A Probit Model of Energy Efficiency Technology Decision Making[1]

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ABSTRACT

The diffusion of energy efficient technologies, or lack thereof, has been the subject of numerous studies. The Industrial Assessment Center (IAC) program conducts assessments of plants in small and medium-sized companies and makes energy efficiency recommendations that will result in cost savings and high rates of return. This study uses a detailed database from the IAC program to examine the firm's decision to implement a recommendation. This study estimates two probit models; one captures the probability that a particular recommendation is made, and the other the probability that a recommendation is implemented. The second model, the decision to adopt, is the primary focus of the analysis. The paper interprets the results from the economic variables in terms of the speed of adoption (i.e., in the context of standard diffusion models). Many measures of technology performance have a statistically significant influence on the adoption decision. Higher implementation cost or energy prices reduce the chance of adoption for many technologies, but not all. This effect is in addition to the effect these variables have on payback, which also lowers the chance of adoption as payback rises. In general, many economic variables influencing the cost and energy savings of the technology have a statistically significant effect on the decision to adopt, but the size of the effect is rather small. For example, a longer payback period lowers the probability of adoption by 2% per year. Other effects suggest resource constraints or risk aversion. Higher implementation costs lower the probability of adoption. For every thousand-dollar increase in implementation costs, the probability is lowered by 0.03%.

Introduction

The diffusion of energy efficient technologies, or lack thereof, has been the subject of numerous studies (Jaffe and Stavins, 1994). It is of particular policy interest because of the indirect impact that energy use has on the environment. This impact on the environment implies that the private decision to adopt energy efficient technology can provide public benefits that are in addition to the return from the cost savings that the accrues to the individual or firm. Because of these public benefits, a number of government-sponsored programs to encourage the adoption of energy efficient technology. One is the Industrial Assessment Center (IAC) program conducted by the U.S. Department of Energy (DOE) Office of Industrial Technology.

[1] Work sponsored by the U.S. EPA, Office of Atmospheric Programs.

The IAC conducts energy assessments[2] of plants in small and medium sized companies and makes energy efficiency recommendations to that result in cost savings and high rates of return, as measured by simple payback. Assessments are made by teams composed of engineering faculty and students from the centers, which are located at 30 universities around the country. The recommendations made in an IAC assessment typically have a payback of 3 years or less and average $55,000 in potential annual savings to the company.[3] The company then decides whether to implement the recommendations and reports this decision to the center. Average implementation is nearly 50%.[4] Information on the cost and performance of the specific recommendations and selected data on the company are maintained by Rutgers in a publicly available database. This study uses this detailed database from the IAC program.

A study by the DOE (Woodruff et al. 1996) summarizes the IAC program and the results through 1994 in detail. It reports that 95% of the recommendations implemented by the participating companies have had an estimated payback of 2 years or less and have resulted in $517 million in savings, at a federal program cost of $27 million. Tonn and Martin (2000) report on the benefits of the IAC program, beyond those embodied in the assessment itself, on the basis of a follow-up survey of 42 companies. The report concludes that the program positively influenced the companies' attitudes about energy efficiency decision making. Other effects of the IAC program were also considered in the follow-up survey. In addition to the direct effect of the assessment, questions were asked about the hiring of IAC "alumni" (i.e., students that formerly worked/studied at an IAC university center) and use of Web-based resources associated with the IAC program. Muller, et al. (1995) reports on the results of a follow-up survey of 104 companies. The report notes that 28% of the companies implemented additional recommendations beyond those that they reported on originally. This study does not consider whether the decision process may have changed following the assessment or for subsequent adoption decisions but instead focuses on the decision process directly related to the assessment.

The focus of this study is to examine a firm's decision to implement a recommendation. Specifically, this paper examines which variables in the IAC database influence a firm's decision to adopt. This study estimates two types of binary variable models. The first captures the probability that a particular recommendation is made, and the second captures the probability that a recommendation is actually implemented. Probit models are used to represent the choice function. The first model explores sample selection issues and examines how likely a particular type of energy efficiency option is. The second model, the decision to adopt, is the primary focus of the analysis.

In general, the conclusion is that many economic variables influencing the cost and energy savings of a technology have a statistically significant effect on the decision to adopt, but the size of each effect is rather small. For example, longer payback[5] lowers the probability of adoption, but by only 2.0% per year. Other effects suggest resource constraints

[2] This program has been expanded in include other waste and productivity assessments. This paper considers only the energy assessment information.

[3] Information taken from http://www.oit.doe.gov/iac/ as accessed on October 2, 2000.

[4] Information taken from http://oipea-www.rutgers.edu/documents/doc_f.html as accessed on October 2, 2000.

[5] Simple payback (i.e., total cost/annual savings) is used as a measure of technology performance. The database does not include sufficient information to compute net present value or internal rate of return.

or risk aversion. Recommendations that have higher implementation cost, but a similar payback have a lowered probability of adoption. For every thousand-dollar increase in implementation costs, the probability is lowered by 0.03%. Larger firms, in the sense of having more employees, are more likely to adopt. For every 100 employees, the adoption probability increases 0.5%. A wide range of technology-specific and energy-price-specific effects are also found.

Industrial Assessment Centers

The IAC program and description of results are described in detail in Woodruff et al. (1996), so are not repeated here. The assessment reports are confidential, but data from the assessment on selected firm data (sales, energy costs, employees, etc.) and on the actual recommendations (cost, savings, specific technology, etc.) are maintained by Rutgers in two databases. In order to organize the assessment data in a useful way, a coding system called the Assessment Recommendation Code (ARC) has been developed to list each recommendation; see Muller and Kasten (1998) for more details.

The ARC system is a hierarchical classification system, much like the Standard Industrial Classification (SIC) system of classifying products into industry groups. This paper concerns itself only with the energy recommendations and does not distinguish between detailed applications, which are very detailed. For the analysis, these detailed ARC codes are grouped into 27 two-digit codes. These categories are used to capture technology-specific differences in the modeling.

The analysis uses data obtained from Rutgers that include assessments through 1995. The plant-specific data records (6,356 plant visits) were merged with the recommendation data (54,335), resulting in a database that is quite large. Sales, implementation, and energy cost data were deflated to 1992 dollars by using a producer price index. Observations with no reported employees or sales were dropped. The data were further restricted to those that used both natural gas and electricity as primary energy types. Although this approach was a bit restrictive, it enabled us plant-level energy prices for the two types of energy that are common in industry. Even with this restriction, the database includes 27,144 records. Summary statistics are shown in Table 1 (more detailed statistics are available from the author).

Diffusion Models

The typical view of technology adoption is that of an epidemic model, or S-curve. Technologies are adopted slowly at first, then more rapidly as they gain acceptance. Adoption slows as the maximum feasible market share is reached. The speed of adoption may be influenced by a number of firm and technology characteristics. Harrington et al. (1999) presents an analysis of a firm's decision to adopt various types of energy-efficient technologies, express in terms of the speed of adoption. Following that report's notation, we let $X_{i,t}$ be the presence of the technology for plant i at time t and $\overline{X}_t$ be the average level of adoption at time t. The diffusion model can be described by

$$P(\Delta X_{i,t} = 1 \mid X_{i,t-1} = 0) = 4c \cdot X_{t-1} \ . \qquad (1)$$

The constant, c, represents the speed of adoption. Harrington et al. (1999) estimates the speed of adoption across a range of technologies and industry sectors and concludes that it is remarkably similar, c = 0.22. We computed the speed of adoption for each of the 27 technology groups in a similar manner. We computed the fraction of cumulative adoptions since the start of the IAC program in any year, relative to the total number of plants that have received that technology recommendation. We see that this speed of adoption varies substantially across time and technology. In particular, the speed of adoption tends to be much lower in the late 1980s and early 1990s. This lower speed may be due to the substantial energy price decline that occurred after 1986. We return to this issue later in the paper.

Table 1. Summary Statistics of the Variables Used in the Analysis

Variable name	Description	Mean	Std. Dev.	Units
ACCEPT	Recommendation adopted = 1	55%	0.50	fraction
EMPLOYEE	Number of employees	0.18	0.16	thousand
SALES	Gross annual sales	24.88	31.57	million
PLANT_AR	Plant area	38.30	131.76	thousand
PRODHOUR	Production hours per year	4.99	2.19	thousand
IMPCST92	Implementation cost	8.77	102.37	thousand $
C_TOT92	Total energy expenditures	0.46	0.66	million $
NG_PRICE	Natural gas price	5.11	2.61	$/million Btu
E_PRICE	Electricity price	20.77	7.41	$/ million Btu
PAYBACK	Simple payback (cost/annual savings)	1.11	1.55	years
REBATE2	Dummy for a rebate program	0.02	0.14	fraction
NUMARS	Number of recommendations at site	7.72	2.99	

Since the estimate by Harrington et al is for a 3-year time period, 1991-1994, the last column of Table 2 gives the speed of adoption for that period, using the IAC data. Only four technology groups have a speed similar to c=0.22. They are generation, motors, compressors, and lighting. For the other technologies, the speed estimates are all lower. The first of these, generation, is an artifact of the data, since the technology is infrequently recommended. The latter three are very commonly recommended; hence they may be more comparable to the common technologies studied by Harrington et al.

Statistical Model

It is relatively common to represent the conditional probability to adopt a new technology as a function of plant-specifc and technology-specific characteristics; hence, the speed of adoption is similarly a function of those variables. We use the probit model to represent the technology choice:

$$z = \beta' X + \varepsilon, \ \ y = sign(z), \ \ \varepsilon \sim N(0,1). \qquad (2)$$

Various explanatory variables have been used in technology choice models. The models may include variables that influence the performance of the technology or firm/plant-specific differences between the potential adopters. This analysis differs from other models of technology because

- A wide range of technologies and practices are involved rather than a single technology.
- We do not observe the overall level of penetration of any given technology.

The first issue is handled in two ways. To the extent that these technologies are all "equal," they can be evaluated in terms of a financial criterion. We use simple payback (i.e., annual savings divided by implementation costs). While this criterion has its drawbacks, the program is frequently couched in those terms, and information on technology lifetimes is not sufficient to compute a criterion like internal rate of return. However, the technologies that are recommended may not be equal in the minds of the decision makers, so a technology-specific fixed effect is included in the vector of explanatory variables.

Table 2. Annual Speed of Adoption

Tech code	Description	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1991-1994
11	Furnaces	0.11	0.08	0.05	0.04	0.03	0.01	0.02	0.01	0.03	0.02	0.01	0.06
12	Boilers	0.13	0.10	0.06	0.07	0.06	0.04	0.03	0.03	0.04	0.03	0.01	0.10
13	Fuel switching	0.18	0.17	0.08	0.04	0.03	0.05	0.07	0.04	0.03	0.04	0.00	0.10
21	Steam	0.14	0.11	0.09	0.06	0.08	0.04	0.05	0.06	0.06	0.07	0.02	0.19
22	Heating	0.14	0.10	0.02	0.03	0.03	0.02	0.01	0.04	0.03	0.03	0.00	0.10
23	Heat treating										0.00	0.00	
24	Heat recover.	0.16	0.09	0.07	0.05	0.05	0.03	0.05	0.04	0.02	0.02	0.01	0.07
25	Heat containment	0.13	0.09	0.09	0.07	0.03	0.04	0.04	0.04	0.04	0.05	0.01	0.12
26	Cooling	0.00	0.25	0.16	0.11	0.14	0.08	0.05	0.05	0.04	0.04	0.02	0.14
27	Drying	0.10	0.08	0.04	0.03	0.00	0.03	0.00	0.00	0.00	0.03	0.00	0.03
31	Demand mngmnt	0.17	0.09	0.05	0.03	0.04	0.02	0.04	0.05	0.03	0.04	0.01	0.12
32	Power factor	0.08	0.03	0.12	0.04	0.07	0.06	0.07	0.05	0.05	0.06	0.01	0.16
33	Generation			0.00	0.00	0.19	0.00	0.12	0.09	0.14	0.00	0.00	0.23
34	Cogeneration		0.18	0.10	0.00	0.07	0.00	0.15	0.04	0.00	0.00	0.00	0.04
35	Transmission	0.06	0.00	0.09	0.04	0.12	0.02	0.04	0.00	0.04	0.04	0.00	0.08
41	Motors	0.25	0.20	0.15	0.11	0.07	0.06	0.06	0.06	0.07	0.09	0.03	0.23
42	Compressors	0.19	0.10	0.07	0.07	0.05	0.05	0.05	0.06	0.07	0.08	0.03	0.20
43	Other	0.21	0.19	0.07	0.08	0.02	0.04	0.04	0.03	0.03	0.04	0.02	0.10
51	Systems	0.11	0.01	0.05	0.08	0.04	0.01	0.03	0.01	0.05	0.04	0.00	0.09
61	Maintenance	0.17	0.11	0.03	0.04	0.05	0.03	0.02	0.03	0.02	0.03	0.00	0.08
62	Equipment cntrl	0.16	0.10	0.08	0.07	0.05	0.06	0.07	0.06	0.03	0.04	0.01	0.13
71	Lighting	0.15	0.09	0.09	0.07	0.06	0.05	0.06	0.06	0.08	0.10	0.04	0.24
72	Space cond.	0.16	0.10	0.07	0.06	0.04	0.04	0.04	0.03	0.03	0.02	0.01	0.08
73	Ventilation	0.20	0.01	0.06	0.09	0.08	0.03	0.07	0.05	0.03	0.01	0.01	0.10
74	Envelope	0.11	0.04	0.03	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.01	0.08
81	Admin	0.04	0.09	0.26	0.22	0.12	0.07	0.07	0.06	0.07	0.06	0.02	0.19
82	Shipping	0.48	0.12	0.03	0.03	0.03	0.00	0.00	0.03	0.00	0.00	0.03	0.03

The second issue has several ramifications for the analysis. The obvious one is that it is harder to interpret the model estimated in terms of the standard adoption framework presented above. To make the speed of adoption estimates presented above, we were forced to compute adoption only from those plant that received assessments, and only beginning with the IAC program inception. For this reason, the comparisons of impact on speed of adoption in Harrington et al require some caveats. The other ramification for the analysis is that if a technology is already in place, either because it is commonly used in a particular sector on simply happens to be in place at a specific plant, then it will not be in the recommendation database. This raises sample selection issues with regard to the data.

To determine how important this second issue is for the analysis, the study employed a bivariate Probit model with sample selection. In the bivariate probit setting, data on y_1 might be observed only when $y_2 = 1$. Thus, in a bivariate probit model for the two outcomes, the observed default data are nonrandomly selected from the set of applicants.

$$\begin{aligned} &z_1 = \beta_1'X_1 + \varepsilon_1,\ \ y_1 = sign(z_1), \\ &z_2 = \beta_2'X_2 + \varepsilon_2,\ \ y_2 = sign(z_2), \\ &\varepsilon_1, \varepsilon_2 \sim BVN(0,0,1,1,r) \\ &(y_1, X_1)\ is\ observed\ only\ when\ y_2 = 1 \end{aligned} \qquad (2)$$

Abowd and Farber (1982) propose a model where y_1 and y_2 are determined sequentially, and $\varepsilon_1, \varepsilon_2$ are uncorrelated. This framework seems to represent the process whereby a firm agrees to an assessment and recommendations are made ($y_2 = 1$). We then observe the firms decision to implement the recommendation ($y_1 = 1$ or 0). In this case, the probability model is as follows,

$$\begin{aligned} &\text{Prob}[y = 1] = \text{Prob}[y_1 = 1] \times \text{Prob}[y_2 = 1] = \Phi(\beta_1'X_1)\Phi(\beta_2'X_2), \\ &\text{Prob}[y = 0] = 1 - \text{Prob}[y = 1]. \end{aligned} \qquad (3)$$

If we completely observed the assessment process (including the decision of firms to participate in an assessment, whether or not a recommendation is made, and the final implementation of the recommendation), the process could be represented by a multistage probit. Each equation could be estimated separately, but would be statistically inefficient. Since we do not completely observe the process of selection and recommendation, this step is treated as sample selection.

We can infer something about the recommendation step in this process from the IAC data. Since there is a system in the IAC data that enumerates the "possible" recommendations, we may infer that any recommendation not in the data was deemed inappropriate for that firm.

How assessment teams find different technical opportunities will differ because of production-specific issues (i.e. some technologies are not used in different production processes) and past implementation (i.e. a technology may have high potential but also has largely been implemented). As a separate analysis, we examine the likelihood of a specific recommendation being made, from a small group of frequently recommended technologies.

Probability of Recommendation

This section reports on the analysis of recommendation probability, followed by the results of the adoption probability model. We cannot combine this analysis with the sample selection analysis, since we do not observe the technology-specific explanatory variables when a technology is not recommended (i.e. when $y_2 = 0$ then data for X_1 are not observed).

The question of sample selection, which includes both the process by which a firm is contacted and decides to participate in an assessment and the process of making a specific recommendation, is a potentially important statistical issue. The likelihood of making a specific recommendation, given that a firm participates, is interesting in its own right. It is possible to construct a data set that shows for every assessment whether a recommendation for a particular technology is made or not. These data become the basis for analysis of the likelihood of a technology being recommended, given a firm's characteristics. Some technologies are so infrequently recommended that we focused on a subset of technology for this analysis.

A probit model in the form of Equation 2 was estimated for each of the 14 two-digit technology classes with recommendation rates greater than 10%. The explanatory variables included dummy variables for the two-digit SIC reported by the plant, dummy variables for each year, and plant-specific sales, number of employees, production hours, and energy prices for electricity and natural gas. The sales and employment variables were included to capture scale effects. Production hours capture plants that operate continuously versus cyclically. The results for the plant-specific variables, represented as an increase in the recommendation probability given a doubling (100% increase) of the corresponding variable, are shown in Table 3. The estimates shown in bold are statistically significant at the 95% confidence level.

Table 3. Change in Recommendation Probability for a 100% Increase in the Corresponding Variable

Technology Description	Recommendation Frequency	SALES	EMPLOYEE	PRODHOUR	E_PRIC	NG_PRIC
Boilers	26%	0.20%	**3.32%**	0.59%	1.34%	-0.56%
Fuel switching	12%	-0.39%	0.73%	**1.59%**	**8.97%**	-0.27%
Heat recovery	31%	0.19%	**2.22%**	1.30%	**-9.37%**	**1.41%**
Heat containment	25%	-0.19%	1.03%	**3.60%**	0.41%	0.28%
Demand mngmnt	17%	0.03%	0.82%	-0.18%	2.35%	**1.67%**
Power factor	11%	**0.45%**	**-1.44%**	**1.24%**	**-11.94%**	**-1.93%**
Motors	59%	**1.85%**	-0.54%	**13.67%**	**4.95%**	0.80%
Compressors	63%	0.47%	**2.23%**	-2.06%	**3.62%**	0.53%
Other	17%	0.50%	0.91%	0.66%	**2.72%**	0.63%
Equipment control	28%	-0.73%	0.15%	**-3.39%**	**-3.94%**	**1.24%**
Lighting	84%	**-1.00%**	-0.64%	-1.17%	-0.52%	**2.26%**
Space conditioning	38%	0.15%	1.31%	**-7.78%**	0.49%	0.59%
Envelope	20%	**-1.12%**	-1.00%	**-2.29%**	**2.64%**	0.98%
Admin	11%	**-0.98%**	0.54%	-0.26%	**3.67%**	0.57%

We observe that many of the estimated effects are modest in size relative to the hypothesized 100% increase in the plant-specific variable. There is also no dominant pattern regarding the sign of many of the significant coefficients. Smaller plants (in terms of sales) recieve more lighting, envelope, and administrative recommendations, while larger plants recieve higher power factor and motor recommendations. Plants with more employees have higher rates of recommendation for boiler, heat recovery, and compressors, but lower rates for power factor. Lower production hours result in more space conditioning, envelope, and equipment control recommendations and less fuel switching, heat containment, power factor and motor recommendations. Energy prices also do not have a dominant sign, but frequently are reasonable when the technology type is considered. High electricity prices result in more frequent fuel switching, motor, compressor, other, envelope, and administrative recommendations. Many of these technology classes are electricity specific. Heat recovery, power factor, and equipment controls have the opposite sign. When significant, higher gas prices increase the recommendation rates for heat recovery, demand management, equipment controls, and lighting and lower rates for power factor recommendations. The detailed dummy variable results are available from the author.

Probability of Adoption

The probability of recommendation is one step in the decision process for these energy-efficient technologies. Recommendation does play an important role in the sample selection issues, discussed above. The previous section showed that the recommendation process is complex and difficult to fully observe. The next step in the decision process is taken by the plant/firm decision-maker.

In light of statistical concerns over sample bias and evidence from the previous section that there are systematic effects on the recommendations, we attempted to estimate a model in the form of Equation 2 using the Abowd and Farber approach. The results were unsatisfactory. For many specifications of the explanatory variables, X_1 and X_2, the covariance matrix was singular or nearly so. In the cases where this was not the problem, an examination of the predicted values found that the model tended to correctly predict adoptions at very high rate and nearly none of the non-adoptions. Since the adoptions slightly outnumber the "non-adoptions", the sample selection model degenerated into a naïve form. By "naïve," we mean that a naïve prediction would always guess that all of the technologies were adopted. Since the sample adoption/non-adoption rate was closer to 60/40, the naïve model will at least perform better than a 50/50 guess. The sample selection models estimated were slightly better than this, but not much. The reason suspected for this poor performance is two-fold. The first is that many variables that could be included in the sample selection equations are quite clearly of interest in the adoption equation, because the recommendation should capture many, if not all, of the interests of the decision-maker. The second is that industry and technology-specific effects could easily be included in the sample selection or adoption equation. The paper only reports results from the simpler model.

The adoption decision may be influenced by technology effects (e.g. cost savings, and firm effects, e.g. size). The model presented here considered a number of both firm and technology effects. The technology effects include initial cost, simple payback, rebate, a technology class dummy variable, and a technology class price variable. Firm effects include size, number of recommendations made, a dummy variable indicating whether a recommendation ranked in the top half of the total list of recommendations (in terms of simple payback), and a SIC dummy variable. Firm size is measured by number of employees. Earlier versions of the model included both employment and sales as in the recommendation model, but the sales coefficient was consistently insignificant. Other firm-specific effects that were initially included in the model were energy intensity (energy expenditures relative to sales and employment), energy mix, and production hours. Other technology-specific effects that were initially included in the model were the ratio of initial cost to sales and a dummy variable for recommendations that reported no (zero) initial cost. These variables were never significant and so they were dropped from the specification reported below. The logic for trying these specifications is discussed when interpreting the other results. The results for the nondummy variables are reported in Table 4. The results are expressed as the change in adoption probability resulting from a 100% change in the corresponding variable, evaluated at the data mean.[6]

Table 4: Change in Adoption Probability for a 100% Increase in the Corresponding Variable

Variable	Change in adoption probability	t-ratio
Employees (hundreds of persons)	0.86%	2.36
Number of recommendations	1.89%	2.32
Payback	-2.24%	-8.00
Implementation cost (thousand 1992$) direct effect	-0.29%	-2.94
Implementation cost (thousand 1992$) total effect	-0.57%	-5.47
"Lower" payback	3.80%	4.78
Rebate	7.29%	3.16

Doubling the number of employees increases adoption by about one percentage point. This result supports the notion that larger firms are more likely to adopt. Since the sales variable is not significant, but the employee variable is, we interpret this result as supporting the notion that more employees are a valuable resource for implementation. If recommendations compete with each other, then increasing the number of recommendations might actually reduce the chance of adoption. The estimate supports the opposite hypothesis rejecting the notion that more recommendations, at least in absolute number, might result in a "squeezing out" effect. The simple payback (i.e. the ratio of initial cost divided by savings[7]) is a simplistic measure of economic return attributable to the recommendation. Nearly all the recommendations in the IAC have a payback of 3 years or less.[8] As such, most of these recommendations would be "economic" by many simple rate-of-return criteria. However, differences in the payback do influence the decision. Increasing the number of years of payback from 1 to 2, i.e. about a 100% increase from the sample mean, lowers the adoption probability by 2.24%. Payback includes the effect of the technology in terms of savings, cost of energy, and initial cost.

We consider the possibility that differences in the cost or price may have a separate impact beyond that embodied in the payback ratio. We return to the price effect issue below. The model estimates that this separate cost effect is about –0.3% for each 100% increase in the cost. The total effect of an increase in cost is the direct effect and the indirect effect due to a change in the payback, which we compute as about double the individual components, (i.e., 0.6%).

[6] It might be more accurate to represent these results in terms of the change in probability for a *smaller change* in the variable, say 1%, since the results are based on the derivative of the adoption probability with respect to the variable evaluated at the mean.

[7] Since some recommendations are fuel switching or have operating costs, net savings are computed from the data reported to the IAC and are used to compute payback.

[8] Since many recommendations have no reported (capital) cost, the payback for which is zero, an earlier version of the model included a dummy for this group of recommendations, but it was never significant.

Another effect that the payback ratio may have in the context of the decision process is the comparison of the recommendations, since they are presented to the decision-maker at the same time. Aside from the role that payback has in measuring the economic desirability of the recommendation, it provides a ranking of the recommendations. To see if this ranking effect is significant, we construct a dummy variable that indicates whether the recommendation is above or below the median for that assessment. The estimates show that recommendations with lower payback have a 3.8% greater adoption probability, demonstrating a significant ranking effect. The IAC data also indicate whether there is a rebate from some demand-side management or some other similar program. Those technologies have a 7.3% larger adoption probability. It is not clear from the IAC documentation whether the rebate is included in the cost estimate (i.e., if cost is net of the rebate). If this is the case, then the rebate variable acts as a signal to the decision-maker that the technology has been preapproved. Even if the rebate is not accurately reflected in the cost, the impact of this variable, in terms of adoption probability, is more than 12 times larger than that of the indirect implementation cost estimate and is likely to be larger than the effect on cost alone. For this reason, it is concluded that the rebate variable does serve an important signaling function.

Energy prices also affect the payback of a technology, for a given level of savings. In the same manner that costs are allowed to have a separate effect on adoption, energy prices are allowed to have a separate effect. Since some technologies are energy specific (e.g., can only result in electricity savings), a technology-specific electricity and natural gas prices are included in the model.[9] These price effects are shown in Table 5 as the change in the adoption probability for a one-dollar increase in the corresponding price. The expected sign of the energy price effect is positive (i.e., higher prices make a technology economic and more likely to be adopted). The impact of energy prices in terms of the payback variable, as discussed above, is 0.1% for electricity prices and 0.5% for fuel prices. Table 5 shows that there are four recommendations that have a statistically significant (10% confidence level) positive effect for both electricity and natural gas. However, there are two statistically significant negative effects estimated for electricity and four for natural gas. One way that these negative effects would have economic meaning is if there was a substitution effect in the technology or a squeezing out effect in terms of competition between technologies.

The final form of the model estimated included dummy variables for SIC and technology class effects. The dummy variable for SIC 34 was dropped to avoid a dummy variable trap. The results show that the petroleum industry (SIC 29) is more likely to adopt, with pulp & paper, rubber & plastics, and instruments being less likely to adopt. For technology-specific effects, furnace, steam, motors, compressors, lighting and administration are significantly more likely to be adopted. Fuel switching, heat recovery, demand management, and cogeneration are significantly less likely to be adopted, other effects held constant. Detailed results are available from the author.

[9] In an earlier version of the model, electricity and natural gas prices were included and were either insignificant or the wrong sign. When the technology-specific prices were included, the overall price effects were not significant and were dropped from the model presented here.

Table 5. Change in Adoption Probability for a One Dollar per MBtu Increase in the Corresponding Price (estimates in bold are significant at 90% confidence)

Recommendation Description	Two-digit ARC Code	Electric Price Change	Electric Price t-ratio	Natural Gas Price Change	Natural Gas Price t-ratio
Furnaces	11	-0.20%	-0.61	**-3.06%**	**-1.53**
Boilers	12	0.24%	1.13	0.94%	0.91
Fuel switching	13	-0.13%	-0.36	1.70%	1.05
Steam	21	**0.43%**	**1.67**	-0.67%	-0.61
Heating	22	0.08%	0.09	1.57%	0.38
Heat recovery	24	0.10%	0.43	**2.47%**	**2.72**
Heat containment	25	0.04%	0.23	0.50%	0.55
Cooling	26	**-1.17%**	**-1.65**	**4.16%**	**1.56**
Drying	27	2.09%	1.00	-3.21%	-0.47
Demand management	31	**0.53%**	**1.74**	-1.01%	-0.69
Power Factor	32	-0.34%	-0.80	0.06%	0.03
Cogeneration	34	0.09%	0.08	**13.67%**	**1.90**
Transmission	35	-0.66%	-0.52	1.48%	0.27
Motors	41	0.10%	0.74	-0.56%	-0.85
Compressors	42	0.14%	1.00	0.72%	1.14
Other	43	**-0.90%**	**-2.84**	**2.66%**	**1.89**
Systems	51	1.00%	1.38	**-5.31%**	**-1.71**
Maintenance	61	**1.15%**	**2.17**	**-3.46%**	**-1.48**
Equipment control	62	-0.10%	-0.46	0.68%	0.72
Lighting	71	0.03%	0.26	-0.01%	-0.01
Space conditioning	72	**0.57%**	**3.14**	-0.72%	-0.86
Ventilation	73	-0.67%	-1.02	3.13%	1.06
Envelope	74	0.20%	0.76	0.36%	0.29
Admin	81	-0.42%	-1.21	**-4.07%**	**-2.01**
Shipping	82	0.73%	0.43	0.61%	0.08

Conclusion

This paper presents an analysis of the process of identifying (recommending) and adopting energy-cost-saving technologies. This analysis provides insight into the speed at which energy saving technologies are adopted and into the decision process.

The simple speed of adoption estimate computed here for motors, compressors and lighting technologies is similar to those reported by (Harrington, Kopp et al. 1999), but our estimate is lower for the other technologies examined. The speed of adoption estimate is conditioned on the recommendation and subsequent adoption of the technology, which may be influenced by firm and technology-specific variables. The influence of these variables may be examined as two separate probability models or a joint model, which reflects sample selection. To estimate the effect of firm and technology-specific variables both approaches are considered, but ultimately the separate model approach was chosen and reported.

For both the recommendation and adoption stage, a probit model is used to estimate the impact of firm-specific and technology-specific variables. Firm variables reflect conditions that influence the decision for energy technologies in general, while technology variables capture the differences between the recommendations. Larger firm size tends to increase the probability of recommendation, although not for every technology examined. Larger firm size also leads to higher adoption rates. Employment was the preferred measure for firm size for the adoption decision and resulted in slightly more coefficients with significant and economically consistent results for the recommendation models. SIC-specific firm effects were also found.

The technology-specific effects included payback, costs, and prices. The payback variable behaves consistently with economic theory, increasing adoption as payback falls and the corresponding economic return rises. However, there is an additional impact of higher costs, which suggests that decisions operate under a capital constraint. This result is consistent with the hypothesis of capital rationing. Attempts were made to capture this constraint with a ratio of cost to sales, but it was not significant, since sales are not a good proxy for financial health. Other results suggest this rationing effect. Recommendation that ranked better in terms of payback (i.e., were in the upper half for the recommendation made to a firm), were more likely to be adopted when payback was held constant. In other words, the adoption decision was made in light of other better or worse recommendations, not an absolute criterion alone. The presence of a rebate for a technology also has a signaling function, greatly increasing the adoption probability.

The price effect on adoption is more elusive. On one hand, prices have a direct influence on payback, and this effect was significant but relatively small. In this sense, prices tended to have an economically consistent impact on recommendation, but direct effects on adoption (beyond those embodied in payback) were less consistent and difficult to interpret. Nevertheless, this analysis does provide evidence of a small, statistically significant price effect on both recommendation and adoption and hence on the resulting speed of adoption.

This analysis may understate the influence of variables from the observed data in the IAC. Muller et al. (1995) reports the results from a callback survey of 104 past assessments that 28% more recommendations were implemented beyond those originally reported. In addition, this analysis also did not have information on whether a technology had already been implemented and hence never recommended, so nonrecommendation does not imply that a given technology is not economic and could possibly mean the opposite. This would tend to bias our speed-of-adoption estimates.

References

Abowd, J. and H. Farber (1982). "Job Queues and the Union Status of Workers." *Industrial and Labor Relations Review* 35: 354-367.

Harrington, W., R. Kopp, et al. (1999). *Public Policy, Technology Adoption, and Aggregate Energy Efficiency.* Washington, DC, working paper Resources for the Future.

Jaffe, A. and R. Stavins (1994). "The Energy Paradox and the Diffusion of Conservation Technology." Resource and Energy Economics 16(2): 91-122.

Muller, M. R., T. Barnish, et al. (1995). "On Decision Making Following an Industrial Energy Audit." 17th National Industrial Energy Technology Conference, Houston, TX.

Muller, M. R. and D. J. Kasten (1998). *The ARC Manual: Assessment Recommendation Code System for the DOE Industrial Assessment Center Database*, Rutgers, The State University of New Jersey.

Tonn, B., and M. Martin (2000). "Industrial Energy Efficiency Decision Making." Energy Policy 28: 831-843.

Woodruff, M., J. Roop, et al. (1996). *Analysis of Energy Efficiency Investment Decisions by Small and Medium Sized Manufacturers*. Washington, DC, U.S. Department of Energy, Office of Policy and Office of Energy Efficiency and Renewable Energy.