SEASONAL ELECTRICITY DEMAND AND PRICING ANALYSIS WITH A VARIABLE RESPONSE MODEL

PREPARED FOR THE LOS ANGELES DEPARTMENT OF WATER AND POWER

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PREFACE

The Los Angeles Electricity Rate Study--a five-year project begun in 1975--is designed to yield information about the effects of alternative pricing structures for residential consumers. The experimental plans include time-of-day, seasonal, and time-invariant rates for approximately 1800 households over a 30 month period. The study is being conducted jointly by the Los Angeles Department of Water and Power and The Rand Corporation, with partial funding from the U.S. Department of Energy.

This report presents the results of behavior under the seasonal and time-invariant experimental plans. In many circumstances, seasonal rates will be the most attractive alternative to conventional rates for residential customers, because they are relatively inexpensive to implement compared with time-of-day rates. The analytic approach includes a flexible statistical model that accurately captures household response to rates, changes in weather, and a variety of household characteristics. With this flexible model, it is possible to make accurate forecasts for a wide range of circumstances beyond the Los Angeles area, where the data were collected.

The report should be of particular interest to electric utilities and regulatory bodies investigating consumer responses to new rates. It should be of more general interest to economists and policy analysts for the analytic framework it provides for evaluating and forecasting the effects of seasonal pricing.

Related Rand research on electricity pricing and demand can be found in the following publications:

- o *Design of the Los Angeles Peak-Load Pricing Experiment for Electricity*, Willard G. Manning, Jr., Bridger M. Mitchell, and Jan Paul Acton, R-1955-DWP, November 1976.
- o *Lessons To Be Learned from the Los Angeles Rate Experiment in Electricity*, Jan Paul Acton, Willard G. Manning, Jr., and Bridger M. Mitchell, R-2113-DWP, July 1978.
- o *Peak-Load Pricing: European Lessons for U.S. Energy Policy*, Bridger M. Mitchell, Willard G. Manning, Jr., and Jan Paul Acton, Ballinger Publishing Company, 1978.
- o *The Los Angeles Senior Citizen Lifeline Electricity Rate*, Timothy J. Sullivan, R-2278-DWP/NSF, January 1979.
- o *Sample Selection in the Los Angeles Electricity Rate Study*, Winston Chow and Bridger M. Mitchell, R-2430-DWP, July 1979.
- o *Conducting a Survey Using the Client's Staff: Evaluation of Interviewer Performance in the Electricity Rate Study*, Sandra Berry, R-2223-DWP, September 1979.
- o *Evaluating Time-of-Day Electricity Rates for Residential Customers*, Jan Paul Acton and Bridger M. Mitchell, R-2509-DWP, November 1979.
- o *Do Time of Use Rates Change Load Curves?*, Jan Paul Acton and Bridger M. Mitchell, R-2588-DWP/EPRI, May 1980.
- o *Residential Energy Demand Under Time-of-Day Pricing: Preliminary Results from the Los Angeles Rate Study*, Willard G. Manning, Jr., and Jan Paul Acton, R-2426-DWP, forthcoming.

- o *Electricity Consumption by Time of Use in a Hybrid Demand System*, Bridger M. Mitchell and Jan Paul Acton, R-2628-DWP, forthcoming.

SUMMARY

In general, economic welfare is improved and electricity pricing more accurately reflects costs of supply if electricity rates incorporate time of use (TOU) in their structure. At the residential level, seasonal pricing may be a cost effective way to introduce TOU considerations because it avoids the need for investing in new meters for small volume users. If seasonal pricing is relatively inexpensive to implement, then its gains--measured in increased efficiency of operation and improved consumer well-being--can serve as a benchmark against which the additional gains of time-of-day pricing can be compared. If on the other hand the gains from introducing seasonal rates are small relative to the implementation costs, the utility should either stay with conventional rates or look to time-of-day rates for significant gains.

To judge the potential changes in consumption, bills, well-being, and efficiency of operation that may accompany the introduction of seasonal rates, we need both good data and appropriate analytic techniques. The Los Angeles Electricity Rate Study gathered data on monthly electricity use for 800 households who faced seasonal rates over a 30-month period. In combination with extensive survey data and climate data, it permits specification and estimation of a detailed econometric model. Because households faced a variety of pricing structures, we can estimate the effects of different seasonal pricing schemes.

Choosing an appropriate analytic technique presents an important

challenge. Month to month changes in weather play an important role in month to month differences in the level of electricity consumption. To extract the maximum amount of information from the experiment, we wish to pool the cross section of household time series observations. In comparison with ordinary least squares estimates, the full information maximum likelihood estimating technique employed here takes account of cross equation and time correlation in error terms and yields more accurate parameter estimates as well as appropriate test statistics.

The model chosen allows household-specific response to weather conditions, depending on household characteristics such as climate control appliances and house size. In the model selected, monthly electricity consumption by each household can be viewed as the sum of four components: (1) the permanent household consumption level, (2) the household-specific response to hot weather, (3) the household-specific response to cold weather, and (4) serially independent transitory variation. The first component incorporates response to price, which can vary from season to season, but price also explains the degree of responsiveness to monthly weather in the second and third components.

By taking account of these different components of consumption, this model permits more accurate estimates of household-specific behavior, and it leads to more flexible and accurate predictions for other utility service territories where important differences may exist in some of the explanatory variables.

The model was estimated using 23 months of data, including 624

households observed with complete data during the period. The parameter estimates are highly statistically significant and lead to very reasonable predictions. The permanent consumption level is significantly related to appliance ownership, housing value, and appliance holdings; income elasticities are very low and the effect of income is primarily reflected through appliance ownership and housing value. Responsiveness to hot and cold weather depends importantly on housing value and climate control appliances; hot weather response also depends significantly on price and number of rooms.

In this model, many of the important variables enter the equation that explains permanent consumption as well as the equations that explain responsiveness to weather; consequently, their predicted effect depends on weather. The price elasticity at mean weather conditions is approximately $-.058$. In addition, a negative price coefficient in the hot weather component of the model means that households are more elastic at hotter temperatures, both in the cross section and in time series. For instance, at a temperature one standard deviation hotter than usual, the mean price elasticity increases to $-.70$, and at a minus one standard deviation it reduces to $-.045$. We also find that the presence of air conditioners and electric space heating increases a household's permanent level of use and, more significantly, the level of use when temperatures become more extreme. These findings lead to substantial differences in predicted level of use as we condition our predictions on the characteristics of different climate zones within the city or on different monthly values of temperature.

We find that permanent differences among households explain about

90 percent of the variation observed in individual household consumption of electricity. Weather-related response, while statistically significant, explains a much smaller proportion.

The model leads to some important implications for evaluating seasonal pricing. The statistically significant differences among households means that there will be important variation in consumption, bills, and welfare if non-time-differentiated rates are replaced with seasonal rates. Furthermore, the predicted gains from introducing seasonal pricing are extremely modest. Even under an assumed seasonal difference of 4¢ per kwh (8.4¢ per kwh peak season, 4.4¢ per kwh off-peak season; each season six months long), welfare gains are predicted to amount to a few cents per customer per month. Seasonal pricing can change consumers' bills importantly from one season to another, but in net the average over the year is relatively small for all major subgroups of the population if the overall rate is designed to raise the same amount of revenue as a nonseasonal rate.

We also observe that the predicted effects of seasonal pricing will vary depending on the particular weather that is experienced. If seasonal pricing is introduced in a year in which weather is more extreme than usual, customers may face bill increases that are much greater than anticipated and the utility may have unexpected revenue shifts. Although things may even out in the long run, the transition period may lead to important problems and misassigning of cause for increase (or decrease) in bills and revenue.

Finally, it appears from the Los Angeles study that the welfare gains from introducing seasonal pricing are very small, even if we

assume zero implementation costs. On average, they are less than \$1 per year per customer, although they approach \$3 per year at higher levels of use. These gains are a fraction of the gains from introducing time-of-day rates that have been estimated with the time-of-day component of the Los Angeles Electricity Rate Study. If the particular estimates are representative for other utility systems, it appears that seasonal pricing has little to offer in comparison with present rates or in comparison with time-of-day rates selectively applied.

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CONTENTS

PREFACE	iii
SUMMARY	vii
ACKNOWLEDGMENTS	xiii

Section

I. INTRODUCTION	1
II. LOS ANGELES ELECTRICITY RATE STUDY SEASONAL DATA	5
III. VARIABLE RESPONSE TO WEATHER: MODEL AND ESTIMATION	10
Estimation	13
Prediction	17
IV. REGRESSION PARAMETER AND VARIANCE COMPONENT ESTIMATES	19
V. EFFECTS OF CHANGES IN WEATHER OR CLIMATE	
CONTROL APPLIANCES	25
Changes in Monthly Weather and Climate Zone	25
Changes in Climate Control Appliance Holdings	27
VI. EVALUATING SEASONAL PRICING	30
Effects of Seasonal Pricing	31
Effects of Seasonal Pricing Under More	
Extreme Weather Conditions	35
VII. CONCLUSIONS	38

APPENDIXES

A. Temperature Weather Values	41
B. Consumption Weights Used in Creating Appliance Aggregates ..	42

REFERENCES.....	43
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I. INTRODUCTION

It is well known that electricity in the United States is priced at levels that may differ significantly from marginal cost, resulting in both efficiency and distributional losses. Historically, residential electricity rates have almost universally been declining block rates in which the price per kilowatt-hour declines as a step function as the level of consumption increases. Such rates may have been cost-justified in a period of declining long-run marginal costs, but in a time of constant or rising marginal costs, they should be reassessed.

The Public Utilities Regulatory Policies Act of 1978 (PURPA) requires state by state evaluation of existing rates and consideration of the suitability of some 11 different standards for electricity pricing, including seasonal, time-of-day (TOD), and declining block rates.[1] In principle, economic efficiency could be increased by introducing time of use (TOU) into the pricing structure. Seasonal pricing requires minimal implementation costs, while time-of-day pricing generally requires the added cost of a new TOD meter (typically \$80-\$150 at today's prices and volume of production). As a consequence, some analysts have urged that time-of-day pricing be adopted only if it shows an increase in economic welfare over seasonal pricing, net of the

[1] See Joskow (1979) for a review of some of the policy implications of its enactment.

incremental metering cost.[1] If the welfare gains from seasonal pricing are large, there may be little additional gain from time-of-day pricing; alternatively, if seasonal pricing produces little welfare gain, then there may still be a significant role for time-of-day pricing at the residential level.

To evaluate the efficiency and distributional changes that will accompany the introduction of seasonal rates, we need good estimates of price elasticity by season, as well as the effect of changes in weather and changes in the stock of household appliances and demographics. Over the last five years, a number of rate experiments have been conducted to gather such information. We employ data from the Los Angeles Electricity Rate Study, a five-year study of approximately 800 households on eight different seasonal pricing schemes, to provide estimates.

Policy analysis that considers the variety of circumstances existing in different utility service territories requires a flexible econometric model precise enough to forecast responses in other geographic locations. The model developed here has several unique features and advantages for such analysis. Not all households respond to changes in weather conditions in the same way. Our approach is to explicitly model behavioral differences and relate them to measured household characteristics. Each household has its own demand parameters, including (1) its permanent or long-run consumption level at the current price, (2) responsiveness to hot weather and to cold weather, and (3) independent transitory month to month variation.

[1] See Wenders and Taylor (1976).

Each household participating in the experiment is observed repeatedly (monthly) for nearly two years at four different prices and a full range of weather conditions. For estimation, we combine eleven months of pre-experimental data, during which a 13.8 percent price increase occurred, with a full year of data at experimental prices which vary between summer and winter by design. This cross section of time series observations allows us to estimate the joint distribution of behavioral responses and to relate them cross sectionally to household characteristics.

This approach has two primary advantages. First, relating behavioral response parameters to household characteristics provides a flexible framework for predicting responses to price changes for population groups other than the one sampled, and for price changes other than those actually observed in the experimental situation. Relating weather responsiveness to household characteristics allows identification of demographic subgroups which potentially aggravate peak load problems in extreme weather. It also allows us to measure more accurately the distribution of bill changes and welfare effects of introducing seasonal pricing.

Second, unexplained differences in household behavior cause heteroscedasticity and correlation in error terms of the regression equation so that ordinary least squares (OLS) techniques produce inefficient parameter estimates and inconsistent estimates of test statistics. Our approach is to explicitly model these sources of unexplained variation with a random coefficient model and to obtain maximum likelihood estimates.

Section II describes the Los Angeles Electricity Rate Study data. Section III outlines the econometric model and estimation procedures. Section IV discusses the estimates, and Section V presents the predicted effects across households, climate zones, and temperature changes. Section VI analyzes the effect of introducing seasonal pricing on bills, level of consumption, and changes in producers' and consumers' surplus. The final section reports our conclusions.

II. LOS ANGELES ELECTRICITY RATE STUDY SEASONAL DATA

The results reported here are based on data from the Los Angeles Electricity Rate Study. Households participating in the experiment were drawn from residential customers of the Los Angeles Department of Water and Power (DWP) in the fall of 1975.[1] The study includes a time-of-day as well as a seasonal experiment. The full study is described in detail by Acton, Manning, and Mitchell (1977) and Manning, Mitchell, and Acton (1979). Only essential features of the data are reported here.

Household consumption was measured over a time series of weather conditions and of pre-experimental and experimental prices; detailed information about the household is available. Our results are based on 23 months of consumption data--11 pre-experimental months (June 1975 to April 1976) and 12 experimental months (October 1976 to September 1977).[2] Consumption is measured as mean daily kilowatt hours (kwh) consumed over the month.[3] There are 624 households included in this analysis.[4] Each household faced a series of four prices over the 23

[1] The sample of households was stratified by three climate zones and four pre-experimental levels of consumption. The empirical covariance matrices are reweighted to population proportions before analysis. See Chow and Mitchell (1979) for a description of the sampling procedure and weights.

[2] Households participate in the experiment for a period of 30 months.

[3] Daily consumption and weather values are used to avoid the problem of long (31 day) and short (30 day, except February) months. In addition, some randomly missing days of consumption were encountered. Daily consumption values are based on days with good data.

[4] Some households were excluded because of missing data on essential variables. A total of approximately 809 households face seasonal rates in the Los Angeles Electricity Rate Study. In order to have a complete series of monthly consumption on each of these households, and to be sure that each household received normal feedback on price via the billing system, we confine our analysis to a subset of these experimental households. The normal DWP billing cycle occurs

months. Before the experiment, all households faced the same declining block rate structure with four blocks: (0-150 kwh/mo), (151-400 kwh/mo), (401-1000 kwh/mo), and (1000 + kwh/mo). In the pre-experimental period, each household was assigned to a consumption block based on its long-run (12 month) mean consumption level. The household was then assumed to behave as if it faced the marginal price associated with that block, every period.[1] Households were observed at two prices pre-experimentally due to a 13.8 percent rate increase in each block effective November 1975. Before the rate increase, and net of fuel charges, the rates in the four blocks were respectively 3.2¢/kwh, 2.14¢/kwh, 1.89¢/kwh, and 1.69¢/kwh.

every 60-61 days in the pre-experimental period and meter-reading takes place every 30-31 days during the experimental period. We excluded any household whose consumption was recorded for (1) less than 50 days or greater than 70 days in the pre-experimental period or (2) less than 25 days or greater than 35 days during the experimental period. We also excluded any household that had any month of observation missing at any time during the period June 1976 to April 1977 or October 1977 to September 1978. The exclusions were not systematically related to plan or any other characteristic of the household that we could detect.

[1] Marginal prices include the mean summer or winter fuel charge. Average fuel charges for summer 1975 and winter 1975-76 were 0.812 cent and 0.874 cent, respectively. This treatment of price can be justified on a number of grounds. First, as will be demonstrated later, household consumption is quite stable over time so that households do not change blocks often from month to month. Second, households cannot easily monitor their consumption within any month and thus do not know when a new block is reached. They may therefore be assumed to behave in any month as if they faced the marginal price of their "usual" block. Third, an alternative approach of assigning households to blocks based on an instrument, regression prediction equation, for long-run consumption yielded essentially the same results. Finally, an alternative model of demand, not reported here, yielded essentially the same results. In that model, the price elasticity was allowed to be variable among households so the mean elasticity (and variance) was estimated. The mean value, each household responding to its own time series of prices, was consistent with results reported here.

Households entering the experiment faced one constant price per kwh regardless of consumption level, but the price varied between summer and winter. Summer rates apply June through September in the experiment. Sample sizes for the six experimental winter/summer rates and four pre-experimental block combinations are presented in Table 1. Thus, there are 24 possible price sequences.

Each household faced a time series of weather conditions measured by daily cooling degree hours (C, for hot temperatures) and daily heating degree hours (H, for cold temperatures).[1] Los Angeles has three climate areas: a coastal area, containing 121 experimental households, with temperate climate (and virtually no air conditioning); a valley area, containing 255 experimental households, with a hot and semi-arid climate (and substantial air conditioning); and a central area, contain-

[1] Daily cooling degree hours C is defined as total number of above 65 degree-hours of exposure in a given month divided by the number of days in the month. For example, a day with 10 hours at 75 degrees contributes 100 cooling degree hours to the monthly total. H is defined similarly (for temperatures below 65 degrees). In estimation procedures, C and H are deviations from their approximate means and are expressed in hundreds of hours:

$$C = \left[\left(\sum_{i=1}^{ND} \sum_{t=1}^{24} \text{Max}(\text{Temp}_{it} - 65, 0) / ND \right) - 90 \right] / 100$$

$$H = \left[\left(\sum_{i=1}^{ND} \sum_{t=1}^{24} \text{Max}(65 - \text{Temp}_{it}, 0) / ND \right) - 105 \right] / 100$$

where ND is the number of days in the month. Consequently, a month that consisted of 12 hours every day about 65° at an average temperature of 72.5°F and 12 hours every day below 65° at an average temperature of 56.25°F would produce a value of C = 0 and H = 0. Note that the model does not assume normality in C and H, so truncation of these variables does not present a problem in estimation. Use of cooling and heating degree hours, rather than the more commonly used degree days (based on mean daily temperature), captures more completely the effect of temperature on consumption.

ing 248 experimental households, with an intermediate climate. The weather variables vary across climate areas, but households within an area are assigned, for each measure, the same sequence of 23 weather values. The weather values used for estimation and prediction are reported in Appendix A.

Several important household characteristics are introduced into the explanatory equations, including three composite appliance variables. These variables are described in Table 2 with their means in the estimation sample and the means used for predicting systemwide effects.

Table 1

SAMPLE SIZE BY EXPERIMENTAL PRICE PLAN
AND PRE-EXPERIMENTAL CONSUMPTION LEVEL

Pre-Experimental Block, kwh/mo	Experimental Plan, Winter/Summer Prices/kwh						
	2¢/2¢	5¢/5¢	2¢/5¢	5¢/2¢	2¢/8¢	8¢/2¢	Marginals
A. 0-150	45	9	20	15	3	1	93
B. 151-400	85	20	28	39	12	4	188
C. 401-1000	117	38	48	46	18	7	274
D. 1000 +	30	8	14	12	3	2	69
Marginals	277	75	110	112	36	14	624

Table 2

MEANS OF EXPLANATORY VARIABLES

Variable	Description	Mean of Estimation Population ^a	Mean of LA System ^a
ln(Rooms)	log of number of rooms in the residence	1.599	1.674
ln(HVALUE)	log of the rental value of the house if owned (monthly equivalent) and rent if a renter.	5.251	5.448
ln(ACE)	log of an aggregate of consumption ratings of cooling appliances reported in the home ^b	2.409	2.098
ln(AHE)	log of an aggregate of consumption ratings of heating appliances reported in the home ^b	.303	.422
ln(AOE)	log of an aggregate of consumption ratings of other appliances reported in the home, including swimming pool characteristics ^b	16.072	17.167
ln(INC)	log of household income (earned and non-earned)	9.490	10.034
ln(FAMSIZ)	log of number of household members	.829	.930
HOMEWD	dummy variable = 1 if an adult is at home on weekdays	.726	.804
POOL	dummy variable for a swimming pool at the residence	.080	.082
H	daily heating degree hours		
Valley		.222 ^c	.153 ^d
Civic Center		.114 ^c	.068 ^d
Coast		.102 ^c	.059 ^d
C	daily cooling degree hours		
Valley		.104 ^c	.183 ^d
Civic Center		-.162 ^c	-.126 ^d
Coast		-.456 ^c	-.414 ^d

^a Mean of log of variables. Estimation population means are weighted by sampling frequency; citywide means are weighted to approximate citywide population characteristics. Sample size for regression estimates is N = 624 and for citywide estimates in N = 2687. See Chow and Mitchell (1979).

^b See Appendix B for details.

^c Mean over 23 sample months.

^d Mean over 53 months used for prediction and welfare analysis.

III. VARIABLE RESPONSE TO WEATHER: MODEL AND ESTIMATION

Because seasonal demand is affected by weather and weather-sensitive appliance holdings, our model permits a household-specific pattern of response to hot and cold weather. This model of the monthly demand for electricity has several unique features. The presentation of the model will highlight those features and will demonstrate that their inclusion adds important insight into the demand behavior. The final part of this section deals with the econometric issues of estimating the model and prediction.

Monthly electricity consumption (log of mean daily kilowatt-hours, K) may be thought of as being the sum of four components: (1) the permanent household consumption level, A; (2) the household's response, B, to hot weather (cooling degree hours, C); (3) the household's response, D, to cold weather (heating degree hours, H); and (4) serially independent transitory variation, E. For household i and in time period t ,

$$K_{it} = A_{it} + B_{it} C_{it} + D_{it} H_{it} + E_{it} \quad (3.1)$$

Each estimated component, A, B, and D, includes a constant term.

The first component, A, is what we call permanent or long-run consumption and is constant through time except for changes in the price of electricity (log of price in cents, P). This long-run level of consumption is a regression function of household characteristics X listed in the data section, but includes the effect of unmeasured household attributes as well. That is,

$$A_{it} = \alpha_0 + \alpha' X_{it} + \alpha_P P_{it} + a_i \quad (3.2)$$

where the residual term a_i is a standard variance component.

The second and third components, B and D, represent a household's responsiveness to weather conditions. Daily cooling degree hours (C) and daily heating degree hours (H) vary both over time for a given household and cross sectionally among households. These individual responsiveness terms B and D are each functions of household demographics, appliance holdings, and the current price of electricity:

$$B_{it} = \beta_o + \beta' X_{it} + \beta_p P_{it} + b_i \quad (3.3)$$

and

$$D_{it} = \delta_o + \delta' X_{it} + \delta_p P_{it} + d_i \quad (3.4)$$

That is, the manner in which a household responds to hot weather as C changes depends specifically on its stock of cooling appliances and on the marginal price of electricity, as well as other variables, X. Similarly, cold weather response depends on heating appliances, price, and X. It is here that the seasonal character of electricity prices influences consumption. In our data, the price varied for each household seasonally during the experimental period, and pre-experimentally via a rate increase, as well as cross sectionally.

Household consumption varies over time as weather conditions change and as price changes. In addition, household consumption may vary

purely transitorily (serially independently) over time. Transitory consumption is assumed to be independent of a , b , and d , and to have a common variance both over time for a given household and among households.[1]

This model incorporates directly individual differences in both the level of consumption and responsiveness to weather. Prediction of the mean effects of a proposed seasonal price plan should incorporate information on seasonal weather variation and on the characteristics of the population for which the prediction is being made. This may be seen by substituting into (3.1) to obtain

$$K_{it} = (\alpha_0 + \alpha_i' X_i + \alpha_p' P_{it}) + (\beta_0 + \beta_i' X_i + \beta_p' P_{it}) C_{it} + (\delta_0 + \delta_i' X_i + \delta_p' P_{it}) H_{it} + a_i + b_i C_{it} + d_i H_{it} + e_{it} \quad (3.5)$$

With the flexible specification employed here, results may be generalized more accurately to a broader set of climates and demographic groups. Prediction with this model is discussed further below.

[1] It is possible to allow e to be autocorrelated (see Lillard and Weiss, 1979). Preliminary tests early in the research indicated a lack of autocorrelation in e after controlling for weather conditions.

ESTIMATION

The parameters of the model are estimated by full information maximum likelihood.[1] Consistent, but inefficient, estimates of the regression parameters α , β , and δ may be obtained by applying OLS to the pooled time series-cross section data. However, the standard errors computed by OLS routines are incorrect due to the variance component and random coefficients b and d . These estimates are used as starting values for the maximum likelihood estimation (MLE) procedure.

The likelihood function is based on the fact that for this model, the sample covariance matrix for K , X , and P is a sufficient set of statistics for all parameters of the model.[2] This is true for each subgroup facing the same time series of weather conditions C and H . There are three weather zones (Valley, Civic Center, and Coast) in our data and thus three subgroups.

The log likelihood function for each group is given (except for an additive constant) by

$$\log L^w \approx -\frac{N^w}{2} \log \left[|\Sigma^w| + \text{tr}(\Sigma^w)^{-1} \right] \quad (3.6)$$

[1] An alternative procedure, generalized least squares, would be to generalize the approach suggested by Lillard and Weiss (1979). That procedure (1) estimates the mean parameters including interactions with X by OLS, (2) estimates the random variance components by maximum likelihood from the residual covariance matrix, and (3) calculates consistent generalized least squares estimates of coefficients and standard errors by application of OLS to appropriately transformed data. This approach is similar to the one suggested by Mundlak (1978).

[2] To obtain unbiased estimates of population variances and regression coefficients, moments are weighted to population values.

where there are N^w observations from weather zone w . Covariance matrices for K , X , and P are denoted by S for the sample and by Σ for the theoretical model. While the parameters can be estimated for each group or combination of groups separately, more efficient estimates are obtained by pooling the information across groups and estimating all parameters jointly. The log likelihood function for the entire sample

of $N = \sum_w N^w$ households is

$$\log L \approx \sum_w \log L^w \quad (3.7)$$

The following discussion develops the theoretical covariance matrix Σ . The components A , B , and D will covary due to commonality and correlation in explanatory variables X and due to covariation in the residual components a , b , and d . Denote

$$\begin{bmatrix} A \\ B \\ D \end{bmatrix} = \begin{bmatrix} \alpha_o \\ \beta_o \\ \delta_o \end{bmatrix} + \begin{bmatrix} \alpha' \\ \beta' \\ \delta' \end{bmatrix} X + \begin{bmatrix} \alpha_p \\ \beta_p \\ \delta_p \end{bmatrix} P_{it} + \begin{bmatrix} a \\ b \\ d \end{bmatrix} \quad (3.8)$$

as

$$\tilde{Y}_t = \tilde{\Lambda}_o + \tilde{\Lambda} \tilde{X} + \tilde{\Gamma} \tilde{P}_t + \tilde{\eta} \quad (3.9)$$

The residual components b and d are random coefficients on C and D respectively[1], representing the effect of unmeasured variables on weather responsiveness. The components a, b, and d may freely covary:

$$V \begin{pmatrix} a \\ b \\ d \end{pmatrix} = \begin{bmatrix} \sigma_{aa} & & \text{Sym.} \\ \sigma_{ba} & \sigma_{bb} & \\ \sigma_{da} & \sigma_{db} & \sigma_{dd} \end{bmatrix} \equiv \sum_{\eta} \eta \eta \quad (3.10)$$

Given cross sectional price variation at time t, the covariance in components is given by

$$\Sigma_{yy} = (\Lambda, \Gamma) \begin{bmatrix} \Sigma_{xx} & \sigma_{xp} \\ \sigma_{px} & \sigma_{pp} \end{bmatrix} \begin{bmatrix} \Lambda' \\ \Gamma' \end{bmatrix} + \sum_{\eta} \eta \eta \quad (3.11)$$

In application, if all households faced identical prices, the σ_{xp} and σ_{pp} terms vanish.

In the present data, there are three weather zones so there are three groups within each of which the time series of weather conditions is the same. For a given weather zone, denote the time series for T time periods of C and H and a constant "one" by the matrix

$$W = \begin{bmatrix} 1 & C & H \\ \sim & \sim & \sim \end{bmatrix} \quad (3.12)$$

[1] We have chosen a random parameter model. An alternative is to estimate a fixed effect model where the parameters are estimated for each household. See Mundlak (1978) for a discussion of these models.

which is TX3. Further, denote the TXT covariance matrix of price (varying cross sectionally and over time) by Σ_{pp} . Then the TXT covariance matrix for consumption K within a weather zone is given by

$$\Sigma_{kk}^w = W \begin{pmatrix} \Lambda & (1' \otimes \Gamma) \\ \Lambda & (1' \otimes \Gamma) \end{pmatrix} \begin{pmatrix} \Sigma_{xx} & \Sigma_{xp} \\ \Sigma_{px} & \Sigma_{pp} \end{pmatrix} \begin{pmatrix} \Lambda \\ (1' \otimes \Gamma) \end{pmatrix} W' + \sigma_{ee} I_t \quad (3.13)$$

where $\otimes$ denotes the Kronecker product. Again, when there is no price variation cross sectionally, the Σ_{px} and Σ_{pp} terms vanish.[1] The covariance between X, P, and K is given by

$$\begin{pmatrix} \Sigma_{kk} \\ \Sigma_{pk} \end{pmatrix} = \begin{pmatrix} \Sigma_{xx} & \Sigma_{xp} \\ \Sigma_{px} & \Sigma_{pp} \end{pmatrix} \begin{pmatrix} \Lambda \\ (1' \otimes \Gamma) \end{pmatrix} W' \quad (3.14)$$

Denote the combined covariance matrix as

$$\Sigma^w = \begin{bmatrix} \Sigma_{kk} & \text{Sym.} \\ \Sigma_{xk} & \Sigma_{xx} \\ \Sigma_{pk} & \Sigma_{px} & \Sigma_{pp} \end{bmatrix} \quad (3.15)$$

The parameters α , β , δ , Γ , and $\Sigma_{\eta\eta}$ are assumed to be the same in all weather zones, but the constant and data matrices W , Σ_{xx} , Σ_{xp} , and Σ_{pp} may differ across zones. The corresponding sample covariance

[1] Households were assigned randomly to plans in the experiment so Σ_{px} is approximately zero.

matrices[1] provide a sufficient set of statistics for all parameters.

PREDICTION

The parameter estimates may be used to predict the effects of differences in household characteristics, and changes in weather conditions and changes in price. From Equation (3.5), assuming all households face the same price,

$$\begin{aligned}\hat{K}(X_i, P_t, C_{it}, H_{it}) &= (1, C_{it}, H_{it}) \left(\hat{\Lambda}_0 + \hat{\Lambda}_0 X_i + \hat{\Gamma} P_t \right) \\ &= \left(\hat{\alpha}_0 + \hat{\alpha}_0 X_i + \hat{\alpha}_0 P_t \right) + \left(\hat{\beta}_0 + \hat{\beta}_0 X_i + \hat{\beta}_0 P_t \right) C_{it} \\ &\quad + \left(\hat{\delta}_0 + \hat{\delta}_0 X_i + \hat{\delta}_0 P_t \right) H_{it}\end{aligned}\tag{3.16}$$

This equation predicts log daily consumption, $\ln(KWH)$. To predict daily consumption, KWH, it is necessary to make the usual variance correction before taking the antilog of $\hat{K}$, that is,

$$\widehat{KWH}(X_i, P_t, C_{it}, H_{it}) = \exp \left\{ \hat{K}(X_i, P_t, C_{it}, H_{it}) + \frac{1}{2} V(C_{it}, H_{it}) \right\}\tag{3.17}$$

The variance correction depends on weather conditions in period t in the location of household i , given by

$$V(C_{it}, H_{it}) = (1, C_{it}, H_{it}) \hat{\Sigma}_{\eta\eta} \begin{pmatrix} 1 \\ C_{it} \\ H_{it} \end{pmatrix} + \sigma_{ee}\tag{3.18}$$

[1] Again, weighted to population values.

Prediction of mean values for a population or subpopulation group is accomplished by making the prediction for each member of the group and averaging. When a sample is used, the mean prediction is population weighted.[1] To make a prediction for the City of Los Angeles at various price and weather combinations, for example, the values of explanatory variables X are taken from a pre-enrollment baseline survey of 2687 households.

[1] If w_i is the population weight for household i (with values of explanatory variables X_i , C_i , etc.), the mean predicted consumption is given by Equation (3.17) as $\bar{kwh} = \sum_i w_i kwh_i / \sum_i w_i$.

IV. REGRESSION PARAMETER AND VARIANCE COMPONENT ESTIMATES

In this section we present estimates of the parameters of the model based on the Los Angeles data. Table 3 displays the regression coefficients α , β , and δ , and Table 4 the parameters of the covariance structure. All parameters are estimated jointly ($-2 \ln L = 13039$). Let us first consider the regression coefficients, then the components of variation.

Table 3
REGRESSION PARAMETERS^a

Variable Name	Permanent Consumption, A	Daily Cooling Degree Hours(C) Response, B	Daily Heating Degree Hours(H) Response, D
	α Estimates	β Estimates	δ Estimates
Constant	-.4430 (.2494)	-.3398 (.0958)	-.3242 (.0631)
ln(PRICE)	-.0576 (.0062)	-.0249 (.0142)	.0061 (.0110)
ln(ROOMS)	.4083 (.0563)	-.0577 (.0242)	-.0095 (.0164)
ln(HVALUE)	.1916 (.0435)	.1061 (.0205)	.0790 (.0132)
ln(ACE)	.0179 (.0053)	.0178 (.0021)	
ln(AHE)	.0245 (.0114)		.0311 (.0031)
ln(AOE)	.0369 (.0029)		
ln(INC)	.0221 (.0234)		
ln(FAMSIZ)	.3522 (.0325)		
HOMEWD	.0120 (.0213)		
POOL	.1583 (.0680)		

^aStandard deviations in parentheses.

Permanent, or long-run (log), consumption, A, is significantly higher for households with greater house value, more rooms, and larger family size. A greater stock of heating, cooling, and other appliances each significantly increases permanent consumption. Even though a rating for pool is included in the "other appliance stock" variable, the dummy variable for pool is statistically significant, indicating that the existence of a swimming pool directly increases consumption approximately 16 percent. The family income elasticity of consumption is an insignificant .02.[1]

The estimated price elasticity at mean annual temperature values ($C = H = 0$) is $\tilde{\alpha}_p = -.0576$. This elasticity is small, but statistically quite significant. At other temperature values, the price elasticity is different. The interaction between price and temperature has a dual interpretation. First, as weather conditions vary over time, the degree to which a household responds to extreme temperatures depends on the price it pays for electricity, among other things. Second, the response to a price change will be different, depending on climatic conditions in the affected residential area, and will differ from month to month depending on weather conditions. The latter point means that the measured response to a price change will depend on whether one compares before and after consumption in a month of moderate temperature or of extreme temperature.

[1] In the rather rich specification reported here, the principal long-run effects of income may act through housing value, appliances, and pool ownership. Some other simpler versions of the model (including fewer months) produced a statistically significant income elasticity of .07.

The full price elasticity is given by

$$\hat{\alpha}_P + \hat{\beta}_P C + \hat{\delta}_P H = -.0576 - .0249C + .0061H \quad (4.1)$$

The interaction between price and daily cooling degree hours C is significantly negative, while the interaction between price and daily heating degree hours H is not significantly different from zero. One standard deviation in C is approximately .50. A value of C one standard deviation above the mean increases the price elasticity to -.0701 and below the mean reduces it to -.0452.

The mean response to daily cooling degree hours based on a sample of 2687 households is .122, so that a one standard deviation increase in C increases consumption by approximately 6.1 percent. Responsiveness to hot weather is significantly greater for households with a greater stock of cooling appliances and greater housing value, and, strangely, responsiveness is reduced with more rooms. The mean response to daily heating degree hours is .096, so that one standard deviation (.26) increase in H increases consumption by 2.5 percent. Responsiveness to cold weather significantly increases with a greater stock of heating appliances and greater housing value.

Each of the residual variance components is highly significant as reported in Table 4. Total variance components for A, B, and D, including variation due to X, are also reported. We may compute R^2 -type components for each of these. For the moment, price is excluded as an explanatory variable in this calculation, since in an actual application, prices will not generally vary as much as in the experimental

design. The nine household variables in X account for 73.8 percent of permanent consumption differences among households,

$$\sigma_{AA} = \alpha' S_{xx} \alpha + \sigma_{aa} \quad (4.2)$$

$$\begin{array}{ccc} .5400 & = & .3987 + .1413 \\ (100\%) & & (74\%) \quad (26\%) \end{array}$$

Table 4
VARIANCE - COVARIANCE MATRICES, TOTAL AND RESIDUAL

	Constant A/a	C B/b	H D/d	Transitory Residual e
A	.5400			
a	.1413 (.0081)			
B	.0302	.0172		
b	.0085 (.0029)	.0117 (.0020)		
D	.0128	.0017	.0087	
d	.0006 (.0020)	-.0004 (.0012)	.0056 (.0010)	
e				.0449 (.0006)

Note: A typical entry in position ij is σ_{ij} . Standard errors of variance-covariance estimates are in parentheses. Totals are calculated as, for example,

$$\sigma_{AA} = \alpha' S_{xx} \alpha + \sigma_{aa} \quad \text{and} \quad \sigma_{AB} = \alpha' S_{xx} \beta + \sigma_{ab}$$

These variables, at temperature values $C = H = 0$, account for 68.2 percent of total consumption variation including transitory variation:

$$\begin{aligned} \sigma_{KK} &= \alpha' S_{xx} \alpha + \sigma_{aa} + \sigma_{ee} \\ .5849 &= .3987 + .1413 + .0449 \\ (100\%) & \quad (68\%) \quad (24\%) \quad (8\%) \end{aligned} \tag{4.3}$$

The transitory component e accounts for 31.8 percent of residual variation ($a + e$) and only 7.7 percent of total variation ($A + e$). That is, at identical prices for all customers, 92.3 percent of variation among households in consumption in a given month at mean temperatures represents permanent differences among the households.

Cooling appliance stock, number of rooms, and house value account for 32.0 percent of variation among households in responsiveness to hot weather C (excluding price as a source of variation on both sides):

$$\begin{aligned} \sigma_{BB} &= \beta' S_{xx} \beta + \sigma_{bb} \\ .0172 &= .0055 + .0117 \\ (100\%) & \quad (32\%) \quad (88\%) \end{aligned} \tag{4.4}$$

Heating appliance stock, number of rooms, and house value account for 35.6 percent of variation among households in responsiveness to cold weather H :

$$\begin{aligned} \sigma_{DD} &= \delta' S_{xx} \delta + \sigma_{dd} \\ .0087 &= .0031 + .0056 \\ (100\%) & \quad (36\%) \quad (64\%) \end{aligned} \tag{4.5}$$

Because some households respond to extreme weather more than others, total variation in consumption among households increases under these conditions. Total variation in consumption, including weather-related variance effects, is given by Equation (3.18), substituting $\Sigma_{\eta\eta}$ and $\tilde{\sigma}_{ee}$. A one standard deviation increase in C alone (.50) increases the variance among households in consumption by .0345 or 5.9 percent from a base of .5849, while one standard deviation increase in H alone (.26) increases the variance by only .007. The variance effects of weather are small relative to the mean effects and to the other variance components.

V. EFFECTS OF CHANGES IN WEATHER OR CLIMATE CONTROL APPLIANCES

Changes in appliance holdings, changes in weather, and changes in price all combine to yield significant differences across individuals and across time in the level of predicted consumption. To illustrate the range of response that is expected from different values of selected explanatory variables, we create predictions for the Los Angeles system, weighted to reflect city characteristics. We first illustrate the effect on mean consumption of changing weather, holding all other variables constant, and then the effect of changing appliance holdings. The effect of changes in price level is treated in Section VI.

CHANGES IN MONTHLY WEATHER AND CLIMATE ZONE

Los Angeles has three climate areas--a mild coastal area, an inland valley with greater extremes of hot and cold weather, and a civic center area that is intermediate. We have measures of temperature C and H for each zone for a period of 53 months and can use these values for prediction and calibration. That span of time includes a September month with extremely hot weather and a December month with the coldest temperatures recorded in over 50 years.

Table 5 reports monthly values of electricity use at mean values of X and mean values of C and H in the summer and winter. The overall prediction for the city at mean summer weather is 367 kwh/month at a price of 6.4¢/kwh (which approximates the spring 1980 price).

As expected, there is large variation among individual households. Overall, monthly consumption is slightly higher at mean winter temperatures than at mean summer temperatures, at the same price. The effects

Table 5

EFFECTS OF DIFFERENT WEATHER CONDITIONS ON MEAN MONTHLY CONSUMPTION^a

(P = 6.4¢/kwh)

	△ kwh (Mean Summer Temp)	△ kwh (Mean Winter Temp)	△ kwh (Hot Summer) -kwh (Mean Summer)	△ kwh (Cold Winter) -kwh (Mean Winter)
All City	367 (257)	404 (297)	66 (112)	27 (53)
Coastal Zone	410 (247)	466 (297)	30 (36)	56 (61)
Civic Center	302 (178)	331 (207)	27 (38)	30 (39)
Valley	481 (332)	529 (383)	148 (162)	48 (67)

^aStandard deviations in parentheses.

of the temperature during a hot summer month (September 1979) and a cold winter (December 1978) are compared in the last two columns. A very hot summer month increases mean consumption 17 percent above a month at mean summer temperatures. A very cold winter month increases mean consumption more than 9 percent compared with consumption at mean winter temperatures.

Moving across climate zones, we find the greatest mean values of summer and winter consumption in the valley and the lowest values in the civic center. The effects of extreme hot weather are greatest in the

valley (+31 percent), and the civic center (+9 percent) where air conditioning is more common. The effects of extreme cold weather are greatest, on average, in the coast area (+12 percent) where electric space heating is somewhat more common.

CHANGES IN CLIMATE CONTROL APPLIANCE HOLDINGS

Table 6 illustrates the effect on predicted monthly consumption when household characteristics are held constant but air conditioning or electric space heating is either forced to be present or absent for each household.[1] All prices are held constant at 6.4¢/kwh.

Mean monthly use increases only slightly at mean summer temperatures when air conditioning is taken from absent to present (+16 kwh/month for the citywide mean; +24 kwh/month in the valley mean). This is not surprising since a mean summer value of C (about 0.38) could result from a mean daily temperature of 75°F for 12 hours each day, which would cause relatively little air conditioning use. But when a hot month (which could correspond to 12 hours daily at 85°F) is compared with a normal summer month for households with and without air conditioning, use is increased dramatically: by almost 100 kwh/month in the citywide average and by 167 kwh in the valley for households with the appliance versus 32 and 60 kwh for households without central air conditioning.

[1] Predictions assume central refrigerative air conditioning or central electric heat for the full sample or absence of air conditioning or electric heat for the full sample.

Table 6

EFFECT OF CLIMATE CONTROL APPLIANCES ON MEAN MONTHLY CONSUMPTION^a
(P = 6.4¢/kwh)

	SUMMER			
	With Central Air Conditioning		Without Air Conditioning	
	kwh (Mean Summer Temp)	kwh (Hot Summer) -kwh (Mean Summer)	kwh (Mean Summer Temp)	kwh (Hot Summer) - kwh (Mean Summer)
All city	376 (258)	98 (98)	359 (246)	32 (43)
Coast	421 (253)	72 (52)	409 (246)	27 (25)
Civic Center	312 (183)	65 (46)	299 (176)	17 (20)
Valley	486 (330)	167 (136)	462 (314)	60 (60)
	WINTER			
	With Electric Heating		Without Electric Heating	
	kwh (Mean Winter Temp)	kwh (Cold Winter) -kwh (Mean Winter)	kwh (Mean Winter Temp)	kwh (Cold Winter) -kwh (Mean Winter)
All city	721 (519)	211 (167)	388 (278)	34 (37)
Coast	783 (494)	219 (155)	448 (283)	47 (43)
Civic Center	592 (365)	173 (119)	319 (197)	25 (26)
Valley	950 (669)	281 (217)	503 (354)	49 (48)

^aStandard deviations in parentheses.

By comparison, adding electric space heating increases mean monthly use at mean winter temperatures and at more extreme temperatures by a substantial amount. Citywide, mean monthly use is 333 kwh/month greater (86 percent) with electric heating at mean temperatures and an additional 177 kwh greater in a cold month than a normal month if electric heating is compared with no electric heating. This notable difference at mean winter temperatures is reasonable since a mean winter temperature value of $H = 0.87$ could correspond to an average value of 49°F for a 12-hour period and would cause a significant heating demand. A cold month at $H = 2.0$ could correspond to an average temperature of 40°F for 12 hours daily.

VI. EVALUATING SEASONAL PRICING

The introduction of seasonal variation into electricity pricing offers the theoretical prospect of increasing the efficiency with which electricity is used and increasing consumer well-being. Because implementation costs are likely to be minimal, even small changes in producers' and consumers' surplus should yield net gains in economic welfare. However, since the administrative procedures of rate reformulation may be costly and disruptive, and since any change in rate structure will cause bill changes, policymakers will generally demand non-trivial Pareto-potential improvements before undertaking the costs of transition.

Setting aside considerations of consumer attitudes and satisfaction--which are important, but a subject for a different analysis--let us turn to a welfare assessment of seasonal pricing using the empirical results just presented. The large variance in demand for electricity across households leads to a rich pattern of distribution of effects on bills, level of use, and changes in welfare. We use the demand curves just estimated, as well as the citywide characteristics of Los Angeles, for the predictions. However, to determine if any welfare gain is likely, we take hypothetically large values of seasonal prices (which increase the measure of economic well-being from introducing seasonal prices).

EFFECTS OF SEASONAL PRICING

Electricity is more costly to supply at some times than at others. During peak hours or peak seasons, higher running costs are incurred and increased capacity must be available. Moving from non-time differentiated to time-of-use pricing--especially if based on marginal costs--will be potentially Pareto-superior.

The magnitude of the welfare gain is reflected in the net changes in producers' and consumers' surplus, shown in Fig. 1.[1] For specificity, we will assume that the present rate is $P¢/kwh$ in all seasons--leading to purchases of K_p in the peak season and K_{op} in the off-peak season--and that marginal costs in the peak season and off-peak season are MC_p and MC_{op} . If price is set equal to marginal cost in each season, monthly demand in the peak season falls to K_p^* and the welfare gain is given by the net change in producers' surplus, ΔPS . In the off-peak

FIG. 1—ILLUSTRATION OF MONTHLY WELFARE GAINS FROM INTRODUCING SEASONAL PRICING

[1] See Harberger (1971) and Turvey (1974) for the development of this benefit/cost framework, and Acton and Mitchell (1980) for an application to time-of-day electricity pricing.

season, monthly demand increases to K_{op}^* and the gain in welfare is given by the net change in consumers' surplus, ΔCS . [1]

We assume in this analysis that cross-price effects are zero between seasons of the year. This appears reasonable and no cross-price effects were estimated with the data, although non-zero cross-price elasticities can be easily incorporated into the welfare analysis (see Acton and Mitchell, 1980).

For illustration, we assume that $P = 6.4\text{¢/kwh}$ (the approximate price in Los Angeles in spring 1980). We will illustrate the effects of introducing seasonal rates with assumed differences of 4¢/kwh between two 6-month seasons. [2] Since present residential demand under uniform prices is almost equal in each season, an ex ante revenue neutral seasonal tariff could charge 8.4¢/kwh and 4.4¢/kwh . [3]

The impact of seasonal pricing depends on both the distribution of characteristics across individuals and the distribution of weather changes through time. The calculations reported in Table 7 are based on 53 months of weather in each of the three climate zones. Changes in electricity use, electricity bills, and welfare are calculated for each individual and then averaged over the relevant season. Table 7 reports weighted means and standard deviations of these household-specific averages for the city and for selected subgroups of the population.

[1] When peak load pricing is introduced but the full difference in marginal costs is not reflected in the prices, these welfare triangles understate the gains in welfare.

[2] The seasons selected are Winter = November-April and Summer = May-October. Within these seasons, C and H lie almost uniformly above or below their annual average values.

[3] Note, the empirical equality of residential demand between two seasons does not rule out policy interest in seasonal pricing. Seasonal cost differentials can arise from higher aggregate demand by season or from exogenous cost considerations (e.g., availability of hydroelectric resources).

Table 7
EFFECTS OF INTRODUCING SEASONAL PRICING ON CONSUMPTION,
BILLS, AND ECONOMIC WELFARE^a
($P_{\text{sum}} = 8.4\text{¢/kwh}$, $P_{\text{wint}} = 4.4\text{¢/kwh}$) vs $P = 6.4\text{¢/kwh}$

Item	kwh at Seasonal Rates	Change in kwh	Bill at Seasonal Rates (\$)	Change in Bill (\$)	Change in Welfare (\$)
<u>All city (N = 2687)</u>					
Av. of winter months	373 (262)	5.2 (3.7)	16.4 (11.5)	-7.13 (4.99)	0.05 (0.03)
Av. of summer months	362 (270)	-7.6 (6.4)	30.4 (22.7)	6.74 (5.01)	0.08 (0.07)
Mean annual	4,410 (3,176)	-14.4 (17.8)	280.8 (204.4)	-2.33 (5.71)	0.77 (0.60)
<u>Households by level of pre-experimental monthly consumption</u>					
A. (0 - 150 kwh/mo.)					
Av. of winter months	159 (56)	2.2 (0.8)	7.0 (2.5)	-3.03 (1.06)	0.02 (0.01)
Av. of summer months	151 (53)	-3.0 (1.1)	12.7 (4.4)	2.83 (0.99)	0.03 (0.01)
Mean annual	1,858 (647)	-4.5 (2.5)	117.9 (41.1)	-1.24 (1.13)	0.31 (0.11)
B. (151 - 400 kwh/mo.)					
Av. of winter months	305 (124)	4.3 (1.7)	13.4 (5.4)	-5.83 (2.36)	0.04 (0.02)
Av. of summer months	291 (121)	-6.0 (2.8)	24.5 (10.2)	5.45 (2.25)	0.06 (0.03)
Mean annual	3,580 (1,460)	-10.2 (7.6)	227.5 (93.1)	-2.32 (2.77)	0.61 (0.27)
C. (401 - 1000 kwh/mo.)					
Av. of winter months	493 (231)	6.9 (3.3)	21.7 (10.2)	-9.42 (4.41)	0.06 (0.03)
Av. of summer months	479 (244)	-10.3 (5.9)	40.2 (20.5)	8.92 (4.51)	0.11 (0.06)
Mean annual	5,831 (2,822)	-20.2 (18.3)	371.5 (182.3)	-2.97 (7.04)	1.03 (0.54)
D. (1001 + kwh/mo.)					
Av. of winter months	1,242 (509)	17.5 (7.3)	54.6 (22.4)	23.72 (9.73)	0.16 (0.07)
Av. of summer months	1,272 (551)	-28.8 (13.7)	106.9 (46.3)	23.61 (10.15)	0.30 (0.14)
Mean annual	15,086 (6,267)	-67.6 (46.0)	969.2 (406.7)	-0.67 (20.13)	2.79 (1.25)
<u>Households by climate zone</u>					
<u>Coast</u>					
Av. of winter months	417 (252)	5.3 (3.2)	18.3 (11.1)	-8.00 (4.83)	0.05 (0.03)
Av. of summer months	361 (211)	-5.9 (3.4)	30.3 (17.7)	6.85 (4.00)	0.06 (0.04)
Mean annual	4,668 (2,769)	-3.2 (3.4)	292.1 (172.4)	-6.90 (6.56)	0.67 (0.40)
<u>Civic Center</u>					
Av. of winter months	307 (181)	4.3 (2.5)	13.5 (8.0)	-5.86 (3.47)	0.04 (0.02)
Av. of summer months	283 (165)	-5.5 (3.2)	23.8 (13.9)	5.31 (3.10)	0.06 (0.03)
Mean annual	3,538 (2,074)	-7.4 (5.1)	223.6 (130.9)	-3.31 (3.83)	0.58 (0.34)
<u>Valley</u>					
Av. of winter months	489 (338)	7.0 (4.8)	21.5 (14.9)	-9.34 (6.45)	0.07 (0.05)
Av. of summer months	510 (364)	-12.0 (8.7)	42.9 (30.6)	9.44 (6.72)	0.13 (0.09)
Mean annual	5,998 (4,196)	-30.1 (23.9)	386.4 (271.8)	0.59 (6.98)	1.15 (0.81)

^aStandard deviations in parentheses.

Effect on Consumption

As expected, the introduction of seasonal pricing increases use in the winter off-peak season and decreases use during the peak season. However, given the small price elasticities, the effects of even this 4¢ winter/summer differential is relatively small within each season. Over the year, total use is reduced by a fraction of 1 percent. This pattern is repeated for subgroups identified by their pre-experimental average level of use[1] as well as climate zone. Given the presence of greater price response among households in the upper strata of use, the percentage reduction in consumption increases.

Effect on Bills

Seasonal pricing also has an important effect on bills within each season, averaging -\$7.13 in the winter and +\$6.74 in the summer, city-wide. Over an average 12-month period, bills would fall by \$2.33 compared with a uniform price of 6.4¢/kwh. If ex post revenue neutrality were desired, the price could be raised 0.053¢/kwh or a monthly customer charge of \$0.19 could be made. As expected, the absolute effect on bills is smallest at low levels of consumption and greatest at high levels, although in percentage terms, it diminishes with level of use. Across zones, the bill impacts are greatest in each season in the valley zone with its more extreme climate and greater average level of use. However, over an average 12-month period, bill impacts are smallest in

[1] The four groupings of households by stratum of pre-experimental use reflects respectively 21.5, 45.5, 27.7, and 5.4 percent of residential customers citywide. The values of explanatory variables for households in each of these strata are used for prediction.

the valley, due to almost identical offsetting effects in each season.

Effect on Welfare

The predicted changes in welfare are shown in the last column of Table 7. As expected from small price elasticities, the corresponding net changes in producers' and consumers' surplus are quite small in absolute value, and they are small in comparison with bill effects. For all but the highest levels of use, welfare changes are less than 10¢ per month per customer on average. If implementation costs are actually zero, then presumably even these small improvements are worthwhile, and in a system of about 1 million customers, they amount to approximately \$770,000 per year.

EFFECTS OF SEASONAL PRICING UNDER MORE EXTREME WEATHER CONDITIONS

The calculations presented in Table 7 show the effect of seasonal pricing over a period of 53 months of weather variation. Ratemakers often find after the fact that a new rate structure has been introduced under conditions that are in some way atypical. This can lead to significant misprediction of revenue[1] and to unusually high or low bills which customers may attribute to the new rate rather than the altered circumstances. As mentioned earlier, the 12-month period beginning in the fall of 1978 includes both the coldest winter month in 50 years (December 1978) and a very hot summer month (September 1979). If seasonal pricing were introduced under such circumstances, the short run effects would differ notably from those shown in Table 7.

[1] A misprediction of revenue may not be a serious problem if price is set equal to short run marginal cost because changes in revenue will be accompanied by identical changes in operating costs. Such a forecasting problem exists as well under conventional rate structures.

Table 8 presents the effects of seasonal pricing over the 12-month period beginning October 1978. The first row shows average effect in winter and summer, comparing effects under seasonal pricing against demand at 6.4¢/kwh, and using actual weather each month during this period. Over the full 12-month period, the effect on predicted consumption and change in use, change in bill, and change in welfare are slightly more extreme than those reported in Table 7, but the differences are relatively minor.

The effect of comparing a single extreme winter or summer month under seasonal pricing with a normal month under uniform pricing is much sharper, and the effects are much stronger in the summer than in the winter. Citywide, in a cold winter month with seasonal pricing, consumption grew 44 kwh/month and on average bills fell by only \$5.36 (versus 5 kwh and a bill reduction of \$7.13 in Table 7). A similar pattern of differences is found at different strata of use and across weather zones.

In an unusually hot summer, the adverse effects of seasonal pricing are exacerbated. When compared with mean summer temperatures, the weather in September 1979 is sufficiently extreme to cause an increase in usage even in the face of a 31 percent price increase (from 6.4 to 8.4 ¢/kwh). Citywide, bills increase in this extreme month by \$11.79 (versus \$6.74 for seasonal pricing under average summer conditions). These effects range up to bill increases of \$20.96, on average, for valley customers and \$57.37 for high consumption stratum customers (versus \$9.44 and \$23.61 at mean temperature).

Table 8

EFFECTS OF SEASONAL PRICING UNDER EXTREME WEATHER CONDITIONS^a(P_{Wint} = 4.4¢/kwh; P_{Sum} = 8.4¢/kwh) vs P = 6.4¢/kwh

All city	Six Winter Months ^b				Six Summer Months ^b			
	△ kwh	△ kwh	△ Bill	△ Welfare	△ kwh	△ kwh	△ Bill	△ Welfare
Average over season	383 (270)	5 (3)	-7.37 (5.20)	.04 (.03)	372 (288)	-9 (8)	6.89 (5.28)	.09 (.08)
	Cold Winter Month ^c				Hot Summer Month ^c			
	408 (299)	44 (56)	-5.36 (3.64)	--	420 (362)	53 (101)	11.79 (13.40)	--
<u>Households by level of pre-experimental monthly consumption</u>								
A. (0-150 kwh/mo.)	168 (61)	13 (10)	-2.52 (.90)	--	162 (60)	9 (14)	3.82 (1.85)	--
B. (151-400 kwh/mo.)	328 (136)	30 (22)	-4.65 (1.95)	--	323 (145)	27 (35)	8.18 (4.71)	--
C. (401-1000 kwh/mo.)	545 (263)	65 (56)	-6.77 (3.63)	--	568 (330)	82 (99)	16.62 (12.54)	--
D. (1000 + kwh/mo.)	1404 (620)	193 (171)	-15.72 (7.68)	--	1663 (816)	377 (294)	57.37 (34.52)	--
<u>Households by climate zone</u>								
Coast	471 (300)	64 (65)	-5.32 (3.10)	--	387 (237)	21 (32)	9.11 (6.41)	--
Civic Center	334 (209)	35 (42)	-4.44 (2.56)	--	306 (190)	18 (34)	7.26 (5.57)	--
Valley	533 (387)	56 (72)	-7.10 (4.71)	--	644 (504)	126 (146)	20.96 (19.18)	--

^aStandard deviations in parentheses.^bDeviations calculated each month at seasonal rate versus 6.4¢/kwh; weather identical.^cDeviations calculated each month at seasonal price and extreme value of H and C versus 6.4¢/kwh and mean seasonal values of H and C. Welfare calculations are not made since the demand curve shifts under this calculation.

VII. CONCLUSIONS

In summary, this report has presented a model emphasizing differences by households in permanent consumption level and in responsiveness to weather variation. Estimation of the model using a cross section of household time series data from the Los Angeles Electricity Rate Study revealed significant variation among households. Responsiveness to hot and cold weather conditions separately, as well as permanent consumption level, are significantly related to household characteristics, including appliance stocks, house characteristics, and family characteristics. These relationships lead to more robust forecasts of responses to price changes in other populations, to more efficient estimation of parameters, and to consistent statistical tests.

Permanent differences among households in their long-run consumption level (due to measured variables and to a household component) account for more than 92 percent of cross sectional variation in consumption in any given month. The remainder of cross sectional variation is due to differences in weather conditions and to uncorrelated transitory variation. Weather and transitory variation increase variation through time, but permanent differences across households still account for over 87 percent of observed variations. Our limited set of measured household characteristics--such as house value and size, family size, and appliance stock--accounts for a substantial 74 percent of permanent consumption variation.

The estimated mean price elasticity is $-.06$, and the price elasticity increases with hotter weather. Both hot weather and cold weather substantially affect the mean level of consumption. A one standard

deviation increase increases mean consumption by 6.1 percent in hot weather and 2.5 percent in cold weather . There is, however, significant variation among households in responsiveness to these weather conditions, and each is significantly related to the appliance stock and household demographics. As a consequence, we can expect important differences across households from introducing seasonal pricing.

At the outset we suggested that the welfare gains associated with seasonal pricing might serve as a yardstick against which incremental gains from time-of-day pricing could be measured. It now appears, empirically, that the welfare gains associated with a difference of 4¢/kwh (an almost 2:1 ratio) between seasonal prices are quite small--averaging less than \$1/year per customer. Since seasonal differences in marginal costs in most systems are likely to be less than 4¢/kwh, the welfare gains would generally be a fraction of those shown in Table 7, even under the assumption of zero implementation costs.[1]

In contrast to these small welfare gains from seasonal pricing, Acton and Mitchell (1980) estimate that welfare gains associated with time-of-day pricing in Los Angeles would exceed these values by a factor of 4 at low levels of use and more than 10-fold at higher levels of use, and that TOD rates would produce a net gain in welfare even after incurring costs of \$150 for metering, in households averaging over 1100 kwh per month. Thus, although seasonal pricing may represent a hypothetical alternative to TOD pricing of electricity, with the magnitudes of price

[1] Seasonal pricing may still be judged desirable on distributional grounds if it more accurately reflects costs of service to individual customers.

elasticities estimated in the Los Angeles study, seasonal pricing does not represent an important alternative on the basis of efficiency and welfare criteria.

Appendix A
TEMPERATURE WEATHER VALUES

Sample Month	Daily Cooling Degree Hours, C ^a			Daily Heating Degree Hours, H ^a		
	Coast	Civic Center	Valley	Coast	Civic Center	Valley
June 75	-.66	-.44	-.08	-.30	-.27	-.30
July 75	-.11	.45	1.08	-.91	.93	-.90
August 75	-.21	.39	1.11	-.80	-.80	-.81
September 75	.08	.75	1.26	-.91	-.90	-.85
October 75	-.47	-.23	.02	-.41	-.33	-.15
November 75	-.61	-.46	-.35	.64	.64	.89
December 75	-.78	-.72	-.60	1.32	1.45	1.44
January 76	-.52	-.45	-.34	1.04	1.17	1.23
February 75	-.81	-.75	-.69	1.05	1.41	1.31
March 76	-.75	-.61	-.47	.93	1.08	.99
April 76	-.82	-.72	-.56	.82	1.11	.96
October 76	.07	.25	.47	-.85	-.78	-.61
November 76	-.18	.10	.08	-.27	-.17	.11
December 76	-.56	-.53	-.54	.70	.79	1.23
January 77	-.80	-.73	-.74	1.04	1.09	1.53
February 77	-.66	-.35	-.21	.63	.33	.59
March 77	-.84	-.76	-.72	1.26	1.17	1.38
April 77	-.77	-.47	-.18	.37	.08	.23
May 77	-.79	-.66	-.50	.22	.14	.27
June 77	-.62	-.10	.36	-.49	-.74	-.67
July 77	-.02	.91	1.68	-.78	-.94	-.93
August 77	.30	1.11	1.58	-1.01	-1.04	-1.02
September 77	.30	.29	.73	-.93	-.95	-.82

^aSee footnote 1, page 7 for definitions.

Appendix B
CONSUMPTION WEIGHTS USED IN CREATING
APPLIANCE AGGREGATES

<u>Aggregate Appliance</u>		<u>Individual Appliances</u>
<u>Variable Name</u>	<u>Name</u>	<u>Consumption Weight</u> (kwh /month)
ACE	Refrigerative Central Air Conditioning	328
	Evaporative Central Air Conditioning	120
	Refrigerative Window Air Conditioning	60
	Evaporative Window Air Conditioning	40
AHE	Central Electric Heating	1059
AOE	Refrigerator, Manual	52
	Refrigerator, Frost Free	106
	Freezer	95
	Electric Stove	87
	Dishwasher	25
	Washer	8
	Electric Dryer	72
	Electric Water Heater	333
	Television	30
	Swimming Pool	312

Source: Adapted by Los Angeles Department of Water and Power Engineers
from EEI estimates of national consumption averages.

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