Information Programs for Technology Adoption: The Case of Energy-Efficiency Audits

Soren T. Anderson and Richard G. Newell

September 2002 • Discussion Paper 02-58

RESOURCES FOR THE FUTURE

Resources for the Future
1616 P Street, NW
Washington, D.C. 20036
Telephone: 202–328–5000
Fax: 202–939–3460
Internet: http://www.rff.org

Information Programs for Technology Adoption: The Case of Energy-Efficiency Audits

Soren T. Anderson and Richard G. Newell

Abstract

We analyze technology adoption decisions of manufacturers in response to energy audits provided by Department of Energy Industrial Assessment Centers. Using fixed effects logit estimation to control for unobserved plant characteristics, we find that plants respond as expected to financial costs and benefits, though there are unmeasured project-related factors that also influence investment decisions. *Revealed* behavior of plants suggests that most require a payback of 15 months or less as their investment threshold, corresponding to an 80% or greater hurdle rate. This is consistent with survey results for *stated* investment thresholds, suggesting that these programs do not lower hurdle rates, as some suggest. Plants reject about half of recommended projects; the primary rationale given is their economic undesirability, as opposed to remaining market or organizational barriers. This raises concerns regarding engineering-economic estimates of the degree to which there are feasible no-net-cost opportunities for reducing energy consumption and carbon emissions.

Key Words: energy efficiency, information, technology adoption, energy audits

JEL Classification Numbers: Q41, Q48, O33, O38

Contents

Information Programs for Technology Adoption: The Case of Energy-Efficiency Audits

Soren T. Anderson and Richard G. Newell*

1. Introduction

Interest in energy-efficiency improvements has been reinvigorated by concerns ranging from the environmental effects of fossil fuel combustion—such as climate change due to carbon emissions or environmental damage caused by other pollutants (e.g., SO_2 and NO_x)—to energy price volatility and national security. The U.S. National Energy Policy, for example, recommends establishing "a national priority for improving energy efficiency" (White House 2001), which supports the Bush Administration's climate policy goal of decreasing the "greenhouse gas intensity" of the economy. As policies that would entail significant energy price increases are unlikely to be politically attractive in the near term, the focus has been on the development and diffusion of technology through other means. Thus, policy proposals have tended to emphasize programs that foster research, development, and deployment of technologies, government-industry partnerships, tax credits and other financial incentives, minimum appliance efficiency standards, voluntary agreements, and information programs.

Information programs—which seek to encourage energy efficiency by increasing awareness of conservation opportunities and offering technical assistance with their

---

* Newell is a Fellow and Anderson is a Research Assistant at Resources for the Future, Washington, DC.
We thank Kelly See for research assistance and Michael Muller at Rutgers University and Sandy Glatt at the Department of Energy for information on the program. We also acknowledge financial support from U.S. DOE grant DE-FG02-98ER62702. None of these institutions or individuals are implicated for any conclusions or errors that remain.

implementation—are an important element of this energy-efficiency policy portfolio. These programs take a variety of forms, including educational workshops and training programs for professionals, advertising, product labeling, and energy audits of manufacturing plants. In addition to alerting firms to profitable conservation opportunities, access to more accurate performance information can reduce the uncertainty and risk associated with adopting technologies that are new, or that receive differing reviews from equipment vendors, utilities, or consultants. The economic rationale for these programs lies primarily in public good aspects of knowledge and information provision. Although these programs are not free, the cumulative benefit of educating many users with similar information may well exceed the costs. Such information, however, tends to be underprovided by the private sector. Concerns about environmental externalities associated with energy production and use provide additional justification for these programs.

Despite the role that information programs play in existing and proposed energy-efficiency policy portfolios, surprisingly little is known about how participants respond to such programs. Although a reasonably large literature surveys various market barriers and market failures in energy-efficiency investment,[1] few analyses have focused specifically on information programs—in part because of a lack of adequate data for analysis. One exception is Morgenstern and Al-Jurf (1999), who use data from the Department of Energy's 1992 Commercial Buildings Energy Consumption Survey. They find that information provided through demand-side-management utility programs appears to make a significant contribution to the diffusion of high-efficiency lighting in commercial buildings. Although not the focus of their examination of energy-saving product innovation, Newell et al. (1999) find that the responsiveness of energy-

[1] See, for example, Ruderman et al. (1987); Sutherland (1991); Jaffe and Stavins (1994); and, Metcalf (1994).

efficient innovation in home appliances to energy price changes increased substantially during the period after energy-efficiency product labeling was required.

DeCanio and Watkins (1998) investigate voluntary participation in the U.S. Environmental Protection Agency's Green Lights Program, which offers companies technical expertise while committing them to a set of energy-efficient lighting improvements. They find that the characteristics of individual firms influence their decision to participate in the program. By exploiting information we have on multiple potential projects at each plant in our sample, we can control for the influence on adoption of unobserved characteristics across different plants using a logit model that includes plant fixed effects.

We focus here on actions taken by manufacturing plants in response to energy audits offered through the U.S. Department of Energy's Industrial Assessment Centers (IAC) program, which has been providing free energy assessments to small and medium-sized manufacturers since 1976. This program is of interest for several reasons. First, significant opportunities to conserve energy may exist in the industrial sector, which represents 37% of total national energy consumption. Second, the opportunity to focus on the behavior of small and medium-sized firms is rare because of data constraints, even though these firms represent more than 98% of all manufacturing firms and more than 42% of total manufacturing energy consumption. This focus is particularly appropriate given that smaller firms seem more likely to benefit from access to information and expertise, which may be more readily available to larger firms. Finally, the IAC program has generated an unusually extensive set of data on the characteristics of conservation opportunities identified and actions taken under the program (U.S. DOE 2001). One attractive aspect of these data is that there are multiple observations available for each firm, allowing us to control for unobserved differences in the propensity to adopt technology by employing a fixed effects model.

Because of their detail, these data provide a unique opportunity to quantify the factors that encourage small and medium-sized industrial firms to invest in energy-conserving technologies. After summarizing the general character of projects adopted under the IAC program, we explore the influence of technology costs, expected energy savings, and individual firm characteristics on the likelihood of technology adoption. We employ models of varying flexibility to examine and compare the degree of response to differences in capital costs and operating cost savings, as well as the price and quantity differences that underlie savings. The results strengthen our understanding of how certain factors influence technology adoption decisions, and whether this behavior is consistent with economic expectations. In addition, the results offer evidence on the likely relative effectiveness of policies for increasing energy efficiency, such as energy or carbon price increases, technology subsidies, and policies that directly alter the energy use of technologies.

Another important aspect of this type of investment decisionmaking is the "payback period," "hurdle rate," or other discounting factor that firms employ when measuring current costs against future benefits. There is a substantial literature suggesting that "implicit discount rates," which one can calculate based on the capital cost versus operating cost savings of alternative projects, can be quite high in practice (Hausman 1979; Train 1985). A related literature further contends that these high implicit discount rates are attributable to various market barriers and failures—including information problems—and that these problems can be ameliorated by appropriate policies, resulting in a lowering of the implicit discount rate (e.g., Ruderman et al. 1987).

This has led to an approach used in several analyses of carbon mitigation costs, whereby the effect of information programs and other policies is incorporated into modeling efforts by significantly lowering the discount rate used for energy conservation decisions. The Clean Energy Futures study (Brown et al. 2001; Interlaboratory Working Group 2000), for example, lowered investment hurdle rates in the industrial sector from 30% to 15% to capture the effect of various energy conservation policies. Such lowering of the discount rate results in a decrease in estimated energy use, as well as an increase in the rate at which energy use declines in response to energy price increases that result from, for example, a carbon permit system or carbon tax. This implies a lowering of the cost of carbon mitigation efforts through carbon price policies.

We explore this issue by examining the rates of return for potential projects faced by firms that participated in the IAC program, to determine whether the level of implicit discounting used by plants that received information assistance actually decreased to the levels that some studies suggest. Finally, we analyze the reasons given by firms for not adopting recommended projects to determine whether this decision is due to the economic undesirability of the projects, or to some remaining type of market barrier or failure.

We find that about half the projects recommended by energy assessment teams are actually adopted by the plants, although we cannot say how many of these projects might have been adopted in the absence of the energy audit. We find that the choice of whether to adopt a project depends on the financial characteristics of the project (i.e., technology costs, energy prices, the quantity of energy saved, energy operating cost savings, and the payback period) in ways predicted by economic theory, although there appear to be other unmeasured project-specific factors that influence the investment decision. Surprisingly, however, we find that plant size had no measurable effect on adoption decisions, whereas most previous studies have found a positive relationship between plant size and technology adoption rates.

Furthermore, we estimate that the implicit investment threshold typically used by the plants in evaluating energy audit recommendations was about a 1.25- to 1.5-year payback, which corresponds to about a 65% to 80% hurdle rate for projects lasting 10 years or more. These thresholds are consistent with what surveys of plant managers suggest they use for these types of investments, and do not therefore represent a significant decline. Finally, information regarding the reasons given for rejecting certain recommendations suggests that the primary rationale is that the projects are economically undesirable. Remaining market and organizational barriers do not seem to play a large role in rejecting information provided under this program.

Overall, one can view the glass as either half full or half empty. The results suggest that although the IAC program led to the adoption of many financially attractive energy conservation projects, plants found about half the projects recommended by assessment teams to be unattractive. This raises potential concerns about engineering-economic estimates of the degree to which there are profitable or zero-net-cost opportunities for reducing energy consumption and carbon emissions.

2. Data

2.1. The Industrial Assesment Center Program and Database

The IAC program has been providing free industrial assessments to small and medium-sized manufacturers since 1976. The program operates as an extension service through 26 participating universities, whereby teams of engineering students and faculty help manufacturers identify opportunities to conserve energy, reduce waste, and improve productivity (U.S. DOE 2002). In addition to these direct benefits, the program may generate certain indirect benefits by educating university students (who may become future employees) and participating firms to the presence of potential future energy-conserving investment opportunities (Tonn and Martin 2000). Of the program's current federal outlay of about $7 million per year, each school receives about $180,000 annually, or about $7,000 per assessment.

Since 1981, a record of each assessment has been stored in the IAC database.[2] With entries for more than 10,000 assessments (recommending some 70,000 individual projects), the database covers virtually every U.S. geographic region and manufacturing industry. Nearly half of these assessments have been conducted in the foods, rubber and plastics, fabricated metals, and commercial machinery industries.

Assessments provided by the IAC program generally follow a typical protocol. Manufacturers expressing interest in the program must first meet several eligibility requirements.[3] IAC teams then perform a preliminary assessment (e.g., reviewing the plant's energy bills) followed by a one- or two-day visit to the plant site, where they interview managers, take a thorough tour of the plant, and gather technical data (e.g., measure lighting levels or check for air leaks). Within 60 days of the visit, IAC teams provide plant managers with an assessment report that highlights specific opportunities to increase energy efficiency, reduce waste, and improve productivity. Finally, two to six months following the delivery of the report, IAC teams contact plant managers by phone to determine which projects were actually implemented. For projects that were rejected, IAC teams try to determine the reason(s) why (U.S. DOE 2002, 2000).

The information garnered during the assessment process provides the substance of the IAC database. The database contains information for each recommended project, including the project type, estimated implementation cost, quantity of energy conserved, and annual operating

---

[2] The database is compiled and maintained by the Office of Industrial Productivity and Energy Assessment (OIPEA) at Rutgers University, http://oipea-www.rutgers.edu.

[3] Plants must have a Standard Industrial Classification (SIC) code of 20–30 (i.e., manufacturing) and be within 150 miles of an IAC host campus. In addition, plants must have gross annual sales of less than $100 million, fewer than 500 employees at the plant site, annual energy bills between $100,000 and $2 million, and no professional in-house staff to perform the assessment.

cost savings, as well as confirmation of whether the recommended project was implemented. The database also contains other useful variables, such as the date of the assessment and plant-specific variables like manufacturing sector (SIC code), annual sales, annual energy costs, and number of employees. Finally, for many rejected projects, the database contains information indicating why the project was not implemented (U.S. DOE 2002, 2000b). A rare aspect of these data is that they include multiple project investment decisions for each plant, allowing us to control for plant-level fixed effects that may affect the adoption decision.

2.2. Data Procedures

Our data come from the IAC database for the years 1981–2000.[4] We focus exclusively on energy management projects, which are present in 97% of all assessments and represent 83% of all recommended projects during this period.[5] We adjust all monetary figures for inflation, scaling to U.S.$2000 using the Producer Price Index from the U.S. Bureau of Labor Statistics (2001, finished goods, series WPUSOP3000). We omit approximately 35% of energy-related projects for various reasons, as explained below, resulting in a sample of 38,920 projects from assessments at 9,034 plants. Our results are robust to the inclusion or exclusion of these observations.

[4] The database covered 1981–2001, but the data were incomplete for many assessments conducted during 2001, presumably because many plants had not yet received their callback interviews at the time the data were downloaded. Thus, we focus on the period 1981–2000.

[5] The sample includes 9,827 assessments and 59,961 recommended energy management projects before cleaning.

In our econometric estimation of the project adoption decision, we employ a discrete dependent variable indicating whether a plant adopted a recommended project.[6] Each project is classified by a four-digit assessment recommendation code (ARC), and we include dummy variables for eight two-digit ARC classifications: combustion systems, thermal systems, electrical power, motor systems, industrial design, operations, buildings and grounds, and ancillary costs.[7] These variables are intended to capture heterogeneity across different types of projects (e.g., project lifetimes).

In addition to implementation codes and project type classifications, IAC data contain information regarding the estimated implementation cost and annual operating cost savings of each project. Using these figures, we generate the simple payback for each project, which is defined as cost divided by annual savings. This figure can be interpreted as the number of years before the cost of a project is recovered through annual savings. We focus only on projects with paybacks between 0.025 and 9 years, because careful inspection revealed that data outside this rage were of dubious quality.[8]

[6] The IAC database codes most projects as *I* (implemented), *N* (not implemented), *P* (pending), or *K* (data excluded or unavailable); some projects are missing this code. Our dependent variable equals 1 for projects coded as *I*, and 0 for projects coded as *N*. We omit projects with *P*, *K*, or missing implementation codes.

[7] There are a total of nine two-digit ARC classifications for energy management. We omit three observations classified as "alternative energy usage" because of a lack of degrees of freedom for the corresponding dummy variable.

[8] Overall, we observe that adoption rates fall from approximately 65% to 40% as payback increases from 0.025 years to 9 years. Adoption rates for projects outside this range do not follow the same pattern, however. In fact, adoption rates for these projects regress toward the mean for all projects, suggesting that the information supposedly conferred by these payback values is of negligible value.

The data for most projects also include information regarding the estimated quantity of energy that would be conserved annually (e.g., kWh or Btu).[9] We compute the average energy price associated with each project by dividing annual savings by the corresponding quantity of energy conserved.[10] To make these prices comparable, in percentage terms, across different energy types (e.g., electricity versus natural gas), we normalize the prices within each energy type to have a mean of one. For example, we divide each natural gas price by the mean natural gas price in our sample, and we divide each electricity price by the mean electricity price. We call these new prices our *energy price index.* Finally, we divide annual savings by our new energy price index to generate quantity figures that are also comparable in percentage terms across different energy types.[11] We call these new quantities our *energy saved quantity index*. To ease interpretation of parameter estimates, continuous variables are normalized so that their means equal unity, or zero after taking natural logarithms.

2.3. Descriptive Statistics

As shown in Table 1, the 9,034 manufacturing plants in our sample average about $30 million in annual sales. Our sample of 38,920 energy conservation projects recommended to

---

[9] In some cases, net savings are associated with more than one energy type (e.g., switching from electric to natural gas heating), making it impossible to identify individual energy prices and quantities. Thus, we focus only on projects with positive annual savings for a single energy type. Electricity-related savings are often the result of reductions in electricity usage (i.e., kWh x $/kWh) plus reductions in demand charges (i.e., max kW x $/kW). We treat all electricity-related dollar savings as having come directly from reductions in usage.

[10] We focus only on projects whose prices and quantities have a clear and interpretable meaning (e.g., “other gas” or “other energy” would not qualify). After generating prices, we drop projects whose prices are clear outliers. The average annual energy prices derived from the data are consistent with historical energy prices.

[11] Equivalently, the quantity index can be calculated by weighting the original quantities within each energy type by the mean price for that energy type.

these plants over the period 1981–2000 has an estimated average implementation cost of $7,400 and savings of $5,600 per year. The average payback period for these projects is only 1.29 years. Despite the seemingly quick payback periods, however, firms adopted just 53% of these projects. The IAC audit teams estimate that over the 20-year period 1981–2000, the adopted projects in our sample represented about $103 million in energy conservation investment, resulting in aggregate annual savings of about $100 million, as shown in Table 2.[12] This represents an estimated aggregate payback period of about 1 year for adopted projects.

Breaking these numbers down by project type, Table 2 shows that 90% of the projects in our sample affect *building and grounds* (e.g., lighting), *motor systems*, and *thermal systems*; a smaller but significant number of projects affect *combustion systems* and *operations*. Finally, just a handful of projects affect *electrical power*, *industrial design*, and *ancillary costs*.

We also see significant variation in terms of cost, annual savings, payback periods, and adoption rates. *Thermal systems*, *electrical power*, and *industrial design* projects have high costs and low adoption rates. *Building and grounds* and *ancillary costs* projects have average costs, close-to-average annual savings, and longer-than-average payback periods; firms adopt these projects about 50% of the time. *Combustion systems* and *motor systems* projects have lower-than-average costs, average or less-than-average paybacks, and relatively high adoption rates. Overall, it appears that project types with high annual savings relative to cost (as reflected by short payback periods) are correlated with high rates of adoption, as long as costs are not too high.[13] This is consistent with survey findings (e.g., U.S. DOE 1996) that suggest projects above

[12] By contrast, rejected projects would have cost $186 million for an aggregate annual savings of only $117 million. These numbers imply that firms tend to adopt the most profitable projects.

[13] The exception is *operations* projects, which have low implementation costs and short payback periods yet are adopted only 50% of the time. *Operations* projects may be associated with significant unmeasured opportunity costs, however (e.g., temporary plant shutdowns).

a certain cost may not get adopted, regardless of their benefits, because of budget constraints or requirements for additional management approvals.

Most energy savings have come from the adoption of projects affecting *building and grounds*, *motor systems*, and *thermal systems*. This is not surprising, given that these projects represent the bulk of all recommended and adopted projects. In terms of return on investment, however, it is clear that *combustion systems* and *operations* projects have been the most profitable. The aggregate annual savings for adopted projects in these categories are roughly double their aggregate cost. *Thermal systems* projects have also proven profitable overall, with aggregate annual savings exceeding aggregate cost by 21%. Overall, these numbers suggest that the IAC program has alerted manufacturers to a number of energy conservation investment opportunities that appear profitable based on the IAC audit teams' estimates of costs and benefits. It is conceivable, of course, that some of the adopted projects would have been implemented with or without IAC program involvement. Client firms may have already recognized attractive investment opportunities, for instance, but had not yet implemented these projects at the time of IAC program participation.

To gain a more systematic understanding of firms' behavior in response to the IAC program, we develop an econometric model that formally relates the energy conservation investment decision to the economic incentives of projects, including payback period, cost, annual savings, energy prices, and quantities of energy conserved. We discuss the econometric model and results below.

3. Modeling and Estimation Approach

Given a set of potential energy-conserving projects recommended by IAC auditors, we posit that a firm will adopt a particular project if the expected change in discounted profits is positive given the characteristics of the project and the firm's investment hurdle rate. We begin by defining π_{ij}^*, the expected change in profits resulting from the adoption of project i at plant j,

$$\pi_{ij}^* = \varphi(C_{ij}, B_{ij}, Z_{ij}) + \varepsilon,$$

where C is the expected cost of a project, B is the expected annual benefits of the project, Z is a vector of individual plant and project characteristics (e.g., investment hurdle rates and project lifetimes), φ is a function relating C, B, and Z to π^*, and ε is a mean-zero independent, identically distributed error term.[14] The error term reflects uncertainty in the expected profitability of projects, leading to rejection of projects that appear to be profitable, and vice versa.

We do not observe the expected change in profits, π^*. Rather, we observe only whether a project is implemented. We therefore define a dichotomous variable, π, which indicates whether a project is adopted:

$$\pi_{ij} = 1 \text{ if } \pi_{ij}^* > 0,$$

and

$$\pi_{ij} = 0 \text{ if } \pi_{ij}^* \leq 0.$$

It follows that

$$\begin{aligned}\Pr[\pi_{ij}^* > 0] &= \Pr[\pi_{ij} = 1] \\ &= \mathrm{F}(\varphi(C_{ij}, B_{ij}, Z_{ij})),\end{aligned}$$

where F is a cumulative distribution function for ε. Assuming F is logistic leads to the familiar logit model, whereas assuming F is standard normal leads to the probit model (Maddala 1983). As discussed further below, because we have observations for multiple potential projects at each

[14] Note that we suppress subscripting in the text where this does not lead to confusion.

plant, we can estimate a logit model with plant-level fixed effects (Chamberlain 1980; Hamerle and Ronning 1995), thereby controlling for unobserved plant differences in the propensity to adopt.

Our most basic econometric specification, the *payback* model, is given by

$$(1) \qquad \varphi = \beta_1 \ln PB_{ij} + \beta_2 \ln PB_{ij}^{\ 2} + \gamma A_i + \alpha_j + \varepsilon,$$

where *PB* is the simple payback period for the project (cost divided by annual savings, *PB=C/B*), *A* is a vector of dummy variables indicating the project type, and *α* is a firm-specific fixed effect. Although it is well known that using a payback threshold is inferior to the net present value criterion (Lefley 1996), in the case of constant annual cash flows the two criteria lead to the same investment threshold, for a given investment hurdle rate and project lifetime.[15] More importantly, simple payback analysis is the most common technique for project appraisal among the types of firms that receive IAC audits (Muller et al. 1995; U.S. DOE 1996), and much more widely (Lefley 1996).

We found that entering *PB* and the other continuous variables described below in their logged form improved the model's fit of the data and eased interpretation of the results, since changes in the probability of adoption correspond to percentage changes in the logged variables. Further, *PB* has been normalized so that the marginal probability of adoption at the mean payback is given directly by the coefficient on the linear term. That is, the marginal change in probability of adoption associated with a 1% increase in payback (at its mean) is β_1 %. The plant fixed effects control for unobserved individual plant differences in the propensity to adopt, as

[15] The three most serious flaws with applying a constant payback criterion across many projects are that it does not take account of differences across projects in (i) the time profile of the flows of cost and benefits, (ii) project lifetimes, and (iii) the total net benefits from implementation (i.e., it uses the ratio).

well as other assessment-related factors, such as the assessment date and the school conducting the assessment.

Because payback is equal to cost divided by annual savings, equation (1) implies that percentage changes in costs and savings have the same effect on the probability of adoption. Theory suggests that they *should* have the same effect. Nonetheless, previous empirical studies have found that implementation cost has a stronger effect on energy conservation investments than energy savings (Jaffe and Stavins 1995; Hassett and Metcalf 1995). To test whether this is in fact the case, we explore less restrictive specifications. The *cost-savings* model is given by

$$\varphi = \beta_3 \ln C_{ij} + \beta_4 \ln C_{ij}^{\ 2} + \beta_5 \ln B_{ij} + \beta_6 \ln B_{ij}^{\ 2} + \gamma A_i + \alpha_j + \varepsilon, \tag{2}$$

where C is the expected implementation cost of a project, B is expected annual savings in energy costs, and the other variables are as above. Like PB in equation (1), both C and B have been normalized and enter in their logged forms. Note that although it is discounted energy savings that matter for the investment decision (rather than simply the annual flow of savings, B), the discount factor multiplying B becomes additive after taking logs. As the discount factor depends on the firm's investment hurdle rate and the project lifetime, its effect will be captured in the plant and project-type fixed effects, α and A.

The *cost-benefit* model can also be made less restrictive. Because annual savings equal the quantity of energy conserved multiplied by the energy price, equation (2) implies that percentage changes in energy prices and quantities have the same effect on the probability of adoption. But one might conjecture, for instance, that energy prices are perceived as being less permanent than the quantity of energy saved, or that plant managers with engineering backgrounds are more sensitive to physical energy savings than to differences in the dollar value of these savings. For this reason we explore the possibility that energy prices and quantities have different effects on the probability of adoption. Our *price-quantity* model is given by

(3)
$$\varphi = \beta_7 \ln C_{ij} + \beta_8 \ln C_{ij}^{\;2} + \beta_9 \ln P_{ij} + \beta_{10} \ln P_{ij}^{\;2} + \beta_{11} \ln Q_{ij} + \beta_{12} \ln Q_{ij}^{\;2} + \gamma A_i + \alpha_j + \varepsilon,$$

where *P* and *Q* are the price and quantity indexes described in section 2.2, and the other variables are as above.

We estimate the *payback*, *cost-benefit*, and *price-quantity* models using a maximum likelihood, conditional fixed effects logit estimator, with plant-level fixed effects (Chamberlain 1980; Hamerle and Ronning 1995). First note that assessments with all positive or all negative outcomes do not contribute to the log-likelihood and are therefore dropped from the estimation. Second, note that variables like annual sales, number of employees, and year of assessment are perfectly collinear with the plant-level fixed effects and cannot therefore be included in the estimation. We also estimated logit, random-effects logit, probit, random-effects probit, linear, linear fixed effects, and linear random-effects models, adding plant size and dummy variables for year, SIC code, project type, and IAC school to models without plant-level fixed effects. Our overall results (i.e., the effect of payback, cost, annual savings, prices and quantities) are robust to these alternatives. In addition, unlike other studies, we do not find a significant effect for plant size in models where it was included, whether measured by annual sales, annual energy costs, floor area, or employees. The results of the fixed effects logit estimations are presented below.

4. Results

4.1. Estimation Results

Table 3 presents the results of our three econometric models of increasing flexibility. We transformed the coefficient estimates and standard errors so that they are presented as marginal effects at the means of the continuous variables.[16] Note that we have transformed the variables so that the marginal effects for continuous variables are given directly by the coefficient on the linear terms, as discussed above in section 3. Effects for the project type dummy variables have also been transformed so that they reflect the full change in predicted probability associated with each project type, relative to building and grounds projects (the omitted dummy variable).[17]

Overall the results are consistent with economic expectations. To provide a sense of how our model fits the pattern of the data, Figure 1 plots the observed fraction of projects actually adopted at various payback levels, along with the estimated probability of adoption based on the *payback* model. As expected, projects with a longer payback period (i.e., greater ratio of costs to annual benefits) are less likely to be adopted. Further, the predicted probability corresponds quite well to the actual adoption rates of projects with various payback.

Specifically, the results indicate that a 10% increase in payback leads to about a 0.8% decrease in the probability of adoption. The negative coefficient on the squared term for payback indicates that percentage increases in the payback period have an increasingly negative effect on

[16] Given the form of the logistic distribution, $\Lambda(\boldsymbol{\beta}'\mathbf{x}) = \exp(\boldsymbol{\beta}'\mathbf{x})/(1+\exp(\boldsymbol{\beta}'\mathbf{x}))$, marginal effects in a logit model are equal to $\partial E[\pi]/\partial \mathbf{x} = \boldsymbol{\beta}\exp(\boldsymbol{\beta}'\mathbf{x})/(1+\exp(\boldsymbol{\beta}'\mathbf{x}))^2$ for continuous variables. With all continuous variables normalized to one at the mean, or zero after taking logs, and setting all fixed effects to zero, the marginal effects simplify dramatically to $\partial E[\pi]/\partial \mathbf{x} = \boldsymbol{\beta}/4$ at the mean. The assumption of setting the fixed effects to zero is both convenient and necessary because the conditional logit estimator does not produce individual parameter estimates for the fixed effects. Standard logit estimates of the same specification yielded a constant term estimate of –0.07, suggesting that the "average" fixed effect is indeed close to zero. Including a fixed effect of this magnitude in the calculation of marginal effects would reduce the factor multiplying $\boldsymbol{\beta}$ only negligibly from 0.2500 to 0.2497.

[17] The effect of a categorical variable, such as our project-type fixed effects, is found by taking the difference in the predicted probability with and without the categorical variable set to one. Given our normalizations described above, this results in the following simple relationship for the effect of categorical variable x_i: $E[\pi|x_i = 1] - E[\pi|x_i = 0] = \exp(\beta_i)/(1+\exp(\beta_i)) - ½$.

adoption rates. This result manifests itself in Figure 1 as downward curvature in the adoption function.

The *cost-benefit* model relaxes the implicit restriction that costs and benefits have the same effect. According to the results of this model, a 10% increase in cost decreases the probability of adoption by 0.8%. The negative coefficient on the squared term for costs indicates that the effect of costs is increasingly negative, suggesting that very costly projects are especially unlikely to be adopted. This is consistent with survey findings showing that most firms consider an investment of $5,000 or more to be large, regardless of the benefits, and higher-cost projects ($10,000 or more) are subject to greater scrutiny since they must be approved on a capital budgeting basis rather than paid out of production and maintenance budgets (Muller et al 1995; U.S. DOE 1996).

On the other hand, a 10% increase in annual savings increases the probability of adoption by only 0.6%. The magnitudes of the cost versus savings effects are statistically different at the 99% level.[18] These results are consistent with previous literature, which finds that up-front implementation costs have a larger effect on energy conservation decisions than future annual savings. The magnitude of the difference, however, is much less pronounced in our results. Although we find that costs have a 40% greater percentage effect relative to future energy savings (at the mean of the data), Jaffe and Stavins (1995) found that costs had about three times the effect, and Hassett and Metcalf (71995) found that costs had about eight times the effect of energy savings. One difference, however, is that we have data directly measuring the estimated dollar value of energy savings, which includes both price and quantity information, whereas the

[18] Using Wald tests, we reject the hypotheses that $\beta_3 = -\beta_5$ (Chi-square, 1 = 37.22) and that $\beta_4 = \beta_6$ (Chi-square, 1 = 5.16).

other studies used only variation in energy prices to identify the effect of future energy dollar savings. We return to this issue below in the context of the *price-quantity* model.

The *price-quantity* model relaxes the implicit restriction that changes in energy prices have the same percentage effect as changes in the quantity of energy conserved. The results indicate that a 10% increase in energy prices increases the probability of adoption by 0.4%, and a 10% increase in the quantity of energy conserved increases the probability of adoption by 0.6%. Although the parameter estimates therefore indicate that energy conservation *quantities* have about a 40% greater effect on adoption likelihood than energy *prices* (i.e., the per unit value of conservation), these estimated effects are not statistically different at any reasonable confidence level.[19] Still, they suggest that plant managers may be more responsive to differences in the quantity of energy conserved for alternative projects than to changes in energy prices. Perhaps plant managers with engineering backgrounds are inherently more responsive to technical energy savings than to their dollar value. Alternatively, quantity differences may be perceived as less uncertain and subject to change than price changes.

The *price-quantity* model also permits a more direct comparison to other studies regarding the relative effect of up-front costs versus energy prices on the energy conservation decision. The results indicate that costs have a little more than double the effect of energy prices, which is more dramatic than the difference based on our less flexible cost-savings model above, but still not as large as the threefold or eightfold effect cited in the studies above.

Although our results demonstrate that firms respond as predicted by economic theory to the incentives of payback, cost, savings, prices, and quantities, these variables do not fully

[19] Using Wald tests, we cannot reject the hypotheses that $\beta_9 = \beta_{11}$ (Chi-square, 1 = 0.87) or the joint hypothesis that $\beta_9 = \beta_{11}$ and $\beta_{10} = \beta_{12}$ (Chi-square, 2 = 2.69).

explain the technology adoption decision. Indeed, holding these variables constant, certain types of projects are more likely to be adopted than others, as measured by the project type dummy variables. *Motor systems* projects are the most attractive type of project, with a 9.2% greater probability of being adopted than *building and grounds* projects, the omitted group. *Combustion systems* and *ancillary costs* projects are about as likely to be adopted as *building and grounds*. Projects affecting *operations*, *thermal systems*, *industrial design* and *electric power* have, respectively, a 10%, 17%, 20%, and 25% lower probability of being adopted than *building and grounds* projects.

Those results are consistent with the descriptive statistics on relative adoption rates for the various project types listed in Table 2. Further, they suggest that the IAC program's simple measures of costs and benefits do not fully capture the relative desirability of alternative projects. There may be many missing factors—such as individual project lifetimes, unmeasured costs and benefits, uncertainty regarding costs and benefits, project complexity, and risks—that are crucial to understanding the adoption decision. Measurement error in the true costs and benefits of projects could also be leading to an "errors in variables" bias of the coefficients toward zero, resulting in estimated effects that are smaller in magnitude than their true values.

4.2. Payback Thresholds and Implicit Discount Rates

Previous literature has posited that information programs and other policies may lower the sometimes high implicit discount rates observed for firms with respect to their energy-efficient investment decisions. We address this issue by looking at the observed level of implicit discounting for firms that participated in the IAC program. We focus on the 5,264 firms in our final sample that adopted some but not all of the energy-related projects recommended through IAC energy audits. This group is equivalent to the estimation sample from our econometric analysis. By sorting the payback periods of each plant from shortest to longest, one can in principle locate a "payback threshold" for that plant, below which projects are adopted and above which projects are rejected. The payback threshold is an analogue to an investment hurdle rate. The presumption that all rejected projects will have higher paybacks than all adopted projects, however, ignores any uncertainty or measurement error in the estimation of project costs and benefits. In reality, we observe overlap in the paybacks of adopted and rejected projects for most firms. For each plant, we therefore find the adopted project with the highest payback and the rejected project with the lowest payback, and we take midpoint of these two paybacks as an estimate of the plant's payback threshold. Conducting the same analysis but using only the sample of plants for which there is no such overlap in the paybacks of adopted and rejected projects yields very similar results.

Figure 2 shows the distribution of payback thresholds. In addition, the figure shows the implicit discount rate or hurdle rate that corresponds to various payback thresholds.[20] More than 98% of firms have estimated payback thresholds less than 5 years, and about 79% have payback thresholds less than 2 years. The mean payback threshold is 1.4 years, and the median is 1.2 years, corresponding to implicit discount rates of about 70% and 80%, respectively.

Although these payback periods may seem quick, and the corresponding hurdle rates high, they are consistent with the investment thresholds that small and medium-sized manufacturers directly report that they routinely employ. For example, a series of industry roundtables conducted by the Alliance to Save Energy found that acceptable projects were typically limited to a 2-year payback or shorter, although larger companies sometimes considered 3-year paybacks to be acceptable (U.S. DOE 1996). This is consistent with other broad surveys of the use of the payback criterion, not just for energy conservation projects but

[20] Implicit discount rates are given by solving $PB = 1/r - 1/(r(1 + r)^T)$ for r, where PB is the payback cutoff value, T is the project lifetime, and r is the investment hurdle rate to be calculated. For this purpose we use a project lifetime of 10 years.

much more widely (Lefley 1996). Likewise, in a followup survey of plants that had received an IAC audit, Muller et al. (1995) found that 85% of firms reported that they considered paybacks of longer than 2 years financially unattractive. The median threshold in this survey was a 1- to 1.5-year payback, which is consistent with our findings. This suggests that participation in the IAC program had little or no effect on the discount rate for most firms. Further, since these high discount rates are based on projects and technologies that firms knew about, they cannot be explained by informational market failures. These firms simply use higher discount rates than many energy analysts commonly apply to them. Furthermore, what the firms state they do is fully consistent with their revealed behavior. This evidence seems to cast doubt on modeling approaches that significantly lower discount rates for energy-efficiency investment decisions in response to information programs.

4.3. Analysis of Reasons for Project Rejection

Finally, to assess whether these high discount rates are the result of remaining market failures or imperfections, we examine the reasons given by firms for not adopting projects. Since about 1991, these reasons have been coded and recorded in the IAC database. For the purposes of our analysis, we focus only on rejected projects with at least one concrete reason for rejection. We classify these reasons as *economic*, *financing*, or *bureaucratic* , as shown in Table 4. [21]

As can be seen from Table 4, more than 75% of projects were rejected for what we consider legitimate *economic* reasons. Many reasons suggest an unattractive balance between the

[21] Since 1991, 51% of rejected projects in our sample include a rejection code that falls into one of these three categories. We omit projects whose sole reason for rejection is “to be implemented after two years,” “considering,” “unknown,” “could not contact plant,” or “other.” Some projects list more than one reason for rejection. A relatively small number of projects have rejection codes in more than one of the broad classifications (e.g., economic *and* bureaucratic reasons), and we do not consider these projects in our analysis.

financial costs and benefits of a project (e.g., "too expensive initially" or "unsuitable return on investment"), which should be reflected in IAC estimates of implementation cost and annual savings. But some reasons hint at opportunity costs (e.g., "unacceptable operating changes" or "personnel changes") and various project risks (e.g., "risk or inconvenience to personnel" or "suspected risk of problem with equipment") that are not typically reflected in the IAC cost estimates. Firms report that the risk of the technologies' not work properly, and potentially leading to production halts or changes in product quality and cost, is in fact a strong deterrent to adopting certain projects (U.S. DOE 1996). The implication of this result is that simple financial measures alone do not determine the decision to invest in energy-efficient technologies. Analysts or policymakers who look at these measures, see that measured financial benefits outweigh financial costs, and then assume that rejected projects reflect market barriers or market failures may be overlooking many unmeasured costs and benefits.[22]

Although most projects are rejected for legitimate economic reasons, market imperfections may play a role in the rejection of some projects. According to the IAC data, about 10% of rejected projects were rejected for *financing* reasons—i.e., limited cash flow—perhaps indicating a failure of capital markets to efficiently allocate financial resources. It is possible that loans directed at energy conservation could be effective in ameliorating this problem.

Finally, *institutional* reasons account for 14% of rejected projects. A lack of staff needed for project analysis and implementation was cited in 11% of rejected projects—ironic, since project analysis is partly what the IAC program attempts to provide. It may be that this reason for project rejection reflects real economic costs that render a project financially undesirable,

[22] In our econometric model, many of these differences should be captured with our project-type dummy variables and plant fixed effects.

however, and not simply a bureaucratic constraint. There were also a small number of projects rejected because of bureaucratic restrictions within the firm—as when plant managers need executive approval before undertaking energy conservation projects—perhaps indicating certain principal-agent market failures. Overall, however, most projects appear to be rejected for legitimate economic reasons. Consequently, there does not appear to be much potential at these firms for encouraging adoption through the further removal of failures and imperfections in energy conservation decisions.

5. Conclusion

The U.S. Department of Energy's Industrial Assessment Centers program provides a unique opportunity to quantify the effects of an information program for energy-efficient technology adoption. We find that about half of the projects recommended through the IAC program were adopted, though we cannot say how many of these projects would have been adopted in its absence. Overall, our results indicate that firms respond as expected to the economic incentives of different energy-conserving investment opportunities, such as payback periods, implementation cost, annual energy savings, energy prices, and quantities of energy conserved. These simple financial measures do not explain everything, however. Indeed, holding these factors constant, we find that certain project types are more likely to be adopted than others, suggesting that there may be many economic costs, benefits, and risks that the IAC program's simple financial measures do not capture.

We find evidence that firms are more responsive to implementation costs than to annual energy savings, although this difference is not as pronounced as in previous studies. Similarly, firms seem to be more responsive to energy savings based on the quantity of energy conserved than to energy prices, though the effects are not statistically different. These results suggest that policy mechanisms to reduce costs (e.g., tax breaks or subsidies for implementation) and directly promote technical efficiency improvements (e.g., direct support for energy-efficiency R&D) may be somewhat more effective in the short term than price mechanisms (e.g., energy or carbon taxes). Only price mechanisms, however, also provide the continuing incentive to reduce energy use.

Like previous studies, we found that firms demand quick payback periods of two years or less and use high implicit discount rates for project adoption, as revealed through their technology adoption decisions. These results suggest that the information provided by the IAC program did not lower the rate of return demanded by firms, as some studies have suggested. Further, our assessment of the reasons for project rejection reveals that most projects are rejected for legitimate economic reasons, though some of these reasons may be difficult to quantify financially. Remaining market and organizational barriers do not seem to play a large role in rejecting information provided under this program.

Overall, one can view the glass as either half full or half empty. The data suggest that during the two decades 1981–2000, the IAC program has led to the adoption of many financially attractive energy conservation projects, yielding an estimated $100 million in annual energy savings for an outlay of about $103 million (if we assume none of the projects would have been adopted in the absence of the program). Still, nearly half the projects recommended by the program are rejected, and implicit discount rates remain seemingly high relative to the cost of capital, despite the provision of free information. Some would argue that the routine use of short payback periods is a symptom of remaining market imperfections in corporate management, such as problems of agency, moral hazard, imperfect or asymmetrical information, and incentive design (DeCanio 1993). Although this is clearly possible, and perhaps likely, it seems doubtful there are any available energy policy instruments that could significantly improve so pervasive a situation at reasonable cost. In addition, we find evidence for many unmeasured costs and risks not captured in the IAC program's simple financial estimates, so that *estimated* rates of return likely differ from *realized* rates of return. Further, the reasons given by firms for rejecting projects confirm that most are rejected for legitimate economic reasons. This raises potential concerns about engineering-economic estimates of the degree to which there are profitable or zero-net-cost opportunities for reducing energy consumption and carbon emissions.

References

Brown, Marilyn A., Mark D. Levine, Walter Short, and Jonathan G. Koomey. 2001. Scenarios for a Clean Energy Future. *Energy Policy* 29(14): 1179–96.

Chamberlain, G. 1980. Analysis of Covariance with Qualitative Data. *Review of Economic Studies* 47:225–38.

DeCanio, S.J. 1993. Barriers within Firms to Energy-Efficient Investments. *Energy Policy* 21: 906–14.

DeCanio, S.J., and W.E. Watkins. 1998. Investment In Energy Efficiency: Do the Characteristics of Firms Matter? *Review of Economics and Statistics* 80(1): 95–107.

Hamerle, A., and G. Ronning. 1995. Panel Analysis for Qualitative Variables. In *Handbook of Statistical Modeling for Social and Behavioral Sciences,* ed. G. Arminger et al. New York: Plenum Press, 401–51.

Hassett, Kevin A., and Gilbert E. Metcalf. 1995. Energy Tax Credits and Residential Conservation Investment: Evidence from Panel Data. *Journal of Public Economics* 57: 201–17.

Hausman, Jerry A. 1979. Individual discount rates and the purchase and utilization of energy-using durables. *Bell Journal of Economics* 10: 33–54.

Interlaboratory Working Group. 2000. *Scenarios for a Clean Energy Future.* Oak Ridge, TN: Oak Ridge National Laboratory.

Jaffe, Adam B., and Robert N. Stavins. 1994. The Energy Paradox and the Diffusion of Conservation Technology. *Resource and Energy Economics* 16(2): 91–122.

———. 1995. Dynamic Incentives of Environmental Regulations: The Effects of Alternative Policy Instruments on Technology Diffusion. *Journal of Environmental Economics and Management* 29: S-43–S-63.

Lefley, Frank. 1996. The Payback Method of Investment Appraisal: A Review and Synthesis. *Journal of Production Economics* 44: 207–24.

Maddala, G.S. 1983. *Limited Dependent and Qualitative Variables in Econometrics*. Cambridge, UK: Cambridge University Press.

Metcalf, Gilbert E. 1994. Economics and Rational Conservation Policy. *Energy Policy* 22(10): 819–25.

Morgenstern, Richard D., and Saadeh Al-Jurf. 1999. Can Free Information Really Accelerate Technology Diffusion? *Technological Forecasting and Social Change* 61: 13–24.

Muller, Michael R., Timothy Barnish, and Peter P. Polomski. 1995. On Decision Making Following an Industrial Energy Audit. Proceedings of the 17th National Industrial Energy Technology Conference, 150–55.

Newell, Richard G., Adam B. Jaffe, and Robert N. Stavins. 1999. The Induced Innovation Hypothesis and Energy-Saving Technological Change. *Quarterly Journal of Economics* August: 941–75.

Ruderman, Henry, Mark D. Levine, and James McMahon. 1987. The Behavior of the Market for Energy Efficiency in Residential Appliances Including Heating and Cooling Equipment. *Energy Journal* 8(1): 101–24.

Sutherland, R.J. 1991. Market Barriers to Energy-Efficiency Investments. *Energy Journal* 12(3): 15–34.

Tonn, Bruce, and Michaela Martin. 2000. Industrial Energy Efficiency Decision making. *Energy Policy* 28: 831–43.

Train, Ken. 1985. Discount Rates in Consumers' Energy-Related Decisions: A Review of the Literature. *Energy* 10: 1243–53.

U.S. Bureau of Labor Statistics. 2001. http://www.bls.gov/ppi/

U.S. Department of Energy (DOE). 1996. *Analysis of Energy-Efficiency Investment Decisions by Small and Medium-Sized Manufacturers.* DOE/PO-0043. Washington, DC.

———. 2000. *The DOE Industrial Assessment Database: User Information, Version 8.1.* Rutgers University, Office of Industrial Productivity and Energy Assessment, http://oipea-www.rutgers.edu/. Accessed November 2001.

———. 2001. *The DOE Industrial Assessment Center Database.* Rutgers University, Office of Industrial Productivity and Energy Assessment, http://oipea-www.rutgers.edu/. Accessed September 24, 2001.

———. 2002. Industrial Assessment Centers website. http://www.oit.doe.gov/iac/.

White House. 2001. National Energy Policy. Report of the National Energy Policy Development Group. Washington, DC: U.S. Government Printing Office.

Table 1: Descriptive Statistics

Variable	*Mean*	*Standard dev.*	*Minimum*	*Maximum*
Adopted	0.53	0.50	0.00	1.00
Payback (years)	1.29	1.29	0.03	9.00
Implementation cost ($)	7,400	82,714	3.47	10,100,000
Annual savings ($)	5,574	27,881	8.45	2,661,508
Energy price index	1.00	0.38	0.12	4.56
Energy saved quantity index	6,091	42,853	6.96	4,650,939
Annual sales ($)	29,156,398	37,715,612	41,503	684,192,832
Employees	170	147	1	4,000
Floor area (square feet)	253,887	3,208,579	300	150,000,000
Annual energy costs ($)	486,969	702,126	2,502	11,951,324

Note: Statistics are based on the sample of 38,920 observations for energy-related project recommendations, representing 9,034 plant assessments. Monetary figures are in U.S.$2000.

Table 2: Adoption Rates, Payback, Cost, and Annual Savings by Project Type

Project type	*Number of projects*	*Adoption rate*	*Mean payback (years)*	*Mean cost ($)*	*Mean annual savings ($)*	*Aggregate cost of adopted projects ($)*	*Aggregate annual savings of adopted projects ($)*
Building and grounds (e.g., lighting, ventilation, building envelope)	14,208	0.51	1.47	6,217	4,347	39,995,506	31,349,388
Motor systems (e.g., motors, air compressors, other equipment)	13,783	0.60	1.22	5,297	4,123	36,891,259	32,818,958
Thermal systems (e.g., steam, heat recovery and containment, cooling)	6,790	0.44	1.23	9,021	8,273	16,670,472	20,203,020
Combustion systems (e.g., ovens, furnaces, boilers, fuel switching)	2,358	0.56	0.99	5,131	7,442	4,611,227	9,570,203
Operations (e.g., use reduction, maintenance, scheduling , automation)	1,471	0.50	0.93	2,617	4,267	1,716,740	3,483,098
Electrical power (e.g., demand management, generation, transmission)	155	0.30	1.82	287,100	94,215	953,399	602,745
Industrial design (e.g., modify thermal, mechanical systems)	145	0.38	1.44	34,013	25,537	1,634,788	1,487,817
Ancillary costs (e.g., administrative, shipping, distribution)	10	0.50	1.76	7,160	4,715	43,788	15,363
All projects	38,920	0.53	1.29	7,401	5,574	102,517,178	99,530,592

Note: Statistics are based on sample of 38,920 project recommendations, broken down by project type. Aggregate cost and aggregate annual savings are for the years 1981–2000. Monetary figures are in U.S.$2000.

Table 3: Fixed Effect Logit Estimates of Project Adoption

	Payback model	*Cost-benefit model*	*Price-quantity model*
ln(*payback=savings/cost*)	-0.083**		
	(0.005)		
ln(*payback=savings/cost*)^2	-0.009**		
	(0.002)		
ln(*project cost*)		-0.087**	-0.085**
		(0.005)	(0.005)
ln(*project cost*)^2		-0.005**	-0.005**
		(0.001)	(0.001)
ln(*annual savings*)		0.061**	
		(0.006)	
ln(*annual savings*)^2		0.000	
		(0.002)	
ln(*price of energy*)			0.043**
			(0.016)
ln(*price of energy*)^2			-0.030
			(0.018)
ln(*quantity of energy saved*)			0.058**
			(0.006)
ln(*quantity of energy saved*)^2			-0.001
			(0.001)
motor systems	0.092**	0.090**	0.090**
	(0.008)	(0.008)	(0.008)
thermal systems	-0.167**	-0.165**	-0.165**
	(0.011)	(0.011)	(0.011)
combustion systems	0.002	-0.002	-0.003
	(0.016)	(0.016)	(0.016)
operations	-0.094**	-0.095**	-0.095**
	(0.019)	(0.019)	(0.019)
electrical power	-0.273**	-0.253**	-0.250**
	(0.060)	(0.061)	(0.062)
industrial design	-0.214**	-0.198**	-0.197**
	(0.060)	(0.061)	(0.061)
ancillary costs	-0.038	-0.048	-0.049
	(0.211)	(0.213)	(0.213)
Log likelihood	-10,133	-10,118	-10,116
Likelihood ratio	1,278**	1,308**	1,312**

Note: Asterisks denote statistical significance at various levels: * = 95%, ** = 99%. Data are observations of energy-conserving project recommendations made under IAC program from 1981 to 2000. Dependent variable equals 1 if project is adopted and 0 otherwise. Estimation method is ML conditional fixed effects logit with plant-specific fixed effects. Each model is estimated on an effective sample of 5,263 plant visits representing 26,068 recommended projects. 3,771 plants (12,852 projects) in the full sample were dropped because they had no variation in whether projects were adopted. Marginal effects at variable means are given directly by linear terms, setting fixed effects and project-type dummies at zero. Marginal effects for dummy variables give change in predicted probability associated with changing dummy variable from 0 to 1. See sections 2 and 3 for further detail.

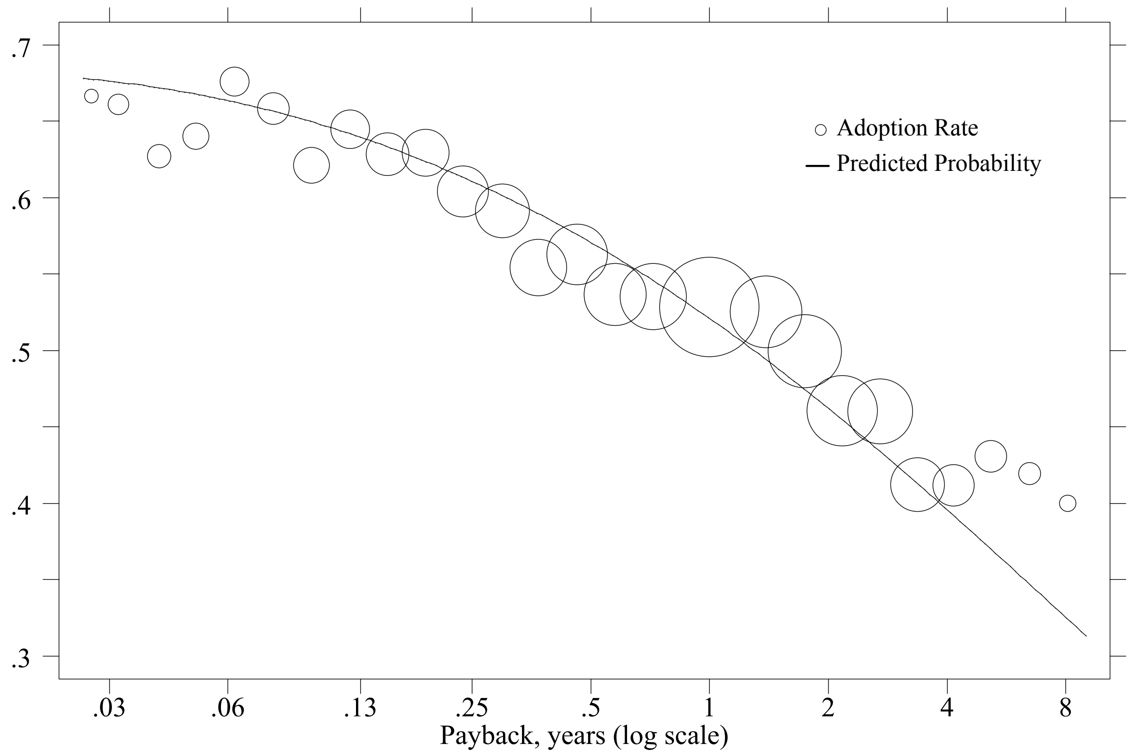

Figure 1: Probability of Adoption versus Payback

Note: Circles represent the observed adoption rates for fixed intervals of payback in log scale. The areas of the circles are proportional to the number of observations in each interval. The solid line is the predicted probability of adoption for the *payback* model (see Table 3). All fixed effects are set to zero for the figure.

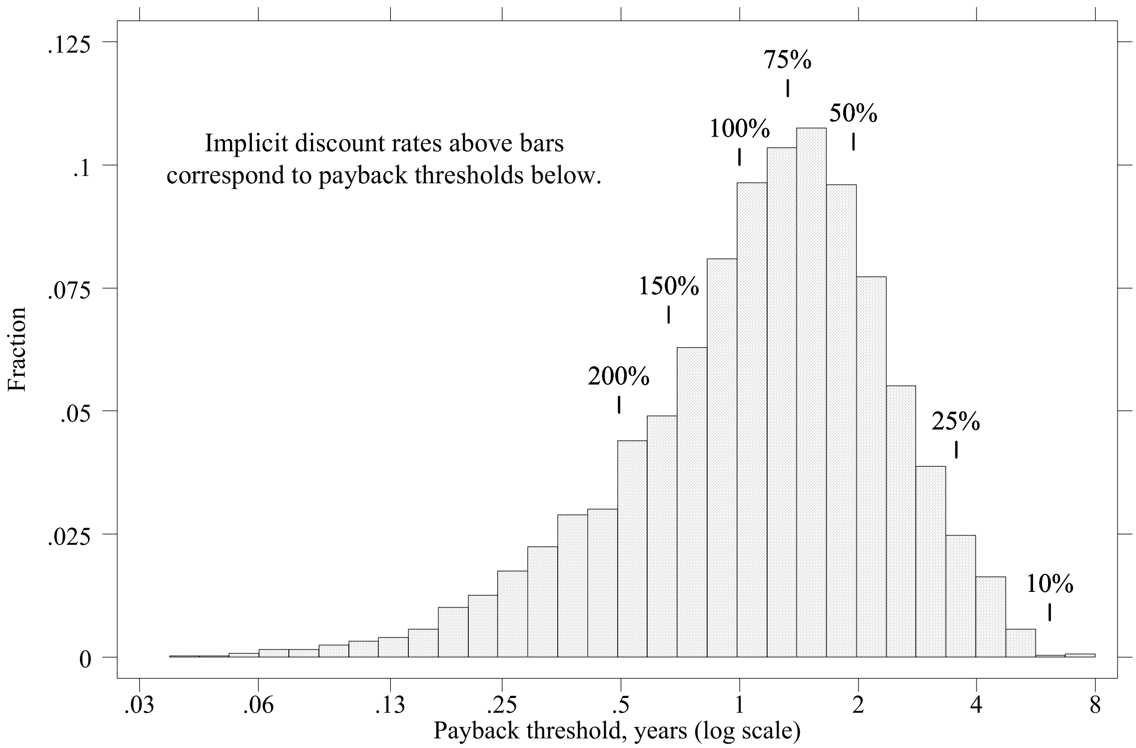

Figure 2: Histogram of Payback Threshold Values

Note: Figure shows fraction of plants having a payback threshold within fixed intervals of payback in log scale. Based on sample of 5,263 plants that adopted some (but not all) projects. Payback threshold values are given by midpoint between maximum payback for adopted projects and minimum payback for rejected projects within each assessment. Mean payback threshold is 1.4 years; median is 1.2 years. Implicit discount rates above bars correspond to payback thresholds assuming a 10-year project lifetime. See section 4.2 for further detail.

Table 4: Reasons Given for Project Rejection

Reason for project rejection	*Number of rejected projects*	*Percentage*
Economic reasons	***5,099***	***76***
Too expensive initially	805	12
Not worthwhile	677	10
Unsuitable return on investment	603	9
Impractical	589	9
Facility changes	566	8
Process and/or equipment changes	506	8
Unacceptable operating changes	421	6
Personnel changes	323	5
Disagree	288	4
Suspected risk of problem with equipment	215	3
Risk or inconvenience to personnel	121	2
Rejected after implementation failed	73	1
Production schedule changes	68	1
Material restrictions	33	1
Financing reasons		
Cash flow prevents implementation	***705***	***10***
Institutional reasons	***926***	***14***
Lack of staff for analysis and/or implementation	723	11
Bureaucratic restrictions	209	3
All reasons	***6,730***	***100***

Note: Some projects list more than one rejection code. Thus, numbers and percentages may not sum to totals for each broad category. A small number of projects had rejection codes in more than one of the broad categories and are not included here. See section 4.3 for further detail.