of 14,585 firm-year observations for 2,644 unique firms over 1992-2009. These firms combined have applied for and been granted 537,021 patents, which involve 86,592 inventors living in the state of firm headquarters at the time of innovation production.

4.2 Measurement of Key Variables

Empirical research on innovation has primarily relied on patent data, since patents are widely recognized as the major form of innovation outputs. I use market value of new patents as a proxy for innovation value to infer the return on innovation investment. An advantage of this measure over patent or citation counts is that it directly quantifies the *economic value* generated by a patent. This is also a standardized measure, allowing to analyze innovation quality across firms and over time while alleviating the truncation problem of citation-based measures. Also, Balsmeier et al. (2017) point out that increases in patents or citations do not necessarily imply increases in creative activities.[24] Finally, another issue is that higher mobility of scientists is associated with a higher propensity for firms to patent (Kim and Marschke

[24] This is because the increases could simply be an artifact of changes in search strategy towards more crowded areas or familiar areas. They suggest that using simple patent or citation counts is insufficient and might lead to inaccurate inferences on innovation.

2005), which means that patents and citations could increase without creating real value after non-compete enforceability declines.[25] I analyze patent value at both firm and patent levels to address this concern.

To construct firm-level measures, I aggregate market value of new patents by firm and application year. *Patent Value* is the future market value of patents that a firm applied for in a year. By this way of construction, *Patent Value* is a forward measure because the time lag between filing and receiving an approval is often one to two years. Following KPSS (2017), I also calculate *Patent Value/Assets* as the market value of patents that a firm applied for in the year scaled by the firm's book assets. Motivated by Hirshleifer et al. (2013), *Patent Value/ R&D stock* is computed as total market value of patents that a firm applied in the year divided by past R&D stock from years $t-2$ to $t-6$ with a 20% depreciation rate. This variable helps evaluate how efficient the firm is in turning R&D dollars into realized value from innovation. To gauge average value creation of an inventor, *Patent Value Per Inventor* is calculated as total market value of patents that a firm applied in the year divided by the total number of inventors filing these patents.

In the patent-level analysis, I zero in on patents produced in the firm's state of headquarters to tease out noises due to treatment misassignment. In addition, I employ several new measures of innovation search (Balsmeier et al. 2017; He and Hirshleifer 2022) to examine inventors' exploratory efforts. *Exploratory 90%* is an indicator equal to one if at least 90% of the patent's backward citations are based on new knowledge coming outside of the firm's existing knowledge base, which consists of all patents granted to the firm and patents cited by the firm in the past five years. *Exploratory Ratio*, a continuous variable, is the fraction of the patent's backward citations based on new knowledge. *Purely Exploratory* is a dummy equal to one if the patent does not cite any patents owned by the same firm. *Backward self-cites* is the ratio of citations made to patents owned by the same firm over total citations made. *Forward self-cites* is the ratio of self-citations received by the patent over total citations received. Higher values on the last two measures indicate more search within known areas and less exploratory effort toward areas new to the firm.

[25] Despite these concerns, I also test the impact of non-compete policy reforms on patent and citation counts. These results are reported in the Internet Appendix Table IA1 and discussed in Section 5.

Lastly, using a sample of inventors residing in HQ states, I measure inventor characteristics in terms of skill, ability and experience. Following Marx et al. (2009), *Inventor Skill Specialization* is a Herfindahl concentration measure based on the share of patents in each three-digit technology class among all the patents that the inventor has filed in the past five years. Balsmeier et al. (2017) indicate that uncited patents are more likely to be failed innovations. I use the cumulative share of uncited patents in an inventor's patent portfolio (i.e., the cumulative number of uncited patents over the total number of patents produced up to the year) as an inverse proxy for the inventor's innovation ability. An inventor's patenting experience or career stage is proxied by number of years since the inventor's first granted patent application.

Table 2 reports descriptive statistics of the samples. All continuous variables are winsorized at their 1st and 99th percentiles. Dollar values are CPI-adjusted in 2016 dollars. Panel A presents summary statistics for the firm-level sample. On average, new patents that a firm applied in a year generate $1,778 million shareholder value, which accounts for 17.8% of the firm's assets. Patent value over R&D stock has a mean value of 1.9, and patent value created by each inventor is estimated to be $11.3 million. The average firm has a book value of assets of $3.9 billion and a leverage ratio of 16.1%. It is 18.6 years old. It has a Market-to-book ratio of 2.5, a cash flow ratio of -1.1%, a tangibility of 20.8% and a R&D-to-assets ratio of 10.2%. In Panel B on patent characteristics, the market value of an average patent is 0.78% of the firm's assets. 27.6% of the patents have an exploratory ratio over 90%. The average patent has an exploratory ratio of 57.7%, has made 15.1% backward self-citations and receives 13.9% forward self-citations. On the inventor characteristics displayed in Panel C, an average inventor has a skill specialization ratio of 49.7%, 8.5% uncited patents in the portfolio and 7.3 years of patenting experience. The Appendix provides detailed definitions for all variables.

4.3 Empirical Methodology

I adopt a difference-in-differences (DID) test design to analyze how changes in non-compete legislation affect innovation value. To capture the individual treatment effect of a strengthening or weakening enforcement, I define two indicators—*CNC Enf. Up* equal to one for firms headquartered in states after experiencing an increase in the enforceability, and zero otherwise, and *CNC Enf. Down* equal to one for firms in states after a reduced enforceability, and zero otherwise. Table 2 Panel A reports that 1.8% and 4.0% of firm-years are affected by, respectively, a stronger and weaker non-compete enforcement. I then estimate the following DID specification:

$$Y_{i,s,t} = \alpha + \beta_1\ CNC\ Enf.\ Up_{s,t} + \beta_2\ CNC\ Enf.\ Down_{s,t} + \beta'\ X_{i,s,t-1} + \mu_i + \omega_s + \gamma_j \times d_t + \varepsilon_{i,s,t}\ , \qquad (1)$$

where $Y_{i,s,t}$ is one of the aforementioned measures of innovation value and efficiency of firm i headquartered in state s in year t. The key independent variables are $CNC\ Enf.\ Up_{s,t}$ and $CNC\ Enf.\ Down_{s,t}$. as defined above. β_1 and β_2 are DID estimates assessing how changes in non-compete enforceability affect subsequent innovation performance of treated firms relative to that of all other firms. I also follow prior literature to define *Increased CNC Enf.*, which equals one for firms in states after experiencing a higher enforceability, equals negative one for those in states after a lower enforceability, and is set to zero otherwise.

$X_{i,s,t-1}$ is a set of firm- and state-level controls measured in year $t - 1$. It includes well-known determinants of innovation performance such as firm *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility* and *R&D/Assets*. To ensure local market conditions not driving the results, I include *State Industry HHI* (a proxy for in-state competition), *State GDP Growth* and *ln(State Unemployment)* (proxies for economic environment). Lastly, I control *IDD* (an indicator for whether the state has adopted the Inevitable Disclosure Doctrine) to mitigate concern that states with stronger enforcement of non-competes also provide greater protection on trade secrets by adopting the IDD.

Equation (1) incorporates firm fixed effects (μ_i), HQ state fixed effects (ω_s), and industry × year fixed effects ($\gamma_j \times d_t$), where industry is defined at the two-digit SIC code level. The firm and HQ state fixed effects control for any unobserved time-invariant heterogeneity across firms and states, respectively. Incorporating industry × year fixed effects allows to account for intertemporal technological shocks across industries and for the possibility that unobserved time-varying industry factors might be driving the results. Since changes in non-compete regulation affect all firms headquartered in the state, I cluster standard errors at the HQ state level—the level of treatment—to correct for possible autocorrelations of the error terms for firms within the same state (Bertrand, Duflo, and Mullainathan 2004).

I next test the treatment effects at the patent level using Equation (2) specified below. The benefits of this unit-level analysis come from more accurate treatment assignment—by focusing on patents produced in the firm's state of headquarters—and mitigating the concern that the effects on innovation are driven more by quantity rather than the quality side of innovation activities.[26]

$$Y_{i,j,s,t} = \alpha + \beta_1\, CNC\ Enf.\ Up_{s,t} + \beta_2\, CNC\ Enf.\ Down_{s,t} + \beta'\, X_{i,s,t-1} + \mu_i + \gamma_k \times d_t$$

$$+ \omega_s + \varepsilon_{i,j,s,t}\,, \qquad (2)$$

where $Y_{i,j,s,t}$ is the market value of patent j scaled by the assets of firm i (*Patent Value/Assets*) headquartered in state s in application year t. β_1 and β_2 are the DID estimates measuring the impact of changes in non-compete enforceability on subsequent market value of new patents filed after the law changes. This specification includes firm (μ_i) and HQ state (ω_s) fixed effects and incorporates technology class × year ($\gamma_k \times d_t$) fixed effects to account for time-varying technology shocks that might be correlated with both the legal changes and patent value. $X_{i,s,t-1}$ is a set of controls including *Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD.* Standard errors are clustered by firm HQ state.

5. EMPIRICAL RESULTS

5.1 Non-competes, Innovation Value and Efficiency

Table 3 presents the baseline results from Equation (1) examining the effect of changes in non-compete enforceability on patent value at the firm level. The dependent variable in columns (1)-(2) is *ln(Patent Value)*, the natural logarithm of one plus subsequent market value of new patents that a firm applied in the year, and in columns (3)-(4) is *Patent Value/Assets*, the ratio of market value of new patents that a firm applied in the year over its book assets.

[26] Information on assignee state is obtained from NBER patent database supplemented by HBS patent files, as Kogan et al. (2017) do not have this information.

In column (1), the estimated coefficients of *CNC Enf. Up* and *CNC Enf. Down* are −0.383 (t = −3.59) and 0.272 (t = 3.22), respectively. These results suggest that new patents filed after a stronger enforcement of non-competes in the state receive less positive stock market reactions when subsequently granted, whereas those applied after a weaker enforcement are valued higher by equity investors. Alternatively, using the categorical variable, column (2) reports a significant and negative coefficient estimate on *Increased CNC Enf.* (t = −4.63), indicating that on average an increase in non-compete enforceability leads to a 26.6% reduction in subsequent patent value.

The next two columns for *Patent Value/Assets* show consistent results. The estimated coefficients of *CNC Enf. Up* and *CNC Enf. Down* in column (3) are −0.058 (t = −1.76) and 0.069 (t = 5.75), respectively, indicating a 32.6% decline in patent value as a fraction of assets (relative to its sample mean of 0.178) following an increase in the enforceability and a 38.8% increase in patent value after enforceability weakens. In column (4), *Increased CNC Enf.* again has a negative and significant coefficient estimate indicating a treatment effect of similar size. These regressions include a set of firm-level determinants of innovation, local economic conditions, firm and state fixed effects to control for time-invariant heterogeneity across firms and states, and industry-year fixed effects to absorb time-varying industry shocks. Overall, the results in Table 3 provide support for *Hypothesis 1*.[27]

To investigate how changes in non-compete enforceability affect investment efficiency, I measure R&D efficiency based on the market value of patents, which has an intuitive interpretation: how efficient a firm is when turning R&D dollars into realized value from innovation outputs. Table 4 reports the results using Equation (1). The dependent variable in columns (1)-(2) is *Patent Value/R&D Stock*, computed as the total market value of patents that a firm applied in the year divided by past R&D stock from years $t-2$ to $t-6$ with a 20% depreciation rate. The results show a negative coefficient on *CNC Enf. Up* (t = −3.75) and a positive coefficient on *CNC Enf. Down* (t = 4.39), suggesting that a stronger enforcement undermines

[27] Table IA1 in the Internet Appendix reports the results for the number of patents, citation-weighted patents and raw citations. In calculating citation-weighted patents, the weight for each patent is calculated as the number of future citations divided by the average number of citations received by patents in the same technology class and year. The results are largely consistent with those for patent value. Increased enforceability is negatively associated with the number of patents and citation-weighted patents.

the efficacy of R&D expenditures to generate value whereas a weaker enforcement boosts value created from R&D. Column (2) shows that the result using *Increased CNC Enf.* offers consistent inference.

Another related question is how efficient the firm is in using labor inputs to create valuable outputs after the law changes. To show this, I calculate *ln(Patent Value per Inventor)*, the natural logarithm of one plus the total market value of patents that a firm applied in the year divided by the number of inventors filing these patents.[28] The results presented in columns (3)-(4) of Table 4 closely mirror those for R&D efficiency—patent value created by each inventor on average drops significantly after a stronger enforcement but increases significantly after non-competes become less enforceable. These results also imply that weaker enforcement might stimulate greater inventor effort to create value.

5.2 Non-competes and Allocative Inefficiency

The results so far provide supportive evidence that higher enforceability of non-competes generates inefficiency in creating value from innovation for a given amount of R&D expenditures or innovative labor. To explore sources of inefficiency, I further investigate firms' allocation decisions on capital and labor by analyzing how they invest in R&D projects and manage innovative workforce.

5.2.1 Capital Allocation—R&D Investment

Table 5 panel A shows the results examining firms' investment in R&D projects. The dependent variable is a firm's *R&D-to-assets* ratio. Based on the specification of Equation (1) without including any controls, the results in column (1) show positive and significant coefficient estimates on both treatment indicators. These results remain similar after including full set of controls as reported in column (2)—the estimates of *CNC Enf. Up* and *CNC Enf. Down* are 0.023 ($t = 3.56$) and 0.019 ($t = 9.53$), respectively. These estimates suggest that compared with firms in unaffected states, a higher enforceability of non-competes leads to a 22.5% increase in R&D spending (relative to the sample mean) among treated firms, and a weaker

[28] Alternatively, I use the number of employees to scale patent value and find consistent results in unreported tests.

enforceability increases R&D of affected firms by 18.6%. Given this, it is not surprising to see an insignificant coefficient estimate on *Increased CNC Enf.* in column (3) as found in previous research.

Indeed, economic theories offer ambiguous predictions on how enforcing/using non-competes could affect innovation investments such as R&D. As mentioned, a stronger enforcement may foster more R&D investment by solving the hold-up problem. On the other hand, less enforceable non-competes might encourage more R&D owing to greater knowledge spillovers in a more fluid labor market. As such, if both of these mechanisms are at work, I expect that firms invest more in R&D if they benefit more from knowledge spillovers after a weaker enforcement and that higher enforceability stimulates more R&D for those facing a higher hold-up risk from their employees.

To capture the extent of knowledge spillovers that a firm is exposed to, I obtain the spillover measure from Bloom et al. (2013) that is based on a firm's position in technology space, and create *Closer Tech Space*, which is an indicator equal to one for firms with above-median technology spillovers every year. I then interact the treatment indicators (*CNC Enf. Up* and *CNC Enf. Down*) with *Closer Tech Space* and estimate Equation (1) with the interaction terms included. Column (4) in Table 5 reports the results. The coefficient estimate on *CNC Enf. Down* × *Closer Tech Space* is positive and significant at a 10% level, supporting the theory that weakening non-compete enforcement fosters more R&D when firms can benefit from greater knowledge spillovers via mobile workers.

Turning to the theory of hold-up problem, I use a firm's reliance on knowledge workers to proxy for the potential hold-up risk faced by the firm. Using data from Occupational Employment Statistics (OES) survey, I compute the fraction of managers and professional workers employed in a given industry every year to measure the intensity of knowledge workers. *More Knowledge Workers* is an indicator equal to one for firms in industries with the fraction of managers and professional workers above the median level across all industries every year, which is then interacted with the two treatment indicators. Column (5) reports the results based on Equation (1) while including the interaction terms. The estimate on *CNC Enf. Up* × *More Knowledge Workers* is positive and significant at a 1% level, suggesting that increased enforceability spurs more R&D among firms relying more on highly skilled workers. This result supports the theory that stronger non-compete enforcement fosters R&D by mitigating the hold-up problem.

Combined with previous findings on patent value, these results provide corroborative evidence that more enforceable non-competes bring about inefficiency in turning R&D dollars into valuable outputs.

5.2.2 Labor (Re)allocation—Inventor Turnover

I next investigate how firms manage innovative labor (i.e., net expanding or downsizing) after non-compete policy shocks by analyzing their ability to attract and retain inventors. Following the approach of Brav, Jiang, Ma, and Tian (2018), I use information of patent assignee for two successive patents filed by the same inventor to identify new hires and departing inventors. I then calculate *ln(New Hires)*, defined as the natural logarithm of one plus the number of newly joined inventors in the firm, and *ln(Leavers)*, defined as the natural logarithm of one plus the number of inventors leaving the firm. Using one of these two variables as the dependent variable, I estimate Equation (1) and report the results in Panel B of Table 5.

Column (1) shows the results for *ln(New Hires)* and column (2) for *ln(Leavers)*. The coefficient on *CNC Enf. Up* is negative and significant at a 1% level in both regressions, suggesting that higher enforceability reduces the numbers of newly hired inventors and inventor departures in the firm. The coefficient on *CNC Enf. Down* is positive but only significant (at a 1% level) in the regression of *ln(New Hires)*, indicating that a weaker enforcement increases firm access to new talent. These results provide evidence for the role of non-competes in hindering talent reallocation across firms. Noteworthy, these findings also imply that the negative impact of stronger non-compete enforcement on patent value mainly occurs at the intensive margin as more inventors stay with the firm, raising the possibility that allocative inefficiency of innovative labor could further lead to inefficiency in innovation investments.

5.3 Patent-level Analysis

I now analyze the treatment effects at the patent level using Equation (2). Doing so allows me to focus on patents produced in the firm's state of headquarters—the level of treatment in previous analysis, thereby minimizing errors in treatment assignment.[29] This unit level analysis also mitigates the concern that the observed effects on innovation are driven mainly by quantity rather than quality of innovation activities. Table 6 presents the estimation results. The dependent variable is *Patent Value/Assets,* the ratio of the market value of a patent over the firm's book assets (multiplied by 100).

In column (1) in which I include all patents, *CNC Enf. Up* has a negative coefficient estimate significant at a 5% level and *CNC Enf. Down* has a positive coefficient significant at a 1% level. The results become stronger when only including patents produced within HQ states, as shown in column (2). These results consistently suggest that patents applied after increased non-compete enforceability create less value when eventually granted, whereas those filed after decreased enforceability are valued higher at the time of approval, reinforcing previous findings in the firm-level analysis. I then replicate these results with the categorical variable *Increased CNC Enf.* and obtain similar inference as conveyed in columns (3)-(4).

Lastly, column (5) shows that the value-destroying effect of a stronger enforcement is negligible for patents filed outside of HQ states after additionally controlling for assignee state fixed effects. This is expected since out-of-state inventors are least likely to be affected by changes in labor laws passed in the HQ states. But still, these inventors may be affected via spillover effects from firm headquarters, which explains why a lower enforceability enhances the value of out-of-state patents to a lesser degree than that of in-state patents.

5.3.1 Timing of the Treatment Effects

Having established robust average treatment effects of these laws on patent value, another important question is when the effects start to materialize. To show this, I replace *CNC Enf. Up* in Equation (2) with *CNC Enf. Up* $^{-2}$, *CNC Enf. Up* $^{-1}$, *CNC Enf. Up* ^{0}, *CNC Enf. Up* ^{1}, *CNC Enf. Up* ^{2}, and *CNC Enf. Up* $^{3+}$, which are dummy variables equal to one during two years and before, one-year prior to, current year, one-year post to, two-year post to, and three years after, respectively, the increase of the enforceability in

[29] In unreported tests, I find results to be similar when using assignee state as the level of treatment.

the state, and zero otherwise. I then run regressions using the sample of HQ patents while excluding patents affected by a weaker enforcement. I also create *CNC Enf. Down* $^{-2}$, *CNC Enf. Down* $^{-1}$, *CNC Enf. Down* ^{0}, *CNC Enf. Down* ^{1}, *CNC Enf. Down* ^{2} and *CNC Enf. Down* $^{3+}$ in a similar fashion and carry out similar analysis. Figure 1 plots the coefficient estimates of these variables along with the 95% confidence intervals.

Panel A displays that the coefficient estimates on *CNC Enf. Up* $^{-2}$ and *CNC Enf. Up* $^{-1}$ are both small and indistinguishable from zero, confirming that there was no pre-existing trend before the increased enforceability. The coefficient estimates on *CNC Enf. Up* ^{2} and *CNC Enf. Up* $^{3+}$ are negative and significant, suggesting that the decline in innovation value materializes two years after the policy change. Panel B shows that the positive effect of decreased non-compete enforceability on patent value increases during this window but the estimated coefficients on *CNC Enf. Down* $^{-2}$ and *CNC Enf. Down* $^{-1}$ are insignificant, reaffirming the identification assumption of no pre-existing trends.

5.3.2 Innovation Exploration

If higher enforceability of non-competes undermines innovation value by disincentivizing inventors, it may also discourage search and exploratory efforts. To test this, I use measures of innovation search from Balsmeier et al. (2017) as dependent variables when estimating Equation (2). Table 7 reports the regression results. The dependent variables in the first three columns are *Exploratory 90%*, *Exploratory Ratio*, and *Purely Exploratory*. The results show that after non-compete enforceability increases, patents score lower on these exploratory measures, whereas a weaker enforceability leads to higher levels of these metrics. For example, in column (2), the coefficient estimates on the two treatment indicators, both significant at a 1% level, indicate that higher enforceability leads to an 11.8% reduction in exploratory ratio whereas lower enforceability results in a 9.5% increase in the ratio.

The next two columns examine citation patterns to infer direction of innovation search. Column (4) shows that following increased enforceability, patents have a higher fraction of backward self-citations—an 18.5% increase (t = 2.17), indicating that inventors rely more on previous knowledge inside the firm to develop innovation. These patents also receive a higher fraction of forward self-citations, which increases by 55.4% (t = 9.63) as column (5) shows, suggesting that they are cited more heavily from patents owned by the same firm. Taken together, the results in Table 7 imply that enforcing non-competes more strictly might change inventors' innovative behavior to explore less toward areas new to the firm and rely more on previously known areas of expertise inside the firm.

5.4 Inventor Outside Options and Incentives to Innovate

The evidence documented thus far supports the first hypothesis that increased non-compete enforceability reduces innovation value and efficiency. To investigate potential explanations for this valuation loss, I now test *Hypothesis 2*, which involves analyzing heterogeneous treatment effects across inventors likely to be affected more negatively by the legal changes. I estimate the following specification at patent-inventor level and only include inventors residing in HQ states in these tests as they are most likely working at firm headquarters.

$$
\begin{aligned}
Y_{i,j,l,s,t} = \alpha &+ \beta_1\, CNC\ Enf.\ Up_{s,t} \times Z_{l,s,t} + \beta_2\, CNC\ Enf.\ Down_{s,t} \times Z_{l,s,t} + \beta_3\, Z_{l,s,t} \\
&+ \beta_4\, CNC\ Enf.\ Up_{s,t} + \beta_5\, CNC\ Enf.\ Down_{s,t} + \beta'\, X_{i,s,t-1} + \Phi'\, L_{l,s,t} + \delta_l \\
&+ \mu_i + \gamma_k \times d_t + \omega_s + \varepsilon_{i,j,l,s,t}\,, \qquad (3)
\end{aligned}
$$

where $Y_{i,j,l,s,t}$ is the market value of patent j scaled by the assets of firm i (*Patent Value/Assets*), which is produced by inventor l residing in HQ state s and filed in year t. $Z_{l,s,t}$ is a vector containing dummy variables for inventors with higher skill specialization, having lower innovation ability and in early career stages. Thus, β_1—the coefficient on the interaction term of *CNC Enf. Up* and Z—tests how the detrimental effect of higher enforceability on patent value varies with inventors' outside options, bargaining power, and ex ante incentives to move across firms.

Equation (3) includes inventor (δ_l) fixed effects to account for any fixed unobserved inventor characteristics (such as innate talent), in addition to firm (μ_i) and HQ state (ω_s) fixed effects and technology class × year ($\gamma_k \times d_t$) fixed effects. $X_{i,s,t-1}$ is the same set of controls as in Equation (2). $L_{l,s,t}$ contains inventor-level controls including the inventor's past productivity (the natural logarithm of total number of patent grants in the past five years), number of inventors on the patent, inventor's patent experience, and the inventor's network size (the natural logarithm of one plus the cumulative number of unique coinventors on all patents previously filed by the inventor). δ_l and L are included to mitigate the concern that unobserved and observed inventor characteristics (i.e., productivity and network) that might be correlated with Z also affect patent value. Standard errors are again clustered by HQ state.

Table 8 reports the results. I first test whether inventors with higher skill specialization, whose job prospects are more jeopardized, produce less valuable innovation than other inventors after a stronger enforcement. The key variable is the interaction term of *CNC Enf. Up* and *Specialized Inventor*, which is an indicator equal to one if the inventor's skill specialization is above the sample median every year. Column (1) shows a negative and significant coefficient on this variable, after controlling for firm and inventor characteristics and a set of fixed effects at the inventor, firm, HQ state and technology class-year levels. Column (2) replicates the result by using *Increased CNC Enf.* to interact with *Specialized Inventor* and continues to show a negative and significant coefficient estimate. These results support the hypothesis that more enforceable non-competes dampen incentives to innovate by weakening inventor outside options.

The second test analyzes whether the value-decreasing effect on patent value is stronger among inventors with lower innovation ability who tend to be in a weaker bargaining position. I use the cumulative share of uncited patents in the inventor's portfolio as a proxy for failure rate and define *More Uncited Patents* as a dummy equal to one if the failure rate is above sample median every year. Using the two specifications as described above, columns (3) and (4) show negative and significant coefficient estimates on *CNC Enf. Up* × *More Uncited Patents* and *Increased CNC Enf.* × *More Uncited Patents*, respectively, supporting my hypothesis that higher non-compete enforceability disincentivizes inventors more if they are in a weaker bargaining position in which non-competes are more binding.

The third test examines whether the negative treatment effect on patent value is more pronounced among inventors in early patenting careers who often have stronger incentives to switch employers. This is done by including an interaction of *CNC Enf. Up* and *Young Inventor*, which is an indicator equal to one if the number of years since the inventor's first patent is in the bottom quartile of the sample every year.

Column (5) reports a negative and significant coefficient estimate on this interaction term. In column (6), the coefficient of *Increased CNC Enf.* × *Young Inventor* is also negative but not significant. These results largely support the idea that stronger enforcement of non-competes discourages inventors who are more motivated by outside options but have little leverage to bargain.

Noteworthy, an alternative mechanism is that reduced mobility after a stronger enforcement limits idea circulation among inventors across firms, thereby impeding idea recombination that is important for innovation. This view, however, is hard to explain directly why specialists or "young" inventors are affected more negatively than other inventors. My results are consistent with the interpretation that enforceable non-competes reduce incentives to innovate by weakening inventors' outside options and bargaining power.

5.5 Additional Analyses and Robustness Checks

5.5.1 On the Role of Employee Incentives

The findings documented here reflect the overarching theme that highlights the importance of (non-executive) employee incentives in fostering corporate innovation (e.g., Chang et al. 2015). If employee incentives indeed drive these results, I expect changes in non-compete enforceability to have a stronger effect on innovation value and efficiency in firms where incentives of rank-and-file employees are more important. To test this, I follow Chang et al. (2015) to calculate the Black-Scholes value of outstanding options held by non-executive employees (using data from IRRC and ExecuComp databases) as a proxy for the firm's reliance on employee incentives. *High Employee Options* is an indicator equal to one if the per-employee value of non-executive stock options is above the sample median every year. I then interact the two treatment indicators with *High Employee Options* and estimate the baseline Equation (1).

Table 9 shows the results. The dependent variables in columns (1)-(4) are *ln(Patent Value)*, *Patent Value/Assets*, *Patent Value/R&D Stock*, and *ln(Patent Value Per Inventor)*, respectively. The results support my prediction as the coefficient estimates on *CNC Enf. Up* × *High Employee Options* are all negative and significant at a 1% level and the coefficient estimates on *CNC Enf. Down* × *High Employee Options* are all positive and significant (t-stats ranging from 1.89 to 6.13) for the four outcome measures, suggesting that firms in which employee incentives are of greater importance experience larger reductions in patent value and innovation efficiency after non-compete enforceability increases, whereas a lower enforceability leads to larger gains for such firms in terms of these measured outcomes. The results also show positive associations between *High Employee Options* and innovation outcomes, consistent with Chang et al. (2015).

5.5.2 A stacked event-study approach

Recent research has raised a concern over using two-way fixed effect (TWFE) to estimate treatment effects in a setting of staggered events (see e.g., Baker et al., 2022), as this approach might be subject to a bad control problem—early treated groups serve as control units for later treated groups. To address this concern, I follow Cengiz et al. (2019) to employ a stacked event-study approach. For each treatment event, I collect a cohort set consisting of the treated state and all clean control states from three years before to seven years after the event. Clean control states are those that never experienced any material enforceability changes during the sample period. I then stack all cohort sets and estimate Equation (1) while additionally controlling for Cohort × State and Cohort × Year fixed effects. This set of fixed effects allows to examine treatment effects using never treated states as control units in each cohort, thus circumventing the bad control problem. Standard errors are clustered by the firm's headquarter state in each cohort.

Table 10 presents the results. The dependent variables are *ln(Patent Value)*, *Patent Value/Assets*, *Patent Value/R&D Stock*, and *ln(Patent Value Per Inventor)*, respectively. I find consistent results using the stacked events framework. For all four outcome measures, the estimated coefficients on *CNC Enf. Up* are negative and significant, and the coefficient estimates on *CNC Enf. Down* are all positive and significant, suggesting that the main results are robust to correcting the biases of TWFE estimator.

5.5.3 Identification Tests

Selection of Headquarters Location: One potential endogeneity concern here is that firms might choose their headquarters location (often proximate to research labs) based on state non-compete enforcement policies. If firms with better innovation potential are more likely to move to states weakly enforcing non-competes (for better access to talent from incumbents), then the estimated treatment effect would be biased upward due to this sorting. However, it could also be the case that these firms prefer stronger enforcement regime that provides greater protection on intellectual property. To mitigate the impact from sorting on the results, I exclude firms that have changed headquarters and rerun the firm-level regressions. Panel A of Table IA2 in the Internet Appendix shows that the results of this test remain similar as previously discussed, suggesting that firm sorting has little bearing on the estimated treatment effects.

Matched Sample Analysis: Another potential concern is that firms affected by changes in non-compete enforceability (treated firms) might be different enough from other firms in unaffected states (control firms) such that this control group may not provide the best counterfactual. To alleviate this concern, I replicate the firm-level analyses using a matched sample based on industry and firm size. Specifically, for each treated firm, I select five control firms that are closest in size and in the same industry from unaffected firms one year prior to the policy change taking place to the treated firm. Panel B of Table IA2 reports similar results using this matched sample as those from the full sample. Thus, the estimated effects are unlikely to be confounded by the differences between treated and control firms.

Law-based Weakening of the Enforcement: Ewens and Marx (2018) point out one concern over the identification from new laws that weakened the enforceability of non-competes. Due to the forward-looking nature of laws, if these laws were applied only to prospective contracts, firms might be unwilling to update their agreements with existing employees, leaving the previous provisions unchanged and rendering a limited effect of these new laws.[30] There is only one such case during my sample period, which took place in Oregon. Though a small representation in the sample, I exclude firms in Oregon and find that results after this exclusion, reported in Table IA2 Panel C, remain quantitatively and qualitatively similar.

5.5.4 Alternative CNC Enforceability Indexes

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[30] This is less of a concern for new laws that aim to strengthen the enforceability because firms have incentives to revise employee contracts in order to take advantage of the new law, especially in states where continued employment is the only consideration for a valid non-compete (Ewens and Marx 2018).

I also use alternative indexes that measure the strength of state non-compete enforceability from Kini et al. (2019) and Ertimur et al. (2018) as a robustness check. Both studies follow Garmaise's approach closely to extend the data on enforceability scores for each state (see more detailed description of variable definitions in the Internet Appendix Table IA6). I rescale these scores to generate values ranging from 0 to 1 and estimate a specification similar to Equation (1). Table IA3 in the Internet Appendix shows negative coefficient estimates on the two enforceability indexes significant mostly at 1% level for all the outcome measures of patent value and efficiency. Thus, in the cross-section, firms in states with a higher non-compete enforceability are associated with lower patent value and value per input (i.e., capital and labor).[31]

5.5.5 Potential Firm Response

Do firms react to non-compete policy reforms by changing the locations of their innovation activities so that they can circumvent the value-destroying effect of a stronger enforcement? To investigate this possibility, I follow Bradley, Kim, and Tian (2017) to consider the locality of patents. Specifically, I ask whether a firm is more likely to produce patents out of state of headquarters after non-compete enforceability increases. The dependent variable is *Out-of-HQ patent*, an indicator equal to one if the patent is applied outside of the firm's HQ state. I then estimate Equation (2) to test the treatment effects at the patent level. Table IA5 in the Internet Appendix reports the results. In column (1), *CNC Enf. Up* has a positive estimated coefficient, which is insignificant, and *CNC Enf. Down* has a negative coefficient significant at a 1% level. Column (2) reports a positive and significant coefficient on *Increased CNC Enf.* These results largely support the conjecture. Moreover, cross-sectional analysis in columns (3)-(4) shows positive and significant coefficients on non-compete enforceability indexes, suggesting that firms in states strongly enforcing non-competes are more likely to produce out-of-state patents. Overall, these results imply that firms may respond to non-compete policy reforms by shifting their innovation activities to states with a lower enforceability where workers have stronger innovation incentives.

[31] I also replicate the results analyzed at the patent level with the two enforceability indexes and continue to find a robust negative relationship between non-compete enforceability and patent value. These results are reported in the Internet Appendix Table IA4.

6. CONCLUSION

Motivated by the contrasting effects of non-competes on firm incentives to invest and worker incentives to innovate, this paper investigates how changes in non-compete laws affect value creation in innovation, which further sheds light on investment efficiency. Exploiting staggered changes in state non-compete enforceability, I find that patents filed subsequent to a stronger enforcement create significantly less economic value, as they receive less positive stock market reactions when granted. Measures of innovation efficiency also suggest deterioration after enforceability increases. Moreover, patents tend to be less exploratory, indicating that inventors explore less toward new areas and rely more on known areas of expertise inside their firm following a higher non-compete enforceability.

I attempt to explain this valuation loss from a behavioral perspective by analyzing inventor characteristics. I expect that inventors whose external opportunities are more weakened, who are in a weaker bargaining position, and who have greater incentives to move across firms are discouraged more by a stronger enforcement. Indeed, I find that higher enforceability reduces patent value more among inventors with higher skill specialization, lower innovation ability and in early patenting career, supporting the notion that non-competes dampen incentives to innovate by weakening worker outside options and bargaining power. These results also indicate that this disincentive effect dominates the incentive effect on firm investments, which implies that labor allocative inefficiency owing to mobility restrictions could compromise value creation from real investments.

Much has been discussed on the benefits of non-competes to firms. This paper is among one of the few studies that discover the costs on employers, which is underexplored in the extant literature. The only study that offers similar implications is Samila and Sorenson (2011), who find inefficiency in venture capital investment in states that strongly enforce non-competes. They suggest that non-compete laws matter for the effectiveness of government programs that attempt to stimulate such investment. In a broader view, stricter protection on intellectual property via constraining labor mobility may reduce efficiency by undermining the worker incentives and power that are vital to value creation.

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Table 1. Predictive Regressions

This table presents results examining whether a state's macroeconomic, political, and legal institutional conditions predict the reform of non-compete laws. The dependent variable is *CNC Enf. Down* in columns (1) and (2), *CNC Enf. Up* in columns (3) and (4), and *Increased CNC Enf.* in columns (5) and (6). *CNC Enf. Down* is an indicator equal to one if a state has decreased non-compete enforceability in the year. *CNC Enf. Up* is an indicator equal to one if a state has increased non-compete enforceability in the year. *Increased CNC Enf.* is a categorical variable that takes the value of one if a state has increased non-compete enforceability in the year, takes the value of negative one if a state has decreased non-compete enforceability in the year, and is set to zero otherwise. All predicting variables are lagged by one year. *State GDP Growth* is the annual state GDP growth rate. *Ln(State Unemployment)* is the natural logarithm of state's unemployment rate. *ln(State Population)* is the natural logarithm of total population in the state. *ln(Per Capita Personal Income)* is the natural logarithm of per capita personal income in the state. *State Labor Force (Pct.)* is the ratio of labor force over total population in the state. *State Republicans (Pct.)* is the ratio of Republican to Democrat legislators in state legislatures and government. *Inevitable Disclosure Doctrine* is an indicator equal to one for firms headquartered in states after the recognition of IDD in the year. *State UTSA (Trade Secrecy)* is an index that measures the strength of legal protection of trade secrets based on the effective UTSA and case law precedents. Details on variable construction are described in the Appendix. All regressions control for state and year fixed effects. The *t*-statistics in parentheses are based on robust standard errors clustered by state. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	CNC Enf. Down		CNC Enf. Up		Increased CNC Enf.	
State GDP Growth	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.999)	(0.984)	(0.109)	(0.124)	(-0.267)	(-0.249)
ln(State Unemployment)	-0.008	-0.008	-0.005	-0.007	0.002	0.002
	(-0.870)	(-0.992)	(-0.211)	(-0.274)	(0.095)	(0.066)
ln(Per Capita Personal Income)	-0.075	-0.079	-0.129	-0.132	-0.055	-0.053
	(-1.211)	(-1.295)	(-1.547)	(-1.512)	(-0.538)	(-0.500)
State Labor Force (Pct.)	-0.080	-0.076	0.051	0.061	0.132	0.138
	(-1.148)	(-1.053)	(0.141)	(0.168)	(0.365)	(0.380)
ln(State Population)	-0.007	-0.009	-0.006	-0.007	0.001	0.002
	(-0.242)	(-0.319)	(-0.081)	(-0.088)	(0.013)	(0.032)
State Republicans (Pct.)	-0.015	-0.015	-0.048	-0.057	-0.033	-0.042
	(-0.261)	(-0.253)	(-0.937)	(-1.062)	(-0.429)	(-0.530)
Inevitable Disclosure Doctrine		0.004		0.009		0.004
		(0.467)		(0.575)		(0.245)
State UTSA (Trade Secrecy)		-0.010		0.047		0.058
		(-1.031)		(0.902)		(1.131)
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	833	833	833	833	833	833
Adjusted R^2	0.1031	0.1011	0.0260	0.0259	0.0515	0.0508

Table 2. Summary Statistics

Panel A reports descriptive statistics of firm-level variables of interest for the main sample over 1992–2009. This sample comprises publicly traded U.S. industrial firms having at least one patent grant in any given year, having non-missing R&D expenditures in Compustat and with identifiable historical headquarters location information in SEC 10-K filings, a total of 14,585 firm-year observations. Panel B reports summary statistics for patent-level sample containing 537,021 observations, and Panel C for inventor characteristics at the patent-inventor level with 567,867 observations. *Patent Value* is the total market value of patents ($ millions) that a firm applied for in a given year. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *Patent Value per Inventor* is the total market value of patents applied for in the year divided by the number of inventors in the firm. *Noncompetition (CNC) Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *Noncompetition (CNC) Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that equals one for firms headquartered in states after an increase in non-compete enforceability, equals negative one for firms headquartered in states after a reduction in the enforceability, and is set to zero otherwise. All other variables are defined in the Appendix. All continuous variables are winsorized at their 1st and 99th percentiles. Dollar values are CPI-adjusted in 2016 dollars.

Variable	Mean	S.D.	25th Percentile	Median	75th Percentile
A. Firm Level					
Patent Value ($mil)	1741.035	10162.000	4.481	23.590	199.301
Patent Value/Assets	0.178	0.267	0.026	0.073	0.203
Patent Value/R&D stock	1.935	3.413	0.207	0.661	1.962
Patent Value per Inventor	11.317	24.142	1.056	3.337	10.165
Noncompetition (CNC) Enf. Up	0.018	0.132	0.000	0.000	0.000
Noncompetition (CNC) Enf. Down	0.040	0.197	0.000	0.000	0.000
Increased CNC Enf.	-0.023	0.227	0.000	0.000	0.000
Assets ($mil)	3891.670	25771.000	54.838	212.312	1119.518
Leverage	0.161	0.165	0.007	0.117	0.268
Age	18.575	14.548	7.000	13.000	26.000
MktBk	2.538	2.219	1.234	1.763	2.923
Cash Flow	-0.011	0.245	-0.037	0.071	0.121
Tangibility	0.208	0.162	0.084	0.170	0.290
R&D/Assets	0.102	0.123	0.019	0.058	0.132
State Industry HHI	0.390	0.266	0.185	0.300	0.532
State GDP Growth	0.053	0.032	0.037	0.053	0.072
State Unemployment	5.651	1.650	4.575	5.375	6.417
Inevitable Disclosure Doctrine (IDD)	0.517	0.500	0.000	1.000	1.000
B. Patent Level					
Patent Value/Assets (%)	0.784	1.921	0.037	0.149	0.581
Exploratory 90%	0.276	0.447	0.000	0.000	1.000
Exploratory Ratio	0.577	0.351	0.250	0.619	0.933
Backward Self-cites	0.151	0.220	0.000	0.048	0.226
Forward Self-cites	0.139	0.242	0.000	0.000	0.188
C. Inventor Patent Level					
Patent Value/Assets (%)	1.032	2.252	0.053	0.223	0.837
Inventor Specialization	0.497	0.323	0.240	0.444	0.755
Fraction of Uncited Patents	0.085	0.170	0.000	0.000	0.100
Inventor Past Productivity	11.299	26.279	1.000	4.000	11.000
Inventors of the Patent	3.621	3.035	2.000	3.000	5.000
Inventor Patent Experience (years)	7.317	7.243	2.000	5.000	11.000
Inventor Network Size	17.170	20.387	5.000	11.000	22.000
Firm Knowledge Specialization	0.231	0.249	0.063	0.126	0.285

Table 3. Noncompete Enforceability and Patent Value

This table presents the regression results examining the effect of changes in CNC enforceability on patent market value at the firm level. The dependent variable is *ln(Patent Value)* in columns (1)-(2) and is *Patent Value/Assets* in columns (3)-(4). *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that takes the value of one for firms headquartered in states after an increase in non-compete enforceability, takes the value of negative one for firms headquartered in states after a reduction in non-compete enforceability, and is set to zero otherwise. All control variables are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The sample includes firms granted at least one patent during a given year. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ln(Patent Value)		Patent Value/Assets	
CNC Enf. Up	**-0.383*** **		**-0.058***	
	(-3.587)		**(-1.759)**	
CNC Enf. Down	**0.272*** **		**0.069*** **	
	(3.215)		**(5.753)**	
Increased CNC Enf.		**-0.309*** **		**-0.065*** **
		(-4.625)		**(-5.689)**
Size	0.872***	0.872***	0.045***	0.045***
	(32.434)	(32.431)	(5.757)	(5.829)
Leverage	-0.591***	-0.590***	-0.077***	-0.077***
	(-4.959)	(-4.932)	(-2.833)	(-2.823)
ln(age)	0.077	0.077	0.031**	0.031**
	(1.267)	(1.263)	(2.253)	(2.267)
MktBk	0.166***	0.166***	0.032***	0.032***
	(20.694)	(20.700)	(14.247)	(14.230)
Cash Flow	0.026	0.026	-0.047*	-0.047*
	(0.327)	(0.326)	(-1.946)	(-1.944)
Tangibility	0.184	0.185	0.053	0.053
	(1.187)	(1.194)	(1.298)	(1.295)
R&D/Assets	1.311***	1.308***	0.214***	0.214***
	(10.070)	(10.046)	(5.134)	(5.131)
State Industry HHI	0.032	0.034	0.015	0.015
	(0.278)	(0.295)	(0.581)	(0.578)
State GDP Growth	1.980**	1.988**	0.498***	0.498***
	(2.122)	(2.104)	(2.731)	(2.698)
ln(State Unemployment)	0.008	0.008	-0.001	-0.001
	(0.081)	(0.092)	(-0.037)	(-0.041)
IDD	-0.051	-0.049	-0.001	-0.001
	(-1.100)	(-1.102)	(-0.108)	(-0.130)
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	14585	14585	14585	14585
Adjusted R^2	0.9335	0.9335	0.6514	0.6514

Table 4. R&D Efficiency and Inventor Value Creation

This table presents the regression results examining the effect of changes in CNC enforceability on productivity of R&D investment and inventors based on subsequent patent market value. The dependent variable is *Patent Value/R&D Stock* in columns (1)-(2) and is *ln(Patent Value per Inventor)* in columns (3)-(4). *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that takes the value of one for firms headquartered in states after an increase in non-compete enforceability, takes the value of negative one for firms headquartered in states after a reduction in non-compete enforceability, and is set to zero otherwise. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, R&D/Assets* (not in columns 1-2), *State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* which are measured in year $t-1$. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The sample includes firms granted at least one patent during a given year. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	Patent Value/R&D Stock		ln(Patent Value per Inventor)	
CNC Enf. Up	**-2.037*** **		**-0.162*** **	
	(-3.749)		**(-3.080)**	
CNC Enf. Down	**1.563*** **		**0.232*** **	
	(4.386)		**(4.442)**	
Increased CNC Enf.		**-1.721*** **		**-0.209*** **
		(-7.962)		**(-4.733)**
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	9751	9751	9631	9631
Adjusted R^2	0.7028	0.7028	0.7174	0.7174

Table 5. Decomposing Inefficiency

This table presents the regression results examining the effect of changes in CNC enforceability on R&D investment and inventor turnover. The dependent variable in Panel A is a firm's *R&D-to-assets* ratio. In Panel B, the dependent variables are *ln(New Hires)* and *ln(Leavers)*. *ln(New Hires)* is the natural logarithm of one plus the number of newly joined inventors in the firm. *ln(Leavers)* is the natural logarithm of one plus the number of inventors leaving the firm. *CNC Enf. Up* is an indicator equal to one for firms in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms in states after a lower enforceability. *Increased CNC Enf.* is a variable equal to one for firms in states after increased enforceability, equal to negative one for firms in states after decreased enforceability, and is set to zero otherwise. *Closer Tech Space* is an indicator equal to one for firms with above-median technology spillovers every year. *More Knowledge Workers* is an indicator equal to one for firms in knowledge worker intensive industries. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, R&D/Assets* (not in Panel A), *State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* all measured in year $t-1$. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Capital Allocation—R&D Investment

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	R&D/Assets				
CNC Enf. Up	**0.026*** **	**0.023*** **		0.009	-0.007
	(3.538)	**(3.556)**		(0.692)	(-0.734)
CNC Enf. Down	**0.014*** **	**0.019*** **		0.013***	0.019***
	(5.550)	**(9.528)**		(3.594)	(3.188)
Increased CNC Enf.			-0.005		
			(-0.388)		
CNC Enf. Down				**0.007***	
× Closer Tech Space				**(1.713)**	
CNC Enf. Up				0.018	
× Closer Tech Space				(1.569)	
Closer Tech Space				-0.002	
				(-0.796)	
CNC Enf. Down					-0.004
× More Knowledge Workers					(-0.699)
CNC Enf. Up					**0.021*** **
× More Knowledge Workers					**(3.601)**
More Knowledge Workers					0.002
					(0.974)
Controls	No	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes	Yes
N	14583	14583	14583	14455	14583
Adjusted R^2	0.7769	0.7933	0.7931	0.7938	0.8089

Panel B. Labor Reallocation--Inventor Turnover

	(1)	(2)
Dependent Variable:	ln(New Hires)	ln(Leavers)
CNC Enf. Up	**-0.129*** **	**-0.126*** **
	(-4.961)	**(-2.767)**
CNC Enf. Down	**0.107*** **	0.006
	(3.277)	(0.060)
Controls	Yes	Yes
Firm FEs	Yes	Yes
State FEs	Yes	Yes
Industry × Year FEs	Yes	Yes
N	9630	9630
Adjusted R^2	0.6348	0.6924

Table 6. Evidence from Patent Location at the Patent Level

This table presents the regression results examining the effect of changes in CNC enforceability on subsequent patent value at the patent level. The dependent variable is the market value of a new patent scaled by the firm's book assets, multiplied by 100. Columns (1) and (3) report results for the full sample, columns (2) and (4) for a subsample including patents filed in the firm's state of headquarters, column (5) for patents filed outside of the firm's headquarters state. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that takes the value of one for firms headquartered in states after an increase in non-compete enforceability, takes the value of negative one for firms headquartered in states after a reduction in non-compete enforceability, and is set to zero otherwise. Control variables include *Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* which are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, technology class × year, and state of headquarters fixed effects. Column (5) additionally includes assignee state fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	(Patent Value/Assets) × 100				
Sample	All Patents	HQ Patents	All Patents	HQ Patents	Out-of-HQ Patents
CNC Enf. Up	**-0.367****	**-0.410****			-0.351
	(-2.358)	**(-2.205)**			(-1.251)
CNC Enf. Down	**0.538*****	**0.654*****			0.136**
	(5.492)	**(5.868)**			(2.104)
Increased CNC Enf.			**-0.511*****	**-0.606*****	
			(-5.990)	**(-6.489)**	
Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
HQ State FEs	Yes	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes	Yes
Assignee State FEs	No	No	No	No	Yes
N	537021	447598	537021	447598	73639
Adjusted R^2	0.6317	0.6388	0.6316	0.6387	0.7238

Table 7. Exploratory Innovations

This table presents the regression results examining the effect of changes in CNC enforceability on the exploratory nature of innovation at the patent level. The dependent variables across the columns are *Exploratory 90%, Exploratory Ratio, Purely Exploratory, Backward Self-cites*, and *Forward Self-cites*, respectively. *Exploratory 90%* is an indicator equal to one if at least 90% of the patent's backward citations are based on new knowledge coming outside of the firm's existing knowledge base, which consists of all patents granted to the firm and patents cited by the firm in the past five years. *Exploratory Ratio* is the fraction of the patent's backward citations based on new knowledge coming outside of the firm's existing knowledge base. *Purely Exploratory* is an indicator equal to one if the patent does not cite any previous patents owned by the same assignee. *Backward Self-cites* is the ratio of citations made to patents owned by the same assignee over total citations made by the patent. *Forward Self-cites* is the ratio of self-citations received by the patent over total citations received. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. Control variables include *Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* which are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, technology class × year, and state of headquarters fixed effects. The sample includes patents filed in the firm's state of headquarters. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Exploratory 90%	Exploratory Ratio	Purely Exploratory	Backward Self-cites	Forward Self-cites
CNC Enf. Up	**-0.123*** **	**-0.068*** **	**-0.146*** **	**0.028** **	**0.077*** **
	(-4.983)	**(-2.925)**	**(-4.763)**	**(2.171)**	**(9.629)**
CNC Enf. Down	**0.041*** **	**0.055*** **	**0.054*** **	**-0.022*** **	-0.000
	(3.412)	**(3.893)**	**(3.054)**	**(-4.422)**	(-0.023)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes	Yes
N	421525	421525	424393	424393	355555
Adjusted R^2	0.1617	0.2200	0.1497	0.1629	0.1608

Table 8. Channel Tests: Evidence from Inventors

This table presents the regression results examining the differential effect of changes in CNC enforceability on patent value produced by inventors with greater skill specialization (columns 1-2), inventors with lower innovation ability (columns 3-4), and inventors who are relatively young in their innovation careers (columns 5-6). The dependent variable is the market value of a new patent scaled by the firm's book assets, multiplied by 100. *Specialized Inventor* is an indicator equal to one if the inventor's *skill specialization* is ranked above the sample median every year. *Inventor Skill Specialization* is an Herfindahl-Hirschman concentration measure based on the share of patents in each three-digit technology class among all the patents that the inventor has filed in the past five years. *More Uncited Patents* is an indicator equal to one if the cumulative fraction of uncited patents in the inventor's patent portfolio is greater than the sample median every year. *Young Inventor* is an indicator equal to one if number of years since the inventor's first patent application is in the bottom quartile of the sample every year. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms in states after a reduction in the enforceability. *Increased CNC Enf.* is a categorical variable equal to one for firms in states after an increase in the enforceability, equal to negative one for firms in states after a reduction in the enforceability, and zero otherwise. All regressions include controls—*Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD*. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	(Patent Value/Assets) × 100					
CNC Enf. Up	**-0.282*** **					
× Specialized Inventor	**(-4.966)**					
CNC Enf. Down	0.024*					
× Specialized Inventor	(1.956)					
Increased CNC Enf.		**-0.033** **				
× Specialized Inventor		**(-2.134)**				
CNC Enf. Up			**-0.241*** **			
× More Uncited Patents			**(-3.872)**			
CNC Enf. Down			0.088			
× More Uncited Patents			(1.566)			
Increased CNC Enf.				**-0.098***		
× More Uncited Patents				**(-1.750)**		
CNC Enf. Up					**-0.759*** **	
× Young Inventor					**(-9.600)**	
CNC Enf. Down					-0.023	
× Young Inventor					(-0.316)	
Increased CNC Enf.						-0.037
× Young Inventor						(-0.407)
Firm Knowledge Specialization	0.324	0.326	0.325	0.327	0.321	0.325
	(1.365)	(1.378)	(1.373)	(1.382)	(1.357)	(1.384)
ln(Inventor past productivity)	0.011	0.011	0.013	0.013	0.012	0.012
	(0.461)	(0.467)	(0.527)	(0.530)	(0.485)	(0.496)
ln(Inventors of the Patent)	0.026***	0.026***	0.026***	0.026***	0.026***	0.026***
	(3.085)	(3.078)	(2.946)	(2.941)	(3.056)	(3.059)
ln(Inventor Patent Experience)	-0.040	-0.040	-0.036	-0.037	-0.034	-0.035
	(-1.421)	(-1.423)	(-1.332)	(-1.333)	(-1.532)	(-1.594)
ln(Inventor Network Size)	-0.030	-0.030	-0.029	-0.029	-0.028	-0.029
	(-1.060)	(-1.068)	(-0.998)	(-1.000)	(-0.991)	(-1.012)
All other controls	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	567808	567808	567808	567808	567808	567808
Adjusted R^2	0.6587	0.6590	0.6915	0.6915	0.6915	0.6914

Table 9. The Role of Employee Incentives

This table presents the regression results examining the differential effect of changes in CNC enforceability on patent value and innovation efficiency when employee incentives are more important to the firm. The dependent variables across columns are *ln(Patent Value), Patent Value/Assets, Patent Value/R&D Stock*, and *ln(Patent Value per Inventor)*, respectively. *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. *High Employee Options* is an indicator equal to one if the per-employee Black-Scholes value of non-executive stock options is above the sample median every year. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. All control variables are measured in year $t-1$ and are included in the regressions but not reported. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The sample includes firms granted at least one patent during a given year. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	(1) ln(Patent Value)	(2) Patent Value/Assets	(3) Patent Value/R&D Stock	(4) ln(Patent Value per Inventor)
CNC Enf. Up	**-0.314*** **	**-0.098*** **	**-1.389*** **	**-0.448*** **
× High Employee Options	**(-3.939)**	**(-6.395)**	**(-3.904)**	**(-5.547)**
CNC Enf. Down	**0.203***	**0.054*** **	**1.029*** **	**0.511*** **
× High Employee Options	**(1.892)**	**(3.641)**	**(3.285)**	**(6.127)**
High Employee Options	0.165***	0.031***	0.437***	0.135***
	(5.363)	(4.636)	(3.380)	(3.327)
CNC Enf. Up	-0.039	-0.015	-0.757**	0.128
	(-0.297)	(-0.493)	(-2.146)	(1.591)
CNC Enf. Down	0.136	0.064***	1.314**	-0.141
	(1.124)	(5.425)	(2.507)	(-1.036)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	5328	5328	4218	4874
Adjusted R^2	0.9342	0.7541	0.7428	0.6898

Table 10. A Stacked Event Study Approach

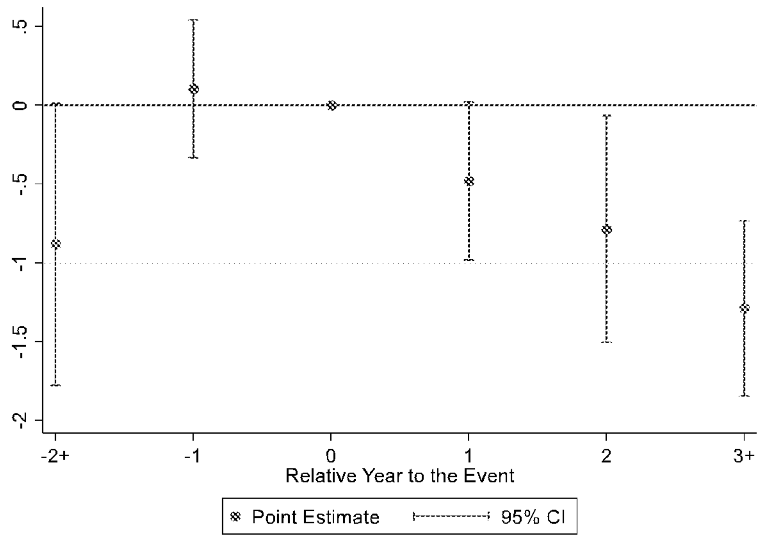
This table presents stacked event-study regression results examining the effect of changes in CNC enforceability on innovation value and efficiency. Each cohort consists of one treatment state and clean control states during three years before and seven years after the event. Clean control states are those that did not experience material changes in CNC enforcement during the sample period. The dependent variables across columns are *ln(Patent Value)*, *Patent Value/Assets*, *Patent Value/R&D Stock*, and *ln(Patent Value per Inventor)*, respectively. *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states following a reduction in the enforceability of non-competes, and zero otherwise. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states following an increase in the enforceability of non-competes, and zero otherwise. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, State Industry HHI, State GDP Growth, ln(State Unemployment), IDD* and *R&D/Assets*, which are measured in year *t-1*. All regressions incorporate control variables, firm fixed effects, industry × year, cohort × state, cohort × year fixed effects. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's headquarter state in each cohort. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ln(Patent Value)	Patent Value/Assets	Patent Value/R&D Stock	ln(Patent Value per Inventor)
CNC Enf. Up	**-0.396*** **	**-0.089*** **	**-2.132*** **	**-0.178*** **
	(-4.519)	**(-4.258)**	**(-5.462)**	**(-4.233)**
CNC Enf. Down	**0.319*** **	**0.080*** **	**1.247** **	**0.241*** **
	(5.351)	**(5.157)**	**(2.565)**	**(6.436)**
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
Cohort × State FEs	Yes	Yes	Yes	Yes
Cohort × Year FEs	Yes	Yes	Yes	Yes
N	53151	53151	35673	28367
Adjusted R^2	0.9475	0.7161	0.7408	0.7759

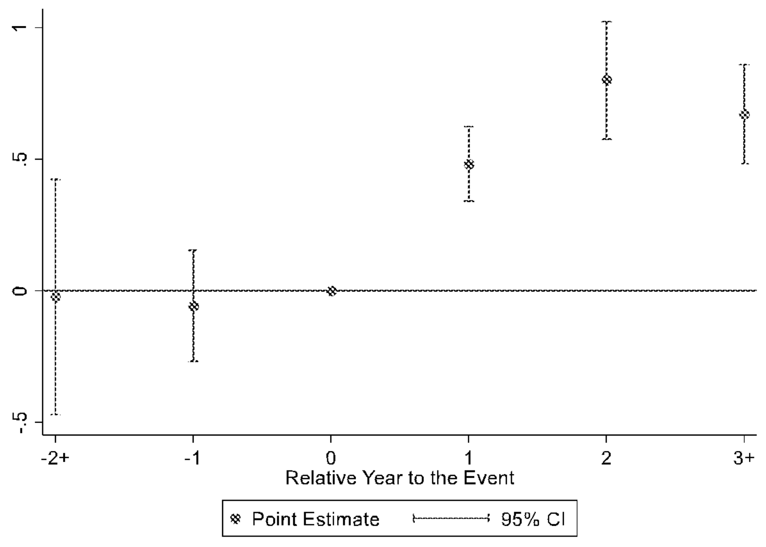
Figure 1. Dynamic Effects of Changes in CNC Enforceability on Patent Value

This figure shows the timing of the effect of changes in CNC enforceability on patent value at the patent level by estimating a dynamic DID regression. The dependent variable is the market value of a new patent over the firm's book assets, multiplied by 100. Panel A examines the dynamic effects of strengthening enforceability in the state of the firm's headquarters. This sample excludes patents affected by a decrease in the enforceability. Similarly, Panel B presents the estimation results of the reduction of CNC enforceability in the state of the firm's headquarters. This sample excludes patents affected by an increase in the enforceability. The 95% confidence intervals are based on robust standard errors clustered by the firm's state of headquarters.

Panel A. CNC Enforceability Up



Panel B. CNC Enforceability Down



Appendix A. Variable Definitions

Variable	Description
A. Firm-level	
Patent Value	Total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date, converted into 2016 dollars; source: Kogan, Papanikolaou, Seru, and Stoffman (2017)
Patent Value/Assets	Total market value of patents applied for by a firm in the year scaled by the firm's book assets (AT).
Patent Value/R&D stock	Total market value of patents applied for by a firm in the year divided by past R&D stock from years $t-2$ to $t-6$ with a 20% depreciation rate, akin to the innovation efficiency measures developed by Hirshleifer, Hsu, and Li (2013).
Patent Value Per Inventor	Total market value of patents applied for by a firm in the year divided by the number of inventors in the firm. Data on inventor are obtained from Harvard Patent Network Dataverse (Li et al. 2014) available at https://dataverse.harvard.edu/dataverse/patent
R&D/Assets	The ratio of R&D expenditures (XRD) to book assets (AT) of the firm
Noncompetition (CNC) Enf. Down	An indicator equal to one for firms headquartered in states after a reduction in Noncompetition enforceability, and zero otherwise; source: Garmaise (2011) and Ewens and Marx (2018). Information on firm historical headquarters location is extracted from Securities and Exchange Commission (SEC) 10-K filings in the EDGAR database.
Noncompetition (CNC) Enf. Up	An indicator equal to one for firms headquartered in states after an increase in Noncompetition enforceability, and zero otherwise; source: Garmaise (2011) and Ewens and Marx (2018).
Increased CNC Enf.	A categorical variable that takes the value of one for firms headquartered in states after an increase in Noncompetition enforceability, takes the value of negative one for firms headquartered in states after a reduction in Noncompetition enforceability, and is set to zero otherwise.
Size	Natural Logarithm of the firm's book assets (AT), converted into 2016 dollars.
Leverage	The ratio of long-term debt (DLTT) plus debt in current liabilities (DLC) to total assets (AT).
Age	Number of years the firm is listed with a non-missing stock price on COMPUSTAT.
MktBk	The ratio of total assets (AT) minus book value of common equity (CEQ) plus the market value of common equity (PRCC_F × CSHO) over total assets (AT).
Cash Flow	Operating income before depreciation (OIBDP), less interest (XINT) and taxes (TXT), scaled by total assets (AT).
Cash Holdings	The ratio of cash plus marketable securities (CHE) over book assets (AT).
Tangibility	The ratio of total net property, plant, and equipment (PPENT) over total assets (AT).
State Industry HHI	Sales-based Herfindahl-Hirschman Index within firms in the same two-digit SIC industry and headquartered in the same state.
State GDP Growth	Annual state GDP growth rate; source: Bureau of Economic Analysis (BEA)
ln(State Unemployment)	Natural logarithm of state unemployment rate; source: US Bureau of Labor Statistics.

Inevitable Disclosure Doctrine (IDD)	An indicator equal to one for firms headquartered in states after a recognition of Inevitable Disclosure Doctrine (IDD); source: Klasa et al. (2018)
ln(Per Capita Personal Income)	Natural logarithm of per capita personal income (dollars) in the state; source: Bureau of Economic Analysis (BEA)
State Labor Force (Pct.)	the ratio of labor force over total population in the state; source: Bureau of Economic Analysis (BEA)
Ln(State Population)	the natural logarithm of total population in the state; source: Bureau of Economic Analysis (BEA)
State Republicans (Pct.)	the ratio of Republican to Democrat legislators in state legislatures and government. Nebraska is not included because members are elected on a nonpartisan basis. Data are obtained from the National Conference of State Legislatures and Book of the States.
State UTSA (Trade Secrecy)	an index that measures the strength of legal protection of trade secrets based on the effective UTSA and case law precedents; source: Png (2017)
Closer Tech Space	an indicator equal to one for firms with above-median technology spillovers every year using the measure based on a firm's position in technology space from Bloom et al. (2013).
Industry-level Knowledge Workers	the fraction of managers and professional workers employed in an industry at the 3-digit SIC code level before 2001 and at the 4-digit NAICS code level afterwards. Data on employment estimates are obtained from the Occupational Employment Statistics (OES) survey from the Bureau of Labor Statistics. The OES provides detailed breakdown of the total number of people employed in each industry by the occupational code. Because OES used its own taxonomy (with 258 broad occupations) before 1998, managerial occupations take codes from 10,000 to 19,999, and professional workers are assigned with occupational codes under the major group of 20,000, which includes scientists, engineers, technologists, heath practitioners, accountants, editors, computer programmers, and so forth. In 1999, the OES changed the occupation definitions to Standard Occupational Classification (SOC) system (with 444 broad occupations). Thus, from 1999 onward, managerial occupations are in the major group of 11-0000; professional workers are in the major groups with the first two digits of 13, 15, 17, 19, 21, 23, 25, 27, 29, followed by 0000. The OES data is available at https://www.bls.gov/oes/tables.htm.
More Knowledge Workers	An indicator equal to one for firms in knowledge worker intensive industries, defined as industries with the fraction of managers and professional workers above the median level across all industries every year.
ln(New Hires)	Natural logarithm of one plus the number of newly joined inventors in the firm
ln(Leavers)	Natural logarithm of one plus the number of inventors leaving the firm
High Employee Options	An indicator equal to one if the firm's option value per employee is above sample median every year. Option value per employee is the value of options granted to nonexecutive employees divided by the number of employees. Option value is estimated by Black-Scholes option pricing model. source: ExecuComp and IRRC
B. Patent Level	
Patent Value/Assets (%)	Market value of the patent scaled by the firm's book assets (AT), multiplied by 100.
Exploratory 90%	An indicator equal to one if at least 90% of the patent's backward citations are based on new knowledge coming outside of the firm's existing knowledge base, which consists of all patents granted to the firm and patents cited by the firm in the past five years.

Exploratory Ratio	Fraction of the patent's backward citations based on new knowledge coming outside of the firm's existing knowledge base.
Purely Exploratory	An indicator equal to one if the patent does not cite any previous patents owned by the same assignee.
Backward self-cites	the ratio of citations made to patents owned by the same assignee over total citations made by the patent
Forward self-cites	the ratio of self-citations received by the patent over total citations received
C. Inventor-patent Level	
Inventor Skill Specialization	Herfindahl-Hirschman concentration measure based on the share of patents in each three-digit technology class among all the patents that the inventor has filed in the past five years, following Marx, Strumsky, and Fleming (2009).
Specialized Inventor	An indicator equal to one if the inventor's skill specialization is above the sample median every year.
Fraction of Uncited Patents	Share of uncited patents in the inventor's patent portfolio, calculated as the cumulative number of uncited patents divided by the total number of patents that the inventor has produced up to a given year.
More Uncited Patents	An indicator equal to one if the inventor's cumulative share of uncited patents is above the sample median every year.
Young Inventor	An indicator equal to one if the number of years since the inventor's first applied patent (and eventually granted) is in the bottom quartile of the sample every year
Inventor past productivity	Total number of patents applied by the inventor (and eventually granted) in the past five years.
Inventors of the Patent	Number of coinventors on the patent
Inventor Patent Experience (years)	Number of years since the inventor's first filed and granted patent
Inventor Network Size	Cumulative number of unique coinventors on all prior patents filed by (and eventually granted to) the inventor.
Firm Knowledge Specialization	Herfindahl-Hirschman Index sum of squared percentages of patents within three-digit technology classes filed by the firm over the past five years. Information on primary technology classes for all patents is obtained from National Bureau of Economic Research (NBER) and Harvard Business School (HBS) Patent files.

Internet Appendix for

"Motivating Inventors: Non-competes, Innovation Value and Efficiency"

Table IA1. Patent and Citation Counts

This table presents the regression results examining the effect of changes in CNC enforceability on patent and citation counts at the firm level. The dependent variables across columns are *ln(patents)*, *ln(cite-weighted patents),* and *ln(cites)*, respectively. *ln(patents)* is the natural logarithm of one plus total number of patents applied for by the firm during the year. *ln(cite-weighted patents)* is the natural logarithm of one plus total number of citation weighted patent counts during the year; weight for each patent is calculated as the number of future citations divided by the average number of citations received by patents in the same technology class and year. *ln(cites)* is the natural logarithm of one plus total number of citations received by the patents applied for by the firm in the year. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. All control variables are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, industry × year, and state of headquarters fixed effects. The sample includes firms granted at least one patent during a given year. The *t*-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) ln(patents)	(2) ln(cite-weighted patents)	(3) ln(cites)
CNC Enf. Up	-0.311***	-0.202**	-0.156
	(-2.845)	(-2.119)	(-1.555)
CNC Enf. Down	0.110	0.076	0.006
	(0.930)	(0.639)	(0.048)
Size	0.370***	0.388***	0.410***
	(10.869)	(11.541)	(9.353)
Leverage	-0.089	-0.112	-0.156
	(-1.191)	(-1.248)	(-1.601)
ln(age)	0.050	-0.087	-0.103
	(0.732)	(-0.953)	(-0.987)
MktBk	0.010***	0.019***	0.023**
	(3.037)	(3.299)	(2.584)
Cash Flow	-0.175**	-0.131*	-0.137
	(-2.523)	(-1.804)	(-1.198)
Tangibility	0.400**	0.286	0.164
	(2.323)	(1.517)	(0.734)
R&D/Assets	0.952***	1.178***	1.370***
	(6.926)	(7.402)	(6.225)
State Industry HHI	0.003	0.041	0.022
	(0.034)	(0.393)	(0.176)
State GDP Growth	0.516	0.265	0.576
	(0.847)	(0.381)	(0.499)
ln(State Unemployment)	-0.162	-0.177	-0.180
	(-1.366)	(-1.443)	(-1.203)
IDD	0.003	0.017	0.057
	(0.061)	(0.285)	(0.825)
Firm FEs	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes
N	14585	14585	14585
Adjusted R^2	0.8616	0.8142	0.7955

Table IA2. Identification Tests

This table presents the regression results examining the effect of changes in CNC enforceability on innovation value and efficiency. Panel A displays results after excluding firms that relocated their headquarters during the sample period. Panel B reports results using a matched sample in which treated and control firms are required to be in the same industry and close in firm size. Panel C shows results after excluding firms experiencing law-based weakening of non-compete enforceability in Oregon. In each panel, the dependent variables across columns are *ln(Patent Value), Patent Value/Assets, Patent Value/R&D Stock*, and *ln(Patent Value per Inventor)*, respectively. *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, State Industry HHI, State GDP Growth, ln(State Unemployment), IDD* and *R&D/Assets*. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Exclude Headquarters Relocations

Dependent Variable:	(1) ln(Patent Value)	(2) Patent Value/Assets	(3) Patent Value/R&D Stock	(4) ln(Patent Value per Inventor)
CNC Enf. Up	-0.434***	-0.059*	-1.976***	-0.244***
	(-4.189)	(-1.685)	(-3.567)	(-4.924)
CNC Enf. Down	0.235***	0.071***	1.724***	0.243***
	(3.354)	(4.518)	(5.540)	(5.153)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	12915	12915	8619	8441
Adjusted R^2	0.9337	0.6542	0.7066	0.7122

Panel B. Matched Sample

Dependent Variable:	(1) ln(Patent Value)	(2) Patent Value/Assets	(3) Patent Value/R&D Stock	(4) ln(Patent Value per Inventor)
CNC Enf. Up	-0.322***	-0.058**	-2.104***	-0.232***
	(-3.256)	(-2.137)	(-4.137)	(-4.058)
CNC Enf. Down	0.230***	0.076***	1.940***	0.263***
	(3.338)	(4.637)	(8.740)	(5.131)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	4051	4051	3151	2828
Adjusted R^2	0.9428	0.6745	0.7410	0.7567

Panel C. Exclude Oregon

Dependent Variable:	(1) ln(Patent Value)	(2) Patent Value/Assets	(3) Patent Value/R&D Stock	(4) ln(Patent Value per Inventor)
CNC Enf. Up	-0.376***	-0.058*	-2.044***	-0.164***
	(-3.501)	(-1.767)	(-3.753)	(-3.187)
CNC Enf. Down	0.229***	0.067***	1.744***	0.227***
	(3.807)	(4.801)	(7.472)	(4.333)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	14374	14374	9602	9490
Adjusted R^2	0.9339	0.6511	0.7025	0.7184

Table IA3. Alternative CNC Enforceability Indexes

This table presents robustness checks using alternative CNC enforceability indexes. Panel A displays results using enforceability scores from Kini et al. (2019). Panel B shows results employing enforceability index of Ertimur et al. (2018). In each panel, the dependent variables across columns are *ln(Patent Value), Patent Value/Assets, Patent Value/R&D Stock*, and *ln(Patent Value per Inventor)*, respectively. *ln(Patent Value)* is the natural logarithm of one plus the total market value of patents ($ millions) applied for by a firm in a given year. Market value of a new patent is based on stock market announcement returns to the approval of the patent surrounding the grant date. *Patent Value/Assets* is the total market value of patents applied for in the year over the firm's book assets. *Patent Value/R&D stock* is the market value of patents applied for in the year over past R&D stock from years $t-2$ to $t-6$ assuming a 20% depreciation rate. *ln(Patent Value per Inventor)* is the natural logarithm of one plus the market value of patents applied for in the year divided by the number of inventors in the firm. Control variables include *Size, Leverage, ln(age), MktBk, Cash Flow, Tangibility, State Industry HHI, State GDP Growth, ln(State Unemployment), IDD* and *R&D/Assets*. All regressions incorporate firm and state of headquarters fixed effects, and industry × year fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Kini et al. (2019) CNC index

	(1)	(2)	(3)	(4)
Dependent Variable:	ln(Patent Value)	Patent Value/Assets	Patent Value/R&D Stock	ln(Patent Value per Inventor)
CNC Enf. Index	-1.051***	-0.307***	-6.866***	-0.933***
	(-3.055)	(-4.280)	(-8.429)	(-4.593)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	14585	14585	9750	9630
Adjusted R^2	0.9335	0.6515	0.7025	0.7174

Panel B. Ertimur et al. (2018) CNC index

	(1)	(2)	(3)	(4)
Dependent Variable:	ln(Patent Value)	Patent Value/Assets	Patent Value/R&D Stock	ln(Patent Value per Inventor)
CNC Enf. Index'	-1.085***	-0.203**	-6.228***	-0.852***
	(-4.289)	(-2.269)	(-3.403)	(-3.652)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Industry × Year FEs	Yes	Yes	Yes	Yes
N	14584	14584	9749	9630
Adjusted R^2	0.9335	0.6515	0.7028	0.7174

Table IA4. Alternative CNC Enforceability Indexes (Patent Level)

This table presents the regression results examining the effect of changes in CNC enforceability on patent market value at the patent level using alternative CNC enforceability indexes. The dependent variable is the market value of a new patent scaled by the firm's book assets, multiplied by 100. Columns (1) and (4) report results for the full sample, columns (2) and (5) for the subsample including patents filed in the firm's state of headquarters, columns (3) and (6) for patents filed outside of the firm's headquarters state. *CNC Enf Index* is the enforceability scores from Kini et al. (2019). *CNC Enf Index'* is the enforceability index of Ertimur et al. (2018). All control variables are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, technology class × year, and state of headquarters fixed effects. Columns (3) and (6) additionally include assignee state fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	(Patent Value/Assets) × 100					
Sample	All Patents	HQ Patents	Out of HQ	All Patents	HQ Patents	Out of HQ
CNC Enf Index	-2.412***	-2.847***	-0.646**			
	(-7.366)	(-7.960)	(-2.331)			
CNC Enf Index'				-2.405***	-2.885***	-0.668**
				(-6.455)	(-7.684)	(-2.317)
Size	-1.608***	-1.772***	-0.792***	-1.608***	-1.773***	-0.792***
	(-8.084)	(-8.892)	(-4.495)	(-8.115)	(-8.932)	(-4.498)
MktBk	0.104***	0.087***	0.135***	0.105***	0.087***	0.135***
	(5.056)	(3.595)	(3.323)	(5.065)	(3.596)	(3.320)
R&D/Assets	2.325***	2.306***	1.496**	2.303***	2.278***	1.498**
	(3.326)	(3.755)	(2.113)	(3.311)	(3.708)	(2.120)
State Industry HHI	0.882*	0.565	0.459	0.885*	0.567	0.458
	(1.699)	(1.579)	(1.493)	(1.692)	(1.568)	(1.487)
State GDP Growth	0.165	-0.533	0.977	0.120	-0.588	0.979
	(0.160)	(-0.453)	(1.522)	(0.116)	(-0.498)	(1.526)
ln(State Unemployment)	-0.349	-0.341	-0.163	-0.335	-0.325	-0.160
	(-1.350)	(-1.049)	(-1.094)	(-1.299)	(-1.002)	(-1.080)
IDD	0.144***	0.104	0.173**	0.156***	0.118	0.176***
	(2.734)	(1.057)	(2.667)	(3.045)	(1.216)	(2.707)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
HQ State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Assignee State FEs	No	No	Yes	No	No	Yes
N	537021	447598	73639	536962	447540	73639
Adjusted R^2	0.6317	0.6388	0.7238	0.6317	0.6388	0.7238

Table IA5. Potential Firm Responses to Changes in Enforceability

This table presents the regression results examining the effect of changes in CNC enforceability on the likelihood of developing innovations outside of the firm's headquarters. The dependent variable is an indicator equal to one if the patent is filed outside of the firm's state of headquarters. *CNC Enf. Up* is an indicator equal to one for firms headquartered in states after an increase in non-compete enforceability. *CNC Enf. Down* is an indicator equal to one for firms headquartered in states after a reduction in non-compete enforceability. *Increased CNC Enf.* is a categorical variable that takes the value of one for firms headquartered in states after an increase in non-compete enforceability, takes the value of negative one for firms headquartered in states after a reduction in non-compete enforceability, and is set to zero otherwise. *CNC Enf Index* is the enforceability scores from Kini et al. (2019). *CNC Enf Index'* is the enforceability index of Ertimur et al. (2018). Control variables include *Size, MktBk, R&D/Assets, State Industry HHI, State GDP Growth, ln(State Unemployment)* and *IDD,* which are measured in year $t-1$ and defined in the Appendix. All regressions incorporate firm, technology class × year, and state of headquarters fixed effects. The t-statistics in parentheses are based on robust standard errors clustered by the firm's state of headquarters. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	Out-of-HQ Patent			
CNC Enf. Up	0.038			
	(0.987)			
CNC Enf. Down	**-0.073*****			
	(-3.257)			
Increased CNC Enf.		**0.067*****		
		(4.422)		
CNC Enf Index			**0.280*****	
			(4.989)	
CNC Enf Index'				**0.296*****
				(4.387)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Tech Class × Year FEs	Yes	Yes	Yes	Yes
N	546919	546919	546919	546860
Adjusted R^2	0.6030	0.6030	0.6030	0.6030

Appendix IA6. Variable Definitions

Variable	Description
CNC Enf. Index	CNC enforceability scores from Kini et al. (2019), who follow Garmaise's methodology and updated the index based on his thresholds by using annual state-by-state survey of employee non-competes from a law firm, Beck Reed Riden LLP, for the period of 2005-2014. The scores are rescaled to range from 0 to 1.
CNC Enf. Index'	CNC enforceability scores from Ertimur et al. (2018), who also extend the enforceability index following Garmaise (2011). They obtained Garmaise's answers to the individual twelve questions analyzed in Malsberger (2004), which served as the basis for the index. They appointed three law students with experience in analyzing employment contracts to perform this task. As described in their Internet Appendix, these law students first need to replicate the index for 2004 using information in Malsberger (2004) and following the detailed process outlined by Garmaise (2011). After learning the construction process and correcting errors if they have made during the replication, the students were provided with Malsberger (2013) to extend the index to 2013. The scores are rescaled to range from 0 to 1.
Out-of-HQ Patent	an indicator equal to one if the patent is applied outside of the firm's state of headquarters.

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THE LABOR MARKET EFFECTS OF LEGAL RESTRICTIONS ON WORKER MOBILITY

Matthew S. Johnson
Kurt J. Lavetti
Michael Lipsitz

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The Labor Market Effects of Legal Restrictions on Worker Mobility
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ABSTRACT

We analyze how the legal enforceability of noncompete agreements (NCAs) affects labor markets. Using newly-constructed panel data, we find that higher NCA enforceability diminishes workers' earnings and job mobility, with larger effects among workers most likely to sign NCAs. These effects are far-reaching: changes in enforceability impose externalities on workers across state borders, suggesting that enforceability broadly affects labor market dynamism. We provide evidence that NCA enforceability primarily affects wages through its effect on workers' outside options; moreover, workers facing high enforceability are unable to leverage tight labor markets to increase earnings. We motivate these findings by embedding NCA enforceability in a search model with bargaining. Finally, higher NCA enforceability exacerbates gender and racial earnings gaps.

Matthew S. Johnson
Sanford School of Public Policy
Duke University
Box #90312
Durham, NC 27708
and NBER
matthew.johnson@duke.edu

Kurt J. Lavetti
Department of Economics
The Ohio State University
1945 N. High St.
Arps Hall 433
Columbus, OH 43210
and NBER
Lavetti.1@osu.edu

Michael Lipsitz
Federal Trade Commission
mlipsitz@ftc.gov

1 Introduction

By several metrics, the U.S. labor market failed to produce economic gains for the majority of workers in the four decades prior to 2020. Average real hourly earnings changed little[1] and the share of income accruing to labor declined from 65 percent in the late 1940s to 63 percent in 2000, before accelerating downward to 58 percent in 2016.[2] Various forces have been posited to underlie these trends, including the decline of labor unions (Farber et al., 2018), the rise of superstar firms (Autor et al., 2017), and the rise of domestic outsourcing (Weil, 2014; Goldschmidt and Schmieder, 2017).

Another potential explanation that has received increasing attention is firms' use of postemployment restrictions, the most salient of which are noncompete agreements (NCAs). NCAs contractually limit a worker's ability to enter into a professional position in competition with his or her employer in the event of a job separation. NCAs are common: Starr et al. (2021) find that approximately 18% of workers in 2014 were bound by NCAs, whereas Colvin and Shierholz (2019) found this range to be between 28 and 47 percent in 2019.[3] The legal *enforceability* of NCAs—that is, the terms under which an employer can enforce one—is determined by state employment law. Making NCAs easier to enforce may hinder earnings growth by limiting workers' ability to seek higher-paying jobs or to negotiate higher earnings at their current job. At the same time, others contend that enforceable NCAs can *increase* earnings by making firms more willing to invest in training, knowledge creation, and other portable assets that raise workers' productivity (Rubin and Shedd, 1981; Starr, 2019).

Though the enforceability of NCAs has received increasing scrutiny from policy-makers at state and national levels,[4] there remains an incomplete understanding of the labor market effects of NCAs, primarily due to three factors. The first is a lack of comprehensive panel data on NCA enforceability. Researchers have, to date, relied largely on either cross-sectional measures of states' enforceability or case studies of

[1]Desilver, Drew, "For Most U.S. Workers, Real Wages Have Barely Budged in Decades," *Pew Research Center*, August 7, 2018.

[2]President's Council of Economic Advisors Issue Brief "Labor Market Monopsony: Trends, Consequences, and Policy Responses" October 2016.

[3]Specifically, 15% of the workers in Starr et al. (2021)'s representative sample reported being bound by NCAs, and another 29.7% were unsure if they were bound by NCAs. Starr et al. (2021) report a level of 18.1% based on a multiple imputation methodology. The range reported by Colvin and Shierholz (2019) represents an imputation based on a survey of business establishments and a broad range of assumptions on the percentage of workers within those establishments bound by NCAs.

[4]The Workforce Mobility Act of 2018 (US Senate Bill 2782, introduced by Chris Murphy) states "No employer shall enter into, enforce, or threaten to enforce a covenant not to compete with any employee of such employer" (`https://www.congress.gov/bill/115th-congress/senate-bill/2782/text?r=6.`). The Freedom to Compete Act of 2019 (US Senate Bill 124, introduced by Marco Rubio) has similar language (`https://www.congress.gov/bill/116th-congress/senate-bill/124/all-info`). In January 2023, the Federal Trade Commission issued a Notice of Proposed Rulemaking which would prohibit NCAs, with limited exceptions, across the economy.

a single state or a handful of states with law changes affecting specific segments of the workforce. This approach has drawbacks: cross-sectional variation in enforceability might be correlated with other unobserved differences across states, and small samples of targeted law changes may not generalize to the population. Second, prior work, which we describe below, has found seemingly conflicting evidence regarding the earnings effect of NCA *use* versus *enforceability*, creating challenges for interpreting the effects of NCAs on worker outcomes. Finally, the literature has not yet thoroughly identified the mechanisms through which enforceable NCAs affect labor markets. Without a clear understanding of *why* NCA enforceability affects workers, it is difficult to generalize empirical evidence to, for example, predict how various proposals to change enforceability might affect the functioning of labor markets.

We present comprehensive evidence on the effect of NCA enforceability on workers' earnings and job mobility. We begin by constructing a new panel dataset to use within-state changes in NCA laws to identify the overall labor market effects of NCA enforceability, including spillover effects within local labor markets. We then provide evidence for a key mechanism through which NCA enforceability affects earnings—namely, its effect on workers' outside options and costs of job mobility. Finally, we show that the earnings effect of NCA enforceability exhibits economically meaningful heterogeneity across demographic groups, contributing a new insight into the determinants of earnings inequality in the United States.

We guide our empirical analysis with a model, based on the search model of Bagger et al. (2014), of how changes in NCA enforceability affect workers' earnings. We show that the effect of increasing NCA enforceability on overall earnings can be decomposed into two terms. The first term relates to the difference in earnings between workers who are and are not bound by enforceable NCAs; the sign of this term is ambiguous due to the offsetting ways that an enforceable NCA raises a worker's earnings (via faster human capital accumulation) and lowers it (via reduced job mobility). The second term reflects the spillover effect of stricter enforceability on the earnings of workers not bound by NCAs. We show that this term is unambiguously negative under the assumption that strict NCA enforceability reduces the job offer arrival rate for all workers. We provide empirical evidence to support this assumption.

To identify the causal effects of NCA enforceability, we created a new dataset with annual measures of NCA enforceability for each of the 50 US states and the District of Columbia from 1991 to 2014. This dataset includes both judicial and legislative decisions that change state-level NCA enforceability, coded to match the criteria developed by leading legal scholars to quantify enforceability. The vast majority of these law changes (90.4%) occur due to judicial decisions via court rulings. An important component of the judicial process is *stare decisis*, or the doctrine of precedent. A consequence is that judges are more constrained than legislators in allowing economic or political trends to affect decisions, a fact that is useful for our research design. We combine our enforceability dataset with earnings and mobility outcomes from a range of datasets including the Current Population Survey, Job to Job Flows, and the Quarterly Workforce Indicators, all from the US Census Bureau, as well as the Job Openings and Labor Turnover Survey from the Bureau of Labor Statistics.

We find that increases in NCA enforceability decrease workers' earnings and mobility. Moving from the 25^{th} to the 75^{th} percentile in enforceability is associated with an approximately 2% decrease in the average worker's earnings. The earnings effects are almost entirely driven by declines in implied hourly wages. The effect is even stronger among occupations, industries, and demographic groups in which NCAs are used more frequently (according to Starr et al. (2021)). We also find that NCA enforceability reduces worker mobility, particularly among groups where NCAs are used more frequently. An out-of-sample extrapolation implies that rendering NCAs unenforceable nationwide would increase average earnings among *all* workers by 3.2% to 14.2%. The midpoint of this interval (8.7%) is roughly equal to the estimated effects of very large increases in employer consolidation on affected workers' earnings (Prager and Schmitt, 2019); it is also approximately equal to the estimated earnings premium that accrues to workers who enter occupations with government-mandated licensing, and roughly half the size of the earnings premium associated with membership in a labor union.

To interpret this overall negative earnings effect, we then conduct an empirical test to isolate the spillover effects of NCA enforceability on workers who are not themselves bound by NCAs. We show that these spillovers are negative—as predicted by our model—and are economically meaningful. Focusing on local labor markets that are divided by a state border, we show that a change in NCA enforceability in one state indirectly affects the earnings and mobility of workers located in an adjoining state. This finding suggests that the treatment effects of NCA enforceability impact a larger population than the relatively small share of workers bound by NCAs, and the magnitudes suggest that spillovers account for a meaningful share of the overall earnings effects of enforceability.

We then conduct two empirical tests of our proposed mechanism that strict NCA enforceability reduces earnings through its effect on workers' job offer arrival rates. First, we test for heterogeneity in the earnings effect using two separate proxies for the extent to which changes in state-level NCA enforceability affect workers' outside options. Strict NCA enforceability has an especially negative earnings effect in industries in which workers are less likely to move jobs across state lines (as measured in the Job-to-Job flows dataset), and in occupations in which workers have lower cross-occupational mobility (as measured by Schubert et al. (2021)). That is, strict NCA enforceability reduces earnings the most when it has the largest impact on workers' outside options.

The second test of our proposed mechanism revisits prior research that considers how tight labor markets enable workers to increase their earnings. We embed NCA enforceability in an empirical model, first used by Beaudry and DiNardo (1991), that considers how a worker's current earnings depend on prior labor market conditions. Previous research has found that workers' current earnings are strongly correlated with the most favorable labor market conditions over their current job spell. This relationship is consistent with the extra job offers workers might receive in tight labor markets enabling them to either negotiate a higher wage with their current employer (Beaudry and DiNardo, 1991) or find a job with higher match quality (Hagedorn and Manovskii, 2013). We find that this relationship continues to hold but only in states where NCAs are relatively unenforceable. In contrast, strict NCA enforceability ties workers' earnings to labor market conditions at the start of their job spell, rather than to the most favorable conditions they have experienced since then. This finding implies that strict NCA enforceability erodes workers' ability to leverage tight labor markets to achieve higher earnings, consistent with the hypothesis that NCAs "undermine workers' prospects for moving up the income ladder" (Krueger, 2017).

Finally, we document economically meaningful heterogeneity in the earnings effect of NCA enforceability across demographic groups. Given gender differences in willingness to commute (Le Barbanchon et al., 2019), geographically-restrictive NCAs (or state-level enforceability changes) may have larger effects on womens' outside options than on mens'. Prior work also suggests women tend to be less willing to violate the terms of their NCA than are men (Marx, 2022). Similar evidence suggests that state-level NCA enforceability changes may disproportionately affect the outside options of Black workers, due to racial differences in the propensity to move in response to economic opportunities (Sprung-Keyser et al., 2022). Consistent with this evidence, we find that stricter NCA enforceability reduces earnings for female and for non-white workers by twice as much as for white male workers. Using a standard earnings decomposition, our estimates imply that the 75-25 differential in NCA enforceability accounts for 1.5-3.8% of the earnings gaps between white men and other demographic groups.

Relationship to the Literature: Our findings most directly contribute to a growing literature on the earnings effects of NCA enforceability. Prior work examining case studies of individual bans on NCAs—including an Oregon ban on NCAs for hourly workers (Lipsitz and Starr, 2021) and a Hawaii ban on NCAs for tech workers (Balasubramanian et al., 2022)—has found that these bans led to higher earnings.[5] Two papers have studied what happens to executives' earnings when NCAs are easier to enforce, with mixed results: Garmaise (2011) uses three NCA law changes and finds that earnings decrease, while Kini et al. (2019) uses a broader set of law changes and interprets their findings as implying that earnings increase. Studies using cross-sectional variation in NCA enforceability have similarly reached mixed results: Starr (2019) finds that earnings are lower in states with higher NCA enforceability, whereas (Lavetti et al., 2018) finds the opposite relationship for doctors.

[5] An exception is Young (2021), who finds that a ban on NCAs in Austria for low-wage workers had limited effects on earnings.

We make several contributions to this literature. Our paper is the first to provide comprehensive panel-based evidence of the earnings effects of enforceability changes for all states and all labor market sectors, using what legal scholars believe is the most accurate measure of NCA enforceability to date (Barnett and Sichelman, 2020). Second, we provide the first panel-based evidence that NCA enforceability has spillover effects onto workers unaffected by legal changes, and that these spillovers account for a meaningful share of the overall earnings effects of NCA enforceability.[6] Finally, we connect our empirical analyses to a job ladder model of the labor market, which provides testable mechanisms through which NCA enforceability affects earnings—namely, by reducing workers' offer arrival rates. The connection to the model aids the interpretation of our empirical findings and provides insight into the types of workers whose earnings would be most affected by proposed policy discussions to make NCAs more or less easily enforceable. We further elaborate on these contributions in Section 8.

We also complement the vibrant literature that considers other economic effects of NCA enforceability, including on entrepreneurship and investment (Jeffers, 2018), employee spinoffs (Starr et al., 2018; Marx, 2022), startup performance (Ewens and Marx, 2018), worker mobility (Marx et al., 2009), and innovation (Johnson et al., 2023).

Our findings also contribute to broader and growing work on employer monopsony power and workers' outside options. Recent work has examined sources of monopsony power, including the role of search frictions (Manning, 2013; Berger et al., 2023; Jarosch et al., 2019), and local employer concentration (Azar et al. (2017), Benmelech et al. (2022), Prager and Schmitt (2019), Berger et al. (2022)). Our results imply that strict NCA enforceability effectively endows employers with a degree of monopsony power, by affecting workers' outside options, even in the absence of explicit changes in employer concentration, which we interpret through a lens of search frictions. In this spirit, our theoretical assumption (and empirical finding) that enforceable NCAs reduce earnings by reducing the value of workers' outside options complements other work showing the importance of outside options on earnings (Caldwell and Danieli, 2018; Schubert et al., 2021). One benefit of our study is that changes in NCA enforceability isolate changes in labor market competition, whereas other factors that might affect labor market power (such as mergers) also directly affect product market competition, though NCAs may have ramifications in product markets as well (Lipsitz and Tremblay, 2021; Johnson et al., 2023).

Finally, our findings provide new insight into a longstanding debate in law and economics regarding freedom of contracting (see, e.g., Bernstein (2008) for an overview).

[6] Starr et al. (2019) also test for spillovers from enforceable NCAs. Our findings complement theirs by 1) focusing on enforceability (rather than on *use* of enforceable NCAs), 2) using within-state variation in enforceability (rather than cross-sectional variation across states), and 3) using a border county design to isolate spillovers from other potential omitted variables that may jointly affect wages and enforceability.

Appealing to the Coase theorem, advocates of the freedom to contract suggest that freely-bargained-for NCAs must increase match surplus, which may be split between workers and employers. Evidence that NCAs are not freely bargained-for (e.g., because employers present them after the beginning of the employment relationship (Marx, 2011), or because workers are unaware of their existence Starr et al. (2021)), already reveals one shortcoming of this argument. Our paper reveals another: enforceable NCAs impose substantial negative externalities on other workers.

2 Conceptual Framework

In this section, we provide a concise overview of NCAs and the role of legal enforceability, and then present a brief conceptual framework (based on a model which is fully described in Appendix A) to guide our empirical analysis.

An NCA prevents a worker from moving to a job at a competing firm. The exact terms of an NCA are contract-specific, and they typically depend on the nature of competition. For example, in a nontradeable industry in which client lists are important for production, an NCA might dictate that the worker cannot move to another job in the same industry and within a specified geographic radius (e.g. within 25 miles, or within the same state). In an industry in which trade secrets are essential for firms to retain a competitive edge, the NCA might dictate that the worker cannot depart for another employer in the same industry anywhere in the country. More generally, the dimensions of employment mobility that an NCA might restrict could be some combination of geographic, temporal, occupational, or industrial.

While in theory any employment contract could include an NCA, the likelihood that an NCA would be upheld in court depends on the conditions under which a court would rule an NCA to be enforceable—that is, the legal enforceability.

Our focus in this paper is on the effects of NCA *enforceability*, as opposed to NCA *use*. One reason for this focus is data limitations: to our knowledge, there do not exist long panel data for a representative sample of workers on the use of NCAs in the US. A more fundamental reason is that restricting attention to *use* would miss at least two important ways that the legal enforceability of NCAs might affect the labor market.

First, changes in the enforceability of NCAs likely impact both the incidence of NCA use (the extensive margin) and the bindingness of NCAs already signed (the intensive margin). On the extensive margin, cross-sectional studies have found that states with higher NCA enforceability have a larger share of physicians (Lavetti et al., 2018), CEOs (Kini et al., 2019), managers (Shi, 2023), and hair stylists (Johnson and Lipsitz, 2019) that sign NCAs.[7] On the intensive margin, a change in enforceability could alter the effect of an NCA for workers who have already signed one. Though

[7]This evidence is not unanimous, however: Starr et al. (2021) find essentially no difference in NCA use by states' enforceability in a representative sample of US workers.

NCAs are used in states in which they are unenforceable (Lavetti et al., 2018; Starr et al., 2021), employers are in a better position to leverage a worker's NCA when enforceability is easier.[8] Higher NCA enforceability could also lead employers already using NCAs to write broader and more restrictive NCAs.

Second, as we will discuss, changes in NCA enforceability could have spillover effects on earnings beyond the set of workers that sign NCAs.

To provide a theoretical foundation for how NCA enforceability affects earnings, we extend a job search model of the labor market developed in Bagger et al. (2014) by allowing workers to have NCAs, and by varying levels of NCA enforceability. Briefly, Bagger et al. (2014) is a job ladder model in which workers match with firms of varying productivities, and they subsequently have the opportunity to take higher-paying jobs or leverage outside offers for pay increases. Worker pay also depends on human capital accumulation. The Bagger et al. (2014) model provides a natural foundation for our purpose, as its focus on the role of human capital accumulation versus job mobility highlights two competing channels through which enforceable NCAs could affect earnings.[9]

We briefly summarize here the insights from the model that guide our empirical analysis. We formally present the extended model in Appendix A.

Let $\bar{w}$ denote average earnings, θ denote NCA enforceability, and γ denote the fraction of workers bound by NCAs. As we derive in Appendix A, the effect of a change in NCA enforceability on average earnings is the sum of two terms:

$$\frac{d\bar{w}}{d\theta} = \gamma(\bar{w}^C - \bar{w}^F) + (1 - \theta\gamma)\frac{d\bar{w}^F}{d\theta} \qquad (1)$$

Here, $\bar{w}^C$ and $\bar{w}^F$ denote the average earnings of the subset of constrained workers bound by an NCA and unconstrained workers not bound by one, respectively.

The first term reflects the difference in average earnings between workers bound and not bound by NCAs, scaled by the proportion of workers bound by NCAs. The sign of this difference is indeterminate. On the one hand, workers with NCAs might

[8]This argument holds even if a worker is not fully informed about the enforceability of the NCA she has signed. As long as employers *are* informed, and there is some probability that workers can learn, then employers will know the NCA has less bite in expectation when it is not legally enforceable. Put another away, a worker may get a signal of the NCA enforceability regime when she informs her employer of an outside offer she has received: for example, if enforceability is weak, the employer is unlikely to contend it, whereas if enforceability is strict the employer might saliently inform the worker of the legal environment.

[9]We use the term "human capital accumulation" to reflect a range of investments that firms could make in workers. This could include general human capital training (Rubin and Shedd, 1981), but also the sharing of trade secrets or client lists. All of these investments raise a worker's productivity, but they come with different (from the firm's perspective) costs. For example, general training is costly at the time of investment, whereas sharing a client list is only costly in expectation (if a worker takes the list to a competitor). Of course, some forms of investment in workers will be unaffected by NCA enforceability, such as training a worker needs to perform her job. Our focus is on investment in "portable" assets a worker can take with them in the event of a job separation.

experience faster human capital accumulation or require a compensating earnings differential for lost future mobility, both of which could make this term positive. On the other hand, workers with NCAs are unable to climb the job ladder to higher-productivity firms or to leverage outside offers for pay increases, both of which make this term negative. This indeterminacy ultimately makes the effect of NCA enforceability on earnings an empirical question. We provide this empirical evidence in Section 4.

The second term reflects the effect of increased NCA enforceability on the earnings of unconstrained workers not bound by NCAs, scaled by the proportion of workers not bound by enforceable NCAs. We show that this term is strictly negative. This negative spillover effect arises because of a key assumption that we make: higher NCA enforceability reduces the arrival rate of new job offers for all workers.[10] A slower offer arrival rate dampens a key element of earnings growth, namely workers' ability to climb the job ladder and leverage outside offers with their current employer.[11] We provide evidence for the validity of this assumption and estimate the spillover effects of NCA enforceability in Section 5.

While the overall earnings effect of enforceability is indeterminate, the mechanism that drags down earnings, for constrained and free workers alike, is the slowed arrival rate of job offers. We generate two testable predictions to assess the explanatory power of this mechanism. First, the earnings effect of enforceability will be more negative for workers whose outside options enforceability affects the most. This relationship arises because such workers will experience a particularly large slowdown of offer arrival rates (but the human capital accumulation of bound workers will not change). Second, strict NCA enforceability will prevent workers from taking advantage of tight labor markets to move to better matches or to negotiate for higher earnings. We test both of these predictions in Section 6.

[10]One reason this might happen is that higher NCA enforceability could decrease the number of searching firms, for example by depressing new firm entry (Starr et al., 2018; Jeffers, 2018). Additionally, the use of enforceable NCAs by some firms can increase recruitment costs for all firms: if firms cannot directly observe whether a job applicant is currently bound by an NCA, this can slow down the recruiting process on average and decrease the value of posting vacancies (Starr et al., 2019; Goudou, 2022).

[11]An alternative mechanism that could give rise to negative spillovers is if firms using enforceable NCAs pay lower wages, and this leads other firms to be able to also pay lower wages by worsening their workers' outside option (Beaudry et al., 2012). However, it is unlikely that this mechanism could fully explain our results, given our evidence (presented in Section 5) that higher NCA enforceability leads firms to post fewer vacancies, which is hard to rationalize under the Beaudry et al. (2012) framework. In addition, there is no clear empirical consensus that workers who *sign* an NCA earn lower wages: some studies find positive correlations between wages and NCA use (Lavetti et al., 2018; Starr et al., 2021).

3 Data

3.1 State-Level NCA Enforceability

The cornerstone of our paper is a state-level panel dataset with annual measures of states' NCA enforceability. The enforcement of NCAs is governed by employment law, which is determined at the state level. As described by Bishara (2010), NCA laws vary widely across states, and over time within states, in subtle but meaningful ways. For example, there is substantial variation in what is considered a "reasonable" contract, or what is considered a protectable business interest that justifies an NCA. The various aspects that govern the enforceability of NCAs change through case law and, more rarely, through statutes passed by state legislators.

We draw from authoritative legal experts to create an index of each state's legal enforceability of NCAs for each year from 1991 through 2014. Our main primary sources are Bishara (2010), who adopts careful legal analysis to quantify enforceability along a meaningful scale, and a series of legal treatises that Bishara draws from titled "Covenants Not to Compete: A State by State Survey," updated periodically by Malsberger, a leading legal expert on the topic (Malsberger, 2023). Bishara (via Malsberger) identifies seven quantifiable dimensions governing the extent to which an NCA is enforceable. For example, one dimension (Q3a) indicates the extent to which employers are legally required to compensate workers who sign NCAs at the beginning of a job spell. Another dimension (Q8) reflects whether the NCA is enforceable when the employer terminates the employee who signed the NCA (as opposed to a voluntary separation). Table C.1 lists each of the dimensions. Bishara (2010) developed a theoretically-grounded approach to quantify states' treatment of each dimension on an integer scale from 0 (unenforceable) to 10 (easily enforceable). To create an overall enforceability index, Bishara proposed a weighted sum of these seven dimensions, and he chose weights designed to reflect the relative importance of each law component, based on his opinion as a subject expert. Using these rules, Bishara (2010) quantified each dimension and an overall index for each state for the years 1991 and 2009.

We use these legal texts to create a panel version of each state's enforceability from 1991–2014 as follows. We obtained Bishara's internal notes that provide explanations of the legal aspects behind each of his coding decisions.[12] We hired law students to familiarize themselves with the quantification system by going through the Malsberger texts and Bishara's notes for the 1991 enforceability scores. The law students then attempted to use the Malsberger texts to match Bishara's 2009 scores for all of the legal components in every state. After calibrating their own scoring of 2009 with Bishara's, they quantified the changes in enforceability between 1991 and 2009 using the Malsberger texts, imposing Bishara's 1991 and 2009 scores as endpoints. They then extended the panel to 2014. See Section C.1 for a more detailed discussion of

[12]We thank Norm Bishara for generously sharing this dataset with us.

the methods, procedures, and principles we used to construct this database.

Once the seven dimensions of enforceability were coded, we constructed a composite *NCA Enforceability Score* for each state-year from 1991-2014 using the same weights for each of the seven dimensions proposed by Bishara (2010).[13]

Differences in how states interpret these dimensions have led to substantial differences in the *NCA Enforceability Score* across states. At the extreme ends of this spectrum, Florida Statute 542.335 explicitly allows the use of NCAs as long as a legitimate business interest is being protected, the agreement is in writing, and the agreement is reasonable in time, area, and line of business.[14] The law allows for a large variety of protectable interests (such as trade secrets, training, and client relationships), permits the beginning of employment or continued employment to act as "consideration" (i.e., compensation) for an NCA, allows the courts to modify NCAs to make them enforceable, and renders NCAs enforceable even when an employer terminates an employee. At the other end of the spectrum, North Dakota Century Code 9-08-06 explicitly bans all NCAs in employment contracts.[15] Quantifying these statutes, Florida has the highest NCA Enforceability Score during our time period (which we normalize to 1), and North Dakota has the lowest score (which we normalize to 0).

Furthermore, law changes have led to sizable changes in the NCA Enforceability Score *within* states over time. Law changes can occur through either statutory provisions (by the state legislature) or through precedent-setting court decisions. Over 90% of the law changes during our sample period arise from court decisions. Each of these involves an instance in which an employer or worker filed a dispute over an NCA, and in deciding whether the NCA was enforceable the judge overruled legal precedent. Consider, for example, a state Superior Court case in Pennsylvania: Insulation Corporation of America v. Brobston (1995). The case concerned an employee of an insulation sales company who had signed an NCA. After being terminated for poor performance, he was hired by a competitor of his original employer, in alleged violation of the NCA. While the NCA in question was ultimately not enforced, the court's decision set new precedent that NCAs may generally be enforced following employer termination: "...the circumstances under which the employment relationship is terminated are an important factor to consider in assessing... the reasonableness of

[13]In some state-years, there is no legal precedent for a particular dimension of the enforceability index. Following Bishara (2010), we code these values as missing. The composite NCA enforceability index is a weighted average of scores on each of the seven legal dimensions. When the score for one of the dimensions is missing, we omit it from the calculation of that weighted average, as in Bishara (2010). Though we defer to Bishara (2010) that this is the appropriate way to treat missing values, there are other sensible approaches. In Section C.2, we show that missingness is ultimately quite rare, and we show that our main estimates are insensitive to how we treat missing values.

[14]Florida Statute 542.335. Full text available at `http://www.leg.state.fl.us/statutes/index.cfm?App_mode=Display_Statute&URL=0500-0599/0542/Sections/0542.335.html`

[15]North Dakota Century Code 9-08-06. Full text available at `https://www.legis.nd.gov/cencode/t09c08.pdf`

enforcing the restrictive covenant."[16] Future cases cited this precedent in adjudicating matters concerning employee termination: for example, in *All-Pak, Inc., v. Johnston* the court wrote that "We emphasized [in Brobston]...that the reasonableness of enforcing such a restriction is determined on a case by case basis. Thus, the mere termination of an employee would not serve to bar the employer's right to injunctive relief."[17] That is, *Brobston* set a precedent that NCAs *could* be enforceable even if the employee was terminated. *Insulation Corp. of America v. Brobston* therefore resulted in the component of the NCA Enforceability Score specific to treatment following employer termination (Q8) to change from 4 (out of 10) to 7 in Pennsylvania; the resulting change in Pennsylvania's overall NCA Enforceability Score was equal to roughly a third of a standard deviation in the distribution across our sample period.

Table 1 summarizes differences in levels of NCA enforceability across the country and within states over time, between 1991 and 2014. With the exception of the numbers of law changes, states, index increases, and index decreases, the descriptive statistics in Table 1 are weighted to reflect population demographics by matching the scores from each state-year to corresponding observations in the CPS ASEC and using the relevant weights provided by the Census Bureau.

There are 73 within-state NCA law changes over our sample period, and these are dispersed roughly evenly across the Northeast, Midwest, South, and West regions. The average law change results in a change in the magnitude of the NCA Enforceability Score that is about 6.4% of the average score over this period, and the within-state standard deviation in enforceability is equal to roughly 12% of the overall standard deviation. Figure B.1 displays this variation visually. Panel A is a histogram of the level of NCA enforceability across all states over our sample period 1991–2014. Panel B is a histogram of the magnitude (in absolute value) of NCA law changes over this same sample period. Ninety-five percent of law changes result in a score change of 0.15 or less; 0.15 is roughly the difference between the 25th (0.66) and 75th (0.81) percentiles of the NCA score distribution (in levels) over our sample period.

Figure 1 shows the timing of NCA law change events. Changes were relatively evenly dispersed throughout the study time period. There are a few more enforceability increases than decreases, though both are well-represented. Figure 2 shows the CPS ASEC sample-weighted mean NCA Enforceability Score across states over the sample period. NCA enforceability has been generally flat or increasing over time, with an especially steep increase during the mid to late 1990s.

[16]Insulation Corp. of America v. Brobston, 667 A.2d 729, 446 Pa. Superior Ct. 520, 446 Pa. Super. 520 (Super. Ct. 1995).

[17]All-Pak, Inc. v. Johnston, 694 A.2d 347 (1997).

3.1.1 Are NCA Law Changes Predictable?

If changes in NCA enforceability were correlated with underlying legal, economic, political, or social trends, this could reflect a potential source of endogeneity that would make it challenging to use these changes to isolate the effects of enforceability on earnings. For example, changes to enforceability might be preceded by an increasingly litigious business climate that could itself be caused by changing labor market conditions.

A priori, there are good reasons to expect this concern to be minimal. In most cases, the judicial decisions that change legal precedent are initiated by a case that is idiosyncratic to a particular occupation, industry, or employment relationship; however, the consequences of these decisions affect the state's labor law more broadly. Relative to legislators, judges are less influenced by stakeholder pressure that could sway their decision-making because of the doctrine of *stare decisis*.[18] Furthermore, evidence overwhelmingly suggests that judges do not base their decisions purely on policy preferences, but rather on a wide range of motivations (Epstein and Knight, 2013), implying that judges' decisions to break from precedent in an NCA case are unlikely to be related to underlying trends in the labor market.

Nonetheless, we use two approaches to empirically test this possibility more thoroughly. First, we test whether NCA law changes are preceded by a spike in court cases involving NCA litigation. Second, we test whether states' political, social, and economic characteristics predict NCA law changes.

As our first approach, we test whether changing litigiousness predicts NCA law changes. Following Hiraiwa et al. (2023) and Marx (2022), we use data from Courthouse News Service to identify instances of a filed dispute over an NCA in a US court. As in Hiraiwa et al. (2023), we collect all filings containing the strings "noncompetition," "non-competition," "not to compete," "noncompete," "restrictive covenant," or "postemployment restraint."[19] The data begin in 2002, and we collapse to the state-year level, tabulating counts of cases.[20]

For each state that experiences an NCA law change, we consider the window of time starting five years prior to the law change,[21] and we use state-year observations with no legal change during the same window as the controls for that state. We refer to a treatment state and its matched controls as a "block." We use a stacked

[18]For a discussion of stare decisis, see Knight and Epstein (1996).

[19]We omit cases including the term "sale," which often refers to NCAs ancillary to the sale of a business, as these cases are typically handled differently than standard employee NCAs under state law

[20]From 2002–2014, there were roughly 700 court filings about NCAs per year. Compare this number to the roughly 2.5 NCA law changes due to court decisions that occur per year during that same period. That is, roughly 0.38% of court filings result in a decision in which the judge overturned precedent. Interestingly, this proportion is quite similar to the proportion (0.5%) of Supreme Court decisions in which the Court reversed its own Constitutional precedent (Schultz, 2022).

[21]We obtain qualitatively similar results if we choose different time windows.

event study (focusing only on the pre-period) to test whether NCA law changes are preceded by a spike in case counts. Formally, we use a Poisson pseudo-maximum likelihood model (due to the dependent variable being count data) to estimate:

$$Y_{s,b,t} = \sum_{\tau=0}^{5} \alpha_\tau I^{\tau}_{s,b} + \mu_{s,b} + \rho_{b,t} + \varepsilon_{s,b,t}$$

where $Y_{s,b,t}$ is the count of cases in state s at time t, observed in estimation block b; α_τ is the event-time coefficient of interest on $I^{\tau}_{s,b}$, which is an indicator for whether a legal change occurred τ years after the observation time t in state s; $\mu_{s,b}$ are fixed state-by-block effects; and $\rho_{b,t}$ are fixed block-by-time effects. $\varepsilon_{s,b,t}$ is the error term. The estimation blocks (b) correspond to sub-experiments in the stacked difference-in-difference design (Cengiz et al., 2019; Deshpande and Li, 2019); see Section 4.2.2 for more details.

We present the $\hat{\alpha}_\tau$ coefficient estimates in Appendix Figure B.2. There is no positive trend in cases prior to legal changes. This alleviates concerns that NCA law changes are due to an increased trend toward conflict or toward legal interest in NCAs, which may itself be due to changing labor market or business conditions.

As our second approach, we use a variety of data sources to test whether other changes in political, social, or economic characteristics predict NCA law changes. These include the University of Kentucky Center for Poverty Research's National Welfare Data (University of Kentucky Center for Poverty Research, 2018) on population, workers compensation beneficiaries, an indicator for whether the state governor is a member of Democratic party, the share of state house and senate representatives (respectively) in the Democratic party, minimum wage, and the number of Medicaid beneficiaries. We also use the database constructed in Caughey and Warshaw (2018) to obtain measures of policy liberalism (liberalism in the state as reflected by government policy) and mass liberalism (liberalism in the state as reflected by responses of individuals to policy questions), both of which are measured separately on social and economic dimensions. From this dataset, we also obtain the percentage of voters who identify as Democrats. For more details on the construction of these measures, see Caughey and Warshaw (2018). Next, we gather data on the ideologies of state legislatures from McCarty and Shor (2015), including the State House and State Senate ideology scores, in aggregate as well as separately by Democrats and Republicans. Finally, we include data on union membership from Hirsch and Macpherson (2019).

Table 2 presents the results from a regression in which the dependent variable is a state's annual NCA enforceability, and the independent variables are each of the 20 characteristics noted above (lagged by one year), as well as state and Census division by year fixed effects (we use these same fixed effects in our subsequent analysis). Out of 20 variables, the vast majority have coefficients that are both economically and statistically insignificant. Only two of these 20 variables are statistically significant at the 10% level (the minimum wage and the State Senate Democrats ideology score), and only the minimum wage is significant at the 5% level. A joint F test on the statistical significance of these predictors is insignificant at the 10% level ($p = 0.197$).[22] Furthermore, the partial R^2 of the model, after residualizing on division by year and state fixed effects, is 0.114, implying that these predictors collectively explain only 11% of the variance in within-state changes to NCA policy. Thus, these results provide supportive evidence that NCA law changes are not strongly determined by underlying economic, political, or social trends. In subsequent analysis, we provide further corroborating evidence by showing that earnings do not differentially change in years *prior* to an NCA law change.

3.2 Data on Earnings and Mobility

We gather data on earnings, employment, mobility, and other labor market outcomes from four sources: the Current Population Survey (CPS) Annual Social and Economic Supplement, the Job-to-Job Mobility dataset, the Quarterly Workforce Indicators (QWI) dataset, and the CPS Occupational Mobility and Job Tenure Supplement (JTS). We describe each of these datasets, and how they fit into our analysis, in turn.

First, we gather individual-level data on earnings and employment from the CPS ASEC (otherwise known as the March Supplement).[23] The ASEC is a CPS supplement collected each March that contains information about the wage and salary income of respondents. The CPS also includes respondents' demographic and geographic information.[24] We restrict the ASEC sample to include individuals who reported having worked for a private-sector employer (not self-employed) in the year prior to being surveyed. We include the years 1991 to 2014, restrict to individuals who were between the ages of 18 and 64 at the time they were surveyed, and remove observations for which earnings or hours variables have been topcoded. The resulting ASEC dataset contains approximately 1.5 million observations, 1.2 million of which represent full-time workers. We deflate earnings and wages in the ASEC using the Consumer Price Index. We match NCA enforceability measures by state and year.

Second, we use the Job-to-Job Flows (J2J) dataset from the U.S. Census Bureau to examine the effect of enforceability on job mobility. Derived from the Longitudinal-

[22]It is not surprising that two out of twenty predictors are statistically significant. The probability of finding two or more significant predictors (at the 10% level) out of twenty, conditional on each of the predictors having zero true effect and each being independent (which is surely not true in practice, but provides an adequate benchmark) is approximately 0.88 ($1 - 0.90^{20}$).

[23]Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]. Minneapolis, MN: IPUMS, 2018. `https://doi.org/10.18128/D030.V6.0`

[24]While the ASEC is relatively small compared with, for example, the American Communities Survey (ACS), its existence precedes our earliest data on NCA enforceability (whereas the ACS does not). We are therefore able to leverage all changes in NCA enforceability from 1991-2014. Our results are quite similar if we instead use the ACS. We corroborate our estimates using the universe of earnings data (the QWI).

Employer Household Dynamics dataset,[25] these data contain aggregate job flows between cells defined by combinations of age, sex, quarter, origin job state, destination job state, origin employer industry, and destination employer industry. We aggregate these data to the level of the state-industry-year, and we create multiple measures of job mobility that could potentially be affected by NCA enforceability: (1): the *total count* of job-to-job separations; (2): the count of job-to-job separations in which the separating worker's destination job is in a *different* industry or (3): *the same* industry, respectively, than his or her origin job; and (4): the count of job-to-job separations in which the separating worker's destination job is in a *different* state or (5): *the same* state, respectively, than his or her origin job.

Third, we use the Quarterly Workforce Indicators (QWI) dataset from the Census Bureau. Like the J2J, the QWI is a public use file that aggregates data from the LEHD, and it contains data on earnings, as well as numbers of hires and separations, at the county-quarter level for the near-universe of private workers, stratified by sex and age group. We use the QWI both to complement the CPS in our estimation of the earnings effects of NCA enforceability, and also to investigate spillovers from enforceability. One drawback with the QWI for our purposes is that the QWI is not a balanced panel over our sample period, as some states did not begin reporting the necessary data until the late 1990s or later. For this reason, we are left with only 44 legal changes (instead of the universe of 73 legal changes) when using the QWI.

Fourth, in our investigation of the mechanism underlying the relationship between enforceability and earnings, we use data from the CPS Occupational Mobility and Job Tenure Supplement (JTS) over the years 1996 to 2014. The JTS is conducted biannually in either January or February. Among other things, it includes questions about the respondent's history of employment, such as "How long have you been working [for your present employer]?"[26] We use responses to this question to calculate the year that the worker began his or her job spell, which allows us to match individuals to the enforceability score at the time of hire. Our outcome variable of interest is weekly earnings, and we use additional variables as controls. We merge in annual national unemployment rates between 1947 and 2014 from the Bureau of Labor Statistics website for the analysis, which we describe in Section 6.

[25]U.S. Census Bureau. (2019). Job-to-Job Flows Data (2000-2019). Washington, DC: U.S. Census Bureau, Longitudinal-Employer Household Dynamics Program, accessed on April 7, 2020 at https://lehd.ces.census.gov/data/#j2j. Version R2019Q1.

[26]Note that "for your present employer" may alternatively be "for company name from basic CPS/as a self-employed person/at your main job." See http://www.nber.org/cps/cpsjan2016.pdf.

4 The Effect of NCA Enforceability on Workers' Earnings and Mobility

In this section, we examine the effect of NCA enforceability on earnings and mobility. We then consider whether these effects are more pronounced among workers who are most likely to have signed an NCA, and we then show that our estimates are stable to numerous robustness checks and sensitivity analyses.

4.1 Main Results on Earnings and Mobility

We use a difference-in-difference design to estimate the effects of NCA enforceability on earnings, leveraging intra-state variation in NCA enforceability over time. Our basic regression model is

$$Y_{ist} = \beta * Enforceability_{st} + X_{it}\gamma + \rho_s + \delta_{d(s)t} + \varepsilon_{ist}, \tag{2}$$

where Y_{ist} is the outcome of interest, $Enforceability_{st}$ is a state's annual composite NCA enforceability score across the 7 dimensions described in Section 3, X_{it} is a vector of individual-level controls, ρ_s is a fixed effect for each state, and $\delta_{d(s)t}$ is a fixed effect for each Census division by year.[27] The coefficient of interest, β, is identified from changes in earnings in states that change their NCA enforceability, relative to other states in the same Census division over the same period. Standard errors are clustered by state. A key identifying assumption is $E(Enforceability_{st}\varepsilon_{ist}|\rho_s, \delta_{d(s)t}) = 0$: conditional on state and division-year effects, changes in enforceability are uncorrelated with the error term. The evidence in Section 3.1.1 supports this assumption.

We report results in Table 3. Columns 1-4 use data from the ASEC, restricted to full-time workers between the ages of 18 and 64 who reported working for wage and salary income at a private employer the prior year.[28] The coefficient in Column 1 implies that an enforceability increase equal to 10% of the observed variation in our sample period leads to a 1.2 percent decline in earnings ($exp(-0.118 * 0.1) - 1, p = 0.002$). As another way to convey the magnitude of this estimate, consider that the 25^{th} and 75^{th} percentiles of *Enforceability* observed in our sample are 0.66 and 0.81, respectively. Moving from the 25^{th} to the 75^{th} percentile in *Enforceability* thus leads to a 1.7 percent average decline in annual earnings ($exp(-0.1175 * 0.15) - 1 = 0.017$). Adding fixed effects for broad occupation codes in Column 2 diminishes the point estimate slightly but improves its precision ($p < 0.001$).

A negative effect of *Enforceability* on annual earnings could reflect either a decline in hours worked or a decline in workers' implied hourly wage. In Column 3, the

[27] There are 9 Census divisions that partition the United States. We include division-year fixed effects to account for potential time-varying shocks to different areas of the country.

[28] All results are very similar if we include part-time workers.

dependent variable is instead the log of a worker's reported weekly hours:[29] While the point estimate is negative, it is relatively small and statistically insignificant ($p = 0.24$). In Column 4 the dependent variable is the individual's implied log hourly wage (calculated as annual earnings divided by fifty-two times usual weekly hours). The estimated coefficient is nearly identical to the coefficient on annual earnings.

Finally, in Column 5, we corroborate the estimates in Columns 1–4 that used the CPS ASEC sample by using data from the QWI. We run essentially the same regression specification as Column 1, except that we are able to include fixed effects for each county (rather than state)[30] and each division-year-quarter (rather than division-year). We weight the regression by county-level employment. The estimated coefficient is slightly larger than that in Column 1 and statistically significant.

Figure 3 visually illustrates the joint distribution of NCA enforceability and log annual earnings using binned semiparametric scatterplots. The dots in each graph depict the conditional mean log annual earnings for bins of NCA enforceability levels, controlling for the same variables included in Column 2 of Table 3 (state fixed effects, Census division-by-year effects, 1-digit occupation effects, and individual demographic controls). The conditional means are constructed using the semiparametric partial linear regression approach developed in Cattaneo et al. (2023).

Panel (a) shows the full joint distribution for all states and years. Panel (b) excludes California and North Dakota to visually focus on the states and years that provide nearly all of the identifying variation in our estimates. Both figures depict a clear negative relationship between enforceability and earnings. Using the test developed in Cattaneo et al. (2023), we fail to reject the hypothesis that the relationship between log earnings and NCA enforceability is linear in the full distribution (p=0.992). This test reinforces the choice of a linear regression specification in Equation 2.

In Appendix Table B.1 we report estimates from the same models shown in Table 3, but in each model we include the additional political and economic controls described in Section 3.1.1. The point estimates are slightly attenuated but similar with these controls: the coefficients in the ASEC log earnings and log wage models are -0.087 and -0.085, respectively ($p < 0.01$ in each model) and the coefficient in the QWI log average earnings model is -0.121 ($p < 0.01$).

It is instructive to benchmark our results against the estimated earnings effects of other labor market characteristics or institutions. One particularly instructive comparison is the effect of explicit employer concentration on earnings: Prager and Schmitt (2019) find that large changes in employer concentration, caused by local hospital mergers, caused a 6.5 percent decline in earnings among the most affected workers. As two comparable institutions, the household income premium associated with membership in a labor union is an estimated 15-20 log points (Farber et al.,

[29]We include part-time workers in this regression to avoid selecting the sample based on the dependent variable.

[30]The estimate is essentially unchanged if we instead use state fixed effects.

2018); the income premium for workers in an occupation that requires a government-issued occupational license is estimated to be 7.5% Gittleman et al. (2018).[31] To derive a comparable effect of NCA enforceability, we can extrapolate our estimates to consider what would happen to earnings under a national policy that rendered all NCAs unenforceable. We generate predicted earnings for each individual in the 2014 ASEC sample using coefficients from Column 1 of Table 3, for two different levels of NCA score: first, the NCA score observed in 2014 in that individual's state, and second, at the lowest observed NCA enforceability level (0). These predictions imply that average earnings among *all* workers would likely increase by 3.2% to 14.2% nationally if NCAs were made unenforceable.[32] The midpoint of this interval (8.7%) is similar to the effect of a large change in employer concentration, roughly one-half the household premium from labor union membership, and comparable to the premium attained by workers in occupations with government-mandated licenses.[33]

Our NCA Enforceability Score pools seven dimensions of NCA enforceability, but these dimensions might differ in their earnings effects. In Appendix Table B.2, we reestimate the effect of changes in NCA law on earnings in a specification analogous to Column 1 of Table 3, but focusing on each individual component of the composite NCA score separately. The first seven rows represent separate regressions identical to Equation 2, except that $Enforceability_{st}$ is replaced with each respective element of the NCA score described in Table C.1.[34] With two exceptions (which are both insignificant at the 10% level), the estimated effect of each score is negative; among those that are negative, the coefficients are significant at the 5% level for three components. Two of the dimensions yielding the largest negative earnings effect are those requiring consideration (i.e. compensation), both at the outset of employment (Q3a)

[31]Estimates of the earnings premium associated with occupational licensing vary widely: for example, Redbird (2017) finds no earnings premium using a 30-year comprehensive panel of licensing laws.

[32]Specifically, let X_i be the vector of the values of all variables (including fixed effects), except for NCA enforceability score, that are present in the regression in Column 1 of Table 3 for each individual, i, in 2014. Let γ be the vector of respective coefficients estimated in the same regression, and let β_{Low} and β_{High} be the bounds of the 95% confidence interval for the coefficient on $Enforceability_i$, the NCA Enforceability Score for individual i's state of residence in 2014. Then, if $\hat{Y}_{i,1,j} = \gamma X_i + \beta_j Enforceability_i$ represents predicted earnings for individual i for $j \in \{Low, High\}$, and $\hat{Y}_{i,2} = \gamma X_i$ represents predicted earnings for individual i when $Enforceability_i = 0$, we report the averages of $[\hat{Y}_{i,2} - \hat{Y}_{i,1,j}]/\hat{Y}_{i,1,j}$.

[33]This prediction of the effect of a national ban on NCAs requires a strong assumption of linearity, since such a ban would lead the average worker to experience an NCA score change far outside the distribution of identifying variation underlying our regressions in Table 3. However, the roughly linear relationship between earnings and NCA enforceability illustrated in Figure 3 suggests that this assumption is not unreasonable.

[34]Estimating a model with each component of the score separately likely introduces some omitted variable bias, as elements of the score are correlated with each other. However, including all individual components of the score in the same regression causes the sample size to shrink significantly due to missingness in some of the components (where missingness indicates that the question has not been legally settled). That model, however, generates coefficients qualitatively similar to those shown in Table B.2.

and after employment has already begun (Q3bc), consistent with evidence in Starr (2019). No single dimension drives our results, and the dimensions with the largest effects are consistent with what one might expect based on theory and prior results.

4.1.1 Effects of Enforceability on Job Mobility

While the main focus of our analysis is the earnings effect of NCA enforceability, we also estimate its effect on worker mobility. This analysis is useful because it serves as validation that the variation in enforceability is capturing what NCAs are designed to do—restrict workers' mobility.

Table 4 presents estimates based on job-to-job flows data from the J2J dataset. We measure the number of job-to-job changes at the state-year-quarter-sex-age group-industry level. We then estimate a Poisson pseudo-maximum likelihood model with the following specification:

$$\mathbb{E}\left[J_{stia}\right] = \exp\left[\beta * NCA_{st} + \lambda * High\ Ind_i\ \times NCA_{st} + \gamma X_{ia} + \theta_{si} + \phi_{d(s)ti} + \varepsilon_{stia}\right]$$

where J_{stia} is the count of job-to-job changes[35] in state s, quarter t, origin industry i, and demographic group (age and sex) cell a. NCA_{st} is the NCA enforceability score, and $High\ Ind_i\ \times NCA_{st}$ is an interaction between industries with high rates of NCA use (as measured in Starr et al. (2021): see Section 4.3.2 for more detail), and the NCA enforceability score. X_{ia} contains indicator variables for male workers and each of the age bins in the J2J data.[36] θ_{si} is a fixed state by origin industry effect, and $\phi_{d(s)it}$ is a fixed census division by origin industry by quarter-year effect.

In Column 1 we estimate the effect of the origin state NCA enforceability score on the overall number of job-to-job changes and find a small and statistically insignificant effect. However, in Column 2 we interact NCA enforceability with an indicator for whether the origin job was in a high NCA-use industry, and find that NCA enforceability substantially reduces job-to-job separations in high-use industries. The coefficient on $High\ Ind_i \times NCA_{st}$ is negative (-0.241) and highly significant ($p < .01$). The estimate implies that moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of NCA enforceability decreases the number of job-to-job changes by 3.7% in high-use industries.

In Columns 3 through 6 we test whether NCA enforceability affects not just the *level*, but also the *direction* of job mobility, based on two forms of restrictions often used in NCA contracts. In Columns 3 and 4 we test for effects on job-to-job transi-

[35]Following Johnson et al. (2023), we use job change counts, instead of rates, as our dependent variable. We do this because NCA enforceability also affects the denominator of the rate—employment—which makes interpretation difficult. In untabulated results, we find that a regression of log employment on NCA enforceability (using QWI data in a specification identical to Column 5 of Table 3, using baseline employment as weights) yields a coefficient of -0.13 ($p = 0.047$), corresponding to a 1.9% decrease in employment when moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of enforceability.

[36]These are age ranges 14-18, 19-21, 22-24, 25-34, 35-44, 45-54, and 55-64.

tions that occur across (Col. 3) and within (Col. 4) the origin job industry. Focusing on high-use industries, we find no statistically significant impact of NCA enforceability on across-industry job transitions, but we find a large and significant negative effect on transitions within-industry in high-use industries. Specifically, we estimate that moving from the 25^{th} to the 75^{th} percentile of NCA enforceability decreases the number of within-industry job changes by 5.9% in high-use industries. This evidence is consistent with Marx (2011) and Mueller (2022), who find that technical professionals and inventors bound by NCAs or subject to stricter NCA enforceability take "career detours" to different industries and occupations to avoid potential lawsuits.

In Columns 5 and 6 we test for effects on job-to-job transitions that occur across (Col. 5) and within (Col. 6) the state of the origin job. We again find no statistically significant impact of NCA enforceability in high-use industries on across-state job transitions, but we find a large and significant negative effect on transitions within the origin state in high-use industries. We estimate that moving from the 25^{th} to the 75^{th} percentile of NCA enforceability decreases the number of within-state job changes by 4.1% in high-use industries. This evidence is consistent with the fact that the restrictions in many NCAs are geography-specific, so are more likely to affect the rates of in-state moves.

This evidence illustrates that our measures of NCA enforceability influence mobility decisions: exactly what NCAs are designed to do. The results also motivate our investigation into one mechanism through which NCA enforceability affects earnings, which we describe in Section 6.

4.2 Dynamic Effects on Earnings and Robustness to Heterogeneous Treatment Effects

We use a distributed lag model to check whether earnings exhibit differential pretrends in the years prior to an NCA law change, and how earnings evolve in the subsequent years after a law change. We corroborate this analysis with an event study model centered around a state's first NCA law change, which also addresses potential bias from heterogeneous treatment effects that might affect our baseline estimates.

4.2.1 Distributed Lag Estimates on Earnings

Two potential concerns with the estimates from difference-in-difference specifications are 1) the plausibility of the parallel trends assumption that treatment and control states would counterfactually follow common trends in the absence of a law change in the treated state, and 2) whether the regression estimates reported in Table 3 mask dynamic treatment effects that change over time.

To address these concerns, we complement our difference-in-difference estimates with a distributed lag model, which allows us to assess the dynamic effects of an

NCA law change in the years immediately before and after the change takes place. A distributed lag model is similar to an event study model: Schmidheiny and Siegloch (2020) show that a distributed lag model with leads and lags is in fact numerically identical to an event study model with binned endpoints.

We estimate the distributed lag regression in first differences, similar to the approach used by Fuest et al. (2018)[37] using the QWI sample, which is based on the universe of jobs in the U.S.. In this specification, the unit of observation is a county $c(s)$, demographic group g (defined as combinations of sex and age), and quarter t. The model we estimate using QWI data is:

$$\ln w_{c(s),g,t} - \ln w_{c(s),g,t-1} = \sum_{k=-3}^{k=5} \beta_k [Enforceability_{s,t-k} - Enforceability_{s,t-k-1}] + \Omega_g + \gamma X_{s,t} + \delta_{d(s),t} + \varepsilon_{c(s),g,t}.$$

The dependent variable, $\ln w_{c(s),g,t}$, is the natural logarithm of average earnings in the relevant bin. Ω_g contains indicator variables for worker sex and each age bin. $X_{s,t}$ includes the same state-level political, economic, and social measures described in Section 4.1. $\delta_{d(s),t}$ is a fixed Census division-by-year-quarter effect. We weight observations by employment and cluster standard errors by state.

As illustrated by Schmidheiny and Siegloch (2020), because the distributed lag model measures treatment effect changes, to obtain event study estimates we calculate the cumulative sum of the distributed lag coefficients away from the normalized year, $j = -1$.

We report the results from this model in Panel A of Figure 4. The figure depicts two noteworthy features. First, there is little evidence of a pre-trend in earnings, supporting the assumptions (and the evidence in Section 3.1.1) that NCA law changes were conditionally exogenous to underlying economic trends and to underlying changes in the frequency of litigation or the use of NCAs which could simultaneously impact earnings. Second, earnings begin to decline in the first year following the law change, and the effects grow in magnitude until year three, becoming statistically significant by year two.[38]

[37]Our setting is similar to that in Fuest et al. (2018), who estimate the effects of corporate tax changes on earnings. They consider tax changes across municipalities that occur at staggered times, can occur multiple times in one municipality over the panel, and are of different magnitudes, all of which is also true in our setting.

[38]The gradual increase in the earnings effect could be due to delays in knowledge about law changes, frictions in adjusting contracting terms, or grandfathering of contractual provisions, among other factors. The earnings effect growing over time is also consistent with our proposed mechanism that higher enforceability leaves workers less able to benefit from outside job offers to improve their earnings—a mechanism we test for in Section 6—which is an effect that would compound over time. Lipsitz and Starr (2021) and Young (2021), who study the effects of NCA bans in the state of Oregon and in Austria, respectively, both also find that the earnings effects of NCA bans grew over time.

4.2.2 Stacked Event Study

While the distributed lag model reported in Panel A of Figure 4 corroborates our baseline two-way fixed effects (TWFE) model, recent research has illustrated that both of these approaches can be biased in the presence of heterogeneous treatment effects. Our empirical design leverages differential timing in changes across states to a continuous treatment that can change multiple times over the sample period. Several recent papers have highlighted that staggered timing of changes can cause TWFE to be biased because of comparisons where states that experience early law changes serve as controls for states with later law changes (Goodman-Bacon, 2018)). While alternative estimators have been proposed to overcome this bias for a binary treatment (e.g., Callaway and Sant'Anna (2021)), continuous variation in treatment can create additional complications that are the subject of ongoing research (De Chaisemartin and D'Haultfoeuille, 2022b).

To address these concerns, we draw inspiration from recent work and conduct a stacked event-study around a state's first law change during our sample period. The stacked design has been used in other recent applied settings (Cengiz et al., 2019; Deshpande and Li, 2019), and De Chaisemartin and D'Haultfoeuille (2022a) show that the treatment effect of a unit's first change can be estimated without bias. We identify the subset of NCA law changes that satisfy the following criteria: 1) they are a state's first law change during the sample period, 2) they occur at least 4 years after the start of the QWI sample period (which varies by state since states entered QWI in different years), 3) they occur at least 5 years before the end of the sample period (2014), and 4) they are not followed by subsequent countervailing law changes.

We use the 11 states that never experienced a law change during our sample period (never changers) as the set of eligible control states. For each treatment state, we create a panel dataset for that treatment and its control states, comprising the three years prior and five years following the treatment state's law change. We consider two sets of control states for each treatment state: 1) all 11 never changer states, and 2) the subset of never changers in the same Census region.[39] Two treatment states satisfy requirements (1) to (4) above but lack a control state in their Census region with QWI data in the pre-period; these two treatment states get dropped from the specification restricting to control states in the same region. Overall, the sample restrictions leave us with 10 law changes (14% of the 73 total changes) when we require controls to be in the same region, and 12 law changes when we allow control states to be out-of-region. Thus, a tradeoff with this specification is that, while it

[39]This model is different than our baseline that compares treated states to control states in the same Census division. The reason is that in this model there are only 11 eligible controls control states, leaving an overly sparse set of control states if we required they be in the same Census division (of which there are 9). We present estimates that do and do not require control states to be in the Census *region* (of which there are four) to balance the tradeoff between accounting for geographic-specific shocks that could matter for wages, while also ensuring we have a large enough comparison group.