Customers' Choice Among Retail Energy Suppliers: The Willingness-to-Pay for Service Attributes

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We examine small/medium commercial and industrial customers' choices among energy suppliers in conjoint-type experiments. The distribution of customers' willingness to pay is estimated for more than 40 attributes of suppliers, including sign-up bonuses, amount and type of renewables, billing options, bundling with other services, reductions in voltage fluctuations, and charitable contributions. These estimates provide guidance for suppliers in designing service options and to economists in anticipating the services that will be offered in competitive retail energy markets.

INTRODUCTION

Under "open access" for retail energy, customers are free to choose among suppliers of the energy commodity, with the traditional utility providing transmission and distribution (at least for now). Several states, including California, Pennsylvania and Massachusetts, currently allow open access for all customers, and many other states are moving in that direction. The outcome of this competition depends critically on customers' choice behavior. The power of competitive pressures to lower prices depends on the degree to which customers are willing to switch suppliers in response to offers of lower prices. The introduction of new products and services depend on the distribution of customers' willingness to pay for service attributes. If there is little variation in

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customers' preferences, and/or those preferences are largely satisfied by incumbents' services, then there will be little opportunity for entry by suppliers with new service attributes or for innovation by the incumbents. Conversely, with large differences in customers' preferences, with existing services not meeting the range of preferences, the opportunity for profitable new service offerings abounds.

There is only limited evidence on the factors that affect customers' choice of energy supplier. In California and Massachusetts, few mass-market customers (i.e., residential and small/medium commercial customers) have switched providers, even though open access has been available for two years in these states. However, as Train and Selting (2000) point out, there have been practically no price discounts offered by new suppliers to mass market customers in these states and, consequently, little opportunity for customers to evidence whatever price-sensitivity that they might have. In Pennsylvania, new suppliers have offered larger discounts, and customers have responded by switching in not insubstantial numbers. Switch rates as high as 20% have been observed in some areas of Pennsylvania.[1] To our knowledge, no formal estimation has been performed on the market data for open access states, presumably because of the limited variation in the attributes of the suppliers' offers.

Cai, et al. (1998), Goett (1998) and Revelt and Train (1998) have used data from conjoint experiments to examine customers' preferences regarding energy suppliers. In these experiments, each surveyed customer is presented with several hypothetical offers by energy suppliers and is asked to identify the offer that he/she would choose.[2] These experiments have the advantage of being able to include service attributes that have not been offered in real-world markets, or have not varied sufficiently in markets to allow estimation. Goett and Revelt/Train examined the type of pricing (fixed, time-of-day, and seasonal), length of contract, and type of supplier (the local utility, a company known by the customer other than the local utility, or an unknown company.) Cai et al. (1998) examined price, outages, and whether the supplier used

1. The difference among these states in the discounts that were offered seems to be due to the way that open access is structured in each state. In California, the incumbent is required to sell energy (i.e., the commodity) to mass-market customers at the price that is established by the power exchange (PX). A new supplier can offer customers a lower price only if it can consistently supply energy at a cost below the PX price; however, if it can supply energy at a cost below the PX price, then the firm would make more profit by selling to the PX rather than selling to customers at the lower price. In Massachusetts and Pennsylvania, the commodity price for the incumbents is set administratively by the regulator, with different prices for different parts of each state. The prices in Massachusetts were set sufficiently low that new suppliers seem unable to beat them, whereas the prices in Pennsylvania were set sufficiently high to engender entry by price-discounters. We are not offering an opinion on which pricing procedures are most appropriate, since there are advantages and dangers associated with each. For example, the rules in California and Massachusetts might be preventing beneficial entry, or the Pennsylvania prices might be inducing inefficient entry.

2. Cai et al. (1998) presented customers with a hypothetical offer and asked whether the customer would switch from its current provider.

renewable sources, had conservation programs, and had as many customer services as the respondent's current supplier.

These studies found substantial variation in preferences across customers. At the mean preferences, customers in the Goett and Revelt/Train studies were found (i) to evaluate time-of-day and seasonal rates as being worse than a fixed price at the average of the variable rates, (ii) to prefer not being locked into a long-term contract, and (iii) to prefer the local utility to a known company, and a known company to an unknown one. The variation in preferences around these means was found to be sufficient to sustain a variety of contracts of different lengths, entry by known companies (though perhaps not by unknown companies), time-of-use and seasonal rates for selected customers, and entry by low-cost suppliers who serve highly price-sensitive customers. Cai et al. (1998) found that the number of outages was by far the most important service attribute, followed by customer service. Renewables and conservation programs were found to be less important for most customers. However, the exact meaning of these service attributes was undefined; e.g., suppliers were described simply as having "fewer customer services" than the customer's current supplier, or having "more outages."

In the current paper, we extend the conjoint-type research of these previous studies by examining more attributes and by attempting to be more precise in our specification of the attributes. In particular, we examine customers' preferences for more than 40 potential service attributes, ranging from the extent of voltage fluctuations to whether the supplier contributes a portion of its profits to local charities. We tried to define these attributes fairly precisely, such as "fluctuations of no more than 2% in voltage for a few cycles at a time no more than 10 times during a year," and "contributes up to 2% of annual profits each year to local not-for-profit organizations." Of course, some attributes by their nature are difficult to pin-down, such that we ended up using terms that still left a degree of ambiguity.

We restrict our analysis to small and medium commercial and industrial customers. We estimate the distribution of preferences among these customers, and their willingness to pay for the various attributes. The results provide guidance to economists and regulators in anticipating and interpreting market outcomes as well as in establishing and administering market rules that serve to enhance the welfare (i.e., satisfy the preferences) of customers. The information can also assist suppliers in designing service offerings.

Our analysis uses mixed logit models, which provide a flexible specification for representing the distribution of preferences in the population and the choices of each customer. The method has been applied previously in transportation (Bhat, 1996; Brownstone and Train, 1999), recreation demand (Train, 1998), and energy (Goett, 1998, and Revelt and Train, 1998, 1999). Our analysis is complicated by the fact that the number of attributes that we examine is greater than can feasibly be included in one choice experiment. The procedure that we adopt is to conduct choice experiments for subsets, called "clusters," of attributes. Price is included in all the experiments, to serve as the link among the experiments. A mixed logit model is estimated on each cluster of attributes separately. The price variable, which is common to all clusters, allows the results in each model to be translated into willingness to pay estimates that are comparable across clusters.

The data are described in section II. The mixed logit procedure is presented in section III. Results are presented and discussed in section IV. Section V concludes.

II. DATA

The sample and instrument were designed by a team of researchers[3] under the sponsorship of the Electric Power Research Institute. A total of 1205 customers were interviewed in a phone-mail-phone format. Customers were first recruited by phone. Each customer who agreed to participate was mailed a packet of materials. This packet included a series of choice experiments. In each experiment, the attributes of four hypothetical suppliers were described. In the subsequent follow-up by phone, the interviewer asked the customer to state which of the four suppliers the customer would choose if facing the choice in the real world.

An important goal was to examine a wide variety of services and attributes that might matter to customers and that might thereby become important in markets in the future. As stated above, more than 40 attributes were included in the survey. The large number of attributes presented challenges for the design of the experiments. It was not feasible (as borne out by pre-tests) to include all of the attributes in any one choice experiment. That is, we could not describe 40 or more attributes for each of four suppliers and then ask the customer to choose among the suppliers. Customers were not able to assimilate such large amounts of detailed information. To make the choice tasks manageable, the attributes were grouped into clusters. The five clusters consisted of the following:

(A) Pricing and contract terms, including time-of-day, seasonal, and hourly rates, contract length, and sign-ups bonuses,

(B) Green energy attributes, namely, the amount and type of renewables,

3. The research approach was conceptualized by Ahmad Faruqui of EPRI and Patricia Garber who is now a principal at Primen. Other members of the research team had lead roles in research content and sample design, including David Lineweber of Primen, Lisa Wood of Hagler Bailly Services, Steve Braithwait and Dan Hansen of Christensen Associates, and Jeol Huber of Duke University. The authors conducted the estimation and contributed to the research and sample design.

(C) Customer services, including billing options, web-based information sources, and availability of service representatives,

(D) Value-added services, such as energy audits, financing for equipment purchases, warranties on new equipment, and reliability,

(E) Community presence, including donations to schools, non-profits, or children's programs, and the presence of local offices.

In each experiment, four hypothetical suppliers were described with respect to the attributes in one cluster only. For example, in the experiments for cluster (A), customers were presented with offers that differed with respect to the type of pricing (fixed, variable, etc.) and contract terms. The customer was told to consider all other attributes of the suppliers to be the same for all suppliers in the experiment. All of the experiments included price (in cents per kWh for the energy commodity) as an attribute, as well as the type of supplier (listed below.) Figure 1 gives an example of a choice experiment.

Figure 1. Example of Choice Experiment

If you had to choose one of these *four electricity supply offers,* which ONE would you choose? *(Circle one letter)*

A	B	C	D
◆ A neighboring electric company	◆ An affiliate of your local electric company	◆ A well-known energy company	◆ An unfamiliar energy company
◆ Fixed price of 4 ¢ per kWh	◆ Fixed price of 5 ¢ per kWh	◆ Fixed price of 3 ¢ per kWh	◆ Fixed price of 5 ¢ per kWh
◆ 50% renewable energy	◆ 25% renewable energy	◆ 50% renewable energy	◆ 100% renewable energy
◆ Mix of renewables, including geothermal, biomass, and solar energy	◆ Primarily wind energy sources	◆ Primarily wind energy sources	◆ Primarily wind energy sources

Customers were presented with four experiments for each cluster of attributes. That is, each customer was presented with four hypothetical suppliers whose attributes within the cluster varied and was asked to choose among them; this exercise was repeated four times for each customer. In total, each customer was presented with 20 choice experiments (four for each of the five clusters.) The levels of the attributes differed over experiments and customers to provide sufficient variation for use in estimation.

The surveyed customers were sampled through a stratified random design, using customer lists from Dunn and Bradstreet. Customers were sampled more than proportionately in the service territories of the energy companies that helped to finance the study with EPRI and less than proportionately in other areas. (The over-sampling allowed each participating energy company to obtain analysis and forecasting for their own area.) Weights were developed that are consistent with the sampling procedure, such that the weighted sample is asymptotically equivalent to a purely random sample drawn from the population of small and medium customers throughout the country. We present results for the weighted sample. Details of the sample and survey design are given by EPRI (2000).

III. MODEL

Part A of this section gives the mathematical formulation of the model, and part B discusses interpretation. We encourage readers who might (with little loss) skip part A to nevertheless read part B, since the issues regarding interpretation affect how the results are meaningfully used.

A. Specification

We use a mixed logit model (e.g., Revelt and Train, 1998) to represent the choices of customers. Each customer, labeled n, faces several choice situations, indexed by t. As explained above, each customer in our survey faced four choice experiments for each of the five clusters of attributes. In each choice situation for a given cluster of attributes, the customer faces a choice among several suppliers, indexed by i. In our survey, there were four suppliers in each choice situation. The attributes of supplier i as described to customer n in experiment t are denoted by the vector X_{nti}. The utility that customer n would obtain from supplier i in experiment t is specified as:

$$U_{nti} = \beta_n' X_{nti} + \varepsilon_{nti} \ ,$$

where β_n denotes the value that the customer places on the attributes, and ε_{nti} is an error term. The coefficients β_n vary randomly over customers, reflecting the fact that different customers have different tastes regarding suppliers' attributes.

We assume that β_n is distributed normally in the population with mean b and covariance W.[4]

The error term, ε_{nti} , captures other factors that might affect the customer's choice. We assume this term is iid extreme value. This assumption is what makes the model a mixed logit instead of another type of choice model, such as mixed or pure probit (see Brownstone and Train, 1999, for a discussion of the types of models). Importantly, McFadden and Train (2000) show that the assumption of an extreme value error term is benign: any choice model can be approximated to any degree of accuracy with a mixed logit, i.e., with a model whose final error term is iid extreme value.

The choice probabilities are derived as follows. Conditional on the customer's tastes as denoted by β_n, the probability that customer n chose supplier i in experiment t is a logit formula, since the remaining random term, ε_{nti} , is iid extreme value (McFadden, 1973):

$$L(i,t,n \mid \beta_n) = \frac{e^{\beta_n' x_{nti}}}{\sum_j e^{\beta_n' x_{ntj}}}$$

Also, since ε_{nti} is independent over experiments, the conditional probability for customer n's sequence of choices in all the experiments is the product of logit formulas:

$$P(y_n \mid \beta_n) = L(y_{n1}, 1, n) \mid \beta_n) \cdot \ldots \cdot L(y_{nT}, T, n \mid \beta_n)$$

where y_{nt} identifies the alternative that customer n chose in experiment t, and y_n is the vector $\{y_{n1}, \ldots, y_{nT}\}$ that identifies the sequence of choices.

The customer's tastes are not known, and so useable choice probabilities cannot be conditioned on β_n. The unconditional probability of the customer's choices is obtained by integrating the conditional probability over all possible values of β_n. using the population distribution of β_n :

$$P(y_n \mid b, W) = \int P(y_n \mid \beta) f(\beta \mid b, W) d\beta$$

where $f(\beta \mid b, W)$ is the normal density with mean b and covariance W.

4. Mixed logit allows any distribution for the random coefficients *bn*. In other applications, log-normal, uniform, triangular, and truncated normals have been used. Our reasons for using a normal distribution are given in section IV below.

The goal of estimation is to obtain information on the population distribution of tastes associated with each attribute of suppliers, that is, on the mean b and covariance W of tastes in the population. Estimation is complicated by the fact that the integral in P_n does not have a closed form. Its value is approximated numerically through direct simulation. The simulated probability for each customer is inserted onto the log-likelihood function, which is maximized with respect to b and W. We used Halton draws in simulation instead of random draws so as to increase the accuracy of the estimation (Bhat, 1999; Train, 1999).[5] For each model, we used 250 draws per customer.

B. Issues Regarding Interpretation

As stated above, a separate model was estimated for each cluster of attributes. The question arises of the extent to which estimates can be compared over clusters. The scale of the parameters in a random utility model like mixed logit is set by the variance of ε_{nti} – that is, by the variance of factors that are not included in the experiments.[6] Since each cluster of attributes excludes different factors, the variance of these excluded factors and hence the scale of the parameters can be expected to differ over the clusters. This means that the estimated coefficient of an attribute in one cluster cannot be meaningfully compared with the estimated coefficient of an attribute in another cluster. However, ratios of coefficients within one cluster can be meaningfully compared across clusters, since the scaling factor cancels out of the ratio. Importantly, the ratio of the coefficient of an attribute in one cluster to the price coefficient in the model for that cluster (which is the willingness to pay for that attribute) can be meaningfully compared to the ratio of the coefficient of an attribute in another cluster to the price coefficient in the model for that other cluster. Stated succinctly: estimates of willingness to pay can be compared across clusters, even though the coefficients themselves cannot.

The issue of the scale factor arises in another important way. In order to build a forecasting module that predicts market shares, the scale of

5. Halton draws are a sequence of points that divide-up, or partition, the distribution in a particular way. They provide better coverage of a distribution than random draws. They also create negative correlation in the simulation noise over observations, unlike random draws which are independent over observations. The negative correlation with Halton draws reduces the expected error over the sum of all observations, since positive simulation error for one observation tends to cancel-out the expected negative simulation error in the next observation.

6. As stated above, the error term in the utility specification, $U_{nti} = \beta_n' X_{nti} + \varepsilon_{nti}$, captures the impact of omitted factors and is assumed to follow an extreme value distribution. The variance of an extreme value term is $k = \pi^2/6$. If the true variance of omitted factors as λ, then utility is divided by $\sqrt{\lambda/k}$ such that the error term, ε_{nti}, has variance k as needed for an extreme value term. (Note that dividing utility by a constant does not affect the model since utility maximization is unaffected by the scale of utility.) The division of utility by $\sqrt{\lambda/k}$ means that all coefficients are scaled by this constant.

coefficients must be set. This scale is determined by the variance of factors that are omitted from the analysis, that is, by the variance of ε_{nti} in the real world. These factors include perceived differences among suppliers (such as customers' being concerned about the reliability even when there is no difference among suppliers), inertia, the relative effectiveness of advertising campaigns, and so on. To transform distributions of willingness to pay, which we estimate and present below, into a forecasting tool, it is customary is to calibrate against market data, using the procedures described by, for example, Brownstone et al. (2000) and Louviere et al. (2000). This calibration determines the scale of coefficients, as well as other adjustments to capture real-world issues that cannot be captured in the conjoint choice experiments. We have not undertaken this calibration. Readers who want to use the information in this article to forecast will probably want to calibrate against market data for the area in which they are planning to forecast or for the market that they consider to be most comparable.

The lack of calibration means that the implications of the distributions of willingness to pay must be delineated carefully. For example, our results indicate that 20% of customers are willing to pay no more than 0.5 cents per kWh to obtain service from their local utility than from an electric company with which they are unfamiliar. This result means that if (i) the only suppliers were the local utility and an unfamiliar electric company, (ii) the unfamiliar company charged 0.5 cents per kWh less than the local utility, and (iii) all other factors were the same for the two suppliers, then the unfamiliar company would capture 20% of the market. However, the third criterion rarely occurs in reality. Inevitably, there are other differences between the companies, whether perceived or real; information about the companies is not equally well known; and a status quo is usually in effect that inertia tends to maintain. The unfamiliar company's actual share will differ from 20% depending on the impact of these factors. The distributions of willingness to pay provide share information under the standard economic concept of all else (observed and unobserved) held constant, whereas a meaningful forecast accounts, insofar as possible, for the impacts of other differences that necessarily occur in markets.

IV. ESTIMATION RESULTS

Tables A-E give the estimated models for each cluster of attributes. There are four salient features of the specification for all of these models as follows:

(1) Price enters both linearly and in log form. We found in preliminary analysis that both forms were needed to accurately represent customers' choices. Entering price only in linear form implies that customers value a one-cent per kWh change the same, independent of the level of prices. For example, with price entering linearly, a change from 3 to 4 cents per kWh is assumed to be valued the same as a change from 6 to 7 cents per kWh. Entering price only in log form implies that customers value a given percent change in price the same,

independent of the absolute price change that the percent represents. For example, with log(price), a change from 3 to 4 cents is assumed to be valued the same as a change from 6 to 8 cents, since both represent a 33% rise. Our preliminary analysis indicated that the reality is somewhere between theses two possibilities. In particular, we found that it takes more to compensate a person for, say, a increase from 5 to 6 cents (20%) than for an increase from 10 to 11 cents (10%), but not twice as much.

The inclusion of both price and its log allows the model to represent the type of "intermediate" behavior that we observed. The willingness to pay for an attribute is calculated as $\partial U/\partial x$ divided by $-\partial U/\partial p$ —that is, the coefficient of the attribute divided by the (negative of the) derivative of utility with respect to price. In our specification, $-\partial U/\partial p = a+(c/p)$, where a and c are the magnitude of the estimated coefficients of price and log(price). The willingness to pay for an attribute is $b/(a+c/p)$, where b is the estimated coefficient of the attribute. If customers are willing to pay a fixed amount for the attribute, independent of price level, then $c=0$ and willingness to pay is b/a, which is constant. If customers are willing to pay a fixed percentage of price, then $a=0$ and willingness to pay is $(b/c)p$, and the ratio b/c is the fixed percent of price that customers are willing to pay. Behaviors in-between these two possibilities are captured by a and c both being non-zero.

(2) The price coefficients are fixed rather than varying over customers. There are several reasons for this specification. First, as discussed above, the willingness to pay for an attribute is the ratio of the attribute's coefficient to the derivative of utility with respect to price. When the price coefficients are fixed, the distribution of willingness-to-pay has the same form as the distribution of the attribute's coefficient. For example, if an attribute's coefficient is normally distributed then the willingness to pay for the attribute is also normally distributed. If the price coefficients were allowed to vary, then the willingness to pay for any attribute would be distributed as the ratio of two distributions, which is more difficult to work with. Also, choosing a distribution for the price coefficient is difficult, and the common distributions pose problems for our purposes. In particular, a normal distribution allows implausible positive price coefficients, and log-normals, which avoid incorrectly signed price coefficients, allow the price coefficient to be arbitrarily close to zero, which provides implausibly high estimates of willingness to pay (since the price coefficient enters the denominator in this calculation.) To avoid these difficulties, we have held the price coefficient fixed.[7]

7. Some applications of mixed logits allow the price coefficient to vary (e.g., Train, 1998) while other do not (Revelt and Train, 1999). The appropriate approach in any setting depends on the data and the goals of the analysis.

(3) The coefficients of the non-price attributes are specified to be normally distributed. Since the normal distribution has support on each side of zero, this specification implies that, for each attribute, there are some customers who like the attribute and others who dislike it. Estimation of the mean and standard deviation of the normal distribution determines the proportion with each kind of preference.

If an attribute is known to be appealing to all customers (or disliked by all customers), then a more appropriate specification would be a log-normal or other distribution that has support on only one side of zero, as in Train (1998), and Revelt and Train (1999). Our discussion with participants in the EPRI project suggested that, for each non-price attribute in the survey, there are customers who like and other customers who dislike the attribute. For example, monetary contributions by suppliers to schools or to non-profit organizations are seen differently by different customers. Some customers see these contributions as commendable, indicating a social conscience by the supplier. Other customers see the contributions as wasteful or as an arrogant usurping of the customer's decision on how and when to contribute. A normal distribution accounts for both of these views and allows the model to estimate the proportion of customers with each view.

(4) Correlation among customers' tastes for different attributes are captured by variable definitions rather than with covariance parameters. We restrict the random coefficients that enter the model to be independent of each other. (That is, we restrict W to be diagonal.) Important correlation is captured, then, by appropriate definition of variables. For example, suppliers might contribute to local not-for-profit organizations or buy computers for local schools. Customers who value one type of contribution are likely to also value the other type. Two variables are entered: one for whether the supplier contributes in either way, and a second one identifying that the contribution is for school computers. The coefficient of the first variable captures the value that the customer places on the supplier contributing to not-for-profit organizations. The second coefficient captures the value of contributing to school computers relative to not-for-profit organizations. (The sum of the two coefficients gives the value of contributions to school computers relative to no contributions). Since the coefficients are normally distributed, the model allows some customers to value school-computer contributions more than contributions to not-for-profit organizations, while others have the opposite preferences.[8]

8. Other applications of mixed logit have estimated off-diagonal elements of the covariance matrix (e.g., Train, 1998, and Revelt and Train, 1998.) In principle either approach could be used in any situation. The variable definition approach is usually easier when only a few correlations are being estimated, such that the covariance matrix would have many elements constrained to zero.

In the paragraphs below, we discuss some of the salient findings. However, the tables provide far more information than we discuss. Readers who are interested in particular attributes can use the information in Tables A-E to determine the estimated distribution of coefficients and willingness to pay for those attributes. For example, it is often useful to determine the portion of customers who are willing to pay more for a service attribute than it costs the supplier to provide the attribute. The information in Tables A-E can be used to calculate, for any attribute, the share of customers whose willingness to pay for the attribute exceeds a specified amount.

Price. As stated above, price is given in cents per kWh and is for the energy itself (which is what the customer is buying from the supplier), exclusive of transmission, distribution, and other charges. Also, price enters both linearly and in log form, so as to account for the observed behavior under which customers respond to price differences differently depending on the level of price. In the experiments for attribute clusters B-E, price is always a fixed price. In the cluster A experiments, rate options are included under which prices vary by time-of-day, seasonally, or hourly. In these experiments, the average price under the schedule enters the model, with the average calculated based on expected load shape for each customer. Other variables capture variations around this average.

Consider the estimated price coefficients in the model for cluster A; the results for the other models are similar. At the estimated coefficients, $\partial U/\partial p = -(0.633 + 1.346/p)$. Customers consider a marginal price increase to be more onerous when price is low than when price is high. For example, in discrete terms, a rise from 3 to 4 cents is viewed as being worse than a rise from 6 to 7 cents. However, customers do not go so far as to consider price changes in percentage terms; that is, they do not consider equal percent increases to be equally onerous. An increase from 3 to 4 c (which is 33%) is considered less onerous than an increase from 6 to 8 c (also 33%.)

In calculating the willingness to pay for an attribute, the attribute's coefficient is divided by $-\partial U/\partial p$. The tables provide figures for the willingness to pay for each attribute when price is 5 cents per kWh. The estimated nonlinearity in $\partial U/\partial p$ implies that willingness to pay for any attribute in Table A is 17% lower when price is 3c than at a price of 5c, and is 15% higher when price is 9c than at a price of 5c. Analogous ranges are obtained for the attributes in Tables B-E.

Cluster A: Pricing/Discount Choices

Variable	param	estimate	t-stat	wtp@5	% > 0
Average or "expected" price, cents/kWh	value	-0.63296	7.83		
Natural log of price	value	-1.34608	3.74		
1 if rate is seasonal, 0 otherwise	mean	-0.75312	4.19	-0.83	14%
	st dev	0.69606	2.94	0.77	
Difference between summer and winter prices (0 for non-seasonal rates)	mean	0.01127	0.25	0.01	54%
	st dev	0.12348	1.55	0.14	
1 if rate is time-of-day, 0 otherwise	mean	-1.23676	4.64	-1.37	12%
	st dev	1.05660	4.19	1.17	
Difference between daily on-peak and off-peak price (0 for non-TOD rates)	mean	-0.03229	0.45	-0.04	41%
	st dev	0.14792	0.98	0.16	
1 if rate is hourly, 0 otherwise	mean	-3.53050	14.19	-3.91	4%
	st dev	1.99551	9.36	2.21	
1 if contract required, 0 otherwise	mean	0.07789	0.69	0.09	54%
	st dev	0.83456	4.00	0.93	
Length of contract (1, 2 or 3 yrs)	mean	-0.32126	5.84	-0.36	29%
	st dev	0.59285	10.26	0.66	
1 if sign-up benefit is "a check for $50 right away", 0 otherwise	mean	-0.15516	1.62	-0.17	17%
	st dev	0.16079	0.67	0.18	
1 if sign-up benefit is "a check for $100 after one year with provider", 0 otherwise	mean	0.08824	0.91	0.10	59%
	st dev	0.38641	1.41	0.43	
1 if sign-up benefit is "a $100 coupon for energy efficient products", 0 otherwise	mean	-0.04219	0.49	-0.05	9%
	st dev	0.03083	0.41	0.03	
1 if electricity supplier is "an affiliate of your local electric company", 0 otherwise	mean	-0.56327	4.10	-0.62	24%
	st dev	0.78141	3.39	0.87	
1 if electricity supplier is "a neighboring electric company", 0 otherwise	mean	-1.17247	7.19	-1.30	8%
	st dev	0.84246	3.86	0.93	
1 if electricity supplier is "a well-known energy company", 0 otherwise	mean	-0.55772	3.78	-0.62	10%
	st dev	0.42630	1.01	0.47	
1 if electricity supplier is "a well-known non-energy company", 0 otherwise	mean	-1.23231	6.91	-1.37	10%
	st dev	0.96515	4.70	1.07	
1 if electricity supplier is "an unfamiliar energy company", 0 otherwise	mean	-2.11213	9.38	-2.34	14%
	st dev	1.97534	9.60	2.19	

Supplier type. The choice experiments included six types of suppliers, identified to respondents as: "your local electric company," "an affiliate of your local electric company," "a neighboring electric company," "a well-known energy company," "a well-known non-energy company," and "an unfamiliar energy company." In the models, "your local electric company" is taken as the base, such that the coefficients of the variables that identify the other types reflect the value that customers place on each type of supplier relative to the local electric company.

The average coefficients imply that, on average, customers prefer their local company to any other type. The second best is the affiliate or a well-known energy company, which are viewed about the same. Next is a neighboring electric company and a well-known non-energy company, which are viewed similarly. Worst is an unfamiliar energy company. Interestingly, a company that specializes in energy but is otherwise unfamiliar to customers is viewed as being worse, by the average preferences, than a company that does not specialize in energy but is familiar to customers. This result might imply that companies like the telecommunications carriers, or even Sears and Home Depot, might be more successful than new energy companies like Enron.

Customers differ in their attitudes toward each type of company. The estimated standard deviations allow us to calculate the share of customers that prefer each type of company to the local utility (and vice versa.) As indicated in the last column of Table A, fourteen percent of customers prefer an unfamiliar energy company to the local utility. These customers might have had a bad experience in the past with their local utility, or have some other reason to want to leave the local company. Importantly, the share is probably large enough for an unknown energy company to enter successfully, provided it can identify and market itself to these customers. On the other hand, the share might not be large enough to be divided up by several unfamiliar energy suppliers.

On average, customers are willing to pay 0.62 cents more per kWh to obtain service from their local company instead of from the affiliate or a well-known energy company. (We give these figures to two decimal places to allow the reader to see the corresponding figure in the table; obviously, the results are not meant to be considered as being this precise, given the standard error on the estimates.) Customers are willing to pay, on average, 1.30c more for the local company compared to a neighboring electric company, 1.37c more compared to a well-known non-energy company, and 2.34c extra compared to an unfamiliar energy company. These average willingness to pay figures need to be viewed appropriately. They do not mean that, for example, an unfamiliar energy company would need to offer a 2.34c discount in order enter the market successfully. Rather, the estimates imply that an unfamiliar energy company would obtain the same market share as the local utility if it offered a 2.34c lower price and all of its other attributes were the same. Few entrants have such optimistic expectations of potential market share. With a smaller discount, the entrant's market share would be lower than the local utility, but still perhaps sufficient to justify entry. The estimated standard deviation of the coefficient implies, for example, that an unfamiliar electricity company that offered a half-cent price reduction (off of a price of 5c) would be preferred to the local electric company by 20% of customers, provided of course that all other attributes were seen as being the same. Similar information can be calculated for other types of suppliers.

Sign-up bonuses. Three kinds of bonuses were included in the choice experiments: a $50 check at the time of sign-up, a $100 check after staying with the supplier for one year, and a coupon given at sign-up worth $100 towards the purchase of energy equipment. The estimated means and standard deviations for these bonuses are all insignificant, and the hypothesis that customers do not value them at all cannot be rejected. Considering the point estimates, the vast majority of customers seem actually to dislike the offer of a $50 sign-up check or a $100 coupon. Only 17% and 9%, respectively, of customers consider these offers to provide a positive inducement. This result perhaps reflects the small size of the bonuses relative to customers' bills, such that customers are disdainful of the offer. It also perhaps reflects customers' negative experience with similar inducements by long-distance telecommunications carriers.

The bonus of a $100 check after a year is viewed as a slightly positive inducement for most customers. The bonus is worth less than one-tenth of a cent per kWh on average, which is small compared to the impact of other attributes. However, this willingness to pay might be sufficiently high for suppliers to consider this option. For example, for a customer with 1000 kWh consumption per month, a 1/10 c higher price translates into $100 over 10 months, which repays the bonus. Of course, this discussion is highly speculative, since the estimated mean and standard deviation are both insignificant. Perhaps the most reasonable conclusion regarding sign-up bonuses is that our analysis indicates that customers do not seem to respond much to them.

Contracts. Four contract options were included in the experiments: no contract, or a contract of 1, 2 or 3 years. Under each of the contracts, the customer was required to pay a penalty equal to its most recent monthly bill if the customer changed suppliers during the contract period. The contract also obligates the supplier to charge the specified price during this period. The contract therefore constrains the customer but also provides the customer insurance against possible price increases. Customers can place either a positive or negative value on having a contract, depending on the relative importance of these factors.

Two variables enter the model regarding contracts: a dummy for whether a contract is required and a variable for the length of the contract in years. The value of a one-year contract is the sum of the two coefficients, while the additional value for each additional year is captured by the second coefficient. This specification induces correlation in the value that customers place on one, two, and three year contracts: customers who have a higher-than-average value for one year contracts will tend to also value two and three year contracts more than average.

The estimates indicate that most customers dislike being locked into a contract more than they value the price guarantee that the contract provides. Nevertheless, there is sufficient variation over customers in their attitudes toward contracts to sustain a variety of contract lengths in a competitive market. The average value of a one-year contract is negative, meaning that on average customers would rather not have a contract than have a one-year contract. A supplier would need to discount its price by 0.27 cents per kWh (i.e., 0.09-0.36) in order to compensate for this negative average valuation. The majority of customers (59%) prefer no contract to a one-year contract. Two- and three-year contracts are considered even more onerous by most customers. On average, customers are willing to pay 0.63 cent per kWh and 0.99 cent per kWh to avoid two and three year contracts, relative to no contract.

Despite the average preferences, a large share of customers do indeed prefer having a contract. As indicated above, 41% prefer a one-year contract to no contract, and 32% and 25% prefer a two- and three-year contract to none. These customers are willing to pay extra in return for a guaranteed price. These customers are a marketing opportunity for suppliers that are able to manage the risk.

Variable rates. The choice experiments included seasonal, time-of-day, and hourly rates in addition to fixed (non-variable) rates. The average price under variable rates was calculated for each customer based on expected load profiles. The model included this average price as well as dummy variables indicating the type of variable rate.

For time-of-use and seasonal rates, the model included the difference between the highest and lowest rates (i.e., the difference between summer and winter rates under seasonal prices and the difference between on- and off-peak prices under time-of-day pricing.) These difference variables obtain insignificant estimates for both the mean and standard deviations of their coefficients. The hypothesis cannot be rejected that all customers ignore the amount of variation in prices around the average price. In contrast, the dummy variables that identify the type of rate schedule enter with highly significant means and standard deviations, with the estimated means being negative. These results in combination suggest that customers have a negative reaction to these rates, without the reaction being related directly to the amount of variation in the prices.

Hourly rates are considered worse, on average, than time-of-day rates; time-of-day rates are considered worse than seasonal rates; and seasonal rates are considered worse than fixed rates. The average price under hourly rates would need to be nearly 3.91 cents per kWh lower than under a fixed price rate in order to compensate for the average preference against hourly rates. For time-of-day and seasonal rates, the comparable compensation is 1.4 and 0.8 cents per kWh. The estimated standard deviations are sufficiently small that fewer than

14% of customers prefer a seasonal rate to a fixed rate when the average price is the same. Comparable figures for customers preferring time-of-use rates and hourly rates are 12% and 4%. Of course, shares of 12% and 14% (and maybe even 4%) are still sufficiently large to justify offering these rates as options to customers.

Renewables. Table B relates to renewable energy sources. In the choice experiments, the customer was told the percentage of the suppliers' energy that was generated through renewable sources (ranging from none to 100%). The customer was also told the type of renewable source, with the possibilities being "primarily from hydro," "primarily from wind," and "primarily by a mix of renewables including geothermal, biomass (landfill gas), and solar. "

Cluster B: Green Energy Choices

variable	param	estimate	t-stat	wtp@5	%>0
Fixed price of electricity, cents/kWh	value	-0.51264	7.75		
Natural log of price	value	-2.11346	6.78		
1 if "primarily hydro energy sources", 0 otherwise	mean	1.19477	7.44	1.28	91%
	st dev	0.89893	4.65	0.96	
1 if "primarily wind energy sources", 0 otherwise	mean	0.67863	4.19	0.73	73%
	st dev	1.12271	7.64	1.20	
1 if "mix of renewables", 0 otherwise	mean	1.23055	7.27	1.32	91%
	st dev	0.89888	4.65	0.96	
Percent renewable (continuous variable with values of 0, .25, .75, and 1)	mean	0.67112	4.15	0.72	60%
	st dev	2.70272	11.76	2.89	
1 if electricity supplier is "an affiliate of your local electric company", 0 otherwise	mean	-0.64314	4.98	-0.69	19%
	st dev	0.72555	1.86	0.78	
1 if electricity supplier is "a neighboring electric company", 0 otherwise	mean	-1.11644	7.79	-1.19	11%
	st dev	0.91533	3.40	0.98	
1 if electricity supplier is "a well-known energy company", 0 otherwise	mean	-0.67635	4.88	-0.72	3%
	st dev	0.34989	0.34	0.37	
1 if electricity supplier is "a well-known non-energy company", 0 otherwise	mean	-1.24005	8.20	-1.33	10%
	st dev	0.95812	4.97	1.02	
1 if electricity supplier is "an unfamiliar energy company", 0 otherwise	mean	-2.17879	10.50	-2.33	7%
	st dev	1.47929	6.73	1.58	

The estimates indicate that the majority of customers prefer hydro or a mix of sources to wind. However, preferences are diverse, with 36% preferring wind to hydro. Suppliers with different mixes of renewable sources can find sufficient customers for each type without difficulty.

The amount that customers are willing to pay is highly non-linear in the percent of energy that is generated with renewables. For hydro, customers, on average, are willing to pay 1.46 cents per kWh (1.28 + 0.72/4) extra for a supplier that has 25% hydro power relative to a supplier with no renewables, and yet are willing to pay only 0.18c (0.72/4) extra for a supplier that has 50% hydro than one that has 25% hydro. These estimates suggest that customers are more concerned about the concept of renewables than the actual impact of the use of renewables on the environment. This result is consistent with contingent valuation studies of environmental damage that have found that the amount that customers are willing to pay to prevent environmental damage (such as saving ducks from being oil slicked) is independent of the amount of damage that is prevented (e.g., the number of ducks that are saved by the prevention efforts); see, e.g., Desvousges et al. (1993) and Boyle et al. (1994).

The estimates suggest that customers are willing to pay, on average, 2.0 cents per kWh (1.28+0.72) for a supplier that uses 100% hydro than for a supplier with no renewable sources, and 1.45c more for 100% wind than for no renewables. Given the estimated standard deviations, some customers are willing to pay considerably more than these average amounts. The results suggest that customers are vitally concerned about the renewables.

Personal Service. Table C includes various attributes relating to customer service. Four levels or types of interaction with the supplier were specified:

- A voice response system answers when the customer calls.
- A real person answers the telephone when the customer calls.
- The customer's service representative answers the telephone and can address the customer's concerns "on the spot."
- The customer's service representative answers the telephone, visits the customer on site, and can address the customer's concerns "on the spot."

Three variables enter the model, designed in a way that establishes correlation in the value for these three levels of service. The first variable indicates that the customer deals with a person rather than a voice response system and indicates any of the levels beyond the first (voice system) level. The second and third variables indicate, respectively, whether the service "rep" answers the phone (level 3) and whether the service "rep" makes on-site visits (level 4).

Cluster C: Customer Service Choices					
variable	param	estimate	t-stat	wtp@5	%>0
Fixed price of electricity, cents/kWh	value	-0.49142	6.12		
Natural log of price	value	-2.68231	7.00		
1 if "deal with real person (by telephone or on site)", 0 otherwise	mean	1.39237	10.32	1.35	85%
	st dev	1.37104	7.91	1.33	
1 if "direct telephone access to your service representative", 0 otherwise	mean	-0.08546	0.98	-0.08	43%
	st dev	0.48364	1.57	0.47	
1 if "on-site visits from your service representative", 0 otherwise	mean	-0.62742	5.00	-0.61	26%
	st dev	0.96694	5.86	0.94	
1 if "choice of payment options", 0 otherwise	mean	0.22894	2.56	0.22	59%
	st dev	1.03371	7.74	1.01	
1 if "customized billing", 0 otherwise	mean	0.38788	4.20	0.38	80%
	st dev	0.46399	2.01	0.45	
1 if "consolidated billing across utility services", 0 otherwise	mean	0.25426	2.30	0.25	60%
	st dev	1.00175	5.27	0.97	
1 if "aggregation of bills", 0 otherwise	mean	0.19677	1.73	0.19	62%
	st dev	0.62986	2.57	0.61	
1 if supplier has any type of website, 0 otherwise	mean	0.43724	3.32	0.43	61%
	st dev	1.55162	9.76	1.51	
1 if "energy use notification website", 0 otherwise	mean	-0.32318	3.29	-0.31	0%
	st dev	0.11155	1.09	0.11	
1 if "energy transactions website", 0 otherwise	mean	-0.26285	2.38	-0.26	24%
	st dev	0.37026	1.00	0.36	
1 if electricity supplier is "an affiliate of your local electric company", 0 otherwise	mean	-0.60969	4.27	-0.59	13%
	st dev	0.55268	1.94	0.54	
1 if electricity supplier is "a neighboring electric company", 0 otherwise	mean	-0.89720	5.41	-0.87	21%
	st dev	1.11243	5.94	1.08	
1 if electricity supplier is "a well-known energy company", 0 otherwise	mean	-0.75000	4.98	-0.73	14%
	st dev	0.70366	2.15	0.68	
1 if electricity supplier is "a well-known non-energy company", 0 otherwise	mean	-1.19421	7.14	-1.16	13%
	st dev	1.06899	3.54	1.04	
1 if electricity supplier is "an unfamiliar energy company", 0 otherwise	mean	-2.12079	10.51	-2.06	5%
	st dev	1.27892	5.95	1.24	