Chapter 3

Factors Affecting Firms' Decisions to Participate in NYISO's Electricity Demand Response Programs and Firms' Valuation of Program Features

In Chapter 1 of this report, we have documented the costs of EDRP and DADRP and have provided estimates of the effects of both programs on various aspects of the New York electricity markets. In the process, we were also able to identify the shapes of the short-run electricity supply curves for NYISO pricing zones across the State.

In Chapter 2, the nature of the load response of existing program participants to higher electricity prices or other program payments for load curtailments was discussed in detail.

Estimates of these price effects and program benefits help determine the value of PRL programs to current participants, other customers, LSE's, and the NYISO. Indirectly, these results also have some implications for market participation and for recruiting customers into the programs. But, they do not address these important issues head on. Part of the difficulty lies in the fact that features other than price or payment can have profound effects on customer participation and response. Moreover, those program features that generate the largest benefits system-wide or market-wide may not be the same as those that are of most value to individual customers.

Therefore, from the standpoint of customer recruitment in the future, it is important to understand better how changes in current program designs are likely to affect customer participation rates. It has been established here and elsewhere that different types of customers have differential capacities to respond to price or other incentives for curtailment (see Chapter 2); thus, the types of customers recruited does make a difference. To establish these relationships, we need to study the characteristics of participants in order to find patterns that lead to identifying good candidates (“revealed” preferences), and evaluate customers’ responses to hypothetical programs (“stated” preferences) to find out how customers value alternative program designs.

Through a statistical analysis of the data collected in Part I of the Customer Acceptance Survey, this chapter documents those customer characteristics, and actions by New York state agencies, market participants, and other institutions that affected a firm’s decision to participate or not to participate in NYISO’s EDRP this past summer.[1] This analysis focuses on information from Part I of the survey, and it represents an analysis of the “revealed” preferences of customers regarding their decisions to participate in EDRP. Analysis of “revealed” preferences is the mainstay of much economic analysis of consumer or firm behavior (McFadden, 2001).

Part II of the Customer Acceptance Survey involved a “conjoint” survey designed to solicit customers’ “stated” (in contrast to “revealed”) preferences for different program characteristics or features. These are “stated” preferences because customers are asked to make choices amongst contingent or hypothetical options regarding new products or programs.[2] To place relative values on different program features, a second discrete

[1] Too few DADRP participants responded to the survey to conduct a parallel analysis for participation in the day-ahead program. Moreover, all participants in DADRP that responded to the questionnaire were also in EDRP. Therefore, we could not disentangle the impact of customer characteristics on the choice between the two programs.

[2] “Stated” preference models are an outgrowth of the “conjoint” methods developed in the 1970’s. A good summary of the methods and applications of conjoint analysis is given by Louviere (1988). These and more recent advances in “stated” preference models have been used extensively in marketing and transportation research, and more recently to examine preferences and values for public or environmental goods not traded in organized markets. See for example, McFadden (2001), Louviere (1988), and Hanley, *et al*. (1998) for discussions of the evolution of these methods. Goett, *et al*. (2000) in an unpublished paper also try to value service attributes from retail energy suppliers. Other applications include studies of how customers value electric service features by Long, *et al.*, (1998), and Wood, *et al*., (2000).

choice model was estimated using this “conjoint” survey information. The model was also used to predict choices among alternative features and feature levels. In addition to assigning values to alternative program features, the results of this second model can be used to forecast the odds of program participation due to changes in program design. These results provide a measure of the relative contribution of features to the value of participation, and therefore are a means by which to assess alternative program designs.

Each of the two models is discussed separately below. The theoretical underpinnings are presented along with a discussion of estimation procedures. A summary of some of the data used in each analysis is provided along with the estimated results and their interpretations and implications for policy.

Modeling the Decision to Participate in EDRP

Before specifying the empirical model of the decision to participate in EDRP, we must outline a conceptual model and discuss some issues in estimation.

The Binary Choice Model

The binary choice model is a special case of a broader set of discrete choice models that are most often cast in the form of an index function or random utility model (Greene, 1990, p. 673). From a statistical standpoint, the discrete choice is assumed to reflect some theoretically consistent underlying model of behavior. In the binary choice case, the choice, for example, could be for a consumer or firm to make a large purchase, or choose to participate in some kind of program. According to the underlying theory, the choice is based on the individual’s or firm’s marginal benefit—marginal cost calculation. If the net benefits of making the purchase or participating in the program (e.g., net consumer utility or a firm's net income or utility of net income), are positive, then the purchase is assumed to be made or the decision is made to join the program.

The binary choice modeling problem is a challenging one because, regardless of the consumer or firm's decision, we can never actually observe the marginal benefit. In economic terms this marginal benefit is embodied in the notion of a consumer or firm's utility, which is difficult, if not impossible to quantifiable in any meaningful way. Therefore, it is necessary to model the difference between the marginal benefit and the marginal cost of the decision as an unobserved variable, call it Y^*. Statistically, let us assume that we can represent net benefit as:

(1) $Y^* = \beta' X + \varepsilon,$

where the error term ε has a logistic distribution with zero mean and unit variance. The individual or firm characteristics, program characteristics, and other factors that affect the decision are captured in a vector X, and β is a vector of parameters to be estimated. The estimated parameters quantify the effects of the intensity or level of the variables in X on the net benefits Y^*.

Since we never observe the benefit of the decision, Y^*, we cannot estimate this function directly. Rather, we only observe the actual decision, Y. Based on the supporting theory, we know that:

(2) $Y = 1$ if $Y^* > 0$, decision to consume or take action is made because the net benefit is positive; or

(3) $Y = 0$ if $Y^* < 0$, decision not to consume or not to take action is made because the net benefit is negative.

In this formulation, the function, $\beta'X$, is often called the index function.[3]

The Logit Formulation

Given this index function, the probability that Y = 1 is:

$$\text{(4)} \qquad \text{Prob}[\, Y^* > 0 \,] = \text{Prob}[\, \beta'X + \varepsilon > 0 \,]$$

$$= \text{Prob}[\, \varepsilon > -\beta'X \,].$$

Further, if the probability distribution is symmetric, as is the case for the logistic model, the probability statement,

$$\text{(5)} \qquad \text{Prob}[\, Y^* > 0 \,] = \text{Prob}[\, \varepsilon < \beta'X \,]$$

$$= F(\beta'X),$$

provides a structural model of the probability of the choice.

To appreciate the logit model fully, Allison (1999) argues that it is helpful to place it into context with the notion of odds and odds ratios as a means to quantify the chances of an event occurring, rather than in terms of the event's probability. The probability of an event occurring is bounded between zero and one. In contrast, the notion of odds is one used in many games of chance—the odds of an event is the ratio of the expected number of times an event will occur to the number of times it is expected not to occur. The simple relationship between odds (O) and probabilities (p) is:

[3] Given that the dependent variable, Y, in the regression implied by this model can take on values of only zero or unity, it is easy to show that two of the five assumptions underlying the standard regression model are violated. Allison (1999) demonstrates these difficulties in an especially transparent way. He shows that while the expected value of the error term, ε, remains zero and the covariance of the error terms remains zero, the model is no longer homoscedastic. That is, the variance must differ by observation, and it varies as a function of the vector X. Further, the error term is no longer normally distributed. For these reasons, ordinary least squares (OLS) estimators of the coefficients are no longer *efficient*, and alternative estimation methods can yield smaller estimates of the standard errors of the coefficients. Further, the expected value of the estimators may not be equal to the true parameter values, the point estimates may be biased, in either an upward or downward direction.

(6) $O = p / (1 - p)$ = [probability of event] / [1 – probability of event].

Alternatively,

(7) $p = O / [1 + O]$.

Thus, if the odds are less than 1, the probability of the event is less than 0.5.

Because of this simple relationship between odds and probability, one can always derive one from the other, and thus the probability model above can be couched in either way. The major advantage for using the odds (or the odds ratio) in comparing the likelihood of two events is that neither the odds of one event nor the odds ratio between two events occurring is bounded between zero and one. Thus, by transforming the probability to an odds and then taking its logarithm, we can remove both the upper and lower bound on the variable of interest. To form the new model, we transform the model in equation (5) by writing the log-odds as a linear function of the explanatory variables, X. Thus, for an individual I, we can now specify the odds of making a choice with probability p_i:

(8) $\log [p_i / (1 - p_i)] = \beta' X_i$

Combining the results from equations (7) and (8), we can solve for p_i:

(9) $p_i = [e^{\beta' Xi}] / [1 + e^{\beta' Xi}]$.

This model is particularly convenient because no matter what values X_i takes on, and no matter what the estimates of β' turn out to be, the estimated value of p_i will always lie on the closed interval [0,1], as it should.

We can also calculate the effect of a marginal change in X_i on p_i as:

(10) $\partial p_i / \partial X_i = \beta_i \, p_i (1-p_i)$.

Thus, the effect of a marginal change in X_i is not constant; it depends on the initial value of p_i.

Model Estimation

Since this binary choice model discussed above inherently has a dichotomous dependent variable (e.g. takes on either a value of 0 or 1), it is only possible to use ordinary least squares (OLS) or weighted least squares (WLS) to estimate the coefficients of the model if the data are collected for naturally occurring groups (e.g., observations for a sample of firms on the probability that an employee is a full-time worker). In this case, one can form the odds ratio directly by calculating each firm's employees as a percentage of all employed. In this way, the model, equation (8), can be estimated directly by OLS, and WLS could be used to correct for heteroscedasticity if need be.

In the case where data are available for individual firms or consumers, the odds ratio is not directly observable, and the only available estimation strategy is the maximum likelihood method, which assigns estimates to the parameters that, if true, would maximize the probability of observing the choices that were actually observed.[4] The ML method involves two steps: 1) construct the likelihood function—the expression for the probability of the data as a function of the model's unknown parameters, and 2) estimate parameter values—typically through an iterative numerical method—that maximize the value of the likelihood function. In the application to follow, these calculations were performed using PROC LOGISTIC in SAS.

[4] Maximum Likelihood estimators are used widely because of their good large sample properties (Allison, 1999). Most econometric texts (e.g. Greene, 1990, and Maddala, 1983) discuss these properties, and under quite general conditions, ML estimators are consistent, asymptotically efficient, and asymptotically normal.

The Empirical Specification of the Decision Model of EDRP Participation

The data used to specify this model empirically comes from Part I of the Consumer Acceptance Survey administered to New York electricity customers by Neenan Associates as part of the evaluation of NYISO's price responsive load programs. There were a total of 111 responses to the survey, which asked customers to provide, among other things, information about their participation in PRL programs, how they learned about the programs, their understanding of the programs, and characteristics about their business operations that might be related to their decision to participate in either EDRP or DADRP.[5] A complete description of the survey methodology and a summary of the descriptive data for all respondents is included in Chapter 4 below.

Of the 111 respondents, 53 are participants in EDRP; 16 of them were also enrolled in DADRP. The remaining 58 respondents are in neither program. They represent the population of customers contacted about PRL participation in 2001 but chose not to participate. As with all surveys of this kind, some respondents fail to answer one or more of the questions, or some answers, for one reason or another, are unusable. After eliminating the unusable responses, there were a total of 76 customers on which to base the analysis; 48 of them are EDRP participants, while the remaining 28 customers are not currently in EDRP.

In specifying the empirical model, we classified factors affecting participation into five general categories: a) the customer's understanding about the features of the program; b) the customer's load profile; c) the nature of the firm's production processes; d) past experience with load management programs; and e) the usefulness of the information they received about the program prior to their decision to join. This categorization resulted from preliminary analysis of the data. There are a number of questions in the survey that are related to each of these categories, and a number of models were estimated using a small number of variables to represent each of these categories. Some of the several variables within each category were understandably correlated with one another. In these cases, as in other types of regression analysis, it was impossible to isolate the separate contributions of each of these variables on the EDRP participation decision. For this reason, the final model specification included only one variable in each of the five categories.

The final model specification is given by:

(11) $\log [p_i / (1 - p_i)] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5$

where

$[p_i / (1 - p_i)]$ = the odds of the firm's decision to participate in the EDRP;

X_1 = Understanding of the EDRP notice (can take on a value of 1 through 6, with a 1 reflecting no understanding and a 6 reflecting complete understanding);

X_2 =1 if the firm's peak electricity use is between 12 noon and 4pm, and 0 otherwise;

X_3 = the number of production shifts during a normal day;

X_4 = 1 if the firm has previously participated in an LSE's load management program, and 0 otherwise; and

X_5 = 1 if the customer viewed the information received about EDRP to be very useful, and 0 otherwise.

A summary of these variables for each group of customers—the EDRP participants and those not in EDRP--is included in Table 3.1. Since four of the variables in the model are categorical variables, the data for these variables in Table 3.1 are counts

[5] The survey is included in Volume II of the report.

of the number of customers in each customer group for which the categorical variable is assigned a "one". In the bottom of the table, we report the number of customers reporting from zero to four production shifts and the average rating for understanding EDRP notice. Nearly a third of the non-participants had been previously enrolled in an LSE's load management program, and the level of understanding of the EDRP notice procedures was nearly as high for the non-participants (4.46) as for the participants (5.2). It is also perhaps not too surprising that just over 50% of participants have their peak electricity consumption during the afternoon period, between noon and 4pm, and that they also in general operated more production shifts than did non-participants.

The Results

The estimated binary choice model is presented in Table 3.2. Overall, the model performed well. The three alternative joint hypothesis tests that all β_i (the coefficients on the explanatory variables X_i) are jointly zero are rejected at very high levels of significance. The results of these statistical tests are provided in the lower right hand corner of Table 3.2. Further, relatively small standard errors on the coefficients and large χ^2 statistics imply the hypothesis tests of the individual coefficients being zero are also rejected convincingly. In all but one case, the significance levels are well inside the 5% level, and even for the remaining variable, "EDRP information very useful", the significance level is 11%, very near the often used 10% level. Finally, the estimated model correctly predicts EDRP participation or non-participation for nearly 85% of the customers in the sample (the bottom left-hand corner of Table 3.2).

In contrast to most OLS regression coefficients, the coefficients in the logistic regression (the values listed in the second column of Table 3.2 as "estimate") are a bit more difficult to interpret. Based on equation (10) we know if $\beta_i > 0$, then a positive change in the associated variable will increase the probability of EDRP participation, while a $\beta_i < 0$ implies that a positive change in the variable will reduce the probability of participation. From this, it also follows directly that if $\beta_i > 0$, then a positive change in the associated variable will increase the odds of participation, and the reverse is true if $\beta_i < 0$.

The most useful way to interpret these coefficients of the logistic regression is found in equation (8). By taking the exponential (e.g. raising e, the base of the natural logarithm, to the power equal to the coefficient), we transform them into marginal odds ratios. These results, provided in Table 3.2 in the column labeled "Odds Ratio Point Estimate", correspond to the "odds ratios", the *ceteris paribus* odds of program participation for a firm with those particular characteristics or variable values relative to those firms not having that particular characteristic or a different value for the relevant variable.

Using this interpretation, the results support statements about the effects of these characteristics and variables on the odds of program participation. For example, firms with peak electricity usage during the afternoon are 3.57 times as likely to participate in EDRP as are other firms. Similarly, firms with prior experience in an LSE's load management program are 3.37 times more likely to participate. Further, firms with an additional production shift are twice as likely to participate, *ceteris paribus,* than those firms with one fewer production shifts.[6]

[6] In any model such as this, the confidence interval on the odds ratio (given in Table 3.1 as the 95% confidence limits) is necessarily larger than it is on the log-odds ratio. As a result, the confidence intervals associated with these point estimates of these odds spans unity for the "shifts" variable and the "EDRP-information" variable. This means that for some points in these confidence intervals the marginal probability of participation changes from below ½ to above ½.

Given these results, some of these variables provide markers (e.g. characteristics of firms) that can be used to identify good candidate firms for participation in EDRP. The number of production shifts, nature of electricity use, and prior experience are clearly in this category. The results also suggest that efforts to educate customers on how to reduce load may be nearly as helpful as prior experience in previous load management programs, because the odds ratio for the variable "understand notice" (2.30) is two-thirds the value of the odds ratio on "prior experience" (3.37). Finally, for firms that found the information they received about EDRP very useful, the odds of participation were only 3 in 10. On the surface this may sound counter intuitive, but there is a good explanation. This result suggests that if initial information about load management programs is effective, then customers can make informed, correct decisions—even if the decision is not to sign up. Thus, if early efforts are made to educate customers effectively about these types of programs, firms will sort themselves into those who find no value in the program and those who see some value and should be recruited seriously. Early efforts to "get the word out" about programs in an effective way will help LSEs and others target their scarce resources in recruiting customers, in that it reduces transactions costs associated with education, without imparting a competitive bias to any LSE or CSP offering PRL service.

Modeling Customers' "Stated" Preferences for PRL Program Features

The modeling of the "stated" preferences of customers for PRL program features can also be accomplished within a random utility formulation. This was facilitated in Part

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Thus, the interpretation of the odds ratio changes somewhat, but in principle, the probability of participation changes continuously across the confidence intervals for any of the variables. Thus, despite this slightly different interpretation of these two variables, it is really no different than the

II of the Customer Acceptance Survey by having respondents select the best choice from among four PRL programs, with different values for five program features, and a “no program” alternative.[7] There was twenty such choice sets survey participants were asked their opinion on. Accordingly, we model this choice situation as though the i^{th} customer is faced with J choices, and the utility of the choice j is given by:

(12) $U_{ij} = \beta' Z_{ij} + \varepsilon_{ij}$.

where

U_{ij} = the utility of customer i making choice j;

Z_{ij} = is a vector of program features and/or customer characteristics;

β' = vector of parameters to be estimated; and

ε_{ij} = an error term.

If the customer chooses program j, then it is assumed that U_{ij} is the maximum of the utilities for all the J alternatives. The statistical model is driven by the probability that choice j is made:

(13) Prob $[U_{ij} > U_{ik}]$ for all $k \neq j$.

This indicates the probability that the utility of choice j for individual i is greater than the utility of any other choice k.

To make this model operational, we must make an assumption about the distribution of disturbances, ε_{ij}. Following McFadden (1973) and Greene (1990), we let Y_i be a random

change in the marginal effect over any regression coefficient associated with the range in points within a confidence interval.

[7] The survey is provided in Volume II of the report. The features used in the choice sets represent the major PRL program characteristics. The range in values used in creating the choice sets reflect those ascertained by the research team as feasible, given NYISO’s operating procedures and market rules.

variable for the choice made. It can be shown that if (and only if) the disturbances are independent and identically distributed according to a Weibull distribution, then

(14) $F(\varepsilon_{ij}) = \exp(-e^{-\varepsilon ij})$,

and we can express the probability of choice j by individual i (Prob $[Y_i = j]$) as:

(15) $\text{Prob}\,[Y_i = j] = \exp[\beta' Z_{ij}] / \{\sum_j [\exp \beta' Z_{ij}]\}$,

is called the conditional logit model.

In this conditional logit model, utility (as expressed through the choice made) is assumed to depend on both characteristics of the choices and the firms. It is helpful, therefore, to distinguish between the two sets of factors. $Z_{ij} = [X_j + W_i]$, where the former, X_j, are the variables that characterize program features, and the latter, W_i, are firm characteristics. The model now can be written more explicitly as.

(16) $\text{Prob}\,[Y_i = j] = \exp[\beta' X_j + \alpha' W_i] / \{\sum_j [\exp(\beta' X_j + \alpha' W_i)]\}$

In this formulation, the alternatives that are explicit to the firm fall out, because while a firm makes 20 decisions as part of the survey exercise, and those choices reflect differences in program features, its firm characteristics do not vary from choice to choice (and do not vary even across the several data observations that must be constructed for each choice set). This will lead to singularities in the data matrix if estimation is attempted in this form. Therefore, if these factors are to be in the model, the model must be modified. An effective modification is to create a set of dummy variables for the choices and multiply each by the common W (Greene, 1990). As a slight extension of this strategy, this modification is incorporated in this analysis by creating dummy variables for each of the individual feature characteristics.[8] The resulting model, as in the case of the binary logit model, is estimated by the method of maximum likelihood. In this case, however, it is estimated in SAS using PROC PHREG.

The Empirical Specification

The key to understanding the empirical specification of the conditional logit model is to discuss explicitly what is in ($\beta' X_j + \alpha' W_i$). In contrast to other applications, each of the programs in the choice sets are characterized exclusively by five separate program features, each of which can assume one of four separate values. These features include (the separate values are in { }):

1. Payment level ($/kWh) { 0.10, 0.25, **0.50**, 0.75 }, what participants are paid for curtailments;

2. Penalty (multiples of payment) { **0**, 1, 1.5, 2 }, the amount participants pay if they fail to comply when called on to do so;

3. Start Time { 11am, 12noon, **1pm**, 2pm }, when the curtailment begins;

4. Notice (prior to curtailment) { 15 min., **2 hrs**, 4 hrs, noon day-ahead }, the length of time prior to the event that customers are notified that they will have to curtail; and

5. Event Duration { 1hr, 2hrs, **4hrs**, 8hrs }, how long the curtailment event lasts.

Each of these values for the program features was assigned a dummy variable [0,1] for inclusion in the model. Since it is necessary to eliminate one of the dummy variables from each of the features so that the data matrix is non-singular, we eliminated the

[8] This conditional logit model suffers from what is called the independence of irrelevant alternatives (IIA), in that the ratio of the probabilities of any two alternatives is always independent of the remaining probabilities. Although this is not a particularly appealing restriction to place on choice behavior, it is not judged to be a particular problem in this application because all firms are given the same 20 choice sets from which the choices are to be made (Allison, 1999). The IIA assumption, as it is called, can only be tested if some sample members have different choice sets Allison, 1999, pp. 167-68), so in this case, there is no way to test for any bias.

variable associated with the values in bold. In this way, the empirical results are normalized on this "base" program. For convenience of interpretation, this "base" program was chosen to resemble the current EDRP.

For empirical purposes, the only firm characteristic included in the estimation was a dummy variable indicating if the firm was a participant in EDRP. To capture this firm effect, the other variables for program features were multiplied by this one firm-level dummy variable to create the necessary interaction variables.[9]

The specification of the linear function ($\beta' X_j + \alpha' W_i$) can now be given as:

(17) $\{ \sum_{k=1,2,4} \beta_{1k}\, PAY_k + \sum_{k=2,3,4} \beta_{2k}\, PEN_k + \sum_{k=1,2,4} \beta_{3k}\, ST_k + \sum_{k=1,3,4} \beta_{4k}\, NT_k$

$+ \sum_{k=1,2,4} \beta_{5k}\, DUR_k \} + \{ \sum_{k=1,2,4} \alpha_{1k}\, PAY_k\, (EDRP\text{-}DUM)$

$+ \sum_{k=2,3,4} \alpha_{2k}\, PEN_k\, (EDRP\text{-}DUM) + \sum_{k=1,2,4} \alpha_{3k}\, ST_k\, (EDRP\text{-}DUM)$

$+ \sum_{k=1,3,4} \alpha_{4k}\, NT_k\, (EDRP\text{-}DUM) + \sum_{k=1,2,4} \alpha_{5k}\, DUR_k\, (EDRP\text{-}DUM) \}$

$+ \gamma\, (NO\text{-}CHOICE) + \gamma\, (NO\text{-}CHOICE)\, (EDRP\text{-}DUM).$

The last two terms in the specification assign a value to the "no-program" choice option that was included in each of the 20 choice sets given to customers.

The Empirical Results

Before discussing the results, it is interesting to note that of the 111 survey respondents, a total of 105 answered the conjoint survey (Part II of the Customer Acceptance Survey). Of that total, 49 were EDRP participants, and 56 were non-participants (Table 3.3). In responding to the 20 choice sets, the non-EDRP participants preferred no program over participation an average of 9.9 times out of 20, and the range

[9] By specifying the model in this way, we also obtain a natural test of the hypothesis that the effects of the various characteristics on program choice are not different for EDRP participants and non-participants.

of responses was from 0 “no-program” choices to 20 “no-program” choices (Table 3.3). In contrast, the EDRP participants selected the “no-program” choice an average of only 4.7 times, and the maximum number of “no-program” choices was 15. This is a good indication that the use of the dummy variables for EDRP participation embodies firm characteristics, the importance of which in the participation in EDRP was explored in the binary choice model above.

The results of the estimated conditional logit model are in Table 3.4. Again the overall performance of this model is very good. The joint tests of all the coefficients being zero are rejected soundly (see the bottom right box of Table 3.4). Further, most of the coefficients, both for the non-participants and the interaction terms for participants, were significant as well. This indicates convincingly that indeed the participants and non-participants value most program features differently.[10]

In interpreting these results, we can think of the “base” program as yielding an average utility of zero. This normalization is convenient because in estimating a model in which dummy variables are used to indicate different levels of program features, it is necessary to eliminate one set of program features. Further, since utility measures are always relative, the results and relative comparisons for programs are independent of this reference point, and it made sense to make this “base” case to mimic EDRP. Thus, if the

[10] It is important to note that even when coefficients were not significant, they were left in the model. This was done for two reasons. First, by doing so, we do obtain a value for the individual feature value, which is in most of those cases very small. Therefore, by leaving them in the model, they have little effect on any analysis that is done. Second, and perhaps equally important, by leaving them in the model, we do not run the risk of introducing bias into the other coefficient estimates if these variables happen to be correlated with the ones that might be dropped. The only “insignificant” variables used in evaluating redesigned programs in the analysis below are those on day-ahead notice and 2-hour duration for the EDRP participants. The Chi-square tests of these coefficients were nearly in the “significant” range. Regardless, only the group differences were affected in our analysis, and only in a minor way.

coefficient on the particular value of a feature is positive, then, *ceteris paribus,* it is preferred to the "base" program feature since it is above the reference level of zero. If the coefficient is negative, then the reverse is true. In Figures 3.1 through 3.5, the relative feature values are graphed for the two sub-groups of respondents. Again, these values are relative to the "base" features: a $500/MW payment, a zero penalty, a 1pm start time, a 2-hour notice, and a 4-hour event duration.

In Figures 3.1 through 3.5, there are several striking relationships in comparing the value of features across the two sub-groups:

- The relative utility of the smallest payment rate is substantially lower for EDRP participants, but higher for the largest payment rate (Figure 3.1). Clearly, the level of payment is very important to participants, but some other factors may have dominated non-participants choices.

- The dis-utility of the penalty is more pronounced for EDRP participants, but for levels about equal to the rate for DADRP, there is no significant difference between the two groups (Figure 3.2). The imposition of penalties would most certainly affect participation, *ceteris paribus*.

- Both sub-groups prefer later event start times, but the preference is more pronounced for the non-participant groups. The difference in value between the two groups for the morning and noon start times is not statistically significant (Figure 3.3). The disutility to non-participants for a start time before 1pm may explain, in part, their decision not to participate in EDRP.

- There is a general preference for a longer notice period by both groups. The value of a noon day-ahead notice period is not significantly different from the 2-hour notice for the EDRP participants (Figure 3.4).

- There is a preference for longer event durations, particularly for current EDRP participants (Figure 3.5).

Preferences for Some Re-Designed Programs

We can now use the results from the conditional logit model to examine customers' preferences for programs with some different features. As seen in Table 3.5, the utility of the "base" program for current EDRP participants (normalized to "yes") is higher than the “no program” option, *ceteris paribus.* The “no program” option reduces utility by 1.24. If the decision were to be made between the “no program” and the “base” program, there are odds of 3.46 to 1 that these customers would sign up (the customer utility value in Table 3.5 for the row “odds of program vs. no program”). As the value for utility and the odds ratio for Program Options P1-P4 in Table 3.5 indicate, customers would also prefer a program with a higher payment, longer notice and longer event duration. They prefer the “base” program to ones with lower payments or a substantial penalty. What is interesting, however, is that in spite of the dis-utility associated with a penalty (Program Option P3) and a lower payment level (Program Option P4), there are slightly better than even odds that current EDRP participants would still subscribe even under these changed and now less desirable conditions. Since Program Option P5 was constructed to mirror the current DADRP (day-ahead notice, penalty = 0.1, and $250/MW strike price), this analysis suggests that there are slightly better than even odds (1.21) that current EDRP customers could be recruited for the day-ahead program as well. This seems a very significant finding, and it is also consistent with the earlier result that customers with prior experience with load relief programs are likely to subscribe to PRL programs.

From Table 3.6, it is not surprising that the utility of the “no program” option for non-EDRP participants is higher than it is for the “base” program. They have already turned down an opportunity to participate in EDRP, and it is extremely encouraging that the results of this “stated” preference model are consistent with the “revealed” preferences of these customers. If this were not the case, one might well question whether their responses to the choice sets could be used to predict future behavior.

For this sub-group of customers, it is not difficult to design programs that are preferred to the "base", but it is a struggle to find programs preferred to the "no program" option. This also is not a surprising result. Since non-participants could not find enough value in EDRP to participate currently, they would need a higher payment, more notice or a later start time in order to generate even odds of participation.[11] Looking at Program Option N4, there is some evidence that some customers in this sub-group could be encouraged to join the day-ahead program if they could bid a 4-hour strip at a $500/MW strike price.

Concluding Remarks

On balance, this analysis of customers' "stated choices" is largely consistent with the "revealed" preferences above. It also highlights the fact that in program design, there must be a substantial tradeoff between those features of value to the market and the bulk power system and those of value to customers.

[11] In Chapter 4, the reasons stated by Non-Partipants for not subscribing to EDRP as recorded in the Customer Acceptance Survey coincide with this finding.

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Table 3.1. Descriptive Data for the Binary Choice Model of 2001 EDRP Participation

		Survey Respondents			
Variable	Number of Customers	Peak Electricity Use 12:00-4:00pm	Previously in an LSE LM Program	EDRP Information Very Useful	Average Score for Understanding EDRP Notice*
Non-Participants	28	9	10	17	4.46
EDRP Participants	48	33	27	28	5.2

	Survey Respondents				
	Number of Production Shifts				
Variable	Zero	One	Two	Three	Four
Non-Participants	1	8	5	14	0
EDRP Participants	0	3	12	32	1

* Rated on a Scale of 1= no understanding to 6=complete understanding.

Source: Customer Acceptance Survey, Part I.

Table 3.2. The Estimated Binary Logit Model for Predicting Participation in EDRP

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq*	Odds Ratio Point Estimate	95% Wald Confidence Limits Lower	95% Wald Confidence Limits Upper
Intercept	-5.91	1.90	9.64	0.00			
understand_notice	0.87	0.34	6.67	0.01	2.38	1.23	4.61
peak_12_4	1.27	0.60	4.53	0.03	3.57	1.11	11.55
shifts	0.69	0.38	3.34	0.07	2.00	0.95	4.21
lse_pgms	1.21	0.60	4.03	0.04	3.37	1.03	11.01
very_useful_edrp_info	-1.18	0.74	2.56	0.11	0.31	0.07	1.30

Predicted Probabilities vs Observed Responses	
Correct Predictions	83
Incorrect Predictions	16
Ties	1

Testing Global Null Hypothesis: BETA=0

Test	Chi Square	PR > ChiSq**
Likelihood Ratio	25.5	0.0001
Score	22.2	0.0005
Wald	15.1	0.0101

* Probability that the estimated coefficients are individually zero.

** Probability that the estimated coefficients are jointly zero

Table 3.3. Summary Data on Customer Acceptance Survey Part II

Item	Number of Customers	Number of "No Program" Choices			
		Average	Standard Deviation	Minimum	Maximum
Non-Participants	56	9.9	8.0	0.0	20.0
EDRP Participants	49	4.7	5.2	0.0	15.0

Table 3.4. Multinomial Model Results for the Choice of PRL Program Characteristics

Variable	For EDRP Non-Participants: Parameter Estimate	Standard Error	Chi-Square	PR > ChiSq	Odds Ratio	Variable	Increment Added to Coefficients for EDRP Participants[#]: Parameter Estimate	Standard Error	Chi-Square	PR > ChiSq	Odds Ratio	Combined Parameter[#]
PAY_1	-0.31	0.15	4.49	0.03	0.73	EDRP-DUM X pay_1	-1.40	0.23	36.01	< .0001	0.25	-1.72
PAY_2	-0.26	0.16	2.68	0.10	0.77	EDRP-DUM X pay_2	-0.65	0.23	8.22	0.00	0.52	-0.91
PAY_3			BASE			EDRP-DUM X pay_3			BASE			
PAY_4	0.43	0.12	12.34	0.00	1.54	EDRP-DUM X pay_4	0.36	0.17	4.54	0.03	1.43	0.79
PEN_1			BASE			EDRP-DUM X pen_1			BASE			
PEN_2	-1.25	0.12	102.55	< .0001	0.29	EDRP-DUM X pen_2*	-0.08	0.17	0.20	0.66	0.93	-1.33
PEN_3	-1.58	0.13	138.76	< .0001	0.21	EDRP-DUM X pen_3	-0.43	0.20	4.81	0.03	0.65	-2.01
PEN_4	-2.17	0.17	162.15	< .0001	0.11	EDRP-DUM X pen_4*	-0.13	0.23	0.30	0.59	0.88	-2.30
ST_1*	-0.09	0.15	0.38	0.54	0.91	EDRP-DUM X st_1*	-0.10	0.22	0.21	0.65	0.91	-0.19
ST_2*	-0.19	0.16	1.49	0.22	0.83	EDRP-DUM X st_2*	0.18	0.22	0.64	0.42	1.19	-0.01
ST_3			BASE			EDRP-DUM X st_3			BASE			
ST_4	0.29	0.14	4.12	0.04	1.34	EDRP-DUM X st_4	-0.27	0.21	1.66	0.20	0.76	0.02
NT_1	-0.70	0.17	17.89	< .0001	0.50	EDRP-DUM X nt_1	-0.28	0.24	1.37	0.24	0.76	-0.98
NT_2			BASE			EDRP-DUM X nt_2			BASE			
NT_3*	0.17	0.14	1.60	0.21	1.19	EDRP-DUM X nt_3*	0.04	0.20	0.05	0.83	1.04	0.22
NT_4	0.26	0.13	3.83	0.05	1.30	EDRP-DUM X nt_4*	-0.28	0.19	2.15	0.14	0.76	-0.02
DUR_1*	-0.12	0.14	0.76	0.38	0.88	EDRP-DUM X dur_1	-0.45	0.20	5.05	0.02	0.64	-0.57
DUR_2	-0.26	0.15	3.06	0.08	0.77	EDRP-DUM X dur_2*	-0.29	0.22	1.67	0.20	0.75	-0.55
DUR_3			BASE			EDRP-DUM X dur_3			BASE			
DUR_4*	-0.01	0.14	0.01	0.94	0.99	EDRP-DUM X dur_4*	0.26	0.20	1.74	0.19	1.30	0.25
NO_CHOICE	0.39	0.16	5.81	0.02	1.48	EDRP-DUM X no_choice	-1.63	0.23	51.59	< .0001	0.20	-1.24

Testing Global Null Hypothesis: BETA=0

Test	Chi Square	PR > ChiSq
Likelihood Ratio	1937	< .0001
Score	1842	< .0001
Wald	1231	< .0001

[#] To find the effects for EDRP participants relative to the non-participants, one added these coefficients to the ones for nonparticipants.
*Note: Although some coefficients for both groups were "not significant" they were retained for the graphic presentation, and they had little effect on the simulation exercises. This is a common practice if it is believed that eliminating a variable will bias the other coefficients.

Table 3.5. Program Preferences for Current EDRP Participants

Program Features	Base Program		No Program		Program Option P1 Higher Payment		Program Option P2 Longer Notice/Duration		Program Option P3 Non-Compliance Penalty		Program Option P4 Lower Payment		Program Option P5 Pseudo-DADRP	
	Feature Value	Customer Utility		Customer Utility	Feature Value	Customer Utility	Feature Value	Customer Utility	Feature Value	Customer Utility	Feature Value	Customer Utility	Feature Value	Customer Utility
Payment	$500/MW	0.00	-		**$750/MW**	0.79	$500/MW	0.00	$500/MW	0.00	**$250/MW**	-0.91	**$250/MW**	-0.91
Penalty	0	0.00	-		0	0.00	0	0.00	**0.5**	-0.66	0.00	0.00	**0.10**	-0.13
Start Time	1300 HRS	0.00	-		1300 HRS	0.00	1300 HRS	0	1300 HRS	0.00	1300 HRS	0.00	1300 HRS	0.00
Notice	2 HRS	0.00	-		2 HRS	0.00	**4 HRS**	0.22	2 HRS	0	2 HRS	0.00	**Noon DA**	-0.02
Event Duration	4 HRS	0.00	-		4 HRS	0.00	**8 HRS**	0.25	4 HRS	0	4 HRS	0.00	4 HRS	0.00
Total Utility		**0**		**-1.24**		**0.79**		**0.46**		**-0.66**		**-0.91**		**-1.05**
Odds of Program vs Base*				**0.29**		**2.21**		**1.59**		**0.51**		**0.40**		**0.35**
Odds of Program vs No Program*		**3.46**				**7.64**		**5.51**		**1.78**		**1.40**		**1.21**

* The odds ratio is exponential of one program's utility divided by the exponential of the other program's utility. Since the utility of the base program is 0, its exponential is equal to unity.

Table 3.6. Program Preferences for Current Non-EDRP Participants

Program Features	Base Program		No Program		Program Option N1 Later Start		Program Option N2 Non-Compliance Penalty		Program Option N3 Higher Payment		Program Option N4 Pseudo-DADRP	
	Feature Value	Customer Utility	Feature Value	Customer Utility	Feature Value	Customer Utility	Feature Value	Customer Utility	Feature Value	Customer Utility	Feature Value	Customer Utility
Payment	$500/MW	0.00	-		$500/MW	0.00	$500/MW	0.00	**$750/MW**	0.43	$500/MW	0.00
Penalty	0	0.00	-		0	0.00	0.5	-0.63	0	0.00	0.1	-0.13
Start Time	1300 HRS	0.00	-		**1400 HRS**	0.29	1300 HRS	0.00	1300 HRS	0.00	**1400 HRS**	0.29
Notice	2 HRS	0.00	-		2 HRS	0.00	2 HRS	0.00	2 HRS	0.00	**DA**	0.26
Event Duration	4 HRS	0.00	-		4 HRS	0.00	4 HRS	0.00	4 HRS	0.00	**4 HRS**	0.00
Total Utility		**0.00**		**0.39**		**0.29**		**-0.63**		**0.43**		**0.43**
Odds of Program vs Base*				**1.48**		**1.34**		**0.53**		**1.54**		**1.53**
Odds of Program vs No Program*		**0.68**				**0.90**		**0.36**		**1.04**		**1.03**

* The odds ratio is exponential of one program's utility divided by the exponential of the other program's utility. Since the utility of the base program is 0, its exponential is equal to unity.

Figure 3.1. Relative Utility Levels for Payment Levels

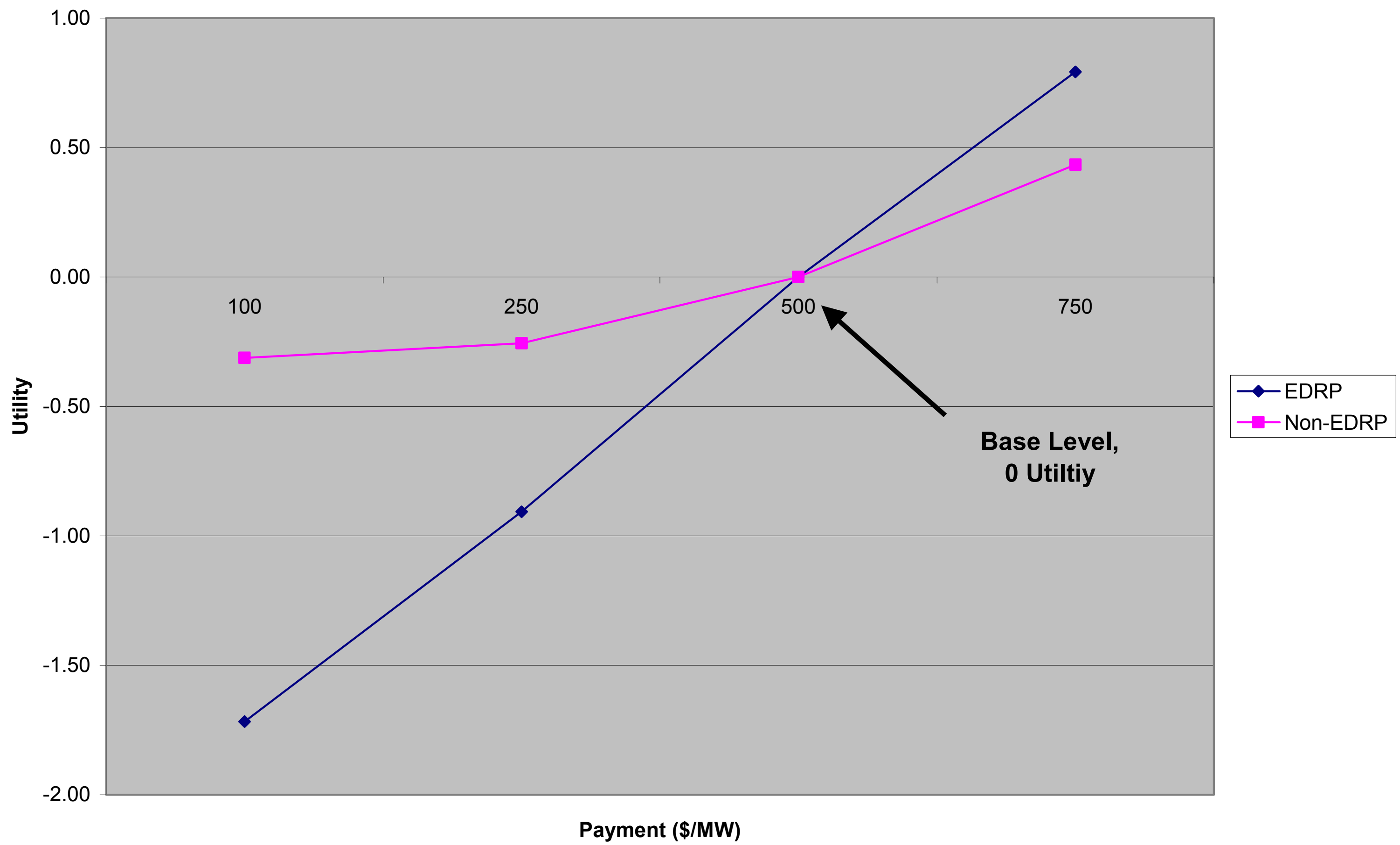


Figure 3.2. Relative Utility Levels for Penalty Rates

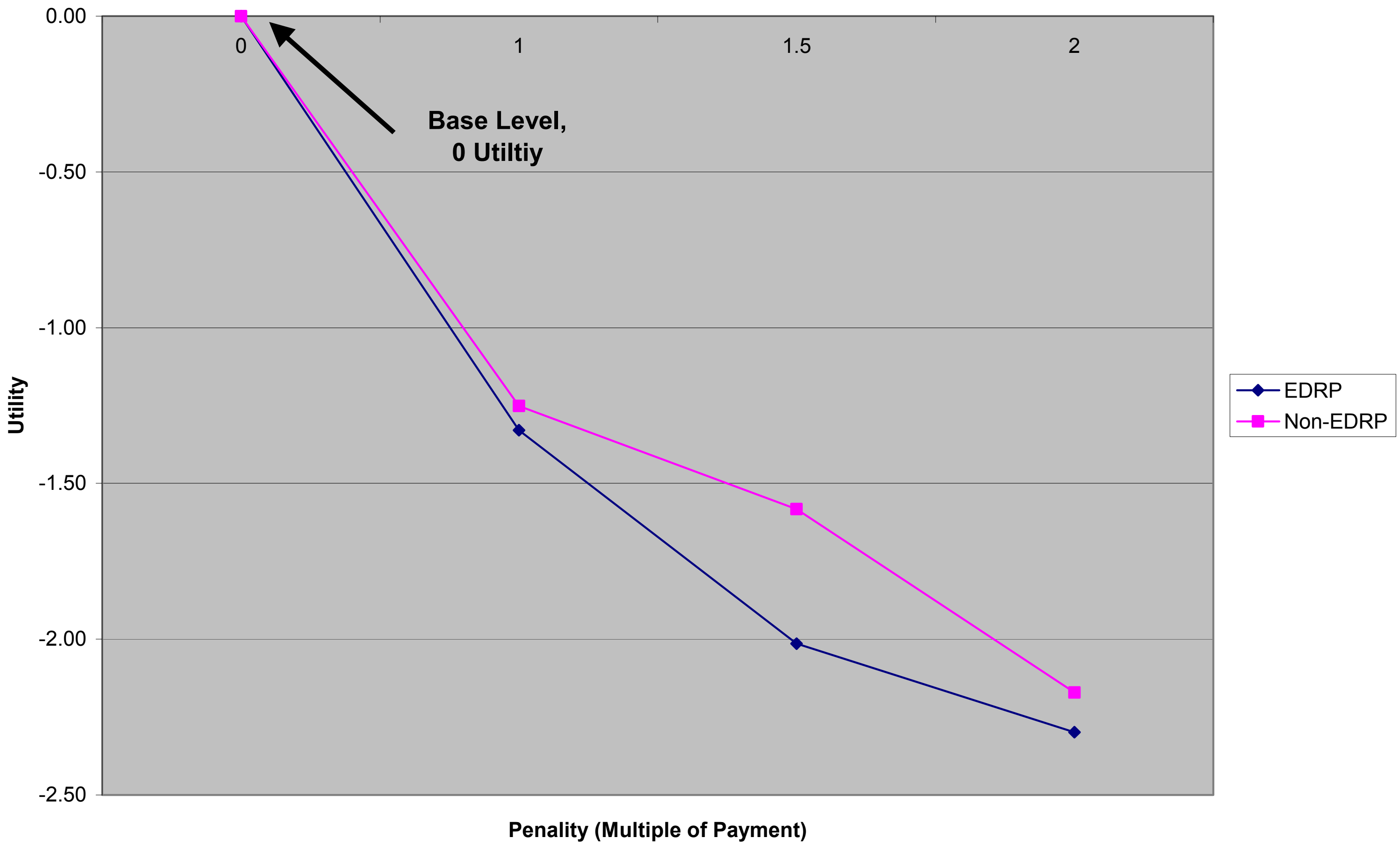


Figure 3.3. Relative Utility Levels for Start Times

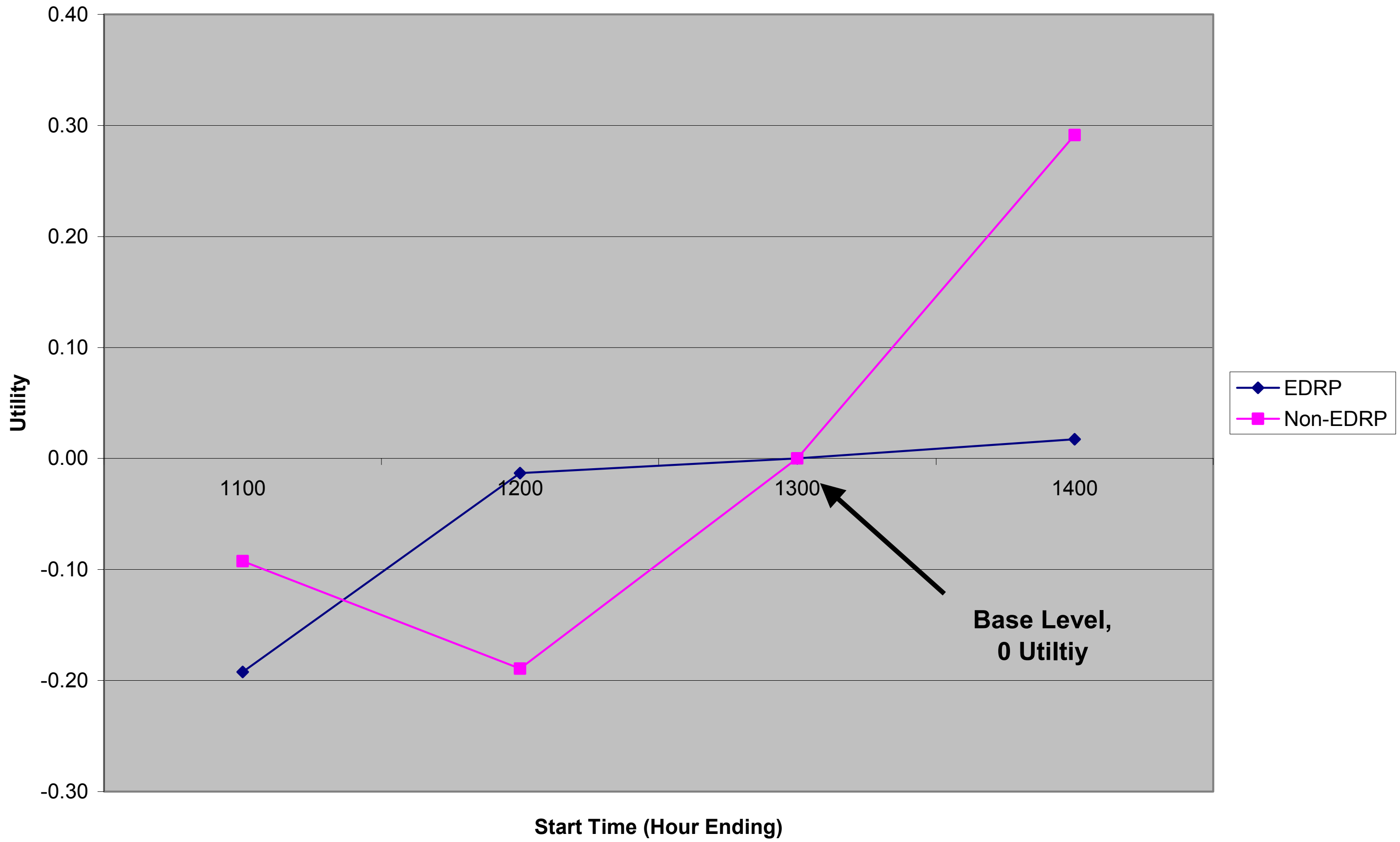
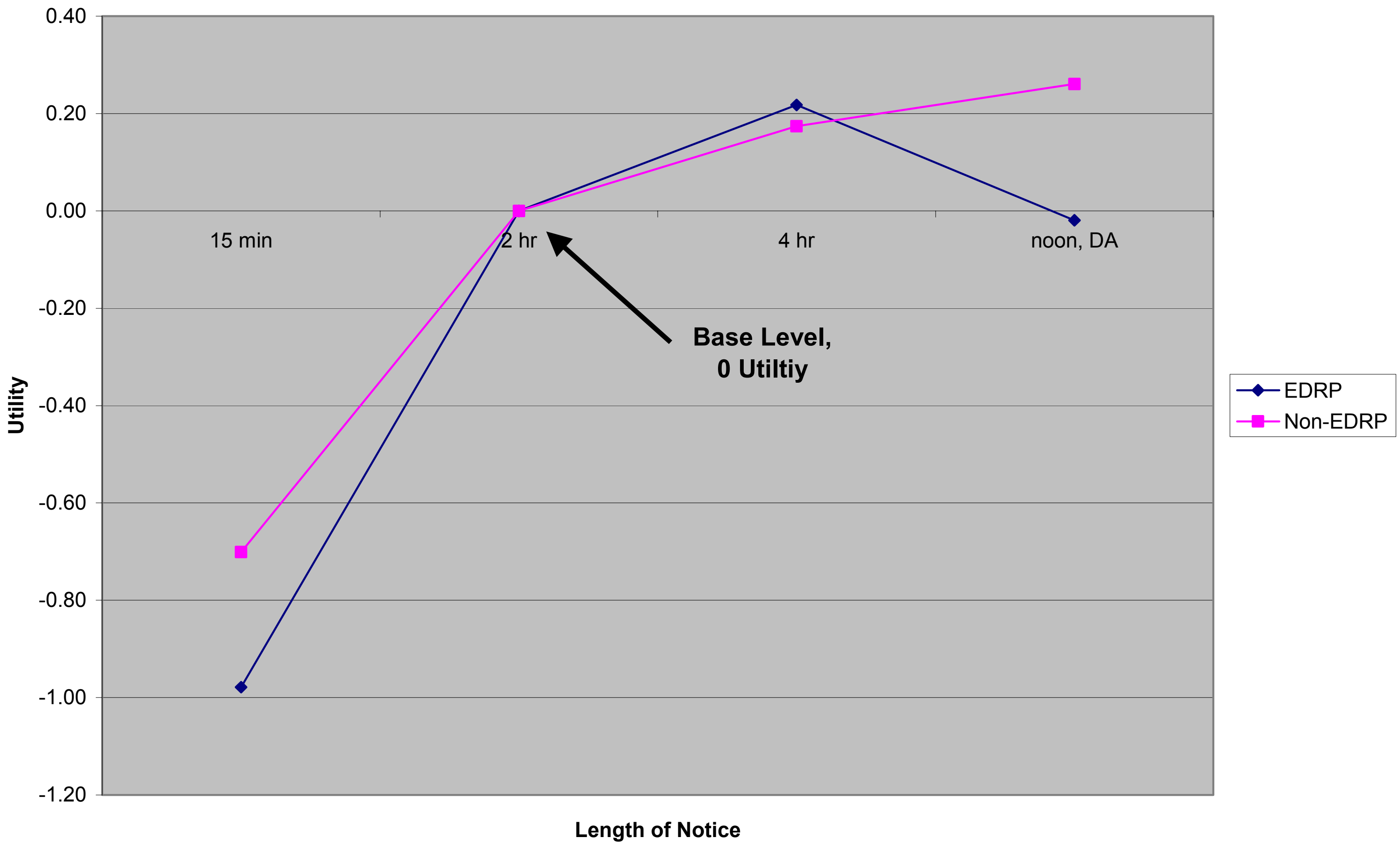


Figure 3.4. Relative Utility Levels for Notice Periods



Documentation for Conjoint Simulation Model

User-Defined Parameters: In order to make this simulation model as flexible as possible, the user can define a hypothetical PRL program through a series of parameters.

Pay: There are four different payment levels that can used to simulate with: **1**=$100/MW, **2**=$250/MW, **3**=$500/MW, and **4**=$750/MW. The base program value is **3**=$500/MW.

Penalty: Although there were four penalty levels used in the conjoint survey (0, 1.0, 1.5, 2.0), the simulation model allows for any value between **0** and **2**. The base program has an associated penalty level of **0**.

Start: The four valid values for the Start Time of a hypothetical PRL program are: **1**=11 AM, **2**=12 Noon, **3**=1 PM, **4**=2 PM. The base program value is **3**=1 PM.

Notice: The conjoint study used four different notice periods: **1**=15 Minutes, **2**=2 Hours, **3**=4 Hours, and **4**=Noon Day-Ahead. The base program value is **2**=2 Hours.

Duration: There were four different values in the conjoint survey to indicate how long an event would last. The valid parameter values are: **1**=1 Hour, **2**=2 Hours, **3**=4 Hours, **4**=8 Hours. The base program has a duration of **3**=4 Hours

EDRP: This parameter is used to indicate if the hypothetical program is being offered to an EDRP Participant, a value of **1**, or to a Non-Participant, a value of **2**.

SAS Code

Every user-defined PRL program feature, with the exception of the penalty, is recoded to be consistent with the way the estimated multinomial logit model is defined. Penalty was the only program feature where we wanted to look at values other than those strictly included in the sample. Since each of the program features was modeled as a dummy variable, to deal with any points between their discrete values we had to interpolate by assuming the existence of a linear relationship.

The hypothetical user-defined PRL program and the estimated multinomial logit model for the type of **EDRP** customer, Participant (**1**) or Non-Participant (**2**), are then merged together. The relative utility levels associated with each program feature are calculated and summarized, yielding an overall level of customer satisfaction with the hypothetical program, the base program, and the "No program" option. Ratios of the probabilities of participating in the hypothetical program to participating in the base program are calculated, as are the odds of being in the hypothetical program versus the "No program" choice.

Finally, the hypothetical program features, the different utility levels associated with the hypothetical program, the base program, and the "No program" options, as well as the odds ratios are all displayed to the user.