IMPACT EVALUATION OF THE CALIFORNIA STATEWIDE PRICING PILOT

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Final Report

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1. Executive Summary

California experienced a major power crisis in its unregulated wholesale markets during 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. One of the unknowns in implementing dynamic pricing is whether and by how much customers would reduce peak loads in response to dynamic price signals.

To help address this uncertainty, California's three investor-owned utilities, in concert with the two regulatory commissions, conducted an experiment to test the impact of time-of-use (TOU) and dynamic pricing among residential and small commercial and industrial customers. The primary objectives of California's Statewide Pricing Pilot (SPP) were to:

- Estimate the average impact of time-varying rates on energy use by rate period and develop models that can be used to predict impacts under alternative pricing plans
- Determine customer preferences and market shares for time-varying rate options
- Evaluate the effectiveness of and customer perceptions about pilot features and educational materials.

This evaluation report addresses the first objective. A previous report presented preliminary impact estimates for selected pilot treatments from the initial summer of the pilot (2003). This report updates and significantly extends those results. It is a comprehensive, standalone document and there is no need to review the previous report. Any discrepancies between results presented previously and those presented here reflect methodological enhancements and, therefore, should be resolved in favor of the current report.

The SPP involved some 2,500 customers and ran from July 2003 to December 2004. Several different rate structures were tested. These included a traditional time-of-use rate (TOU), where price during the peak period was roughly 70 percent higher than the standard rate and about twice the value of the price during the off-peak period. The SPP also tested two varieties of critical peak pricing (CPP) tariffs, where the peak period price during a small number of critical days was roughly five times higher than the standard rate and about six times higher than the off-peak price. One CPP rate, CPP-F, had a fixed critical peak period and day-ahead notification. The other, CPP-V, had a variable peak period on critical days and day-of notification. CPP-V customers had the option of having an enabling technology installed free of charge to help facilitate demand response. The SPP also tested an information treatment that urged customers to reduce demand on critical days in the absence of time-varying price signals.

1. Executive Summary

1.1 METHODOLOGICAL OVERVIEW

Both the overall design of the SPP, as well as the evaluation approach underlying the results presented here, allow not only for estimation of the impact of the specific price levels tested in the SPP, but also for estimation of demand response for prices that were not explicitly used as part of this experiment. The 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. Importantly, they can also be used to estimate the impact of other prices that are within a reasonable range of those tested, as illustrated in some of the figures presented later in this Executive Summary as well as in the report. Most of the demand models also allow one to adjust the magnitude of price responsiveness to account for variation in climate and the saturation of central air conditioning. Thus, demand response impact estimates can be developed for customer segments with characteristics that differ from those included in the experiment.

As noted above, the data used to estimate demand models includes information on both treatment and control customers. For treatment customers, information on energy use by rate period is available both before and after being placed on the new rate. This type of database allows one to separate the impact of the experimental treatments from the impact of other factors that might influence energy use, including self-selection bias.

The demand system estimated for each tariff consists of two equations. One equation predicts daily energy use as a function of daily price and other factors. The second equation predicts the share of daily energy use by rate period. This type of demand system is commonly used in empirical analysis of energy consumption. While the complexity of the experimental design has created numerous empirical challenges, these challenges have been addressed through careful application of widely accepted statistical methods.

1.2 RESIDENTIAL SECTOR SUMMARY

Three rate treatments were examined for residential customers; CPP-F, CPP-V and TOU. An information only treatment was also examined. The CPP-F and TOU rates were implemented among a statewide sample of customers. The sample size for the CPP-F treatment was much larger than for the TOU treatment and the results are more robust. The CPP-V rate was implemented only in the SDG&E service territory and the Information Only treatment in the PG&E service territory.

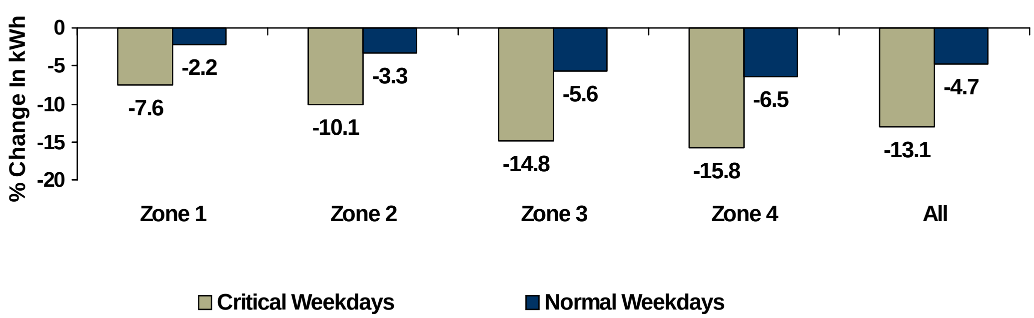
1.2.1 CPP-F Impacts

A key focus of the SPP was to assess the impact of dynamic tariffs. Estimated impacts vary on critical days (when the highest prices are in effect), normal weekdays (when lower peak prices are in effect) and weekends (which have the same prices as off-peak weekday periods).

Figure 1-1 summarizes the impact of the average CPP-F prices on energy use during the peak period on critical and normal weekdays. Statewide, the estimated average reduction in peak-period energy use on critical days was 13.1 percent. Impacts varied across climate zones, from a low of –7.6 percent in the relatively mild climate of zone 1 to a high of –15.8 percent in the hot climate of zone 4. The average impact on normal weekdays was -4.7 percent, with a range across climate zones from –2.2 percent to –6.5 percent.

The statewide impact estimate of -13.1 percent has a 95 percent confidence band of +/- 1 percentage point. This means that there is a 95 percent probability that the actual reduction in peak-period energy use on critical days based on average SPP prices would fall between 12.1 and 14.1 percent.

Figure 1-1
Percent Change In Residential Peak-Period Energy Use
(Avg CPP-F Prices/Avg 2003/2004 Weather)



Other key findings for the CPP-F rate include:

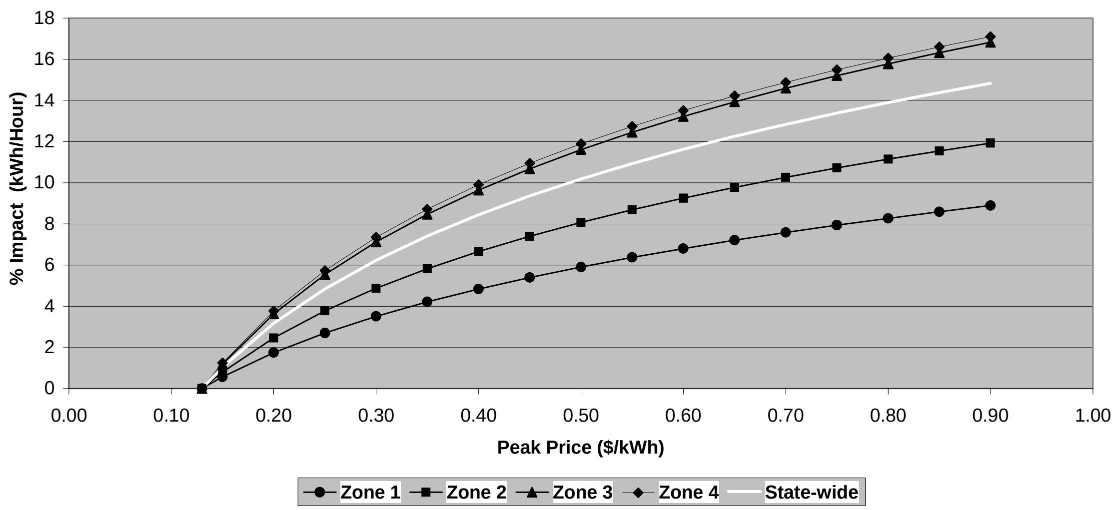
- Differences in peak-period reductions on critical days across the two summers, 2003 and 2004, were not statistically significant
- Differences in impacts across critical days when two or three critical days are called in a row (as might occur during a heat wave) were not statistically significant
- Average impacts on critical days were greater during the hot summer months of July through September (the “inner summer”) than during the milder months of May, June and October (the “outer summer”)

- Households with central air conditioning were more price responsive and produced greater absolute and percentage reductions in peak-period energy use than did households without air conditioning

- Demand response impacts were lower in the winter than in the summer, and lower during the milder winter months of November, March and April (the "outer winter") than during the colder months of December, January and February (the "inner winter").

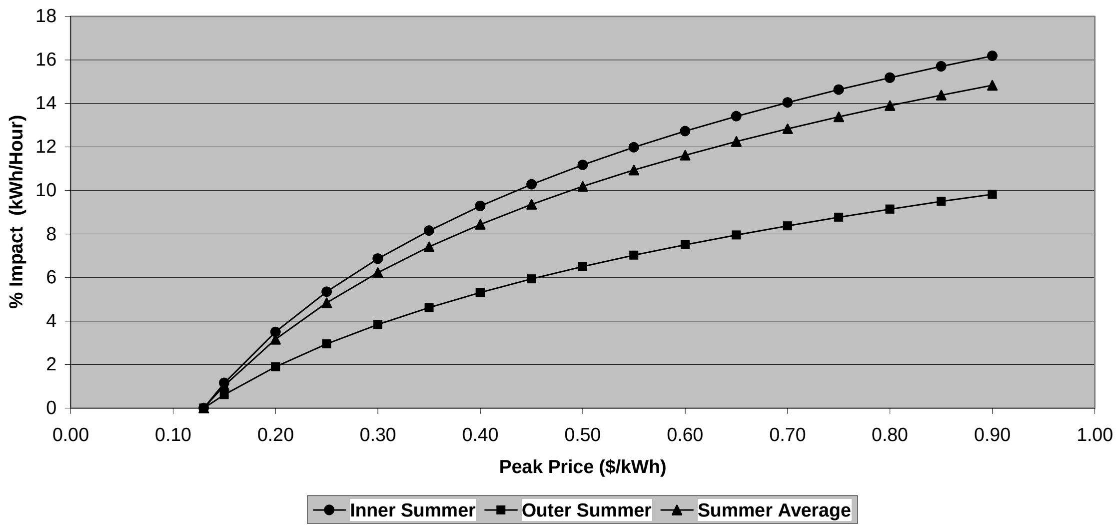
- There was essentially no change in total energy use across the entire year based on average SPP prices. That is, the reduction in energy use during high-price periods was almost exactly offset by increases in energy use during of-peak periods.

Figure 1-2
Percent Reduction in Peak-Period Energy Use on Critical Days
Average Summer, 2003/04



As previously mentioned, one of the primary advantages to developing demand models is to estimate the impact of prices that were not specifically tested in the SPP. Figures 1-2 and 1-3 show how the percent reduction in peak-period energy use on critical days varies with changes in the peak-period price on critical days (when everything else is held constant). The curves indicate that the reduction in peak-period energy use increases as prices increase, but at a diminishing rate. Figure 1-2 shows that 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 1-3 shows that reductions are greater in the inner summer months of July, August and September than in the outer summer months of May, June and October. We believe the greater responsiveness in the inner summer is due primarily to the influence of air conditioning.

Figure 1-3
Percent Reduction in Peak-Period Energy Use on Critical Days by Season



1.2.2 TOU Impacts

The reduction in peak-period energy use resulting from TOU rates in the inner summer of 2003 equaled –5.9 percent. This 2003 value is comparable to the estimate for the CPP-F tariff on normal weekdays when prices were similar to those for the TOU treatment. However, in 2004, the TOU rate impact almost completely disappeared (-0.6 percent). TOU winter impacts are comparable to the normal weekday winter impacts for the CPP-F rate.

Drawing firm conclusions about the impact of TOU rates from the SPP is somewhat complicated by the fact that the TOU sample sizes were small relative to the CPP-F sample sizes. Small sample sizes are more subject to influence by outliers and changes in the sample composition over time. Further complicating the estimation of the daily energy equation is that variation in daily prices over time is quite small, which makes it difficult to obtain precise estimates of daily price responsiveness. In short, there are reasons to take the analysis of the TOU rate treatment with a “grain of salt.” Indeed, an argument could be made that the normal weekday elasticities from the CPP-F treatment may be better predictors of the influence of TOU rates on energy demand than are the TOU price elasticity estimates.

On the other hand, if the TOU results are accurate, they have very important policy implications, since they suggest that the relatively modest TOU prices tested in this experiment do not have sustainable impacts.

1.2.3 CPP-V Impacts

The residential CPP-V rate was tested among two different populations, both within the SDG&E service territory.

Track A customers were drawn from a population of customers with average summer energy use exceeding 600 kWh per month. The saturation of central air conditioning among the Track A treatment group was roughly 80 percent, much higher than among the general population, and average income was also much higher. Track A customers were given a choice of having an enabling technology installed free of charge to facilitate demand response. About two-thirds of participants took one of three technology options and about half of those selected a smart thermostat.

Track C customers were recruited from a sample of customers that had previously volunteered for the AB970 Smart Thermostat pilot. All Track C customers had smart thermostats and central air conditioning.

Key findings for the CPP-V rate treatments include:

- The reduction in peak-period energy use for Track A customers on critical days equaled almost 16 percent, which is about 25 percent higher than the CPP-F rate average

- The peak-period reduction for the Track C treatment equaled roughly 27 percent. About two-thirds of this reduction can be attributed to the enabling technology and the remainder is attributable to price-induced behavioral changes

Although comparisons between Track A and Track C CPP-V treatments and between the CPP-V and CPP-F treatments must be made carefully due to differences in sample composition, the Track C results suggest that impacts are significantly larger with enabling technology than without it. The 27 percent average impact for the Track C, CPP-V treatment is roughly double the 13 percent impact for the CPP-F rate for the average summer. It is also substantially larger than the Track A, CPP-V treatment impact, where only some customers took advantage of the technology offer.

1.2.4 Information Only Impacts

The Information Only treatment was included primarily as a crosscheck on the results of the CPP-F rate treatment. Specifically, the purpose was to determine whether simply appealing for a reduction in energy use on critical days might produce significant impacts even in the absence of any price incentive. Information Only customers were given educational material regarding how to reduce loads during peak periods, and they were notified in the same manner as were CPP-F customers when critical days were called. However, participants were not placed on time varying rates.

The Information Only treatment was implemented in two climate zones in the PG&E service territory. In one of the two zones in 2003, demand response was statistically significant while in the other zone it was not. In 2004, there was no evidence of any response in either zone. At a minimum, one can conclude that demand response in the absence of a price signal is not sustainable. Furthermore, we believe it is not unreasonable to consider the 2003 impact for a single climate zone to be an anomaly and to conclude that there is no clear evidence from the SPP of any significant impact from an appeal to reduce energy use on critical days in the absence of a price signal.

1.2.5 Residential Summary

Table 1-1 summarizes the key findings with regard to reductions in peak-period energy use resulting from the various tariff options tested in the SPP.

The most robust and generalizable estimates from the SPP are for the CPP-F rate. TOU rate impacts vary across years and are suspect due to sample size limitations and other factors. We recommend using the CPP-F models to predict TOU impacts. Although the Track C, CPP-V results are more difficult to generalize to the overall population, they provide useful estimates of the incremental impact of prices and enabling technology.

Table 1-1
Summary of Average Peak-Period Impacts by Treatment Type for Residential Customers

Treatment	Day Type	Avg. Price (¢/kWh)[1]	Impacts	Comments
Track A CPP-F	**Critical Weekday**	P = 59 OP = 9 D = 23 C = 13	-13.1% average summer -14.4% inner summer -8.1% outer summer	No statistically significant difference for inner summer between 2003 and 2004 (differences across the two years can not be estimated for the outer summer or the average summer)
	Normal Weekday	P = 22 OP = 9 D = 12 C = 13	-4.7% average summer -5.5% inner summer -2.3% outer summer	Difference between critical & normal days is primarily due to price differences and secondarily to differences in weather
Track A TOU	**All Weekdays**	P = 22 OP = 10 D = 13 C = 13	-5.9% inner summer 2003 -0.6% inner summer 2004 -4.2% outer summer 2003/04	Results are suspect because of the small sample size and observed variation in underlying model coefficients across the two summers. Recommend using normal weekday CPP-F model to predict for TOU rate.
Track A CPP-V	**Critical Weekday**	P = 65 OP = 10 D = 23 C= 14	-15.8% average summer 2004 Represents average across households with and without enabling technology—could not separate price & technology impacts	Not directly comparable to CPP-F results due to differences in population (CAC saturation for CPP-V treatment group twice that of CPP-F; CPP-V average income much higher; 2/3 of CPP-V customers had enabling tech.; all households located in SDG&E service territory)
	Normal Weekday	P = 24 OP = 10 D = 14 C = 14	-6.7% average summer 2004	See above comments about population differences
Track C CPP-V	**Critical Weekday**	Same as for Track A	-27.2% combined tech & price impact for average summer 2003/04 -16.9% impact for tech only -11.9% incremental impact of price over & above tech impact	Not directly comparable to Track A results due to population differences (All Track C customers are single family households with CAC located in SDG&E service territory). Some evidence that impacts fell between 2003 & 2004
	Normal Weekday	Same as for Track A	-4.5% average summer 2003/04	See above comments about population differences
Track A Info Only	**Critical Weekday**	13 for all periods	Statistically significant response in one of two climate zones in 2003. No response in 2004.	Analysis provides no evidence of sustainable response in the absence of price signals.

It is interesting to compare the results obtained from the SPP with those that have been found elsewhere. There have been dozens of studies of the impact of time-varying rates conducted over the years, many of them quite dated.[2] Very few previous studies

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[1] P = peak period price; OP = off-peak price; D = daily price; C = control group price.

[2] Chris S. King and Sanjoy Chatterjee. *Predicting California Demand Response.* Public Utilities Fortnightly, July 1, 2003.

examined dynamic rates, which was a key focus of the SPP. Making comparisons across studies is very difficult because of differences in methodology, differences in the characteristics of underlying populations and differences in price levels and other factors. Ignoring such complexities, a simple comparison shows that the SPP estimates of price responsiveness in California are at the low end of the range reported in the literature.

One study, conducted in the early 1980s by the Electric Power Research Institute,[3] allows for a more careful comparison between the SPP results and estimates based on several of the well-designed TOU rate experiments that were conducted in the late 1970s. The EPRI study used a similar model specification to the one used here so that we were able to estimate the impact of SPP prices using the price responsiveness measures from the EPRI study. Using these earlier model parameters along with average SPP prices, the estimated peak-period reduction on critical days is roughly 70 percent greater than the estimated value from the SPP (i.e., -22.5 percent versus -13.1 percent).

Based on these comparisons, it would appear that price responsiveness in California today is less than it was in California and elsewhere a quarter century ago. This is not surprising in light of the significant conservation and load management programs that were implemented in the last 25 years. Actions taken by many consumers following the energy crises of 2000 and 2001 may also have reduced the ability or willingness of California's customers to further reduce energy use. Nevertheless, it is also very clear from the results presented here that there still remains a significant amount of demand response that can be achieved through TOU and dynamic pricing.

1.3 COMMERCIAL AND INDUSTRIAL SECTOR SUMMARY

CPP-V and TOU tariffs were also tested among C&I customers. All treatments were implemented in the SCE service territory. The C&I population was segmented into two groups, customers with peak demands less than 20 kW (LT20) and customers with peak demands between 20 and 200 kW (GT20). The CPP-V tariff was implemented among two population samples. The Track A sample was recruited from the general population while the Track C sample was drawn from a pre-existing Smart Thermostat pilot. All Track C customers had central air conditioning and smart thermostats. Most Track A customers had central air conditioning but only about half selected the smart thermostat technology option. In light of these and other differences, direct comparisons between Track A and Track C results must be made carefully.

For the Track A, CPP-V treatment, key findings include:

[3] Results from the EPRI study are summarized in Douglas Caves, Laurits Christensen and Joseph Herriges, *Consistency of Residential Customer Response in Time-of-Use Electricity Pricing Experiments.* Journal of Econometrics 16 (1984) 179-203, North-Holland.

- LT20 customers had a very small but statistically significant demand response, with the average peak-period reduction on critical weekdays equal to 6.0 percent
- The peak-period reduction on normal weekdays for LT20 customers was roughly 1.5 percent
- Although the percent reduction in peak-period energy use was much smaller among LT20 customers than among residential customers on the CPP-F rate, the absolute reduction was slightly larger because average energy use for LT20 customers was about three times larger than for residential customers
- GT20 customers showed a larger percent reduction in peak-period energy use on critical weekdays (-9.1 percent) than did LT20 customers
- Reductions in peak-period energy use on normal weekdays for GT20 customers equaled 2.4 percent
- The absolute size of the reduction in peak-period energy use for GT20 customers was roughly 10 times larger than for LT20 customers, due primarily to the fact that average energy use for GT20 customers was much larger than for LT20 customers and secondarily to the fact that GT20 price responsiveness was greater than it was for LT20 customers.

Key findings for the Track C, CPP-V treatment include:

- LT20 customers reduced peak-period energy use on critical weekdays by 14.3 percent. All of this reduction is attributable to the enabling technology. That is, this customer segment did not have any incremental price response.
- GT20 customers reduced peak-period energy use on critical weekdays by 13.8 percent. Roughly 80 percent of this reduction is attributable to the enabling technology.

For the C&I TOU rate treatment, demand response and impacts varied significantly between summer 2003 and summer 2004. In 2003, price was not statistically significant for the LT20 customer segment. However, price was significant in 2004 and the estimated reduction in peak-period energy use equaled almost 7 percent. Price was statistically significant in both summers for the GT20 segment. Peak period impacts in 2003 equaled –4.0 percent and in 2004 equaled –8.6 percent. These results should be viewed cautiously, however, in light of the small sample size and significant variation in the underlying model coefficients across summers.

Table 1-2 summarizes the key findings for the C&I analysis. The Track C, CPP-V results suggest that technology could have a relatively significant influence on demand response in the C&I sector, although this population is not representative of the overall population of C&I customers. Price responsiveness among the smallest segment (LT20) is quite small in most instances. Responsiveness is greater for GT20 customers than it is for LT20 customers.

Table 1-2
Summary of Average Peak-Period Impacts by Treatment Type for C&I Customers

Treatment/ Customer Segment	Day Type	Avg. Price (¢/kWh)	Impacts	Comments
Track A TOU LT20	**All Weekdays**	P = 28 OP = 12 D = 18 C = 18	-0.3% in 2003 -6.8% in 2004	The 2003 value is not statistically significant. Small sample size and variation in underlying model coefficients across summers suggest estimates may be suspect. Recommend using normal weekday CPP-F model to predict for TOU rate.
Track A TOU GT20	**All Weekdays**	P = 23 OP = 12 D = 16 C = 15	-3.9% in 2003 -8.6% in 2004	The difference between 2003 and 2004 is statistically significant. Same caveat as described above for LT20 customers.
Track A CPP-V LT20	**Critical Weekday**	P = 81 OP = 12 D = 30 C = 17	-6.1% in 2004	This treatment was not implemented in 2003 Price responsiveness measure is small but statistically significant
	Normal Weekday	P = 20 OP = 12 D = 15 C = 17	-1.5% in 2004	Same comments as above
Track A CPP-V GT20	**Critical Weekday**	P = 66 OP = 11 D = 24 C = 15	-9.1% in 2004	This treatment was not implemented in 2003 This segment is more price responsive than LT20 customers
	Normal Weekday	P = 18 OP = 12 D = 14 C = 15	-2.4% in 2004	Same comments as above
Track C CPP-V LT20	**Critical Weekday**	P = 87 OP = 12 D = 33 C = 18	-14.3% combined tech & price impact for average summer 2003/04 -18.2% for tech alone +4.5% incremental impact of price over & above tech impact	The tech only impact is higher than the combined price/tech impact, indicating that price does not provide any incremental impact for this customer segment
	Normal Weekday	P = 21 OP = 12 D = 16 C = 18	+1.1 in average summer 2003/04	The estimate is not statistically significant. Additional evidence that this customer segment is not price responsive.
Track C CPP-V GT20	**Critical Weekday**	P = 71 OP = 11 D = 24 C = 15	-13.8% combined tech & price impact for average summer 2003/04 -11.0% for tech alone -3.2% incremental impact of price over & above tech impact	Incremental impact of price over technology declined by roughly 75% between 2003 and 2004 GT20 participants use significantly less electricity on average than the average control group
	Normal Weekday	P = 19 OP = 11 D = 14 C = 15	-0.9% in average summer 2003/04	Same comments as above

2. Background and Overview

2.1 INTRODUCTION

One of the lessons gleaned from California's energy crisis in 2000/2001 is that the lack of demand response in retail markets makes it very difficult to equilibrate wholesale markets at reasonable prices.[4] Studies have shown that economic efficiency in the allocation of scarce capital, fuel and labor resources can be improved by introducing demand response in retail markets. One method for introducing demand response in retail markets is time-varying pricing. With this in mind, the California Public Utilities Commission (CPUC) initiated a proceeding in July 2002 designed to introduce demand response in California's power market.[5]

As part of this proceeding, three working groups were charged with developing specific tariff proposals to achieve increased demand response in the state. The mission of Working Group 3 (WG3) was to develop a dynamic tariff (or set of tariffs) for residential and small commercial customers with demands less than 200 kW. WG3 included representatives from the state's three investor-owned utilities[6], two regulatory commissions[7], equipment vendors, The Utility Reform Network (TURN) and other interested parties.

In support of the WG3 deliberations, Charles River Associates (CRA) conducted a preliminary analysis of the potential benefits of a variety of time-differentiated rates at Pacific Gas & Electric Company (PG&E). The analysis included static time-of-use (TOU) rates and dynamic rates where high price signals are passed through to consumers on selected days when supply is constrained, the timing of which is unknown. The analysis showed a wide range of potential benefits from the implementation of dynamic pricing at PG&E, with the lower end being $561 million and the high end being $2,637 million. Incremental metering and billing costs associated with the provision of dynamic pricing were estimated at about a billion dollars.[8] Consequently, there is a wide range in estimates of the potential net-benefits of dynamic pricing, depending upon assumptions about meter and rate deployment strategy and costs, the level of customer demand response and the magnitude of avoided energy and capacity costs. Analysis also indicated that conducting an experiment with a few thousand customers could significantly reduce uncertainty in the net benefit estimates.

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4 James L. Sweeney, The California Electricity Crisis, Hoover Institution Press, 2002.

5 Order Instituting Rulemaking on policies and practices for advanced metering, demand response and dynamic pricing, CPUC R. 02-06-001.

6 Pacific Gas & Electric (PG&E), San Diego Gas & Electric (SDG&E) and Southern California Edison (SCE).

7 The CPUC and the California Energy Commission (CEC).

8 This cost estimate was very preliminary and is reported here for illustrative purposes only. All three of the utilities involved in the SPP have developed much more refined cost estimates as part of the ongoing AMI proceeding.

2. Background and Overview

Based in part on this preliminary analysis, WG3 recommended on December 10, 2002 that the state conduct a carefully designed pricing experiment with different tariff options prior to making a decision on full-scale deployment of the automated metering infrastructure required to support such time-varying rates.[9] A decision was made to implement a statewide experiment rather than utility-specific experiments to better leverage scarce budget resources and also to ensure consistency in results across the state. The CPUC approved the experiment, now called the Statewide Pricing Pilot (SPP), on March 14, 2003.[10]

The SPP has three primary objectives:

- Estimate the average impact of time-varying rates on energy use by rate period and develop models that can be used to predict impacts under alternative pricing plans

- Determine customer preferences for tariff attributes and market shares for specific TOU and dynamic tariffs, control technologies and information treatments under alternative deployment strategies

- Evaluate the effectiveness of and customer perceptions of specific pilot features and materials, including enrollment and education material, bill formats, web information, and tariff features.

This report primarily addresses the first objective. Separate reports address the second and third objectives. A report summarizing the pilot results for the first summer of the experiment was issued on August 9, 2004 (and posted in October, 2004).[11] The results presented in the Summer 2003 Report did not cover all SPP treatments and covered only the initial summer period. This report updates and extends those findings for all treatments. To the extent that there are differences between the results presented in the Summer 2003 Report and those contained in this report, the results presented here should be used.

The tariffs tested in the SPP included a traditional TOU rate and two dynamic pricing rates. The dynamic rates included a critical-peak pricing (CPP) element that involved a substantially higher peak price (about 50 to 75 cents/kWh) for 15 days of the year and a standard TOU rate on all other days. One type of CPP rate (CPP-F) featured a fixed peak period on both critical and non-critical days and day-ahead customer notification for critical day events. The peak period for residential customers was between 2 pm and 7 pm weekday afternoons and the peak period for commercial and industrial customers

[9] Report of Working Group 3 to Working Group 1, R.-2-06-001. Proposed Pilot Projects and Market Research to Asses the Potential for Deployment of Dynamic Tariffs for Residential and Small Commercial Customers. Version 5, December 10, 2002.

[10] Decision 03-03-036, Interim Opinion in Phase 1 adopting pilot program for residential and small commercial customers.

[11] Charles River Associates, Inc. *Statewide Pricing Pilot, Summer 2003 Impact Analysis*. August 9, 2004, published October 11, 2003. Hereafter referred to as the Summer 2003 Report.

was from noon to 6 pm on weekdays. The other type of CPP rate (CPP-V) featured a variable-length peak period on critical days, which could be called on the day of a critical event. All SPP rates were seasonally differentiated, with summer running from May through October, inclusive, for residential customers and from the first Sunday in June through the first Sunday in October for commercial and industrial customers.

In addition to the rate treatments described above, an “Information Only” treatment was also tested for residential customers. This treatment involved notifying customers on critical days and asking them to avoid energy use during the peak period. However, prices were the same on critical days as they were on all other days and customers did not face time-varying prices on any day.

Residential customers in the SPP were segmented into four climate zones and commercial/industrial customers into two size strata, those with peak demands less than 20 kW (LT20) and those with peak demands between 20 and 200 kW (GT20). Residential CPP-F and TOU customers were drawn from the service territories of all three participating utilities (PG&E, SDG&E and SCE) while commercial/industrial customers were drawn exclusively from the SCE population. The residential CPP-V tariff was deployed exclusively in the SDG&E service territory and the Information Only tariff was implemented only in the PG&E service territory.

SPP customers were divided into three tracks:

- Track A represented the general population of customers in the state.
- Track B represented the population of relatively low-income customers living in the vicinity of two power plants in the Hunters Point/Potrero division of San Francisco and a control group of customers in the city of Richmond.[12]
- Track C represented the population of customers who had previously volunteered to be in the AB970 Smart Thermostat pilot program in the SCE (small commercial and industrial customers only) and SDG&E (residential customers only) service areas.

The remainder of this section discusses rate design, sample design and customer enrollment issues. Section 3 summarizes the analytical methods and data that were used to estimate the energy and demand impacts attributable to the SPP treatments. Section 4 summarizes the demand modeling and impact evaluation results for the residential CPP-F tariff. Section 5 focuses on the residential TOU tariff and Section 6 on the residential CPP-V rate treatment. Section 7 presents the findings associated with the C&I treatments, which include both TOU and CPP-V tariffs. A glossary of technical terms is contained at the end of this report. Numerous appendices, presented in a

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[12] Results from the Track B analysis are contained in a separate report produced by San Francisco Community Power, the contractor that implemented and evaluated the Track B treatments. See *Statewide Pricing Pilot—Track B: Evaluation of Community-Based Enhanced Information Treatment*, Draft Final Report, March 8, 2005.

separate volume, contain a wide variety of technical details as well as the regression results underlying the information presented in subsequent sections.

2.2 RATE DESIGN

The specific tariffs that were tested in the SPP reflect compromises among WG3 members concerning the rate options that it would be desirable to explore, numerous analytical complexities, historical differences across service territories, and several political realities.

2.2.1 Customer Protection Constraints

The CPUC placed a number of constraints on the rate design process in order to address the concerns of various constituencies within WG3. Specifically, the experimental rates were required to satisfy three constraints:

- be revenue neutral for the class-average customer over a calendar year, in the absence of any change in the customer's load shape,
- not change the bill of low and high users by more than 5 percent in either direction, in the absence of any change in the load shape, and
- provide customers with an opportunity to reduce their bills by 10 percent if they reduced or shifted peak usage by 30 percent.

An additional design constraint, suggested by one of PG&E's rate analysts, was to lower bills when price ratios are high and raise bills when price ratios are low, in order to minimize adverse bill impacts for low and high users. Condition (a) was satisfied by placing customers on a high price ratio in the summer and a low price ratio in winter. The rates are revenue neutral on an annual basis, but not on a seasonal basis. The other conditions were satisfied by testing a variety of price ratios.

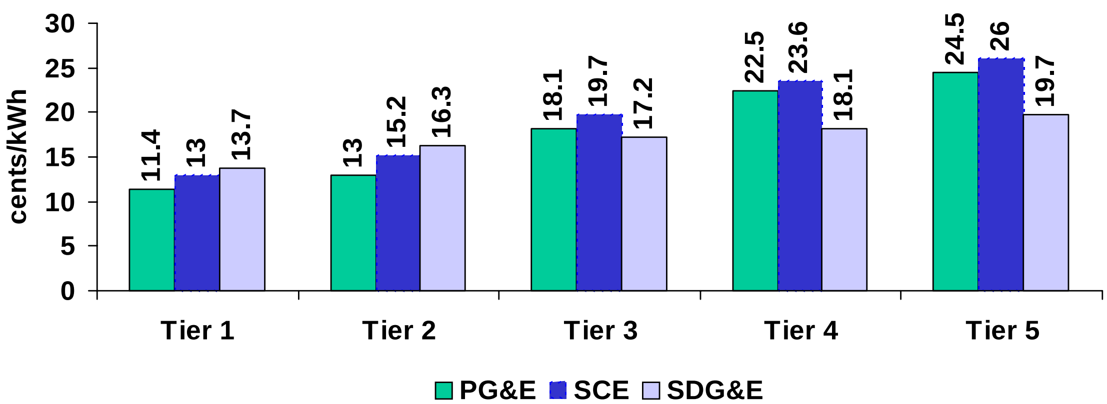
Finally, it is important to note that low-income households in California qualify for a 20 percent discount on their electricity bill under a program called CARE. The maximum eligible income for a CARE household can be no higher than $23,000 with one or two persons in the household; and no higher than $43,500 for a household with six persons. The specific details regarding how the 20 percent CARE discount is implemented varies by utility.

2.2.2 Experimental Considerations

The experimental rates were designed to allow estimation of models of the demand for energy by time-of-use period. Demand models allow for estimation of rate impacts for prices that differ from the specific ones used in the experiment. Each time-varying rate consists of two pricing periods, peak and off-peak. In order to facilitate estimation of demand models, two rate levels were created for each treatment group. When combined with the non-time varying rate for the control group, this yields three price points along the demand curve for energy use in each rate period.

Another rate-related complication was the existence of different base rates across the three utilities. The average prices, expressed in cents/kWh, during the summer of 2003 were 12.7 for PG&E and, rounded, 14.1 for both SDG&E and SCE.[13] As shown in Figure 2-1, the inverted five-tier rate structure differed across utilities. SDG&E customers started out with a higher price in Tier 1 but their prices didn't rise as steeply as they did for PG&E and SCE customers. Thus, customers in SDG&E's service territory paid slightly less than 20 ¢/kWh for Tier 5 usage whereas Tier 5 customers in PG&E's service area paid roughly 24.5 ¢/kWh and in Edison's they paid 26 ¢/kWh.[14]

Figure 2-1
Marginal Prices For Control Group Customers
At Start Of Treatment Period
(Summer 2003)



In developing rates for each utility, a decision was made to expose customers to consistent price differentials by time-of-day while maintaining the differences in the underlying rates across utilities. This approach applies a set of time-varying surcharges and discounts on top of the existing rate structure of each utility. The surcharges and discounts were identical across utilities, causing the effective TOU and CPP prices to differ by small amounts because of the differences in the underlying rates. This approach, which preserved the inverted character of the underlying rate structure, was chosen over an alternative approach that would have used a flat base rate for all

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[13] Prices have changed over the course of the pilot, more for some utilities than others. The prices presented here represent a snap shot in time and are for illustrative purposes only.

[14] Edison's rates fell shortly after the pilot started, especially the Tier 5 marginal price. All tariff changes that were made by each utility during the course of the experiment were passed through to both treatment and control customers so rates varied over time.

consumers, with a time-varying rate structure applying to treatment customers. The primary disadvantage of the second approach is that it would have provided a substantial bill discount to high-use customers relative to low-use customers. As such, many high-use customers would have displayed a strong preference for the time-varying rate because it would have lowered their average rate even in the absence of changing their usage patterns or levels. In addition, the chosen approach automatically reflected changes in the underlying base rates that occurred during the experiment due to the normal course of business by each utility. The alternative approach would have required filing new experimental tariffs every time the underlying tariff changed and was not pursued for this and other reasons.

Given the complex nature of customer bills, customers were provided with a summary sheet showing (a) how much electricity they used by pricing period during the billing cycle, (b) how much they paid for it and (c) the implicit price for each period, expressed in cents per kWh. At the beginning of the experiment, customers were also provided a "shadow bill" that projected their likely electric bill on the experimental tariff during the summer and winter months and compared it with what their bill would have been had they stayed on their existing tariff under different assumptions about the magnitude of load shifting. Customers were provided with another shadow bill after having been in the experiment for twelve months. Customers were given the option of requesting a shadow bill anytime during the experiment. Appendix 1 contains an example of a filed tariff, a summary sheet and a shadow bill.

2.2.3 Critical Peak Dispatch

For the CPP-F and CPP-V tariffs, decisions concerning when to call critical days were based on a variety of criteria. First, about half the time, CPP-F and CPP-V rates were dispatched simultaneously. Second, for residential CPP-V Track C customers, the length of the dispatch period on critical event days was either two hours or five hours. For C&I, CPP-V customers, two, four and five hour dispatch periods were implemented. A total of 12 events were called for each CPP rate treatment in the summer months (May to October) and three were called in the winter. Thus, a total of 27 critical days were called for customers who stayed in the pilot for the entire treatment period. Critical days were chosen based on weather forecasts, system reliability conditions, the need to have a total of 12 days in the summer and to have a variety of days in the week.

In the summer of 2003, all critical events were single days. That is, events were never called on contiguous days. Following this initial period, concerns arose about whether behavioral response to critical day prices would change if events were called on consecutive days, such as might occur during a heat wave. In order to investigate this issue, in the summer of 2004, three critical events involving two or more consecutive days were called. One two-day event was called and two three-day events were called in 2004.

Table 2-1 summarizes the critical events that occurred for each treatment group throughout the pilot. The numbers in each cell indicate the timing and duration of each critical event. All CPP-F events ran for the entire peak period on critical days. CPP-V events varied with respect to start time and duration.

Table 2-1
Critical Peak Pricing Event Summary

Critical Event Date	Residential CPP-F					Residential CPP-V		C&I CPP-V	
	Zone 1	Zone 2	Zone 3	Zone 4	Track B	Track A	Track C	Track A	Track C
07/10/03	2-7	2-7	2-7	2-7	n/a	n/a	2-4	n/a	2-6
07/17/03	2-7	2-7	2-7	2-7	n/a	n/a	2-4	n/a	2-4
07/28/03	n/a	2-7	2-7	2-7	n/a	n/a	2-7	n/a	1-6
08/08/03	n/a	2-7	2-7	2-7	n/a	n/a	3-5	n/a	3-5
08/14/03	n/a	n/a	n/a	N/a	n/a	n/a	n/a	n/a	1-6
08/15/03	n/a	n/a	n/a	N/a	n/a	n/a	2-7	n/a	2-6
08/18/03	2-7	2-7	2-7	2-7	n/a	n/a	n/a	n/a	n/a
08/27/03	2-7	2-7	2-7	2-7	n/a	n/a	4-6	n/a	4-6
09/03/03	2-7	2-7	2-7	2-7	n/a	n/a	2-7	n/a	1-6
09/11/03	2-7	n/a	n/a	N/a	n/a	n/a	n/a	n/a	1-6
09/12/03	2-7	2-7	2-7	2-7	2-7	n/a	2-7	n/a	4-6
09/18/03	2-7	n/a	n/a	N/a	2-7	n/a	n/a	n/a	n/a
09/19/03	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	4-6
09/22/03	2-7	2-7	2-7	2-7	n/a	n/a	n/a	n/a	n/a
09/29/03	n/a	n/a	n/a	n/a	n/a	n/a	2-7	n/a	1-6
10/09/03	2-7	2-7	2-7	2-7	2-7	n/a	3-5	n/a	n/a
10/14/03	2-7	2-7	2-7	2-7	2-7	n/a	2-7	n/a	n/a
10/20/03	2-7	2-7	2-7	2-7	2-7	n/a	3-5	n/a	n/a
10/21/03	n/a	n/a	n/a	n/a	2-7	n/a	n/a	n/a	n/a
01/06/04	2-7	2-7	2-7	2-7	2-7	n/a	2-7	n/a	1-6
01/26/04	2-7	2-7	2-7	2-7	2-7	n/a	2-7	n/a	1-6
01/27/04	n/a	n/a	n/a	n/a	2-7	n/a	n/a	n/a	n/a
02/03/04	2-7	2-7	2-7	2-7	2-7	n/a	2-7	n/a	1-6
07/14/04	2-7	2-7	2-7	2-7	2-7	2-6	2-6	1-6	1-6
07/22/04	2-7	2-7	2-7	2-7	2-7	2-7	2-7	1-6	1-6
07/26/04	2-7	2-7	2-7	2-7	2-7	3-5	3-5	3-5	3-5
07/27/04	2-7	2-7	2-7	2-7	2-7	3-5	3-5	3-5	3-5
08/09/04	2-7	2-7	2-7	2-7	2-7	2-7	2-7	1-6	1-6
08/10/04	2-7	2-7	2-7	2-7	2-7	2-7	2-7	1-6	1-6
08/11/04	2-7	2-7	2-7	2-7	2-7	4-6	4-6	4-6	4-6
08/27/04	2-7	2-7	2-7	2-7	2-7	4-6	4-6	4-6	4-6
08/31/04	2-7	2-7	2-7	2-7	2-7	2-7	2-7	1-6	1-6
09/08/04	2-7	2-7	2-7	2-7	2-7	4-7	4-7	1-6	1-6
09/09/04	2-7	2-7	2-7	2-7	2-7	4-6	4-6	4-6	4-6
09/10/04	2-7	2-7	2-7	2-7	2-7	2-6	2-6	4-6	4-6

2.3 SAMPLE DESIGN

To capture the diversity in California's climate, and to allow customer response to time-varying rates to vary with climate, the SPP experimental design segmented customers into four climate zones. As seen in subsequent sections, demand response impact estimates are presented for each climate zone. Figure 2-2 contains a map of the four statewide climate zones and Figure 2-3 shows the distribution of utility customers across zones. About 48 percent of the population of the three utilities resides in the relatively moderate climate zone 2, 40 percent resides in the hotter zones 3 and 4 and 12 percent resides in the temperate zone 1. A map of the distribution of the SPP sample within each zone appears in Appendix 2.

Figure 2-2
Statewide Climate Zones

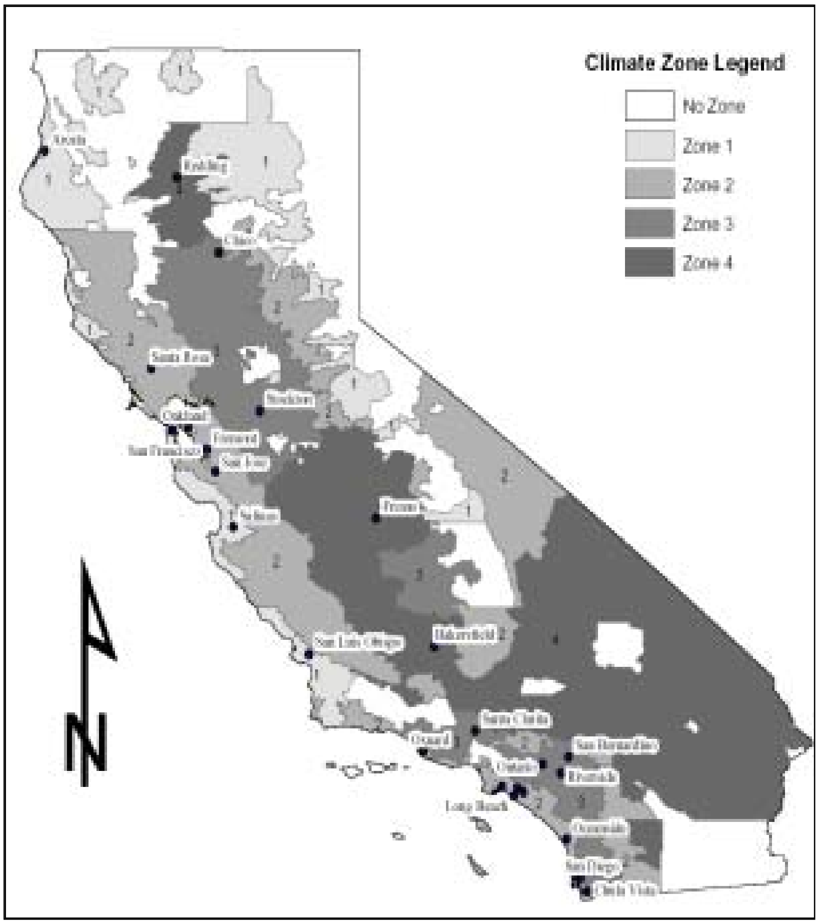
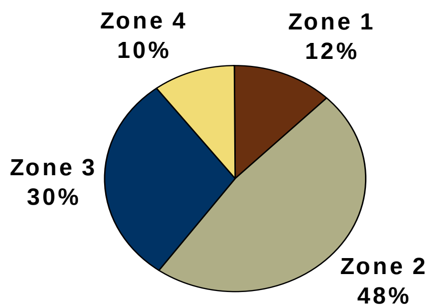


Figure 2-3
Distribution Of Population Across Climate Zones



Roughly 60 weather stations were used across the four climate zones to capture the rather significant number of microclimates that exist in California. Explanatory variables used in the regression models were based on cooling and heating degree hours.[15] The average cooling-degree hour per hour values for each climate zone are shown in Figure 2-4. They represent population-weighted averages based on the weather stations applicable to each climate zone.[16] As seen, there is significant variation in daily cooling degree hours per hour across day types and climate zones. Because cooling degree hours is not a familiar weather statistic, estimates of the average, peak-period temperature by day type and climate zone are shown in Figure 2-5.

[15] These variables are defined and further discussed in Section 3.2.3.

[16] A list of the weather stations and their populations is contained in Appendix 3.

Figure 2-4
Average Daily Cooling Degree Hours Per Hour
July Through September 2003/2004

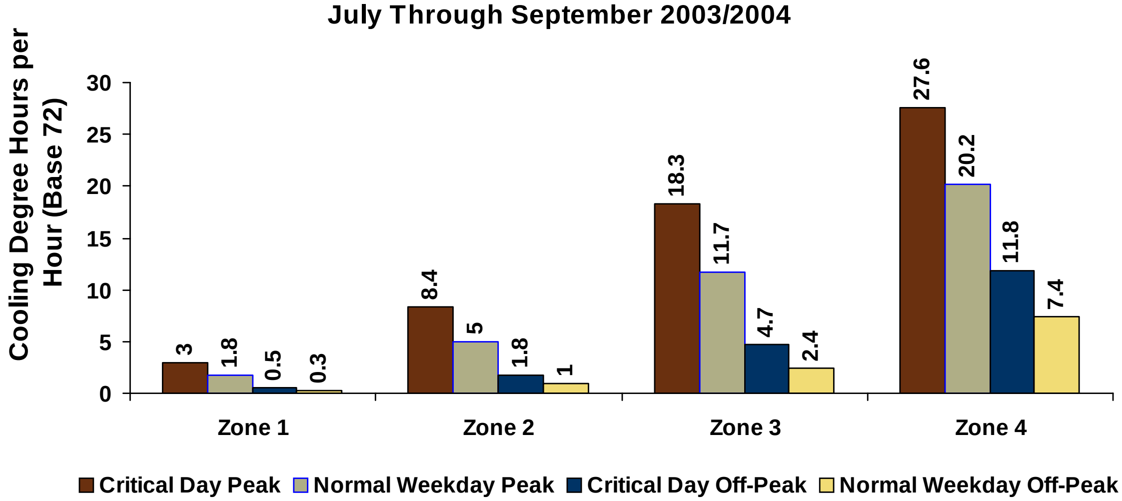
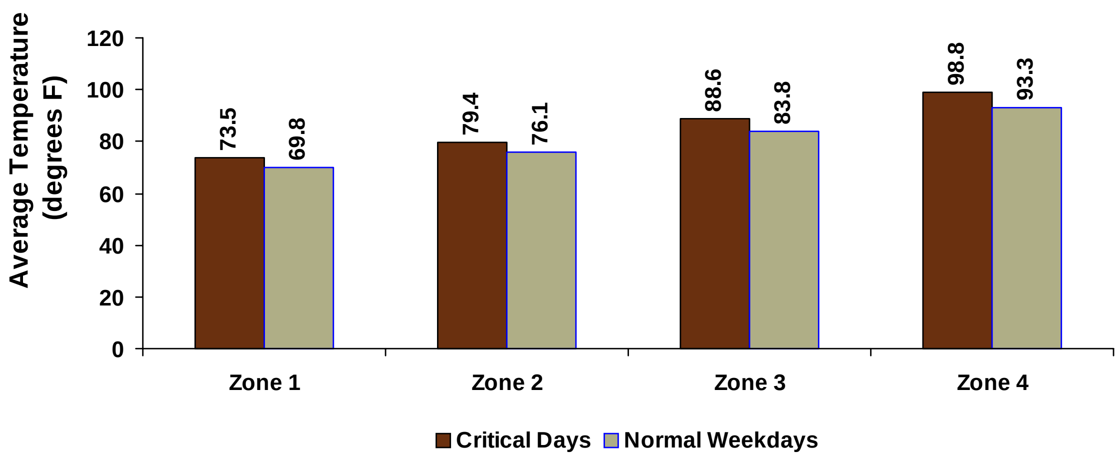


Figure 2-5
Average Temperature During Peak Period
July Through September 2003/2004



2. Background and Overview

Bayesian sampling techniques were used to allocate sample points to each of the various cells in the SPP.[17] In brief, this approach allocates more sample points to cells where prior analysis indicates that the net benefits are potentially large but uncertain and fewer sample points to those cells with small or certain net benefits. The outcome of this sampling approach was that CPP-F and CPP-V cells received the largest sample allocations. Table 2-2 summarizes the original sample allocation resulting from application of the Bayesian approach in combination with judgment regarding coverage for selected cells that the Bayesian analysis otherwise would have excluded.

Within each cell, the samples were optimized to provide the greatest level of accuracy for the pre-specified Bayesian allocations. After stratifying by housing type, the Dalenius-Hodges method[18] was used to determine optimal usage cut points, and the Neyman allocation method[19], which allocates more sample points to strata with greater variance, was applied to increase the explanatory capability of the final sample. A more detailed discussion of the sample design and sample targets by utility, climate zone and treatment, is contained in Appendix 4.

The actual number and allocation of SPP control and treatment customers by time period (e.g., summer 2003, winter and summer 2004) is shown in Table 2-3 for the residential sector and Table 2-4 for the C&I sector. The number of customers participating in the pilot and the number used for estimation purposes differs, as most of the models that were estimated included information on air conditioning ownership that was obtained from a customer survey. Overall, the response rate for the survey was quite high, exceeding 90 percent for nearly all cells. In Tables 2-3 and 2-4, there are two columns representing each time period, one showing the number of customers for which load data were provided by the utility, the second showing the number of customers for which both load and air conditioning ownership data were available. The latter is closest to the number of customers that were used in most of the regression analysis.

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[17] Details are presented in the December 10, 2002 report of WG3.

[18] The Dalenius-Hodges procedure generates optimal stratification boundaries for a fixed number of strata within a homogenous population. Boundaries are optimal in the sense that the variance of the estimate for a given population parameter is minimized. In this instance, the technique was used to define a set of homogeneous sub-populations. Usually the stratifying variable (as is the case for this sample design) is a proxy value for the population parameter of interest. Peak-peiod demand is not known for residential customers, so summer average daily usage was used as a proxy.

[19] The Neyman Optimal allocation technique assigns sampling points to each stratum based on the percentage of the total population standard deviation of the parameter of interest represented by the stratum. Neyman allocation optimizes the fixed sample size (i.e. maximizes the precision). In practice, this technique tends to disproportionately allocate sample units to the high energy users because the variance in these strata is large compared to other strata. Daily average energy use was used as a proxy for the parameter of interest (i.e., energy use during the peak period).

Table 2-2
Original Statewide Pricing Pilot Sample Design

	Control	CPP-F	CPP-F (info)	CPP-V (SDG&E) (1)	Info Only (1)	TOU	Total
Track A: Random Sampling With Opt Out Design							
Residential							
Zone 1	63	52	0	0	0	50	165
Zone 2	100	188	0	0	0	50	338
Zone 3	207	188	0	125	126	50	696
Zone 4	100	114	0	0	0	50	264
Total	470	542	0	125	126	200	**1463**
Commercial				**CPP-V (SCE) (1)**		**TOU (SCE) (1)**	
SCE							
<20 kW	88	0	0	58	0	50	196
>20 kW	88	0	0	80	0	50	218
Total	176	0	0	138	0	100	**414**
All Sectors							
Total	646	542	0	263	126	300	**1,877**
Track B: SF Cooperative							
Residential	**Control**	**CPP-F**	**CPP-F (Info)**	**CPP-V**	**Info Only**	**TOU**	**Total**
PG&E (2)	63	64	126	0	0	0	253
Total	63	64	126	0	0	0	**253**
Track C: AB 970 Sub-Sample							
Residential	**Control**	**CPP-F**	**CPP-F (Info)**	**CPP-V (SDG&E)**	**Info Only**	**TOU**	**Total**
SDG&E (3)	20	0	0	125	0	0	145
Total	20	0	0	125	0	0	145
Commercial		**CPP-F**	**CPP-F (Info)**	**CPP-V (SCE)**	**Info Only**	**TOU**	**Total**
SCE (3)							
<20 kW	42	0	0	56	0	0	98
>20 kW	42	0	0	76	0	0	118
Total	84	0	0	132	0	0	216
All Sectors							
Total	104	0	0	257	0	0	361
SUMMARY							
	Control	**CPP-F**	**CPP-F (Info)**	**CPP-V**	**Info Only**	**TOU**	**Total**
TOTAL SAMPLE SIZE	**813**	**606**	**126**	**520**	**126**	**300**	**2491**

All sample Sizes include the provision for 20% Opt-Out.

Notes:

(1) Entries are to be spread across various climate zones.

(2) This row corresponds to a proposal made by the San Francisco Cooperative and will be based on an opt out random sample located in the Hunter's Point/Potrero Hill districts of San Francisco and West Oakland/Richmond.

(3) These customers will be selected on an opt-out basis from the existing AB970 sample, which has an opt-in structure. In addition to the 20 control customers selected specifically for this study, the control group of 100 customers for the AB970 pilot is also being utilized. For any given event, half of these customers receive the dispatch signal and the other half do not. The 50 who do not are used as part of the control group for that event.

Table 2-3
Number of Residential Customers In the Experiment and Estimating Sample

Cell ID	Customer Segment	Climate Zone	Track	Tariff	Load Data			Load & A/C Ownership Data		
					Summer 2003	Winter	Summer 2004	Summer 2003	Winter	Summer 2004
A01	R	1	A	Standard	68	62	64	51	47	48
A02	R	2	A	Standard	106	107	108	90	92	90
A03	R	3	A	Standard	105	108	108	89	88	81
A04	R	4	A	Standard	106	109	105	87	83	81
A05	R	1	A	CPP-F	59	59	61	54	54	56
A06	R	2	A	CPP-F	212	214	217	205	206	202
A07	R	3	A	CPP-F	214	215	219	200	201	203
A08	R	4	A	CPP-F	129	128	136	121	120	124
A09	R	2	A	CPP-V	n/a	n/a	58	n/a	n/a	53
A10	R	3	A	CPP-V	n/a	n/a	41	n/a	n/a	40
A11	R	2	A	Info Only (Standard)	70	64	68	65	60	64
A12	R	3	A	Info Only (Standard)	68	68	69	63	62	63
A13	R	1	A	TOU	57	57	58	55	55	56
A14	R	2	A	TOU	56	56	57	54	54	55
A15	R	3	A	TOU	58	57	63	54	53	58
A16	R	4	A	TOU	55	55	56	53	53	53
A23	R	2	A	Standard	n/a	n/a	26	n/a	n/a	21
A24	R	3	A	Standard	n/a	n/a	17	n/a	n/a	16
B01	R	1	B	Info Only (Standard)	71	53	52	48	34	33
B02	R	1	B	CPP-F	135	133	133	104	102	102
B03	R	1	B	CPP-F	78	78	78	71	71	71
C01	R	2 & 3	C	Standard	20	21	20	18	19	19
C02	R	2 & 3	C	CPP-V	131	142	135	121	127	124
C07	R	2 & 3	C	Standard	94	97	87	80	80	77

Table 2-4 Number of C&I Customers in Experiment and Estimating Sample							
Cell ID	Customer Segment	Climate Zone	Track	Tariff	Summer 2003	Winter	Summer 2004
A17	C&I <20kW	2	A	Standard	47	46	44
A18	C&I >20kW	2	A	Standard	49	46	47
A21	C&I <20kW	2	A	TOU	53	61	62
A22	C&I >20kW	2	A	TOU	53	58	58
A27	C&I <20kW	2	A	Standard	n/a	n/a	46
A28	C&I >20kW	2	A	Standard	n/a	n/a	42
A31	C&I <20kW	2	A	CPP-V	n/a	n/a	59
A32	C&I >20kW	2	A	CPP-V	n/a	n/a	83
C03	C&I <20kW	2	C	Standard	43	45	43
C04	C&I >20kW	2	C	Standard	47	44	43
C05	C&I <20kW	2	C	CPP-V	57	58	60
C06	C&I >20kW	2	C	CPP-V	89	91	89

Tables 2-5 and 2-6 summarize the evolution of the sample over time. The number of customers who left over the duration of the experiment varies by cell but is typically between 20 and 30 percent. The turnover across the four primary control group cells (A01 through A04), as measured by the total number of customers lost divided by the original starting values, is roughly 22 percent. The same measure for treatment customers (cells A05 through A08) is 21 percent. In other words, the turnover among treatment customers is almost exactly the same as the turnover among control customers, suggesting that relatively few customers dropped off the experiment because of the treatment itself.

Table 2-5 Residential Customers Added and Lost by Time Period									
Cell	Track	Treatment	Climate Zone	Start of Pilot to 10/31/03		11/1/03 to 4/30/04		5/1/04 to 9/30/04	
				Added	Lost	Added	Lost	Added	Lost
A01	A	Control for CPP-F, TOU and Info Only (zones 2 & 3)	1	68	4	0	0	2	3
A02			2	106	6	7	13	14	12
A03			3	105	5	8	11	11	11
A04			4	106	6	9	10	6	6
A05		CPP-F	1	59	4	0	4	2	0
A06			2	212	15	3	19	19	23
A07			3	215	12	3	14	18	16
A08			4	129	10	0	5	10	17
A09		CPP-V	2	0	0	0	0	58	2
A10			3	0	0	0	0	41	4
A11		Info Only	2	70	5	0	0	4	2
A12			3	68	1	1	1	2	3
A13		TOU	3	57	0	0	2	1	1
A14			2	56	5	0	7	6	2
A15			3	57	3	0	2	8	5
A16			4	55	4	0	3	4	3
A23		Control for CPP-V	2	26	0	3	7	4	2
A24			3	18	0	2	5	2	0
B01	B	CPP-F + Info Hunters Point	1	71	18	0	1	0	1
B02		CPP-F Hunters Point	1	135	7	0	3	0	10
B03		CPP-F Richmond	1	77	2	0	6	1	3
C01	C	Control	2,3	20	0	1	4	3	1
C02		CPP-V	2,3	131	5	12	3	4	14
C07		Control	2,3	94	1	4	10	0	3

Table 2-6 C&I Customers Added and Lost by Time Period										
Cell ID	Track	Treatment	Customer Segment	Start of Pilot to 10/31/03		11/1/03 to 4/30/04		5/1/04 to 9/30/04	
				Added	Lost	Added	Lost	Added	Lost
A17	A	Control for TOU	<20 kW	47	5	4	4	2	4
A18			>20 kW	49	5	1	1	3	8
A21		TOU	<20 kW	53	6	1	3	8	4
A22			>20 kW	54	1	0	2	5	2
A27		Control for CPP-V	<20 kW	47	3	1	2	4	5
A28			>20 kW	44	2	2	2	0	6
A31		CPP-V	<20 kW	0	0	0	0	56	0
A32			>20 kW	0	0	0	0	80	3
C03	C	Control for CPP-V	<20 kW	44	2	1	1	2	3
C04			>20 kW	48	5	0	1	2	4
C05		CPP-V	<20 kW	55	4	0	3	6	2
C06			>20 kW	81	5	0	5	6	6

2.4 CUSTOMER ENROLLMENT

Customers to be enrolled in the SPP were selected through a stratified sample design. A primary customer was randomly drawn from each of the strata described in Appendix 4. Nine or more alternative customers, intended to be statistical clones, were also identified. In the original SPP design, customers were to be selected and only allowed to opt-out in the case of significant hardship. However, this was unacceptable to some members of WG 3 appointed by the CPUC to oversee the experiment. A modified design was proposed where customers would be placed on one of the rates and would remain on that rate unless they decided to leave but even that proved difficult for some WG3 participants to accept. The final SPP design involved mailing an enrollment package to selected customers and obtaining an affirmative response regarding the willingness of each customer to participant. As such, it is a voluntary program but one predicated on an opt-out recruitment strategy rather than an opt-in one.

2.4.1 Recruitment

The enrollment package informed customers that they had been selected to participate in an important statewide research project that would test new electricity pricing plans.[20] The package indicated that participants would be given an appreciation payment totaling $175 ($500 for C&I customers above 20 kW demand) in three installments spanning a period of 12 months. The first installment of $25 was tied to the completion of a

[20] An example of an enrollment package is contained in Appendix 5. The packages differed somewhat depending upon the treatment for which customers were recruited.

survey.[21] The second installment, equal to $75 for residential customers, was paid to all customers that stayed on the rate through the end of summer 2003 and the third installment was paid to all customers who remained on the rate through April 2004. Additional incentives will be paid to C&I Track A customers in 2005 to maintain their participation in the experiment but no additional incentives will be paid to any other participants who choose to stay on the rate in 2005.[22]

In the enrollment package, customers were asked to mail in a reply card or call to affirm their willingness to participate in the experiment. If a customer did not call the toll-free number or mail in the reply card, a recruitment consultant retained by the utilities made three attempts to call the customer to affirm their participation in the pilot. In some cases, the consultant did not have a working phone number on the customer and sent out a reminder card via mail. If a customer could not be reached after a 14-day deadline passed, they were dropped from the experiment and the recruitment process moved on to one of the statistical clones to try and fill that slot.

During the first summer of the experiment, customer recruitment activities were initiated on April 8, 2003 and continued through October 17, 2003. For Track A, TOU and CPP-F residential customers, enrollment packages were mailed on April 8th and 9th. Recruitment of Track A, CPP-V customers began on May 13th Track B packages were mailed on June 19th and Track C packages on May 3rd (C&I CPP-V) and May 13th (residential CPP-V). Recruitment of Track A, CPP-V residential and C&I customers lagged that of other treatment groups and a decision was made to terminate this effort for summer 2003 in order to reallocate recruitment resources to other cells to ensure that target levels were achieved.[23] Recruitment procedures were revised prior to the spring of 2004 and the target number of participants for Track A, CPP-V was reached for both residential and C&I customers prior to the summer of 2004.

As the experiment progressed, it became clear that the target enrollment numbers for many cells would not be reached by the July 1 start date without modifying the recruitment plan. A number of modifications were made to speed up the enrollment process, while preserving its statistical integrity. These included: (a) raising the number of phone calls, (b) reducing the 10-day deadline for customers to respond, (c) raising the number of statistical clones beyond the original nine and (d) mailing the enrollment package simultaneously to multiple clones. These changes complicated the enrollment process as multiple customers were enrolled for some slots while other slots were not filled. Customers were subsequently reallocated from slots with multiple enrollments to under-enrolled slots for which they were suitably matched.

[21] The survey is discussed further in Section 3.

[22] The CPUC has decided to extend the experiment through the summer of 2005 for the C&I Track A, CPP-V treatment. Residential customers are being allowed to stay on their treatment tariff but without any incentive payments and they are now being charged a monthly fee for the meter and data collection. The majority of customers have stayed on the new rates rather than switch to the standard tariff.

[23] An analysis of some of the problems associated with the initial Track A, CPP-V enrollment process is contained in a separate report, *Statewide Pricing Pilot—Enrollment Refusal Follow-Up Research*, Focus Pointe, October 2003.

2. Background and Overview

As of October 31, 2003, 8,679 enrollment packages had been mailed out to recruit a target of 1,741 treatment customers (control customers were not recruited, they simply had their meters replaced). This mailing resulted in enrollment of 1,759 treatment customers for the summer of 2003. A total of 1,332 customers who were reached elected not to participate in the experiment and it proved difficult to contact or install meters on 5,134 customers. The vast majority of these were situations where repeated attempts to contact the customer elicited no response. A total of 63 customers, or four percent, elected to opt-out of the experiment between July 1 and October 31, 2003. Details by treatment have been provided in monthly reports to the California Public Utilities Commission. Customers who were enrolled in time were placed on their new rates on July 1st. Customers recruited after July 1st were placed on the rate on their next meter read date following installation of the IDR meter.

As discussed in Section 2.3, roughly 22 percent of participants and control group customers left the pilot, largely due to the normal turnover in the customer population. Most of these customers were replaced during the spring of 2004 in order to have adequate sample sizes for the summer 2004 analysis period.

2.4.2 Participant Education

Once enrolled, customers in various treatment cells were provided with a “welcome package” containing information on how to benefit from the new rate structures. They were also provided a shadow bill, as discussed earlier. Welcome packages varied by rate type and utility. Chart 11 in each package provided information about rates that the typical customer in each treatment cell would be expected to face during the pilot. A copy of one of the welcome packages appears in Appendix 6.

3. Methodology

This section provides a brief overview of the conceptual and analytical approach to the analysis that is summarized in subsequent sections. The conceptual model used is based on the modern theory of economic demand, a brief overview of which is contained in Appendix 7. Demand models are used to estimate the demand response impacts for each SPP tariff, as opposed to alternative methods such as analysis of variance and covariance, in part because they allow for estimation of the impact of prices other than those used in the pilot.

Section 3.1 below provides an overview of the model specification and some of the practical issues that were encountered and addressed as part of the empirical analysis. Section 3.2 provides a brief description of the data that were used to estimate the demand models.

3.1 MODEL SPECIFICATION AND ESTIMATION

After reviewing and testing a variety of model specifications, a decision was made to structure the analysis around the constant elasticity of substitution (CES) demand system.[24] The CES demand system consists of two equations. The first equation models the ratio of peak to off-peak quantities, expressed in logs, as a function of the ratio of peak to off-peak prices, also expressed in logs, and other terms. The second equation models daily electricity consumption, expressed in logs, as a function of the daily price of electricity, also expressed in logs, and other factors. The two equations constitute a system for predicting electricity consumption by rate period. By taking the shares of energy use by rate 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 amount of energy used in each rate period given specific peak and off-peak prices and other determining factors.[25]

The CES demand system can model a variety of behavioral changes. For example, a reduction in peak period energy use with no change in off-peak energy use would be depicted as a reduction in the ratio of peak-to-off-peak energy use in the substitution equation. An increase in off-peak energy use, with no change in peak-period energy use, would also be depicted as a change in the same ratio. Conservation would be depicted by a change in daily energy use and, in the absence of any change in the ratio of peak-to-

[24] Other structural models that were examined included the log-log formulation, the quadratic and the Generalized Leontief demand system. See Appendix 7 for further discussion.

[25] A derivation of the formulas used to predict impacts by rate period based on the CES specification is provided in Appendix 8.

off-peak energy use, would still lead to a reduction in peak-period energy use because the peak-period share would be multiplied by a lower daily use value.

The data set used to estimate the demand models consists of observations on a cross section of customers that are observed over time and constitutes what is referred to in the literature as a panel data set. Given its panel nature, we have 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.[26]

Equation (1) below depicts the energy share or substitution equation from the CES demand system. The equation expresses the peak to off-peak quantity ratio as a function of the peak to off-peak price ratio, a weather term representing the difference in cooling degree hours between the peak and off peak periods[27] and fixed effects variable for each customer.

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

where

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

Q_{op} = average energy use per hour in the off-peak period for the average day

σ = the elasticity of substitution between peak and off-peak energy use (defined below)

P_p = average price during the peak pricing period

P_{op} = average price during the off-peak pricing period

δ = measure of weather sensitivity

CDH_p = cooling degree hours per hour during the peak pricing period[28]

CDH_{op} = cooling degree hours per hour during the off-peak pricing period

θ_i = fixed effect coefficient for customer i

D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise, where there are a total of N customers.

ε = regression error term

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[26] See the excellent discussion in James H. Stock and Mark W. Watson, *Introduction to Econometrics*, Addison Wesley, 2003.

[27] The difference in cooling degree hours per hour between peak and off-peak periods is used rather than the ratio because on some days, there are zero cooling degree hours in the off-peak period and using the ratio would result in division by zero on these days.

[28] The difference in cooling degree hours was used in the CES specification rather than the ratio of cooling degree hours in the two time periods because, in some climate zones, the value for off-peak cooling degree hours equals 0. In these cases, calculating the ratio would involve dividing by zero.

3. Methodology

Equation (2) expresses daily energy use as a function of daily average price, daily cooling degree hours and the fixed effects variables.

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

where

Q_d = average daily energy use per hour

η_d = the price elasticity of demand for daily energy (defined below)

P_d = average daily price (e.g., a usage weighted average of the peak and off-peak prices for the day)

CDH_d = cooling degree hours per hour during the day

ε = regression error term

The two summary measures of price responsiveness in the CES demand system are the elasticity of substitution (σ) and the daily price elasticity of demand (η). The elasticity of substitution equals the ratio of the percentage change in the ratio of peak and off-peak energy use to the percentage change in the ratio of peak and off-peak prices. The daily price elasticity equals the percentage change in daily energy use over the percentage change in daily prices. Two other common measures of price responsiveness are the own and cross-price elasticities of demand. Appendix 9 shows how the own and cross-price elasticities can be derived analytically from the elasticity of substitution and daily price elasticities for small price changes.

It is plausible that the elasticity of substitution and/or the daily price elasticity would differ across customers who have different socio-economic characteristics (e.g., different appliance ownership, different income levels, etc.). The elasticity may also vary between hot and cool days. The CES model can be modified to allow the elasticities to vary with weather and socio-economic factors, such as central air conditioning (CAC) ownership. Equation (3) provides an example of the substitution equation that allows price responsiveness to vary with CAC ownership and weather. Equation (4) shows how the elasticity of substitution would be calculated from this model specification. Equations (5) and (6) show the demand models for daily energy use and the corresponding equation for the daily price elasticity as a function of weather and CAC ownership.

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

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

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

Other customer characteristics, such as income, household size, and number of people in the household, may also influence the elasticities in the CES model. They can be included in the specification by introducing additional price interaction terms in a similar manner to the CAC and weather terms shown above. Formulas for estimating the standard errors of the elasticity estimates when interaction terms are included, and for estimating the standard error of demand impacts based on these models, are provided in Appendix 10.

$$\begin{aligned}\ln\left(Q_D\right)=\alpha+\sum_{i=1}^{N}\theta_i D_i+\eta\ln\left(P_D\right)+\rho(CDH_D)+\chi(CDH_D)\ln\left(P_D\right)\\ +\xi(CAC)\ln\left(P_D\right)+\varepsilon\end{aligned} \tag{5}$$

where

Q_D = average daily energy use per hour
η = the daily price elasticity
P_D = average daily price
ρ = measure of weather sensitivity
χ = the change in daily price elasticity due to weather sensitivity
CDH_D = average daily cooling degree hours per hour (base 72 degrees)
ξ = the change in daily price elasticity due to the presence of central air conditioning
CAC = 1 if a household owns a central air conditioner, 0 otherwise

θ_i = fixed effect for customer i

D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise, where there are a total of N customers.

ε = regression error term.

The composite daily price elasticity in this model is a function of three terms, as shown below:

$$\text{Daily}=\eta+\chi(CDH_D)+\xi(CAC) \tag{6}$$

As described in subsequent sections, the specific price interaction terms used in the demand models vary with the rate treatment. For the CPP-F tariff, the specifications depicted above are the primary ones used, although other customer characteristics were also examined.

The substitution and daily use equations could have been estimated using the generally accepted estimation method known as ordinary least squares (OLS). OLS 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[29], the usual reported standard errors associated with the parameter estimates may be biased. This can happen, for example, if the error terms are either autocorrelated or heteroscedastic. The error terms are considered to be autocorrelated if the error term in a given time period is correlated with the error term in subsequent time periods. The error terms are considered to be heteroscedastic if they don't display a constant variance across cross-sectional units. [30]

In the presence of autocorrelation and heteroscedasticity, the standard errors of the parameter estimates would be biased downward which, in turn, would make the t-statistics, which are used to judge the statistical significance of the parameters, biased in an upward direction.31 Under such circumstances, one could erroneously conclude, for example, that time-varying prices have a statistically significant impact on customer energy use when there may be insufficient precision in the estimation to reach such a conclusion.

Corrections for heteroscedasticity and autocorrelation when estimation is based on panel data can be made using standard estimation software and generalized least squares (GLS) estimation methods if the panel data is balanced.[32] 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 was comprised of participants that were enrolled at different times. This creates an unbalanced panel, that is, one involving repeated observations on a varying set of cross-sectional units.

Given the reality of an unbalanced panel data set, as well as several other practical considerations such as the need for joint estimation of the two demand system equations, weighting and other factors, a variety of pragmatic solutions to the autocorrelation and heteroscedasticity problems were examined.[33] One such approach is averaging across the daily observations for each day type. Under this approach, for each customer, there would be an observation representing average energy use for all pre-treatment days, one

[29] These assumptions require that the error terms to be independently and identically distributed according to the normal distribution with a zero mean and constant variance.

[30] For further discussion of these terms, see any standard textbook on econometrics such as the one by Stock and Watson mentioned earlier, Jeffrey M. Wooldridge, *Introductory Econometrics: A Modern Approach*, South-Western College Publishing, 2003; Jack Johnston and John NiNardo, *Econometric Methods*, Fourth Edition, The Mc-Graw Hill Companies, 1997; or William H. Greene, *Econometric Analysis*, Fifth Edition, Prentice Hall, 2003.

[31] The t-statistic is obtained by dividing the mean estimate of a parameter (regression coefficient) by its standard error. A value of 1.96 for this statistic indicates that the parameter estimate is statistically significantly different from zero at a 95% confidence level.

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

[33] A more detailed discussion of these empirical issues and their resolution is contained in Appendix 11.

for critical event days and one for normal weekdays during the treatment period. That is, there would be three observations for each customer, each one having a different price. A variation of this approach that introduces some additional longitudinal variation in weather would be to divide the day-type observations into days that vary in terms of weather (e.g., hot days and cool days). An approach similar to this was used to produce the results presented in the Summer 2003 report.

After estimating models based on the averaging approach described above, a close examination of the model residuals showed that not all of the residual correlations had been eliminated and there was still some downward bias in the coefficient standard errors. An alternative approach to addressing the autocorrelation problem involves transforming the daily observations using a procedure known as "first differencing." This is a common technique for dealing with serial correlation in which the previous day's observation is subtracted from the current day's observation for each of the variables in the regression equation. Compared with the averaging approach, first differencing allows for more precise estimates of both weather and price effects, 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. In addition, daily data makes it possible to determine the persistence of demand response over a multi-day critical event. First differencing eliminates the fixed effects and reduces the degree of serial correlation. The estimates that were derived using differenced data were similar to those using averages and fixed effects. The degree of "over-differencing" seems to be small because the implied first order serial correlation (from the Durbin Watson statistic) is typically modest.

As seen in subsequent sections, the estimated standard errors and computed standard errors for elasticities and impacts using first differences are quite small compared to the magnitudes of the estimated effects. Given the small amount of apparent over-differencing, it is implausible that there could be any pattern of serial correlation in the errors and in the regressors that would alter the statistical significance or substantially alter the confidence intervals derived from the differenced data. In other words, we don't expect that any decisions about whether or not to deploy advanced metering infrastructure (AMI) would be changed, even if some alternative approach were taken to dealing with any remaining serial correlation in the SPP sample.

One final empirical issue that was addressed concerned the joint estimation of the two equations in the CES demand system. The two equations must be estimated jointly, using a technique known as seemingly unrelated regressions (SUR), in order to obtain the most efficient parameter estimates and to account for the statistical correlations between the daily equation and the substitution equation[34]

[34] 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.

3.2 ESTIMATION DATABASE

In order to estimate the models described in the previous section, four types of data were needed:

- Customer-specific load data
- Weather
- Customer characteristics
- Electricity prices

Each data category is briefly discussed below.

3.2.1 Customer loads

The primary load data for each customer consisted of 96 values for each day representing integrated demand at 15-minute intervals. For model estimation, the interval data were aggregated by rate period. Off-peak period energy consumption for all weekdays covered the time period from midnight until 2 pm and from 7 pm until midnight. Peak-period energy use on all weekdays covered the period from 2 pm to 7 pm for CPP-F customers. For CPP-V customers, the length of a critical event was either the entire five-hour period from 2 pm to 7 pm or a two-hour period that occurred sometime between 2 pm and 7 pm. If only two hours in length, the time corresponding to the critical period varied from day to day. When the peak period was less than five hours, a CPP-V customer would actually have three rate periods for that day: (1) the two-hour period that was priced at the critical peak rate; (2) the remaining three hours within the eligible peak period that was priced at the normal peak rate; and (3) the remaining hours in the day that were priced at the off-peak rate.

3.2.2 Customer Characteristics

Information on household characteristics was gathered through a mail survey conducted among all SPP participants, including treatment and control customers.[35] This data included information on the following variables:

- Appliance holdings
- Appliance usage patterns
- Housing type, age, size and tenure
- Socio-demographic information (e.g., persons per household, education level, language spoken and income)
- Satisfaction with utility performance
- Opinions about the environment.

[35] A copy of the residential survey instrument is contained in Appendix 12. In most instances, the survey data were recoded for use in the regression analysis. The coding instructions are contained in Appendix 13.

In the case of C&I customers, the survey was much shorter than for residential customers.[36] In brief, the C&I survey gathered the following types of information:

- Size of structure (in square feet)
- Percent of structure that is air conditioned
- Tenure (e.g., own or lease)
- Whether the bill is paid directly or as part of the rent
- Hours of operation
- Thermostat setting
- The presence of an energy management system
- Number of employees
- Type of business.

Given the importance of the survey information to the demand analysis, every effort was made to maximize the survey response rate. Multiple mailings and telephone follow-up calls were made and respondents were paid $25 for completing the survey. Toward the end of the data collection process, in some cases, site visits were made to collect information on non-respondents.

The overall survey response rate was 90 percent. In general, treatment customers responded at a higher rate than control customers. The response rates for the CPP-F, TOU and Information Only treatment groups were 96, 95 and 96 percent, respectively, whereas the average response rate for the corresponding control group was 84 percent. The response rate for the CPP-V control groups was also 84 percent while the CPP-V treatment group response rate was near 100 percent.

3.2.3 Weather

Each utility assigned a specific weather station to the control and treatment customers in its service area, based on proximity to the customer's location. This yielded a total of 58 weather stations across the state. Station-specific population values were used to calculate climate-zone-specific, weighted average values for the weather variables.[37]

Each utility provided temperature and humidity data for each weather station. PG&E and SCE provided average temperature data for each hour of each day, whereas the temperature data from SDG&E was the instantaneous reading at the top of each hour. Previous work by a PG&E meteorologist showed that there is very little difference between average hourly values and peak values within an hour, so the instantaneous readings from SDG&E were treated as if they were the same as the average values provided by PG&E and SCE. Each utility also provided data on relative humidity but this data was not used.

[36] The C&I survey questionnaire is contained in Appendix 14.

[37] When a weather station was included in more than one climate zone, the distribution of control group customers in the experiment assigned to that weather station was used to allocate the station population to each climate zone.

3. Methodology

Hourly temperature data were used to calculate cooling and heating degree hours by time period. The number of cooling degree hours in an hour equals the difference between a base value, say 72 degrees, and the average temperature in the hour. For example, if the average hourly temperature equals 80 degrees, the number of cooling degree hours in that hour would equal 8. The number of cooling degree hours over a period of time, say the peak period, equals the sum of the hourly values for that period. Thus, if the hourly temperature values during the 2 pm to 7 pm peak period in a day equaled 80, 82, 84, 82 and 78 degrees, the number of cooling degree hours to base 72 in that period would equal 46. A base of 72 degrees was used in the analysis after testing degree hour values to a variety of bases including 68, 70, 72, 74 and 76 degrees. There was very little difference in the results regardless of which base value was used.

Weather variables for the winter analysis were based on heating degree hours (HDH). HDH equals the difference between a base value and the average temperature in an hour. For example, if the base value is 65 degrees and the temperature in an hour equals 60, there would be 5 heating degree hours in that hour. Various heating degree hour bases were tested and the results varied little. A base of 65 degrees was used for the winter analysis.

Tables 3-1 and 3-2 contain population-weighted estimates of cooling and heating degree hours for selected time periods and seasons for the state as a whole. We have also provided estimates of average temperature for the same periods as a reference, although average temperature was not used in any of the regression models.[38] As seen in Table 3-1, there are nearly twice as many cooling degree hours in each rate period in the inner summer months than in the outer summer months. A similar pattern is seen in Table 3-2 for the difference in heating degree hours between the inner and outer winter periods. Differences in average temperature and degree hours across the two summers are small.

Table 3-1
Selected Weather Values by Season

Season	Day Type	Cooling Degree Hours per Hour			Average Temperature		
		Peak	Off-Peak	Daily	Peak	Off-Peak	Daily
2003 Inner Summer	Critical	11.5	3.2	5.0	82.9	71.1	73.6
	Normal Weekday	7.9	2.1	3.3	77.9	67.6	69.7
2004 Inner Summer	Critical	12.3	3.5	5.3	83.7	71.3	73.9
	Normal Weekday	8.4	2.1	3.4	79.4	68.6	70.8
2003/2004 Outer Summer	Critical	6.6	1.2	2.3	76.5	65.0	67.4
	Normal Weekday	5.1	1.1	1.9	74.4	64.4	66.5

[38] As described above, cooling degree hours per hour for any period are estimated by subtracting 72 from the temperature in each hour and then summing those values over the number of hours in the period and dividing by the number of hours in the period. If the temperature in a particular hour is less than 72, a value of 0 is counted for that hour. As a result, the number of cooling degree hours over a period of time will not equal average temperature in the same period minus 72, unless all hours have non-zero values.

Table 3-2 Selected Weather Values by Season							
Season	Day Type	Heating Degree Hours per Hour			Average Temperature		
		Peak	Off-Peak	Daily	Peak	Off-Peak	Daily
Inner Winter	Critical	10.0	15.9	14.6	55.0	49.1	50.4
	Normal Weekday	7.7	13.8	12.5	57.8	51.3	52.6
Outer Winter	Normal Weekday	2.8	8.2	7.1	66.6	57.9	59.7

3.2.4 Electricity Prices

Given the complexity of electricity tariffs in California, a key issue in the estimation of demand models is how best to represent the price of electricity. There is an extensive literature on this subject dating back to the mid-1970s, and it shows that many different price terms have been used, including current and lagged marginal price with and without infra-marginal price terms, price indices, current and lagged average price and total bills.[39]

Several alternatives, discussed in Appendix 15, were considered for estimating price. The method used was based conceptually on the prices that were communicated to customers in the Welcome Package they received after enrolling in the SPP. Prices using this approach vary by rate type (e.g., CPP-F), rate level (high or low) and utility. These prices appear on Chart 11 of the Welcome Package and generally correspond to the average price faced by the average customer at the outset of the pilot. For example, for the CPP-F rate in the SDG&E territory, the average price under the standard tariff was stated to be 15.5 cents/kWh. The SPP treatment rate was stated to be 10.8 cents/kWh off-peak for 85 percent of the hours in the year, 27.6 cents/kWh on-peak for 14 percent of the hours of the year and 76.8 cents/kWh super peak for 1 percent of the hours of the year. The chart also indicated the specific times for the peak and off-peak periods.

For estimation purposes, prices for all customers were set equal to the average price for a customer with consumption at the midpoint of tier 3. This approach allowed prices to vary with general rate adjustments for each utility over the treatment period. The prices also reflected whether or not a customer received the CARE discount. With this approach, prices primarily reflected the experimental design and did not vary with customer usage, making them excellent instruments for the demand models.

Reasonable results were obtained using the average price for a customer at the midpoint of tier 3. To test the sensitivity of the results to the choice of tiers, initial models were also

[39] The "infra-marginal price" is the amount paid by customers on a multi-part tariff for the electricity used up to the marginal block in which they are consuming. In the simplest case of a two-part tariff with a fixed and variable component, the infra-marginal price would equal the monthly fee. However, if the tariff has two tiers in addition to a fixed monthly charge, and the consumer's usage placed him or her in the second tier, the infra-marginal price would equal the fixed charge plus the marginal price of first-tier usage times the length of the tier.

estimated using the average price for customers at the midpoints of tier 1 and tier 2. The results were quite robust across the three price sets. This is not surprising since the TOU and CPP rates implicitly impose a constant surcharge on the underlying rates during the peak and critical peak period and give a credit during the off-peak period. The amount of the surcharge and credit does not vary by tier. Since customers are spread across all five tiers, and since the average customer in all three utilities has usage that typically ends in tier 3, a decision was made to use the average price for a tier-3 customer.

Finally, demand models were estimated using both average and marginal prices. The difference in demand elasticities across these two price definitions was only 2 percent. A decision was made to use average prices because they correspond more closely to the prices in the Welcome Package. They also are conceptually the same as the prices that customers see in the supplementary billing sheet they receive each month.

4. Residential CPP-F and Information Only Treatments

This section summarizes the analysis associated with the residential CPP-F tariff. Recall from previous sections that the CPP-F tariff consisted of a two-period, TOU rate that applied on every non-holiday, weekday of the year. On normal weekdays, the peak-to-off-peak price ratio was relatively modest, but on up to 15 critical days a year, much higher peak-period prices were in effect. Customers were notified the day before a critical day that prices would be higher during the entire peak period on the following day. The weekend price equaled the weekday, off-peak price.

Table 4-1 contains average prices for the summer and winter periods for the CPP-F tariff. The average control group price was $0.13/kWh. On CPP days, the average peak-period price equaled $0.59/kWh and the off-peak price equaled $0.09/kWh, for an average price ratio of 6.6 to 1. High price-ratio customers faced a peak-period price of roughly $0.68/kWh on critical days and an off-peak price of $0.07/kWh, for a price ratio of nearly 10 to 1. Low price-ratio customers had a peak price of $0.50/kWh and an off-peak price of $0.11/kWh, for a price ratio of 4.5 to 1. The average price ratio on normal weekdays was 2.4 to 1, with a 3 to 1 ratio for the high-ratio customers and roughly a 2 to 1 ratio for low-ratio customers.

Table 4-1
Average Prices For Residential CPP-F Tariff

Season	Customer Segment	Day Type	Rate Period	High Ratio ($/kWh)	Low Ratio ($/kWh)	Average ($/kWh)
Summer (03/04)	Control	All	All	0.13		
	Treatment	Critical	Peak	0.68	0.50	0.59
			Off-peak	0.07	0.11	0.09
			Daily	0.24	0.21	0.23
		Normal Weekday	Peak	0.23	0.21	0.22
			Off-peak	0.07	0.11	0.09
			Daily	0.11	0.13	0.12
		Weekend	Daily	0.07	0.11	0.09
Winter	Control	All	All	0.13		
	Treatment	Critical	Peak	0.53	0.69	0.61
			Off-peak	0.10	0.11	0.11
			Daily	0.20	0.25	0.23
		Normal Weekday	Peak	0.32	0.11	0.21
			Off-peak	0.10	0.11	0.10
			Daily	0.15	0.11	0.13
		Weekend	Daily	0.10	0.11	0.10

A variety of important policy issues are addressed in this section. Section 4.1 presents estimates of the elasticity of substitution and daily price elasticities associated with the CPP-F rate. It also presents estimates of the impact of these rates on energy demand in each rate period. The important issue of whether impacts were similar or different during the two summers over which the SPP ran is examined. Since treatment-period data were only available for the months of July through October in 2003 and May through September in 2004,[40] a comparison across years is, arguably, only meaningful for the common months of July through September. Thus, in order to address the question of change over time, we also had to examine whether responsiveness differed across the months of July through September (designated as the “inner summer”) and the months of May, June and October (designated as the “outer summer”).

Section 4.2 examines the persistence of impacts across the first, second and third days of a multi-day critical event. This is an important question for estimating the benefits associated with CPP rates, as the benefits, which consist primarily of avoided capacity costs, would be much less if responsiveness declined on the second and/or third day of a multi-day event.

Section 4.3 examines how responsiveness varied with changes in customer characteristics, such as appliance holdings, income and average energy use (e.g., high versus low users). Section 4.4 presents the elasticities and demand response impacts for the winter period while Section 4.5 briefly summarizes the overall change in annual energy use resulting from the average CPP-F prices used in the experiment.

Section, 4.6, examines the Information Only treatment. Recall from Section 2 that this treatment left participants on a standard, non-time varying rate, but asked them to voluntarily curtail energy use during the peak period on critical days. This treatment was included as a cross-check on the CPP-F tariff impacts to ensure that it is the time-varying price that primarily drives behavioral response on critical days, not some altruistic desire to reduce demand when asked.

Finally, Section 4.7 provides a brief overview of the experimental design for the Track B treatment. The Track B analysis is summarized in detail in a separate report.

4.1 IMPACT ANALYSIS

This section presents estimates of the elasticity of substitution, the daily price elasticity and average impacts by rate period for the CPP-F tariff.[41] We first examine whether impacts are the same or different across the two summers, 2003 and 2004. While some relatively minor differences are found, we conclude that the most important variables (the critical day impacts and the elasticity of substitution) do not differ. Consequently, we pool the data and examine whether responsiveness differs significantly across the hotter, inner summer months of July through September and the milder shoulder months of May, June

[40] Although the experimental rate was also in effect in October 2004, data for October was not available in time to include in this analysis.

[41] The regression models underlying all of the elasticity and impact estimates discussed in this section as well as Sections 5 and 6 are contained in Appendix 16. As discussed in Section 3, the elasticity and impact estimates presented here are, in many instances, a function of the saturation of central air conditioning. The air conditioning saturations by climate zone and statewide that underlie the values presented in this report are as follows: zone 1, 7 percent; zone 2, 29 percent; zone 3, 69 percent; zone 4, 73 percent; statewide, 43 percent.

and October. Significant differences are found. Nevertheless, we also understand the need for simplicity and see the potential value of having an all-summer average rather than distinguishing between the inner and outer periods. The all-summer estimates are provided in subsection 4.1.3. The final subsection provides graphical illustrations of demand curves for energy by rate period.

As discussed previously, the impact estimates contained in the rest of this report were derived by using the two demand equations in the CES demand system described in Section 3.1. The specific formulas used to predict the change in energy use by rate period given a change in prices are relatively complex (see Appendix 8). Conceptually, the impacts are derived in the following manner. First, the elasticity of substitution and the daily price elasticity are calculated based on the population-specific values for weather and central air conditioning saturations.[42] The elasticity of substitution is used to predict the change in the ratio of peak-to-off-peak energy use given a change in the ratio of peak-to-off-peak prices. The daily price elasticity is used to predict the change in daily energy use given a change in daily average price. The two predicted values are combined to produce a change in energy use by rate period.

4.1.1 Comparison Of 2003 and 2004 Impacts

There are two approaches to examining differences in elasticities and impacts across the summers of 2003 and 2004.

One approach is to examine whether or not price response has changed for customers that participated in the experiment for both summers (designated as "common customers"). This approach addresses the question of whether demand response for the same group of customers increases (as they learn better how to respond to price signals), decreases (as the initial enthusiasm fades) or stays the same (reflecting a quick learning curve that doesn't degrade over time).

A second approach to examining the difference across years is to develop elasticities and impacts for each summer based on the entire sample of customers that participated in each summer, rather than constraining the sample to customers that are common to both years. For the CPP-F rate, approximately 57 control customers and 55 treatment customers were added to the sample after October 31, 2003 as either replacement or new participants.

Both approaches involved the use of a pooled database containing information on energy use during the treatment period for all relevant summer months from both years.[43] As discussed previously, the summer 2003 treatment period included the months of July through October whereas the summer 2004 treatment period covered the months of May through September. Given that responsiveness might vary between the milder months of May, June and October, we introduced a binary variable for the outer summer months of

[42] Not every demand model included these variables as interaction terms with price, but most did. As seen in Section 4.3, sometimes variables representing other customer characteristics were also included in the models and would be treated in this first step in a manner similar to the CAC saturation variable.

[43] The database also contained pretreatment data for all customers, whenever it occurs.

October 2003 and May and June 2004. We then compared the annual differences for the common, inner summer months of July, August and September.

A binary variable was used to represent the summer of 2004 and was interacted with all price and weather variables to assess whether or not price responsiveness varied across the two summers. If there were just a single price/year interaction term, the t-statistic for the interaction term could be used directly to assess whether or not the elasticity of substitution or daily price elasticity differed across years. However, there are three terms that underlie the elasticity estimates (e.g., price, price times weather and price times a variable representing central air conditioning ownership). Thus, standard errors had to be developed for the elasticity of substitution and for the 2004 differential that takes into account the standard errors of each price coefficient as well as the covariance across the coefficients in each equation and across the two equations in the demand system.[44] A detailed description of the calculation of standard errors is provided in Appendix 10.

Table 4-2 contains estimates for the two elasticities for 2003 and 2004 based on a database that is restricted to customers that were in the experiment in both summers.[45] These values are based on average critical-day weather across the two years. The elasticity of substitution in 2003 from the pooled model is -0.090, with a t-statistic of –20.86.[46] Table 4-2 also shows the differential value for each elasticity between the two years. The difference in the elasticity of substitution is 0.004 and, with a t-statistic of 0.64, is not statistically significant.[47]

[44] It should be noted that the standard errors of the elasticities and the impacts vary with the mean values of the weather and air conditioning saturations that underlie them. Furthermore, we note that, when estimating the standard errors, we have taken into account the fact that neither the impacts nor the elasticities are normally distributed -- they are at best approximately—by using the "delta method" for estimating standard errors, which can be applied to all the complex functions underlying the elasticities and impacts simultaneously. It is standard usage in statistics and provides a useful guide to the magnitudes of uncertainty.

[45] The 2003 values reported here differ from those reported in the Summer 2003 report primarily because these represent the inner summer months whereas the Summer 2003 values reported previously included the month of October in the estimating database.

[46] The values for the elasticity of substitution and the daily price elasticity reported in the remainder of this document are negative. When two values are compared, the value that is larger in absolute terms is referred to as "larger" because it means pride responsiveness is greater. In other words, a value of –0.2 is referred to as larger than –0.1 even though mathematically it is smaller (e.g., more negative).

[47] All statistical test results are reported at the 5 percent level of significance. A t-statistic greater than 1.96 indicates statistical significance at the 95 percent confidence level.

Table 4-2 Residential CPP-F Rate Elasticity Estimates for the Inner Summer Period (Based on Average Critical Day Weather in 2003/2004) Common Customers (Customers Present For Both Summers)			
Elasticity Type	**2003 Value**		
	Estimate	**Standard Error**	**t-statistic**
Substitution	-0.090	0.004	-20.86
Daily	-0.035	0.005	-7.18
	2004 Differential		
Substitution	0.004	0.007	0.64
Daily	-0.019	0.008	-2.42
	2004 Value		
Substitution	-0.086	0.005	-16.32
Daily	-0.054	0.006	-8.41

The daily price elasticity in 2003 equaled -0.035, with a t-statistic of -7.18. The annual differential value equaled -0.019 and had a t-statistic equal to -2.42, indicating that the 2003 and 2004 values differed by a statistically significant amount. The 2004 daily price elasticity was –0.054, with a t-statistic of -8.41.

Statewide impacts on peak, off-peak and daily energy use on critical days are presented in Table 4-3. Two impact measures are shown, one labeled the “average customer approach” and one labeled the “zonal weighted average approach.” The average customer approach involves using input values for the impact evaluation model (e.g., weather, air conditioning saturations and starting energy use values by rate period) representing the average customer across all climate zones. The zonal weighted average approach uses input values pertinent to each climate zone and then computes a population-weighted average of the absolute impacts developed for each zone. The zonal average approach is more accurate, but computing standard errors and t-statistics for the overall average impact estimate using this approach is very complex. However, we believe the standard error based on the average customer approach is a good proxy for the standard error for the zonal weighted average approach. Therefore, we recommend that the average customer standard error be used to develop confidence bands around impact estimates based on the “bottoms-up,” zonal average impact.

Table 4-3 Residential CPP-F Rate Statewide Impacts on CPP Days Common Customers (Based on Average Critical Day Weather in 2003/2004)									
Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)	Starting Value (kWh/hr)	Impact (kWh/hr)	Impact (%)
	2003 Impacts Average Customer Approach						2003 Impacts Zonal Weighted Average Approach		
Peak	1.28	-0.171	0.009	-21.47	-13.30	0.62	1.28	-0.188	-14.62
Off-Peak	0.80	0.021	0.003	7.78	2.61	0.34	0.80	0.026	3.19
Daily	0.90	-0.019	0.003	-7.25	-2.09	0.29	0.90	-0.019	-2.08
	2004 Differential Average Customer Approach						2004 Differential Zonal Weighted Average Approach		
Peak	1.28	-0.008	0.014	-0.57	-0.61	1.08	1.28	-0.007	-0.56
Off-Peak	0.80	-0.011	0.004	-2.60	-1.41	0.54	0.80	-0.009	-1.09
Daily	0.90	-0.011	0.004	-2.44	-1.17	0.48	0.90	-0.008	-0.93
	2004 Impacts Average Customer Approach						2004 Impacts Zonal Weighted Average Approach		
Peak	1.28	-0.177	0.010	-17.95	-13.81	0.77	1.28	-0.194	-15.09
Off-Peak	0.80	0.010	0.003	2.81	1.20	0.43	0.80	0.017	2.09
Daily	0.90	-0.029	0.003	-8.55	-3.24	0.38	0.90	-0.027	-2.99

The average customer impact on peak-period energy use on critical days in 2003[48] is –13.30 percent, with a standard error of 0.62 percent. The corresponding zonal average impact in 2003 is –14.62 percent. The average customer impact in 2004 is –13.81 percent, with a standard error of 0.77 percent, and the corresponding zonal average impact is –15.09 percent. The 2003 and 2004 critical day impacts are not statistically different from each other, since the differential of –0.61 percent has a large standard error of 1.08 percent and a t-statistic of -0.57.

In 2003, the average customer impact for off-peak energy use on critical days is +2.61 percent, with a standard error of 0.34 percent. The change in this impact between the two years is –1.41 percent, with a standard error of 0.54 percent. This has an implied t-statistic of –2.60, indicating that the change is statistically significant at the 95 percent confidence level. Thus, the increase in off-peak energy use on critical days was less in 2004 than it was in 2003.

[48] As discussed above, reference to a 2003 or 2004 value expresses a focus on the behavioral activity in each year and whether that differs. As such, the values are calculated based on average weather and starting values across the two years. Thus, when we say “2003 impact” we mean 2003 behavior based on cross-year averages weather values.

The impact on daily energy use on critical days in 2003 was –2.09 percent, with a standard error of 0.29 percent and a t-statistic equal to –7.25, showing that daily price was highly significant. The change in the daily energy use impact on critical days between the two years was –1.17 percent with a standard error of 0.48 percent and an implied t-statistic of –2.44. That is, daily price responsiveness increased between 2003 and 2004 by a statistically significant amount.

In summary, when the comparison is based on the same group of customers and average weather and starting values, the reduction in peak-period energy use on critical days resulting from the CPP-F rate is essentially the same during the inner summers of 2003 and 2004. The increase in off-peak energy use (resulting from the lower off-peak prices) is actually less by a statistically significant amount in 2004 than it is in 2003. The reduction in daily energy use on critical days is greater by a statistically significant amount in 2004 than in 2003.

Table 4-4 contains estimates of the elasticities based on the database that includes all customers who were in the experiment in each summer, not just the common customers. The elasticity of substitution in 2003 is –0.086, with a t-statistic of –20.51. The 2004 value is not statistically different from the 2003 value. The daily price elasticity is –0.032 in 2003, with a t-statistic of –6.80. The 2003 value is statistically different from the 2004 value of –0.054. In general, these results are very similar to those based on the common customer database.

Table 4-4
Residential CPP-F Rate
Elasticity Estimates for the Inner Summer Period
All Customers
(Based on Average Critical 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	-6.80
	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 4-5 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 critical days in 2003 is –12.71 percent, with a standard error of 0.61 percent. The corresponding all zone impact in 2003 is –14.00 percent. The impact in 2004 is –13.93 percent, with a standard error of 0.75 percent, based on the average customer approach, and the all-zone value is –15.19 percent. The two impacts do not differ from each other by a statistically significant amount, since the differential of –1.32 percent has a large standard error of 1.06 percent, and an implied t-statistic of –1.39.

Table 4-5
Residential CPP-F Rate Statewide Impacts on Critical Days for the Inner Summer Period
All Customers
(Based on Average Critical Day Weather in 2003/2004)

Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)	Starting Value (kWh/hr)	Impact (kWh/hr)	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 for off-peak energy use on critical days is +2.57 percent, with a standard error of 0.33 percent. The change in this impact between the two years is –1.29 percent, with a standard error of 0.53 percent. This has an implied t-statistic of –2.43, indicating that the change between the years is statistically significant.

The impact on daily energy use on critical days in 2003 is –1.95 percent, with a standard error of 0.28 percent. The change in the daily use impact between the two years is –1.32 percent with a standard error of 0.47 percent and an implied t-statistic of –2.79. Thus, while the peak period impact for the CPP-F rate in the inner summer is statistically indistinguishable between the years 2003 and 2004, the impacts during the off-peak period and on daily energy use are statistically different.

In summary, whether based on common customers or all customers, the change in peak-period energy use on critical days was constant across the two summers.

4.1.2 Intra-summer Differences

We next examine whether impacts differed between the relatively hot inner summer months of July, August and September and the relatively mild outer summer months of May, June and October. A priori, we would expect less price responsiveness during the outer summer than during the inner summer because impacts are driven in large measure by the presence of air conditioning, and there is less air conditioning use in the outer summer compared with the inner summer. In light of the general conclusion in the previous section, showing only small differences between the two years, for this investigation, we constrained the inner and outer summer values to be the same across the two years.

The model specification used to test for intra-summer differences allows for differences to exist in the daily price elasticity between weekdays and weekends. Since there is only one price on weekends, it is not possible to estimate a weekend substitution elasticity. However, we do allow for a distinct weekend intercept term in the substitution equation, which allows the load shape to differ between weekends and weekdays.

The elasticities of substitution and daily price elasticities for the inner and outer summers for the four climate zones for each day-type are shown in Tables 4-6 and 4-7. Associated standard errors and t-statistics are shown as well. Average weather conditions across the years 2003 and 2004 are used to calculate the mean estimates and standard errors. The weather values are specific to each day type and climate zone within each of the two summer seasons.

Table 4-6 Residential CPP-F Rate Elasticity Estimates Inner Summer					
Zone	Day Type	Elasticity Type	Summer 2003 and 2004		
			Estimate	Standard Error	t- statistic
1	Critical	Substitution	-0.043	0.004	-10.44
		Daily	-0.039	0.005	-7.81
	Normal Weekdays	Substitution	-0.039	0.005	-8.60
		Daily	-0.040	0.005	-7.55
	Weekend	Daily	-0.016	0.007	-2.42
2	Critical	Substitution	-0.068	0.003	-20.08
		Daily	-0.041	0.004	-9.78
	Normal Weekdays	Substitution	-0.065	0.004	-17.47
		Daily	-0.042	0.004	-9.39
	Weekend	Daily	-0.020	0.006	-3.66
3	Critical	Substitution	-0.116	0.004	-29.49
		Daily	-0.042	0.004	-10.18
	Normal Weekdays	Substitution	-0.111	0.004	-30.06
		Daily	-0.045	0.004	-10.76
	Weekend	Daily	-0.029	0.005	-5.28
4	Critical	Substitution	-0.127	0.005	-26.48
		Daily	-0.033	0.008	-4.17
	Normal Weekdays	Substitution	-0.122	0.004	-29.12
		Daily	-0.038	0.006	-6.62
	Weekend	Daily	-0.022	0.009	-2.45
All	Critical	Substitution	-0.086	0.003	-26.05
		Daily	-0.040	0.004	-10.54
	Normal Weekdays	Substitution	-0.081	0.003	-23.97
		Daily	-0.042	0.004	-10.62
	Weekend	Daily	-0.023	0.005	-4.37

In the inner summer, on critical days, the all-zone substitution elasticity is -0.086, with a t-statistic of –26.05. The elasticity of substitution varies across the four climate zones by +/- 50 percent relative to the statewide value, with the lowest value (in absolute terms) of

–0.043 occurring in the coolest zone 1 and the highest value of –0.127 occurring in the hottest zone 4. All estimates are statistically significant at the 95 percent confidence level.

Table 4-7
Residential CPP-F Rate Elasticity Estimates
Outer Summer

Zone	Day Type	Elasticity Type	Summer 2003 and 2004		
			Estimate	Standard Error	t- statistic
1	Critical	Substitution	-0.027	0.007	-3.75
		Daily	-0.045	0.006	-7.59
	Normal Weekdays	Substitution	-0.026	0.007	-3.59
		Daily	-0.045	0.006	-7.55
	Weekend	Daily	-0.007	0.009	-0.81
2	Critical	Substitution	-0.034	0.006	-5.71
		Daily	-0.047	0.005	-8.75
	Normal Weekdays	Substitution	-0.032	0.006	-5.07
		Daily	-0.048	0.005	-9.17
	Weekend	Daily	-0.012	0.008	-1.46
3	Critical	Substitution	-0.045	0.007	-6.85
		Daily	-0.052	0.008	-6.95
	Normal Weekdays	Substitution	-0.043	0.006	-6.74
		Daily	-0.054	0.006	-8.71
	Weekend	Daily	-0.020	0.008	-2.44
4	Critical	Substitution	-0.051	0.009	-5.75
		Daily	-0.050	0.011	-4.56
	Normal Weekdays	Substitution	-0.049	0.008	-6.37
		Daily	-0.049	0.012	-4.16
	Weekend	Daily	-0.015	0.012	-1.31
All	Critical	Substitution	-0.038	0.006	-6.55
		Daily	-0.049	0.006	-8.19
	Normal Weekdays	Substitution	-0.036	0.006	-6.17
		Daily	-0.050	0.005	-9.14
	Weekend	Daily	-0.014	0.008	-1.80

Comparing the values in Tables 4-6 and 4-7, it is evident that the elasticities are smaller in the outer summer than in the inner summer. In the outer summer, the all-zone elasticity of substitution based on critical-day weather is –0.038, with a t-statistic of –6.55. There is significant variation across climate zones in the elasticity of substitution in the outer summer, rising from the coolest zone to the hottest zone. However, the zonal variation is not as great in the outer summer, with the ratio of the high to low elasticity of substitution equal to 1.9, as it is in the inner summer, where the ratio equals 3.0. This is due to the fact that central air conditioning plays a less dominant role in explaining customer price responsiveness in the outer summer months, as evidenced by the large, positive coefficient on the air conditioning/price/outer-summer interaction term in the demand model.[49]

The average daily price elasticity on critical days in the inner summer across all-zones is –0.042, with a t-statistic of –10.54. There is very little variation in this value across climate zones, since the coefficient on the weather/price interaction term in the demand model is very small and statistically insignificant and the coefficient on the air conditioning/price interaction term is also small (but significant). In the outer summer, the daily price elasticity is somewhat larger, with a value of –0.049 and a t-statistic of –8.19.

There is not much variation in the elasticities across critical and normal weekdays since the weather/price coefficients are very small. For example, the all zone elasticity of substitution is –0.081 on normal weekdays compared to -0.086 on critical days. Weekend daily price elasticities are generally much smaller than weekday daily price elasticities.

The associated impacts for the inner and outer summers are shown in Tables 4-8 and 4-9 respectively. These values reflect not only differences in the elasticities between the inner and outer summer, but also differences in the initial load shapes, or “starting values.” The columns labeled “starting value” contain data on average energy use in each rate period and climate zone for control group customers and are a proxy for what treatment customers would use in the absence of the rate treatment. The tables show the impact and standard errors expressed in both absolute and percentage terms.

Table 4-8 shows that the impact on peak-period energy use on critical days in the inner summer for all zones is -13.06 percent using the average customer approach, with a standard error of 0.48 percent. The impact based on the more accurate zonal average approach is –14.37 percent. Thus, a two-standard deviation band representing a 95 percent level of confidence ranges from -13.51 percent to -15.43 percent. As shown earlier with the elasticities, the impacts are smaller in the cooler zones and larger in the hotter zones, with the Zone-1 value equal to –12.34 percent and the Zone-4 value equal to –23.03 percent.

[49] The coefficient on the price/air conditioning saturation interaction term in the inner summer equals –0.09 with a t-statistic equal to –4.28. The coefficient on the price/air conditioning/outer- summer interaction term equals +0.07, with a t-statistic equal to 6.49, indicating that the differential on the price/air-conditioning term is highly significant and lowers the magnitude of the elasticity. That is, the influence of air conditioning on the elasticity of substitution is significantly less in the outer summer than in the inner summer.

Table 4-8
Residential CPP-F Rate Impact Estimates for Inner Summer 2003 and 2004

Climate Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact kWh/hr	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	Critical	P	0.49	-0.0397	0.0032	-12.34	-8.14	0.66
		OP	0.47	-0.0008	0.0013	-0.67	-0.18	0.27
		Daily	0.47	-0.0089	0.0011	-7.89	-1.90	0.24
	Normal Weekday	P	0.49	-0.0126	0.0016	-8.09	-2.58	0.32
		OP	0.46	0.0046	0.0005	10.13	0.99	0.10
		Daily	0.47	0.0010	0.0001	7.54	0.22	0.03
	Weekend	Daily	0.49	0.0026	0.0011	2.41	0.53	0.22
2	Critical	P	0.90	-0.0982	0.0045	-21.94	-10.97	0.50
		OP	0.65	0.0067	0.0016	4.15	1.03	0.25
		Daily	0.70	-0.0151	0.0015	-9.89	-2.15	0.22
	Normal Weekday	P	0.80	-0.0309	0.0018	-16.94	-3.87	0.23
		OP	0.61	0.0099	0.0005	18.81	1.63	0.09
		Daily	0.65	0.0014	0.0002	9.38	0.22	0.02
	Weekend	Daily	0.69	0.0050	0.0014	3.64	0.72	0.20
3	Critical	P	1.83	-0.2984	0.0098	-30.55	-16.30	0.53
		OP	1.00	0.0390	0.0031	12.45	3.90	0.31
		Daily	1.17	-0.0313	0.0030	-10.32	-2.67	0.26
	Normal Weekday	P	1.47	-0.0942	0.0031	-30.29	-6.40	0.21
		OP	0.88	0.0266	0.0009	31.02	3.03	0.10
		Daily	1.00	0.0014	0.0001	10.75	0.14	0.01
	Weekend	Daily	1.11	0.0123	0.0023	5.25	1.11	0.21
4	Critical	P	2.43	-0.4227	0.0184	-23.03	-17.40	0.76
		OP	1.34	0.0679	0.0077	8.83	5.08	0.58
		Daily	1.57	-0.0343	0.0081	-4.21	-2.19	0.52
	Normal Weekday	P	2.02	-0.1484	0.0050	-29.74	-7.35	0.25
		OP	1.17	0.0397	0.0013	29.79	3.40	0.11
		Daily	1.34	0.0005	0.0001	6.63	0.04	0.01
	Weekend	Daily	1.43	0.0123	0.0050	2.44	0.86	0.35
All Avg. Customer Approach	Critical	P	1.28	-0.1676	0.0061	-27.43	-13.06	0.48
		OP	0.80	0.0166	0.0021	7.94	2.07	0.26
		Daily	0.90	-0.0217	0.0020	-10.66	-2.40	0.23
	Normal Weekday	P	1.09	-0.0535	0.0022	-23.92	-4.91	0.21
		OP	0.73	0.0154	0.0006	25.02	2.11	0.08
		Daily	0.81	0.0011	0.0001	10.61	0.13	0.01
	Weekend	Daily	0.87	0.0071	0.0016	4.35	0.82	0.19
All Zonal Average Approach	Critical	P	1.28	-0.1844	n/a	n/a	-14.37	n/a
		OP	0.80	0.0218	n/a	n/a	2.71	n/a
		Daily	0.90	-0.0212	n/a	n/a	-2.34	n/a
	Normal Weekday	P	1.09	-0.0597	n/a	n/a	-5.50	n/a
		OP	0.73	0.0173	n/a	n/a	2.38	n/a
		Daily	0.80	0.0013	n/a	n/a	0.16	n/a
	Weekend	Daily	0.86	0.0076	n/a	n/a	0.88	n/a

On critical days, for all zones, off-peak energy use rises by 2.71 percent, with a standard error of 0.26 percent. Finally, on critical days, daily energy use across all zones falls by –2.34 percent, with a standard error of 0.23 percent.

Impacts are appreciably smaller on normal weekdays, primarily reflecting the lower peak prices on these days. The all-zone average impact during the peak period is –5.50 percent, with a standard error of 0.21 percent. Weekend use rises by 0.88 percent, with a standard error of 0.19 percent.

Table 4-9 shows the impacts for the outer summer period. The impacts are lower in the outer summer compared with the inner summer, reflecting the same pattern that was seen for the elasticity estimates. The drop in peak-period energy use on critical days for all zones is 7.81 percent using the average customer approach, with a standard error of 0.87 percent. The impact using the zonal approach is -8.08 percent. Off-peak energy use on critical days also shows a decline during the outer summer equal to 0.76 percent, with a standard error of 0.39 percent. Finally, daily energy use on critical days falls by 2.65 percent, with a standard error of 0.32 percent.

As in the inner summer, impacts are appreciably smaller on normal weekdays than on critical days, primarily reflecting the lower peak prices on these days. The all-zone impact during peak periods equals –2.65 percent, with a standard error of 0.38 percent. Weekend energy use rises by 0.54 percent, with a standard error of 0.28 percent.

Table 4-9 Residential CPP-F Rate Impact Estimates for Outer Summer								
Climate Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact kWh/hr	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	Critical	P	0.56	-0.0343	0.0059	-5.82	-6.15	1.06
		OP	0.47	-0.0056	0.0020	-2.80	-1.18	0.42
		Daily	0.49	-0.0116	0.0015	-7.69	-2.36	0.31
	Normal Weekday	P	0.52	-0.0085	0.0026	-3.21	-1.65	0.51
		OP	0.49	0.0036	0.0007	4.95	0.73	0.15
		Daily	0.49	0.0011	0.0001	7.54	0.21	0.03
	Weekend	Daily	0.51	0.0012	0.0015	0.81	0.24	0.30
2	Critical	P	0.70	-0.0485	0.0060	-8.07	-6.98	0.86
		OP	0.58	-0.0049	0.0020	-2.43	-0.84	0.35
		Daily	0.60	-0.0140	0.0016	-8.86	-2.31	0.26
	Normal Weekday	P	0.69	-0.0131	0.0029	-4.59	-1.90	0.41
		OP	0.57	0.0051	0.0008	6.59	0.89	0.13
		Daily	0.60	0.0013	0.0001	9.16	0.22	0.02
	Weekend	Daily	0.62	0.0025	0.0017	1.45	0.41	0.28
3	Critical	P	1.07	-0.0963	0.0107	-9.03	-8.97	0.99
		OP	0.75	-0.0054	0.0038	-1.43	-0.72	0.50
		Daily	0.82	-0.0243	0.0034	-7.05	-2.98	0.42
	Normal Weekday	P	1.02	-0.0266	0.0042	-6.34	-2.61	0.41
		OP	0.71	0.0090	0.0011	7.90	1.26	0.16
		Daily	0.78	0.0016	0.0002	8.71	0.21	0.02
	Weekend	Daily	0.83	0.0063	0.0026	2.43	0.75	0.31
4	Critical	P	1.18	-0.1158	0.0163	-7.12	-9.80	1.38
		OP	0.77	-0.0020	0.0058	-0.34	-0.26	0.76
		Daily	0.85	-0.0257	0.0055	-4.64	-3.01	0.65
	Normal Weekday	P	1.35	-0.0412	0.0066	-6.28	-3.04	0.48
		OP	0.87	0.0120	0.0018	6.75	1.37	0.20
		Daily	0.97	0.0009	0.0002	4.16	0.09	0.02
	Weekend	Daily	1.03	0.0059	0.0045	1.31	0.57	0.44
All Avg. Customer Approach	Critical	P	0.84	-0.0657	0.0073	-9.01	-7.81	0.87
		OP	0.64	-0.0053	0.0025	-2.10	-0.83	0.39
		Daily	0.68	-0.0179	0.0022	-8.30	-2.63	0.32
	Normal Weekday	P	0.84	-0.0186	0.0032	-5.78	-2.23	0.38
		OP	0.64	0.0064	0.0009	7.38	1.01	0.14
		Daily	0.68	0.0012	0.0001	9.13	0.18	0.02
	Weekend	Daily	0.72	0.0036	0.0020	1.80	0.50	0.28
All Zonal Average Approach	Critical	P	0.84	-0.0680	n/a	n/a	-8.08	n/a
		OP	0.64	-0.0048	n/a	n/a	-0.76	n/a
		Daily	0.68	-0.0180	n/a	n/a	-2.65	n/a
	Normal Weekday	P	0.83	-0.0195	n/a	n/a	-2.33	n/a
		OP	0.64	0.0068	n/a	n/a	1.07	n/a
		Daily	0.68	0.0013	n/a	n/a	0.20	n/a
	Weekend	Daily	0.71	0.0038	n/a	n/a	0.54	n/a

4.1.3 All Summer Estimates

From a policy perspective, it may be useful to have an estimate of elasticities and impacts for the entire summer period rather than separate estimates for the inner and outer summer periods. These "all summer" estimates are contained in Tables 4-10 and 4-11. These estimates are based on regressions run using data from the months of July-October 2003 and May-September 2004. The weather underlying the elasticity estimates represents the average conditions for these months.

Table 4-10
Residential CPP-F Rate Elasticity Estimates
All Summer Averages

Zone	Day Type	Elasticity Type	Summer 2003 and 2004		
			Estimate	Standard Error	t- statistic
1	Critical	Substitution	-0.039	0.004	-10.60
		Daily	-0.041	0.005	-8.32
	Normal Weekdays	Substitution	-0.034	0.004	-8.54
		Daily	-0.043	0.005	-8.10
	Weekend	Daily	-0.014	0.006	-2.48
2	Critical	Substitution	-0.061	0.003	-20.01
		Daily	-0.042	0.004	-10.39
	Normal Weekdays	Substitution	-0.055	0.003	-16.48
		Daily	-0.044	0.004	-9.90
	Weekend	Daily	-0.018	0.005	-3.87
3	Critical	Substitution	-0.102	0.004	-29.04
		Daily	-0.043	0.004	-10.97
	Normal Weekdays	Substitution	-0.093	0.003	-28.45
		Daily	-0.047	0.004	-11.33
	Weekend	Daily	-0.026	0.005	-5.68
4	Critical	Substitution	-0.113	0.004	-26.24
		Daily	-0.032	0.007	-4.53
	Normal Weekdays	Substitution	-0.105	0.004	-29.08
		Daily	-0.039	0.005	-8.41
	Weekend	Daily	-0.020	0.007	-2.91
All	Critical	Substitution	-0.076	0.003	-25.73
		Daily	-0.041	0.004	-11.29
	Normal Weekdays	Substitution	-0.069	0.003	-22.58
		Daily	-0.044	0.004	-11.14
	Weekend	Daily	-0.020	0.004	-4.66

A comparison of the values in Tables 4-10 and 4-11 with those in Tables 4-6 through 4-9 reveals that, while the all summer values are in between the values for the inner and outer summer periods, they are closer to the inner summer values. This is because much of the CPP price variation is concentrated during the inner summer months. Thus, the all-summer elasticity of substitution on critical days, equal to –0.076, is much closer to the inner summer value of -0.086 than to the outer summer value of –0.038.[50,51]

Table 4-11 contains the all-summer impact estimates. Statewide, the average, peak-period reduction on critical days is 13.06 percent, which compares with a drop of 14.37 percent during the inner summer and a drop of 8.08 percent in the outer summer.

The variation across zones ranges from a low of –7.61 percent in climate zone 1 to a high of -15.83 percent in climate zone 4. The average-summer increase in off-peak energy use on critical days is 2.04 percent, and daily energy use on critical days falls by 2.37 percent. On normal weekdays, peak-period energy use falls by 4.71 percent statewide, with a low of -2.23 percent in climate zone 1 and a high impact of -6.47 percent in climate zone 4. The statewide average change in weekend energy use equals -0.79 percent.

[50] It should be noted that there were only two critical days in the outer summer, which occurred in October 2003. These days were relatively cool compared with the critical days that occurred in July, August and September.

[51] We also note that the all-summer value of –0.076 is identical to the summer 2003 value of –0.076 contained in Table 5-1 of the Summer 2003 report. The all-summer elasticity of substitution on non-CPP days, -0.069, is also nearly identical to the previous estimate of –0.067 reported in the Summer 2003 report. The daily price elasticities contained in Table 4-10 are roughly twice as large as the daily elasticities estimated previously (reported in Table 5-1 of the Summer 2003 report), while the daily elasticity on the weekend is significantly less than the previous value. We believe the new estimates are more accurate as they are based on daily data, whereas the previous estimates relied on data averaged across all the days within a particular day-type, which masked much of the daily variation in energy use.

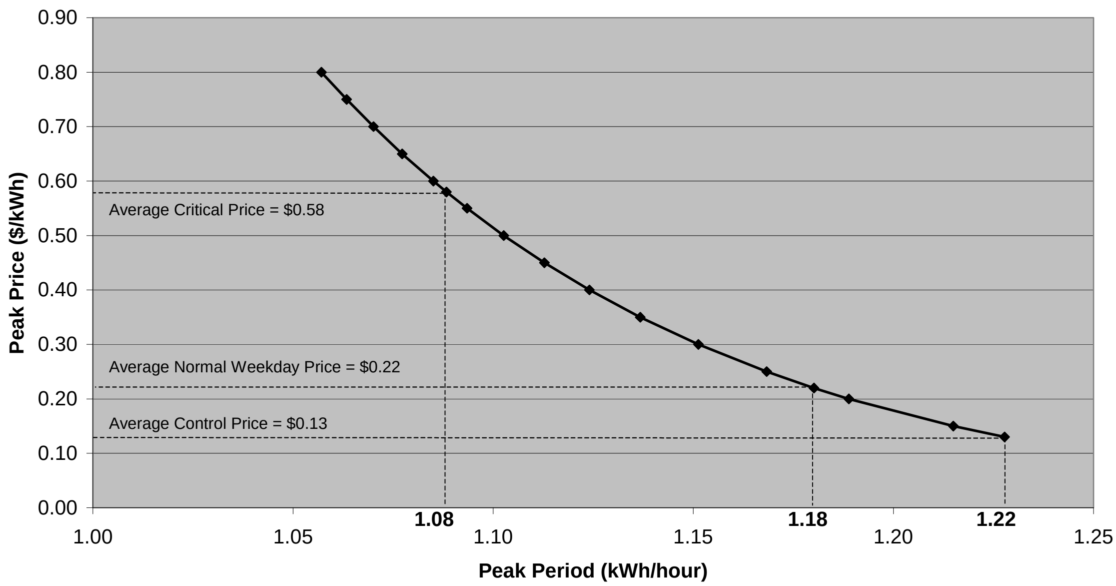
Table 4-11
Residential CPP-F Rate Impact Estimates for All Summer

Climate Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact kWh/hr	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	Critical	P	0.497	-0.038	0.003	-12.67	-7.61	0.60
		OP	0.467	-0.002	0.001	-1.74	-0.45	0.26
		Daily	0.473	-0.010	0.001	-8.41	-2.02	0.24
	Normal Weekday	P	0.498	-0.011	0.001	-7.94	-2.23	0.28
		OP	0.473	0.004	0.000	10.24	0.90	0.09
		Daily	0.478	0.001	0.000	8.09	0.22	0.03
	Weekend	Daily	0.493	0.002	0.001	2.48	0.46	0.18
2	Critical	P	0.870	-0.088	0.004	-21.89	-10.10	0.46
		OP	0.644	0.004	0.002	2.50	0.58	0.23
		Daily	0.691	-0.015	0.001	-10.50	-2.22	0.21
	Normal Weekday	P	0.758	-0.025	0.002	-15.85	-3.33	0.21
		OP	0.598	0.008	0.000	17.96	1.40	0.08
		Daily	0.631	0.001	0.000	9.89	0.22	0.02
	Weekend	Daily	0.666	0.004	0.001	3.85	0.64	0.17
3	Critical	P	1.735	-0.257	0.009	-30.16	-14.80	0.49
		OP	0.968	0.029	0.003	10.47	3.00	0.29
		Daily	1.128	-0.031	0.003	-11.12	-2.71	0.24
	Normal Weekday	P	1.305	-0.072	0.003	-28.50	-5.55	0.19
		OP	0.816	0.021	0.001	29.45	2.54	0.09
		Daily	0.918	0.001	0.000	11.32	0.15	0.01
	Weekend	Daily	1.017	0.010	0.002	5.65	1.01	0.18
4	Critical	P	2.273	-0.360	0.016	-23.09	-15.83	0.69
		OP	1.266	0.056	0.006	8.65	4.39	0.51
		Daily	1.476	-0.031	0.007	-4.57	-2.10	0.46
	Normal Weekday	P	1.775	-0.115	0.004	-29.58	-6.47	0.22
		OP	1.058	0.031	0.001	29.75	2.92	0.10
		Daily	1.207	0.001	0.000	8.40	0.04	0.01
	Weekend	Daily	1.301	0.010	0.004	2.90	0.79	0.27
All Avg. Customer Approach	Critical	P	1.228	-0.147	0.005	-27.17	-11.96	0.44
		OP	0.784	0.012	0.002	6.10	1.47	0.24
		Daily	0.876	-0.021	0.002	-11.43	-2.45	0.21
	Normal Weekday	P	0.998	-0.042	0.002	-22.39	-4.25	0.19
		OP	0.697	0.013	0.001	23.72	1.80	0.08
		Daily	0.759	0.001	0.000	11.13	0.14	0.01
	Weekend	Daily	0.818	0.006	0.001	4.64	0.74	0.16
All Zonal Average Approach	Critical	P	1.228	-0.160	n/a	n/a	-13.06	n/a
		OP	0.783	0.016	n/a	n/a	2.04	n/a
		Daily	0.876	-0.021	n/a	n/a	-2.37	n/a
	Normal Weekday	P	0.994	-0.047	n/a	n/a	-4.71	n/a
		OP	0.695	0.014	n/a	n/a	2.00	n/a
		Daily	0.758	0.001	n/a	n/a	0.17	n/a
	Weekend	Daily	0.815	0.006	n/a	n/a	0.79	n/a

4.1.4 Demand Curves

The relationship between price and energy use by rate period underlying the impact estimates presented in this report can be displayed graphically in what are called demand curves. The demand curve depicted in Figure 4-1 shows how energy use in the peak period varies with peak-period price, other things equal. The curve shows the combined impact of the elasticity of substitution and the daily price elasticity of demand. It should be noted that a number of factors are held constant along the curve. If any of these factors change, such as weather, the saturation of air conditioning or off-peak prices, the curve will shift to the left or right, depending upon the nature of the change in the underlying factors.

Figure 4-1
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 treatment customers faced in the pre-treatment period, peak-period electricity use is 1.22 kWh/hour. At a price of 22 cents/kWh, corresponding to the average peak-period price on normal weekdays, demand falls to 1.18 kWh/hr.

One way of summarizing price responsiveness when price changes are large is the arc elasticity. Arc elasticity equals the percentage change in energy use relative to the average of the new and old values for both quantity and price, as depicted in the following equation:

$$\text{Arc Elasticity} = [(Q_2 - Q_1) \div (Q_2 + Q_1)/2] \div [(P_2 - P_1) \div (P_2 + P_1)/2].$$

In the example in Figure 4-1, a rise in the price from $0.13/kWh to $0.22/kWh (or 51.43 percent using the averaging approach in the formula) produces a drop in electricity use of 3.33 percent (from 1.22 kWh/hr to 1.18 kWh/hr), yielding an implicit arc own-price elasticity of demand of -0.065 (= -3.33%/+51.43%). When the price increases to 58 cents/kWh, corresponding to the average peak-period price on critical days, demand falls to 1.08 kWh/hr. Thus, a rise in the price of 126 percent from the initial average value of 13 cents/kWh produces a drop in electricity use of 12 percent, yielding an implicit arc own-price elasticity of demand of –0.096.

Figure 4-2 shows the demand curve for off-peak electricity use. The curve shows that a reduction in the price of off-peak electricity from the control group value of 13 cents/kWh to an average off-peak price on critical days of 9 cents/kWh increases hourly energy use from 0.78 kWh to 0.80 kWh. That is, a 36 percent decrease in price induces a rise in demand of 2 percent, yielding an implicit arc own-price elasticity of off-peak demand of -0.05, a value slightly higher than that observed for peak-period energy use based on the normal weekday peak-period price.

Figure 4-2
Off-Peak Period Demand Curve, Statewide Average

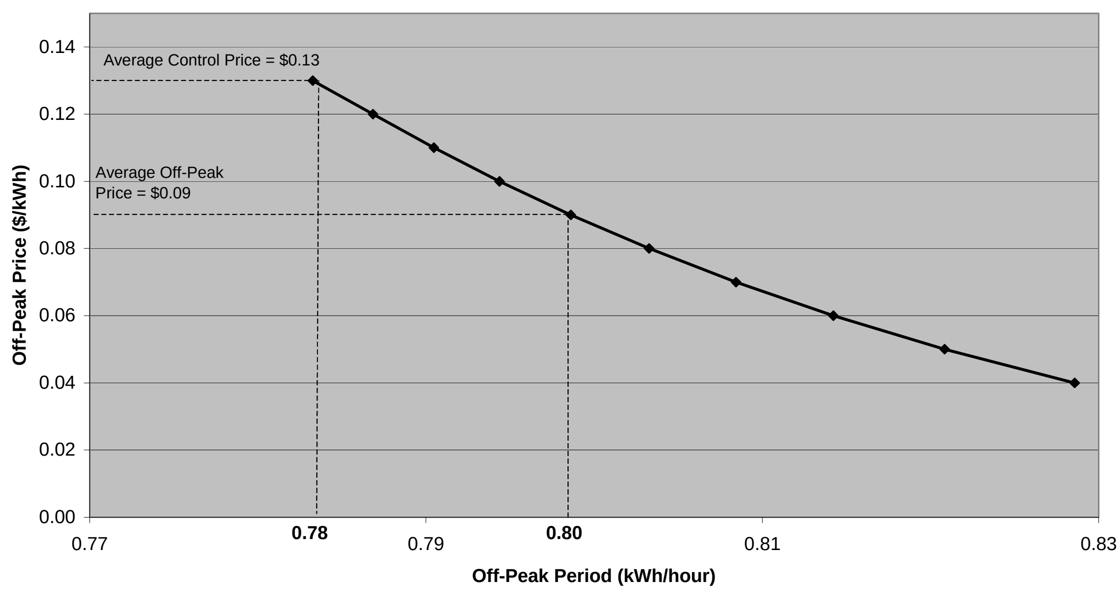


Figure 4-3 shows the influence of central air-conditioning on the demand curve for peak-period electricity use. The demand curve for customers without central air-conditioning has a much steeper slope than the average statewide demand curve, indicating a lower degree of price responsiveness. For customers with central air-conditioning, the demand curve is flatter, indicating that as the saturation of central air-conditioning increases, price responsiveness also increases.

Figure 4-3
Peak Period Demand Curves, Default and CAC Variations, Statewide

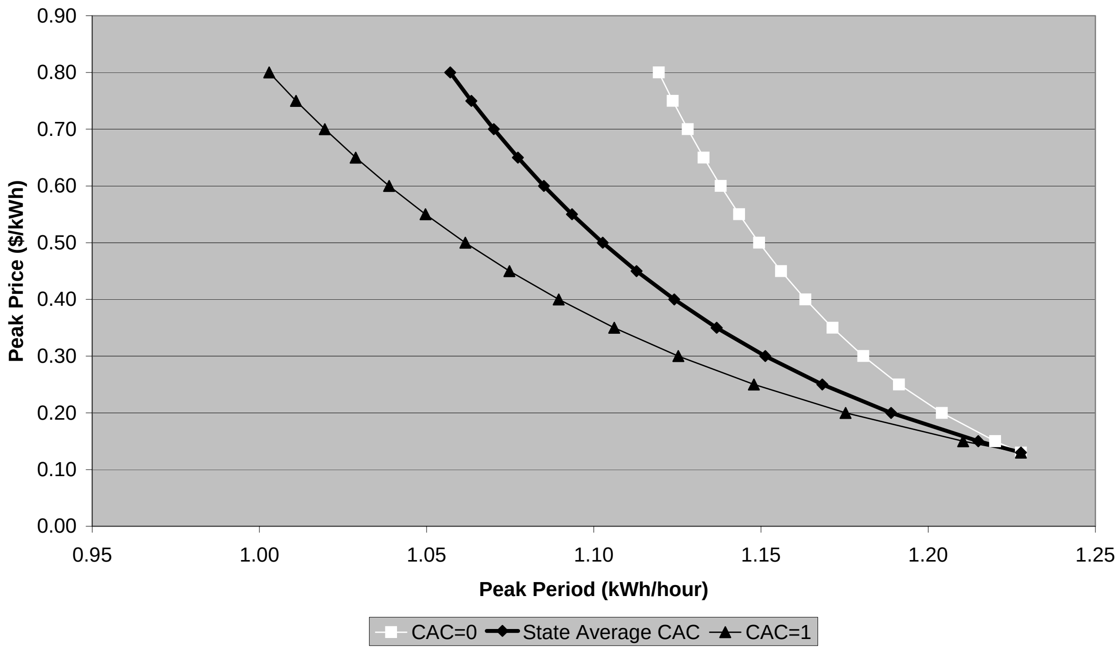
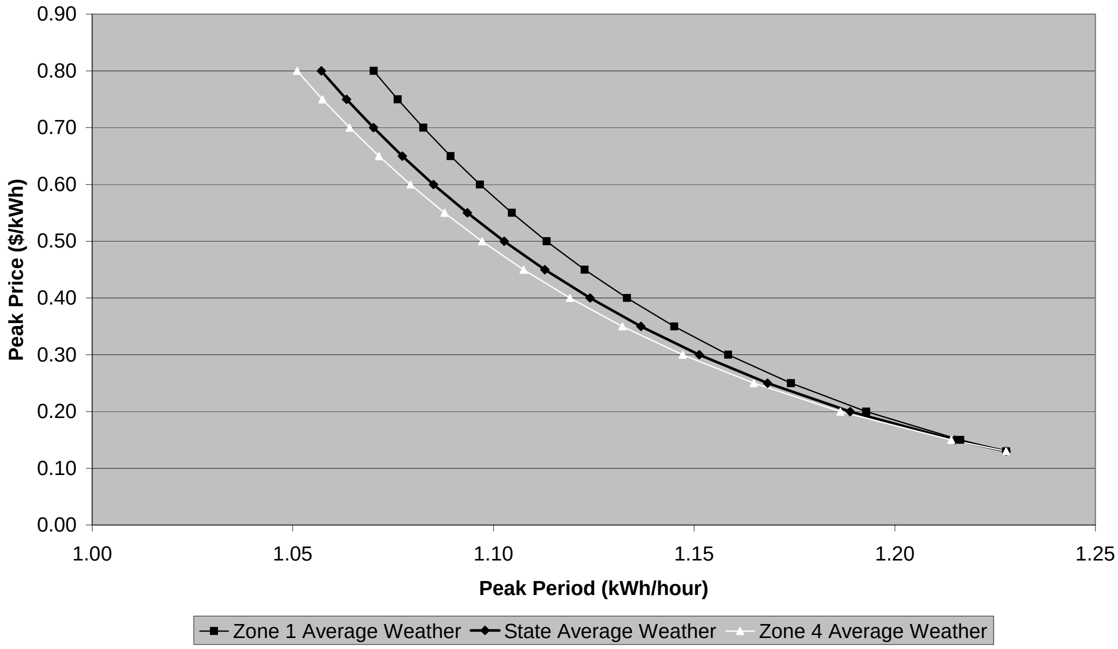


Figure 4-4 shows the influence of weather on the slope of the demand curve. Hotter weather conditions produce a slightly flatter, more price-responsive demand curve, and cooler weather conditions produce a slightly steeper, less price-responsive demand curve.

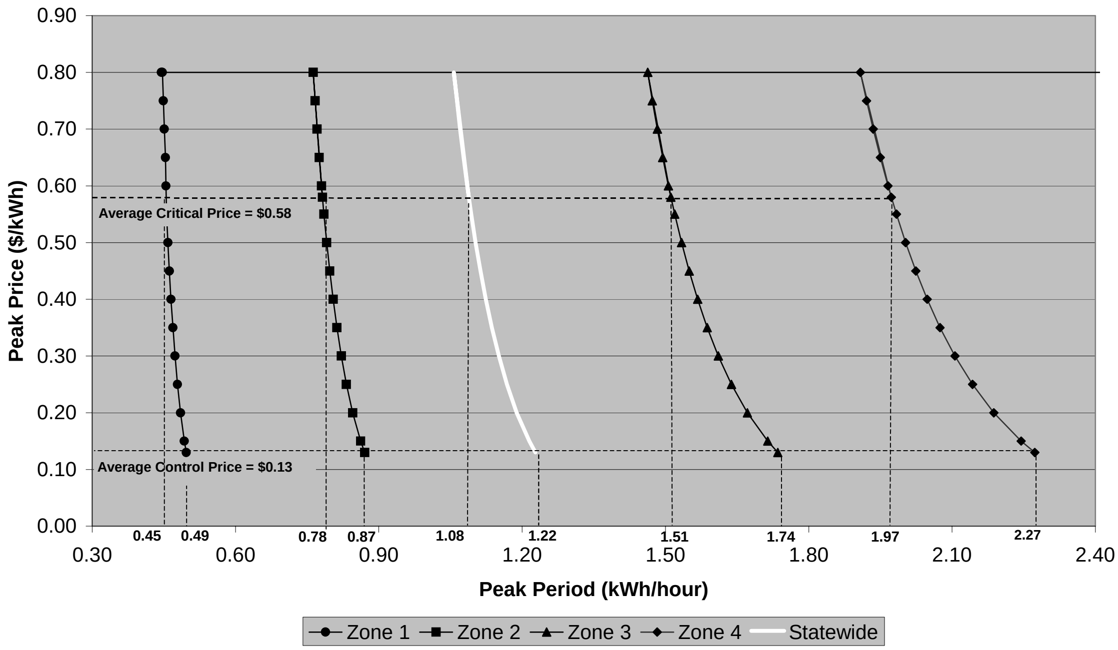
Figure 4-4
Peak Period Demand Curves, Default and Weather Variations, Statewide



Similar demand curves can be constructed for peak and off-peak energy use in each of the four climate zones. The demand curves would be expected to vary across zones, because weather conditions and the saturation of central air conditioning vary by zone, which causes variation in the elasticity of substitution and in the daily price elasticity. Values for these variables and parameters were reported earlier in Tables 4-6, 4-7 and 4-10.

Figure 4-5 displays demand curves for each of the four zones, and also repeats the statewide demand curve for comparison. The steepest demand curve (showing the least amount of price responsiveness, as evidenced by an elasticity of substitution of -0.04 and a daily price elasticity of –0.04 on critical days for the average summer) is found in Zone 1, and the flattest curve is found in zone 4 (showing the highest amount of price responsiveness, as evidenced by an elasticity of substitution of –0.11 and a daily price elasticity of –0.03). The figure also 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 percent), followed by Zone 3 (-12.9 percent), Zone 2 (-9.03 percent) and Zone 1 (-6.64 percent). The implied arc elasticities of demand equal -0.112 in Zone 4, -0.109 in Zone 3, -0.079 in Zone 2 and –0.054 in Zone 1.

Figure 4-5
CPP Day Peak Period Demand Curves by Climate Zone



4.2 PERSISTENCE ACROSS MULTIPLE-DAY CRITICAL EVENTS

In 2004, several multiple-day, critical events were conducted 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 of a multi-day event.

There were no multi-day critical events in 2003. In 2004, two three-day events and one two-day event were called. Thus, of the 12 critical days called during the summer of 2004, there were a total of seven days that were either stand-alone days or the first day of a multi-day event, three days that were the second days of a multi-day event and two days that were the third day of a multi-day event.

To test for differences across the critical day types, binary variables representing each day type (e.g., first, second and third days) were developed and used as interaction terms with each of the price and weather terms in the basic model specification. Two approaches were used to test for differences across the day types. The first approach involved the use of binary variables representing the second and third critical days in a multi-day event. This test measures whether the second and third days differ from the average responsiveness for single critical days, the first day of a multi-day event, and normal weekdays. The test was conducted using a model specification that allows responses to differ across the two years and between the inner and outer summers, in addition to differing across the critical day types.

The second approach involved the use of binary variables for the first, second and third critical day. This approach measures whether or not the deviations in price responsiveness on each critical day type are statistically different from each other. This test is based on the chi-squared statistic.

The results of the first persistence test, using second and third day binary variables, are reported in Tables 4-12, 4-13 and 4-14. Table 4-12 contains the elasticity estimates and the following two tables contain the impact estimates. Results are reported by climate zone and for the state as a whole based on the average customer approach.[52] All values in the table are based on average weather across the three critical day types and the two summers. For example, the 2nd-Day differential is calculated using the average weather across all critical days, not the average for only 2nd CPP days. Average weather is used, rather than weather for each day type, since our focus is on behavioral change across the day types, not developing actual impact estimates for each day type.

The first two columns in Table 4-12 contain the substitution and daily elasticities for summer 2003. Since there were no mult-day events called in 2003, these elasticities represent the average responsiveness on normal weekdays and first critical days. Columns 3 and 4 in Table 4-12 contain the same elasticities for summer 2004. Columns 5 through 8 contain estimates of the differentials between the average elasticity for normal weekdays and first critical days and the elasticities on the second and third critical days of 2004.

Table 4-12
Residential CPP-F Elasticity Estimates
(All Estimates Based On Average Critical Day Weather For 2003/2004)

Zone	Elasticity Type	Summer 2003		Summer 2004		2nd Critical Day Differential		3rd Critical Day Differential	
		Estimate	t-statistic	Estimate	t- statistic	Estimate	t- statistic	Estimate	t- statistic
1	Substitution	-0.044	-8.128	-0.038	-5.79	-0.020	-2.49	-0.009	-0.76
	Daily	-0.029	-4.658	-0.058	-6.71	0.001	0.18	0.015	2.66
2	Substitution	-0.068	-15.294	-0.065	-11.95	-0.017	-2.47	-0.007	-0.69
	Daily	-0.032	-6.227	-0.058	-8.04	0.006	1.06	0.017	2.19
3	Substitution	-0.113	-22.286	-0.116	-17.88	-0.011	-1.24	-0.002	-0.18
	Daily	-0.038	-7.151	-0.055	-7.69	0.017	1.49	0.024	1.53
4	Substitution	-0.122	-19.901	-0.129	-16.11	-0.009	-0.79	0.002	0.15
	Daily	-0.032	-3.222	-0.037	-2.63	0.033	1.29	0.053	1.49
All	Substitution	-0.085	-19.764	-0.084	-15.68	-0.014	-2.08	-0.005	-0.48
	Daily	-0.034	-6.982	-0.055	-8.36	0.011	1.29	0.023	1.84

[52] Recall from the previous discussion that the zonal weighted average approach is preferred, and produces somewhat higher impacts, but it is difficult to estimate standard errors for the statewide estimate using this approach and the standard errors for the average customer approach are good proxies for the zonal average approach.

The first thing to note is that, consistent with the earlier discussion, the average value for the elasticity of substitution for the normal-weekday/first-critical-day type, -0.084, is essentially constant across the two years, while the daily price elasticity rises from –0.034 to –0.055 in 2004. Focusing next on the differentials associated with the second and third critical days, we find that only one of the four differentials is statistically significant at the average customer level, namely the differential corresponding to the elasticity of substitution on the second day, which has a t-statistic of –2.08. This indicates that the elasticity of substitution on the second day is larger in absolute terms by a statistically significant amount than on normal-weekdays/first-critical days for the average California customer. This difference in behavior appears to originate in zones 1 and 2 where the t-statistics on the differentials are both roughly –2.5. The daily price elasticity differential on the third critical day is also statistically significant in zones 1 and 2, and suggests a dampening of response. However, the average customer daily price elasticity differential on the third day, while numerically sizeable at 0.023, is not statistically significant at the 95 percent confidence level.

The normal-weekday/first-critical-day impacts are shown in Table 4-13. For the average customer, the impact on peak-period energy use on critical days rises from –12.54 percent to –13.57 percent between 2003 and 2004. The impact differentials for days 2 and 3, compared to the normal-weekday/first-critical-day value, are shown in Table 4-14. For the average customer, peak-period impacts on the second and third critical days of a multi-day event are not statistically different from the normal-weekday/first-critical-day average. In zones 1 and 2, the impacts are larger on the second day by a statistically significant amount.

Table 4-13
Residential CPP-F Rate
Impact Estimates For Inner Summer Critical Days
(All Estimates Based On Average Critical Day Weather For 2003/2004)

Zone	Rate Period	2003 Impacts						2004 Impacts					
		Starting Value kWh/hr	Impact kWh/hr	Standard Error	t-stat	Impact (%)	Standard Error (%)	Starting Value KWh/hr	Impact kWh/hr	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	P	0.49	-0.04	0.004	-9.09	-7.84	0.86	0.49	-0.04	0.005	-7.79	-8.23	1.06
	OP	0.47	0.00	0.002	0.98	0.34	0.35	0.47	-0.01	0.002	-2.91	-1.31	0.45
	Daily	0.47	-0.01	0.001	-4.69	-1.43	0.30	0.47	-0.01	0.002	-6.81	-2.80	0.41
2	P	0.90	-0.09	0.006	-16.22	-10.55	0.65	0.90	-0.10	0.007	-14.01	-11.33	0.81
	OP	0.65	0.01	0.002	4.58	1.46	0.32	0.65	0.00	0.003	-0.10	-0.04	0.41
	Daily	0.70	-0.01	0.002	-6.28	-1.73	0.27	0.70	-0.02	0.003	-8.17	-3.04	0.37
3	P	1.83	-0.29	0.013	-22.84	-15.70	0.69	1.83	-0.31	0.016	-19.23	-16.98	0.88
	OP	1.00	0.04	0.004	10.11	4.05	0.40	1.00	0.03	0.005	5.81	3.06	0.53
	Daily	1.17	-0.03	0.004	-7.24	-2.38	0.33	1.17	-0.04	0.005	-7.83	-3.46	0.44
4	P	2.43	-0.41	0.023	-17.44	-16.81	0.96	2.43	-0.43	0.031	-13.86	-17.87	1.29
	OP	1.34	0.07	0.010	6.76	4.89	0.72	1.34	0.07	0.014	4.84	4.91	1.02
	Daily	1.57	-0.03	0.010	-3.26	-2.12	0.65	1.57	-0.04	0.014	-2.66	-2.46	0.92
All	P	1.28	-0.16	0.008	-20.37	-12.54	0.62	1.28	-0.17	0.010	-17.42	-13.57	0.78
	OP	0.80	0.02	0.003	7.20	2.40	0.33	0.80	0.01	0.003	2.45	1.07	0.43
	Daily	0.90	-0.02	0.003	-7.05	-2.02	0.29	0.90	-0.03	0.003	-8.50	-3.26	0.38

Table 4-14 Residential CPP-F Rate Impact Differentials For Consecutive Inner Summer Critical Days (All Estimates Based On Average Critical Day Weather For 2003/2004)													
Zone	Rate Period	Critical Day 2 Differential						Critical Day 3 Differential					
		Starting Value kWh/hr	Impact kWh/hr	Standard Error	t-stat	Impact (%)	Standard Error (%)	Starting Value KWh/hr	Impact kWh/hr	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	P	0.49	-0.01	0.006	-2.49	-2.89	1.16	0.49	0.00	0.009	-0.35	-0.64	1.81
	OP	0.47	0.00	0.002	2.17	0.84	0.39	0.47	0.01	0.003	1.90	1.13	0.60
	Daily	0.47	0.00	0.001	0.18	0.03	0.19	0.47	0.00	0.001	2.65	0.75	0.28
2	P	0.90	-0.02	0.009	-1.99	-1.93	0.97	0.90	0.00	0.013	-0.02	-0.03	1.49
	OP	0.65	0.01	0.003	2.64	1.13	0.43	0.65	0.01	0.004	2.01	1.29	0.64
	Daily	0.70	0.00	0.002	1.06	0.32	0.30	0.70	0.01	0.003	2.18	0.94	0.43
3	P	1.83	-0.01	0.027	-0.21	-0.30	1.45	1.83	0.02	0.039	0.60	1.27	2.13
	OP	1.00	0.02	0.008	2.15	1.75	0.81	1.00	0.02	0.012	1.46	1.71	1.17
	Daily	1.17	0.01	0.009	1.48	1.08	0.73	1.17	0.02	0.012	1.51	1.57	1.03
4	P	2.43	0.03	0.060	0.43	1.07	2.47	2.43	0.10	0.088	1.08	3.92	3.63
	OP	1.34	0.04	0.023	1.59	2.75	1.72	1.34	0.05	0.033	1.41	3.45	2.44
	Daily	1.57	0.03	0.027	1.27	2.20	1.73	1.57	0.06	0.039	1.46	3.60	2.46
All	P	1.28	-0.02	0.014	-1.08	-1.21	1.13	1.28	0.01	0.022	0.44	0.74	1.69
	OP	0.80	0.01	0.005	2.46	1.49	0.61	0.80	0.01	0.007	1.90	1.68	0.88
	Daily	0.90	0.01	0.005	1.28	0.69	0.54	0.90	0.01	0.007	1.83	1.40	0.77

The impact differential for off-peak energy use for the average customer for the second critical day-type is positive and statistically significant on the second day, with a value of 1.49 percent. This impact differential is statistically significant in zones 1, 2 and 3 as well. It is also significant on the third day for zone 2. The third day differential is not statistically significant at the 95 percent confidence level for the average customer, but it is at the 90 percent confidence level.

The impact differentials for daily energy use are not statistically significant for the average customer on either the second or third day. However, they are significant in zones 1 and 2.

To summarize, based on the first approach, the impact differentials for peak-period energy use on critical days are not statistically significant for the average customer statewide on either the second or third day of a multi-day event. However they are significant in zones 1 and 2, and show an increase in impacts on these days compared with the average of normal weekdays and first critical days.

The results of the second persistence test, which includes binary variables representing all three critical day-types, are reported in Tables 4-15, 4-16 and 4-17. Table 4-15 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 4-16 contains estimates of the differentials by climate zone. To make the estimates comparable across the three day-types, the estimates are all based the same average weather conditions, which represent the average across all critical days during the inner summer months for both years.

Table 4-15 CPP Persistence Test: Average Customer						
Measure	Elasticity of Substitution			Daily 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 4-15, the base-value substitution elasticity for the average customer is –0.069 and the daily price elasticity is –0.074. Both are statistically significant. The differential between the base value and the value on the first critical day-type is –0.016 and is statistically significant with a t-statistic equal to –2.31. The daily elasticity is lower by 0.015 but the difference is not statistically different. On the second critical day type, the substitution elasticity is larger than the base value by –0.028 and the difference is statistically significant. The daily elasticity is smaller by 0.021 but the difference is not significantly different at the 95 percent confidence level. Finally, on the third critical day type, the substitution elasticity is also greater than the base value, –0.018, but the difference is not significantly significant. The daily elasticity is lower by 0.034 and the difference 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. The results are reported at the bottom of Table 4-15. They indicate that the null hypothesis that the differentials are the same cannot be rejected for either the elasticity of substitution or the daily price elasticity at the 5 percent level of significance.

Table 4-16 Differential Impact By Critical Day-Type							
Climate Zone	Elasticity Type	1st Critical Day Differential		2nd Critical Day Differential		3rd 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	-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	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	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	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	0.015	1.26	0.021	1.81	0.034	2.28

Table 4-17 contains estimates of the differential impact for each critical day-type compared with the base value. As seen, none of the differentials for peak-period energy use on the first critical day-type are statistically significant at either the 90 or 95 percent confidence level. 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, but it is at the 90 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 4-17 Differential Impact by Critical Day-Type (Inner Summer)													
Climate Zone	Rate Period	1st Critical Day Differential				2nd Critical Day Differential				3rd 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

4.3 CUSTOMER CHARACTERISTICS

Understanding how price responsiveness varies with differences in selected customer characteristics can be useful from both a policy and marketing perspective. For example, if high users are more responsive than low users, different tariffs might be targeted at each customer segment in order to maximize demand response and/or minimize implementation costs. If swimming pool owners are more responsive than households that do not have swimming pools, it may be possible to improve overall demand response from a voluntary program by targeting pool owners.

The impact on price responsiveness of the following variables was examined using the CES model specification and interaction terms between the price variable and a variable representing each characteristic:

- Average daily energy use in Summer 2002 (e.g., the summer prior to the start of the SPP)
- Central air conditioning ownership

- Housing type (single family versus other)
- Number of bedrooms in the house
- Annual income
- Swimming pool ownership
- Spa ownership
- Electric cooking ownership
- Whether or not the head of household is a college graduate
- Persons per household
- Whether or not a customer receives the CARE discount.

A statistically significant coefficient on the interaction term for each variable indicates that price response varies between customers who either own or don't own a particular end use represented by the variable or between customers that have different values for a particular continuous variable (e.g., households with two or four bedrooms or high income and low income households). On the other hand, and importantly, a statistically insignificant coefficient does not necessarily mean that the characteristic of interest does not influence price response. It may simply mean that there is insufficient variation in the presence or absence of that particular characteristic in the experimental sample to precisely determine causality. Ensuring that there is sufficient variation in the sample to precisely measure the impact of all variables of interest would have required a much larger sample and a much more expensive experiment than the SPP. In order to maximize the variation in each characteristic in the existing sample, the analysis was done using data pooled across climate zones, as there is often more variation in certain characteristics across zones (e.g., air conditioning ownership, pool ownership, etc.) than there is within a specific climate zone.

The influence of each customer characteristic was examined individually. That is, we did not estimate a model that included all of the variables at once. Since many of these variables are correlated, including all of the variables in a single regression would make it difficult to isolate the specific impact of each variable. On the other hand, examining them one at a time means that the impact of each variable may be overstated in terms of the influence of that particular factor, as the variable is actually a proxy not only for the factor it represents but also for other factors with which it is correlated. This may be irrelevant from a policy perspective, however. Indeed, the combined impact may be exactly what is needed, since few policies are likely to vary across all of the many market segments that might be partially represented by each individual variable. For example, the coefficient on the high user variable may represent the combined impact of higher income, more air conditioning ownership, more pool ownership and perhaps other factors. But since policies are more likely to be targeted at all high users than to high users who do and don't have an air conditioner or who do and don't have a swimming pool, knowing how impacts vary across these sub-segments of high users is largely irrelevant.

Of the eleven characteristics examined, only pool ownership was statistically insignificant in both the substitution and daily equations, with t-statistics of –1.55 and –1.32 respectively. All of the remaining variables were statistically significant at the 95 percent confidence level in both the substitution and daily equations except for the spa variable in the daily equation, which was significant at the 90 percent confidence level.

Table 4-18 shows how the elasticity of substitution varies with each of the significant variables and Table 4-19 shows the variation in peak-period energy use on critical days across customer characteristics. Key findings include:

- The differential impact of central air conditioning ownership on peak-period energy use is quite large, with critical day, peak-period reductions being more than twice as large for households with central air conditioning than for those without. The elasticity of substitution is nearly three times larger for CAC households than for non-CAC households, and the daily price elasticity is 50 percent larger for CAC households.

- Variation in average daily energy use (ADU) has only a modest impact on price responsiveness. The reduction in peak-period energy use on critical days for households that have ADU equal to 200 percent of the population average is 14.7 percent, or 1.6 percentage points greater than for the average household. Critical-day, peak-period reductions are one percentage point lower for households with ADU equal to 50 percent of the population average compared with the average household.

- Spa ownership has a moderate impact on price responsiveness, with the elasticity of substitution being roughly one-third larger for customers with a spa than for those without. The daily price elasticity for households with a spa is actually less than for households without a spa. As such, the variation in peak-period impacts is less than the variation in the elasticity of substitution. Households with spas reduce peak-period energy use on critical days by roughly 16 percent whereas those without spas reduce peak-period demand by roughly 13 percent.

- Households with electric cooking are less price responsive than households without electric cooking, suggesting that consumers are less willing to shift their dinner hour in response to price signals than they are to shift or reduce the use of other appliances. The average reduction in energy use during the peak-period on critical days is 11.5 percent for households with electric cooking and 14.1 percent for households without electric cooking.

- Price responsiveness falls with the number of persons per household. The elasticity of substitution is about 25 percent larger for a two-person household than for a four-person household, and peak-period reduction in energy use is about 15 percent (1.9 percentage points) larger for a two-person household.

- High-income households are more price-responsive than low-income households. The percent reduction in peak-period energy use on critical days is nearly 50 percent (5.3 percentage points) greater for households with average annual income equal to $100,000 than for households with average annual income equal to $40,000.

- Housing type (e.g., single versus multi-family housing) also influences demand response, with single-family households responding more to time-varying price signals than do multi-family households.

- Housing size, as measured by the number of bedrooms in the house, is positively correlated with demand response. Households with four bedrooms reduce peak-period demand on critical days by roughly 15.7 percent whereas households with only two bedrooms reduce peak-period demand by roughly 11.6 percent. There is a high correlation between the number of bedrooms and housing type. Indeed, housing type and the number of bedrooms has a correlation coefficient equal to –0.6, the highest correlation of any two variables that were examined.

- There is significant variation in demand response between households where the head of the house is a college graduate and those where the head did not graduate from college. Indeed, the variation is comparable to that caused by variation in CAC ownership. The reduction in peak-period demand on CPP days for households where the head graduated from college is 18.5 percent whereas the reduction for households where the head did not graduate is only 8.6 percent. Of course, college education is highly correlated with income (the correlation coefficient of 0.46 is the second highest among all of the two-way correlations).

- Customers who receive the CARE discount are much less price responsive than those who don't. Indeed, the elasticity of substitution for CARE households is essentially zero and the daily price elasticity is less than half the magnitude of the price elasticity for non-CARE households.

Table 4-18 Variation in Elasticity Given a Change in Customer Characteristics			
Variable	**Customer Characteristic**	**Elasticity of Substitution**	**Daily Elasticity**
None	**Average**	-0.076	-0.041
Central A/C	**Yes**	-0.116	-0.051
	No	-0.045	-0.034
Average Daily Use	**200% of Average**	-0.083	-0.052
	50% of Average	-0.071	-0.035
Spa	**Yes**	-0.101	-0.037
	No	-0.075	-0.042
Electric Cooking	**Yes**	-0.058	-0.054
	No	-0.088	-0.033
Persons Per Household	**Four**	-0.067	-0.047
	Two	-0.084	-0.041
Annual Income	**$100,000**	-0.101	-0.045
	$40,000	-0.061	-0.035
Housing Type	**Single Family**	-0.085	-0.037
	Multi-Family	-0.060	-0.054
# Bedrooms	**Four**	-0.093	-0.054
	Two	-0.067	-0.034
College Education	**Graduate**	-0.119	-0.049
	Did Not Graduate	-0.043	-0.032
CARE Discount	**Yes**	-0.005	-0.014
	No	-0.102	-0.029

Table 4-19 Percent Impact on Peak Period Energy Use on Critical Days Given a Change in Customer Characteristics				
Variable	Customer Characteristic	Peak Period	Off-Peak Period	Daily Period
None	Average	-13.06	2.04	-2.37
Central A/C	Yes	-17.43	3.21	-2.82
	No	-8.05	0.68	-1.87
Average Daily Use	200% of Average	-14.70	1.77	-3.04
	50% of Average	-12.15	2.21	-1.99
Spa	Yes	-15.84	3.53	-2.13
	No	-12.94	1.93	-2.41
Electric Cooking	Yes	-11.53	0.32	-3.14
	No	-14.09	3.16	-1.87
Persons Per Household	Four	-12.13	1.51	-2.47
	Two	-13.99	2.46	-2.35
Annual Income	$100,000	-16.15	2.99	-2.60
	$40,000	-10.92	1.68	-2.00
Housing Type	Single Family	-13.98	2.72	-2.16
	Multi-Family	-11.78	0.43	-3.14
# Bedrooms	Four	-15.67	2.12	-3.07
	Two	-11.59	2.01	-1.96
College Education	Graduate	-18.52	3.69	-2.79
	Did Not Graduate	-8.56	0.93	-1.84
CARE Discount	Yes	-2.87	0.00	-0.84
	No	-15.56	4.04	-1.68

4.4 WINTER ANALYSIS

The winter rate period for residential CPP-F customers in the SPP ran from November 1, 2003 through April 30, 2004. For purposes of simplicity, the 2 pm to 7 pm peak period that was in effect during the summer was maintained for the winter period as well. As discussed in Section 2.2.1, customers who experienced the high price ratio during the summer months were placed on the low price ratio in the winter period and vice versa.

The regression analysis for the winter period was conceptually similar to the approach used for the summer period, but there were some important differences. First, no winter pretreatment data were available so the winter analysis does not include any pretreatment data in the estimating database. Second, the weather term used in the substitution equation equals heating degree hours (HDH) per hour in the peak period minus HDH/hour in the off-peak period and the term in the daily equation is daily HDH/hour. Both of these terms were constructed using a base of 65^{o}F.[53] Third, the price/CAC interaction term used in the summer equations was dropped, as air conditioning does not occur during the winter period. A price/space-heater interaction term was tested but it was not significant in either the substitution or daily equations.

A regression was run using data pooled across all four climate zones and binary variables representing zones 2, 3 and 4 were interacted with the price and price/weather variables to test whether elasticities varied across zones for reasons other than the variation in weather. Only one of the twelve[54] binary variable interaction terms had a significant t-statistic, namely the price term by itself for climate zone 2 in the daily energy use equation. Based on these results, we concluded that the data could be pooled across all zones without accounting for zonal differences in the elasticities.[55]

As with the summer analysis, tests were done to see if there are significant seasonal differences in price response within the winter period. The inner winter was defined as the months of December, January and February and the outer winter by the months of November, March and April. Table 4-20 shows the elasticity of substitution and the daily price elasticity for the outer winter and the coefficients on the inner winter interaction terms that test for differences between the inner and outer periods. As seen, the average elasticity of substitution for all zones in the inner winter on normal weekdays is –0.033. The corresponding value on normal weekdays in the outer winter is -0.012. With a t-statistic equal to –1.82, the outer winter value is not quite statistically significant, although it is significant in zones 1 and 2. The delta value (not shown), equal to –0.021 at the 95 percent confidence level, indicates that the elasticity of substitution is greater in the inner winter than in the outer winter, and the t-statistic of –2.40 (shown) indicates that this difference is statistically significant. There is very little variation in values across climate zones in the inner winter period, as the price-weather interaction term is essentially zero. There is slightly more variation in the outer winter. The daily price elasticities are also significantly different across the two seasons. However, in this instance, price responsiveness is less (and not significant) in the inner winter than in the outer winter.

[53] HDH variables to base 55^{o}F, 60^{o}F and 65^{o}F were all tested and the general results were similar regardless of the variable used. We also note that, since HDH/hr is often greater at night than during the day, the variable used in the substitution equation often has a negative value.

[54] There are 6 variables in each of the substitution and daily energy equations, two for each zone with one interacting with price alone and the other interacting with the price/weather interaction term, for a total of 12 variables.

[55] As seen below, there are still zonal variations in the elasticities due to differences in weather across zones.

Table 4-20
Residential CPP-F Rate
Elasticity Estimates for the Outer Winter Period and the Inner/Outer Differentials

Zone	Day Type	Elasticity Type	Inner Winter			Outer Winter			Inner/Outer Differential
			Estimate	SE	t-stat	Estimate	SE	t- stat	t-stat
1	Critical	Substitution	-0.033	0.006	-5.549	n/a	n/a	n/a	n/a
		Daily	-0.008	0.008	-1.037	n/a	n/a	n/a	n/a
	Normal Weekday	Substitution	-0.033	0.006	-5.950	-0.014	0.007	-1.97	-2.16
		Daily	-0.005	0.008	-0.597	-0.041	0.013	-3.09	1.78
	Weekend	Daily	0.004	0.012	0.348	0.040	0.013	3.10	n/a
2	Critical	Substitution	-0.033	0.005	-6.272	n/a	n/a	n/a	n/a
		Daily	-0.005	0.008	-0.576	n/a	n/a	n/a	n/a
	Normal Weekday	Substitution	-0.033	0.005	-6.345	-0.014	0.007	-2.04	-2.21
		Daily	-0.002	0.010	-0.153	-0.043	0.013	-3.23	2.31
	Weekend	Daily	0.010	0.012	0.812	0.039	0.012	3.18	n/a
3	Critical	Substitution	-0.033	0.005	-6.264	n/a	n/a	n/a	n/a
		Daily	-0.007	0.008	-0.901	n/a	n/a	n/a	n/a
	Normal Weekday	Substitution	-0.033	0.005	-6.216	-0.010	0.007	-1.43	-2.58
		Daily	-0.003	0.009	-0.379	-0.043	0.013	-3.24	2.07
	Weekend	Daily	0.005	0.012	0.457	0.040	0.012	3.22	n/a
4	Critical	Substitution	-0.034	0.006	-6.089	n/a	n/a	n/a	n/a
		Daily	-0.014	0.011	-1.288	n/a	n/a	n/a	n/a
	Normal Weekday	Substitution	-0.034	0.006	-6.061	-0.011	0.007	-1.58	-2.40
		Daily	-0.009	0.008	-1.055	-0.043	0.013	-3.24	1.44
	Weekend	Daily	-0.002	0.013	-0.135	0.040	0.012	3.24	n/a
All	Critical	Substitution	-0.033	0.005	-6.372	n/a	n/a	n/a	n/a
		Daily	-0.007	0.008	-0.870	n/a	n/a	n/a	n/a
	Normal Weekday	Substitution	-0.033	0.005	-6.386	-0.012	0.007	-1.82	-2.40
		Daily	-0.003	0.009	-0.360	-0.043	0.013	-3.24	2.09
	Weekend	Daily	0.007	0.012	0.560	0.040	0.012	3.23	n/a

Table 4-20 also shows the difference between weekend daily elasticities in the outer versus inner winter. The weekend daily elasticities in the inner winter are slightly positive but not significant whereas the outer winter values are positive and significant, indicating that treatment customers, in spite of lower weekend energy prices, use less energy on weekends than do their control group counterparts.

Also shown in Table 4-20 are the critical day elasticities for the inner winter period. There were only three critical days during the inner winter and none in the outer winter. As was true for normal weekdays, there is very little variation in the elasticity of substitution across the four climate zones. Although there is some variation across zones in the daily elasticity, the average value is close to zero and not significant.

Table 4-21 shows the impacts for the inner winter period on both critical and normal weekdays. The statewide impact during the peak period is -4.73 percent on critical days and -1.80 percent on normal weekdays. The impacts in other periods and on weekends are largely zero.

Table 4-21 Residential CPP-F Rate Impact Estimates For Inner Winter								
Zone	**Day Type**	**Rate Period**	**Starting Value (kWh/hr)**	**Impact (kWh/hr)**	**Standard Error**	**t-stat**	**Impact (%)**	**Standard Error (%)**
1	Critical	P	0.84	-0.041	0.008	-5.10	-4.89	0.96
		OP	0.71	0.006	0.004	1.68	0.86	0.51
		Daily	0.74	-0.004	0.004	-1.04	-0.50	0.48
	Normal Weekday	P	0.71	-0.013	0.002	-5.92	-1.88	0.32
		OP	0.63	0.003	0.001	5.66	0.53	0.09
		Daily	0.65	0.000	0.000	-0.60	-0.02	0.04
	Weekend	Daily	0.65	0.000	0.001	-0.35	-0.07	0.21
2	Critical	P	0.84	-0.038	0.007	-5.27	-4.58	0.87
		OP	0.69	0.008	0.003	2.24	1.10	0.49
		Daily	0.72	-0.002	0.003	-0.58	-0.27	0.47
	Normal Weekday	P	0.83	-0.014	0.002	-6.32	-1.72	0.27
		OP	0.69	0.004	0.001	6.38	0.54	0.09
		Daily	0.72	0.000	0.000	-0.15	0.00	0.02
	Weekend	Daily	0.74	-0.001	0.002	-0.81	-0.19	0.24
3	Critical	P	0.97	-0.045	0.008	-5.55	-4.69	0.85
		OP	0.78	0.008	0.004	2.23	1.02	0.46
		Daily	0.82	-0.003	0.004	-0.90	-0.39	0.43
	Normal Weekday	P	0.91	-0.017	0.003	-6.26	-1.87	0.30
		OP	0.77	0.004	0.001	6.26	0.58	0.09
		Daily	0.80	0.000	0.000	-0.38	0.00	0.00
	Weekend	Daily	0.83	-0.001	0.002	-0.46	-0.12	0.27
4	Critical	P	0.91	-0.048	0.009	-5.37	-5.26	0.98
		OP	0.77	0.005	0.005	0.92	0.59	0.64
		Daily	0.80	-0.006	0.005	-1.29	-0.80	0.62
	Normal Weekday	P	0.89	-0.016	0.003	-6.10	-1.82	0.30
		OP	0.76	0.004	0.001	6.09	0.55	0.09
		Daily	0.79	0.000	0.000	-1.05	0.00	0.00
	Weekend	Daily	0.83	0.000	0.002	0.13	0.04	0.28
All Avg. Customer Approach	Critical	P	0.89	-0.042	0.008	-5.56	-4.72	0.85
		OP	0.73	0.007	0.003	2.13	0.99	0.47
		Daily	0.76	-0.003	0.003	-0.87	-0.39	0.45
	Normal Weekday	P	0.85	-0.015	0.002	-6.39	-1.80	0.28
		OP	0.71	0.004	0.001	6.44	0.55	0.09
		Daily	0.74	0.000	0.000	-0.36	0.00	0.01
	Weekend	Daily	0.77	-0.001	0.002	-0.56	-0.14	0.24
All Zonal Average Approach	Critical	P	0.88	-0.042	n/a	n/a	-4.73	n/a
		OP	0.73	0.007	n/a	n/a	0.99	n/a
		Daily	0.76	-0.003	n/a	n/a	-0.39	n/a
	Normal Weekday	P	0.85	-0.015	n/a	n/a	-1.80	n/a
		OP	0.71	0.004	n/a	n/a	0.55	n/a
		Daily	0.74	0.000	n/a	n/a	0.00	n/a
	Weekend	Daily	0.77	-0.001	n/a	n/a	-0.13	n/a

Table 4-22 shows the impacts for the outer winter period for normal weekdays and weekends. All of the impacts fall into the +/- 1 percent range.

Table 4-22
Residential CPP-F Rate
Impact Estimates For Outer Winter

Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	Normal Weekday	P	0.57	-0.005	0.002	-2.244	-0.904	0.403
		OP	0.54	0.001	0.001	0.878	0.099	0.113
		Daily	0.54	-0.001	0.000	-3.088	-0.122	0.039
	Weekend	Daily	0.58	-0.004	0.001	-3.107	-0.760	0.245
2	Normal Weekday	P	0.72	-0.006	0.003	-2.162	-0.799	0.369
		OP	0.60	0.001	0.001	1.665	0.190	0.114
		Daily	0.63	0.000	0.000	-3.227	-0.046	0.014
	Weekend	Daily	0.65	-0.005	0.002	-3.189	-0.818	0.256
3	Normal Weekday	P	0.82	-0.005	0.003	-1.508	-0.589	0.391
		OP	0.69	0.001	0.001	1.189	0.144	0.121
		Daily	0.71	0.000	0.000	-3.238	-0.031	0.010
	Weekend	Daily	0.75	-0.007	0.002	-3.235	-0.895	0.277
4	Normal Weekday	P	0.84	-0.005	0.003	-1.509	-0.566	0.375
		OP	0.71	0.002	0.001	1.819	0.218	0.120
		Daily	0.73	0.000	0.000	3.236	0.031	0.009
	Weekend	Daily	0.78	-0.007	0.002	-3.252	-0.918	0.282
All Avg. Customer Approach	Normal Weekday	P	0.74	-0.005	0.003	-1.928	-0.728	0.378
		OP	0.63	0.001	0.001	1.457	0.168	0.115
		Daily	0.65	0.000	0.000	-3.239	-0.044	0.014
	Weekend	Daily	0.69	-0.006	0.002	-3.239	-0.846	0.261
All Zonal Average Approach	Normal Weekday	P	0.74	-0.005	n/a	n/a	-0.713	n/a
		OP	0.63	0.001	n/a	n/a	0.169	n/a
		Daily	0.65	0.000	n/a	n/a	-0.040	n/a
	Weekend	Daily	0.69	-0.006	n/a	n/a	-0.849	n/a

Regression models were also run in which seasonal variation was not allowed. The all-winter average elasticities are shown in Table 4-23. As expected, these elasticity estimates fall within the range of the inner and outer winter elasticities. The average elasticity of substitution across the four climate zones is -0.025 for both critical and normal weekdays and is statistically significant in both cases, with a t-statistic of –6.07 and –6.11, respectively. The average daily elasticity does varies day types: on critical days, the value is about 40 percent less (and not significant) than on normal weekdays. This result is similar to the values reported above for the inner and outer winter. Also similarly, the weekend daily elasticities are positive.

Table 4-23 Residential CPP-F Rate Elasticity Estimates for the Entire Winter Period					
Zone	Day Type	Elasticity Type	All Winter		
			Estimate	SE	t-statistic
1	Critical	Substitution	-0.027	0.005	-5.94
		Daily	-0.010	0.007	-1.33
	Normal Weekdays	Substitution	-0.026	0.004	-6.16
		Daily	-0.017	0.007	-2.35
	Weekend	Daily	0.020	0.009	2.29
2	Critical	Substitution	-0.026	0.004	-6.17
		Daily	-0.013	0.007	-1.95
	Normal Weekdays	Substitution	-0.026	0.004	-6.17
		Daily	-0.020	0.008	-2.42
	Weekend	Daily	0.025	0.009	2.98
3	Critical	Substitution	-0.024	0.004	-5.60
		Daily	-0.011	0.007	-1.54
	Normal Weekdays	Substitution	-0.024	0.004	-5.80
		Daily	-0.019	0.008	-2.42
	Weekend	Daily	0.023	0.008	2.71
4	Critical	Substitution	-0.024	0.004	-5.28
		Daily	-0.004	0.010	-0.40
	Normal Weekdays	Substitution	-0.024	0.004	-5.78
		Daily	-0.017	0.007	-2.34
	Weekend	Daily	0.019	0.009	2.22
All	Critical	Substitution	-0.025	0.004	-6.08
		Daily	-0.011	0.007	-1.58
	Normal Weekdays	Substitution	-0.025	0.004	-6.11
		Daily	-0.019	0.008	-2.42
	Weekend	Daily	0.023	0.008	2.76

Table 4-24 shows the estimates for the average impact across the entire winter, based on the average prices used in the pilot. The winter average peak-period price was \$0.61/kWh and the off-peak price was \$0.11/kWh. As seen, the average critical day, peak-period impact hovers around 4 percent, notably less than the average summer impact of around 14 percent. The peak period impact on normal weekdays was less than 2 percent for the state as a whole.

Table 4-24
Residential CPP-F Rate
Impact Estimates For All Winter

Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	Critical	P	0.84	-0.036	0.007	-5.41	-4.25	0.79
		OP	0.71	0.004	0.003	1.19	0.55	0.46
		Daily	0.74	-0.004	0.003	-1.32	-0.58	0.44
	Normal Weekday	P	0.64	-0.010	0.002	-6.31	-1.56	0.25
		OP	0.58	0.002	0.000	5.24	0.37	0.07
		Daily	0.59	0.000	0.000	-2.35	-0.06	0.03
	Weekend	Daily	0.62	-0.002	0.001	-2.29	-0.36	0.16
2	Critical	P	0.84	-0.034	0.006	-5.87	-4.09	0.70
		OP	0.69	0.002	0.003	0.79	0.31	0.40
		Daily	0.72	-0.005	0.003	-1.96	-0.75	0.38
	Normal Weekday	P	0.77	-0.011	0.002	-6.28	-1.39	0.22
		OP	0.64	0.003	0.000	5.81	0.40	0.07
		Daily	0.67	0.000	0.000	-2.42	-0.03	0.01
	Weekend	Daily	0.70	-0.004	0.001	-2.98	-0.51	0.17
3	Critical	P	0.97	-0.036	0.007	-5.24	-3.70	0.71
		OP	0.78	0.003	0.003	1.04	0.42	0.40
		Daily	0.82	-0.005	0.003	-1.54	-0.59	0.38
	Normal Weekday	P	0.86	-0.012	0.002	-5.85	-1.38	0.24
		OP	0.73	0.003	0.001	5.76	0.42	0.07
		Daily	0.76	0.000	0.000	-2.42	-0.01	0.00
	Weekend	Daily	0.80	-0.004	0.002	-2.72	-0.52	0.19
4	Critical	P	0.91	-0.031	0.008	-4.02	-3.39	0.84
		OP	0.77	0.006	0.004	1.30	0.76	0.58
		Daily	0.80	-0.002	0.005	-0.40	-0.23	0.56
	Normal Weekday	P	0.86	-0.011	0.002	-5.80	-1.33	0.23
		OP	0.73	0.003	0.001	5.82	0.41	0.07
		Daily	0.76	0.000	0.000	2.34	0.00	0.00
	Weekend	Daily	0.81	-0.003	0.002	-2.22	-0.43	0.19
All Avg. Customer Approach	Critical	P	0.89	-0.035	0.006	-5.58	-3.92	0.70
		OP	0.73	0.003	0.003	1.03	0.42	0.41
		Daily	0.76	-0.005	0.003	-1.59	-0.63	0.40
	Normal Weekday	P	0.79	-0.011	0.002	-6.20	-1.40	0.23
		OP	0.67	0.003	0.000	5.85	0.40	0.07
		Daily	0.70	0.000	0.000	-2.42	-0.02	0.01
	Weekend	Daily	0.73	-0.004	0.001	-2.77	-0.49	0.18
All Zonal Average Approach	Critical	P	0.88	-0.035	n/a	n/a	-3.91	n/a
		OP	0.73	0.003	n/a	n/a	0.43	n/a
		Daily	0.76	-0.005	n/a	n/a	-0.62	n/a
	Normal Weekday	P	0.79	-0.011	n/a	n/a	-1.39	n/a
		OP	0.67	0.003	n/a	n/a	0.40	n/a
		Daily	0.70	0.000	n/a	n/a	-0.02	n/a
	Weekend	Daily	0.73	-0.004	n/a	n/a	-0.49	n/a

4.5 ANNUAL IMPACTS

The change in annual energy use was calculated for the average CPP-F prices that were used in the pilot. The calculation was done at the zonal level by using starting values and impacts estimated separately for the inner and outer summer and inner and outer winter periods for each day type (e.g., critical days, normal weekdays and weekends). The population-weighted average change in energy use across all zones is zero. The change in each zone is essentially zero as well (-0.04 percent in zone 1, -0.01 percent in zone 2, 0.02 percent in zone 3 and –0.01 percent in zone 4).

4.6 INFORMATION ONLY TREATMENT

The Information Only treatment was included primarily as a cross-check on the results of the CPP-F rate treatment. Specifically, it's purpose is to determine whether simply appealing for a reduction in energy use on critical days might produce significant impacts even in the absence of any price incentive. If this were true, dynamic demand-response could be achieved at a much lower cost than that associated with a CPP-F rate as there would be no need for the interval metering that is required when dynamic tariffs are implemented.

In order to test the hypotheses that customers might reduce peak-period energy use in response to a critical event notification, customers were recruited for the Information Only treatment from PG&E's climate zones 2 and 3. These customers were given educational material in the form of a welcome package that provided information on how to reduce loads, and they were notified in the same manner as were CPP-F customers when critical days were called. However, participant's prices did not change from what they were prior to going on the treatment—that is, participants were not on time varying rates.

In order to test for the impact of critical-day notifications on peak-period energy use, a binary variable was used in both the substitution and daily energy use equations. The variable is equal to 1 for Information Only treatment customers on critical days, zero otherwise. If treatment customers reduced demand during the peak period on critical days, or reduced demand overall on critical days in response to the notification, the coefficient on the binary variable would be statistically significant and have a negative value. Separate models were estimated for each climate zone and each year. The regression results are summarized in Table 4-25. Regressions were run using the statewide sample as a control group as well as using a subset of the statewide sample consisting of just PG&E customers, since the treatment group was located only in PG&E's service territory. The value of the coefficients were similar in both cases, but the t-statistics for the regressions using the statewide control were larger, probably due to the larger sample sizes. The results reported here are based on the statewide control group.

Table 4-25 Coefficient On Binary Variable Representing Critical Day Notification For Information Only Treatment Customers					
Climate Zone	**Year**	**Substitution Equation Coefficient**	**t- statistic**	**Daily Energy Equation Coefficient**	**t-statistic**
2	**2003**	0.001	0.04	-0.022	-1.84
3	**2003**	-0.101	-3.86	-0.026	-1.87
2	**2004**	0.036	1.35	0.014	0.86
3	**2004**	0.010	0.28	0.017	0.85

As seen in the table, the critical-day notification appears to have little impact on the ratio of peak-to-off-peak energy use on critical days in climate zone 2 in either 2003 or 2004. Both the regression coefficient and the t-statistic are very close to zero in 2003 and the coefficient is positive in 2004, but highly insignificant. The same thing can be said for climate zone 3 in 2004. However, in 2003, the price coefficient is large and highly significant, with a t-statistic equal to –3.86. We examined the data to try and identify what might be causing the anomaly of a large impact in zone 3 in 2003 and found nothing. Nevertheless, given the absence of any significant impact in zone 2 in 2003, and the fact that the large impact in zone 3 in 2003 is completely absent in 2004, at a minimum, we believe it is fair to conclude that the impact of critical day notification on the usage ratio in the absence of price signals is not sustainable. Furthermore, we believe it is reasonable to consider that the zone 3, 2003 estimate is an unexplained anomaly. In other words, it is not unreasonable, in our opinion, to conclude that there is no credible evidence from this experiment that there is any impact from the Information Only treatment on the ratio of peak-period energy use to off-peak energy use.

It would appear from the results summarized in Table 4-25 that there may have been some modest impact of the critical-day notification on daily energy use on critical days in 2003. The coefficients are almost identical in climate zones 2 and 3, as are the t-statistics, which indicate that the treatment is significant at the 90 percent confidence level (but not at the 95 percent level of confidence). However, the modest impact disappears completely in both zones in 2004. Indeed, the results suggest that treatment customers actually use a bit more energy on critical days than do control customers, although the difference is not statistically significant. Again, at a minimum, one can conclude that the influence of the information treatment is not sustainable.

4.7 TRACK B ANALYSIS

The Track B treatment examined whether customer price responsiveness can be enhanced by an information treatment, provided in the context of a community program housed within a contiguous geographic area faced with environmental problems associated with power generation. This section provides a brief summary of the Track B pilot design. Additional details on the design and a presentation of the results are contained in a separate report produced by San Francisco Community Power (SF Power), the contractor that implemented and evaluated the Track B treatments. See *Statewide Pricing Pilot—Track B: Evaluation of Community-Based Enhanced Information Treatment*, Draft Final Report, March 8, 2005.

Track B customers were located within the service area of Pacific Gas & Electric company. They were located entirely within climate zone 1 but had very different socio-economic and demographic characteristics from the average zone 1 customer. Track B customers reside in the Bay View, Hunters Point, and Potrero Hill districts of San Francisco (home to two aging power plants that generate above-average levels of air pollutants). SF Power provided these customers with information about the economic and environmental consequences associated with peak power energy use, and informed them of the potential to reduce reliance on a locally polluting power plant through adoption of the CPP-F tariff. Participants received educational information regularly to reinforce this message and were informed through a variety of communication channels when critical peak prices were in effect. The SPP also included a control group of PG&E customers randomly selected from another Bay Area community [Richmond] situated near a known and publicized environmental hazard. Customers in Richmond had similar socio-economic and demographic characteristics to those in the Hunter's Point/Bay View area, in addition to being located in a similar climatic region.

Track B began on July 14, 2003 and the new rates went into effect on August 14, 2003. Winter treatments began on November 1, 2003 and continued through April 30, 2004. Summer 2004 began on May 1, 2004 and continued through October 31, 2004.

The pilot design for Track B allows for the estimation of two treatments. One involves estimating the impact of the CPP-F rate, conditional on both treatment and control customers receiving an extended community-based information treatment. The other involves comparing the impact of the extended information treatment, conditional on both groups being on the CPP-F rate.

Table 4-26 summarizes the experimental design for Track B. It should be noted that there is no pure control group that received neither an information treatment nor a price treatment. As such, it is not possible to estimate the impact of information without a dynamic rate or the impact of the dynamic rate without information.

Table 4-26
Overview of Track B Pilot Design

Treatment Type		CPP-F Rate	
		Yes	**No**
Information	**Yes**	CELLID = B02 Reference Name = Treatment Values: TREATMENT =1, INFORMATION = 1. Location = Hunters Point, CA	CELLID = B01 Reference Name: Rate Control Values: TREATMENT =0, INFORMATION = 1. Location = Hunters Point, CA
	No	CELLID = B03 Reference Name = Information Control Values: TREATMENT =1, INFORMATION = 0. Location = Richmond, CA	NA There are no customers for this combination. Values: TREATMENT =0, INFORMATION = 0.

The Track B analysis involved three comparisons. One involved a regression using the B01 and B02 cells only, both of which are located in Hunter's Point. A second comparison involved the B02 and B03 cells and a third involved all three cells.

As with Track A, the Track B model specification included two equations, one for modeling peak/off-peak substitution and one for modeling daily electricity consumption. Each equation included an intercept term, a price term and a weather term. In addition, when measuring the impact of the extended information treatment on price responsiveness, a binary variable representing the provision of information was interacted with the price term.

5. Residential TOU Rate Treatment

This section examines the impact of the residential TOU rate on energy use by rate period. Before discussing the results, it is useful to recall the purpose of the TOU treatment cells in the design of the SPP. The CPP-F tariff consists of a TOU rate that differs on critical and normal weekdays. As such, the CPP-F rate can be used to estimate response to both the very high peak-period prices on critical days as well as the more moderate TOU rates on normal weekdays. However, in the early design stages of the SPP, some felt that it would be useful to have a pure TOU treatment to allow for comparisons with other studies. Since there was a fixed budget for conducting the SPP, the bulk of it was devoted to populating the CPP-F treatment cells, given that there was greater uncertainty about customer response to CPP-F rates than to TOU rates and greater potential benefits that might be achievable from these dynamic rates. As such, the final sample design allocated only 57 customers on average to each TOU treatment cell versus 161 customers on average for each climate zone for the CPP-F rate.

The TOU rate analysis relied on the same control groups that were used to analyze the impact of the CPP-F treatment. Like the CPP-F treatment, the TOU treatment was implemented statewide and customers were segmented into the same four climate zones.[56]

Table 5-1 shows the average TOU prices that were used in the experiment. The average peak-period price across the two summers for high price-ratio customers was $0.24/kWh and the off-peak price was $0.09/kWh, for a peak-to-off-peak price ratio of roughly 2.7 to 1. The price ratio for low-ratio customers was roughly 1.7 to 1 while the average price ratio across the two prices was 2.2 to 1. During the winter period, customers that faced the high price ratio in the summer were placed on the low price ratio and customers that faced the low price ratio in the summer were given the high price ratio. The average peak-period price in the winter was $0.19/kWh.

[56] In light of the small sample sizes associated with this treatment, the statewide allocation of samples to SDG&E was very small. Consequently, to simplify pilot implementation, the original samples allocated to SDG&E were reallocated to SCE and PG&E. That is, no SDG&E customers were included in the TOU rate treatment.

Table 5-1 Average Prices For Residential TOU Tariff						
Season	**Customer Segment**	**Day Type**	**Rate Period**	**High Ratio ($/kWh)**	**Low Ratio ($/kWh)**	**Average ($/kWh)**
Summer (03/04)	**Control**	**All**	**All**		0.13	
	Treatment	**Weekday**	**Peak**	0.24	0.20	0.22
			Off-peak	0.09	0.12	0.10
			Daily	0.13	0.14	0.13
		Weekend	**Daily**	0.09	0.12	0.10
Winter	**Control**	**All**	**All**		0.13	
	Treatment	**Weekday**	**Peak**	0.18	0.20	0.19
			Off-peak	0.12	0.09	0.11
			Daily	0.13	0.12	0.12
		Weekend	**Daily**	0.12	0.09	0.11

5.1 SUMMER ANALYSIS

The model specification used for the summer TOU rate analysis was quite similar to the one that was used for the CPP-F analysis. The model included price interaction terms for weather and central air conditioning ownership. Preliminary model runs indicated that, once these variables were included, there were no significant differences across climate zones. Consequently, the models were run on data pooled across the four zones.

Separate model runs were initially made for each of the two summers over which the SPP operated. Unlike with the CPP-F tariff, where differences across the summers were minor, these initial results indicated that there were significant differences in response across the two summers. Consequently, we pooled the data across the two summers and used a binary variable representing the summer of 2004 interacting with each price term in the specification to test conclusively whether there were statistically significant differences. A binary variable representing the inner and outer summer periods was also included in the specification, interacted with each of the price terms.

Table 5-2 summarizes the elasticity estimates associated with each of the inner summer periods and with the outer summer, which spans 2003 and 2004. The last column of the table shows the t-statistic associated with the differential between 2003 and 2004 for the inner summer period. Examining the statewide values first, the most dramatic finding is the large change in the elasticity of substitution between the two summers. In 2003, the estimated elasticity of substitution in the inner summer equaled –0.099 and was highly significant, with a t-statistic equal to –10.17. This value is similar to the summer 2003 elasticity of substitution for the CPP-F rate, which equals –0.090 (see Table 4-2). Indeed,

-0.090 is within two standard deviations of the TOU value (based on the TOU standard error estimate of 0.010). In contrast to the CPP-F analysis, which showed no statistically significant change in the elasticity of substitution between the two summers, the elasticity of substitution for the TOU rate essentially dropped to zero in the inner summer of 2004. This dramatic decline in price responsiveness is evident not just statewide but also in every climate zone.

Table 5-2
Elasticity Estimates for the Residential TOU Treatment

			Inner Summer 2003			Outer Summer 2003/2004			Inner Summer 2004			03/04 Diff
Zone	Day Type	Elasticity Type	Estimate	SE	t- stat	Estimate	SE	t- stat	Estimate	SE	t- stat	t- stat
1	Weekday	Sub	-0.073	0.013	-5.79	-0.045	0.014	-3.24	0.005	0.016	0.32	3.82
		Daily	-0.090	0.023	-3.89	-0.104	0.023	-4.43	-0.107	0.037	-2.90	-0.44
	Weekend	Daily	-0.007	0.019	-0.39	0.019	0.020	0.96	0.041	0.025	1.64	n/a
2	Weekday	Sub	-0.090	0.010	-8.64	-0.057	0.012	-4.73	0.001	0.013	0.07	5.35
		Daily	-0.109	0.020	-5.46	-0.123	0.021	-5.90	-0.125	0.032	-3.87	-0.44
	Weekend	Daily	-0.042	0.016	-2.64	-0.004	0.018	-0.24	0.002	0.022	0.11	n/a
3	Weekday	Sub	-0.120	0.011	-11.29	-0.077	0.012	-6.55	-0.007	0.014	-0.47	6.39
		Daily	-0.142	0.019	-7.45	-0.159	0.021	-7.63	-0.155	0.030	-5.15	-0.37
	Weekend	Daily	-0.104	0.015	-6.76	-0.051	0.017	-2.95	-0.069	0.022	-3.21	n/a
4	Weekday	Sub	-0.109	0.013	-8.51	-0.071	0.015	-4.85	0.018	0.018	0.99	5.77
		Daily	-0.118	0.031	-3.81	-0.168	0.032	-5.21	-0.127	0.053	-2.38	-0.14
	Weekend	Daily	-0.137	0.026	-5.35	-0.075	0.024	-3.11	-0.126	0.038	-3.27	n/a
All	Weekday	Sub	-0.099	0.010	-10.17	-0.063	0.011	-5.61	0.001	0.013	0.06	6.21
		Daily	-0.117	0.019	-6.26	-0.137	0.020	-6.72	-0.132	0.030	-4.42	-0.42
	Weekend	Daily	-0.066	0.015	-4.49	-0.023	0.017	-1.38	-0.028	0.021	-1.36	n/a

The change in the daily price elasticity across the two years was much more modest than the change in the elasticity of substitution. There actually was a nominal increase in the daily price elasticity from 2003 to 2004, but the change is not statistically significant.[57] The daily price elasticities estimated for the TOU rate in both summers are significantly larger than those estimated for the CPP-F rate. This would suggest that the primary impact of the TOU rate, indeed the only impact in 2004, is load reduction overall, not load

[57] Recall from Section 4 that the CPP-F daily elasticity also increased between the two summers (see Table 4-3)

shifting. However, this conclusion must be tempered by the fact that the variation in the average daily price between treatment and control customers and between high-ratio and low-ratio customers is very small.[58] This fact could suggest that the estimated daily price elasticities have less to do with prices than they do with the education and awareness regarding energy costs and ways to reduce cost that customers received through participation in the pilot. That is, they may represent more of an education impact than a price impact.

Table 5-2 also shows the elasticity estimates for the outer summer. Recall that the outer summer is based on October 2003 and May and June 2004. The elasticity of substitution in the outer summer is -0.063 and is statistically significant with a t-statistic equal to –5.61. It is roughly 40 percent less than the summer 2003 value. Given the significant drop in the elasticity of substitution in the inner summer between 2003 and 2004, it is difficult to know how much of the inner-summer/outer-summer difference is due to seasonality and how much of it is due to the drop-off in responsiveness in the second year of the experiment.

Tables 5-3 through 5-5 contain impact estimates for the inner summer of 2003, the inner summer of 2004, and the outer summer (which spans the two years), respectively. Recall from the discussion in Section 4 that there are two approaches to estimating the statewide average, the “average customer” approach and the “zonal weighted average” approach. The latter approach is more accurate but it is more difficult to estimate standard errors using this approach. Thus, we use the standard errors and t-statistics based on the average customer approach as a proxy for the statistics associated with the zonal average impact estimates.

As seen in Table 5-3, the statewide average impact on peak-period energy use in the inner summer of 2003, based on the average SPP price for TOU customers, was –5.92 percent and it was highly significant. Off-peak energy use increased by 1.53 percent and the change in daily energy use was a modest –0.59 percent. The peak-period impact is very similar to the impact of the CPP-F rate on normal weekdays, -4.15 percent, reported in Table 4-7. Off-peak and daily impacts for the CPP-F treatment on normal weekdays, 1.77 percent and 0.13 percent, respectively, are also comparable to the TOU impacts.

The variation in impacts across climate zones in 2003 is quite small. The peak-period impacts range from a low of –4.67 percent in climate zone 1 to a high of –6.72 percent in climate zone 4. This modest variation reflects the offsetting influences of weather and air conditioning saturations in the underlying regression equations. Unlike for the CPP-F regressions, where the coefficients on both the weather and CAC interaction terms were negative, in the TOU regressions, the coefficient on the price/CAC interaction term was negative and highly significant, with a t-statistic equal to –6.90, while the coefficient on the price/weather interaction term was positive, with a t-statistic equal to 2.66. With both air

[58] As seen in Table 4-1, daily prices for the CPP-F tariff varied by more than a factor of two between critical and normal weekdays and by more than a factor of three between critical days and weekends. For the TOU tariff, there is no variation across weekdays, the weekday/weekend variation is less than 1.5 to one, and the cross-sectional variation (e.g., across high and low price ratio customers) is very small.

conditioning saturation and cooling degree hours increasing going from climate zone 1 to climate zone 4, the countervailing influences largely offset each other.

As seen in Table 5-4, the statewide impacts in summer 2004 were close to zero in both the peak and off-peak periods, reflecting the significant decline in the estimated elasticity of substitution between 2003 and 2004. The average daily impact was roughly the same between the two summers. There was very little variation in the impacts across climate zones.

As seen in Table 5-5, the outer summer, peak-period impact was –4.21 percent. This is roughly 1.5 percentage points less than the 2003 inner summer value. The difference is approximately equal to two-standard deviations from the outer summer estimate. The zonal variation was comparable to that of the inner summer 2003 variation.

Table 5-3
Residential TOU Rate Impact Estimates for Inner Summer 2003

Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	Weekday	P	0.487	-0.023	0.004	-6.26	-4.67	0.75
		OP	0.463	0.004	0.001	3.84	0.82	0.21
		Daily	0.468	-0.002	0.000	-3.90	-0.37	0.09
	Weekend	Daily	0.485	0.001	0.002	0.39	0.13	0.34
2	Weekday	P	0.814	-0.039	0.004	-9.02	-4.77	0.53
		OP	0.618	0.009	0.001	7.96	1.44	0.18
		Daily	0.659	-0.001	0.000	-5.46	-0.16	0.03
	Weekend	Daily	0.687	0.006	0.002	2.63	0.91	0.35
3	Weekday	P	1.537	-0.102	0.008	-12.44	-6.67	0.54
		OP	0.898	0.017	0.002	7.81	1.87	0.24
		Daily	1.031	-0.008	0.001	-7.48	-0.78	0.10
	Weekend	Daily	1.107	0.027	0.004	6.68	2.44	0.37
4	Weekday	P	2.094	-0.141	0.016	-9.07	-6.72	0.74
		OP	1.197	0.016	0.005	3.25	1.32	0.41
		Daily	1.384	-0.017	0.004	-3.83	-1.22	0.32
	Weekend	Daily	1.433	0.040	0.008	5.28	2.81	0.53
All Average Customer Approach	Weekday	P	1.125	-0.063	0.006	-11.08	-5.60	0.51
		OP	0.744	0.011	0.002	7.08	1.44	0.20
		Daily	0.823	-0.005	0.001	-6.28	-0.57	0.09
	Weekend	Daily	0.867	0.013	0.003	4.46	1.45	0.32
All Zonal Average Approach	Weekday	P	1.122	-0.066	n/a	n/a	-5.92	n/a
		OP	0.743	0.011	n/a	n/a	1.53	n/a
		Daily	0.822	-0.005	n/a	n/a	-0.59	n/a
	Weekend	Daily	0.865	0.015	n/a	n/a	1.77	n/a

Table 5-4 Residential TOU Rate Impact Estimates for Inner Summer 2004								
Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat (%)	Impact	Standard Error (%)
1	Weekday	P	0.487	-0.001	0.005	-0.13	-0.13	1.00
		OP	0.463	-0.002	0.001	-1.79	-0.53	0.29
		Daily	0.468	-0.002	0.001	-2.91	-0.44	0.15
	Weekend	Daily	0.485	-0.004	0.002	-1.64	-0.75	0.46
2	Weekday	P	0.814	-0.001	0.006	-0.18	-0.13	0.71
		OP	0.618	-0.001	0.001	-0.82	-0.20	0.24
		Daily	0.659	-0.001	0.000	-3.87	-0.18	0.05
	Weekend	Daily	0.687	0.000	0.003	-0.11	-0.05	0.47
3	Weekday	P	1.537	-0.018	0.012	-1.57	-1.18	0.75
		OP	0.898	-0.006	0.003	-2.09	-0.70	0.34
		Daily	1.031	-0.009	0.002	-5.17	-0.85	0.16
	Weekend	Daily	1.107	0.018	0.006	3.19	1.61	0.51
4	Weekday	P	2.094	-0.008	0.024	-0.35	-0.40	1.13
		OP	1.197	-0.021	0.008	-2.68	-1.72	0.64
		Daily	1.384	-0.018	0.008	-2.40	-1.30	0.54
	Weekend	Daily	1.433	0.037	0.011	3.23	2.57	0.80
All Average Customer Approach	Weekday	P	1.125	-0.007	0.008	-0.85	-0.60	0.70
		OP	0.744	-0.005	0.002	-2.33	-0.65	0.28
		Daily	0.823	-0.005	0.001	-4.44	-0.64	0.14
	Weekend	Daily	0.867	0.005	0.004	1.36	0.61	0.45
All Zonal Average Approach	Weekday	P	1.122	-0.007	n/a	n/a	-0.61	n/a
		OP	0.743	-0.005	n/a	n/a	-0.66	n/a
		Daily	0.822	-0.005	n/a	n/a	-0.65	n/a
	Weekend	Daily	0.865	0.009	n/a	n/a	0.99	n/a

Table 5-5 Residential TOU Rate Impact Estimates for Outer Summer 2003 and 2004								
Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat (%)	Impact	Standard Error (%)
1	Weekday	P	0.515	-0.016	0.004	-3.78	-3.16	0.84
		OP	0.487	0.001	0.001	1.15	0.28	0.24
		Daily	0.493	-0.002	0.001	-4.44	-0.47	0.11
	Weekend	Daily	0.507	-0.002	0.002	-0.96	-0.34	0.36
2	Weekday	P	0.687	-0.022	0.004	-4.85	-3.13	0.65
		OP	0.575	0.005	0.001	4.57	0.93	0.20
		Daily	0.598	0.000	0.000	-5.90	-0.05	0.01
	Weekend	Daily	0.616	0.001	0.002	0.24	0.10	0.39
3	Weekday	P	1.023	-0.051	0.007	-7.67	-5.03	0.66
		OP	0.717	0.006	0.002	3.13	0.78	0.25
		Daily	0.781	-0.006	0.001	-7.66	-0.81	0.11
	Weekend	Daily	0.821	0.009	0.003	2.93	1.15	0.39
4	Weekday	P	1.356	-0.073	0.012	-6.31	-5.39	0.85
		OP	0.871	-0.001	0.004	-0.27	-0.11	0.42
		Daily	0.972	-0.016	0.003	-5.25	-1.65	0.31
	Weekend	Daily	1.029	0.015	0.005	3.09	1.44	0.46
All Average Customer Approach	Weekday	P	0.839	-0.033	0.005	-6.39	-3.96	0.62
		OP	0.639	0.004	0.001	3.15	0.68	0.22
		Daily	0.680	-0.003	0.001	-6.74	-0.51	0.08
	Weekend	Daily	0.709	0.003	0.003	1.38	0.49	0.36
All Zonal Average Approach	Weekday	P	0.836	-0.035	n/a	n/a	-4.21	n/a
		OP	0.637	0.004	n/a	n/a	0.67	n/a
		Daily	0.678	-0.004	n/a	n/a	-0.58	n/a
	Weekend	Daily	0.707	0.004	n/a	n/a	0.63	n/a

5.2 WINTER ANALYSIS

Table 5-6 contains estimates for the elasticity of substitution and daily price elasticity for the TOU rate during the winter period. As seen, the difference in estimates for the elasticity of substitution between the inner and outer winter are statistically significant but the differences in daily elasticities are not. The values for both the elasticity of substitution and the daily price elasticity are quite large. Indeed, the inner winter value for the elasticity of substitution is larger than the inner summer value for both the TOU and CPP-F rate treatments, and the daily elasticity is much larger than the estimates for any of the other treatments or seasons. Such large estimates, and such large differences from the other estimated values (even for the same treatment group), are troubling and may indicate a problem that we have not been able to identify.

Table 5-6
Residential TOU Price Elasticities

Zone	Day Type	Elasticity Type	Inner Winter			Outer Winter			Inner Differential	Inner Differential
			Estimate	SE	t-statistic	Estimate	SE	t-statistic	SE	t-statistic
1	Weekday	Substitution	-0.106	0.014	-7.468	-0.027	0.013	-2.01	0.02	-3.99
		Daily	-0.233	0.036	-6.451	-0.171	0.037	-4.59	0.06	-1.07
	Weekend	Daily	-0.158	0.025	-6.223	-0.044	0.027	-1.64	n/a	n/a
2	Weekday	Substitution	-0.109	0.014	-8.087	-0.028	0.013	-2.10	0.02	-4.24
		Daily	-0.248	0.037	-6.663	-0.178	0.038	-4.68	0.05	-1.28
	Weekend	Daily	-0.162	0.026	-6.336	-0.049	0.026	-1.90	n/a	n/a
3	Weekday	Substitution	-0.114	0.014	-8.293	-0.019	0.014	-1.37	0.02	-4.74
		Daily	-0.240	0.036	-6.596	-0.176	0.038	-4.69	0.06	-1.13
	Weekend	Daily	-0.159	0.025	-6.277	-0.048	0.026	-1.87	n/a	n/a
4	Weekday	Substitution	-0.115	0.014	-8.227	-0.021	0.014	-1.55	0.02	-4.56
		Daily	-0.218	0.038	-5.806	-0.177	0.038	-4.69	0.06	-0.63
	Weekend	Daily	-0.155	0.027	-5.787	-0.047	0.026	-1.82	n/a	n/a
All	Weekday	Substitution	-0.111	0.013	-8.237	-0.024	0.013	-1.83	0.02	-4.50
		Daily	-0.241	0.036	-6.606	-0.176	0.038	-4.69	0.06	-1.14
	Weekend	Daily	-0.160	0.025	-6.313	-0.048	0.026	-1.86	n/a	n/a

Tables 5-7 and 5-8 contain impact estimates for the TOU rate for the inner and outer winter periods, respectively. The impacts in the outer winter are very small. The inner winter estimates show a reduction of around 4 percent for the peak period and an increase in energy use of around 2 percent for the off-peak, weekday period. Weekend energy use increases by roughly 3 percent.

Table 5-7
Residential TOU Rate
Impact Estimates For Inner Winter

Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
1	Weekday	Peak	0.71	-0.039	0.0045	-8.77	-5.54	0.63
		Off-Peak	0.63	0.002	0.0014	1.43	0.32	0.22
		Daily	0.65	-0.007	0.0010	-6.48	-1.02	0.16
	Weekend	Daily	0.65	0.012	0.0020	6.17	1.89	0.31
2	Weekday	Peak	0.83	-0.031	0.0052	-5.94	-3.67	0.62
		Off-Peak	0.69	0.020	0.0021	9.79	2.97	0.30
		Daily	0.72	0.010	0.0015	6.62	1.36	0.21
	Weekend	Daily	0.74	0.029	0.0047	6.21	3.94	0.63
3	Weekday	Peak	0.91	-0.040	0.0051	-7.86	-4.40	0.56
		Off-Peak	0.77	0.014	0.0015	9.66	1.84	0.19
		Daily	0.80	0.003	0.0004	6.58	0.36	0.05
	Weekend	Daily	0.83	0.024	0.0038	6.19	2.85	0.46
4	Weekday	Peak	0.89	-0.047	0.0053	-8.76	-5.26	0.60
		Off-Peak	0.76	0.009	0.0014	6.73	1.23	0.18
		Daily	0.79	-0.002	0.0004	-5.81	-0.29	0.05
	Weekend	Daily	0.83	0.020	0.0036	5.72	2.46	0.43
All Average Customer Approach	Weekday	Peak	0.85	-0.037	0.0049	-7.54	-4.34	0.58
		Off-Peak	0.72	0.015	0.0015	9.84	2.04	0.21
		Daily	0.74	0.004	0.0006	6.59	0.53	0.08
	Weekend	Daily	0.77	0.024	0.0039	6.22	3.15	0.51
All Zonal Average Approach	Weekday	Peak	0.85	-0.036	n/a	n/a	-4.28	n/a
		Off-Peak	0.72	0.015	n/a	n/a	2.12	n/a
		Daily	0.74	0.004	n/a	n/a	0.60	n/a
	Weekend	Daily	0.77	0.025	n/a	n/a	3.20	n/a

Table 5-8 Residential TOU Rate Impact Estimates For Outer Winter								
Zone	**Day Type**	**Rate Period**	**Starting Value (kWh/hr)**	**Impact (kWh/hr)**	**Standard Error**	**t-stat**	**Impact (%)**	**Standard Error (%)**
1	**Weekday**	**Peak**	0.57	-0.010	0.0035	-2.75	-1.69	0.61
		Off-Peak	0.54	-0.001	0.0010	-0.83	-0.15	0.19
		Daily	0.54	-0.003	0.0006	-4.60	-0.49	0.11
	Weekend	**Daily**	0.58	0.003	0.0020	1.64	0.56	0.34
2	**Weekday**	**Peak**	0.72	-0.001	0.0047	-0.15	-0.10	0.66
		Off-Peak	0.60	0.010	0.0021	4.70	1.66	0.35
		Daily	0.63	0.008	0.0017	4.65	1.24	0.27
	Weekend	**Daily**	0.65	0.008	0.0044	1.88	1.26	0.67
3	**Weekday**	**Peak**	0.82	-0.003	0.0048	-0.58	-0.34	0.58
		Off-Peak	0.69	0.005	0.0015	3.26	0.72	0.22
		Daily	0.71	0.003	0.0007	4.68	0.46	0.10
	Weekend	**Daily**	0.75	0.007	0.0038	1.86	0.93	0.50
4	**Weekday**	**Peak**	0.84	-0.010	0.0051	-1.96	-1.18	0.60
		Off-Peak	0.71	0.000	0.0013	0.16	0.03	0.19
		Daily	0.73	-0.002	0.0004	-4.70	-0.26	0.05
	Weekend	**Daily**	0.78	0.006	0.0032	1.82	0.74	0.40
All Average Customer Approach	**Weekday**	**Peak**	0.74	-0.004	0.0045	-0.86	-0.51	0.60
		Off-Peak	0.63	0.006	0.0015	3.91	0.93	0.24
		Daily	0.65	0.004	0.0008	4.68	0.59	0.13
	Weekend	**Daily**	0.69	0.007	0.0037	1.85	1.00	0.54
All Zonal Average Approach	**Weekday**	**Peak**	0.74	-0.003	n/a	n/a	-0.46	n/a
		Off-Peak	0.63	0.006	n/a	n/a	0.97	n/a
		Daily	0.65	0.004	n/a	n/a	0.63	n/a
	Weekend	**Daily**	0.69	0.007	n/a	n/a	1.02	n/a

5.3 CONCLUSIONS

Drawing firm conclusions about the impact of TOU rates from the SPP is somewhat complicated by the fact that the TOU sample sizes were small relative to the CPP-F sample sizes. Small sample sizes are more subject to influence by outliers and changes in the sample composition over time. Further complicating the estimation of the daily energy equation is that longitudinal variation in daily prices is quite small, especially compared with the variation in daily prices found in the CPP-F database, where the daily price is much higher on critical days than on normal weekdays. As discussed in Section

5.1, there is reason to believe that the reduction in daily energy use among treatment customers may be due as much or more to the influence of education as it is to any differences in price between treatment and control customers. In short, there are reasons to take the analysis of the TOU rate treatment with a "grain of salt." Indeed, an argument could be made that the normal weekday elasticities from the CPP-F treatment may be better predictors of the influence of TOU rates on energy demand than are the TOU price elasticity estimates.

On the other hand, if the TOU results are accurate, they have very important policy implications as they suggest that the relatively modest TOU prices tested in this experiment do not have sustainable impacts. One interpretation of the results is that, by the summer of 2004, customers had concluded that they saved little by responding to the rates and stopped doing so. Another possible interpretation is that customers need the frequent reminders associated with critical day notifications and the increased sensitization resulting from the much higher peak period prices on critical days in order to ingrain changes in behavior that result in sustainable impacts even on normal weekdays.

6. Residential CPP-V Treatment

The CPP-V tariff examined in the SPP was similar to the CPP-F tariff except for the following differences. First, customers on the CPP-V rate were notified of a critical event on the day of the event rather than the day before. Notification could be sent up to four hours prior to when critical peak prices would go into effect. Second, the high-price period on critical days could vary in length from one to five hours during the normal 2 pm to 7 pm peak period, and the starting time could also vary.[59] Finally, all customers on the CPP-V rate either already had or were offered an enabling technology to facilitate demand reduction on critical days. Customers were not charged for the technology installation or operation.

During the summer of 2003, two groups of customers were recruited onto CPP-V rates. Track A customers were drawn from a population of customers with average summer energy use exceeding 600 kWh per month. Track C customers were recruited from a sample of customers that had previously volunteered for the AB970 Smart Thermostat pilot. All Track A and C customers resided in the SDG&E service territory. Track A recruitment and technology installation went more slowly than necessary to meet sample targets in time for inclusion in the summer 2003 analysis and recruitment was halted part way through the first summer. A satisfactory sample of Track A customers was successfully recruited prior to summer 2004. Consequently, Track A analysis was only possible for the summer of 2004 whereas Track C analysis was completed for both summer periods as well as for the winter.

The Track A sample is segmented into two climate zones, which are part of statewide zones 2 and 3. However, the weather in SDG&E zones 2 and 3 is generally milder than in statewide zones 2 and 3. Track C participants are largely drawn from SDG&E climate zone 3.

Table 6-1 shows the average price by rate period for Track A CPP-V customers for summer 2004. Track C prices were very similar. CPP-V prices were typically five to ten percent higher than CPP-F average prices, which are shown in Table 4-1.

[59] Table 2-1 in Section 2 summarizes the dispatch dates and time periods that were implemented during the course of the pilot for both Track A and Track C customers.

6. Residential CPP-V Treatment

Table 6-1 Average Summer 2004 Prices For Residential CPP-V Tariff, Track A					
Customer Segment	**Day Type**	**Rate Period**	**High Ratio ($/kWh)**	**Low Ratio ($/kWh)**	**Average ($/kWh)**
Control	**All**	**All**	0.14		
Treatment	**Critical**	**Peak**	0.74	0.55	0.65
		Off-peak	0.08	0.12	0.10
		Daily	0.23	0.22	0.23
	Normal Weekday	**Peak**	0.25	0.23	0.24
		Off-peak	0.08	0.12	0.10
		Daily	0.13	0.15	0.14
	Weekend	**Daily**	0.08	0.12	0.10

The remainder of this section presents the analysis for both Track A and Track C treatments. The Track A analysis is discussed in Section 6.1 and the Track C analysis in Section 6.2.

6.1 TRACK A ANALYSIS

Track A customers were given the option of going on the CPP-V rate with or without the installation of an enabling technology. For those choosing a technology, customers were given the option of having a control device placed on their central air conditioner, their electric water heater or their pool pump. Of the 57 customers in zone 2 who went on the rate, only 33, or roughly 60 percent, chose an enabling technology. Of the 38 customers in zone 3, 29, or roughly 75 percent, chose some technology option. Fourteen of the 33 customers in zone 2 who chose technology selected air conditioning controls, 7 selected water heater controls and 12 selected pool pump controls. In zone 3, 15 out of 29 customers who chose technology selected smart thermostats, 5 selected electric water heater controls and 8 selected pool pump controls.

Both treatment and control customers for the Track A, CPP-V sample represent single-family households using more than 600 kWh/month. Thus, while the Track A, CPP-V treatment group is arguably more representative of the general population than is the Track C, CPP-V sample, the average household still differs from the general SDG&E population and from the statewide population.

Track A treatment and control customers also differ significantly from each other in a couple of important ways. For example, the saturation of central air conditioning for treatment customers is roughly 80 percent whereas the saturation of air conditioning among control customers is closer to 40 percent. The latter is much closer to SDG&E's general population average of 35 percent (25 percent in zone 2 and 49 percent in zone 3). The average income of treatment customers, at $122,000 in zone 2 and $90,000 in zone

3, is also much higher than either the SDG&E control group ($86,000 in zone 2 and $60,000 in zone 3) or the statewide averages of $71,000 in zone 2 and $66,000 in zone 3. In light of these differences, and the fact that price response varies with air conditioning ownership, elasticity and impact estimates are presented separately based on control group average air conditioning saturations and treatment group average air conditioning saturations.

Regression models were initially estimated separately for climate zones 2 and 3. The results were quite similar so the data were pooled across climate zones in subsequent model runs.

A price/weather interaction term was included in the initial regressions. The coefficient had a positive sign and was statistically significant in the substitution equation. It had a negative sign and was statistically significant in the daily equation. However, the term was dropped from the specification because it produced unreasonable results when extrapolating outside of the mild weather of San Diego County. Recall from the discussion in Section 4 that the weather term in the substitution equation equals the difference between CDH/hr during the peak period and CDH/hr during the off-peak period. The average value for this variable for all statewide climate zones is positive, since temperatures are typically higher during the peak period than during the off-peak period. However, in SDG&E climate zones 2 and 3, the opposite appears to be the case on many days. An examination of hourly temperature curves shows that the highest daily temperatures typically occur in the late morning and early afternoon, especially in zone 2 in San Diego, and there is a significant drop in temperature in the last couple of hours of the peak period. This typical summer pattern leads to very low or even negative values for the weather term in the substitution equation. When the weather/price interaction term was included in the model and the much larger, statewide zonal average values were used to estimate the elasticities, the variation in elasticities across zones was quite large and the results often were unreasonable. As such, we do not believe it is appropriate to extrapolate in such a way to the statewide climate zones and we dropped the price/weather interaction term from the specification.[60]

There are a couple of important implications of the decision to drop the weather term in the model specification. One is that it means there is no variation in elasticities across critical and normal weekdays. Second, it means that the estimation of elasticities for populations outside of the estimating sample (e.g., statewide climate zones) will not reflect variation in weather (although variation due to differences in CAC saturations can still be estimated). As discussed later, we believe this may lead to an overestimation of price response in statewide climate zones 1 and 2 and to an underestimation of response in statewide climate zones 3 and 4.

[60] The CPP-V treatment was limited to the SDG&E service territory for several reasons. The preexisting AB970 thermostat pilot was only conducted in SDG&E's service territory so that was the only option for Track C. Many people on WG3 involved in pilot design saw advantages to drawing the Track A and Track C samples from the same service territory so results could more easily be compared. Finally, SDG&E staff already had experience with the smart thermostat technology that was being used because of the AB970 pilot.

6. Residential CPP-V Treatment

The final model specification that underlies the results reported in Tables 6-2 and 6-3 includes price, weather (by itself, not as an interaction term with price) and price/CAC interaction terms in the substitution equation, and price and weather in the daily equation. The price/CAC interaction term in the daily equation was not statistically significant and was dropped.

The variation in air conditioning saturations across climate zones 2 and 3 is small for both control and treatment groups (e.g., control group zone 2 and 3 saturations equal 0.38 and 0.43, respectively, and treatment group zone 2 and 3 saturations equal 0.82 and 0.79, respectively). Consequently, results are presented based on the average air conditioning saturations across the two zones rather than for each zone separately. As seen in the parentheses in the first column of Table 6-2, the saturation of air conditioning for the treatment group is nearly twice as large as for the control group. That is, even though relatively few participants accepted the smart thermostats that were offered as part of the recruitment process, for some reason, customers with central air conditioning volunteered at a much higher rate than did those without central air conditioning. Because of the significant differences in the air conditioning saturation between treatment and control customers, results are presented under two sets of assumptions. The first assumes that the average treatment participant is like the control group while the second assumes the participant is like the treatment group.

Table 6-2
Residential Track A CPPV Elasticity Estimates

CAC Saturation	Day Type	Elasticity Type	Estimate	SE	t-statistic
Control Group (0.41)	Weekday	Substitution	-0.091	0.013	-7.09
		Daily	-0.027	0.016	-1.70
	Weekend	Daily	-0.043	0.016	-2.74
Treatment Group (0.80)	Weekday	Substitution	-0.111	0.009	-11.76
		Daily	-0.027	0.016	-1.70
	Weekend	Daily	-0.043	0.016	-2.74

As seen in Table 6-2, the elasticity of substitution for Track A, CPP-V customers based on the control group air conditioning saturation value equals –0.091 and the daily price elasticity equals –0.027. If the treatment group saturations are used as input values, the CPP-V elasticity of substitution equals -0.111, which is about 20 percent larger than when the control group saturations are used. The daily price elasticity does not vary with air conditioning ownership. The weekend price elasticity, -0.043, is roughly twice as large as the weekday, daily price elasticity.

While comparisons between the CPP-V and CPP-F elasticities are tempting, they must be made carefully in light of the different model specifications, the unusually high air conditioning saturation of CPP-V treatment customers, and differences between San Diego's climate and the statewide climate. The absence of the price/weather interaction term in the model specification for the CPP-V tariff makes the comparisons more difficult.

If the statewide, zonal air conditioning saturations are used to calculate CPP-V elasticities, the resulting values for CPP-V customers are -0.074 for zone 1, –0.085 for zone 2, -0.105 for zone 3 and -0.107 for zone 4. The corresponding values for the CPP-F rate, reported in Table 4-10, are –0.039, -0.061, -0.102 and –0.113, respectively. Using the statewide average saturation of air conditioning (43 percent), the CPP-V elasticity equals –0.092 while the comparable CPP-F value is –0.076. Thus, based on the statewide average, it would appear that Track A, CPPV customers are more price responsive than CPP-F customers. However, while it is difficult to know for sure, we suspect the zone 1 and zone 2 estimates for the CPP-V rate may overstate what is achievable in these climate zones while the zone 3 and 4 estimates may understate the true value. It should also be kept in mind, however, that if the evidence from the pilot is indicative of what would occur in a large scale application, the saturation of air conditioning among households that would volunteer for a CPP-V rate in each climate zone is likely to be higher, perhaps much higher, than the average saturation in the climate zone. As such, the peak-period impact estimates based on the average saturation rate may significantly understate the per customer impact of the typical participant in a full-scale rollout of the voluntary rate.

As seen in Table 6-3, the change in peak-period energy use on critical days resulting from the CPP-V rate is -13.35 percent based on the control group air conditioning saturations and almost 16 percent based on the treatment group air conditioning saturations. Off-peak energy use on critical days increases by 2.5 to 3.5 percent. The change in daily energy use on critical days is negative but statistically insignificant at the 95 percent confidence level, with a t-statistic equal to –1.71.

Table 6-3
Residential Track A CPPV Impact Estimates

CAC Saturation	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
Control Group (0.41)	Critical	P	2.14	-0.2858	0.0392	-7.29	-13.35	1.83
		OP	1.33	0.0341	0.0113	3.03	2.56	0.85
		Daily	1.46	-0.0187	0.0109	-1.71	-1.28	0.75
	Normal Weekday	P	1.62	-0.0899	0.0122	-7.37	-5.54	0.75
		OP	1.16	0.0237	0.0039	6.14	2.04	0.33
		Daily	1.26	0.0001	0.0000	1.70	0.00	0.00
	Weekend	Daily	1.30	0.0173	0.0063	2.72	1.33	0.49
Treatment Group (0.80)	Critical	P	2.14	-0.3374	0.0310	-10.89	-15.76	1.45
		OP	1.33	0.0445	0.0104	4.26	3.34	0.78
		Daily	1.46	-0.0187	0.0109	-1.71	-1.28	0.75
	Normal Weekday	P	1.62	-0.1085	0.0090	-12.09	-6.69	0.55
		OP	1.16	0.0286	0.0028	10.06	2.46	0.24
		Daily	1.26	0.0001	0.0000	1.70	0.00	0.00
	Weekend	Daily	1.30	0.0173	0.0063	2.72	1.33	0.49

Peak-period energy use on normal weekdays declines between 5.5 and 6.7 percent depending upon the underlying saturation of air conditioning. Off-peak energy use on normal weekdays increases by roughly 2 percent, and the change in daily energy use is essentially zero.

An important policy question is whether demand response varies between households with and without an enabling technology. Two binary variables were used to test for differences, one representing the presence of any enabling technology and the other representing the presence of a Smart Thermostat. Neither variable was statistically significant. This does not necessarily mean that technology does not produce any significant incremental impact, simply that the data from the SPP cannot be used to prove that it does. Recall from earlier discussion that roughly two-thirds of participants accepted some form of technology and less than one-third accepted a smart thermostat. The lack of significance associated with either variable may simply reflect the relatively small overall sample size of customers with and without the technology.

It is also possible that some technologies, such as smart thermostats, control load better than others. To probe this possibility further, we examined load shapes for treatment customers who chose the pool pump and water heater control technologies with those of control group customers. This comparison revealed that these technologies had little impact on energy use, as many pool pumps appear to already be controlled by time clocks (based on examination of load shapes on normal weekdays) and that water heating loads are not very prevalent during the peak period in the summer. This evidence suggests that the lack of significant impacts for these two technology options is probably an accurate reflection of reality.

As evidenced by the Track C results reported in the next section, it would appear that smart thermostats have the potential to increase responsiveness compared to what would occur in the absence of technology. The fact that the Track A, CPP-V impacts are somewhat larger than the CPP-F impacts for zones 2 and 3 (See Table 4-11) also lends credence to this possibility.

6.2 TRACK C ANALYSIS

As previously discussed, both control and treatment group customers in Track C were recruited from among participants in the preexisting AB970 Smart Thermostat pilot. All Track C treatment and control customers live in single-family households with central air conditioning and are located in SDG&E's service territory and both treatment and control customers have smart thermostats. These households are not representative of the general population of households, either in SDG&E's service territory or for the state as a whole. As such, direct comparisons between Track C and Track A CPP-V results, or between Track C and the CPP-F treatment, should be made with caution.

As previously mentioned, the Track C, CPP-V treatment was in effect for two summers and for the winter period. The Track C control group consisted of roughly 100 customers that were randomly divided into two equal sized groups. On critical days, one control group was dispatched at the same time as treatment customers but the other control group was not. By including both control groups and the treatment group in the estimating sample, it is possible to separate the impact of the enabling technology from the price impact. A binary variable was created that has a value of 1 for both treatment and control customers whose technology is dispatched on a critical day and a value of 0 for customers whose technology is not dispatched. The coefficient on the binary variable represents the impact of the technology and the coefficient on the price term represents the average impact of time-varying prices on normal weekdays and the incremental impact of prices on critical days over and above the technology impact. The binary variable was included in both the substitution and daily energy use equations.

The remaining variables in the model specification include a standalone weather term, a price term and weekend binary variables. A variable representing CAC ownership could not be included in the specification because all households have central air conditioning. A price/weather interaction term was not included for the same reason it was excluded from the Track A specification, as discussed in Section 6.1.

Separate regressions were initially run on the 2003 and 2004 data. The coefficient on the technology impact variable was essentially identical across the two summers but the value of the elasticity of substitution decreased by nearly 50 percent, from roughly –0.101 to –0.057, between the two summers. The daily price elasticity dropped by about 25 percent, from –0.047 in 2003 to –0.035 in 2004. In the interest of simplicity, we pooled the data across the two summers and estimated a single model. The resulting elasticity estimates represent the average value across the two summers.

Table 6-4 contains estimates of the elasticity of substitution, the daily price elasticity and the coefficients on the technology impact variables for the substitution and daily equations. The elasticity of substitution equals –0.077 and is highly significant. The coefficient on the technology impact variable is -0.214. The daily price elasticity on weekdays equals –0.044, while the technology variable coefficient equals –0.019. The weekend price elasticity equals –0.041. It is difficult to determine the relative contribution of price and technology to overall demand response by simply examining the elasticity and technology coefficients because overall impacts and the percent contribution of price vary with price level but the technology impact is constant across different price levels. The fact that the technology coefficient is roughly three times larger than the elasticity of substitution does not mean that three-quarters of the change in peak-period energy use is due to technology and one quarter to prices. The relative contribution can only be determined once a specific set of prices is used to predict the overall impact.

Table 6-4 Elasticities and Impact Coefficients For CPP-V Track C				
Day Type	**Variable**	**Estimate**	**SE**	**t-statistic**
Critical	**Elasticity of Substitution**	-0.077	0.007	-10.61
	Technology Impact Substitution Equation	-0.214	0.009	-24.04
	Daily Price Elasticity	-0.044	0.013	-3.49
	Technology Impact Daily Equation	-0.019	0.006	-3.35
Weekend	**Daily Price Elasticity**	-0.041	0.010	-4.12

Table 6-5 contains impact estimates for price, technology and the combination of the two on critical days and for price on normal weekdays based on average SPP prices. The total reduction in peak-period energy use on critical days is 27.23 percent. Off-peak energy use on critical days increases by roughly 3.52 percent, and daily energy use falls by roughly four percent.

On normal weekdays, peak-period energy use falls by about 4.5 percent while off-peak energy use increases by 1.7 percent. Daily energy use falls by roughly 0.2 percent. Weekend energy use increases by a modest 1.2 percent.

The 27 percent reduction in peak-period energy use is significantly larger than either the Track A, CPP-V rate impact or the CPP-F rate impact. This larger value could be due in large part to the fact that all Track C participants have enabling technology in the form of a smart thermostat. However, it must also be kept in mind that there are other important differences between Track C and Track A participants, including the fact that Track C participants all have central air conditioning, they all live in single family structures and they all had previously volunteered to be in the AB970 Smart Thermostat pilot.

The total impact of the CPP-V tariff with technology can be decomposed into the impact due to technology and the incremental impact due to price. Based on the average SPP price, roughly 60 percent of the total impact is due to the enabling technology and roughly 40 percent is due to price-induced behavioral response over and above the technology-driven impact. It must be kept in mind, however, that these percentages will change if prices change, as the technology impact is constant but the overall impact and the incremental impact due to price will change as prices change.

Table 6-5 Residential Track C CPPV Impact Estimates								
Zone	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
Impact of Technology and Price	Critical	P	2.33	-0.6352	0.0181	-35.03	-27.23	0.78
		OP	1.26	0.0444	0.0139	3.19	3.52	1.11
		Daily	1.43	-0.0597	0.0061	-9.85	-4.17	0.42
	Normal Weekday	P	1.87	-0.0844	0.0078	-10.82	-4.52	0.42
		OP	1.11	0.0192	0.0019	9.92	1.73	0.17
		Daily	1.27	-0.0024	0.0007	-3.50	-0.19	0.05
	Weekend	Daily	1.34	0.0161	0.0039	4.10	1.20	0.29
Impact of Technology Only	Critical	P	2.33	-0.3946	0.0202	-19.53	-16.92	0.87
		OP	1.26	0.0368	0.0135	2.72	2.91	1.07
		Daily	1.43	-0.0274	0.0082	-3.35	-1.91	0.57
Differential Impact of Price	Critical	P	2.33	-0.2770	0.0269	-10.28	-11.88	1.15
		OP	1.26	0.0153	0.0085	1.79	1.21	0.68
		Daily	1.43	-0.0328	0.0093	-3.53	-2.29	0.65

Regressions were also run for the winter period. There were only three critical days in the winter and the enabling technology was only dispatched on one of the three days. Given that the technology is aimed at central air conditioning and not space heating, it has no relevance in the winter. As such, a variable representing technology dispatch was not included in the specification. No statistically significant differences were found between the inner and outer winter periods. The final winter regressions showed a statistically significant price term in the substitution equation but a statistically insignificant price term in the daily equation. The estimated elasticity of substitution for the winter period equaled –0.022, with a t-statistic equal to –2.94. The substitution elasticity in the winter was significantly less than in the summer, where it had a value of –0.077. This phenomenon was also observed with the CPP-F rate and can be attributed to the presence of central air conditioning use in the summer months.

6.3 SUMMARY

Comparisons between the CPP-V Track A and Track C results, and the CPP-V and CPP-F results are difficult because of differences the sample compositions. The most important policy question motivating inclusion of the CPP-V treatment in the experiment was the determination of whether demand response impacts increased significantly in the presence of enabling technology.

In spite of important caveats that must be considered due to the nature of the voluntary sample, the Track C results suggest that impacts are significantly larger with enabling technology than without it. The 27 percent average impact for the Track C, CPP-V treatment is roughly double the 13 percent impact for the CPP-F rate for the average summer. It is also substantially larger than the Track A, CPP-V treatment impact, where only some customers took advantage of the technology offer. Importantly, the Track C impact is more than 50 percent larger than the CPP-F impact for households with central air conditioning (see Table 4-19). Whether or not this incremental difference of roughly 10 percentage points in the average peak-period reduction produces sufficiently large incremental benefits in the form of avoided capacity and energy costs to offset the incremental cost of the technology is the key policy questions that utilities and regulators must answer before deciding whether enabling technology should be offered for free (as it was in this experiment) or partially subsidized.

7. Commercial and Industrial Sector Analysis

For C&I customers, the SPP tested two tariffs, a two-period TOU rate and a CPP-V rate that is layered on top of a TOU rate, as described in Section 2. The CPP-V rate is similar to a CPP-F rate except for three differences: (1) the length of the peak period can vary between 1 and 5 hours within the six-hour peak period from noon until 6 pm on weekdays; (2) notification of a critical event can occur up to four hours prior to the CPP price going into effect and (3) CPP-V treatment customers either already had (in the case of Track C customers) or could choose to have (in the case of Track A customers) an enabling technology (i.e., a smart thermostat) free of charge.

All C&I customers were located in the SCE service area. Separate samples were drawn for customers with peak demands below 20 kW (LT20 customers) and between 20 and 200 kW (GT20 customers).

The experimental tariff limited the critical dispatch period to five hours during the noon to 6 pm peak period and roughly half of the dispatch events lasted for only two hours. Thus, on critical days, treatment customers actually faced a three-period rate consisting of the CPP price during the critical event period, the normal weekday, peak-period price for the remaining hours of the peak period, and the off-peak price.[61] To simplify modeling, and in light of the limited number of critical days and the variable length of the shoulder period, we did not estimate separate substitution equations for the peak-shoulder and shoulder-off-peak periods. Instead, we estimated a single substitution equation with the ratio of peak-to-off-peak energy use per hour on all days. On normal weekdays, this ratio was based on six peak-period hours and 18 off-peak hours. On critical days with a five-hour dispatch period, the ratio was based on five peak-period hours and 18 off-peak hours, and when the dispatch period was only two hours in length, the ratio was based on the two-hour dispatch period and the 18-hour off-peak period. In all cases, the energy use in each period was divided by the number of hours in the period.

The CPP-V rate was offered to two groups of customers designated as Tracks A and C. The Track A sample was recruited from the general population after screening out customers below a minimum usage threshold (to increase the likelihood that customers had air conditioning) and also screening out customers that did not live in a two-way paging area. The Track C sample was drawn from a pre-existing Smart Thermostat pilot. All Track C customers had central air conditioning and smart thermostats. Most Track A customers had central air conditioning but only 19 out of 58 LT20 customers selected the smart thermostat technology option and 49 out of 83 GT20 customers did so. During the experiment, for Track C customers, both control and treatment customers had their smart thermostats dispatched on critical days. Thus, for Track C customers, responsiveness on critical days represents price response over and above the amount resulting from dispatch of the enabling technology. For Track A customers, responsiveness reflects both the impact of behavioral changes as well as technology for those customers who selected the

[61] Given that the maximum number of critical hours allowed was five, even though the peak-period covered six hours, every critical day had at least one hour where the normal weekday, peak-period price was in effect.

enabling technology.[62] As a result of these and other differences, comparisons between Track A and Track C customers should be made with care.

In 2003, participants were recruited for both Tracks A and C. However, due to recruitment problems and insufficient participants, the Track A treatment sample was not available for analysis in 2003 (the control group was installed). Another recruitment phase was conducted in 2004 based on the original sample design. The estimating sample for the LT20 segment consists of 47 control and 58 treatment customers. The sample for the GT20 segment has 42 control and 83 treatment customers.

The model specification used for the C&I analysis is conceptually similar to the one used for the residential analysis. The basic model includes a weather term in both the substitution and daily usage equation. It also includes a price ratio term in the substitution equation but there is no price term in the daily use equation. When price was included in the daily equation in preliminary regressions, the coefficient was almost always insignificant. Price/weather and price/CAC interaction terms were also insignificant in initial regression runs.[63] As with the residential models, the C&I models were estimated using the first difference transformation and the SUR regression estimator.

7.1 CPP-V TARIFF, TRACK A CUSTOMERS

Table 7-1 summarizes the prices that were included in the experiment for Track A, CPP-V customers. Briefly, the peak-period price on critical days for LT20 customers was roughly $0.70/kWh for low-price-ratio customers and was $0.92/kWh for high-price-ratio customers. The average peak-period price on critical days was approximately $0.81/kWh. The off-peak price on critical days for high-ratio customers was roughly $0.09/kWh, creating a peak/off-peak price ratio on critical days of roughly 10 to 1. With an off-peak price of approximately $0.15/kWh, low-price-ratio customers faced a price ratio of roughly 5 to 1. The average price ratio on critical days across the two price-offerings was approximately 7 to 1. The price ratios on normal weekdays was approximately 2 to 1 for high-ratio customers and 1.5 to 1 for low-ratio customers. The average price for control customers equaled $0.17/kWh in all rate periods.

[62] Importantly, the difference in approach for Tracks A and C does not mean that the impact estimates should be added to get the combined impact of enabling technology and other behavioral changes. The Track A results already reflect this combined impact, whereas the Track C results reflect behavioral changes on normal weekdays and the incremental impact of behavior over and above technology on critical days.

[63] A CAC ownership variable could not be included in the Track C regressions because all treatment and control customers had CAC. Even with Track A customers, there was a very high saturation of CAC, which is probably the reason why the variable was insignificant.

Table 7-1 Average Summer Prices For C&I CPP-V Tariff, Track A (2004)					
Customer Segment	Day Type	Rate Period	High Ratio ($/kWh)	Low Ratio ($/kWh)	Average ($/kWh)
LT20 Control	All	All	0.17		
LT20 Treatment	Critical	Peak	0.92	0.70	0.81
		Off-peak	0.09	0.15	0.12
		Daily	0.30	0.30	0.30
	Normal Weekday	Peak	0.18	0.23	0.20
		Off-peak	0.09	0.15	0.12
		Daily	0.12	0.18	0.15
GT20 Control	All	All	0.15		
GT20 Treatment	Critical	Peak	0.75	0.58	0.66
		Off-peak	0.09	0.13	0.11
		Daily	0.24	0.24	0.24
	Normal Weekday	Peak	0.17	0.19	0.18
		Off-peak	0.10	0.13	0.12
		Daily	0.12	0.15	0.14

For GT20 customers, the peak-period price on critical days for the high-ratio group was approximately $0.75/kWh and the off-peak price was $0.09/kWh, for a price ratio around 8 to 1. The low-ratio customers, with a peak-period price of $0.58/kWh and an off-peak price of $0.13/kWh, faced a price ratio of approximately 4.5 to 1 on critical days. The average price ratio across both treatment groups was 6 to 1.

Estimates of price elasticities and demand impacts for Track A customers are only available for the summer 2004 period. As mentioned previously, the daily price term was not significant so the only elasticity that could be estimated was the elasticity of substitution during weekdays.[64] The substitution elasticity is not relevant on weekends, when prices are the same all day long, and the weekend daily price elasticity was not significant. The C&I summer rate season was only four months long, commencing on the first Sunday in June and ending on the first Sunday in October. Thus, there is no reason to examine seasonal differences within the summer period as was done with the inner/outer summer designation for residential CPP-F customers.

Given the lack of statistically significant price-interaction terms in the substitution equation, the elasticity of substitution is simply equal to the coefficient of the price-ratio term in the regression equation. For LT20 customers, the elasticity of substitution equals –0.045. The standard error equals 0.014 and the t-statistic equals –3.10, indicating that small C&I customers respond to price, but their responsiveness is modest. The elasticity is less

[64] An insignificant daily price coefficient does not mean that price doesn't matter, only that it couldn't be estimated in this case. The lack of significance could be due to the relatively small sample size combined with the limited variation in daily prices relative to the significant heterogeneity in energy use in the estimating sample.

than half the estimated value for residential CPP-F customers and also about half the value of the residential CPP-V estimate. The modest price responsiveness measured in this pilot for this customer segment is consistent with the limited literature on C&I energy demand, which indicates that small C&I customers have limited ability or willingness to respond to time-varying price signals.[65]

The elasticity of substitution for GT20 customers equals –0.069. The standard error equals 0.008 and the t-statistic equals –8.34, indicating a highly significant price response. The elasticity is roughly fifty percent larger than the LT20 elasticity and is comparable to the all-summer average for residential CPP-F customers (-0.076). The elasticity of substitution estimated here is similar to the value estimated by Aigner and Hirschberg, -0.074, based on a pricing pilot done in the SCE service territory in the early 1980s. The Aigner and Hirschberg estimate was for a group of customers with demands between 50 and 200 kW (e.g., similar to the GT20 segment, which includes customers between 20 and 200 kW).

Table 7-2 contains estimates of the impact of the CPP-V tariff on energy use by day type, rate period and customer segment.[66] For LT20 customers, the experimental tariffs induced a 6 percent reduction in peak-period energy use on critical days and a 2.4 percent increase in off-peak energy use. On normal weekdays, the reduction in peak-period energy use was only 1.5 percent, while the increase in off-peak energy use was around 1.0 percent. It is useful to note that these modest reductions on critical days are driven by a very high peak-to-off-peak price ratio of roughly 7 to 1. Residential customer response was more than twice as large in percentage terms on critical days and the residential price ratio, at 6.6 to 1, was slightly less than the LT20 price ratio. Nevertheless, the average absolute reduction in peak-period energy use provided by LT20 customers is actually slightly larger than the reduction achieved by residential customers (e.g., -0.22 kWh/hr for LT20 customers versus –0.19 kWh/hr for residential customers in the inner summer). This is because LT20 customers use about three times as much energy use per hour in the peak period as does the average residential customer.

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[65] D.J.Aigner and J. G. Hirschberg, "Commercial/industrial customer response to time-of-use electricity prices: some experimental results," Rand Journal of Economics, Vol. 16, No. 3, Autumn 1985.

D.J. Aigner, J. Newman and A. Tishler, "The Response of Small and Medium-size Business Customers to Time-of-Use Electricity Rates in Israel," Journal of Applied Econometrics, Volume 9, 1994.

J.C. Ham, D.C. Mounta in and M.W.L. Chan, "Time-of-Use Prices and Electricity Demand: Allowing for Selection Bias in Experimental Data," Rand Journal of Economics Vol. 28, No. 0, 1997.

Chi-Keung Woo, "Demand for Electricity of Small Nonresidential Customers Under Time-Of-Use Pricing," The Energy Journal, Vol. 6, No. 4, 1985.

[66] The regression models underlying the elasticity and impact estimates presented in this section are contained in Appendix 17.

Table 7-2 Impact Estimates for the CPP-V Rate for C&I Track A Customers								
Customer Segment	**Day Type**	**Rate Period**	**Starting Value (kWh/hr)**	**Impact (kWh/hr)**	**Standard Error**	**t-statistic**	**Impact (%)**	**Standard Error (%)**
LT20	**Critical**	**Peak**	3.67	-0.22	0.07	-3.17	-6.04	1.91
		Off-peak	1.83	0.04	0.01	3.14	2.36	0.75
	Normal Weekday	**Peak**	3.24	-0.05	0.02	-3.11	-1.47	0.47
		Off-peak	1.72	0.02	0.01	3.11	0.92	0.30
GT20	**Critical**	**Peak**	24.66	-2.24	0.26	-8.65	-9.08	1.05
		Off-peak	15.28	0.46	0.05	8.55	3.01	0.35
	Normal Weekday	**Peak**	23.23	-0.56	0.07	-8.39	-2.41	0.29
		Off-peak	14.09	0.19	0.02	8.39	1.32	0.16

The impact of the CPP-V rate on peak-period energy use for GT20 customers is larger than for LT20 customers on a percentage basis and much larger in absolute terms given the much higher starting values associated with GT20 customers. On critical days, the average reduction in peak-period energy use for GT20 customers equals roughly 9.1 percent, while the increase in off-peak energy use equals 3.0 percent. On normal weekdays, peak-period energy use changed by roughly –2.4 percent, and off-peak energy use increased by roughly 1.3 percent. The average absolute reduction in peak-period energy use associated with GT20 customers is approximately 10 times larger than the LT20 impact on both critical and normal weekdays.

When examining the price elasticities and impacts associated with the experimental CPP-V tariff, several factors must be kept in mind. First, as discussed above, only about a third of the LT20 customers accepted the enabling technology and about 60 percent of the GT20 customers did so. Furthermore, because of difficulties associated with installation, the technology was only operational for about fifty percent of those who chose it in July 2004 and for about 80 percent for the first two critical events in August. Thus, the technology was fully operational for only six of the twelve critical events in 2004, and was partially operational for the other six events. In light of these facts, the demand response estimates for 2004 can, at best, be described as partially enabled by technology, with the majority being a pure price response. Consequently, these estimates may be reasonable approximations for a rate program that offered technology as an option, but there are reasons to believe that they may underestimate what might be achieved from such a program because of the late implementation of the technology described above. Indeed, the estimates may be closer to what might be achieved by a CPP-F tariff than a technology enabled CPP-V tariff. If a full-scale CPP-V program was implemented that made it mandatory for customers on the rate to have an enabling technology, the elasticities and impacts presented here may understate the impacts, perhaps significantly so.[67] They may even underestimate what could be achieved from a program offering technology as an option.

An attempt was made to determine the influence of enabling technology on demand response for Track A customers by including a binary variable representing the presence of the technology interacting with price. The variable was not statistically significant for either the LT20 or GT20 customer segment. The coefficient on the interaction term for LT20 customers equaled –0.04 and the t-statistic equaled –1.49. For GT20 customers, the coefficient had a value near 0 and the t-statistic equaled –0.45.

We also examined whether responsiveness varies with customer size within each customer segment. Two variables were tested, one being average daily use (ADU) in the summer prior to the treatment going into effect, the other being building size measured by square footage reported in the SPP customer characteristics survey. Since the building size variable is self reported and not measured by a third party, it may be prone to reporting error. The ADU variable is from SCE's customer information system.

Table 7-3 summarizes the results of the analysis concerning ADU and building size. For LT20 customers, the interaction terms between price and both ADU and building size are statistically significant, but they have opposite signs. The coefficient on the price/ADU interaction term equals –0.00143 and has a t-statistic equal to –3.43. The mean value for ADU among control group customers is 45.8 kWh. The value of the elasticity of substitution based on this mean value is –0.067, as shown in Table 7-3. The value of the elasticity of substitution at twice the mean value for ADU is –0.132 while the value at half the mean value for ADU is –0.034.

Table 7-3
Elasticity of Substitution By Customer Size
Track A CPP-V, Summer 2004

Customer Segment	Variable	Average Size	Half the Average	Twice the Average
LT20	SQFT	-0.049	-0.065	-0.018
	ADU	-0.067	-0.034	-0.132
GT20	SQFT	-0.062	-0.078	-0.029
	ADU	-0.074	-0.077	-0.070

The coefficient on the price/building size variable is 4.494×10^{-6} and the t-statistic equals 2.28. Building size is measured in square feet and the average value for LT20 customers is 6,690. The elasticity of substitution at the mean value is -0.049. The elasticity of substitution calculated using a value for building size equal to twice the mean value equals –0.018 and, at half the mean value, equals –0.065. The fact that these two

[67] Of course, a mandatory technology component could negatively affect participation rates for a voluntary rate program.

variables have the opposite sign is puzzling, as size and energy use are typically positively correlated. However, we ran a correlation between ADU and square footage and found that the correlation, while positive, was relatively small. Given the likely reporting errors in the building size variable, we are more inclined to believe the ADU regressions than the regressions with building size.

For the GT20 customer segment, the coefficient on the price/ADU interaction term is quite small and highly insignificant, with a t-statistic equal to 0.68. The price/building-size coefficient, on the other hand, is statistically significant (t-statistic equal to 3.86) and, as with the LT20 segment, positive. The mean value for building size for the GT20 segment is 23,693. At this mean value, the elasticity of substitution equals -0.062. At twice the mean value, the elasticity of substitution falls to –0.029. At half the value, the elasticity equals –0.078.

In summary, analysis indicates that price responsiveness increases with customer size, as measured by average daily energy use, for the smallest customer segment. For customers with demands between 20 and 200 kW, responsiveness does not vary with size. The opposite relationship is found when size is measured in terms of square feet of building space rather than energy use. It is difficult to reconcile these two results but we put more credence in the energy use variable than in the square foot variable because of concerns about the accuracy of the latter. Limited evidence from the literature also suggests that the correlation between size and price responsiveness is positive, which supports our conclusion to trust the ADU results over the square footage results.

7.2 CPP-V TARIFF, TRACK C CUSTOMERS

The general model specification and approach described above for the Track A analysis was also applied to the Track C, CPP-V treatment. Recall that both treatment and control customers for Track C were selected from among participants in the pre-existing AB90 Smart Thermostat pilot. All participant and control customers had smart thermostats and central air conditioning. In addition, on most critical days, both control and treatment customers were dispatched simultaneously so that the estimated price response should reflect behavioral changes over and above any impacts associated with the enabling technology. Comparisons between Track A and Track C results, if they are made at all, must be made with full awareness of the differences in the underlying sample characteristics, the saturation of control technologies, and differences in dispatch procedures for control group customers between the two treatments.

Track C customers participated in the pilot during both the summer of 2003 and 2004, as well as during the winter period. Tables 7-4 and 7-5 contain the average prices that applied to Track C customers in the summer and winter periods, respectively. The summer values were similar to those underlying the Track A analysis. In the winter, the high-ratio summer customers were given lower price ratios and vice versa. In the tables, customers labeled as high ratio customers refer to the summer price ratios, not the winter ratios.

Table 7-4 Average Summer Prices For C&I CPP-V Tariff, Track C (2003/2004 Average values)					
Customer Segment	Day Type	Rate Period	High Ratio ($/kWh)	Low Ratio ($/kWh)	Average ($/kWh)
LT20 Control	All	All	0.18		
LT20 Treatment	Critical	Peak	0.99	0.75	0.87
		Off-peak	0.09	0.16	0.12
		Daily	0.34	0.33	0.33
	Normal Weekday	Peak	0.19	0.24	0.21
		Off-peak	0.09	0.16	0.12
		Daily	0.14	0.20	0.16
GT20 Control	All	All	0.15		
GT20 Treatment	Critical	Peak	0.81	0.62	0.71
		Off-peak	0.08	0.13	0.11
		Daily	0.24	0.24	0.24
	Normal Weekday	Peak	0.18	0.20	0.19
		Off-peak	0.09	0.13	0.11
		Daily	0.12	0.16	0.14

Table 7-5 Average Winter Prices For C&I CPP-V Tariff, Track C					
Customer Segment	Day Type	Rate Period	High Ratio[68] ($/kWh)	Low Ratio ($/kWh)	Average ($/kWh)
LT20 Control	All	All	0.13		
LT20 Treatment	Critical	Peak	0.58	0.81	0.69
		Off-peak	0.11	0.06	0.08
		Daily	0.27	0.31	0.29
	Normal Weekday	Peak	0.22	0.21	0.22
		Off-peak	0.10	0.05	0.08
		Daily	0.15	0.12	0.14
GT20 Control	All	All	0.13		
GT20 Treatment	Critical	Peak	0.55	0.84	0.70
		Off-peak	0.10	0.06	0.08
		Daily	0.22	0.26	0.24
	Normal Weekday	Peak	0.20	0.21	0.20
		Off-peak	0.09	0.05	0.07
		Daily	0.13	0.10	0.11

[68] "High ratio" refers to the summer price ratio, even in the winter. High ratio summer customers faced lower price ratios in the winter in order to maintain annual revenue neutrality.

7. Commercial and Industrial Sector Analysis

As previously mentioned, all Track C customers had a smart thermostat that was dispatched for the same time period that critical prices were in effect. Thus, the observed impacts represent a combined effect of price and technology. The control group was dispatched on nine of twelve critical days in the summer of 2003 and on all twelve critical days in the summer of 2004. By comparing the behavior of the control group on critical and normal weekdays, after adjusting for the effects of weather, one can back out the impact of the enabling technology. When a combined regression of both control and treatment groups is run, it becomes possible to decompose the combined price and technology impact into a pure price-induced behavioral component and a technology component.

Table 7-6 presents the elasticities of substitution and technology response coefficients for Track C customers for a pooled database that combines data for the summers of 2003 and 2004. Initial regression runs were made to test for differences across the two summer periods. No statistically significant differences were found for the LT20 customer segment. For the GT20 segment, the technology impact was stable across the two summers, but the price impact dropped by roughly 75 percent from summer 2003 to summer 2004. For simplicity, we retained the pooled model. The elasticities reported here represent the average of the two summer periods.

For LT20 customers, the technology impact in the substitution equation is strong and negative at –0.229. However, the price impact is small and positive. This suggests that the price impact is zero and, in addition, there is a difference in the dispatch technology impact between the treatment and control group customers. This difference is being picked up by the price term, since only the treatment group customers receive the critical price signal. Technology also has an impact on daily electricity use.

For GT20 customers, the price impact in the substitution equation is small and negative. It is supplemented by a technology impact of –0.118, which is about half the size of the technology impact for LT20 customers. The fact that the GT20 technology coefficient is less than that of the LT20 segment is not surprising, since the enabling technology only works on air conditioning usage, which is a smaller portion of total energy use for GT20 customers than it is for LT20 customers.

In all cases, we were unable to find statistically significant and negative daily price elasticities. In most cases, they were statistically insignificant. In a couple of cases, they were positive and significant. Consequently, we dropped the price term from the daily use equation.

Table 7-6 Elasticities for C&I, CPP-V Track C Customers					
Customer Segment	**Day Type**	**Elasticity Type**	**Estimate**	**SE**	**t-statistic**
LT 20	**Weekday**	**Substitution, price**	0.034	0.012	2.72
		Substitution, technology	-0.229	0.015	-15.28
		Daily, technology	-0.036	0.013	-2.82
GT 20	**Weekday**	**Substitution, price**	-0.022	0.005	-4.10
		Substitution, technology	-0.118	0.007	-17.44
		Daily, technology	-0.022	0.006	-3.91

As was discussed for the residential CPP-V treatment in Section 6, it is difficult to draw strong conclusions about the relative contribution of price and technology without first estimating impacts, as both total and incremental impacts vary with price. Nevertheless, in this instance, it is clear that technology makes a very a strong contribution to demand response. Indeed, as discussed above, price does not appear to contribute to demand response for LT20 customers at all for this Track C treatment group. The very small value for the elasticity of substitution for GT20 customers, and the large value for the technology coefficient, would also suggest that technology is the dominant factor for this customer segment.

These tentative conclusions are corroborated by the load impact estimates displayed in Table 7-7. The combined effect of technology and price for LT20 customers is –14.30 percent. A t-statistic of –7.45 indicates that the combined impact is highly statistically significant. The estimated impact of the enabling technology for this customer segment, -18.22 percent, is actually larger than the combined effect of price and technology. Stated differently, there is no economically rational, incremental price response for this customer segment over and above the technology impact. This result is not necessarily inconsistent with the finding of a modest price response for the Track A, CPP-V rate treatment. The combined results for Track A and C imply that the primary behavioral response for Track A customers who did not have enabling technology involved adjustments to the air conditioning thermostat. With the enabling technology substituting for this behavioral adjustment, there is no incremental behavioral adjustment being made. Furthermore, it is important to note the much larger technology impact effect of –18.22 percent, compared with the price effect of only –6.04 percent for Track A customers. While comparisons across these two groups must be made carefully for reasons stated previously, such a large difference suggests that technology may significantly increase demand response for LT20 customers compared with price alone

For GT20 customers, the combined effect of technology and price is –13.84 percent. Roughly 80 percent of this total is attributable to the technology effect. The total impact is larger than the Track A, CPP-V impact (-9.1 percent), but the difference is not as great as for the LT20 customer segment. Nevertheless, it would not be unreasonable to conclude that technology improves demand response for the GT20 customer segment compared to a rate treatment where not all customers have technology. The fact that the difference in the total impacts between the Track A and Track C treatments is greater for LT20 customers than it is for GT20 customers may be due, in part, to the fact that only about 33 percent of LT20, Track A customers had technology whereas 60 percent of GT20 did.

Table 7-7
Impact Estimates for the CPP-V Rate for C&I Track C Customers

Customer Segment	Impact Measure	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
LT 20	Technology and Price	Critical	Peak	6.70	-0.9586	0.1286	-7.45	-14.30	1.92
			Off-Peak	2.42	0.0207	0.0313	0.66	0.85	1.30
			Daily	3.26	-0.1154	0.0402	-2.87	-3.54	1.23
		Normal Weekday	Peak	5.69	0.0641	0.0236	2.72	1.13	0.41
			Off-Peak	2.28	-0.0169	0.0062	-2.72	-0.74	0.27
	Technology Only (C07 dispatched)	Critical	Peak	6.70	-1.2217	0.1092	-11.18	-18.22	1.63
			Off-Peak	2.42	0.0693	0.0294	2.36	2.86	1.21
			Daily	3.26	-0.1154	0.0402	-2.87	-3.54	1.23
	Differential of Price	Critical	Peak	6.70	0.3008	0.1117	2.69	4.49	1.67
			Off-Peak	2.42	-0.0543	0.0201	-2.70	-2.25	0.83
			Daily	3.26	0.0000	0.0000	n/a	0.00	0.00
GT 20	Technology and Price	Critical	Peak	22.69	-3.1406	0.2075	-15.14	-13.84	0.91
			Off-Peak	13.95	0.1533	0.0760	2.02	1.10	0.55
			Daily	15.72	-0.3442	0.0870	-3.96	-2.19	0.55
		Normal Weekday	Peak	20.24	-0.1800	0.0437	-4.12	-0.89	0.22
			Off-Peak	13.05	0.0474	0.0115	4.12	0.36	0.09
	Technology Only (C07 dispatched)	Critical	Peak	22.69	-2.4842	0.1916	-12.96	-10.95	0.84
			Off-Peak	13.95	0.0252	0.0724	0.35	0.18	0.52
			Daily	15.72	-0.3442	0.0870	-3.96	-2.19	0.55
	Differential of Price	Critical	Peak	22.69	-0.7203	0.1734	-4.15	-3.17	0.76
			Off-Peak	13.95	0.1386	0.0334	4.14	0.99	0.24
			Daily	15.72	0.0000	0.0000	n/a	0.00	0.00

As with the Track A analysis, we investigated whether price responsiveness varied with customer size using both an ADU and building size interaction variable. The results are shown in Table 7-8.

For LT20 customers, price responsiveness increases with increasing ADU but the technology coefficient in the substitution equation falls with ADU. The interaction term between price and square footage is statistically insignificant and, thus, the elasticity of substitution does not change with this variable. The value of the technology coefficient falls slightly with increasing building size. The impact of technology on daily energy use increases with ADU and falls with square footage.

For GT20 customers, the incremental impact of price over and above the technology impacts falls as both ADU and building size increase. The magnitude of the technology coefficient in the substitution equation also falls with increasing ADU and building size, but the rate of decline is modest. The magnitude of the technology coefficient in the daily energy use equation rises with ADU but falls significantly with increases in building size.

Table 7-8
Variation in the Elasticity of Substitution and Technology Coefficients by Customer Size

Customer Segment	Characteristic Variable	Response Variable	Average Size	Half the Average	Twice the Average
LT20	ADU	Substitution, price	0.035	0.080	-0.056
		Substitution, technology	-0.232	-0.281	-0.132
		Daily, technology	-0.036	-0.002	-0.105
	SQFT	Substitution, price	0.033	0.032	0.037
		Substitution, technology	-0.231	-0.237	-0.218
		Daily, technology	-0.038	-0.049	-0.015
GT20	ADU	Substitution, price	-0.033	-0.044	-0.012
		Substitution, technology	-0.112	-0.121	-0.095
		Daily, technology	-0.023	-0.008	-0.053
	SQFT	Substitution, price	-0.038	-0.045	-0.024
		Substitution, technology	-0.113	-0.119	-0.102
		Daily, technology	-0.022	-0.031	-0.006

Regression models were also estimated for the winter period for Track C customers. For the LT20 customer segment, the elasticity of substitution was negative but quite small

(-0.009) and highly insignificant, with a t-statistic equal to –0.92. For the GT20 segment, the daily price elasticity was insignificant but the elasticity of substitution, equal to –0.018, was statistically significant with a t-statistic equal to –4.17. This value is similar to the summer elasticity estimate (absent the technology effect) of –0.022.

7.3 TOU RATE ANALYSIS

The SPP also examined the impact of a two-period TOU rate on energy consumption by rate period. As with the CPP-V analysis, all customers in the experiment were located in the SCE service territory. Table 7-9 contains the average TOU prices used in the experiment. The average peak-to-off-peak price ratio for LT20 customers was 2.3 to 1 and the average for GT20 customers was 1.9 to 1. High ratio customers faced price ratios equal to 2.9 to 1 and 2.1 to 1, respectively. Low ratio customers faced price ratios of 2 to 1 and 1.7 to 1, respectively.

Table 7-9
Average Summer Prices For C&I TOU Tariff, Track A
(2003 - 2004)

Customer Segment	Day Type	Rate Period	High Ratio ($/kWh)	Low Ratio ($/kWh)	Average ($/kWh)
LT20 Control	All	All	0.18		
LT20	All	Peak	0.26	0.30	0.28
		Off-Peak	0.09	0.15	0.12
		Daily	0.15	0.21	0.18
GT20 Control	All	All	0.15		
GT20	All	Peak	0.21	0.24	0.23
		Off-Peak	0.10	0.14	0.12
		Daily	0.14	0.18	0.16

Table 7-10 contains the elasticity estimates for the TOU rate treatment in the summer period. Price was not included in the daily equation so only the elasticity of substitution is presented.

For the LT20 customer segment, price was not statistically significant in summer 2003 but was highly significant in 2004. The 2004 elasticity of substitution equals –0.130 and has a t-statistic equal to –4.12. For the GT20 customer segment, price was statistically significant in both 2003 and 2004, but the 2004 value is much larger. These estimated values are large relative to the Track A, CPP-V results and also large compared with results found in the limited literature on this customer segment.

Table 7-10 Elasticity of Substitution for C&I TOU Summer				
Customer Segment	**Period**	**Elasticity of Substitution**	**SE**	**t-statistic**
LT20	**2003**	-.005	.032	-0.15
	2004	-.130	.032	-4.12
	'04 Differential	-.126	.045	-2.80
GT20	**2003**	-.093	.021	-4.37
	2004	-.211	.022	-9.47
	'04 Differential	-.118	.031	-3.83

Table 7-11 contains summer impact estimates for the TOU tariff. The 2003 estimate for LT20 customers was essentially zero but the 2004 reductions during the peak period equaled almost 7 percent. The 2003 peak-period reduction for the GT20 segment is almost 4 percent, and in 2004, the estimated reduction equaled 8.6 percent.

Table 7-11 C&I TOU Rate Impact Estimates									
Customer Segment	Period	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
LT 20	2003	Weekday	Peak	2.857	-0.007	0.048	-0.15	-0.25	1.67
			Off-Peak	1.503	0.002	0.016	0.15	0.16	1.06
	2004	Weekday	Peak	2.857	-0.193	0.046	-4.18	-6.77	1.62
			Off-Peak	1.503	0.064	0.015	4.18	4.29	1.03
	2004 Differential	Weekday	Peak	2.857	-0.187	0.066	-2.84	-6.53	2.30
			Off-Peak	1.503	0.062	0.022	2.84	4.14	1.46
GT 20	2003	Weekday	Peak	26.638	-1.026	0.232	-4.41	-3.85	0.87
			Off-Peak	16.728	0.342	0.077	4.41	2.04	0.46
	2004	Weekday	Peak	26.638	-2.298	0.237	-9.69	-8.63	0.89
			Off-Peak	16.728	0.766	0.079	9.69	4.58	0.47
	2004 Differential	Weekday	Peak	26.638	-1.298	0.335	-3.88	-4.87	1.26
			Off-Peak	16.728	0.433	0.112	3.88	2.59	0.67

Regressions were also run for the winter period. For LT20 customers, the elasticity of substitution had a value of –0.008 but was highly insignificant, with a t-statistic equal to –0.58. The GT20 customers, on the other hand, were quite price responsive even in the winter period, with an elasticity of substitution equal to –0.072 and a t-statistic equal to –8.30. Table 7-12 summarizes the TOU impact estimates for the winter period.

Table 7-12 C&I TOU Rate Impact Estimates for the Winter Season									
Customer Segment	Period	Day Type	Rate Period	Starting Value (kWh/hr)	Impact (kWh/hr)	Standard Error	t-stat	Impact (%)	Standard Error (%)
LT 20	2003	Weekday	Peak	2.249	-0.013	0.023	-0.58	-0.59	1.02
			Off-Peak	1.383	0.004	0.008	0.58	0.32	0.55
GT 20	2003	Weekday	Peak	22.345	-1.137	0.135	-8.42	-5.09	0.60
			Off-Peak	15.192	0.379	0.045	8.42	2.49	0.30

8. Glossary

Analysis of variance	A commonly used statistical methodology for assessing the *impact* of a specific *treatment* on some variable of interest. The results cannot be easily generalized for other levels of the treatment. If that is of interest, it is better to use *regression models* (e.g., *demand models*).
Autocorrelation	A statistical term that refers to a problem frequently encountered in *regression models* involving time series data. It arises when the error term in a given time period is correlated with the error term in preceding time periods. When autocorrelation is present, *parameter* estimates are unbiased but their standard errors are downward biased.
Control group	A group of customers in an experiment that are used to establish a benchmark against which the effects of varying *treatments* can be measured. In well-designed experiments, the control group is selected randomly to allow valid inferences to be drawn about the impact of treatments.
Cooling degree hours	The number of cooling degree hours in an hour equals the difference between a base value, say 72 degrees, and the average temperature in the hour. For example, if the average hourly temperature equals 80 degrees and the base value is 72, the number of cooling degree hours in that hour would equal 8. By definition, cooling degree hours can never be less than zero. That is, it the temperature in an hour is less than the base value, cooling degree hours in that hour would equal 0.
Critical-peak pricing (CPP)	A dynamic rate that allows a short-term price increase to a predetermined level (or levels) to reflect real-time system conditions. In a *fixed-period* CPP (CPP-F), the time and duration of the price increase are predetermined, but the days when the events will be called are not. The maximum number of called days per year is also usually pre-determined. The events are typically called on a day-ahead basis. In a *variable-period* CPP (CPP-V), the time, duration and day of the price increase are not predetermined. The events are usually called on a day-of basis.

8. Glossary

Critical day	A day on which the highest peak-period price in a CPP tariff is in effect.
Demand charge	A charge expressed in dollars per kW of billing demand that often is levied on large commercial and industrial customers. This charge co-exists with charges based on kWh of energy consumption and a monthly customer charge.
Demand model	A mathematical function that expresses the quantity of a particular good, such as electricity, that a consumer will purchase as a function of the price of that good, prices of related goods, and measures of economic activity such as income. Demand models also often include other terms, such as customer characteristics, that can influence the relationship between price and quantity purchased. Demand models for electricity typically include weather terms as factors that drive electricity use.
Demand response (DR)	The ability of an individual electric customer to reduce or shift usage or demand from peak periods in response to a financial incentive such as a higher price or a cash payment.
Dispatch	A broadcast from a utility signaling the initiation of a control strategy or price adjustment.
Dynamic rate	A tariff in which prices can be adjusted on short notice (typically an hour or day ahead) as a function of system conditions. A dynamic rate cannot be fully predetermined at the time the tariff goes into effect; either the price or the timing is unknown until real-time system conditions warrant a price adjustment. *Examples: real-time pricing (RTP), critical peak pricing (CPP)*
Elasticity	A measure of how one variable responds to changes in another variable, everything else being held constant. Common examples are *price* and income elasticities of demand. Another commonly used measure is the *elasticity of substitution*.
Elasticity of substitution	The elasticity of substitution equals the ratio of the percentage change in the ratio of peak and off-peak energy use to the percentage change in the ratio of peak and off-peak prices.

8. Glossary

Enabling technology	Any technology that allows a customer or electric service provider to pre-program a control strategy - for an individual electric load, group of electric loads, or an entire facility - to be automatically activated in response to a dispatch. A Smart Thermostat (see below) is one type of enabling technology. Others include swimming pool pump and water heater controls.
Error term	That portion of the dependent variable in a regression model that cannot be explained by the independent variables in the model.
Experimental design	A statistical device that is used for measuring the effect of various *treatments* on a sample of participants in order to draw valid inferences for the population of interest.
Heating degree hours	The number of heating degree hours in an hour equals the difference between a base value and the average temperature in that hour. For example, if the base value is 65 degrees and the temperature in an hour equals 60, there would be 5 heating degree hours in that hour. By definition, heating degree hours can never be less than zero. That is, if the temperature in an hour is greater than the base value, heating degree hours in that hour equal 0.
Heteroscedasticty	A statistical problem that arises in *regression models* involving cross-sectional data. When heteroscedasticity is present, the variance of the error term is not constant across cross-sectional units. This causes the standard errors of the estimated *parameters* to be downward biased.
Impact	The change in energy use during a pricing period resulting from customer response to a time-varying rate, an enabling technology or a combination of the two. Impacts may be expressed in absolute terms (kWh/hour) or in percentage terms (i.e., the absolute impact divided by the baseline usage that existed prior to the implementation of time-varying rates).
Impact evaluation	A statistical analysis that seeks to quantify the *impact* of various treatments on specific variables of interest. Commonly used techniques include *analysis of variance* and *regression models* (e.g., *demand models*).
Load shape	A graph showing how electricity use varies across the hours in a day or across pricing periods such as peak, shoulder and off-peak periods.
Normal weekday	A weekday that is not a critical day.

8. Glossary

Notification	Information provided to customers regarding price adjustments or system conditions. 'Day-ahead' notification provides at least 24 hours advance notice. 'Hour-ahead' notification provides at least one hour of advance notice.
Parameter	The coefficient associated with one or more explanatory variables in a *regression model*. Typically, the mean value of the coefficient is reported along with its *standard error*.
Price elasticity	A measure of the sensitivity of customer demand to price. Price elasticity is a dimensionless quantity and is expressed as the ratio of the percent change in demand to the percent change in price, everything else held constant. For example, a 10% load drop in response to a 100% price increase yields a price elasticity of -0.10. 'Own-price' elasticity relates changes in peak period demand to changes in peak period price. 'Cross-price' elasticity relates changes in usage in one period to changes in price in another period.
Pricing period	A time period within which the price of electricity is constant. Often, peak and off-peak periods are used to express variation in electric rates by time periods. Some times additional "shoulder" periods are introduced to allow for more discrete price variation.
Regression model	A mathematical relationship between quantitative variables that is established by performing a variety of statistical procedures.
Revenue neutrality	A regulatory requirement that any alternative rate design must recover the same total revenue requirement as the default rate design, assuming that the average customer in the class makes no change in their usage patterns.
Seasonal rate	A rate in which electricity prices vary by season.
Self-selection bias	When experimental participants can select themselves into an experiment, rather than be randomly selected and assigned to treatment groups, the effects of treatments that are estimated may not be representative of the population of interest. They are then said to suffer from self-selection bias.

8. Glossary

Smart thermostats	A heating, ventilation and air-conditioning (HVAC) thermostat that: (1) automatically responds to different electricity prices that are dispatched by the utility by adjusting the temperature set point (or the operation of the HVAC equipment) using pre-programmed thresholds that are typically specified by the customer; (2) displays energy information and rates, and notifies the customer of rate changes; and/or (3) can be programmed to control devices other than the HVAC system.
SPP	Statewide pricing pilot
Standard error	An estimate of the uncertainty in a *parameter*.
Starting value	The value of energy consumption in a time period prior to the introduction of a time-varying rate. These values are used to calculate percent *impacts*. In this report, starting values are expressed in kWh/hr for each rate period or for a day.
Tariff	A public document setting forth the services offered by an electric utility, rates and charges with respect to the services, and governing rules, regulations and practices relating to those services.
Tiered rate	A rate in which predetermined prices change as a function of cumulative customer electricity usage within a predetermined time frame (usually monthly). Prices in an 'inverted tier' rate increase as cumulative electricity usage increases. Prices in a 'declining tier' or 'declining block' rate decrease as cumulative electricity usage increases.
Time-of-day (TOD) rate	A rate in which predetermined electricity prices vary across two or more preset time periods within a day.
Time-of-use (TOU) rate	A rate in which the price of electricity varies as a function of usage period, typically by time of day, by day of week, and/or by season. *Examples: TOD rate, seasonal rate.*
Time-varying rate	A rate in which prices change or can be changed within a 24-hour period or between seasons. Examples: TOD rate, dynamic rate, seasonal rate.
Treatment	A technical term used in the experimental design literature for concepts such as medications, rates or information whose effect is of interest to the researcher
Treatment group	Experimental participants who are given varying *treatments*. In a properly designed experiment, customers are randomly assigned to control and treatment groups.

t-statistic	The t-statistic is obtained by dividing the mean estimate of a parameter (regression coefficient) by its standard error. A value of 1.96 for this statistic indicates that the parameter estimate is statistically significantly different from zero at a 95% confidence level.