Incentives for Appliance Efficiency in a Competitive Energy Environment

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Rebate programs that promote energy efficiency might be difficult to maintain in a competitive environment. We investigate the impact of programs that offer loans rather than rebates for the purchase of energy-efficient refrigerators. A random-parameters logit model is estimated for households' choices of efficiency level and program participation under rebate and loan programs. Using the estimated model, the choices of customers under various loan programs are simulated. The predictions indicate that (i) zero-interest loans are more cost-effective for the utility than rebates at inducing customers to buy high efficiency refrigerators, and (ii) loans with interest rates above the utilities' cost of funds have greater impact than rebates and also generate profits for the firm. The latter result suggests that loans might constitute a viable option for promoting energy efficiency in a competitive energy industry. The study is limited, however, by the assumption that loans are not also available, through credit cards and vendors, on standard efficiency refrigerators.

INTRODUCTION

Demand side management (DSM) programs by electric utilities have relied heavily on rebates as a mechanism for promoting energy efficiency. In a competitive energy environment, the feasibility of rebate programs is questionable: rebates raise rates while competition places pressure on utilities to lower rates. A potentially attractive alternative to rebate programs are programs that offer low-interest loans on high efficiency equipment. In particular, if the interest rate is low from the customers' perspective and yet is higher than the utility's cost of capital, then the utility earns profits from the loans while at the same time inducing energy efficiency.

In this paper, we examine the potential effectiveness of loans relative to rebates. We employ a random-parameters logit model that describes customers' choices among efficiency levels and whether to obtain a loan or rebate. Random-parameters logit is a generalization of standard logit and is estimated through simulation procedures. It is more realistic than standard logit, in that it allows for the fact that different customers have different taste parameters and does not exhibit the restrictive forecasting patterns of standard logit (i.e., does not exhibit independence from irrelevant alternatives.) The model also allows efficient estimation when there are repeated choices by the same customers, as occurs in our application.

The model is estimated on a combination of stated- and revealed-preference data. A sample of residential customers of Southern California Edison (SCE) were presented in a survey situation with a series of choice experiments. In each experiment, two or three refrigerators with different efficiency levels were described, with a rebate, loan, or no incentive offered on the high efficiency units. The customer was asked which appliance he/she would choose. These stated-preference data were supplemented with information on the efficiency level of the refrigerator that the customer actually purchased, for customers who had bought a refrigerator within the last three years. The combining of revealed- and stated-preference data follows the analysis of Atherton and Train (1995). The use of the random-parameters logit model is new and provides a more powerful and realistic method for examining the data and forecasting the impacts of loans. A more complete discussion of the model, alternative specifications, and other issues is contained in Revelt and Train (1996).

RANDOM-PARAMETERS LOGIT

Random-parameters logit (RPL) models have taken different forms in different applications; their commonality arises in the integration of the logit formula over unobserved random factors. The early applications (Boyd and Mellman, 1980, and Cardell and Dunbar, 1980) were restricted to situations in which explanatory variables do not vary over decision-makers, such that the simulation in estimation (described below) is required for only one ''decisionmaker'' using aggregate share data rather than for each decisionmaker in a sample. Advances in computer speed have allowed estimation of models with explanatory variables varying over decisionmakers. Examples include Bolduc, Fortin, and Fournier (1993), Erdem (1995), and Mehndiratti (1996). The form of the random-parameters logit that we utilize in our investigation is described as follows.

A person faces a choice among the alternatives in set J in each of T time periods or choice situations. The number of choice situations can be one (as in standard logit) and can vary over people. The choice set can vary over people and choice situations. The utility that person n obtains from alternative i in choice situation t is $U_{nit} = \beta_n' x_{nit} + \epsilon_{nit}$ where x_{nit} is a vector of observed variables, parameter vector β_n is unobserved for each n and varies in the population as described below, and ϵ_{nit} is an unobserved random term that is distributed iid extreme value, independent of β_n and x_{nit}. Conditional on β, the choice probabilities in each situation are standard logit:

$$L_{nit}(\beta) = \exp(\beta' x_{nit}) / \Sigma_j \exp(\beta' x_{njt})$$
$$\text{for all } i \in J,\ t = 1,...,T$$

and the conditional probability of the person's sequence of choices over the repeated situations is the product of standard logits:

$$S_n(\beta) = \Pi_t\, L_{ni(n,t)t}(\beta),$$

where i(n,t) is the alternative that the person chose in situation t. The unconditional probability for the person's sequence of choices is the integral of the conditional probability over all possible values of β:

$$P_n = \int S_n(\beta)\, f(\beta)\, d\beta$$

where f(.) is the density of β.

The probability is approximated through simulation; more specifically, the integration in P_n is approximated by a summation over randomly chosen values of β. A value of β is drawn from its distribution, and $S_n(\beta)$—the product of standard logits—is calculated for this value of β. This process is repeated for many draws and the average of the resulting $S_n(\beta)$'s is taken as the approximate choice probability:

$$SP_n = (1/R)\, \Sigma_{r=1,...,R}\, S_n(\beta^r)$$

where R is the number of repetitions (i.e., draws of β), β^r is the r-th draw from $f(\beta)$, and SP_n is the simulated probability of person n's sequence of choices. By construction SP_n is an unbiased estimator of P_n whose variance decreases as R increases. The simulated log-likelihood function is constructed as $SLL = \Sigma_n \ln(SP_n)$, and the estimated parameters are those that maximize SLL. Note that, even though the simulated probability is an unbiased estimate of the true probability, the log of the simulated probability with finite number of repetitions is not an unbiased estimate of the log of the true probability. The bias in SLL decreases as the number of repetitions increases. We use 500 repetitions in estimation, which is sufficient for bias to be negligible.

We specify the elements of β to be independently normally distributed with mean vector b and standard deviation vector w. The goal of estimation is to estimate b and w—that is, to estimate the mean and standard deviation of customers' tastes. Utility becomes: $U_{nit} = b' x_{nit} + \mu' W x_{nit} + \epsilon_{nit}$ where μ is a vector of standard normal deviates and W is a diagonal matrix whose diagonal elements are w. The unobserved portion of utility is $\mu' W x_{nit} + \epsilon_{nit}$, which, in contrast to standard logit, is correlated over alternatives and over time. The random-parameters logit model does not exhibit the independence from irrelevant alternatives property of standard logit, and very general patterns of correlation over alternatives and time (and hence very general substitution patterns) can be obtained through appropriate specification of variables and parameters. For example, a variable can enter the unobserved portion of utility (thereby affecting correlation patterns) without entering the observed portion of utility by constraining the mean of its coefficient (i.e., the appropriate element of b) to be zero while estimating a standard deviation (i.e. the element of w). An analog to nested logit is obtained by entering a dummy variable that identifies the alternatives in a nest; the variance in the coefficient of this dummy induces a correlation in the unobserved portion of utility across all alternatives within the nest, while not inducing correlation with alternatives outside the nest.

ESTIMATION ON STATED-PREFERENCE DATA

Four generic options could be available to customers when purchasing a particular type of refrigerator:

(A) Standard efficiency,

(B) High efficiency without financial incentive from the utility,

(C) High efficiency with a rebate from the utility, and

(D) High efficiency with a loan from the utility.

Depending on the situation, some or all of these options are actually available. If the utility does not offer any incentives, then only options A and B are available. If the utility offers rebates but not loans, then options A-C are available; this situation has historically been the case for SCE's customers. Note that option B is available in this situation because customers can (and many do) purchase high efficiency refrigerators but not apply for the rebate. In the future, loans may be offered instead of rebates, in which case options A, B and D would be available. If loans and rebates are offered, with the customer able to choose which to receive, then all four options are available.

In the stated-preference choice experiments, each sampled customer was offered a series of binary choices, followed by a series of trinary choices. For the binary choices, the purchase price and operating cost of a standard efficiency and a high efficiency refrigerator was described and the customer was asked which he/she would choose. The high efficiency unit was offered either without any incentive, with a rebate, or with a financing package with specified interest rate, amount borrowed, repayment period, and monthly payment. That is, the customer was presented, in the binary experiments, with a choice between option A and either option B, C, or D. Trinary choices were then offered to the customer. In these experiments, the customer was offered three high efficiency units, one with no incentive, one with rebates, and one with financing. The purchase price and operating cost of the units differed, such that the unit with no incentive was not necessarily dominated. That is, options B, C, and D were described, and the customer was asked which he/she would choose. In total, responses to 6081 choice experiments were obtained from 401 surveyed customers, with each customer providing responses to 12 binary choice experiments and up to four trinary experiments. Details of the survey design are provided in SCE(1994).

Table 1 gives estimation results. The coefficients for all parameters except price were specified to be random. By holding the price coefficient fixed and letting the others be normally distributed, the willingness-to-pay for each attribute (which is the ratio of the attribute's coefficient to the price coefficient) is normally distributed, which is convenient for interpretation of the model. The estimated standard deviations of coefficients are highly significant, indicating that parameters do indeed vary in the population. Also, the magnitudes of the estimated standard deviations are reasonable relative to the estimated means. For example, the distribution of the savings coefficient has an estimated mean of 3.03 and an estimated standard deviation of 2.24. Given the estimated price coefficient, the model implies that the willingness to pay for one dollar of annual savings, on the margin, is normally distributed in the population with mean of \$2.46 and standard deviation of \$1.81—which is a fairly substantial variation in willingness to pay. If customers consider refrigerators to have a ten year life, and expect no real growth in energy prices, a willingness to pay of \$2.46 implies a discount rate 28%.

The model implies that about 9% of the population place a negative coefficient on savings. This implication could reflect reality or could be an artifact of the assumption of normally distributed coefficients. It is possible that some customers are highly skeptical of energy conservation claims and become more mistrustful the greater the claim of savings is. In this case, negative coefficients for savings reflect the mistrust of these customers and are an accurate representation of reality. On the other hand, the assumption of a normal distribution implies that some share of the population has negative coefficients for savings, whether or not this is true.

The parameters associated with amount borrowed imply that the mean willingness to pay for being able to borrowing an extra dollar is \$0.32 and the standard deviation is \$0.40. Interest rates are denoted in digits (e.g., an interest rate of 9% is denoted as 0.09). The mean willingness to pay for a 1% reduction in interest rate is therefore \$39 with a standard deviation of \$36. For both the interest rate and amount borrowed, the variation in coefficients is fairly substantial, implying that different people respond quite differently to loan terms.

An efficiency dummy enters for options B, C, and D. Its mean coefficient indicates that, on average, customers choose the high efficiency unit in the choice experiments more readily than can be explained by the price, savings, and other financial matters. The standard deviation indicates that 88% of the population have a ''high efficiency preference''. This ''preference'' is largely an artifact of the experiments, where customers perhaps feel that the interviewer wants them to say they would purchase the high efficiency unit, or would think well of them if they did. When the model is calibrated against revealed-choice data (next section), the mean drops considerably. However, it is still significantly different from zero, indicating that there is some preference for high efficiency units, independent of price and savings, even in customers' actual choices.

Rebates can be viewed by customers in a variety of ways independent of the reduction in price that they provide. Customers seem to be skeptical of information from their energy utility, including information about the supposed savings that high-efficiency appliances provide (Constantzo, et al., 1986; Bruner and Vivian, 1979; Craig and McCann, 1978). For some customers, the offer of a rebate lends credibility to the savings claim: these customers interpret the rebate as evidence that the utility is willing to ''put its money where its mouth is'' (Train, 1988). For these customers, the rebate dummy has a positive coefficient. Other customers might see the rebate as the opposite kind of signal, namely, as a sign that the appliances are too poor to sell on their own merit. These customers have a negative coefficient for the rebate dummy. Table 1 indicates that the mean coefficient for the rebate dummy is slightly positive but not significantly different from zero, while the standard deviation is fairly large and highly significant. These results indicate that there is a wide variety of views that customers hold about rebates, with about as many seeing the rebates as a negative signal as see it as a positive signal.

Table 1. Estimated Model on Stated-Preference Data

	Variables	Estimates	Standard Errors
Price net of rebate[1]	Coefficient	−1.23	0.108
Savings[2]	Mean coefficient	3.03	0.345
	Standard deviation of coefficient	2.24	0.281
Amount borrowed[3]	Mean coefficient	0.392	0.066
	Standard deviation of coefficient	0.489	0.057
Interest rate[4]	Mean coefficient	−48.5	10.1
	Standard deviation of coefficient	44.4	7.53
Efficiency dummy[5]	Mean coefficient	3.70	0.421
	Standard deviation of coefficient	3.20	0.398
Rebate dummy[6]	Mean coefficient	0.022	0.212
	Standard deviation of coefficient	1.30	0.204
Finance dummy[7]	Mean coefficient	1.56	0.621
	Standard deviation of coefficient	0.284	0.475
	Likelihood ratio index	.461	

[1] Price in options A, B, D. Price minus rebate in option C. In hundreds of dollars.
[2] Annual savings relative to standard efficiency, in options B, C, D. In hundreds of dollars. Zero in option A.
[3] Amount borrowed in option D. In hundreds of dollars. Zero in options A–C.
[4] Interest rate in option D. Zero in options A–C.
[5] One in options B–D. Zero in option A.
[6] One in option C. Zero in options A, B, D.
[7] One in option D. Zero in options A–C.

The coefficient of the financing dummy obtains an insignificant mean and standard deviation: the hypothesis that customers examine loans only on the basis of their financial terms cannot be rejected. The difference in how customers respond to loans versus rebates is plausible. Rebates are a ‘‘give-away;’’ customers naturally wonder about the motivation for the give-away and tend to read a signal into it even if there is none. Loans are not a give-away; the customer realizes that the lender makes money from the loans. The customer need not read a signal into the offer of loans, since the motivation for the offer is clear.

CALIBRATION TO REVEALED-PREFERENCE DATA

Once estimated, the models are calibrated to revealed-preference data. The actual choices of customers were determined as follows. Each surveyed customer was asked whether he/she had purchased a refrigerator during the last three years. Those who responded in the positive were asked to locate the serial number or other identifying information for the unit that they purchased. With this information, we determined, using product specification sheets, the efficiency level of the refrigerator. Program files were then used to determine which of the customers who had purchased a high efficiency refrigerator had received a rebate. In combination, this information identified, for those customers who had purchased a refrigerator, whether they had chosen option A (standard efficiency), option B (high efficiency without a rebate), or option C (high efficiency with a rebate.) Since financing had not been offered by SCE’s DSM programs, option D was not available.

For brevity, the calibration results are not reported; they can be found in Revelt and Train (1996). The mean and standard deviation of the efficiency dummy coefficient drop considerably, consistent with the notion that people say they would buy high efficiency equipment more readily than they actually do. The mean of the rebate dummy coefficient decreases, but the standard deviation increases. This result is consistent with rebates being more burdensome to obtain in the real-world than in the hypothetical experiments, and the value that people place on the time and hassle required to obtain the rebate varying considerably across customers. In simulation, the mean and standard deviation of the financing dummy coefficient are adjusted by the same amount by which the calibration adjusted the rebate dummy's mean and standard deviation. This adjustment reflects the presumption that the hassle associated with obtaining rebates will also occur for obtaining a loan.

PREDICTIONS

We use the calibrated model to predict the effect of DSM programs that offer loans for the purchase of high efficiency refrigerators. Simulation is performed on the sample of customers used in calibration and therefore represents a prediction of the choices of efficiency level and program participation that customers who bought new refrigerators would have made if DSM programs had offered loans instead of rebates.

For comparison, consider the impact of the rebate program. From the calibrated model, 15.8% of refrigerator purchasers obtained a rebate, 46.1% purchased a standard efficiency unit, and 38.1% purchased a high efficiency unit but did not obtain a rebate. The average rebate was $64. To determine the impact of the rebates on customer choices, the behavior of customers was predcited under a scenario with no DSM program, i.e., with only options A and B available. 54.6% of customers were predicted to purchase a standard unit with the other 45.4% buying a high efficiency unit. These predictions imply that the rebates reduced the standard efficiency share from 54.6% to 46.1%. The rebate program is therefore predicted to have induced 8.5% of buyers to switch from a standard to a high efficiency refrigerator. The cost per induced switch is $116 (i.e., $64 per rebate times .155 who obtain rebates divided by .085 who were induced to switch.)

Consider now the impact of loan programs. Table 2 presents results under various interest rates for loans on the entire amount of the purchase price of high efficiency refrigerators. (Loans for the incremental price—that is, the difference in price between the high efficiency and standard units—were predicted to attract very few customers, primarily because the loan amounts were so small.)

A program of zero-interest loans offered on the entire price of a high efficiency refrigerator is predicted to attract nearly 40% of refrigerator purchasers, which is far greater participation than the rebate program. Compared to no program, such loans would induce 22.6% of buyers to switch from standard to high efficiency, which is nearly three times greater than the rebate program's impact. (The 22.6% is calculated as follows. From the second paragraph above, 54.6% would buy standard refrigerators if there were no program. From Table 2, 32.0% would buy standard units with the zero-interest loan program. The difference, 22.6%, is the program-induced reduction in the percent who buy standard units.) The average loan in this scenario is $1031; the cost to the utility of holding $1031 at a 6% cost of funds and a two-year repayment period is $64—the same as the average rebate. The cost per induced switch is $112, which is slightly lower than the rebate program. The total outlay by the utility is higher with the loans than with the rebates, since participation is greater. Loans with slightly positive rates would decrease the utility's costs and still attract customers. For example, with 4% loans, the outlay by the utility is lower than with rebates ($21 for each of 28% of the buyers versus $64 for 15%) and yet the impact is higher (16.5% of buyers switch versus 8.5%) and the cost per induced switch is lower ($36 versus $116.)

Table 2. *Predicted Choices of Refrigerator Buyers when Loans are offered on High Efficiency*

	Predicted Shares		
Interest Rate	Standard Efficiency	High-Efficiency Without Loan	High-Efficiency With Loan
0%	.320	.283	.397
2%	.354	.314	.332
4%	.381	.336	.283
6%	.402	.351	.246
8%	.418	.362	.220
10%	.430	.370	.201
12%	.438	.375	.186

The utility earns a profit on loans when the interest rate is above its cost of funds. At 8% interest, 22% of refrigerator purchasers are predicted to obtain the loans, with 12.8% switching from standard efficiency. At 12% interest, the predicted share is 19% with over 10% switching. These loans induce more switching than the rebates and also generate profit for the firm—a ‘‘win-win’’ situation.

LIMITATIONS

An important limitation of the analysis is the implicit assumption that only the utility offers loans on appliance purchases. In reality, many retailers allow their customers to pay for appliances over time, and customers can use their credit cards if their limit is sufficiently high. These loans are available for standard efficiency units as well as high efficiency units. The structuring of an effective utility-sponsored loan program is complicated in this context. To induce buyers to switch from standard to high efficiency units when loans are available on both, better loan terms must be offered on the high efficiency units. But would utilities want to compete with retailers by offering loans that have better terms than the retailers offer? Doing so could actually reduce the sales of high efficiency units, since retailers would have an incentive to ‘‘push’’ customers toward standard units for which only the retailer offers loans. The question also arises of whether the utility can earn money on loans that are more attractive than credit cards and the retailers’ loans. The utility would have an advantage if its cost of funds is lower than the retailers’ and credit card companies, or if the utility can assure repayment of the loan more cost-effectively. The interest rates on credit cards and retailers’ loans are fairly high, certainly above the utilities’ cost of funds. However, whether the difference represents a premium for non-payment and management, which the utility must also bear, is a critical issue. The utility might be able to enforce repayment more cost-effectively, particularly if regulators allow the utility to discontinue service to customers who do not maintain payment. However, if regulators do not allow disconnects for nonpayment of loans, then the utility is perhaps in no better position than the retailers and credit card companies in dealing with repayment.

Given these issues, what conclusions can be drawn from the analysis? In a narrow context, the conclusions are specific. Many appliance retailers do not offer credit, and many customers do not have credit cards or sufficient limits. In these cases, the analysis indicates that utility-sponsored loan programs would be effective at inducing energy efficiency and generating profits. In a broader context, where credit is generally available, the conclusions are less precise. The utility can offer loans in competition with retailers and credit cards, or can collaborate with retailers and perhaps credit card companies to offer jointly sponsored loans. Under either arrangement, the outcome depends on underlying fundamentals, such as the relative cost of funds to each party, the relative ability of each to enforce repayment, and the cost-effectiveness of their loan management. With competition, the utility can only succeed in generating profit and inducing energy-efficiency if it has an advantage on one or more of these factors. With collaboration, the ability of the utility to generate profits from the collaboration depends on the same factors, since the utility must bring to the retailers/credit card companies something of value in order for the them to be willing to collaborate. In this context, the analysis can perhaps best be taken as a signal that loans might be an avenue to generate profits and greater energy efficiency, and that attention to this potential by utilities and regulators is warranted.

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