

USING DEMAND MODELS TO ESTIMATE THE IMPACT OF DYNAMIC PRICING IN CALIFORNIA

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ABSTRACT

This paper analyzes the impact of a dynamic pricing tariff in California's large-scale experiment with time-varying rates. Called the Statewide Pricing Pilot (SPP), it was designed to estimate the impact of a variety of time-varying rates for residential and small commercial and industrial customers. The experiment began in July 2003 and ended in December 2004 and involved some 2,500 customers who were allocated to control and treatment groups in three utility service territories and placed on either a standard time-of-use (TOU) rate or one of two types of critical-peak pricing (CPP) rates. In this paper, we focus on the impact of one of the CPP rates. The SPP was designed to allow the estimation of impacts not only for the specific price levels tested in the experiment but also enable the estimation of demand responses for prices that were not used in the experiment. In other words, it allowed for the estimation of demand models that express customer demand as a function of factors such as price, weather conditions, the saturation of central air conditioning and other factors. The impact evaluation methodology used in the SPP was successful in measuring the impact of customers to dynamic prices. It found statistically significant evidence of response to a wide variety of prices. The SPP project has yielded demand models capable of simulating the impact of dynamic prices in geographically diverse locations both within California and outside of California.

Introduction

This paper analyzes the impact of a dynamic pricing tariff in California's large-scale experiment with time-varying rates. Called the Statewide Pricing Pilot (SPP), it was designed to estimate the impact of a variety of time-varying rates on average energy use by rate period for residential customers and small commercial and industrial (C&I) customers under 200 kW in size. The experiment began in July 2003 and ended in December 2004.²

The roots of the experiment can be traced back to the power crisis in the Western United States that took place in 2000 and 2001. The crisis was exacerbated by the lack of dynamic pricing in retail markets, which would have given customers an incentive to lower loads during peak times. After the crisis abated, interval meters were installed on all customers with billing demands greater than 200 kW, at a cost of \$34 million. However, meters were not installed on smaller customers. There was much uncertainty about the response of smaller customers to time-varying rates, since prior work was limited to standard time-of-use (TOU) rates and was more than two decades old.

To help address this uncertainty, California's three investor-owned utilities, in concert with the two regulatory commissions, conducted the SPP to test the impact of time-varying rates among residential and small C&I customers. The primary evaluation objective was to estimate the average impact of time-varying rates on energy use by rate period and develop models that can be used to predict

¹ Questions and comments can be directed to afaruqui@crai.com. We would like to acknowledge the exceptional research assistance of Joanna Burleson and John Winfield in the execution of the project on which this paper is based.

² At the end of the experiment, customers had the option of continuing on the experimental rate if they were willing to pay an incremental monthly metering charge. A very large majority has exercised this option.

impacts under alternative pricing plans. Other objectives included the identification of customer preferences for time-varying rates and an evaluation of the effectiveness of various pilot features and educational materials.

The experimental design allocated some 2,500 customers to control and treatment groups in the service territories of Pacific Gas & Electric Company, San Diego Gas & Electric Company, and Southern California Edison. Customers in the treatment groups were placed on either a TOU rate or one of two types of critical-peak pricing (CPP) rates.³ Some customers were simply given information treatments. In this paper, we focus on the impact of the CPP rate.

The SPP was designed to allow for the estimation of demand models that express customer demand as a function of factors such as price, weather conditions, the saturation of central air conditioning and other factors. Demand models are inherently more useful from a policy perspective than simpler methods such as the analysis of variance, which can only quantify the impact of specific rate treatments used in the experiment. The SPP experimental design included control groups that stayed on the standard tariff and treatment groups that were placed on new time-varying tariffs or information programs. The treatment groups for each tariff were divided into subgroups that faced different price levels so that statistical relationships between energy use by rate period and prices could be estimated. These statistical relationships, referred to as demand models, were used to estimate the demand response impact for the average prices used in the SPP.

Section 1 provides an overview of the model specification and some of the practical issues that were encountered and addressed in model estimation. Section 2 provides a brief description of the data that were used to estimate the demand models. Section 3 presents the main empirical results and includes a comparison with results in the literature. Section 4 presents the conclusions.

1.0 Model Specification and Estimation

After reviewing and testing a variety of demand model specifications, we decided to structure our analysis around the widely used constant elasticity of substitution (CES) demand system. This consists of two equations, where one equation models the ratio of peak to off-peak quantities as a function of the ratio of peak to off-peak prices and other terms and the second models daily electricity consumption as a function of the daily price of electricity and other terms. The two equations constitute a system for predicting electricity consumption by time period where the first equation predicts changes in the shape of a unitized load curve and the second equation predicts changes in the level of daily electricity consumption.

By taking the shares of energy use by period that are predicted by the first equation and multiplying them by predictions of daily energy use from the second equation, one can generate predictions of the quantity levels for peak and off-peak energy use given specific peak and off-peak prices and other determining factors.⁴

³ One of these, CPP-F, was a day-ahead tariff with a critical peak period whose duration was set equal to the duration of the normal peak period. The other one, CPP-V, was a day-of tariff with a peak period whose length was variable but bounded by the normal peak period.

⁴ A derivation of the formulas used to predict impacts by rate period based on the CES specification is provided in Appendix 8 of Charles River Associates, "Impact Evaluation of the California Statewide Pricing Pilot," Oakland, California, March 16, 2005

The SPP data set contains observations on a cross section of customers that are observed over time and constitutes what is known in the literature as a panel. Initially, we used the “fixed effects” estimation procedure to derive the model parameters. This procedure assigns a binary variable to each customer that represents the unique and unexplainable lifestyle of each customer.⁵ Subsequently, we re-estimated the model using first differences, to eliminate autocorrelation of the error term.⁶ This had the effect of mechanically removing the fixed effect terms from the equation but conceptually, they still underlie the formulation.

The substitution equation was specified as follows:

$$\ln\left(\frac{Q_p}{Q_{op}}\right) = \alpha + \sigma \ln\left(\frac{P_p}{P_{op}}\right) + \delta(CDH_p - CDH_{op}) + \sum_{i=1}^N \theta_i D_i + \varepsilon \quad (1)$$

where

Q_p = average energy use per hour in the peak period for the average day

P_p = average price during the peak pricing period

σ = the elasticity of substitution between peak and off-peak energy use

δ = measure of weather sensitivity

CDH_p = cooling degree hours per hour during the peak pricing period

θ_i = fixed effect for customer i

D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise,

ε = regression error term

Daily energy use was specified as follows:

$$\ln(Q_d) = \alpha + \eta_d \ln(P_d) + \delta(CDH_d) + \sum_{i=1}^N \theta_i D_i + \varepsilon \quad (2)$$

where

Q_d = average daily energy use per hour

P_d = average daily price, which was computed as a weighted average of peak and off-peak prices, using quantity shares from the pre-treatment period⁷

CDH_d = cooling degree hours per hour during the day

η_d = the price elasticity of demand for daily energy

The two summary measures of price responsiveness are the elasticity of substitution (σ) and the daily price elasticity of demand (η). It is plausible that these elasticities would differ across customers and days. The ES equation can be modified to allow the elasticities to vary with weather and socio-economic factors, such as central air conditioning (CAC) ownership, as shown in Equation (3):

⁵ See Stock, James H. and Mark W. Watson, “Introduction to Econometrics”, Addison Wesley, 2003.

⁶ Given the unbalanced nature of the panel data set, it was not possible to use more complex autoregressive schemes with standard estimation software. We explored alternative specifications in Gauss and concluded that first differences corrected just about all the bias in the standard errors.

⁷ I.e., the daily price is a Laspeyres index number of the peak and off-peak prices, akin to the cost of living index.

$$\ln\left(\frac{Q_p}{Q_{op}}\right) = \alpha + \sum_{i=1}^N \theta_i D_i + \sigma \ln\left(\frac{P_p}{P_{op}}\right) + \delta(CDH_p - CDH_{op}) + \lambda(CDH_p - CDH_{op}) \ln\left(\frac{P_p}{P_{op}}\right) + \phi(CAC) \ln\left(\frac{P_p}{P_{op}}\right) + \varepsilon \quad (3)$$

The elasticity of substitution (ES) in this model is a function of three terms:

$$ES = \sigma + \lambda(CDH_p - CDH_{op}) + \phi(CAC) \quad (4)$$

These two equations can be estimated using ordinary least squares (OLS), which yields unbiased parameter estimates under fairly general assumptions about the distribution of the error term. However, if the error terms do not conform to the basic assumptions of the classical regression model, the standard errors associated with the parameter estimates may be biased. This can happen, for example, if the error terms are affected by autocorrelation (AC) or heteroscedasticity (HS).

In the presence of AC or HS, the standard errors of the parameter estimates would be biased downward which, in turn, would lead to t-statistics that were upward biased. Such biases could lead one to erroneously conclude that time-varying prices have a statistically significant impact on customer usage when they do not.

Procedures for dealing with AC and HS are available using standard estimation software and generalized least squares (GLS) estimation methods if the panel data is balanced.⁸ A balanced panel data set involves repeated observations of the same set of cross-section units. Unfortunately, the dataset used for estimating the SPP demand models is comprised of participants that were enrolled at different times and is unbalanced. Enrollments began in April 2003 and continued until the necessary sample sizes had been reached by experimental cell. Sample evolution occurred throughout the pilot as customers left and were replaced, largely due to normal turnover in the population.

Initially, we considered addressing the AC and HS issues by averaging the daily observations for each customer into three day-types that had different prices. Subsequently, to obtain additional longitudinal variation in weather, we further sub-divided each day-type observation into five observations corresponding to weather quintiles. Unfortunately, neither procedure eliminated correlations among the model residuals. Finally, we decided to transform the daily data into first differences, by subtracting the previous day's observation from the current day's observation for each variable. Compared with the averaging approach, first differencing allows for more precise estimation since averaging suppresses the daily variation in weather and also suppresses some of the variation in prices over the course of the experiment as various (mostly minor) rate changes were rolled out by each utility. To maximize the efficiency of parameter estimates, we estimated the two equations jointly using the "seemingly unrelated regressions (SUR)" procedure due to Zellner.⁹

⁸ For example, the TSCS PROC in SAS could be used if the panel dataset was balanced.

⁹ For an explanation of SUR, see Arnold Zellner, "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias," *Journal of the American Statistical Association*, 57, 1962, 348-68. See Appendix 11, "Econometric Issues in Model Estimation," *Impact Evaluation of the California Statewide Pricing Pilot*. This report can be found at the website referenced in footnote 11.

2.0 Estimation Database

In order to estimate the models described in the previous section, we needed four types of data: Customer loads, customer characteristics, weather and electricity prices. The primary load data for each customer consists of 96 values for each day representing integrated demand at 15-minute intervals. For model estimation, we chose to work with peak and off-peak periods. Off-peak period energy consumption for all weekdays covers the time period from midnight until 2 pm and from 7 pm until midnight. Peak-period energy use on all weekdays covers the period from 2 pm to 7 pm for CPP-F customers.

Data on household characteristics were gathered through a mail survey conducted on all SPP participants, including treatment and control customers. This data included information on the following variables: appliance holdings, appliance usage patterns, housing type, age, size and tenure, socio-demographic information, satisfaction with utility performance and opinions about the environment. Through repeated mailings and the payment of a \$25 incentive, a very high overall survey response rate of 96 percent was reached.

Each utility assigned a specific weather station to the control and treatment customers in its service area, based on the customer's location, which yielded a total of 58 weather stations across the state. The population values were used to calculate weighted average weather variables.

Prices were based largely on the rates that were communicated to customers in a Welcome Package, and which varied by rate type, rate level (high or low) and utility. These prices correspond to the average price faced by the average customer. For example, for the CPP-F rate in the SDG&E territory, the current average rate was stated to be 15.5 cents/kWh. The SPP treatment rate was stated to be 10.8 cents/kWh for 85 percent of the annual "off peak" hours, 27.6 cents/kWh for 14 percent of the annual "on peak" hours and 76.8 cents/kWh for 1 percent of the annual "critical peak" hours.

These prices were modified slightly by setting prices for all customers equal to the average price paid by the average customer. This approach allowed prices to vary as general rate adjustments occurred for each utility over the treatment period. The prices also reflect applicable low-income discounts. Since prices primarily reflect the experimental design and do not vary with customer usage, we avoid the simultaneity bias that would be introduced in model estimation if customer-specific average prices (defined as monthly bill divided by monthly usage) were used.

3.0 Empirical Results

We first examined whether impacts are the same or different across the two summers of the experiment, 2003 and 2004. Next, we examined whether responses differed across multiple CPP days that were called sequentially. Finally, we derived demand curves from the estimated demand models to predict how customers would behave when faced with prices other than the ones they were placed on during the pilot.

3.1 Comparison of 2003 and 2004 Elasticities and Load Impacts

Table 3-1 contains elasticity estimates for the two years. The statewide average elasticity of substitution in 2003 is -0.086 .¹⁰ The 2004 value is not statistically different from the 2003 value. The daily price elasticity is -0.032 in 2003, which however is statistically different from the 2004 value.

Table 3-1. Residential CPP-F Rate Elasticity Estimates for the Inner Summer Period All Customers (Based on Average CPP-Day Weather in 2003/2004)

Elasticity Type	2003 Value		
	Estimate	Standard Error	t-statistic
Substitution	-0.086	0.004	-20.51
Daily	-0.032	0.005	-6.804
	2004 Differential		
Substitution	-0.001	0.007	-0.08
Daily	-0.022	0.008	-2.77
	2004 Value		
Substitution	-0.087	0.005	-16.84
Daily	-0.054	0.006	-8.55

Table 3-2 contains the impact estimates for each year based on all customers who participated in each summer using common starting values and average weather for both years. The average customer impact on peak-period energy use on CPP days in 2003 is -12.71 percent and it does not differ statistically from the year 2004. An impact of -12.71 percent means that the average customer, who uses 1.28 kWh/hr during the peak period, reduces load by -0.163 kWh.¹¹ The impact in 2003 using a zonal weighted average approach is -14.00 percent, which is also not statistically distinguishable from its 2004 value. This suggests that the average customer reduces load by -0.180 kWh/h.

¹⁰ Often times, elasticities of substitution are reported as positive numbers and price elasticities as negative numbers. To avoid confusion, we are reporting both elasticities as negative numbers.

¹¹ Much higher elasticities and impacts were obtained for the second type of CPP rate that was accompanied with enabling technology in the form of a smart, price-sensitive thermostat. These are described in the final impact report of the SPP project that can be found at <http://www.energy.ca.gov/demandresponse/documents/index.html>.

Table 3-2. Residential CPP-F Rate Statewide Impacts for Inner Summer Period All Customers

Rate Period	Starting Value (kWh/h)	Impact (kWh/h)	Standard Error	t-stat	Impact (%)	Standard Error (%)	Starting Value (kWh/h)	Impact (kWh/h)	Impact (%)
	2003 Impacts Average Customer Approach						2003 Impacts Zonal Weighted Average Approach		
Peak	1.28	-0.163	0.008	-20.94	-12.71	0.61	1.28	-0.180	-14.00
Off-Peak	0.80	0.021	0.003	7.80	2.57	0.33	0.80	0.025	3.11
Daily	0.90	-0.018	0.003	-6.88	-1.95	0.28	0.90	-0.018	-1.95
	2004 Differential Average Customer Approach						2004 Differential Zonal Weighted Average Approach		
Peak	1.28	-0.018	0.013	-1.32	-1.39	1.06	1.28	-0.017	-1.36
Off-Peak	0.80	-0.010	0.004	-2.43	-1.29	0.53	0.80	-0.008	-0.97
Daily	0.90	-0.012	0.004	-2.79	-1.32	0.47	0.90	-0.010	-1.09
	2004 Impacts Average Customer Approach						2004 Impacts Zonal Weighted Average Approach		
Peak	1.28	-0.178	0.010	-18.49	-13.93	0.75	1.28	-0.195	-15.19
Off-Peak	0.80	0.010	0.003	2.95	1.25	0.42	0.80	0.017	2.09
Daily	0.90	-0.029	0.003	-8.70	-3.24	0.37	0.90	-0.027	-3.02

In 2003, the average customer impact on off-peak energy use on CPP days is +2.57 percent. The change in this impact between the two years is -1.29 percent, which is statistically significant.

The impact on daily energy use on CPP days in 2003 is -1.95 percent. The change in the daily use impact between the two years is -1.32 percent and it is also statistically different from its 2004 value. Thus, the peak period impact for the CPP-F rate in the inner summer is statistically indistinguishable between the years 2003 and 2004 but the impacts during the off-peak period and on daily energy use are statistically different between the two years.

3.2 Persistence across sequential critical events

In 2004, several critical events were called sequentially in order to examine whether people respond differently on the second and/or third days of a multi-day critical event. This is an important question for estimating the benefits associated with CPP rates, as the benefits consist primarily of avoided capacity costs, and avoided capacity would be much less if responsiveness declined on the second and/or third day.

To test for differences across multiple critical day types, binary variables representing each day type were developed and used as interaction terms with each of the price and weather terms in the basic model specification.

Table 3-3 contains base value elasticity estimates and estimates of the differential between the base value and the value for the first, second and third days of a multi-day event for the average customer. Table 3-4 contains estimates of the differentials by climate zone. To make the estimates comparable across the three day-types, the estimates are all based on the average weather across all critical days during the inner summer months for both years.

Table 3-3. CPP Persistence Test, Average Customer

Measure	Elasticity of Substitution			Daily Price Elasticity		
	Estimate	SE	t-statistic	Estimate	SE	t-statistic
Base Value Elasticity	-0.069	0.008	-9.13	-0.074	0.011	-6.58
Day 1 Differential	-0.016	0.007	-2.31	0.015	0.012	1.26
Day 2 Differential	-0.028	0.008	-3.50	0.021	0.012	1.81
Day 3 Differential	-0.018	0.011	-1.63	0.034	0.015	2.28
Chi-Square Statistic	Statistic	D.F.	P-Value	Statistic	D.F.	P-Value
	2.66	2	0.26	2.17	2	0.34

As seen in Table 3-3, the differential between the base value and the value on the first critical day type is -0.016 and is statistically significant. The corresponding differential for the daily price elasticity is not statistically different. On the second critical day type, the differential in the substitution elasticity is statistically significant but that for the daily price elasticity is not. Finally, on the third critical day type, the differential for the substitution elasticity is not significantly significant but that for the daily price elasticity is statistically significant.

The key question, of course, is whether or not the differentials in the CPP elasticities are statistically different from each other. This can be determined using the chi-squared test, whose results are reported in Table 3-4. The test fails to reject the null hypothesis of the differentials being insignificant for either elasticity at the 5 percent level of significance.

Table 3-4. Differential Elasticities By Critical Day-Type

Climate Zone	Elasticity Type	1 st Critical Day Differential		2 nd Critical Day Differential		3 rd Critical Day Differential	
		Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	Substitution	-0.005	-0.66	-0.025	-2.84	-0.015	-1.17
	Daily Price	-0.001	-0.23	0.001	0.11	0.016	2.62
2	Substitution	-0.011	-1.70	-0.027	-3.47	-0.017	-1.56
	Daily Price	0.006	0.84	0.010	1.40	0.023	2.45
3	Substitution	-0.023	-2.65	-0.029	-2.90	-0.021	-1.47
	Daily Price	0.021	1.43	0.031	2.05	0.040	2.07
4	Substitution	-0.028	-2.53	-0.031	-2.45	-0.020	-1.14
	Daily Price	0.053	1.59	0.069	2.02	0.090	2.10
Average Customer	Substitution	-0.016	-2.31	-0.028	-3.49	-0.018	-1.63
	Daily Price	0.015	1.26	0.021	1.81	0.034	2.28

Table 3-5 contains estimates of the differential impact for each critical day-type compared with the base value. None of the differentials for peak-period energy use on the first critical day-type are statistically significant. Of greater importance is whether the second and third day differentials are significant. On a statewide basis, the second day differential is not significant at the 95 percent confidence level. The differential impacts for climate zones 1 and 2 are significant at the 95 percent level. The results indicate that responsiveness is actually greater on the second critical day than it would be under the same weather and price conditions on a day that was not the second in a multi-day event. Statewide, the incremental impact is -2.35 percent. The incremental impact on peak-period energy use on the third critical day is not statistically significant at either the statewide level or for any climate zone.

In contrast to the peak-period impacts, the differential impacts in off-peak and daily energy use are significant in most instances on the second and third days in a multi-day critical event. Indeed, off-peak energy use increases by a statistically significant amount statewide and in every climate zone on both the second and third critical days of a multi-day event, and daily energy use increases by a statistically significant amount in all but two climate zones (zones 1 and 2). These results indicate that customers are shifting load from the peak to the off-peak period on these days, not merely curtailing load during the peak period.

Table 3-5. Differential Impact by Critical Day-Type

Climate Zone	Rate Period	1 st Critical Day Differential				2 nd Critical Day Differential				3 rd Critical Day Differential			
		Impact kWh/hr	t-stat	Impact (%)	Standard Error (%)	Impact kWh/hr	t-stat	Impact (%)	Standard Error (%)	Impact kWh/hr	t-stat	Impact (%)	Standard Error (%)
1	P	-0.004	-0.70	-0.80	1.15	-0.018	-2.85	-3.76	1.32	-0.007	-0.76	-1.44	1.90
	OP	0.001	0.43	0.16	0.38	0.005	2.43	1.07	0.44	0.007	2.27	1.42	0.63
	Daily	0.000	-0.23	-0.05	0.20	0.000	0.12	0.03	0.23	0.004	2.60	0.80	0.31
2	P	-0.011	-1.22	-1.19	0.98	-0.027	-2.74	-3.05	1.11	-0.010	-0.68	-1.07	1.58
	OP	0.006	1.79	0.86	0.48	0.012	3.50	1.84	0.53	0.014	2.89	2.07	0.72
	Daily	0.002	0.84	0.31	0.37	0.004	1.39	0.54	0.39	0.009	2.44	1.24	0.51
3	P	-0.029	-1.04	-1.58	1.53	-0.031	-1.01	-1.71	1.70	-0.001	-0.03	-0.08	2.32
	OP	0.028	2.64	2.79	1.06	0.038	3.47	3.81	1.10	0.038	2.72	3.84	1.41
	Daily	0.016	1.42	1.36	0.96	0.024	2.04	2.02	0.99	0.030	2.04	2.57	1.26
4	P	-0.002	-0.03	-0.09	2.81	0.014	0.19	0.56	3.03	0.085	0.86	3.50	4.09
	OP	0.072	2.27	5.40	2.37	0.089	2.74	6.67	2.43	0.100	2.42	7.49	3.09
	Daily	0.057	1.56	3.62	2.32	0.074	1.97	4.70	2.38	0.097	2.04	6.20	3.04
Average Customer	P	-0.015	-1.01	-1.20	1.19	-0.030	-1.78	-2.35	1.32	-0.004	-0.18	-0.32	1.83
	OP	0.014	2.28	1.76	0.77	0.023	3.52	2.84	0.81	0.025	2.96	3.10	1.05
	Daily	0.008	1.25	0.89	0.71	0.012	1.80	1.30	0.72	0.019	2.26	2.09	0.93

3.3 Demand Curves

One way to illustrate the performance of the demand model is to derive and plot its demand curves. The demand curve in Figure 3-1 shows how energy use in the peak period varies with peak-period price, other things including the off-peak price and weather equal. The curve shows the combined impact of the elasticity of substitution and the daily price elasticity of demand.

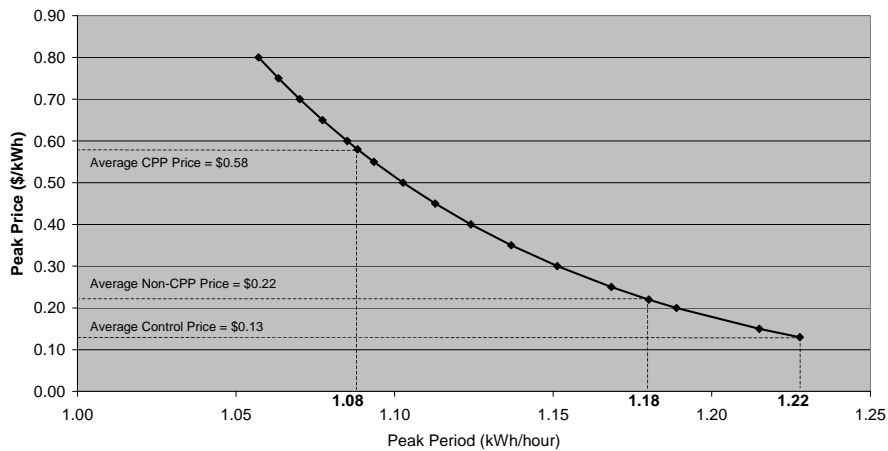


Figure 3-1. Peak Period Demand Curve, Statewide Average

The demand curve shows that at a price of 13 cents/kWh, which is the approximate price facing the control group and the price that the treatment customers faced in the pre-treatment period, electricity use is 1.22 kWh/h during the peak period. At a price of 22 cents/kWh, corresponding to the average Non-CPP peak-period price, demand falls to 1.18 kWh/h. Finally, at a price of 58 cents/kWh, corresponding to the average CPP peak-period price, demand falls to 1.08 kWh/h.

One way of summarizing price impacts when price changes are large is the arc elasticity. In our example, the initial rise in price of 51.43 percent produces a drop in electricity use of 3.33 percent, yielding an implicit arc own-price elasticity of demand of -0.065 ($= -3.33\%/+51.43\%$). The subsequent rise in price of 126 percent produces a drop in electricity use of 12 percent, yielding an implicit arc own-price elasticity of demand of -0.096 .

Figure 3-2 shows the influence of central air-conditioning on the demand curve for peak-period electricity use. The demand curve for customers without central air-conditioning has a steeper slope than the average statewide demand curve, indicating a lower degree of price responsiveness.

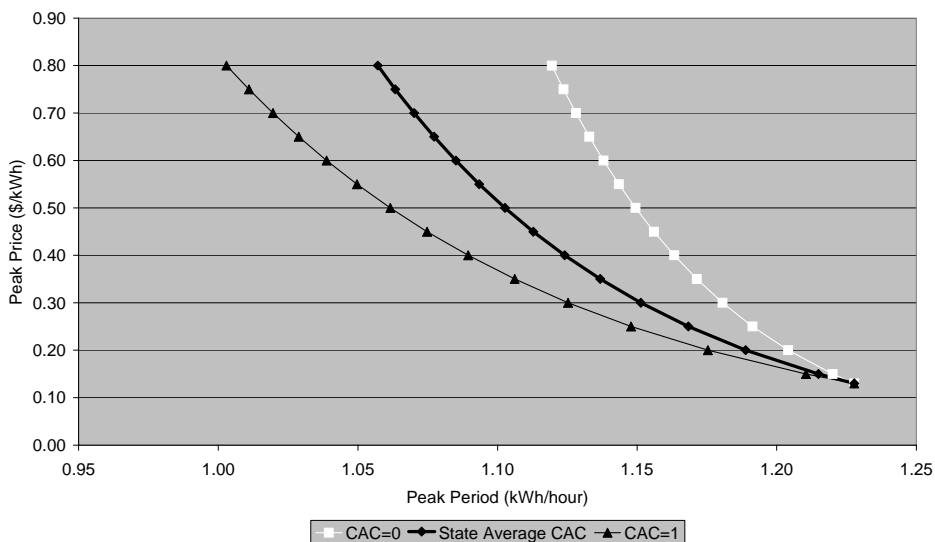


Figure 3-2. Peak Period Demand Curves, Default and CAC Variations, Statewide

Similar demand curves can be constructed for peak and off-peak energy use in each of the four climate zones. The steepest demand curve was found in Zone 1, and the flattest one in Zone 4. Figure 3-3 displays these demand curves. It shows how much the quantity consumed in the peak period would change by zone as the price of electricity moves up from 13 cents/kWh to 58 cents/kWh. The biggest impact is observed in Zone 4 (-13.2%), followed by Zone 3 (-12.9%), Zone 2 (-9.03%) and Zone 1 (-6.64%). The implied arc elasticities of demand are -0.038 in Zone 4, -0.038 in Zone 3, -0.029 in Zone 2 and -0.023 in Zone 1.

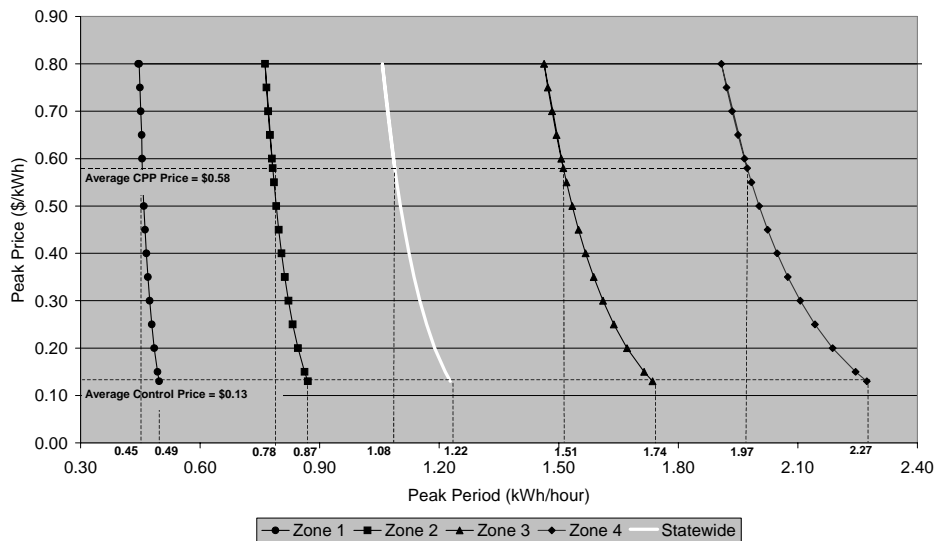


Figure 3-3. CPP Day Peak Period Demand Curves by Climate Zone

Another way to show the empirical results is to show how the percent impacts change with price. This is shown in Figure 3-4. The curves, which are displayed by zone and statewide, show that higher prices bring about greater reductions in peak-period energy use, but at a diminishing rate. Reductions are greater in percentage terms (and even greater in absolute terms) in hotter climate zones (where air conditioning saturations are high) than in cooler zones.

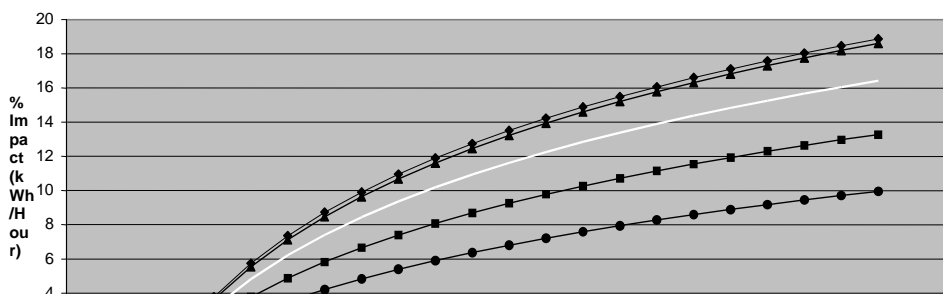


Figure 3-4. Percent Reduction in Peak-Period Energy Use on Critical Days Average Summer, 2003/04

4.0 Conclusions

The impact evaluation methodology used in the SPP was successful in measuring the impact of customers to dynamic prices. It found statistically significant evidence of response to a wide variety of prices. On a statewide basis, in the year 2003, the elasticity of substitution is -0.086 and the daily price elasticity is -0.032 . The price elasticity of peak demand, derived through model simulation, lies in the range of -0.065 to -0.096 . Elasticities vary with climate zone and ownership of central air conditioning, being higher for customers with central air conditioning that live in hot climate zones within the state.

The impact of dynamic pricing on peak energy use in 2003 using a zonal weighted average approach is -14.00 percent. This suggests that the average customer, who uses 1.28 kWh/h during the peak period, reduces load by -0.180 kWh/h. In other words, if a critical peak pricing program were able to attract one million participants out of California's ten million residential customers, that would yield a savings of 180 MW per year. If the program were targeted toward customers with central air conditioning in the hotter climate zones, larger savings would ensure. Still larger savings would accrue if customers were provided with enabling technologies.

Two recent studies of critical peak pricing programs in humid eastern climates have reported substantially larger impacts during the critical peak period than have been observed for the average customer in California, both in percentage terms and in absolute terms. This may be due to larger existing usage per customer and to the presence of enabling technologies in those studies.¹²

Using a t-test, we have compared impacts on peak usage in 2003 with impacts in 2004 and found that the two estimates are not statistically significantly different from each other. Thus, there is temporal consistency in customer price responsiveness across the two summers of the experiment, 2003 and 2004. In addition, using a chi-squared test, we find evidence of temporal consistency of response across multiple CPP days that were called sequentially.

¹² Personal correspondence with Steve Braithwait, April 18, 2005.

Finally, we derived demand curves from the estimated demand models to predict how customers would behave when faced with prices other than the ones they were placed on during the pilot. The demand curves are flatter in hotter zones and for customers with central air conditioning.

The SPP project has also yielded demand models capable of simulating the impact of dynamic prices in geographically diverse locations that differ in terms of weather conditions and the saturation of central air conditioning.