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CONSUMER RESPONSE TO CONTINUOUS-DISPLAY ELECTRICITY-USE MONITORS IN A TIME-OF-USE PRICING EXPERIMENT

by

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Abstract

Continous Display, Electricity-Use Monitors provide more comprehensive electricity cost information than previously considered initiatives. This study analyzes their effect in a time-of-use pricing experiment. The research involves two components: (1) a logit analysis of consumers' monitor use/nonuse decision, and (2) investigation of monitoring's effect on consumers' monthly peak-period, off-peak period and total electricity consumption using an ANCOVA framework. Results support a cost-benefit model of the use/nonuse decision and indicate that monitoring significantly contributed to shifting electricity use from peak to off-peak periods.

CONSUMER RESPONSE TO CONTINUOUS-DISPLAY
ELECTRICITY-USE MONITORS IN A TIME-OF-USE PRICING EXPERIMENT

Rising electricity costs have stimulated considerable research into consumers' electricity demand. Two important foci have been analysis of consumers' response to: (1) information about electricity consumption and its costs, and (2) programs that set prices for electricity according to its time of use (TOU). The goal of the first group of studies has been to investigate the conservation potential of various types of information, while the latter group has been concerned with shifting consumption from peak to off-peak periods through pricing incentives.

This study analyzes consumer response to continuous-display, electricity-use monitors (CDEUMs) during a TOU pricing experiment and, therefore, is germane to both lines of research. CDEUMs provide more diversified and continuous electricity cost information than other initiatives considered to date. For example, the model used in this study can instantaneously display the current rate of electricity use in cents per hour, the accumulated monthly electricity cost, and the amount of the last bill. Their continous display feature means CDEUMs can provide a fairly accurate estimate of the electricity costs attributable to each household activity.

This study's CDEUM was also designed to reinforce TOU pricing by informing users when peak or off-peak rates were in effect and by displaying the per KWH cost during either pricing period. In addition, it facilitated budgeting by comparing a projected electricity bill based on usage to date with a preset budget. Warning lights indicated when the budget was exceeded.

The study has two broad objectives: The first is to analyze the factors which influence consumers' decisions concering adoption of a major information initiative such as monitoring. A cost-benefit model of this decision is specified and tested, where the costs of monitoring are time-related opportunity costs, and the benefits flow from the prospect of reducing errors in household electricity consumption. The second goal is to determine if monitoring may supplement a TOU pricing program by stimulating overall conservation and/or shifting use from peak to off-peak periods. An analysis of covariance (ANCOVA) framework is used to analyze CDEUMs peak, off-peak and total consumption effects. The results suggest monitoring did not stimulate overall conservation but did contribute to shifting consumption from the peak to the off-peak period. Before describing the data and the experiment in more detail, we provide a brief review of the relevant literature.

PREVIOUS RESEARCH

Conservation and Feedback

The cost effectiveness of most energy information programs has yet to be demonstrated. Surveys by Shippee (1980), Katzev, Cooper, and Fisher (1980-81), and McDougall *et al*. (1981) conclude that most types of commonly-used information initiatives produce little or no impact on actual energy consumption. Examples include energy efficiency labels (McNeill and Wilkie 1979), messages (Craig and McCann 1978), and workshops (Geller 1981).

Extensive analysis of programs that provide direct feedback to consumers about their electricity consumption has tended to indicate that feedback alone, especially when administered infrequently, has little effect on consumption. However, feedback augmented by other factors such as commendation (Seaver and Patterson 1976), goal setting (Becker 1978), dissonance (Kantola, Syme, and Campbell 1984), and conservation rebates

(Kohlenberg, Phillips, and Proctor 1976 and Battalio et al. 1979) has proven a more effective conservation stimulant.

The specific results have depended on the type of feedback, its frequency, and on the nature of any jointly-provided stimulants (Winett and Kagel 1984). Increasing feedback's frequency appears to increase its effectiveness. For example, Seligman and Darley (1977) attained 10.5 percent electricity savings from an experiment involving daily feedback. Weekly feedback and money rebates for conservation stimulated 12 percent savings for Battalio et al. (1979), and the conservation rate increased to about 15 percent when Winett et al. (1982) accompanied daily feedback with extensive information and goal setting.

Programs that provide frequent written feedback and/or extensive intervention through rebates, commendation, goal setting, etc., are costly to provide. Hence, experiments have usually involved very small treatment groups and have been conducted over short time intervals. The same cost considerations appear to limit real-world opportunities to implement these programs for large groups or extended time periods. Yet, evidence suggests that (1) the effects of short-term programs often diminish quickly once the treatment is discontinued (e.g., Kohlenberg, Phillips, and Proctor 1976; Battalio et al. 1979; Winett, Neale, and Grier 1979; and Hayes and Cone 1981) and (2) less costly programs that provide infrequent feedback are usually ineffective.

Two feedback alternatives may address this problem: Consumers may be taught to provide their own feedback via the standard electric meter (Winett, Neale, and Grier 1979), or in-house, automatic feedback devices such as CDEUMs may be installed to eliminate the need for human intervention. Between the two alternatives, CDEUMs require less extensive investment in time for training and use and provide more diversified and useful feedback.

Only limited analysis of CDEUMs has been conducted to date. McClelland and Cook (1979) found on average 12 percent savings in an 11 month experiment involving 25 all-electric households, while Filiatrault, Hutton, and Meuser (1984) reported mixed results from a joint U.S.-Canadian experiment on CDEUMs. A small three to five percent savings was discerned for two Canadian test sites, but no statistically significant conservation was obtained at two U.S. sites. The Tennessee Valley Authority (1984) also indicated few, if any, significant consumption effects at a third U.S. test site.

Time-Of-Use Pricing

Meeting peak period demand is especially costly to electrical utilities. Therefore, considerable interest has recently been focused on TOU pricing as a means of reducing peak demands. The data analyzed here are from the Southern California Edison (SCE) Company's TOU experiment, one of 14 projects sponsored by the U.S. Department of Energy (DOE) to study the impact of TOU and seasonal electricity rates on residential customers. Aigner and Lillard's analysis (1984) of the SCE experiment indicated that TOU pricing induced up to 20 percent reductions in peak-period consumption and a small net conservation effect. These findings are generally consistent with those from the other DOE-sponsored projects (Miedema, Lee, and White, 1981). Kasulis, Huettner, and Dikeman's study (1981), however, provides an instance when TOU pricing had few discernable effects.

THE SCE EXPERIMENT

The SCE experiment began in March 1979 and continued for 24 months. Approximately 480 SCE residential customers faced TOU prices for electricity. A control group of 120 households faced SCE's normal rate structure. The sample households were stratified into three temperature zones, five consumption groups, two definitions of P:OP periods, and four P:OP price ratios. These were 3:1, 5:1, 7:1, and 9:1 with the specific KWH prices chosen to generate billings consistent with SCE's prevailing rate structure. The alternative peak periods were Rate A: nonholiday weekdays, 10 a.m. to 8 p.m., and Rate B: nonholiday weekdays, 12 noon to 10 p.m. The distribution of TOU groups across consumption classes and temperature zones is provided in Table 1 along with the cell definitions. Participation in the experiment was not mandatory, but the refusal rate was low. Participants received an annual $100 payment.

In April and May 1980, Dupont energy monitors were installed free of charge in 68 of the TOU treatment households selected randomly from the three largest consumption classes and across all temperature zones and rate structures. The selected households each received instructional material concerning use of the monitor.[1] The numbers in parentheses in Table 1 provide the distribution of monitoring households across cells.

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Insert Table 1 about here

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Electricity consumption data were digitally recorded at 15-minute intervals over the course of the experiment. These observations summed over each month comprise the basic measure of electricity usage for each household.

Temperature data were also obtained at 15-minute intervals from 20 SCE weather stations.[2]

A post-experiment questionnaire provided information on households' demographics, housing stock, appliance stock, and attitudes and perceptions of the experiment. In contrast to most other feedback-related studies, the SCE experiment is distinguished by its long duration, large sample size, and rich accounting of exogenous variables. In addition, because the refusal rate was low and comsumption was machine recorded, the SCE study was not subject to volunteer-induced biases, errors in meter reading, and/or those caused by consumer self reports.

THE MONITOR USE/NONUSE DECISION

An Economic Model

One factor which limits the effectiveness of feedback or other information initiatives is that consumers may not use (adopt) the material provided. Usage involves time costs even if the material is provided free of explicit charge. Nonuse may be a particularly important consideration in experimental settings when participants are not volunteers. However, little research has been devoted to factors underlying the information use/nonuse decision.

The model developed in this section assumes that households faced with a new information initiative make a dichotomous use/nonuse decision based upon subjective evaluation of the benefits and costs of usage. Although the theory is applicable to most types of energy information initiatives, the model is developed in terms of the decision to acquire and use an electricity monitor. Households living in homes equipped with monitors must decide whether to use them and those without monitors must decide whether to acquire them.

The expected benefits (EB) from monitoring accrue from its potential to provide information to reduce household electricity consumption errors and associated utility losses. Although it is typically assumed that households are prone to overconsume electricity, in fact, either overconsumption or underconsumption may occur, and information which reduces either condition provides private benefits. Conservation activity may provide additional social benefits, but these will not enter into a household's decision-making process in the absence of special programs to reward conservation.

The expected costs (EC) of usage are opportunity costs of time spent learning to use the monitor and processing its information. These costs are augmented by the monitor purchase price for homes without an already-installed unit. An expression of the typical household's decision is:

$$D = \begin{cases} 1 \text{ if } EB > EC \\ 0 \text{ otherwise,} \end{cases} \qquad (1)$$

where 1 denotes use (buy) and 0 denotes nonuse (don't buy).[3]

To formulate a model of utility loss due to consumption errors, let $A = \{A_1, \ldots, A_n\}$ represent a vector of a representative household's stock of electricity-consuming appliances, where the A_j are measured in terms of the household's total kilowatt capacity per unit of time for each appliance.

The household's short-run electricity demand may be expressed in terms of utilization rates, $U = \{U_1, \ldots, U_n\}$, for the fixed stock of appliances (Taylor 1975). From consumer theory, utilization depends upon the price(s) for electricity, the household's income, Y, and a vector, Z, of other economic, social, or demographic variables affecting demand.

Household electricity consumption, Q, is the sum of the utilization rate and appliance stock products:

$$Q = AU' = \sum_{j=1}^{n} A_j U_j \qquad (2)$$

The true price per-unit of service for the j^{th} appliance is $P_j^* = M^* K_j$, where M is the marginal electricity price per KWH and K_j is the number of kilowatt hours required by the j^{th} appliance per unit of service.[4] Consumers' perception of the unit-of-service prices, $\hat{P}_j$, may differ from the true values due to erroneous perceptions of M* and/or because of errors in estimating the K_j (Baird and Brier 1981).

For given Y and Z, the utilization rate may be expressed as $U_j = U_j(P_j)$. The per-period consumption error for appliance j is then $E_j = A_j[U_j(\hat{P}_j) - U_j(P_j^*)]$, where $E_j > 0$ indicates overconsumption (underestimation of P_j) and $E_j < 0$ indicates underconsumption (overestimation of P_j).

The utility loss from consumption errors may be closely approximated using consumer surplus (Sexton 1981, and Senauer, Kinsey, and Roe 1984). The basic idea is that households which underconsume forgo attainable surplus while those which overconsume expend resources for some units of consumption in excess of their true economic value.

The Figure depicts the economic loss from either circumstance. $A_j U_j(P_j)$ is the consumer's demand for services for the j^{th} appliance. Overconsumption occurs when $P_j^* = a$, $a > \hat{P}_j$, in which case the actual amount expended on services in excess of their value is the triangular area ABC. The analogous welfare loss from underconsumption ($P_j^* = b$, $b < \hat{P}_j$) is the area CDE, i.e., the amount of net surplus which would have been attained had consumption been expanded beyond $\hat{Q}_j$ to its optimal level, Qb_j.

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Insert Figure about here
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Denoting this welfare loss as L_j, the total welfare loss in period t from erroneous perception of the unit-of-service prices for electricity is $L_t = \sum_{j=1}^{n} L_{jt}$. Value accrues to electricity-related information through the extent to which it can reduce these losses. Because losses continue over time in the absence of improved information or ad hoc learning, the benefit from information may be extended to future time periods. For example, given a τ-period planning horizon, the discounted value of the economic loss would be $L = \sum_{t=1}^{\tau} L_t/(1+r)^t$, where r is is an appropriate discount rate.

Any single information initiative may be insufficient to displace the total misallocation loss, yet CDEUMs appear to offer more comprehensive and timely information than do alternatives.[5] Therefore, as an approximation, L may be considered the prospective value of monitor usage. It can be shown that L increases for larger price evaluation errors, larger appliance stocks, and higher or more price elastic utilization rates.[6] However, consumers are likely to estimate L imperfectly so that $EB = L + \mu$, where μ is an error term assumed to have zero mean and finite variance, σ_μ.

For households with an already-installed monitor, the cost of use relates solely to the time required to obtain and disseminate the available information. Based on the dichotomous choice assumption, a single usage time requirement, T, exists for each household. T is dependent upon members' ability to acquire and process the monitor-provided information. The per-unit value of the time expended, W, is an opportunity cost. The household's cost of monitoring is, thus, $C = WT$. Assuming also that C cannot be estimated with complete accuracy, expected costs are formulated as $EC = WT + \nu$, where ν is assumed to be uncorrelated with μ and have mean zero and finite variance, σ_ν.

Substituting these results into equation (1), obtains:

$$D = \begin{cases} 1 \text{ if } (\mu - \nu) > WT - L, \\ 0 \text{ otherwise.} \end{cases} \tag{1a}$$

To develop an estimating equation from (1a), define X_L as a column vector of the factors which influence L and β_L as a column vector of coefficients. Let $L = \beta_L^{'}X_L$. Also let $C = \beta_C^{'}X_C$ denote a similar formulation for the cost of monitoring, where the X_C are variables which affect C, and the β_C are coefficients. Finally, $\varepsilon = \mu - \nu$, where ε has mean zero and variance $\sigma_\varepsilon = \sigma_\mu + \sigma_\nu$.

An underlying response variable, $\bar{D}$, may be formulated and expressed from (1a) as:

$$\bar{D} = \beta_L^{'}X_L - \beta_C^{'}X_C + \varepsilon. \tag{3}$$

In practice, $\bar{D}$ is not observed, but, rather, the dummy variable D is observed and defined by $D = 1$ if $\bar{D} > 0$, and $D = 0$ otherwise. Therefore, the probability, Pr, that $D = 1$ is, from (3),

$$\begin{aligned} Pr(D = 1) &= Pr(\varepsilon > \beta_C^{'}X_C - \beta_L^{'}X_L) \\ &= 1 - F(\beta_C^{'}X_C - \beta_L^{'}X_L), \end{aligned}$$

where F is the cumulative distribution function for ε (Maddala 1983).

The observed values of D are realizations of a binomial process where the outcome for each trial depends upon the X_L and X_C. The estimation problem is one of maximum likelihood,[7] where, if F is assumed to have a logistic distribution, the standard logit model is obtained.[8]

Specific hypotheses are set forth according to whether their postulated influence is on the benefits or the costs of monitoring.

The benefits of monitor usage are expected to be relatively greater among households with

H1: larger stocks of appliances, particularly those with a discretionary-use element,

H2: electric heat and/or air conditioning,

H3: larger total levels of electricity consumption, and

H4: lower education levels.

H1, H2, and H3 suggest that uncertainty losses will be relatively larger for households with greater stocks of discretionary-use appliances including electric heat and air conditioning and larger levels of electricity consumption. H4 posits that less-educated households will be less informed and make greater consumption errors than more-educated counterparts.

The model suggests that the costs of monitoring will be relatively higher for households with

H5: lower education levels,

H6: higher income levels,[9] and

H7: more members employed outside the home and/or more children living at home.

The time cost of monitoring is expected to be inversely correlated with household members' education levels, while the opportunity cost of monitoring time should be higher for upper income households and those with multiple working members or children living at home (Heckman 1974).

A final hypothesis concerns monitoring's potential to reinforce TOU pricing by helping households shift usage from peak to off-peak periods. The greater the P:OP price differential, the greater the savings attainable through redistribution of consumption. Therefore:

H8: Among TOU-pricing households, the incidence of usage will be positively related to the peak-nonpeak price differential.

Because monitor households were selected exclusively from the TOU treatment groups, only the within-TOU treatment effects can be analyzed in this study.

Estimation Results

Use/nonuse variables for the logit estimation were derived from responses to the post-test questionnaire. Two alternative measures were developed. In the first, denoted as MODEL 1, users were those who indicated that an adult used the energy monitor. Nonusers were both those who indicated that children used the monitor, or those who provided no affirmative answer to the query concerning usage. Answers provided to other post-test questions suggested that some households classified as nonusers under MODEL 1 may actually have used the device. MODEL 2, the alternative use/nonuse specification, therefore, classifies a user household as any which provided a usage-indicating response to any of the post-test questions.

Complete data for the logit models were available for 50 of the 68 original monitoring households. Thirty of these were classified as users under MODEL 1, while 41 were considered users under MODEL 2's broader classification. The 60 percent MODEL 1 user rate for the 50 sample households compared to a 59.4 percent user rate among the 64 monitor households who answered that post-test question, so no bias should have resulted from the loss of observations.

Among the explanatory variables, benefit-side measures included households' total monthly electricity consumption (KWH) averaged over both years of the experiment (H3), and indices HTAC and DISTOCK which measured, respectively, their electric heating and cooling appliance stock (H2) and their stock of discretionary-use appliances excluding the heating and cooling system (H1).[10] Each of these variables was hypothesized to have a positive sign.

The cost-side measures included household income (INCOME), reported as the midpoint of seven classifications within the \$0-39,999 range and as \$45,000 for incomes over \$40,000 (H6), the number of persons in the home employed more than 35 hours per week (WORKERS) (H7), and MEMBERS, the number of persons living in the home full time (H7). Each of these variables was hypothesized to have a negative sign.

Education was measured as a dummy variable (HEADED) set to 1 if the household head had a college education and 0 otherwise. Because education was hypothesized to have offsetting effects on the benefits and costs of monitoring, there was no a priori expectation for its sign.

To test the effect of the TOU pricing rates and still maintain the parsimony of the model, the four P:OP rate classes were combined into two: a low TOURATE = 0 which included the 3:1 and 5:1 groups and a high TOURATE = 1 which included the 7:1 and 9:1 groups. Sample means for the variables used here and in the next section are provided in Table 2.

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Insert Table 2 about here

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In estimating the logit model, the average monthly consumption variable consistently performed poorly and ultimately was dropped from the estimating equation. Its sign was inconsistent and the coefficient was never statistically significant. This result may have been caused by the monitor group being drawn mainly from consumption groups four and five, thus affording less-than-desirable variation in the average consumption variable.

Due to high collinearity between them, WORKERS and MEMBERS were not included together for estimation purposes. Models with either variable performed similarly, and only the results using MEMBERS are reported here.

Estimation results are reported in Table 3. The explanatory power of both the MODEL 1 and MODEL 2 regressions as measured by R^2 are quite satisfactory based on logit standards (Morrison 1972). The likelihood ratio statistic provides a test of the overall significance of each regression. Its distribution is χ^2 with degrees of freedom equal to the number of estimated coefficients excluding the constant. MODEL 1 is significant for $p \leq 0.05$, while MODEL 2 narrowly misses the $p \leq 0.10$ cutoff.

The individual explanatory variables are generally supportive of the hypotheses set forth earlier. The coefficients' signs conform to the theoretical predictions for all variables except DISTOCK in MODEL 2.

Insert Table 3 about here

Hypothesis testing of the maximum likelihood coefficients may be done using the t-ratios, which for large samples are approximately distributed as standard normal random variables. Where the model yielded theoretical predictions for the signs, one-tailed tests were used. On this basis, INCOME and MEMBERS were significant for $p \leq 0.05$ in MODEL 1, while HTAC was significant for $p \leq 0.10$ in MODEL 2. The sign of HEADED was negative in MODEL 1 and positive in MODEL 2. Neither was statistically significant for a two-tailed test. Failure of the dummy variable to capture education's full effect may have contributed to its erratic performance.

In sum, the logit results generally support the theoretical model. The absence of more statistically significant coefficients is not surprising given the nature of the data and the size of the sample. The cost-side variables, in particular, were important determinants suggesting that the benefits of adding complexity to information must be carefully balanced against its detrimental impact upon usage.

The comparative significance of the cost-side measures may be rooted in the fact that usage costs are easier to discern and estimate than are the prospective benefits. For example, DISTOCK's failure to perform as predicted may have been a result of households' inability to estimate the savings from usage cutbacks or nominally discretionary appliances in reality becoming "fixed" as part of households' daily routines.

MODEL 3 in Table 3 provides results for an exploratory analysis of consumers' satisfaction or dissatisfaction with the monitor. Of the 41 user households in MODEL 2, 28 were classified as "satisfied" ($s^i = 1$) and 13 as "dissatisfied" ($s^i = 0$), based upon an affirmative response to either of two post-test questions concerning (1) whether or not the device was useful in monitoring the electric bill, and (2) whether or not it saved money on the bill. The determinants of satisfaction/dissatisfaction were analyzed via logit using the explanatory variables from MODELS 1 and 2.

The explanatory power of MODEL 3 is quite high, and the overall regression is significant for $p \leq 0.10$. In terms of the theoretical model, dissatisfied users are households which, upon _ex post_ reflection, should not have been users. However, the model offers no criteria to identify dissatisfied users, and it does not follow that coefficients' signs should necessarily be the same as those for the use/nonuse decision. Therefore, hypothesis testing of coefficients was based upon two-tailed tests. Under this criterion, significant coefficients are obtained for MEMBERS and TOURATE ($p \leq 0.10$) _and_ INCOME ($p < 0.05$).

TOURATE'S negative sign suggests that users did not find the monitor useful in responding to high P:OP rates. HTAC's positive sign suggests it may have been more useful in controlling heating and air conditioning usage. A possible explanation for income's positive impact upon the probability of satisfaction is that low income users may have attached more significance to monitoring as a money-saving opportunity than did higher income users. Yet, as the next section's results indicate, monitoring did not on average stimulate conservation, suggesting, perhaps, that many low income users' expectations were not met.

THE EFFECTS OF MONITORING ON PEAK, OFF-PEAK AND TOTAL ELECTRICITY USAGE

According to the model, monitoring will increase or decrease a household's electricity usage depending upon whether on average the costs of electricity consumption are overvalued or undervalued. *A priori*, there appears to be no reason to expect one result relative to the other.

In this context it is important to recognize that whenever initiatives such as monitoring affect consumers in opposite ways, the effects will tend to cancel in an ANOVA or ANCOVA between the treatment and control groups. Hence, this type of result cannot be used to make inferences about the initiative's effect on individual consumers' behavior. However, the netting of effects obtained in cross-sectional ANOVA or ANCOVA is often precisely what is desired. Net results are the focus here because they address three of the more important questions relative to monitoring and electricity cost information in general:

1. Is it useful as a conservation stimulant?

2. Is it a useful supplement to a TOU pricing program, i.e., does it contribute to shifting consumption from peak to off-peak periods?

3. Is its effectiveness in a TOU program influenced by the alternative P:OP rates?

Empirical Specification

Monitoring's net effects were studied using an ANCOVA framework similar to Taylor's (1979) and Aigner and Lillard's (1984). Monthly short-run electricity demand equations were estimated from (2) for total (T), peak-period (P) and off-peak period (OP) electricity consumption. Analyzing data for individual months rather than using a single pooled regression simplified the empirical models (i.e., indicator variables to account for monthly effects were avoided) and provided a simple means to check for dynamic patterns in consumers' response to monitoring.

Three types of explanatory variables were included in the empirical model: (1) quantitative variables (covariates, in ANCOVA terminology) that typically appear in electricity demand equations and which account for uncontrollable factors in the experiment, (2) indicator variables relating to the TOU phase of the experiment, and (3) indicator variables relating to the monitoring phase of the experiment.

The covariates included INCOME, the dwelling unit's square feet (HSQFT), and weather conditions. Two indices were used to measure the appliance stock. HTAC accounted for electric heating and cooling appliances, and APSTOCK accounted for holdings of the other major appliances. APSTOCK included appliances contained in DISTOCK (Footnote 10) and automatic defrost refrigerators, manual refrigerators, and electric water heaters.

Weather effects were measured via heating and cooling degree days (HEAT and COOL) during the period under analysis (T, P or OP). Because only sustained deviations of temperature from the 65-75 degree range were expected to induce significant demand for heating or cooling, degree days were computed to net out short-term deviations of temperature from the 65-75 degree range. The mean daily temperature at each weather station in the P and OP periods was computed from its 15 minute temperature readouts. Heating (cooling) degree days were measured for each period as the monthly sum of the deviations of its daily mean temperatures from 65 (75) degrees. Heating and cooling degree days for the total period were the sum of their values in the P and OP periods.

The alternative P:OP price ratio's were accounted for by the 0-1 indicator variables X3--3:1, X5--5:1, X7--7:1, and X9--9:1. For example, X5 = 1 for households in the 5:1 P:OP group, and X5 = 0 otherwise. The Rate A and Rate B subgroups were pooled to generate the largest possible number of monitor households. The indicator variable, RATEA (equal to 1 for Rate A households, equal to 0 otherwise) was added to account for possible effects due to the two alternative definitions of P and OP periods.

Monitoring was included as the indicator variable MTR set equal to 1 for households who had the Dupont Monitor installed and set equal to 0 otherwise. To examine monitoring's effects in conjunction with the alternative TOU rates, the monitor indicator and the P:OP indicators were included interactively. For example, the variable X5(MTR) was set equal to 1 for households in the 5:1 P:OP group who had the Dupont Monitor installed and was set equal to 0 otherwise.

Because monitor households came predominantly from consumption groups four and five (Table 1), the statistical analysis was conducted only over the monitor and nonmonitor households in those two groups. In addition, all members of the TOU control group were dropped because none had monitors. After making other necessary deletions for bad or missing data, 269 total observations including 51 monitor households were available for statistical analysis.

In summary, the regression model was:

$$\left.\begin{matrix} KWH^{P} \\ KWH^{T} \\ KWH^{OP} \end{matrix}\right\} = \beta_0 + \beta_1 MTR + \beta_2 X5 + \beta_3 (X5) MTR$$

$$+ \beta_4 X7 + \beta_5 (X7) MTR + \beta_6 X9 + \beta_7 (X9) MTR$$

$$+ \beta_8 HTAC + \beta_9 APSTOCK + \beta_{10} INCOME + \beta_{11} HSQFT + \beta_{12} RATEA$$

$$+ \beta_{13} \left\{\begin{matrix} HEAT^{P} \\ HEAT^{T} \\ HEAT^{OP} \end{matrix}\right. + \beta_{14} \left\{\begin{matrix} COOL^{P} \\ COOL^{T} \\ COOL^{OP} \end{matrix}\right. + \varepsilon ,$$

where ε is a random error term. In this specification, nonmonitor households in the 3:1 P:OP treatment cell are the reference group to which all others are compared.

Results

The estimation results are summarized in Tables 4, 5, and 6 for the peak, off-peak, and total periods, respectively. The model's overall explanatory power (R^2 between one-fourth and one-half) is consistent with other electricity demand studies using similar data.

With very few exceptions the behavior of the covariates was as expected. Both appliance measures, APSTOCK and HTAC, exhibited strong positive effects on consumption that were statistically significant ($P \leq 0.10$) in nearly all instances. The HSQFT coefficient was also positive in each case and was significant in all but two.

The heating and cooling measures also worked well. Given the generally mild Southern California climate, COOL was the more potent predictor of the two. Its sign was positive in all instances, and significant in all but two. HEAT's coefficient was positive except for two months and was signicant about half the time.

INCOME was the only covariate to fail to consistently contribute to the model's explanatory power. Its sign tended to be positive during off-peak periods and negative during peak times. The effects were never statistically significant, however.

Insert Tables 4, 5, and 6 about here

A test of monitoring's overall significance in the regressions is H_0: $\beta_1 = \beta_3 = \beta_5 = \beta_7 = 0$. Under H_0, the test statistic is distributed as $F_{4,254}$. Its values for each month are reported at the bottom of Tables 4, 5, and 6. Curiously, monitoring's effect was significant ($P \leq 0.10$) in the off-peak and total periods during each of the first seven months of monitoring but not in any of the last three. The peak period effect was significant in three of the first seven months and none of the last three.

Monitoring was generally associated with an increase in total electricity consumption. Nearly all of the increase, though, was in the off-peak period, as monitoring did contribute significantly to shifting usage away from the peak period. These conclusions are best verified through Table 7, which reports monitoring's estimated monthly effect on KWH consumption for each TOU group and an average effect across all groups.

The estimated effect on the 3:1 group is simply the value of the MTR coefficient. For the other P:OP groups, it is MTR + Xi(MTR), i = 5,7,9. The total effect is estimated as the weighted average of the individual group effects with the proportion of monitoring households in each group serving as the weights. The percentage effect is calculated in conjunction with an estimated base level of consumption.[11]

The monthly monitor effects in Table 7 demonstrate a consistent shifting of usage from peak to off-peak periods. Monitoring was associated with an overall decline in peak-period consumption in six of the ten months, working out to a 1.7 percent average monthly decrease. Off-peak period usage rose among monitor households in all but one month with an average increase of 12.2 percent. Monitor households' total usage also rose in nine of the ten months with an average increase of about 5.5 percent.

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Insert Table 7 about here
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The monitor effects also demonstrated a strong seasonal pattern. Overall usage increases attributable to monitoring, were largest, 10 to 15 percent, during the summer months of July, August, and September. The range of spring (May, June) and fall (October, November) monitor-induced consumption increases were much lower, 2 to 8 percent, and monitoring was actually associated with an average 2.8 percent decline in peak period usage during the spring and fall months. The monitor households began to show some tendency towards overall conservation during the winter months with the pervasive shifting from peak to off-peak periods remaining in effect.

The similarity of spring and fall effects is strong evidence that the seasonal pattern was related to climate and not to the evolution of the experiment itself. Air conditioning usage provides the most logical explanation for the observed pattern. Evidently, consumers found air conditioning costs to be lower than expected, particularly in the off-peak period, and reacted by increasing use of air conditioners. Air conditioning's significance as a component of total electricity consumption also probably explains the preponderance of statistically significant effects for monitoring in the summer months.

As to the individual TOU groups, monitoring was unambiguously associated with an increase in electricity usage in both the peak and off-peak periods for the 3:1 group. The MTR coefficient, though, was statistically significant in only a handful of instances. Monitoring's total effect was generally positive for the 5:1 and 7:1 groups as well, but in all cases the increase was concentrated in the off-peak period, with monitor households' peak period consumption declining in a number of months (particularly those in the fall and winter). The X5(MTR) and X7(MTR) coefficients were generally not statistically significant, however. Monitor households in the 9:1 group showed strong consistent conservation tendencies in both the peak and off-peak periods throughout the experiment, and the (X9)MTR coefficient was usually statistically significant.

Table 7 also indicates that monitoring became generally more effective in shifting consumption away from peak periods as the P:OP differential increased. For example, the peak-period ordering from least to most monitor-induced conservation among the four TOU groups precisely followed the 3:1, 5:1, 7:1, and 9:1 delineation in 6 of the 10 months. The off-peak effect generally followed the opposite ordering, although the 9:1 group's strong conservation tendencies prevented the pattern from being as precise as in the peak period.

This general ordering of P:OP effects is consistent with the model. As the P:OP differential increases, households are given greater incentive to find ways to shift usage from the peak to the off-peak period. The benefits from monitoring, therefore, rise as does the likelihood of usage. In this context, monitoring's success in stimulating P:OP shifting does not agree with the earlier result that the Tourate was inversely related to the likelihood of satisfaction with the monitor program (MODEL 3).

Given the control group's absence from the sample, overall TOU effects are examined relative to the 3:1 reference group. For example, the total TOU effect relative to the 3:1 rate for the 5:1 P:OP rate is X5 + X5(MTR)δ_5, where δ_5 is the proportion of monitor households in the X5 rate group. As the accompanying table indicates, except for the 5:1 group, higher P:OP prices did not induce greater overall conservation among the sample group. Most of the higher average consumption recorded in the 7:1 and 9:1 groups did, however, occur in the off-peak period.

	Average Monthly KWH Effect Relative to 3:1 Group		
P:OP Rate	Peak Period	Off-Peak Period	Total
5:1	-106.0	48.9	-56.3
7:1	8.8	125.9	137.0
9:1	19.4	168.8	189.5

Finally, the coefficients for the RATEA indicator variables were negative for each month during the peak period and positive for each off-peak period regression, suggesting that the Rate A peak period, 10 a.m. to 8 p.m., was more conducive to shifting usage from peak to off-peak periods than the 12 noon to 10 p.m. Rate B peak period.

CONCLUDING REMARKS

This study has analyzed the effect of continuous-display electricity-use monitors in conjunction with a time-of-use pricing experiment. The two phases of the study were (1) a logit analysis of consumers' decisions whether or not to use the monitor, and (2) an investigation of monitoring's overall effects on electricity consumption using an analysis of covariance framework.

To place the study's results in proper perspective, its relationship to its cousins in the behavior modification field must be borne in mind. Monitoring was evaluated here as an information-providing device, not necessarily as a tool to promote conservation. No overt intervention in the form of goal setting, commendation, dissonance, etc., was implemented to promote conservation or shifting of consumption from peak to off-peak periods. Hence, monitoring's role in the experiment was purely informational.

Monitoring's tendency to increase off-peak period consumption and decrease peak period usage suggests that households were on average overestimating off-peak electricity costs and underestimating their peak-period counterparts. These conclusions suggest, in turn, that participants in the time-of-use (TOU) experiment had not completely adjusted to their P:OP prices at the time the monitors were installed (the beginning of the experiment's second year) and that the monitors performed a useful role in enabling users to converge to their desired consumption levels.

We advise caution in interpreting these results outside of a time-of-use pricing context. Our opinion is that, in a period of stable information, overestimation and underestimation of electricity costs are equally likely to occur. These effects would generally cancel in an aggregative ANOVA to generate a conclusion of "no effect." We believe that this phenomenon explains the minimal effects often attributed to monitoring or other information initiatives. This signifcant information effects found here even after a full year of a stable TOU price regime suggest that there are important behavioral lags or other impediments to consumer adjustment. The broader significance of these conclusions for TOU pricing is that short-term TOU experiments may not accurately reflect the magnitude of desired (long-term) consumer response to peak:off-peak pricing.

FOOTNOTES

[1]The Dupont monitor is manufactured by Dupont Energy Management Company of Dallas, Texas.

[2]Temperature data for the study's final two months were collected independently from the National Oceanic and Atmospheric Administration.

[3]Framing the decision dichotomously is an abstraction. Households actually may choose a level of monitor usage rather than merely choosing between use or nonuse. This feature may be incorporated into the model at the expense of considerable additional complexity.

[4]Units of service may be a load of clothes washed, an hour of television watched, etc. The K_j will differ across households based on an appliance's size, age, quality, state of repair, etc.

[5]Upwards of one-half of the participants in the joint U.S.-Canada monitoring experiments reported using the devices to discern usage levels for individual appliances and to conduct experiments to test out different energy saving ideas (Filiatrault, Hutton and Meuser 1984).

[6]For example, the dollar-value loss from misinformation which induces a 10 percent consumption error will clearly be greater for a consumer who utilizes 30,000 kilowatts annually relative to one who consumes only 3,000. And a given percentage error in estimating a unit-of-service price will produce relatively larger percentage consumption errors and, hence, larger surplus losses for those consumers with the more elastic demands.

[7]The likelihood function is:

$$L = \prod_{D^i=0} F(\beta_C' X_C^i - \beta_L' X_L^i) \prod_{D^i=1} [1 - F(\beta_C' X_C^i - \beta_L' X_L^i)],$$

where $i = 1, \ldots, m$ are the sample households.

[8]The logistic distribution in this case is:

$$F(\beta_C' X_C^i - \beta_L' X_L^i) = 1/[1 + \exp(\beta_L' X_L^i - \beta_C' X_C^i)].$$

[9]The model yields no clear prediction concerning income's effect when the monitor must be purchased. Its presumably positive effect on the purchase decision works opposite to its effect on the opportunity cost of time.

[10]The indices were constructed by weighting electrical appliances and heating-cooling apparatus according to their mean usage across the SCE system. The discretionary appliances were electric range, self-cleaning oven, microwave oven, dishwasher, clothes washer, electric clothes dryer, color TV, black and white TV, pool, and jacuzzi. The heating-cooling index was based upon central air conditioning, room air conditioning, evaporative coolers, and electric main heating.

[11]Base consumption for each month was determined by solving its regression equation with all indicator variables set equal to zero and all other variables evaluated at their means. For example, from Tables 2 and 4 base consumption in December is -36.22 + 817.53(0.12) + 1176.69(0.77) + 1.13(27.95) + 0.20(2024) + 0.57(195) = 1515.5.

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Table 1.

STRATIFICATION AND CELL DEFINITION FOR THE SCE EXPERIMENT

		Rate Subgroup Population[a]				
Cell	Definition	3:1	5:1	7:1	9:1	Total
Consumption Group:						
CG1	0-2,160 annual kwh usage	8	8	8	8	32
CG2	2,161-3,360 annual kwh usage	8	8	8	8	32
CG3	3,361-4,920 annual kwh usage	10 (1)	10	10 (1)	10 (2)	40 (4)
CG4	4,921-8,880 annual kwh usage	34 (6)	34 (7)	34 (1)	34 (8)	136 (22)
CG5	8,881-30,000 annual kwh usage	60 (9)	60 (9)	60 (14)	60 (10)	240 (42)
Total		120 (16)	120 (16)	120 (16)	120 (20)	480 (68)
Temperature Zone:						
TZ1	Local peak design temp. = 90°F	64 (8)	64 (8)	64 (7)	64 (11)	256 (34)
TZ2	Local peak design temp. 100°F	42 (7)	42 (8)	42 (7)	42 (7)	168 (29)
TZ3	Local peak design temp. 110°F	14 (1)	14	14 (2)	14 (2)	56 (5)

[a]The value in parenthesis is the number of monitor households in the cell.

Table 2

LIST OF VARIABLES AND MEANS

Variable		Mean Consumption Effects	Sample Use/Nonuse
Consumption			
KWH^{T}	Total monthly electricity consumption in Kilowatt hours	3283[a]	
KWH^{P}	Monthly peak period electricity consumption in Kilowatt hours	1506[a]	
KWH^{OP}	Monthly off-peak electricity consumption in Kilowatt hours	1777[a]	
Prices	[0,1] indicator variable, set to 1.0 for households facing the:		
X3	3:1 peak: off-peak price ratio	0.26	
X5	5:1 peak: off-peak price ratio	0.24	
X7	7:1 peak: off-peak price ratio	0.25	
X9	9:1 peak: off-peak price ratio	0.25	
TOURATE	High (7:1 or 9:1) peak: off-peak price ratio		0.46
Appliances			
HTAC	Stock of electric heating and cooling appliances	0.12	0.12
DISCAP	Stock of discretionary-use appliances		0.50
APSTOCK	Total appliance stock excluding HTAC	0.77	
Household Characteristics			
INCOME	Total annual income in thousands	27.95	27.18
HEADED	[0,1], set to 1.0 if head has a college education		0.24
MEMBERS	Number of persons living in the home full time		3.38
WORKERS	Number of full-time workers		1.30
Weather			
$HEATING^{T}$	Total monthly heating degree days	859[b]	
$HEATING^{P}$	Monthly peak period heating degree days	195[b]	
$HEATING^{OP}$	Monthly off-peak period heating degree days	665[b]	
$COOLING^{T}$	Total monthly cooling degree days	469[c]	
$COOLING^{P}$	Monthly peak period heating degree days	415[c]	
$COOLING^{OP}$	Monthly off-peak period heating degree days	54[c]	
MTR	[0,1], set to 1.0 for households with a Dupont monitor	0.19	
RATEA	[0,1], set to 1.0 for households in group A	0.47	
HSQFT	House square footage	2024.	

[a]Average mean for all monitor months--May 1980 - February 1981
[b]December 1980 mean values
[c]July 1980 mean values

Table 3.

LOGIT ESTIMATION RESULTS

Explanatory Variables	Coefficient estimates (t-ratios are in parenthesis) MODEL 1	MODEL 2	MODEL 3
HTAC	0.0106 (1.1626)	0.0282 (1.4004)[a]	0.0054 (0.5841)
DISTOCK	0.0024 (0.5984)	-0.0111 (-1.9286)	-0.0013 (-0.2819)
HEADGO	-1.2978 (-1.4705)	0.8356 (0.6568)	-0.2226 (-0.2457)
INCOME	-0.0921 (-2.3222)[b]	-0.0541 (-1.1497)	0.0990 (1.9750)[b]
MEMBERS	-0.6764 (-2.5975)[b]	-0.37512 (-1.2159)	0.4396 (1.6960)[a]
TOU RATE	0.4744 (0.6911)	0.3663 (0.4024)	-1.5433 (-1.8186)[a]
Constant	4.7010 (2.5347)[b]	5.8364 (2.3414)[b]	-2.1708 (-1.1452)
R^2	0.2328	0.2104	0.3051
Likelihood ratio test	14.0269	10.0442	11.3727

[a]Significant for $p \leq 0.10$.
[b]Significant for $p \leq 0.05$.

Table 4

PEAK PERIOD ELECTRICITY CONSUMPTION ANALYSIS[a]

Variable	May	June	July	August	September	October	November	December	January	February
MTR	136.17	143.99	381.49	839.76	404.99	468.27	197.12	191.94	48.10	42.34
	(0.76)	(0.55)	(0.88)	(2.21)[c]	(1.72)[b]	(2.08)[c]	(1.04)	(0.81)	(0.20)	(0.21)
X5	-47.72	-74.82	-319.20	-180.87	-119.76	-41.03	65.51	68.48	30.06	-19.26
	(-0.43)	(-0.47)	(-1.20)	(-0.77)	(-0.82)	(-0.30)	(0.56)	(0.46)	(0.20)	(-0.15)
X5(MTR)	-72.89	-106.65	-155.29	-554.49	-311.29	-424.10	-186.78	-226.34	-87.57	-110.64
	(-0.28)	(-0.28)	(-0.25)	(-1.01)	(-0.91)	(-1.30)	(-0.68)	(-0.66)	(-0.25)	(-0.37)
X7	104.75	83.48	-4.14	95.86	-23.29	57.50	111.09	61.55	6.87	-15.42
	(0.97)	(0.53)	(-0.02)	(0.42)	(-0.16)	(0.43)	(0.98)	(0.43)	(0.05)	(-0.12)
X7(MTR)	-187.85	25.56	-94.72	-468.90	-282.45	-549.78	-283.57	-321.14	-153.07	-113.25
	(-0.73)	(0.07)	(-0.15)	(-0.85)	(-0.83)	(-1.69)[b]	(-1.04)	(-0.94)	(-0.43)	(-0.38)
X9	162.00	173.82	165.16	328.63	126.62	178.10	200.43	205.74	194.04	170.10
	(1.46)	(1.07)	(0.61)	(1.39)	(0.86)	(1.27)	(1.69)[b]	(1.40)	(1.26)	(1.31)
X9(MTR)	-435.35	-631.70	-1158.23	-1389.47	-714.64	-882.25	-689.54	-678.19	-522.24	-472.61
	(-1.76)[b]	(-1.76)[b]	(-1.93)[b]	(-2.65)[d]	(-2.20)[c]	(-2.84)[d]	(-2.65)[d]	(-2.07)[c]	(-1.54)	(-1.66)[b]
HTAC	515.16	1591.92	3831.78	2429.75	1005.89	862.63	258.85	817.53	746.48	627.41
	(1.77)[b]	(3.78)[d]	(5.47)[d]	(3.94)[d]	(2.58)[d]	(2.34)[d]	(0.84)	(2.12)[c]	(1.88)[b]	(1.90)[b]
APSTOCK	836.05	796.17	1447.44	1471.09	1038.13	1090.11	1094.98	1176.69	1283.25	1008.14
	(6.32)[d]	(4.15)[d]	(4.46)[d]	(5.24)[d]	(5.93)[d]	(6.54)[d]	(7.86)[d]	(6.69)[d]	(6.96)[d]	(6.62)[d]
INCOME	-0.02	2.86	5.13	-0.40	-0.91	2.29	-1.67	1.13	-1.27	-1.30
	(-0.01)	(0.85)	(0.91)	(-0.08)	(-0.30)	(0.79)	(-0.69)	(0.37)	(0.40)	(-0.48)
HSQFT	0.16	0.12	0.10	0.24	0.15	0.15	0.16	0.20	0.15	0.10
	(3.86)[d]	(1.99)[c]	(0.96)	(2.66)[d]	(2.70)[d]	(2.89)[d]	(3.66)[d]	(3.57)[d]	(2.59)[d]	(2.02)[c]
RATEA	-73.88	-8.67	-56.53	31.25	34.17	-56.20	-64.95	-117.72	-101.27	-128.26
	(-1.04)	(-0.08)	(-0.33)	(0.21)	(0.36)	(-0.63)	(-0.87)	(-1.25)	(-1.04)	(-1.57)
HEAT	0.67	-	-	-	-	0.26	0.87	0.57	-0.06	-0.09
	(1.74)[b]	-	-	-	-	(0.19)	(3.15)[d]	(2.26)[c]	(-.30)	(-.35)
COOL	1.23	0.87	1.31	1.15	1.07	1.28	-	-	-	-
	(3.11)[d]	(3.51)[d]	(4.87)[d]	(4.11)[d]	(4.94)[d]	(3.13)[d]	-	-	-	-
CONSTANT	89.19	160.30	-386.20	-558.62	-1.86	-64.20	80.15	-36.22	134.32	332.73
R^2	0.32	0.25	0.32	0.33	0.32	0.32	0.36	0.32	0.29	0.27
F for total monitor effect	0.98	1.16	1.25	2.13[b]	1.31	2.06[b]	2.23[b]	1.42	1.10	1.29

[a] t ratios in parentheses
[b] significant at 0.10
[c] significant at 0.05
[d] significant at 0.01

Table 5

OFF-PEAK PERIOD ELECTRICITY CONSUMPTION ANALYSIS[a]

Variable	May	June	July	August	September	October	November	December	January	February
MTR	32.27	166.44	531.63	344.18	315.54	447.42	393.98	289.02	395.70	25.98
	(0.14)	(0.79)	(1.84)[b]	(1.22)	(1.40)	(1.84)[b]	(1.38)	(0.85)	(1.14)	(0.09)
X5	3.59	70.00	-38.25	44.64	74.03	110.94	-4.59	60.14	102.30	56.66
	(0.03)	(0.54)	(-0.22)	(0.21)	(0.53)	(0.74)	(-0.03)	(0.28)	(0.47)	(0.32)
X5(MTR)	306.90	147.69	-18.36	87.03	22.10	-198.22	-79.85	-37.47	-160.31	-19.80
	(0.93)	(0.48)	(-0.04)	(0.26)	(0.07)	(-0.56)	(-0.19)	(-0.08)	(-0.32)	(-0.05)
X7	8.74	38.39	100.43	101.03	58.09	137.26	61.03	102.64	75.03	19.34
	(0.06)	(0.30)	(0.57)	(0.59)	(0.42)	(0.94)	(0.36)	(0.50)	(0.36)	(0.11)
X7(MTR)	548.25	734.41	401.86	501.26	542.47	84.16	52.65	168.75	129.71	300.46
	(1.66)[b]	(2.40)[d]	(0.96)	(1.22)	(1.66)[b]	(0.24)	(0.13)	(0.34)	(0.26)	(0.73)
X9	292.58	247.37	280.63	321.41	310.86	383.41	386.15	414.40	407.99	381.01
	(2.06)[c]	(1.88)[b]	(1.56)	(1.82)[b]	(2.21)[c]	(2.52)[d]	(2.16)[c]	(1.96)[b]	(1.88)[b]	(2.14)[c]
X9(MTR)	-495.54	-629.07	-1152.24	-770.05	-667.68	-900.62	-922.99	-801.23	-861.42	-494.67
	(-1.57)	(-2.16)[c]	(-2.88)[d]	(-1.97)[b]	(-2.15)[c]	(-2.68)[d]	(-2.34)[d]	(-1.70)[b]	(-1.79)[b]	(-1.26)
HTAC	842.18	332.94	1555.37	656.45	15.02	256.24	1017.19	1500.41	1273.02	1063.01
	(1.31)	(0.98)	(3.32)[d]	(1.43)	(0.04)	(0.65)	(2.18)[c]	(2.73)[d]	(2.28)[c]	(2.35)[d]
APSTOCK	1799.50	1630.08	2126.67	2027.05	1858.35	1889.78	2116.80	2250.66	2321.87	1733.66
	(10.67)[d]	(10.46)[d]	(9.84)[d]	(9.70)[d]	(11.11)[d]	(10.48)[d]	(10.02)[d]	(8.91)[d]	(8.91)[d]	(8.28)[d]
INCOME	2.97	3.07	3.54	1.66	0.80	4.56	0.91	3.55	-0.03	0.72
	(1.00)	(1.12)	(0.94)	(0.45)	(0.27)	(1.43)	(0.25)	(0.80)	(-.01)	(0.19)
HSQFT	0.10	0.11	0.14	0.20	0.14	0.15	0.17	0.16	0.15	0.08
	(1.84)[b]	(2.24)[c]	(2.13)[c]	(3.09)[d]	(2.76)[d]	(2.63)[d]	(2.51)[d]	(2.02)[c]	(1.82)[b]	(1.15)
RATEA	63.76	48.71	35.91	95.62	143.62	139.28	168.89	182.42	132.00	60.40
	(0.70)	(0.58)	(0.31)	(0.85)	(1.60)	(1.44)	(1.49)	(1.35)	(0.96)	(0.54)
HEAT	0.37	-	-	-		0.47	0.36	0.28	0.03	0.13
	(1.19)	-	-	-	-	(1.33)[c]	(2.11)[c]	(1.40)	(0.15)	(0.61)
COOL	14.07	0.92	1.31	1.03	1.68	2.10	-	-	-	-
	(1.07)	(1.21)	(3.34)[d]	(2.02)[c]	(1.73)[b]	(0.44)	-	-	-	-
CONSTANT	-348.29	-105.17	-493.52	-486.55	-377.97	-611.61	-758.79	-810.60	-628.41	-193.55
R^2	0.44	0.45	0.47	0.43	0.47	0.45	0.44	0.39	0.37	0.33
F for total monitor effect	3.13[c]	6.04[d]	5.14[d]	3.51[d]	4.90[d]	3.08[c]	2.25[b]	1.33	1.43	1.06

[a]t ratios in parentheses
[b]significant at 0.10
[c]significant at 0.05
[d]significant at 0.01

Table 6

TOTAL PERIOD ELECTRICITY CONSUMPTION ANALYSIS[a]

Variable	May	June	July	August	September	October	November	December	January	February
MTR	198.52	304.08	889.53	1776.82	719.86	909.89	579.04	471.34	458.95	77.30
	(0.55)	(0.72)	(1.32)	(1.91)[b]	(1.73)[b]	(2.12)[c]	(1.33)	(0.87)	(0.82)	(0.17)
X5	-65.78	-8.64	-364.63	-139.52	-47.21	64.70	61.50	128.83	146.16	45.53
	(-0.29)	(-0.03)	(-0.88)	(-0.37)	(-0.18)	(0.24)	(0.23)	(0.38)	(0.42)	(0.16)
X5(MTR)	245.28	62.26	-113.12	-433.44	-262.64	-589.81	-269.00	-262.37	-272.54	-142.41
	(0.47)	(0.10)	(-0.12)	(-0.49)	(-0.44)	(-0.94)	(-0.43)	(-0.33)	(-0.34)	(-0.21)
X7	115.03	124.71	100.19	203.28	40.78	194.93	165.81	160.98	95.99	11.24
	(0.53)	(0.49)	(0.25)	(0.55)	(0.16)	(0.75)	(0.63)	(0.49)	(0.28)	(0.04)
X7(MTR)	333.63	759.98	298.75	31.87	253.14	-459.39	-231.99	-153.07	-37.43	179.30
	(0.64)	(1.25)[d]	(0.31)	(0.04)	(0.42)	(-0.74)	(-0.37)	(-0.20)	(-0.05)	(0.27)
X9	438.22	423.43	452.68	657.22	441.62	564.31	584.19	622.05	598.55	546.29
	(1.95)[b]	(1.61)	(1.08)	(1.70)[b]	(1.70)[b]	(2.10)[c]	(2.14)[c]	(1.85)[b]	(1.72)[b]	(1.88)[b]
X9(MTR)	-952.99	-1248.88	-2280.38	-2142.22	-1365.21	-1759.74	-1613.19	-1480.07	-1393.99	-969.19
	(-1.91)[b]	(-2.14)[c]	(-2.45)[d]	(-2.51)[d]	(-2.38)[d]	(-2.95)[d]	(-2.67)[d]	(-1.98)[c]	(-1.81)[b]	(-1.51)
HTAC	855.84	1866.36	5237.18	2987.06	903.16	1018.92	1292.20	2320.99	1984.99	1659.79
	(1.46)	(2.73)[d]	(4.81)[d]	(2.97)[d]	(1.32)	(1.44)	(1.81)[b]	(2.64)[d]	(2.22)[c]	(2.24)[c]
APSTOCK	2630.19	2431.19	3589.76	3508.08	2903.25	2997.61	3217.27	3427.25	3602.75	2738.71
	(9.86)[d]	(7.82)[d]	(7.14)[d]	(7.69)[d]	(9.41)[d]	(9.35)[d]	(9.98)[d]	(8.52)[d]	(8.61)[d]	(7.99)[d]
INCOME	3.03	5.88	8.81	1.13	-0.10	6.76	-0.58	4.80	-1.21	-0.42
	(0.65)	(1.08)	(1.01)	(0.14)	(-0.02)	(1.20)	(-0.10)	(0.68)	(-0.17)	(-0.07)
HSQFT	0.28	0.24	0.26	0.45	0.31	0.31	0.33	0.36	0.31	0.18
	(3.33)[d]	(2.41)[d]	(1.63)	(3.12)[d]	(3.17)[d]	(3.04)[d]	(3.19)[d]	(2.82)[d]	(2.35)[d]	(1.66)[b]
RATEA	3.80	47.99	-4.03	140.02	190.68	89.66	102.55	66.90	31.47	-69.23
	(0.03)	(0.29)	(-0.02)	(0.57)	(1.15)	(0.52)	(0.59)	(0.31)	(0.14)	(-0.38)
HEAT	0.88	-	-	-	-	0.15	0.50	0.40	0.09	0.15
	(2.46)[d]	-	-	-	-	(0.20)	(2.56)[d]	(1.85)[b]	(0.38)	(0.55)
COOL	2.61	1.04	1.58	1.33	1.45	2.13	-	-	-	-
	(3.13)[d]	(3.13)[d]	(4.98)[d]	(3.80)[d]	(4.42)[d]	(1.99)[c]	-	-	-	-
CONSTANT	-608.74	9.05	-1042.37	-1130.52	-474.13	-698.00	-717.62	-891.98	-620.27	35.36
R^2	0.44	0.38	0.41	0.39	0.43	0.42	0.44	0.38	0.36	0.32
F for total monitor effect	2.14[b]	3.12[c]	2.62[c]	2.75[c]	2.90[c]	2.54[c]	2.26[b]	1.326	1.10	1.11

[a]t ratios in parentheses
[b]significant at 0.10
[c]significant at 0.05
[d]significant at 0.01

TABLE 7

THE EFFECT OF MONITORING ON ELECTRICITY USE BY TOU CLASS

	May	June	July	August	Sept	Oct	Nov	Dec	Jan	Feb
				--PEAK PERIOD--						
Monitor Effect (KWH):										
3:1	136.2	144.0	381.5	839.8	405.0	468.3	197.1	191.9	48.1	42.3
5:1	63.3	37.3	226.2	285.3	93.7	44.2	10.3	-34.4	-39.5	-68.3
7:1	-51.7	169.6	286.8	370.9	122.5	-81.5	-86.5	-129.2	-105.0	-70.9
9:1	-299.2	-487.7	-776.7	-549.7	-309.6	-414.0	-492.4	-486.3	-474.1	-430.3
Total	-37.6	-31.7	32.4	243.5	81.6	8.1	-91.2	-112.4	-141.8	-130.3
Base Usage (KWH)	1276.0	1460.3	2097.4	1710.8	1387.4	1398.7	1310.9	1515.5	1461.2	1325.3
Total Percentage Effect	-3.0	-2.2	1.5	14.2	5.9	0.6	-7.0	-7.4	-9.7	-9.8
				--OFF-PEAK PERIOD--						
Monitor Effect (KWH):										
3:1	32.3	166.4	531.6	344.2	315.5	447.4	394.0	289.0	395.7	26.0
5:1	339.2	314.1	513.3	431.2	337.6	249.2	314.1	251.6	235.4	6.2
7:1	580.5	900.9	933.5	845.4	858.0	531.6	446.6	457.8	525.4	326.4
9:1	-463.3	-462.6	-620.6	-425.9	-352.1	-453.2	-529.0	-512.2	-465.7	-468.7
Total	121.6	233.1	343.7	301.6	293.9	198.4	159.0	124.1	177.0	-24.6
Base Usage (KWH)	1618.6	1515.1	1796.4	1644.6	1381.3	1438.1	1569.3	1724.2	1646.2	1528.6
Total Percentage Effect	7.5	15.4	19.1	18.3	21.3	13.8	10.1	7.2	10.8	-1.6
				--TOTAL--						
Monitor Effect (KWH):										
3:1	198.5	304.1	889.5	1776.8	719.9	909.9	579.0	471.3	459.0	77.3
5:1	443.8	366.3	776.4	1343.4	457.2	320.1	310.0	209.0	186.4	-65.1
7:1	532.2	1064.1	1188.3	1808.7	973.0	450.5	347.1	318.3	421.5	256.6
9:1	-754.5	-944.8	-1390.9	-365.4	-645.4	-849.9	-1034.2	-1008.7	-935.0	-891.9
Total	104.4	203.0	372.0	550.2	383.5	215.6	54.8	2.1	38.5	-151.3
Base Usage (KWH)	2842.6	2978.2	3895.8	3347.2	2768.9	2842.0	2897.0	3251.3	3100.8	2840.7
Total Percentage Effect	3.7	6.8	9.6	16.4	13.9	7.6	1.9	0.1	1.2	-5.3

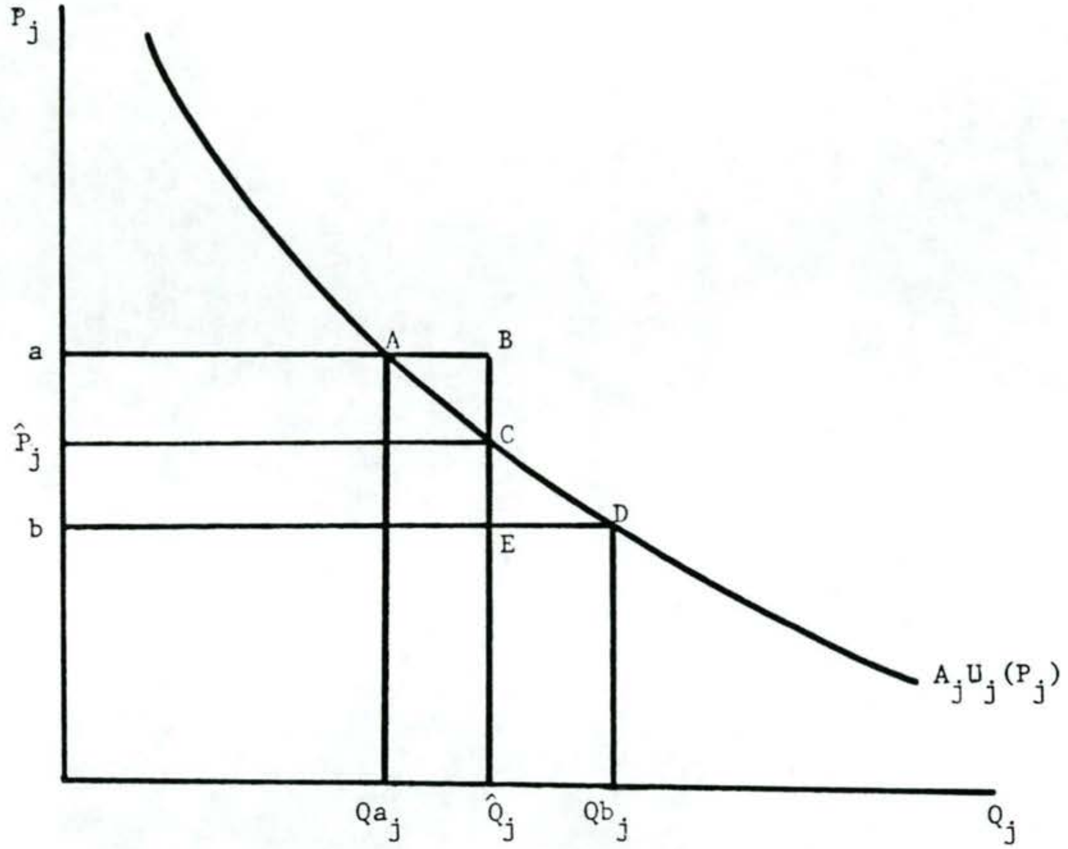

Figure A. Consumer Welfare Loss Due to Incomplete Information on Electricity Usage.