Learning to Fail? Evidence from Frequent IPO Investors

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Abstract

We examine the effects of bidding experience on two groups of investors – individuals and institutions – in terms of their decisions to bid again and their bidding returns. Bidding histories are tracked for all 31,376 individual investors and 1,232 institutional investors across all 84 IPO auctions during 1995-2000 in Taiwan. For individual bidders: (1) high initial returns in IPO auctions increases the likelihood of participating in future auctions; (2) bidder returns steadily decrease as they participate in more auctions; (3) auction selection ability does not improve (and may get worse) with experience; and (4) greater experience is associated with more aggressive bid prices. These findings are consistent with naïve reinforcement learning wherein individuals become unduly optimistic after receiving good returns. In sharp contrast, there is little sign that institutional investors exhibit such behavior.

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1. Introduction

There has been growing interest in economics and finance in studying the effect of experience on decision making. On the one hand, economic agents may learn through experience to make better decisions as they acquire better information about the environment or about the quality of their information signals (e.g., Arrow (1962), Grossman, Kihlstrom and Mirman (1977), Mahani and Bernhardt (2007), and Linnainmaa (2009)).

On the other hand, there are also psychological biases in learning processes which can result in even worse decisions after gaining experience than without it. There is evidence that people learn through naïve reinforcement, wherein they expect what they personally experienced before to happen again in the future, regardless of whether such expectations are logically justified. In other words, they expect success in an endeavor to indicate favorable prospects for future success, while failure foreshadows future failure. Although a rational Bayesian may indeed draw such inferences to some extent, under naïve reinforcement learning individuals overweight their personal experience compared to information obtained by communication with or observation of others (Cross (1973), Arthur (1991), Roth and Erev (1995), and Camerer and Ho (1999)).

A good understanding of how investors learn is essential for accurate modeling of financial and economic decisions. In traditional economic models, economic agents are often assumed to solve complex decision problems flawlessly. A common justification for this approach is that in repeated settings individuals will eventually learn to play correct strategies. However if learning does not improve decision-making, such an argument is unjustified. It is therefore important to examine evidence from a variety of settings to determine in what contexts individuals are able to learn their way out of bias, and in what contexts learning exacerbates bias.

In this paper, we explore whether investors learn to improve their strategies through experience, or whether experience causes them to invest less effectively. To do so, we use a dataset with complete bid information for all the 84 IPO auctions during 1995-2000 in Taiwan. We are able to track the bidding histories of 31,376 individual investors and 1,232 institutional investors during that period.

The fact that this dataset includes the first IPO auction in Taiwan and *all* the IPO auctions during 1995-2000 is important for studying the effects of experience, because as a result we know the complete bidding history of all bidders prior to each IPO auction. Furthermore, our data include large numbers of both individual and institutional investors. As a result, we are able to explore whether past experience influences individual and institutional investors in different ways.

We first examine the relationship between an investor's past returns from previous IPO auctions and her inclination to participate in a future IPO auction. We find that individual investors tend to bid again if they receive high past returns and tend to stop bidding if they receive poor past returns. We also test the learning behavior of institutional investors, and find that their decisions to bid are much less, if at all, influenced by their past returns.

It is possible that individual investors have good reasons to pay more attention to their past performance than institutional investors do. For example, individual investors may have less information about their trading abilities than do institutional investors. On the other hand, it is also possible that individual investors are subject to naïve reinforcement learning, and that the greater sophistication of institutional investors allows them to avoid drawing mistaken and excessive inferences about their abilities from past performance.

To differentiate between the rational and naïve reinforcement learning hypotheses, we examine investor return performance as they gain more experience. If investors rationally learn about their abilities, and if those who learn that they have better skills tend to bid again, then experienced bidders should on average be more highly skilled. Similarly, if investor bidding skills increase with experience, again experienced bidders should tend to be more skilled. Hence we should observe higher average returns for experienced bidders, i.e., returns increase with experience. In contrast, if investors bid repeatedly because they become unduly optimistic after receiving good returns from previous auctions, then their returns will decline with experience as their optimism causes greater aggressiveness in participation and perhaps bidding.

Consistent with the naïve reinforcement learning hypothesis, we find that individual investors' returns steadily decrease as they gain more experience. In contrast, institutional investors' returns do not decrease. Together with the evidence that institutions' decisions to bid in the future are not significantly influenced by their past returns, our findings suggest that institutional investors are not subject to naïve reinforcement learning.

Sherman (2005) and Chiang, Qian and Sherman (2009) discuss two kinds of bidding skills needed for investors to achieve good returns from participating in IPO auctions: the ability to judge firm quality (i.e., auction selection), and to shave bids sufficiently (to address the winner's curse and to compensate for information costs). We investigate here how these two types of bidding abilities *change* as investors learn from experience. For individual investors, we find that auction selection ability does not improve (and may get worse) with experience, and that experience causes greater aggressiveness in bid prices. Together these learning failures cause average individual investor returns to decline with experience. For institutional investors, however, neither of these two bidding skills deteriorates with experience.

Our study makes two contributions to the learning literature. First, we provide evidence that individual investors in IPO auctions are subject to *naïve* reinforcement learning. Their declining returns cannot be explained by rational learning. Second, we document that institutional investors do not seem to be subject to this learning bias.

Our paper is far from the first to address the issue of how decision-makers learn from experience. For example, several studies examine learning in laboratory experiments (Erev and Roth (1998), Camerer and Ho (1999), and Charness and Levin (2005)). Using survey data, Malmendier and Nagel (2008) document that individuals' expectations about future inflation rates are largely influenced by their own experiences of inflation, consistent with reinforcement learning.

Other papers have studied effects of learning using actual trading and asset allocation data. Consistent with the rational-learning hypothesis, Feng and Seasholes (2005) and Dhar and Zhu (2006) find that investors' trading experience reduces the behavioral bias of the disposition effect. Nicolosi, Peng and Zhu (2008) and Seru, Shumway and Stoffman (2009) present evidence that individual investors learn from trading experience and improve performance. On the other hand, consistent with reinforcement learning, Barber, Odean, and Strahilevetz (2004) document that investors tend to repurchase stocks they previously sold for a gain and shun stocks they previously sold for a loss. Choi, Laibson, Madrian and Metrick (2007) find that an investor' 401(K) contribution rate increases more if her account has recently experienced a high return or low return variance, and that such behavior is not welfare-improving.[1] These papers all focus on individual investors. A distinctive aspect of our paper is that we examine whether individual

[1] There is evidence consistent with biased learning for other market participants: Billett and Qian (2008) find that CEOs that frequently engage in acquiring other firms see more negative wealth effects in their later deals while their insider trading prior to those deals become more bullish. Hilary and Menzly (2006) find that analysts who have predicted earnings more accurately in the recent past tend to be less accurate and further from the consensus in subsequent earnings predictions, although there are mixed results regarding the effect of long-term experience on analyst forecast accuracy (See Mikhail, Walther and Williams (1997) and Jacob, Lys and Neale (1999)).

versus institutional investors differ in how they react to past experience and in their abilities to improve their performance.

Kaustia and Knupfer (2008) provide evidence suggesting that individual investors are more likely to participate in IPOs after good returns from past IPOs. This evidence is valuable in documenting that belief updating in IPOs does occur in response to experience. However, their tests are not able to distinguish the key hypotheses of our paper — whether investors rationally learn to improve their profits, or whether investors update naively, and thereby 'learn to fail'. Although the authors interpret their results as consistent with naïve reinforcement learning, their evidence is not inconsistent with the hypothesis that investors learn rationally. If investors learn about their investing abilities through experience, then those who have high abilities will continue more often than those with low abilities (Mahani and Bernhardt (2007) and Seru, Shumway and Stoffman (2009)), consistent with Kaustia and Knupfer's finding.

There are two key differences between our paper and that of Kaustia and Knupfer. First, by examining performance over time, we assess whether investors are engaged in rational learning, or are 'learning to fail' through naive reinforcement learning. The IPO auctions in our sample are discriminatory price auctions, i.e. bidders pay what they bid when they win. This implies that winning bidders will receive different initial returns even from the same auction. These auctions therefore provide a great deal of relevant information for exploring the effects of personal experience on returns. In contrast, Kaustia and Knupfer (2008) use data from offerings in which retail investors play no price-setting role, since they choose only whether or not to order shares. All investors pay the same offer price and receive the same initial returns from the same IPO.

Second, Kaustia and Knupfer focus on individual investors, whereas we test whether individual and institutional investors differ in their abilities to learn valid lessons from past experience. An added advantage of our dataset is that, in contrast with IPOs that use bookbuilding or fixed price public offer methods, underwriters in IPO auctions have no discretion over either pricing or allocation. Thus, our study is not complicated by the interfering effects of underwriter discretion.

Our findings also have implications for IPO design. Chiang, Qian and Sherman (2009) document that institutional investors are informed bidders with sophisticated bidding strategies, while individual investors are not. The authors thus raise the question of whether individual investors as a group have the sophistication to price highly risky securities such as IPO stocks. Our paper differs in studying how different kinds of investors *learn from experience* in IPO auctions. Our findings further suggest that experience with the IPO auction method does not seem to make individuals better investors in these IPO auctions. This raises the question of whether regulatory protections are needed for individual investors participating in IPO auctions.

2. Data and Sample

2.1 IPO auctions in Taiwan

IPO auctions in Taiwan are multiple-unit, multiple-bid discriminatory-price sealed-bid auctions. A bidder can submit multiple bids (different combinations of price and quantity) and he pays what he bids if he wins.[2] Both individuals and institutions can participate in these IPO auctions. A bidder is allowed to win no more than 6% of the auction shares, which for an average

[2] IPO auctions in Taiwan are a hybrid IPO method – half of the IPO shares are to be sold in an auction, and then the other half of the shares are to be sold in a subsequent fixed-price public offer. Chiang, Qian and Sherman (2009) show that there are no strategic interaction between the two stages and they are essentially two independent sales from investors' point of view. Hence we focus on auctions only in this paper.

auction is NT$58.0 million at the average winning price.[3] Institutions bid in all but two of the auctions in our sample.

Bidders submit sealed bids during a pre-announced bid-tender period which lasts for 4 business days. At the time of submitting bids, investors need to pay a transaction fee of NT$500 for each bid and a bid deposit that is no less than 20% of the bid size. During the bid-tender period, underwriters are not allowed to open the sealed bids and are explicitly forbidden from revealing bid information (Taiwan Securities Association Rules Governing Underwriting and Resale of Securities by Securities Firms, Article 14). By 9:00 A.M. on the morning after the auction closes, the bid log is delivered to the Taiwan Securities Association, where the bids are opened and allocations are determined. We call this date the auction date.

The clearing price is the maximum bid price that clears the supply. All bids that are strictly above the clearing price are filled in full, while bids at the clearing price are awarded by lottery. Bidding results including the clearing price, subscription ratio, and winning price and quantity for each winner are then announced. Information on losing bids is not made publicly available (but is available in our data).

Shares are seldom able to trade freely during their first official day on the aftermarket, due to limits on daily price changes. In Taiwan, a daily return limit of 7% in each direction is imposed on all publicly traded stocks, including IPO shares, during our sample period. IPO shares frequently hit this limit for the first few days in a row. The first day when the stock price falls within the limit is known as the first non-hit day. We compute an investors' initial return (or IPO underpricing) based on the closing price of the first non-hit day. This initial return is comparable to an IPO's first-day return in the US, where IPOs do not face daily price limits. In

[3] All NT$ values are in constant year 2000 NT$'s. The end of 2000 exchange rate was US$1 = NT$32.99. Thus the limit on winning bids per bidder averaged around US$1.75 million.

our sample, the 'honeymoon period' (the time from the first trading day to the first non-hit day) has a mean (median) of 5.4 (3) trading days and ranges between 1 and 28 trading days. For more institutional details on IPO auctions in Taiwan, see Chiang, Qian and Sherman (2009).

2.2 Sample

The sample includes all the 84 IPO auctions in Taiwan during 1995-2000.[4] We obtain detailed bidding information on each auction from the Taiwan Securities Association, including bidder IDs and the bid price and quantity of every bid by each bidder. The format of the bidder ID tells us whether the bidder is an institutional or individual investor. A bidder uses the same ID across auctions and therefore the dataset allows us to track the bidding history of each bidder. The dataset also includes information on the auction size, the reservation price, the clearing price and the auction proceeds.

Background information about the IPO firms such as assets, venture capital ownership and P/E ratio are collected from the firms' prospectuses, which are available from the Taiwan Securities & Futures Information Center database. Stock returns for individual stocks and the market are from the Taiwan Economic Journal (TEJ).

Table 1 displays summary statistics of the sample. Panel A reports firm characteristics. The average IPO firm has assets of NT$10.4 billion and raises NT$880.6 million in the auction. Panel B reports the means of IPO initial returns and numbers of bidders for the whole sample period and by year. We compute the initial return for each auction as the closing price on the first non-hit day over the quantity-weighted average winning price. We also compute the weighted average initial return in each auction separately for individuals and institutions. The mean IPO

[4] There are seven IPO auctions that came after 2000 – three in 2001, two in 2002, one in 2003 and one in 2008. Bid data for these auctions are not available due to the new privacy policy of the Taiwan Securities Association.

initial return over the sample period is 7.3%. On average, 676.8 individuals and 32.0 institutions bid in each IPO auction.

Not surprisingly, the mean return for individual investors is very close to that for the whole sample since most bidders are individuals. Institutional investors on average earn higher returns, with a mean return of 8.7% for institutional investors and 7.2% for individuals. Across years, the average winning bidder performs best in the year 1996, which, however, is immediately followed by a bad year in 1997. A similar mini-cycle seems to be repeated in 1999 and 2000. The time-series variations are similar for individual and institutional investors. There is no obvious time-trend for investor participation.

Table 1 Panel C reports bidder activity and returns for individual and institutional investors, respectively. Unlike in Panels A and B where we treat each IPO auction as an observation, in Panel C we treat each auction-bidder as an observation. There are 31,467 (1,232) unique individual (institutional) bidders with 56,849 (2,687) bidder-auction observations. Of these, there are 16,037 (971) winning individual (institutional) bidder-auction combinations for which returns can be calculated. The average individual investor participates (i.e., bids) in 1.8 auctions with a mean bid size of NT$2.3 million and wins shares in 0.5 auctions. The average winning individual bidder invests NT$2.8 million. In comparison, the average institutional investor participates in 2.2 auctions with a mean bid size of NT$22.7 million and wins shares in 0.8 auctions. The average winning institutional bidder invests NT$28.0 million. Individual investors earn a mean (median) initial return of 5.5% (0%), whereas institutional investors earn a mean (median) initial return of 11.5% (4.6%). All the differences are significant at the 1% level.

Despite the positive mean (nonnegative median) returns, investments in these IPOs are highly risky, and a positive return is far from guaranteed. The standard deviation of returns is

22.8% for individual investors and 26.1% for institutional investors. Individual investors' returns range from -50.0% to 110.6%, and institutional investors' returns from -33.8% to 110.6%. Moreover, individual investors receive positive returns only 49.4% of the time and institutional investors 64.1% of the time.

Most investors in our sample (74.8% of individuals and 66.5% of institutions) bid in only one auction. The proportion of investors bidding in two auctions is 11.7% for individuals and 11.9% for institutions. The proportion of investors bidding in three or more auctions is 13.5% for individuals and 21.6% for institutions. However, bidders with two or more auctions count for 60.1% of all bidder-auction observations.[5]

3. Past returns and the likelihood of participating in further auctions

In this section, we examine the relationship between a bidder's past returns and her likelihood of bidding again. As in Kaustia and Knupfer (2008), we divide the sample into two halves, and investigate whether returns received in the first half affect a bidder's inclination to bid in the second half. We examine this question for both individuals and institutions.

We divide the sample in such a way that the two subsamples have similar numbers of winning bidder-auction observations. The first half of the sample includes 44 (out of 84) auctions and 8,442 (out of 17,008) winning bidder-auction observations. We compute a bidder's return in the first half as the investment-weighted average of her returns from all the auctions for which she wins shares during that period.

Table 2 Panel A reports the probability of bidding in the second half for each quartile of

[5] As will be discussed later, due to the time overlaps of some auctions, bidders might have multiple first auctions. In other words, a bidder may have two auctions but both auctions may be defined as her first auctions. Bidders with 2nd or later auctions count for 50.4% of all bidder-auction observations.

returns in the first half, for individual and institutional investors respectively.[6] For individual investors, the probability of bidding again in the second half jumps from 29.8% in the lowest return quartile (mean return of -8.9%) to 38.5% in the 2nd quartile (mean return of 5.3%), and continues to increase to 41.9% in the 3rd quartile (mean return of 17.8%). It then levels off at 40.0% in the 4th quartile (mean return of 47.9%). Thus, the difference between a positive and negative return seems to have a major impact on the decisions of these investors to bid again. Higher positive returns are also more encouraging than lower positive returns, but the marginal effect seems to be decreasing.

Overall, individual bidders are more likely to bid in the second half if they receive higher returns in the first half. This pattern, however, does not apply to institutional investors. Institutions, on average, have a higher tendency to bid again than individuals. However, there is no relationship between past returns and the probability of bidding in the 2nd half. The probability of bidding in the 2nd half is 46.3%, 37.8%, 43.9% and 47.3% for the 1st, 2nd, 3rd and 4th return quartile respectively.

It is likely that different investors have different propensities to bid (even apart from past returns). To control for this, we look at bidders with different numbers of auctions in the first half separately. Table 2 Panel B shows the bidding probability by return quartiles for bidders with one, two, and three or more auctions respectively. We find that bidders with more auctions in the first half indeed are more likely to bid again in the second half, holding return quartile fixed. Nonetheless, for each bidder category, past returns still have a large positive effect on individual investors' decision to participate in future auctions. For individual investors with any number of auctions in the first half, their bidding probability in the 2nd half steadily increases

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[6] Although we examine individual and institutional investors' probability of bidding separately, the return quartiles are determined for all bidders together.

across return quartiles. In contrast, for institutional investors in each auction-number group, we do not observe such a relationship between past returns and bidding probabilities.

Table 3 describes logit regressions in which the dependent variable is a dummy equal to one if the bidder bids again in the 2nd half of the sample. The main variable of interest is a bidder's past return in the first half. We control for the number of auctions in which she participates in the first half, as well. The coefficient on the number of auctions is significantly positive in regressions for both individual and institutional investors, suggesting that this variable is a good indicator of the bidder's inherent propensity to bid. The coefficient on past return is significantly positive for individuals, but not significant for institutions. In terms of economic significance for individual investors, when the past return moves from the 25th percentile to the 75th percentile holding the control variables at their means, the probability of bidding increases from 32.3% to 39.2%.

In summary, we find that for the discriminatory auction IPOs in our sample, individual investors' bidding decisions are significantly influenced by their returns from previous IPO auctions. This is consistent with the findings in Kaustia and Knupfer (2008) for individual investors in fixed-price IPO offerings. We further find, in sharp contrast, that institutional investors' bidding decisions are not affected by their own past returns.

4. Bidder experience and returns

We have shown that individual investors are more likely to bid again if they receive high returns from previous IPO auctions, whereas institutional investors do not have this responsiveness to past performance. In this section, we perform further tests to disentangle whether the behavior of individual investors reflects rational learning about their bidding abilities, versus naïve reinforcement learning. To do so, we examine whether the bidder's return performance in subsequent IPO auctions increases with experience. Since each investor's bid determines the price that he or she pays, any skill improvement in either selecting offerings to participate in or in selecting the level of bids should lead to an increased return.

4.1 Univariate Tests

To measure bidding experience, we use *the number of previous IPO auctions* a bidder has participated in prior to the current auction. Each bidder-auction is assigned an *auction order.* An auction is a bidder's 1^{st} (2^{nd}, 3^{rd}, etc.) auction if the bidder has 0 (1, 2, etc.) previous IPO auctions. Thus, a given auction may be one bidder's 3^{rd} auction but another bidder's 1^{st} auction. An auction is counted as a previous auction if its first non-hit date occurs before the current auction's auction date (so that we can compute the initial return from the previous auction).[7]

We examine bidder returns as auction order increases. If investors rationally learn about their abilities, with those who have better skills tending to bid more (and hence entering higher-order auctions), average investor skill should be higher among investors' higher-order auctions than in investors' lower-order auctions. Hence we should observe higher average returns in investors' higher-order auctions.

Similarly, investors may learn to make smarter bids when they have more experience, even if they do not start with better skill. This, too, would imply that returns should increase with auction order. In contrast, if investors become unduly optimistic after receiving good returns from previous auctions and thus tend to bid too aggressively, their returns will decline owing to their excessive aggressiveness in auction participation and bidding levels.

[7] Under this definition, a bidder may have multiple auctions that have the same auction order, for example if a bidder participates in a total of 3 auctions, and for the first two, the periods from auction date to first non-hit day overlap partially. In this case, the bidder's auctions have the following auction order respectively: 1^{st}, 1^{st} and 3^{rd}.

Table 4 reports the mean (and median) return of bidders in their 1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th} and higher-order auctions. Panel A reports results for the entire sample. For individual bidders, returns in general decrease when investors' auction order increases from 2^{nd} to subsequent auctions. We test the significance of the differences in returns for 2^{nd} vs. 1^{st}, 3^{rd} vs. 2^{nd}, 4^{th} vs. 3^{rd}, 5^{th} vs. 4^{th}, and higher-order vs. 5th auctions. The differences are significantly negative for 3^{rd} vs. 2^{nd}, 4^{th} vs. 3^{rd} and higher-order vs. 5^{th} auctions. These results suggest that individual investors' returns deteriorate with experience in bidding. A notable exception is that the average return for 2^{nd} auctions is significantly higher than for 1^{st} auctions.

This particular result (i.e., 2^{nd} auctions have higher returns than 1^{st} auctions), however, is driven entirely by one outlier auction – Chung Hwa Telecom, which is a privatization of a state-owned company and the biggest IPO in Taiwan ever (including other IPO methods). Chung Hwa has an asset value of NT$443.1 billion compared to NT$10.4 billion for the average IPO firm in our sample and it raises NT$22.7 billion compared to the average NT$0.9 billion. It also attracts the highest number of bidders: 4,286 compared to an average of 708.7 bidders, among whom 4,240 (98.9%) are first-time bidders. In addition, all bidders in this case won shares and all of them received negative returns ranging from -37.6% to -3.4%. Not surprisingly, inclusion of this auction greatly reduces the mean return of first-time bidders.

Table 4 Panel B reports the mean (and median) returns of bidders excluding this outlier auction. Now for individual investors, the average return for 1^{st} auctions is higher than for 2^{nd} auctions, and returns steadily decrease as the auction order increases. This indicates that greater bidding experience is associated with *worse* return performance. Overall, the declining returns are inconsistent with the hypothesis that investors learn about their abilities and are more likely to continue bidding if they have learned that they have better skills, as well as with the hypothesis that investors learn to bid more skillfully through experience. Instead, the evidence is consistent with the hypothesis that bidders become unduly optimistic and bid more aggressively in their later auctions.[8]

As for institutional investors, returns are much more stable across auction orders. Table 4 Panel B shows that the differences in the mean returns are all insignificant for 3^{rd} vs. 2^{nd}, 4^{th} vs. 3^{rd}, 5^{th} vs. 4^{th}, and higher-order vs. 5^{th}. The only exception is that the mean return for 2^{nd} auctions is significantly lower than 1^{st} auctions. For median returns, none of the differences are significant. Taken together with the previous result that institutions' bidding probability is not significantly influenced by their past returns, our findings suggest that institutions' bidding decisions (whether to bid and how high to bid) depend much less on their own experience. There is little evidence that they are subject to naïve reinforcement learning.

To ensure that the declining returns across auction orders are indeed due to differences in bidding experience but not due to other differences in bidders, we compute a bidder's *own* change in returns across auctions. Table 5 reports the means and medians of change in returns for 2^{nd} vs. 1^{st}, 3^{rd} vs. 2^{nd}, 4^{th} vs. 3^{rd}, 5^{th} vs. 4^{th} and higher-order vs. 5^{th} auctions. Results are consistent with those in Table 4. For individual investors, their changes in returns are significantly negative for 2^{nd} vs. 1^{st}, 3^{rd} vs. 2^{nd}, and 4^{th} vs. 3^{rd} auctions. For institutional investors, the changes are all insignificant except for 2^{nd} vs. 1^{st} auctions. Possibly institutions also develop some undue confidence after experiencing one good return and bid more aggressively, but they recover much faster than individuals.

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[8] Although steadily declining, returns remain positive even in individual bidders' sixth or higher-order auctions: the mean (median) return is 14.2% (10.0%) for 1st auctions and 2.5% (1.6%) for 6th and higher-order auctions. This, however, does not necessarily mean that these investors are better off from participating in more auctions. According to IPO auction theory, positive returns are required to compensate for information and participation costs (Sherman (2005)). It is unclear whether the returns these experienced bidders receive are adequate compensation for these costs.

In short, we find that individual returns steadily decline as they gain more experience, consistent with the hypothesis that they become overly optimistic and bid more aggressively. In sharp contrast, there is little evidence that institutions are subject to such naïve learning.

One possible explanation for the evidence that returns decrease for individuals when they bid more is that the average auction returns happen to decrease over time during our sample period. However, several data oppose this. First, the average returns from auctions do not steadily decrease. As can be seen in Table 1 Panel B, the average bidder performs best in the year 1996, which is immediately followed by a bad year in 1997. A similar mini-cycle is repeated in 1999 and 2000. Second, this argument does not explain why institutional returns *across auction orders* do not exhibit the same pattern. The time-series pattern of the *average institutional return* is very similar to that of the individuals. Finally, we performed robustness checks by excluding the 4 auctions with the highest and lowest average returns, or excluding auctions in year 2000 (in which most auctions have negative average returns; overall it is the worst year during the sample period). The results are similar to those in Tables 4 and 5.

4.2 Multivariate Tests

It is important to verify whether our conclusions are robust to controlling for other factors that may affect returns. We therefore run regressions of bidders' returns on the experience variable, log(number of previous auctions +1), and a set of controls based on those in Chiang, Qian and Sherman (2009).We control for the following firm-specific characteristics: firm size measured as the natural logarithm of assets, VC ownership in the firm, P/E ratio measured as the auction's reservation price over earnings per share, % of shares auctioned, a dummy equal to one if the firm is in a high-tech industry, and a dummy equal to one if the firm is traded on the

Taiwan Stock Exchange (TSE) as opposed to on the OTC. To control for market conditions, we include market volatility in the three months prior to the auction, and recent auction return computed as the weighted average of the returns of previous IPO auctions with weights based on (720-N), where N is the number of days between a previous auction's first non-hit day and the recent auction's auction day, as well as year dummies.[9, 10]

We also include unexpected entry (i.e., unexpected number of bidders) of institutions and individuals respectively and the average bid premium of institutions and individuals respectively.[11] Based on the auction model of Sherman (2005), Chiang, Qian and Sherman (2009) argue that if a group of bidders bid optimally based on information, they will be more likely to bid and will bid higher when the expected return is higher. On the other hand, if a group of bidders are uninformed and follow a suboptimal bidding strategy, then a higher number of these participants and/or their higher bids will lead to lower returns for all bidders. Hence, unexpected entry and bid premia can reflect either private information of investors or investor sentiment about the IPO. The unexpected entry and bid premium variables could also reflect other public information not captured by the other controls.

To ensure that our results are not driven by the specific form of the unexpected entry measures, in unreported tests we used raw entry instead of unexpected entry in the regression tests corresponding to those in Tables 6, 7 and 8. Alternatively, we excluded unexpected entry and bid premium of institutions and individuals from the tests. The findings are similar using either of these alternative sets of control variables.

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[9] The return of an IPO auction refers to the quantity-weighted average return of all winning bidders in the auction.

[10] We lose the first two auctions in our sample for including the variable *recent auction return*. We lose the second auction because its auction date occurred before the first IPO shares began to trade.

[11] Unexpected entry of institutions is measured as the residual from the following regression (following Chiang, Qian and Sherman (2009) Table 3): log(number of institutional bidders) = b_1 + b_2*log(assets) + b_3*VC ownership + b_4*P/E ratio + b_5*High tech dummy + b_6*TSE dummy + b_7*% shares auctioned + b_8*Market volatility + b_9*recent auction return + ε. Unexpected entry of individuals is similarly measured.

Table 6 reports the results for regressions estimated separately for individual and institutional investors, and for all bidders versus frequent bidders, where frequent bidders are those whose highest auction order is greater than one. In each regression, we compute *t*-statistics with standard errors adjusted for auction clustering and heteroskedasticity. The coefficients on the control variables are consistent with those of Chiang, Qian and Sherman (2009) – both individual and institutional returns increase with the unexpected entry and average bid premium of institutions, and decrease with unexpected entry and average bid premium of individuals, which they interpret as evidence that institutional investors bid based on information and shave bids optimally, whereas individual investors as a group do not bid optimally.

Our main test variable is bidder experience. For individual bidders, the coefficient on this variable is -0.0163 for all bidders and -0.0196 for frequent bidders only, both significant at the 5% level. As the explanatory variable increases by one standard deviation (0.87 for all individual bidders and 0.95 for frequent individual bidders), the expected return decreases by 1.4% for the sample of all individual bidders and by 1.9% for the sample of frequent individual bidders.

In contrast, the coefficient on experience is 0.0007 (t = 0.06) for the sample of all institutional investors and -0.0012 (t = -0.13) for the sample of frequent institutional bidders. This suggests that the returns of institutional investors do not depend on the amount of experience the bidder has.

In summary, we have shown in this section that the returns to individual investors decrease as they participate in more auctions, whereas the returns to institutional investors do not. For individual investors, this is consistent with naïve reinforcement learning, and inconsistent with rational learning.[12] In sharp contrast, there is little evidence of naïve reinforcement learning on the part of institutional investors.

5. Effects of experience on auction selection and bid aggressiveness

In this section, we explore why returns decline with bidding experience for individual investors but not for institutional investors. As discussed in Sherman (2005), Chiang, Qian and Sherman (2009) and Jagannathan, Jirnyi and Sherman (2009), to ensure an adequate return from IPO auctions, bidders need two types of skills: the ability to judge firm quality (i.e., to select the right auctions) and the expertise to shave bids adequately (so as to avoid the winner's curse and to compensate for information costs). We therefore examine whether and how bidders change in terms of these two abilities when they gain more experience.

We first examine the effect of experience on auction selection ability. To measure bidder *i*'s auction selection ability, we look at other bidders' quantity-weighted average return in an auction in which bidder *i* bids. Since all winning bidders pay what they bid, other bidders' average return depends on the firm quality but does not depend on bidder *i*'s bidding strategy.[13] In other words, if bidder *i* has auction selection ability but does not shave bids optimally, she herself may receive a poor return but other bidders in the same auction should on average receive good returns. As an alternative measure for bidder *i*'s auction selection ability, we also use the ratio of the closing price on the first non-hit date over the reservation price in the auction she participates. This measures the 'underpricing' of the shares at the reservation price. Results are

[12] There are other theories of bias in learning processes, such as the hypothesis that investors overweight information that suggests that they are skillful (as modeled in Daniel, Hirshleifer, and Subrahmanyam (1998) and Gervais and Odean (2001)). We do not rule out the possibility that other forms of learning bias could help explain our findings. Even if so, investors would still be 'learning to fail' rather than learning to succeed as implied by rational learning.

[13] IPO auction theory predicts partial adjustment of pricing to information, i.e., IPO underpricing (or initial returns) will increase with firm quality (see Sherman (2005)).

robust.

We regress the measure of auction selection ability – other bidders' return – on bidder *i*'s experience measured by the natural log of one plus the number of previous auctions. If auction selection ability improves with experience, we expect to see a positive regression coefficient on experience. We include the same control variables as those in Table 6.

Table 7 Panel A reports the regression results for individual investors, institutional investors, frequent individual investors and frequent institutional investors separately. For both samples of individual investors, the coefficient on experience is negative but insignificant; for both samples of institutional investors, the coefficient on experience is positive but insignificant. The results provide little evidence for either group that bidders' auction selection abilities change with experience.

As a robustness check, we run the same regression including only auctions in which the current bidder (bidder *i*) wins. Arguably a bidder may be more certain about her information on firm quality when she bids more aggressively and wins shares, hence these auctions better reflect her selection ability than auctions in which she participates but does not win.

Table 7 Panel B reports the regression results for the sample where the current bidder wins. This time we find that the coefficient on experience is significantly negative for individual bidders (for both the overall sample and the frequent-bidder sample), suggesting that their selection ability gets worse as they participate in more auctions. The coefficient for institutional bidders remains insignificant (for both the overall sample and the frequent-bidder sample), suggesting that institutional bidders' selection abilities do not depend on how many IPO auctions they have participated in before.

As another robustness check, we run auction-level regressions. The dependent variable is an auction's weighted average return. The main variables of interest are the average experiences of individual and institutional bidders in the auction. The average experience of individual (institutional) investors is measured as the natural logarithm of one plus the average number of previous auctions for individual (institutional) investors. A set of control variables as in Table 7 Panel A are also included.

Results are reported in Table 7 Panel C. In the first specification, we calculate average experience of all individual (institutional) investors that bid in the auction. In the second specification, we calculate average experience of all winning individual (institutional) bidders. In both cases, the coefficient on average experience of individuals is insignificantly negative, although both the coefficient and the t-value become more negative in the second specification where only winning bidders' experience is considered. For both specifications, the coefficient on average experience of institutional investors is insignificantly positive.

Overall, we find that experience does not improve investors' auction selection ability. There is some evidence that it may even hurt individual investors' selection abilities, consistent with the notion that individual investors become reckless and unselective after gaining confidence through previous auctions.

Next we examine whether and how an investor's tendency to bid a high price (which we call bid aggressiveness) changes as she participates in more auctions. We measure bid aggressiveness as the percentile of a bidder's bid price out of all bids (including losing bids) in an auction.[14] We also use auction-mean (or median) adjusted bid premia as alterative measures for bid aggressiveness, and the results are similar.[15] We relate bid aggressiveness to the bidder's

[14] For bidders with multiple bids, we use their quantity-weighted average bid price.

[15] As these are discriminatory or pay-what-you-bid auctions, there is no free rider problem. In uniform price or `Dutch' auctions, on the other hand, the free rider problem might lead some investors to bid unrealistically high amounts simply to be 'first in line' (see Sherman, 2005).

experience measured as the natural log of one plus the number of previous auctions, and include the same control variables as in Table 7.

Table 8 reports the regression results for individual investors, institutional investors, frequent individual investors and frequent institutional investors separately. For individual bidders, the coefficient on experience is 5.98 for all bidders and 3.03 for frequent bidders only, both significant at the 1% level. As the explanatory variable increases by one standard deviation (0.87 for the sample of all individual bidders and 0.95 for the sample of frequent individual bidders), an individual bidder's bid increases by 5.2 percentiles for the sample of all individual bidders and by 2.9 for the sample of frequent individual bidders. In the average auction, a percentile increase in bid price (relative to clearing price) has a mean of 0.6%. That the coefficient is smaller for the frequent bidder sample suggests that frequent bidders on average tend to bid more aggressively than one-time bidders regardless of their bidding histories.

In contrast, the coefficient on experience is insignificant for the sample of all institutional investors and significantly negative for the sample of frequent institutional bidders. This suggests that institutional investors do not bid more aggressively as they participate in more auctions.

In summary, we find that individual investors' auction selection abilities do not improve (and there is some evidence that they become less selective) as they gain more experience. Moreover, they tend to bid more aggressively in their later auctions. Institutional investors' bidding abilities, in contrast, do not deteriorate as they participate in more auctions.

6. Conclusion

We examine how bidding experience affects a bidder's decision to participate in an IPO auction, and the resulting return performance. Individual investors are more likely to bid in the future if they receive high returns from their previous IPO auctions. However, their returns steadily decline as they participate in more auctions. Furthermore, as individual investors gain more experience, their auction selection ability does not improve, but they become more aggressive in the levels of their bids.

This evidence indicates that individual investors are subject to naïve reinforcement learning. When individual investors receive high returns from previous auctions, they become more optimistic about receiving high returns from future auctions, making them more likely to participate in future auctions and to bid more aggressively.

In sharp contrast, there is little sign that institutional bidders are subject to this bias. Their decisions to participate in an IPO auction are unrelated to their past returns. Furthermore, their returns do not decline with experience as they bid in more auctions, and their auction selection and bid shaving abilities do not deteriorate with experience.

Teachers often tell their students that the important thing that education provides is not a given set of facts, but an ability to 'learn how to learn'. Overall our findings indicate that individual investors do not know how to learn from their past experience, and naively overweight their personal experiences. However, a more optimistic message from this paper is that it is *possible* for investors to learn how to learn, as reflected in the fact that institutional investors do not seem to be subject to naïve reinforcement learning. A direction for future research is to understand what it is about institutional managers that makes them better at learning (or at least, at avoiding pernicious pseudo-learning), and whether there are ways to help individual investors, despite their more limited resources, to train themselves to similarly improve their learning skills.

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Table 1
Summary statistics

The sample includes 84 IPO-auctions in Taiwan during 1995-2000. Panel A reports firm characteristics. Firms are listed on either the Taiwan Stock Exchange (TSE) or on the over the counter (OTC) market. A firm is known to be in high-tech industry if it is categorized as in electronic sector by its exchange. *Assets* and *auction proceeds* are in millions of constant year 2000 New Taiwan Dollars (NT$). The exchange rate at the end of year 2000 is US$1 = NT$32.99. *VC ownership* is the percentage of shares held by venture capitalists prior to the IPO. *P/E* is the ratio of the reservation price of the auction to the annual earnings per share prior to the IPO. *% of shares auctioned* is the number of shares to be auctioned divided by the total number of shares outstanding. Panel B shows by year the average initial returns of these IPO auctions. We compute the initial return for each auction as the closing price on the first non-hit day over the quantity-weighted average of the winning price. Panel C reports bidder activity and returns for individual and institutional investors, respectively.

Panel A. IPO auction firm characteristics, N=84

	Mean	Median	Std. Dev.	25%	75%
% of IPOs on TSE	55.95				
% of IPOs in high tech industry	53.57				
Assets (in NT$MM)	10,382.46	1,936.35	49,900.46	1,189.78	3,414.02
Auction proceeds (in NT$MM)	880.58	417.72	2522.74	149.87	886.28
VC ownership (%)	13.46	6.82	16.24	0.00	23.18
P/E	18.34	16.24	13.26	11.82	20.11
% of shares auctioned	6.51	6.65	2.88	3.75	9.81

Panel B. IPO initial returns, N=84

	All	1995	1996	1997	1998	1999	2000
IPO initial return (%)	7.25	6.82	35.46	0.72	4.21	11.98	-11.51
IPO initial return – individuals (%)	7.19	6.82	35.89	0.36	4.01	12.18	-11.54
IPO initial return – institutions (%)	8.70	.	37.03	3.34	5.31	15.15	-11.31
# of individual bidders per auction	676.77	235	1,595.27	763.05	373.52	452.87	771.44
# of institutional bidders per auction	31.99	2	49.82	24.37	27.45	33.73	41.33
# of IPO auctions	84	1	11	19	29	15	9

Panel C. Bidder activity and returns

	Individuals	Institutions	Difference
N (# of bidder-auction obs.)	56,849	2,687	
Average # of IPO auctions per bidder	1.81	2.18	-0.37***
Average # of winning IPO auctions per bidder	0.51	0.79	-0.28***
Average NT$ bid size (in thousands)	2,292.96	22,740.20	-20,447.24***
Average NT$ investments (winning size) (in thousands)	2,807.28	27,999.76	-25,192.48***
Mean initial return (%)	5.50	11.54	-6.04***
Median initial return (%)	0	4.61	-4.61***
Standard deviation of initial return (%)	22.83	26.08	
Minimum initial return (%)	-50.00	-33.77	
Maximum initial return (%)	110.59	110.59	
% of positive initial returns (%)	49.44	64.09	

Table 2
Summary statistics: Past return and probability of subsequent bidding

The sample is divided into two halves with similar numbers of winning bidder-auction observations. The first half of the sample includes 44 (out of 84) auctions and 8,442 (out of 17,008) winning bidder-auction observations. A bidder's past return in the first half is the investment-weighted average of her initial returns from all the auctions she wins shares during that period. Return quintiles are determined for all bidders together.

Panel A. Probability of bidding in the second period by return quintile in the first period

	Individuals			Institutions		
Return Quartile	N	Avg. Past Return	Prob. of bidding.	N	Avg. Past Return	Prob. of bidding
Lowest	1,200	-8.93%	29.83%	41	-6.57%	46.34%
2	1,131	5.26%	38.46%	111	5.64%	37.84%
3	1,185	17.81%	41.86%	57	16.84%	43.86%
Highest	1,167	47.89%	40.02%	74	63.39%	47.30%

Panel B. Probability of bidding in the second period by number of auctions and return quintile in the first period

		Individuals			Institutions		
# of auctions In the first half	Return Quartile	N	Avg. Past Return	Prob. of bidding	N	Avg. Past Return	Prob. of bidding
1	Lowest	660	-9.59%	18.64%	31	-6.49%	45.16%
	2	660	4.86%	26.52%	68	5.59%	22.06%
	3	757	18.19%	30.38%	30	17.11%	33.33%
	Highest	930	51.32%	33.66%	55	67.90%	40.00%
2	Lowest	172	-8.78%	28.49%	5	-12.09%	60.00%
	2	123	5.31%	43.09%	19	5.61%	47.37%
	3	132	17.66%	60.61%	8	14.91%	62.50%
	Highest	105	35.77%	60.95%	4	66.99%	75.00%
>=3	Lowest	368	-7.81%	50.54%	5	-1.57%	40.00%
	2	348	5.98%	59.48%	24	5.80%	75.00%
	3	296	16.89%	62.84%	19	17.24%	52.63%
	Highest	132	33.40%	68.18%	15	45.93%	66.67%

Table 3
Logit regressions: Past return and probability of subsequent bidding

The sample is divided into two halves so that the two subsamples have similar numbers of winning bidder-auction observations. The first half of the sample includes 44 (out of 84) auctions and 8,442 (out of 17,008) winning bidder-auction observations. The dependent variable is a dummy equal to one if a bidder bids again in the second half. A bidder's *past return* in the first half is the investment-weighted average of her initial returns from all the auctions she wins shares during that period. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

	Individuals	Institutions
Intercept	-1.18	-0.74
	(25.27)***	(4.12)***
Past return	1.31	0.43
	(10.89)***	(1.04)
# of past auctions	0.84	0.80
	(20.02)***	(4.16)***
Pseudo R^2	0.10	0.07
Observations	4,683	283

Table 4
Bidder returns by auction order

This table shows the mean and median values of bidder initial returns by auction order. *Auction order* is defined as follows: an auction is a bidder's 1st (2nd, 3rd, etc.) auction if the bidder has 0 (1, 2, etc) previous IPO auctions. An auction is counted as a previous auction if its first non-hit date occurs before the current auction's auction date. The column labeled as (*n*th-(*n*-1)th) shows the difference in mean or median returns in nth and (*n*-1)th auction order. We use t-test for differences in means, and Wilcoxon-Mann-Whitney test for differences in medians. ***, **, and * denote the difference is significant at the 1, 5, and 10 percent level, respectively.

Panel A. Whole sample

	Individuals					Institutions				
Auction order	N	Mean return	*n*th-(*n*-1)th	Median return	*n*th-(*n*-1)th	N	Mean return	*n*th-(*n*-1)th	Median return	*n*th-(*n*-1)th
1	10,366	5.22%		-3.55%		613	11.45%		3.48%	
2	1,559	10.89%	5.67%***	7.80%	11.36%***	108	12.26%	0.81%	7.83%	4.35%***
3	870	7.76%	-3.13%***	4.75%	-3.05%***	63	14.83%	2.57%	5.85%	-1.97%
4	547	4.75%	-3.01%***	2.82%	-1.93%***	50	13.30%	-1.53%	6.33%	0.48%
5	424	5.02%	0.27%	2.38%	-0.44%	42	13.01%	-0.29%	6.49%	0.16%
>=6	2,271	2.48%	-2.54% **	1.59%	-0.79%	95	7.56%	-5.46%	4.99%	-1.50%

Panel B. Excluding the largest auction

	Individuals					Institutions				
Auction order	N	Mean return	*n*th-(*n*-1)th	Median return	*n*th-(*n*-1)th	N	Mean return	*n*th-(*n*-1)th	Median return	*n*th-(*n*-1)th
1	6,307	14.21%		10.00%		422	19.83%		9.63%	
2	1,524	11.34%	-2.88%***	8.33%	-1.68%	107	12.41%	-7.43%***	7.85%	-1.78%
3	870	7.76%	-3.58%***	4.75%	-3.57%***	63	14.83%	2.43%	5.85%	-2.00%
4	547	4.75%	-3.01%***	2.82%	-1.93%***	50	13.30%	-1.53%	6.33%	0.48%
5	424	5.02%	0.27%	2.38%	-0.44%	42	13.01%	-0.29%	6.49%	0.16%
>=6	2,271	2.48%	-2.54% **	1.59%	-0.79%	95	7.56%	-5.46%	4.99%	-1.50%

Table 5
Change in return by auction order

This table shows the mean and median values of a bidder's own change in returns across auctions. *Auction order* is defined as follows: an auction is a bidder's 1st (2nd, 3rd, etc.) winning auction if the bidder has won shares in 0 (1, 2, etc.) previous IPO auctions. An auction is counted as a previous auction if its first non-hit date occurs before the current auction's auction date. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

	Individuals			Institutions		
Auction order	N	Mean	Median	N	Mean	Median
2nd-1st	1,447	-12.91%***	-10.28%***	119	-12.33%***	-8.69%***
3rd-2nd	643	-7.59%***	-6.85%***	45	0.71%	0.07%
4th-3rd	340	-4.11%***	-2.33%***	18	-8.85%	-0.91%
5th-4th	203	0.28%	0.24%	6	4.85%	1.26%
>=6th-5th	339	-2.14%*	-0.96%	9	-7.73%	-13.39%

Table 6
Regressions: The effects of experience on returns

The dependent variable is a bidder's initial return. *VC ownership* is the percentage of shares held by venture capitalists prior to the IPO. *P/E* is the ratio of the reservation price of the auction to the annual earnings per share prior to the IPO. *High-tech dummy* equals one if the firm is categorized as in electronic sector by the exchange and zero otherwise. *TSE dummy* equals one if the firm is listed on Taiwan Stock Exchange and zero otherwise. *% of shares auctioned* is the number of shares to be auctioned divided by the total number of shares outstanding. *Market volatility* is the standard deviation of daily market returns during the three months prior to the auction day. *Recent auction return* is the weighted average initial return of IPO auctions for which returns have been observed, with weights based on (720 – N) (zero weight if 720– N < 0), where N is the number of days between a previous auction's first non-hit day and the current auction's auction day. An auction is counted as a previous auction if its first non-hit date occurs before the current auction's auction date. *Unexpected entry* of institutions (individuals) is the unexpected number of institutional (individual) bidders as constructed in Chiang, Qian and Sherman (2009). *Bid premium* of institutions (individuals) is the quantity-weighted average bidding price of all institutional (individual) bids (including losing bids) relative to the reservation price. Frequent bidders are those whose highest auction order is more than one, where auction order is assigned as follows: an auction is a bidder's 1st (2nd, 3rd, etc.) auction if the bidder has 0 (1, 2, etc.) previous IPO auctions. *t*-statistics are adjusted for auction clustering and heteroskedasticity. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

	Overall sample				Frequent Bidders			
	Individuals		Institutions		Individuals		Institutions	
Independent variables	Estimate	*t*	Estimate	*t*	Estimate	t	Estimate	t
Intercept	-1.6842	-3.12***	-2.5460	-3.67***	-1.9713	-3.55***	-2.8237	-4.42***
log (assets)	0.0598	3.15***	0.0873	3.91***	0.0749	3.37***	0.0894	3.12***
VC ownership	-0.0507	-0.42	-0.0184	-0.15	-0.0324	-0.25	-0.0434	-0.38
P/E	-0.0043	-3.07***	-0.0054	-3.37***	-0.0057	-3.93***	-0.0057	-3.09***
High-tech dummy	0.2353	4.63***	0.2940	5.62***	0.2475	5.03***	0.2598	5.15***
TSE dummy	-0.1939	-3.03***	-0.2452	-3.06***	-0.2016	-2.78***	-0.2487	-2.49**
% shares auctioned	2.3204	2.09**	3.1388	2.00**	2.0695	1.87*	2.8559	1.83*
Market volatility	30.7240	2.41**	51.6741	2.79***	31.8236	2.36**	53.7361	2.99***
Recent auction return	0.3000	1.01	0.4018	0.91	0.3070	1.06	0.4222	1.00
Unexpected entry of individuals	-0.1188	-1.89*	-0.1343	-2.28**	-0.1581	-2.42**	-0.1754	-2.79***
Bid premia of individuals	-0.6105	-2.14**	-1.0803	-2.83***	-0.7650	-2.14**	-1.2339	-3.08***
Unexpected entry of institutions	0.0983	2.55**	0.1355	4.08***	0.1173	3.02***	0.1287	3.83***
Bid premia of institutions	0.6156	2.15**	1.1130	2.80***	0.8378	2.29**	1.4312	3.62***
Log (# of previous auctions+1)	-0.0163	-2.42**	0.0007	0.06	-0.0196	-2.58**	-0.0012	-0.13
Year dummy	yes		yes		yes		yes	
R^2	0.62		0.69		0.59		0.67	
N	15,820		971		7,880		545	

Table 7
The effects of experience on auction selection ability

The dependent variable is the quantity-weighted average return of other bidders in an auction the current bidder participates (or wins). *VC ownership* is the percentage of shares held by venture capitalists prior to the IPO. *P/E* is the ratio of the reservation price of the auction to the annual earnings per share prior to the IPO. *High-tech dummy* equals one if the firm is categorized as in electronic sector by the exchange and zero otherwise. *TSE dummy* equals one if the firm is listed on Taiwan Stock Exchange and zero otherwise. *% of shares auctioned* is the number of shares to be auctioned divided by the total number of shares outstanding. *Market volatility* is the standard deviation of daily market returns during the three months prior to the auction day. *Recent auction return* is the weighted average initial return of IPO auctions for which returns have been observed, with weights based on (720 – N) (zero weight if 720-N<0), where N is the number of days between a previous auction's first non-hit day and the current auction's auction day. An auction is counted as a previous auction if its first non-hit date occurs before the current auction's auction date. *Unexpected entry* of institutions (individuals) is the unexpected number of institutional (individual) bidders as constructed in Chiang, Qian and Sherman (2009). *Bid premium* of institutions (individuals) is the quantity-weighted average bidding price of all institutional (individual) bids (including losing bids) relative to the reservation price. Frequent bidders are those whose highest auction order is greater than one, where auction order is assigned as follows: an auction is a bidder's 1st (2nd, 3rd, etc.) auction if the bidder has 0 (1, 2, etc.) previous IPO auctions. *t*-statistics are adjusted for auction clustering and heteroskedasticity. ***,**, and * denote significance at the 1, 5, and 10 percent level, respectively.

Panel A. When the bidder bids

	Overall sample				Frequent Bidders			
	Individuals		Institutions		Individuals		Institutions	
Independent variables	Estimate	*t*	Estimate	*t*	Estimate	*t*	Estimate	t
Intercept	-1.6829	-2.98***	-2.1087	-3.69***	-1.9467	-3.43***	-2.3701	-4.22***
log (assets)	0.0661	2.87***	0.0847	3.67***	0.0738	2.72***	0.0867	2.99***
VC ownership	-0.2154	-1.25	-0.2129	-1.44	-0.1934	-1.03	-0.2077	-1.34
P/E	-0.0056	-4.09***	-0.0057	-4.48***	-0.0060	-3.81***	-0.0055	-3.70***
High-tech dummy	0.1921	3.53***	0.2306	4.40***	0.1853	3.41***	0.2204	4.12***
TSE dummy	-0.2485	-4.08***	-0.2706	-3.69***	-0.2433	-3.47***	-0.2779	-3.34***
% shares auctioned	2.8709	2.38**	2.8669	2.00**	2.9622	2.34**	3.0829	1.97*
Market volatility	28.7066	2.42**	30.6530	2.17**	31.9164	2.77***	31.7488	2.57**
Recent auction return	0.4355	1.67*	0.2675	0.95	0.4628	1.58	0.2815	1.03
Unexpected entry of individuals	-0.0797	-1.56	-0.0958	-1.85*	-0.1157	-2.00**	-0.1196	-2.15**
Bid premia of individuals	-0.6017	-1.70*	-0.9940	-2.49**	-0.6294	-1.81*	-1.0169	-2.68***
Unexpected entry of institutions	0.1195	3.67***	0.1411	4.13***	0.1237	3.67***	0.1404	4.26***
Bid premia of institutions	0.6116	1.68*	1.0402	2.36**	0.7198	1.94*	1.1676	2.92***
Log (# of previous auctions+1)	-0.0050	-0.88	0.0118	0.99	-0.0104	-1.65	0.0091	0.91
Year dummy	yes		yes		yes		yes	
R^2	0.66		0.61		0.64		0.62	
N	56,165		2,682		27,886		1,731	

Panel B. When the bidder wins

	Overall sample				Frequent Bidders			
	Individuals		Institutions		Individuals		Institutions	
Independent variables	Estimate	*t*	Estimate	*t*	Estimate	*t*	Estimate	*t*
Intercept	-1.6358	-3.11***	-2.5212	-3.67***	-1.8957	-3.46***	-2.7760	-4.37***
log (assets)	0.0591	3.17***	0.0861	3.88***	0.0724	3.29***	0.0871	3.05***
VC ownership	-0.0458	-0.39	-0.0202	-0.16	-0.0127	-0.10	-0.0297	-0.26
P/E	-0.0042	-3.05***	-0.0054	-3.43***	-0.0055	-3.89***	-0.0056	-3.14***
High-tech dummy	0.2379	4.82***	0.2963	5.67***	0.2506	5.30***	0.2632	5.34***
TSE dummy	-0.1871	-2.96***	-0.2372	-2.93***	-0.1903	-2.66***	-0.2353	-2.35**
% shares auctioned	2.2831	2.05**	2.9990	1.92*	1.9432	1.74*	2.7228	1.74*
Market volatility	29.0493	2.29**	50.5341	2.77***	29.8965	2.25**	52.6779	2.98***
Recent auction return	0.3116	1.05	0.3647	0.84	0.3254	1.12	0.4073	0.99
Unexpected entry of individuals	-0.1249	-2.10**	-0.1328	-2.30**	-0.1666	-2.71***	-0.1725	-2.88***
Bid premia of individuals	-0.6003	-2.19***	-1.1114	-2.87***	-0.7576	-2.25**	-1.2756	-3.09***
Unexpected entry of institutions	0.0997	2.69***	0.1335	4.05***	0.1184	3.16***	0.1284	3.88***
Bid premia of institutions	0.5970	2.17**	1.1485	2.85***	0.8210	2.36**	1.4735	3.60***
Log (# of previous auctions+1)	-0.0127	-1.93*	0.0003	0.02	-0.0161	-2.18**	-0.0031	-0.34
Year dummy	yes		yes		yes		yes	
R^2	0.64		0.70		0.61		0.69	
N	15,820		971		7,880		545	

Panel C. Auction-level regression

Parameter	When the bidder bids: Estimate	When the bidder bids: t	When the bidder wins: Estimate	When the bidder wins: t
Intercept	-1.4054	-2.09**	-1.0888	-1.65
Log (assets)	0.0486	1.92*	0.0388	1.63
VC ownership	-0.0528	-0.42	-0.0364	-0.24
P/E	-0.0031	-1.91*	-0.0028	-1.69*
High-tech dummy	0.2074	3.89***	0.2205	3.93***
TSE dummy	-0.1381	-1.73*	-0.1164	-1.39
% shares auctioned	2.3875	1.56	1.6721	1.10
Market volatility	22.1203	1.38	15.7132	0.98
Recent auction return	0.4187	0.79	0.3372	0.62
Unexpected entry of individuals	-0.0703	-1.05	-0.0794	-1.20
Bid premia of individuals	-0.3906	-1.78*	-0.5580	-1.87*
Unexpected entry of institutions	0.0867	2.39**	0.1067	2.32**
Bid premia of institutions	0.3684	1.49	0.5282	1.68*
Log(avg. # of previous auctions for individuals +1)	-0.0251	-0.33	-0.0933	-1.25
Log(avg. # of previous auctions for institutions +1)	0.0532	1.00	0.0499	0.71
Year dummy	yes		yes	
R^2	0.52		0.52	
N	80		75	

Table 8
Regressions: The effects of experience on bid aggressiveness

The dependent variable is the percentile of a bidder's bid price in an auction. *VC ownership* is the percentage of shares held by venture capitalists prior to the IPO. *P/E* is the ratio of the reservation price of the auction to the annual earnings per share prior to the IPO. *High-tech dummy* equals one if the firm is categorized as in electronic sector by the exchange and zero otherwise. *TSE dummy* equals one if the firm is listed on Taiwan Stock Exchange and zero otherwise. *% of shares auctioned* is the number of shares to be auctioned divided by the total number of shares outstanding. *Market volatility* is the standard deviation of daily market returns during the three months prior to the auction day. *Recent auction return* is the weighted average initial return of IPO auctions for which returns have been observed, with weights based on (720 – N) (zero weight if 720-N<0), where N is the number of days between a previous auction's first non-hit day and the current auction's auction day. An auction is counted as a previous auction if its first non-hit date occurs before the current auction's auction date. *Unexpected entry* of institutions (individuals) is the unexpected number of institutional (individual) bidders as constructed in Chiang, Qian and Sherman (2009). *Bid premium* of institutions (individuals) is the quantity-weighted average bidding price of all institutional (individual) bids (including losing bids) relative to the reservation price. Frequent bidders are those whose highest auction order is more than one, where auction order is assigned as follows: an auction is a bidder's 1^{st} (2^{nd}, 3^{rd}, etc.) auction if the bidder has 0 (1, 2, etc) previous IPO auctions. *t*-statistics are adjusted for auction clustering and heteroskedasticity. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

	Overall sample				Frequent Bidders			
	Individuals		Institutions		Individuals		Institutions	
Independent variables	Estimate	t	Estimate	t	Estimate	t	Estimate	t
Intercept	43.4234	9.44***	49.3700	2.13**	36.4127	3.89***	35.2920	1.93*
Log (assets)	0.3889	2.05**	-1.2891	-1.36	1.1727	2.46**	2.0486	1.89*
VC ownership	-1.2165	-1.23	5.1743	0.67	0.9203	0.28	-5.1346	-0.88
P/E	-0.0096	-0.94	0.0454	1.03	-0.0057	-0.21	-0.0559	-1.08
High-tech dummy	-0.5042	-1.51	2.9569	1.25	2.2506	2.16**	3.4328	1.69*
TSE dummy	-0.1148	-0.23	-0.2964	-0.11	1.0854	1.09	-1.2140	-0.52
% shares auctioned	11.9066	1.27	-39.3870	-0.77	-10.8872	-0.54	37.7100	0.90
Market volatility	-72.7300	-1.03	547.3708	1.14	-412.1918	-2.23**	288.8244	0.92
Recent auction return	2.9124	1.77*	7.7083	0.55	13.9692	3.51***	20.4989	1.99**
Unexpected entry of individuals	1.3466	2.88***	4.5030	1.79*	1.6790	1.93*	6.4003	3.80***
Bid premia of individuals	1.9924	0.89	-95.4825	-4.97***	-15.2520	-2.53**	-113.2322	-8.41***
Unexpected entry of institutions	-0.5295	-1.86*	-1.4783	-0.66	0.4807	0.76	-0.5176	-0.39
Bid premia of institutions	-2.8529	-1.18	101.3058	5.31***	14.7284	2.53**	111.5950	8.70***
Log (# of previous auctions+1)	5.9826	8.44***	0.3429	0.36	3.0310	5.15***	-2.6301	-3.08***
Year dummy	yes		yes		yes		yes	
R^2	0.02		0.10		0.02		0.11	
N	56,165		2,682		27,886		1,731	