Draft Report

STATEWIDE PRICING PILOT
SUMMER 2003 IMPACT ANALYSIS

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1. Executive Summary

This report presents impact estimates, demand models, and elasticities of demand for the Statewide Pricing Pilot (SPP) for the summer of 2003. The SPP involves roughly 2,000 residential and small commercial and industrial (C&I) customers located in the service territories of Pacific Gas & Electric Company, San Diego Gas & Electric Company and Southern California Edison. Most customers enrolled in the pricing pilot were either placed on experimental dynamic pricing tariffs or given dynamic pricing information to encourage demand response. Other customers were selected as a control group and were kept on their existing tariffs and monitored at the same time.

The tariffs being tested in the SPP include a time-of-use (TOU) rate and two types of critical peak pricing (CPP) rates. The TOU rate offers customers an on-peak and off-peak rate schedule, with higher and lower electricity prices between the two periods. The two CPP rates (CPP-F and CPP-V) include a substantially higher on-peak price (about 50 to 75 cents/kWh) for 15 "critical" days of the year and a TOU rate on all other days. CPP-F features a fixed, on-peak period on both critical and non-critical days with day-ahead customer notification, while CPP-V features a variable-length on-peak period on critical days, and customers may be notified on the day of the critical peak event.

All three of the SPP experimental rate types were tested for residential customers, with CPP-F excluded from the small C&I customers. All C&I customers are located in the SCE service area. An additional "Information Only" non-rate treatment was also tested for residential customers in the PG&E service area. This treatment involved notifying customers of CPP event days and asking them to reduce energy use during the peak period. These customers were not placed on any of the SPP tariffs (i.e., their prices did not change). Impact analysis has been carried out for all of these treatment and control group customer combinations, but the results for the Information Only and C&I customers are still under review and are not included in this report.

Customers in the SPP were divided into four climate zones across the three utilities to obtain results that reflected the climatic variation within the state. Customers enrolled in the different rates and control customers were also divided into three sample design "tracks" (A, B and C). Track A was designed to be representative of the state. Track B was geographically-specific to residential low-income customers located in the areas around San Francisco near operating power plants. Track C consisted of residential and C&I customers already participating in a demand response pilot (Smart Thermostat program implemented under Assembly Bill 970) in southern California. Only results from Tracks A and C are provided in this report.

Two types of analyses were conducted. The first developed energy consumption and coincident peak demand impact estimates for the specific treatments tested in the SPP. The second developed demand models that express energy consumption by rate period and coincident peak demand as a function of prices and other explanatory variables. These models then produce estimates of the own and cross-price elasticities of demand

and of the elasticity of substitution between peak and off-peak energy consumption. Price elasticities and elasticities of substitution are summary measures of the relationship between energy consumption and energy prices. One advantage of the demand models developed for the SPP is that they can be used to estimate the impact of alternative prices that differ from the SPP tariffs.

The analysis results reported here can provide useful input into estimates of the cost-effectiveness of time-varying rates and the tariff designs required to develop such rates in California. The experiment has also yielded satisfactory estimates of price elasticities of demand that are in line with the empirical literature on time-varying rates. Almost all the elasticity estimates are statistically significant. However, the estimates presented here should be used with caution, since they are only based on the initial four months of an eighteen-month experiment. Prior research suggests that customers in dynamic pricing pilots will adapt demand response behavior over time.

1.1 IMPACT ESTIMATES FOR RESIDENTIAL RATE TREATMENTS

The impact estimates for CPP-F and TOU rates summarized here represent the target population in each climate zone and statewide. To the extent possible, they have been adjusted for differences between treatment and control customers due to both observable and unobservable factors. The CPP-V sample represents a different target population than the CPP-F or TOU group and, as such, is not directly comparable to the other rates nor can results for this group be generalized to the state's population.

- The impact of CPP-F rates on energy consumption during the on-peak period (five hours), averaged across all four climate zones, is –1.3 kWh on CPP event days and –0.5 kWh on non-CPP days. These impacts are –22.0 percent and –9.4 percent respectively of the electricity consumption of control group customers for the same time period.

- The impact of CPP-V rates on energy consumption in climate zone 3 is –5.4 kWh (– 38.8 percent) on CPP event days and –3.7 kWh (–28 percent) on non-CPP days.[1] It is important to note that the CPP-V rate group includes customers with enabling technologies that provide automatic demand response, and also customers recruited from the demand response pilot program mentioned earlier (AB 970 Smart Thermostat). All of these customers live in single-family dwellings and have central air conditioning.

- The impact of the TOU rates on energy consumption during weekdays (no CPP event days) for all weather zones, is -0.9 kWh, or –16.0 percent of control group usage. The impacts in zone 1 (coastal), however, are positive in both the peak

[1] These impacts were estimated across a variable peak period whose length varied from two to five hours. To make the numbers somewhat comparable to those from the other rates, the impacts were then re-adjusted to reflect the likely impact over a five hour duration peak period.

and off-peak periods, indicating an increase in energy usage during the peak period.

- In general, rate impacts are higher for customers that own major electric appliances, such as a central air conditioner, swimming pool, and electric cooktop. The composite impact for customers with all three appliances is –2.1 kWh (or 400 percent of the average customer's impact value). The impact equals only -0.3 kWh (or 57 percent of the average household's value) for households with none of these three appliances.

- Energy conservation is evident with all SPP rate treatments. CPP-F customers reduce daily energy consumption in all zones by -1.2 kWh (-5.7 percent) on non-CPP days. TOU customers reduce daily energy consumption in all zones by –1.8 kWh (-8.7 percent) on all weekdays.

- Significant impacts on hourly coincident peak demand are also observed. For the CPP-F rate, the estimated impact equals -0.2 kWh/hour (–19.5 percent) for all zones at the time of statewide system peak. The impact is slightly larger for TOU rate customers, at -0.3 kWh/hour (-23.5 percent). Finally, the coincident peak impact of the CPP-V rate customers (with the enabling technologies) is the largest, at –1.4 kWh/hour (-49.4 percent).

These impacts are summarized in tables 1-1 and 1-2.

Table 1-1
Impact on Peak Period Energy Consumption

	kWh	Percent
CPP-F rate on CPP Days	-1.3	-22.0
CPP-F rate on non-CPP Days	-0.5	-9.4
TOU rate on all weekdays	-0.9	-16.0
CPP-V rate on CPP Days	-5.4	-38.8
CPP-V rate on non-CPP Days	-3.7	-28.0

Table 1-2
Impact on Coincident Peak Demand

	kWh/hour	Percent
CPP-F rate on CPP Days	-0.2	19.5
TOU rate on CPP Days	-0.3	23.5
CPP-V rate on CPP Days	-1.4	49.4

1.2 DEMAND MODELS AND ELASTICITIES OF DEMAND AND SUBSTITUTION

The results of the demand modeling process and estimation of price elasticities of demand and of elasticities of substitution are summarized below.

- For on-peak energy consumption, the own price elasticities of demand for the CPP-F rate on both CPP and non-CPP event days lie within an interval of -0.14 and -0.34. The corresponding elasticity for the CPP-V rate is -0.39 on CPP days and -0.66 on non-CPP event days. For TOU rates on all weekdays, the elasticities lie within an interval of 0.00 and -0.59.

- Price elasticities for daily use have also been estimated for the CPP-F and TOU rates on non-CPP days. They lie within an interval from -0.22 and -0.62, with a median value of -0.31.

- Elasticities of substitution, which are an alternative measure of price responsiveness, have been estimated as well. Except for zone 1, which yielded statistically insignificant values, the elasticity of substitution estimates for the CPP-F rate on non-CPP days are found to be significant and contained within an interval between -0.12 and -0.19, with a median value of -0.14. Very similar values are observed for the CPP-F rate on CPP days. Much higher values are obtained for the CPP-V rate, with the value on non-CPP days being -0.26 and that on CPP days being –0.39. However, as noted earlier, these reflect not only the impact of having an automated response capability but also the uniqueness of the Smart Thermostat sample from which the CPP-V customers were recruited.

2 Background and Overview of Experimental Design

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.[2] In the absence of demand response, the normally downward sloping demand curves become vertical, since customers do not change their demand for electricity in response to changes in the wholesale price of electricity. Studies have shown that economic efficiency in the allocation of scarce capital, fuel and labor resources can be realized 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.[3]

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[4], commissions, equipment vendors, The Utility Reform Network (TURN) and other interested parties.

As part 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. 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 the uncertainty in the net benefit estimates.

Based in part on this preliminary analysis, WG3 recommended on December 10, 2002 that the state conduct a carefully designed social experiment with different pricing

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2 James L. Sweeney, The California Electricity Crisis, Hoover Institution Press, 2002.
3 Order Instituting Rulemaking on policies and practices for advanced metering, demand response and dynamic pricing, R. 02-06-001.
4 Pacific Gas & Electric (PG&E), San Diego Gas & Electric (SDG&E) and Southern California Edison (SCE).

options prior to making a decision on full-scale deployment of the automated metering infrastructure required to support such rates. It was decided to go with 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.[5]

The SPP has three primary objectives:

- Estimate average demand impacts and demand curves for electricity consumption by time-of-use period for dynamic tariffs and derive the associated price elasticities of demand

- 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 for the period of time from customer enrollment through the end of the summer period. Separate reports will address the second and third objectives.

The tariffs being tested in the SPP include a traditional TOU rate and two types of dynamic pricing rates. The dynamic rates include a critical-peak pricing (CPP) element that involves 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) features a fixed peak period on both critical and non-critical days and day-ahead customer notification. The peak period for residential customers is between 2 pm and 7 pm weekday afternoons and the peak period for commercial and industrial customers is from noon to 6 pm. The other type of CPP rate (CPP-V) features a variable-length peak period on critical days, which may be called on the day of an "emergency." All SPP rates are seasonally differentiated, with summer running from May through October, inclusive, for residential customers and from June through October 5th for commercial and industrial customers.[6]

In addition to the rate treatments described above, an "Information Only" treatment was also tested for residential customers. This treatment involves notifying customers on CPP days and asking them to avoid energy use during the peak period. However,

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

6 Small commercial and industrial customers are only in the SCE service territory and their summer ends on October 5.

prices do not change on CPP days for these customers and the customers do not face time-varying prices on any day.

Residential customers in the SPP are divided into four climate zones and commercial/industrial customers into two size strata, very small (< 20 kW demand) or small (between 20 and 200 kW demand). Residential customers are drawn from the service territories of all three participating utilities (PG&E, SDG&E and SCE) while the commercial/industrial customers are drawn exclusively from SCE. The customers are divided into three tracks:

- Track A represents the general population of customers in the state.
- Track B represents 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. All these customers reside in the PG&E service area.[7]
- Track C represents 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 revised overall sample design consists of 2,504 customers of which 850 are control customers and 1654 are treatment customers. A total of 1790 customers are in Track A, 253 customers are in Track B and 461 customers are in Track C.[8]

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 presents impact estimates for the residential sector in Tracks A and C. Section 5 presents demand models and elasticities of demand for the residential sector in Tracks A and C. Although extensive analysis has been completed for the Information Only residential treatment and for the C&I rate treatments, the results are still under review and are not included in this report. It is important to note that the SPP will continue in the year 2004 and results will be updated on an ongoing basis.

7 Results from Track B will be presented in a separate report.

8 The original sample design included a total of 2,591 customers (1741 treatment and 850 control customers) of which 1,877 were assigned to track A, 253 to track B and 461 to track C. In early June, recruitment efforts were halted for the CPP-V, track A cells due to poor take rates; this resulted in revising the target number of customers downward (as reflected in the revised target numbers) to reflect actual enrollment in the Track A cells for which recruitment was terminated.

2.2 RATE DESIGN

The specific tariffs that are being 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% 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% if they reduced or shifted peak usage by 30%.

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 qualify for a 20% discount of their electricity bill under a program called CARE. For example, 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 manner in which the 20% CARE discount is passed on to customers varies by utility.

2.2.2 EXPERIMENTAL CONSIDERATIONS

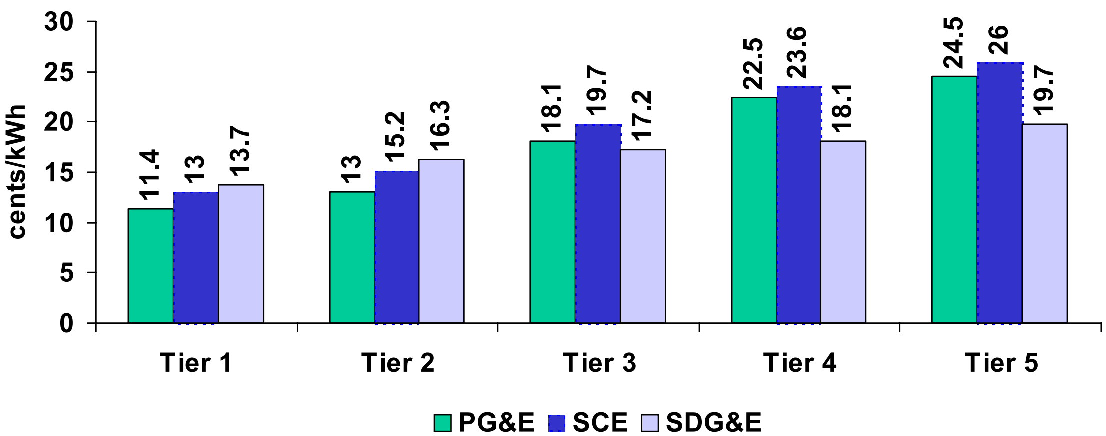
The experimental rates are designed to allow estimation of the own and cross-price elasticities of demand for electricity by time-of-use period.[9] Each time-varying rate consists of two pricing periods, peak and off-peak. As such, there are two own-price and two cross-price elasticities associated with each tariff. In order to estimate all four price

9 In this context, the own price elasticity of demand equals the ratio of the percentage change in energy use in a period (say the peak period) over the percentage change in price in the same period. The cross-price elasticity of demand equals the percentage in usage in one

elasticities, 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 associated with usage in each time period. In order to estimate a statistically valid demand function, it is necessary that the tariffs not be revenue neutral. If they were revenue neutral, there would be perfect collinearity in the price terms, rendering the models statistically unidentifiable.

Another rate-related complication was the existence of different base rates across the three utilities. The average annual rate, expressed in cents/kWh and measured in January 2003, was 12.5 for PG&E, 13.5 for SCE and 14.5 for SDG&E. Prices during the summer were 12.7 for PG&E and, rounded, 14.1 for both SDG&E and SCE. As shown in Figure 2-1, the inverted five-tier rate structure differs across the utilities. SDG&E customers start out with a higher price in Tier 1 but their prices don't rise as steeply as they do for PG&E and SCE customers. Thus, customers in SDG&E's service territory pay slightly less than 20 ¢/kWh for Tier 5 usage whereas Tier 5 customers in PG&E's

Figure 2-1
Marginal Prices For Control Group Customers
At Start Of Treatment Period



service area pay roughly 24.5 ¢/kWh and in Edison's they pay 26 ¢/kWh.[10]

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 are identical across utilities, causing the effective TOU and CPP prices to

period (say the peak period) divided by the percentage change in the price of energy in another period (say the off-peak period).

10 Edison's rates fell shortly after the pilot started, especially the Tier 5 marginal price, which is now equal to roughly 17 ¢/kWh.

differ by small amounts because of the differences in the underlying rates. This approach, which preserves the inverted character of the underlying rate structure, was chosen over an alternative approach that would have used a flat base rate for all 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 usage customers relative to low usage customers. As such, many high-usage customers would have displayed a strong preference for the time-varying rate because it would lower their average rate even in the absence of changing their usage patterns or levels. In addition, the chosen approach automatically reflects changes in the underlying base rates that might occur during the experiment due to the normal course of business by each utility.[11] 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 are being provided with a summary sheet showing (a) how much electricity they used during the billing cycle period by pricing period, (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 will also be provided with another shadow bill after having been in the experiment for 12 months. Finally, customers can request 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

Dispatch of the CPP rates was based on a variety of criteria. First, about half the time, CPP-F and CPP-V rates were dispatched simultaneously. Second, residential CPP-V Track C customers, two peak period lengths were dispatched, one for two hours and another for five hours.[12] For C&I, CPP-V customers, two, four and five hour dispatch periods were implemented over the summer. Finally, to minimize customer discomfort, no more than five events were called in any month and no more than two events per week. A total of 12 events were called for each treatment in the summer months (May to October) and three are planned to be called in the winter. 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. Table 2-1 summarizes the CPP events that occurred during the summer 2003 rate period.

11 Indeed, SCE implemented a significant rate reduction shortly after customers went on the rate.

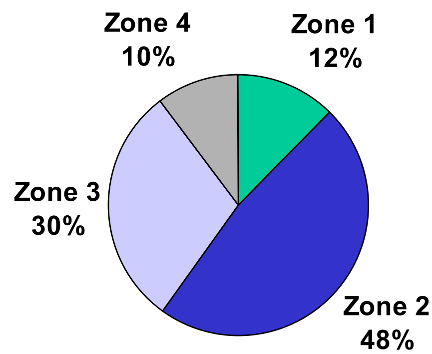
12 The experimental cells in Track A CPP-V did not reach their targeted enrollment levels due to a number of factors that are discussed in the Refusals Report cited in footnote 21.

Table 2-1 CPP Event Summary																		
	July			August					September							October		
Zone	7/10	7/17	7/28	8/8	8/14	8/15	8/18	8/27	9/3	9/11	9/12	9/18	9/19	9/22	9/29	10/9	10/14	10/20
Residential CPP-F Rate Treatments																		
1	X	X					X	X	X	X	X	X		X		X	X	X
2	X	X	X	X			X	X	X		X			X		X	X	X
3	X	X	X	X			X	X	X		X			X		X	X	X
4	X	X	X	X			X	X	X		X			X		X	X	X
Residential CPP-V Rate Treatment																		
3	2-4	2-4	2-7	3-5		2-7	4-6	2-7	2-7		2-7				2-7	3-5	2-7	3-5
Commercial and Industrial CPP-V Rate Treatment																		
SCE	2-4	2-4	1-6	3-5	1-6	2-6		4-6	1-6	1-6	4-6		4-6		1-6			

2.3 SAMPLE DESIGN

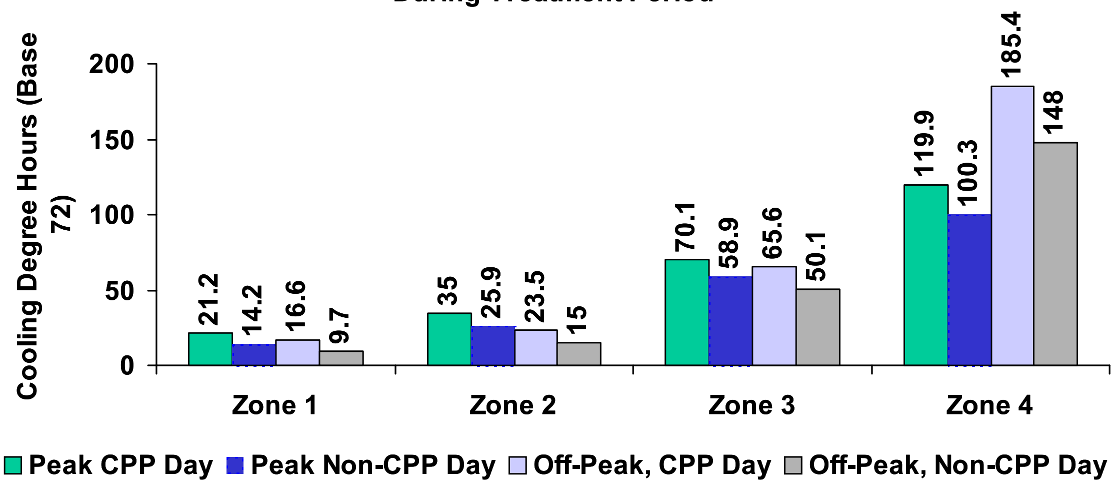
To capture the diversity in California's climate, and to allow customer response to time-varying rates to vary with climate, the SPP experimental design segments customers into four climate zones. As seen in subsequent sections, impact estimates are presented for each climate zone. Figure 2-2 shows the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

Figure 2-2
Distribution Of Population Across Climate Zones



Roughly 60 weather stations have been used across all climate zones to capture the rather significant number of microclimates that exist in California. The average cooling-degree hour values for each climate zone presented in Figure 2-3 represent population-weighted averages based on the weather stations applicable to each climate zone. A list of the weather stations and their populations is contained in Section 3.2.4 of this report.

Figure 2-3
Average Daily Cooling Degree Hours By Climate Zone During Treatment Period*



*Note that the peak and off-peak periods differ in length, being 5 and 19 hours long respectively

Bayesian sampling techniques were used to allocate sample points to each of the various cells in the SPP.[13] 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.

13 Details are presented in the December 10, 2002 report of WG3.

Table 2-2
Sample Design of the Statewide Pricing Pilot

Track A: Random Sampling With Opt Out Design							
	Control	**CPP-F**	**CPP-F (info)**	**CPP-V (SDG&E) (1)**	**Info Only (1)**	**TOU**	**Total**
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) The treatment customers were selected on an opt-out basis from the existing AB970 sample, which has an opt-in structure. An additional 100 AB 970 control c

2.3.1 Residential Sample Design

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 14 was used to determine optimal usage cut points, and the Neyman allocation method15, which allocates more sample points to strata with greater variance, was applied to increase the explanatory capability of the final sample. For multi-family strata, the allocated sample sizes were small, so these cells were not segmented further based on the Neyman allocation method. Table 2-3 summarizes the allocation of samples within each cell for the residential CPP-F and TOU rate treatments based on the Dalenius-Hodges and Neyman processes.

Table 2-3
Sample Allocation for Residential Track A CPP-F , TOU, and Control*
By Climate Zone, Dwelling Type, and Usage Level

				Control				CPP-F				TOU			
Climate Zone	Dwelling Type	Usage	Population Count	Total	PG&E	SCE	SDG&E	Total	PG&E	SCE	SDG&E	Total	PG&E	SCE	SDG&E
1	Single	Low	432,173	17	17	0	0	14	14	0	0	13	13	0	0
		High	188,621	21	21	0	0	18	18	0	0	17	17	0	0
	Multiple	All	406,722	25	25	0	0	20	20	0	0	20	20	0	0
			1,027,516	***63***	***63***	***0***	***0***	***52***	***52***	***0***	***0***	***50***	***50***	***0***	***0***
2	Single	Low	1,848,301	27	10	11	6	51	19	21	11	13	6	7	0
		High	814,877	45	23	16	6	85	44	29	11	22	13	9	0
	Multiple	All	1,259,417	28	10	12	6	53	19	23	11	14	6	8	0
			3,922,595	***100***	***43***	***39***	***18***	***188***	***82***	***73***	***33***	***50***	***25***	***25***	***0***
3	Single	Low	1,249,106	32	7	21	4	60	13	40	7	16	4	12	0
		High	675,729	46	14	29	3	87	26	55	6	23	8	15	0
	Multiple	All	533,557	22	5	14	3	41	9	26	7	11	3	8	0
			2,458,392	***100***	***26***	***64***	***10***	***188***	***48***	***120***	***20***	***50***	***15***	***35***	***0***
4	Single	Low	433,556	30	20	11	0	35	22	12	0	15	10	5	0
		High	257,864	49	31	18	0	56	36	20	0	25	16	9	0
	Multiple	All	173,943	20	13	7	0	23	15	8	0	10	7	3	0
			865,363	***100***	***64***	***36***	***0***	***114***	***73***	***41***	***0***	***50***	***33***	***17***	***0***
Total			***8,273,866***	***363***	***196***	***139***	***28***	***542***	***255***	***234***	***53***	***200***	***123***	***77***	***0***

Table 2-4 summarizes the shares represented by each strata in the sample and control group populations. As indicated there, the primary outcome of the sample allocation process described above is that high usage customers constitute a larger share of the

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14 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. Notice, in this instance, we are actually using this technique 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. On-peak demand is not known for residential customers thus a proxy (summer average daily usage) was used.

15 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 very large

SPP sample than they do in the population at large. The impact estimates presented in this report have been adjusted to reflect differences between the sample and population shares based on the stratification variables.

Table 2-4
Sample And Population Shares For CPP-F And TOU Control Groups
(Shares add to 100% across rows, for sample and population separately)

Zone	Single Family Low Use		Single Family High Use		Multiple Family	
	Sample	Population	Sample	Population	Sample	Population
1	27.0 %	42.1 %	33.3 %	18.4 %	39.7 %	39.6 %
2	27.0 %	47.1 %	45.0 %	20.8 %	28.0 %	32.1 %
3	32.0 %	50.8 %	46.0 %	27.5 %	22.0 %	21.7 %
4	30.0 %	50.1 %	49.0 %	29.8 %	20.0 %	20.1 %
All	29.2 %	47.9 %	44.3 %	23.4 %	26.2 %	28.7 %

For each stratum, a series of potential samples were selected at random and without replacement. The final sample was chosen so that it most closely resembles the population in terms of summer average daily usage. Several types of customers were excluded from the sampling frame, including those who (a) live in master-metered dwellings and therefore cannot be sent a time-varying price signal, (b) are on a medical baseline rate and may not be able to engage in load shifting without endanger their condition, (c) are on an existing time-of-use (TOU) rate or an air conditioner cycling program, which they have chosen on a voluntary basis, (d) are a direct access customer, who buy power from third party suppliers, (e) are a net metering customer, producing their own power, or (f) get power on standby rates or special contract rates.

Sample allocations for Track B and for the Information Only cells in Track A are contained Tables 2-5 and 2-6.

compared to other strata. The daily average usage was used as a proxy for the parameter of interest (usage during on-peak or CPP period) in Neyman allocation.

Table 2-5
Sample Allocation For Track B
By Rate Group and Usage Level

General Population						Climate Zone 1 Only					
						Info Only		CPP-F			
SPP Track	Rate Group	Location	Dwelling Type	Usage Level	Population Count	Cell ID	Sample Size	Cell ID	Sample Size		
									Total	Rate Treatment	
										High	Low
B	E-1	Hunter's Point	MF	Low	2,580	B01	10				
			MF	High	1,574	B01	13				
			SF	Low	4,588	B01	25				
			SF	High	1,723	B01	15				
					10,465		**63**				
	E-3	Hunter's Point	MF	Low	2,580			B02	20	10	10
			MF	High	1,574			B02	26	13	13
			SF	Low	4,588			B02	50	25	25
			SF	High	1,723			B02	30	15	15
					10,465				**126**	**63**	**63**
	E-3	Richmond	MF	Low	5,827			B03	18	9	9
			MF	High	2,311			B03	6	3	3
			SF	Low	10,946			B03	32	16	16
			SF	High	2,685			B03	8	4	4
					21,769				**64**	**32**	**32**

Table 2-6
Sample Allocation For Track A Standard Tariff
Information Only By Rate Group and Usage Level

General Population							
						Info Only	
SPP Track	Rate Group	Climate Zone	Dwelling Type	Usage Level	Population Count	Cell ID	Sample Size
A	E-1	2	MF	All	407,559	A11	15
			SF	Low	661,508	A11	15
			SF	High	408,776	A11	33
					1,477,843		**63**
	E-1	3	MF	All	100,956	A12	11
			SF	Low	248,319	A12	18
			SF	High	195,122	A12	34
					544,397		**63**

The CPP-V Track A sample design called for the selection of 125 customers split between climate zones 2 and 3. The selection criterion was that the customer's usage during the summer months be > 600 kWh a month. This resulted in a pool of approximately 240,000 customers. Current smart thermostat participants were excluded from Track A. Note that the Track A CPP-V target population included approximately 80,000 customers that were originally solicited for the Smart Thermostat program (climate zone 3 only) and that decided not to opt-into that program. The Track A CPP-V was marketed to both multi and single-family residences that met > 600 kWh a month criterion.

SDG&E performed an optimal allocation using the Dalenius-Hodges procedure with stratification boundaries on high and low summer average daily usage. The procedure was applied to the target population frame of approximately 240,000. The treatment group I consisted of 125 primary sample sites with 20 like replacements for each primary sample site. SDG&E anticipated that recruitment for the CPP-V technology treatment customers would require extensive sample replacements.

For the residential Track C CPP-V treatment group, a random sample of 125 primary sites was selected from SDG&E's population of 3,650 AB970 Smart Thermostat Program Participants. The treatment group customers were placed on a CPP-V rate, with the group being split evenly between the high and low rate differentials. Nearly all of the existing Smart Thermostat participants are located in SDG&E's inland climate zone (statewide climate zone 3).

SDG&E utilized an existing sample of 100 Smart Thermostat participants with interval data recorders for its CPP-V Control Group 1. This group of 100 customers was split into two groups of 50. On any given curtailment day, 50 are controlled and 50 are curtailed. SDG&E made these 100 interval metered customers aware that they would be asked to curtail on days other than an ISO stage 2 alert. SDG&E modified the curtailment criteria for its existing smart thermostat control group so that direct comparisons to the treatment group can be made.[16]

SDG&E was able to utilize a control sub-sample from Track A CPP-V. This sub-sample was selected from SDG&E's inland customers (climate zone 3) with more than 600 kWh summer monthly usage. This second control group sample was selected using the Dalenius-Hodges method with a Neyman allocation as described in the prior section. The second control group had initially received the Smart Thermostat Program marketing materials and choose not to participate. Both control group customers were required to have the ability to utilize an enabling technology such as 1-way or 2-way paging.[17]

16 The ISO Stage 2 trigger remains in effect for these customers and will still be one of the criteria for curtailment with the CPP-V rate.

17 Initially, the smart thermostat program was offered only to the customers in SDG&E's inland climate zone whose monthly summer consumption was at least 700 kWh. This resulted in a marketing list of approximately 60,000 customers. SDG&E estimates that 50% of its inland customers have the use of a central air conditioner. Though SDG&E only directly marketed to its inland customers, any residential customer was able to participate if they had central air conditioning. Because initial participation rates were lower than expected, SDG&E reduced the required monthly summer consumption level down to 600 kWh. Lowering the summer monthly kWh threshold resulted in a target-marketing list of approximately 80,000 customers.

Table 2-7 summarizes the CPP-V sample allocation.

Table 2-7
Sample Allocation for Residential Track C, CPP-V Tariff

Statewide Pricing Pilot Sample Design
Sample Allocation for CPP-V Residential Tracks A and C

Climate Zone	Dwelling Type	Usage	Sample	Sample Description	Population	Sample Size		
							Rate Differential	
						Total	High	Low
2	All	Low	CPP-V- Track A	*Treatment Group* (> 600 kWh)	78,335	19	10	9
2	All	High			26,014	43	22	21
3	All	Low	CPP-V- Track A	*Treatment Group* (> 600 kWh)	81,865	21	11	10
3	All	High			30,046	42	21	21
					216,260	***125***	***64***	***61***
2	All	Low	CPP-V- Track A	*Control Group1* (> 600 kWh)	78,335	8	-	-
2	All	High			26,014	18	-	-
3	All	Low	CPP-V- Track A	*Control Group1* (> 600 kWh)	81,865	6	-	-
3	All	High		Also Control 2 for C02	30,046	12	-	-
					216,260	***44***		
2	All	Low	CPP-V- Track A	*Control Group* 2	289,892	8	-	-
2	All	Med		Entire Population Sample Frame	262,788	11	-	-
2	All	High			73,168	17	-	-
3	All	Low	CPP-V- Track A	*Control Group* 2	200,467	7	-	-
3	All	Med		Entire Population Sample Frame	189,059	9	-	-
3	All	High			59,507	11	-	-
					1,074,881	***63***		
3	All	All	CPP-V- Track C	*Treatment Group* - Smart Therm Part Target population > 600 kWh a month	*3,650*	126	62	63
					3,650	***126***	***62***	***63***
3	All	All	CPP-V- Track C	*Control Group 1* (> 600 kWh) Smart Thermostat Participants **	*3,650*	70	-	-
					3,650	***70***		
				Total CPP-V Residential Sample	***3,650***	***428***	***126***	***124***

*** This control group utilizes the existing control group for the residential smart thermostat program. 20 Additional sites were selected to complement the existing control group.*

2.3.2 C&I Sample Design

The objective of the C&I portion of the SPP was to evaluate small commercial customers' abilities to shift or reduce energy consumption during the peak period. The study's plan was to test two forms of time-varying pricing, dynamic pricing (CPP-V) and static pricing (TOU). For the CPP-V rate, the emphasis is on measuring the ability of customers to reduce/shift their air conditioning loads using an enabling technology (e.g., a "smart" or controllable thermostat). For the TOU rate, the intent of the SPP is to measure the ability of customers to reduce/shift their entire load, and not just their air conditioning load. The C&I samples were designed to achieve these objectives.

The target population of the TOU treatment sample is the general population of C&I customers below 200 kW in the SCE service who are likely to have some economic incentive to respond to TOU rates. Very small customers (e.g., daily average usage < 5 kWh) and those who clearly have little or no economic incentive to respond to TOU rates (e.g., bus stops, ATM machines, billboards) were excluded.

The target population for the Track A, CPP-V sample is the general population of C&I customers below 200 kW in the SCE service territory who are likely to have air conditioning and for whom an enabling technology is feasible. When developing the sample, customers were excluded if they did not live in areas with 2-way paging coverage or they did not have enough load to account for air conditioning.[18]

In addition to the treatment groups, two separate control samples were also selected, one from the CPP-V treatment population and one from the population of TOU treatment. As with the residential samples, several types of customers were excluded from the sampling frame, including direct access customers, those on existing TOU rates, those on the air conditioning cycling program, net energy metering customers, and those on standby or special contract rates.

The target population for the Track C sample is C&I customers in SCE's service territory who had already volunteered to participate in the AB970 smart thermostat program.[19] A stratified random sample from this population was selected to recruit for CPP-V rates. A separate blind control sample was also randomly selected from the same population. It is important to keep in mind that the population frame for this sample is by no means a representative sample of the general C&I customers.

In each sample, the total size was first allocated between the two rate groups GS-1 (< 20 kW) and GS-2 (20-200 kW) and then between the treatment rates and control samples using the results from the Bayesian model adjusted to allow for a minimum number in each cell. Stratified random sampling was then applied using size (kW) as the only stratification variable and using standard load research sample design and section methods such as Dalenius-Hodges technique, Neyman optimal allocation, and sample validation. Table 2-8 summarizes the allocation of C&I sample for treatment and control for both tracks A and C.

18 Those with summer daily usage less than 10 kWh (not enough load for having A/C), pumping and lighting SIC codes were excluded.

19 The Smart thermostat program had been offered to about 68,000 customers with commercial SIC codes excluding government accounts, schools, all chain-affiliated customers, customers without 13 months of billing history, and those not meeting the summer/winter ratio of 1.2. Because of this and the opt-in nature of this program, this sample is not a representative sample of small C&I population.

Table 2-8
Sample Allocation for Small Commercial & Industrial (Tracks A and C: TOU, CPP-V, and Controls) by Rate Group and Design

General Population				TOU						CPP-Variable						
				Control (A)		TOU Treatment					Control (B)		CPP-V Treatment			
							Sample Size							Sample Size		
								Rate Treatment*							Rate Treatment*	
SPP Track	Rate Group	Usage Level	Population Count	Cell ID	Sample Size	Cell ID	Total	High	Low	Population Count **	Cell ID	Sample Size	Cell ID	Total	High	Low
A	GS-1	Low	229,423	A17	19	A21	22	11	11	142,724	A27	19	A19	24	12	12
		High	84,096	A17	25	A21	28	14	14	56,233	A27	25	A19	34	17	17
			313,519		*44*		*50*	*25*	*25*	**198,957**		44		***58***	29	29
	GS-2	Low	73,788	A18	17	A22	20	10	10	60,994	A28	17	A20	32	16	16
		High	28,539	A18	27	A22	30	*15*	*15*	*23,389*	A28	27	A20	48	*24*	*24*
			102,327		*44*		***50***	***25***	***25***	***84,383***		44		***80***	***40***	***40***
			415,846		88		100			**283,340**		88		138		

Smart Thermostat (AB970) program				CPP-Variable						
					Control (3)		CPP-V Treatment			
								Sample Size		
									Rate Treatment*	
SPP Track	Rate Group	Usage Level		Population Count	Cell ID	Sample Size	Cell ID	Total	High	Low
C	GS-1	Low		836	C03	17	C05	22	11	11
		High		408	C03	25	C05	34	17	17
				1244		*42*		*56*	***28***	***28***
	GS-2	Low		398	C04	21	C06	38	19	19
		High		381	C04	21	C06	38	19	19
				779		*42*		*76*	***38***	***38***
				2,023		***84***		***132***	***66***	***66***

2.3.3 SUMMARY OF SAMPLE ALLOCATION AND CURRENT ENROLLMENT

Table 2-9 summarizes the final distribution of target customers as well as the number of meters that were installed and activated as of October 31, 2003. As seen, overall, enrollment reached 99 percent of target. If the aborted Track A, CPP-V customers are excluded, the enrollment of 2,490 actually exceeded the target of 2,328 by almost 7 percent.

Of the 2,490 enrolled, 1,776 are Track A customers, 233 Track B and 481 Track C. There are 602 residential control customers and 261 C&I control customers, or roughly 24 and 10 percent of the overall sample, respectively. The number of residential treatment customers equals 1,374, or roughly 55 percent of the sample, and the number of C&I treatment customers equal 243.

As of October 31, 8,679 enrollment packages were mailed out to recruit a target of 1,741 treatment customers (control customers were not recruited because they did not receive a treatment rate of information). This mailing resulted in the enrollment of 1,759 customers. A total of 1,332 customer elected not to participate in the experiment and it proved difficult to contact or install meters on 5,134. 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, have elected to opt-out of the experiment since July

2003. Details by treatment are provided in monthly reports to the California Public Utilities Commission.

Table 2-9
Revised Target Populations And Current Enrollment
As of October 31, 2003[20]

		(1)	(2)	(3)	(4)	(5)
Cell ID	**Cell Description**	**Target Enrollment**	**Meters Installed**	**% of Target** Col (2) / Col (1)	**Meters Activated[6]**	**% of Target** Col (4) / Col (1)
A01	Track A, Control, Climate Zone 1	63	67	106%	63	100%
A02	Track A, Control, Climate Zone 2	100	106	106%	103	103%
A03	Track A, Control, Climate Zone 3	100	103	103%	102	102%
A04	Track A, Control, Climate Zone 4	100	103	103%	107	107%
A05	Track A, CPP-F, Climate Zone 1	52	61	117%	63	121%
A06	Track A, CPP-F, Climate Zone 2	188	217	115%	218	116%
A07	Track A, CPP-F, Climate Zone 3	188	226	120%	227	121%
A08	Track A, CPP-F, Climate Zone 4	114	130	114%	134	118%
A09	Track A, CPP-V, Climate Zone 2	62	22	N/A	22	N/A
A10	Track A, CPP-V, Climate Zone 3	63	20	N/A	20	N/A
A11	Track A, CPP-F Info Only, Zone 2	63	69	110%	68	108%
A12	Track A, CPP-F Info Only, Zone 3	63	69	110%	69	110%
A13	Track A, TOU, Climate Zone 1	50	58	116%	58	116%
A14	Track A, TOU, Climate Zone 2	50	57	114%	56	112%
A15	Track A, TOU, Climate Zone 3	50	58	116%	58	116%
A16	Track A, TOU, Climate Zone 4	50	56	112%	57	114%
A17	Track A, C&I <20kW, Control (TOU)	44	44	100%	44	100%
A18	Track A, C&I >20kW, Control (TOU)	44	45	102%	45	102%
A19	Track A, C&I <20kW, CPP-V	58	14	N/A	14	N/A
A20	Track A, C&I >20kW, CPP-V	80	28	N/A	28	N/A
A21	Track A, C&I <20kW, TOU	50	55	110%	55	110%
A22	Track A, C&I >20kW, TOU	50	55	110%	54	108%
A23	CPP-V Control (>600kWh), CZ 2	26	26	100%	26	100%
A24	CPP-V Control (>600kWh), CZ 3	18	18	100%	18	100%
A25	CPP-V Control #2, Climate Zone 2	36	36	100%	36	100%
A26	CPP-V Control #2, Climate Zone 3	27	27	100%	27	100%
A27	Track A, C&I <20kW, Control (CPP-V)	44	44	100%	44	100%
A28	Track A, C&I >20kW, Control (CPP-V)	44	44	100%	44	100%
B01	Track B, Info Only, HunterPt	63	56	89%	48	76%
B02	Track B, CPP-F, HunterPt	126	115	91%	106	84%
B03	Track B, CPP-F, Richmond	64	81	127%	79	123%
C01	Track C, Control	20	20	100%	20	100%
C02	Track C, CPP-V	125	134	107%	133	106%
C03	Track C, C&I <20kW, Control	42	42	100%	42	100%
C04	Track C, C&I >20kW, Control	42	42	100%	42	100%
C05	Track C, C&I <20kW, CPP-V	56	63	113%	59	105%
C06	Track C, C&I >20kW, CPP-V	76	86	113%	85	112%
C07	Track C, Control	100	100	100%	100	100%
Total		2591	2597	100%	2574	99%

20 This table is taken from the October 15th monthly report that is filed by the Utilities with the CPUC.

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 that were described earlier. Nine 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.[21] The enrollment 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 survey.[22] The second installment, equal to $75 for residential customers, was paid to all customers that stayed on the rate through the end of the summer and the third installment will be paid to all customers who remain on the experimental rate through April 2004.

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 nine statistical clones.

Customer recruitment activities were initiated on April 8th and continued through October 17th. 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). Very low enrollment rates were

21 An example of an enrollment package is contained in Appendix 3. The packages differed somewhat depending upon the treatment for which customers were being recruited.
22 The survey is discussed at length in Section 3.

encountered for Track A CPP-V and active recruitment efforts were halted for this track in mid June.[23]

As the experiment progressed, it became clear that the target enrollment numbers would not be reached by the July 1 start date. 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 from nine and (d) mailing the enrollment package simultaneously to several clones. As a result, the enrollment process became more complex in August. 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 a suitable match.

As of October 31, 8,679 enrollment packages were mailed out to recruit a target of 1,741 treatment customers (control customers were not recruited because they did not receive a treatment rate of information). This mailing resulted in the enrollment of 1,759 customers. A total of 1,332 customer elected not to participate in the experiment and it proved difficult to contact or install meters on 5,134. 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, have elected to opt-out of the experiment since July 2003. Details by treatment are provided in monthly reports to the 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.

2.4.2 Participant Education

Once enrolled, customers in various treatment cells were provided 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 4.

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

3 Data Development and Impact Estimation Methodology

3.1 INTRODUCTION

This section summarizes the data development and impact estimation methodology that underlie the impact estimates and demand models discussed in sections 4 and 5. The residential data are discussed in section 3.2 while the C&I data are summarized in section 3.3. Section 3.4 addresses the important issue of selection bias, which is defined broadly to refer to any statistically significant, pre-existing differences between the treatment and control customers. Section 3.5 summarizes the analysis of covariance methodology underlying the impact estimates presented in section 4. The demand modeling methodology, which enables the estimation of price elasticities of demand, is summarized along with the results pertaining to the elasticities in section 5.

3.2 RESIDENTIAL DATABASE SUMMARY

The residential impact analysis and demand modeling rely on a variety of data from the following broad categories:

- Energy consumption and peak demand
- CPP event information
- Survey information on appliance holdings and socio-demographic information
- Weather
- Price
- Miscellaneous information (e.g., census data, sample characteristics, etc.).

The specific data used from each of these broad categories is described in the remainder of this subsection. In most instances, data for each customer was provided by the utility that serves that customer. Customer-specific data from multiple databases was linked using an intelligent customer ID. Table 3-1 summarizes the content of the customer ID.

Table 3-1

Intelligent Customer ID Nomenclature

Character	Name	**Definition**
1,2,3	Cell ID	Identifies SPP Track (A, B, C), Sample (CPP-F, CPP-V, control, info only), and Climate zone. Cell values range from A01 to C06
4	IOU	Defines each IOU (E=SCE, P=PG&E, S=SDG&E)
5	Dwelling Type	Dwelling Type for residential samples. S=Single

Table 3-1

Intelligent Customer ID Nomenclature

Character	Name	**Definition**
		Family, M=Multiple Family, A=All.
6	Usage Level	H=High, L=Low, A=All
7	Rate	Treatment Rate: 1= high summer rate, 2= low summer rate, 0= control
8,9	Slot	Slot Number in the sampling scheme, sequential from 01 to 99
10,11	Alternate	Alternate number in the sampling scheme, 1= for primary sampled account, 2= alternate # 1, 3=alternate # 2,….,10=alternate # 9 11= Replacement, alternates when additional samples were needed. 81- for the cases we recruited new occupants. If we need to do the same for a new occupant at the same site, we will use 82 and so on. 12= substitutes from another cell (for SCE) 99= Substitutes from another cell (for PG&E)

Based on the nomenclature in Table 3-1, the ID A06ESL10303, for example, represents a customer from cell A06 (the CPP-F treatment in climate zone 2) located in SCE's service territory (E), in a single family dwelling (S), who has low usage (L), on the high summer rate treatment (1), who was enrolled as the second alternate for slot 03.

3.2.1 Load Data

The primary load data provided by each utility for customers located in their service territory consists of 96 values for each day representing integrated demand at 15-minute intervals. For purposes of the analysis, the interval data provided by each utility was aggregated to energy consumption by rate period by summing up over the corresponding 15-minute intervals. Off-peak period energy consumption for all weekdays covers the time period from midnight until 2 pm and from 7 pm until midnight. Peak-period energy use on all weekdays covers the period from 2 pm to 7 pm for CPP-F customers. For CPP-V customers, the length of the CPP event was either two or five hours located in the 2 pm to 7 pm time slot. If the latter, it coincided with the normal peak period from 2 pm to 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 is charged at the critical peak rate; (2) the remaining three hours within the eligible peak period that are charged at the normal peak rate; and (3) the remaining hours in the day that are charged at the off-peak rate. Energy consumption during the critical and peak periods was calculated for each CPP-V customer based on the event information described in section 3.2.2.

Diagnostics that were run on the initial load database (e.g., the one covering the pretreatment period[24] and the month of July) indicated that only about 1 percent of the 15-minute interval data provided by the utilities was missing or had zero values.[25] Furthermore, there did not appear to be any systematic pattern or bias in the distribution of missing values across the sample. Consequently, when aggregating the interval data to produce energy use by rate period, missing values were treated as zero and zero values were added in as if they were legitimate unless all of the values in a time period were missing or zero, in which case the aggregate observation was dropped for that day.

Coincident peak demand data was created by first identifying the hour of the statewide electrical peak for each day as determined from data compiled by the California Independent System Operator. The coincident peak demand for each customer is equal to the energy used in the hour of the statewide system peak and is measured in kWh/hour units.

3.2.1 Event Data

Event data links CPP events to CPP treatment customers. Specifically, event data indicates whether or not a CPP-F or CPP-V customer will be billed at critical peak rates for a CPP event. A customer is not billed at the CPP rate if the auto-dialer that is used to make the call to customers registers a code called ST, which means “signal in transit.” This indicates that call was made but could not be completed. For each utility, on average, between two and three percent of customers were not billed for a CPP event. For CPP-V customers, event data is also used to determine the length of the CPP period. This information was used to construct the peak-period consumption values for each customer on CPP-V days.

24 In general, the period of time designated as the pretreatment period covers the time from when a meter was installed and validated until the customer goes on the treatment. However, there are some differences in the definition of the pretreatment period depending upon treatment type and the specific analysis that is being conducted. The specific period of time covered by the pretreatment period for each treatment type and model is described in Section 3.4, Table 3-9.

25 A zero value could be a legitimate read since the meters do not record usage of less than 8 watts.

3.2.2 SURVEY DATA

Data on household characteristics was gathered through a mail survey conducted among both treatment and control customers. Given the essential nature of the survey information to the impact and demand analysis, every effort was made to maximize survey response. Multiple mailings and telephone follow-up calls were made and respondents were paid $25 for completing the survey and numerous. Toward the end of the data collection process, in some cases, site visits were made to collect information on non-respondents.

Table 3-2 summarizes the response rate by cell.[26] The overall survey response rate of 87 percent was extremely high. However, the final response rate will ultimately be known once data collection has been completed for Track B and cell C07. 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 (cells A01 through A05) was 84 percent. The response rate for the CPP-V control groups (C01 and C07) was 66 percent while the CPP-V treatment group (C02) response rate was 100 percent. However, as noted above, the control group response rate will increase once data collection for C07 is complete.

26 Response rate is defined as the percent of customers for whom load data exists that responded to the survey. This is different from the actual response rate to the survey. For various reasons, (e.g., delays in meter installations; timing differences between when surveys were mailed and when customers enrolled into or left the treatment group, etc.) surveys were sent to some customers who, it was later determined, did not actually participate in the SPP either as a control or treatment customer. Indeed, there are 180 customers, or just under 10 percent of survey respondents, for whom there is survey data but no load data. The problem is most apparent in cell C02 where additional customers were surveyed who did not complete the enrollment installation and activation process.

Table 3-2

Load And Survey Response By Cell

CELLID	Cell Description	In Load Dataset [1] Count	In Survey Data [2] Count	In Both Load And Survey Data [3] Count	Percent of Customers in Load
A01	Track A, Control, Climate Zone 1	68	55	53	77.9%
A02	Track A, Control, Climate Zone 2	105	97	89	84.8%
A03	Track A, Control, Climate Zone 3	105	98	92	87.6%
A04	Track A, Control, Climate Zone 4	106	89	88	83.0%
A05	Track A, CPP-F, Climate Zone 1	60	63	59	98.3%
A06	Track A, CPP-F, Climate Zone 2	209	215	201	96.2%
A07	Track A, CPP-F, Climate Zone 3	216	217	204	94.4%
A08	Track A, CPP-F, Climate Zone 4	132	129	126	95.5%
A09	Track A, CPP-V, Climate Zone 2	17	21	17	100.0%
A10	Track A, CPP-V, Climate Zone 3	18	21	16	88.9%
A11	Track A, CPP-F Info Only, Zone 2	70	66	66	94.3%
A12	Track A, CPP-F Info Only, Zone 3	68	68	66	97.1%
A13	Track A, TOU, Climate Zone 1	57	57	56	98.2%
A14	Track A, TOU, Climate Zone 2	58	51	51	87.9%
A15	Track A, TOU, Climate Zone 3	58	58	56	96.6%
A16	Track A, TOU, Climate Zone 4	55	55	54	98.2%
A23	CPP-V Control (>600kWh), CZ 2	26	28	17	65.4%
A24	CPP-V Control (>600kWh), CZ 3	18	19	14	77.8%
A25	CPP-V Control #2, Climate Zone 2	35	35	26	74.3%
A26	CPP-V Control #2, Climate Zone 3	26	30	20	76.9%
B01	Track B, CPP-F InfoOnly, HunterPt	70	46	38	54.3%
B02	Track B, CPP-F, HunterPt	139	99	85	61.2%
B03	Track B, CPP-F, Richmond	80	73	73	91.3%
C01	Track C, Control	20	27	17	85.0%
C02	Track C, CPP-V	107	152	107	100.0%
C07	Track C, Control	96	62	60	62.5%
Total		2019	1931	1751	86.7%

The customer characteristics survey gathered a variety of information, including data on:

- 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.

A copy of the survey questionnaire is contained in Appendix 5.

The survey vendor recorded the response to each question option as a binary variable. The survey data was typically recoded in order to produce variables that could be used in the analysis. Appendix 6 contains the coding instructions that were used to convert the survey data into regression variables.

The following survey variables were included in the regression models underlying the analysis described in Section 4:[27]

- Persons per household (PPHH)
- Number of bedrooms[28] (BED)
- Central air conditioning binary variable (CAC)[29]
- Electric clothes dryer binary variable (EDRY)
- Electric cook top binary variable (ECOOK)
- Electric spa or hot tub binary variable (SPA)
- Electric water heating binary variable (EWH_MAIN)
- A binary variable indicating the presence of a home business (HBUS)
- A binary variable indicating whether or not the head of household is a college graduate (COLLEGE)
- A categorical variable on utility performance rating, where a value of 1 equals poor, 2 fair, 3 good and 4 excellent (SATISFACTION)
- A binary variable indicating the presence of a swimming pool (POOL)
- A continuous variable indicating the number of freezers (NFRZ)
- A continuous variable indicating the number of well pumps (NPMP)
- A continuous variable indicating the number of heated water beds (NWBED)
- A continuous variable for household income[30] (INCOME)
- A binary variable indicating frequent use of computers in the home (HCUSE) (e.g., sending emails, browsing the internet and/or paying bills on line “several times a week”).

A number of variables that might otherwise have been included in the regression models (such as room air conditioning and air conditioning usage patterns) were not tested because they had a high percentage of missing values and including them in the regression models would have substantially reduced the number of observations. Appendix 7 lists the number and percent of missing values by survey question. Other variables that had a reasonably high response rate were excluded from the models because they were not statistically significant. Table 3-3 contains average population values by climate zone and statewide for each of the regression variables.

Table 3-3

27 The regression models underlying the results presented in section 4 also included a variable indicating whether or not a customer was a treatment customer (T) by itself as well as multiplied by CAC*CDH, POOL and ECOOK, where CDH stands for cooling degree hours.
28 This variable is a proxy for size of structure. The customer characteristics survey included structure size but there were many missing responses compared with the response rate for number of bedrooms.
29 This variable was not used by itself in the regression models but rather as an interaction term with cooling degree hours and with the treatment binary variable.
30 The income question on the survey was categorical, with the lowest category being under $25,000 and the highest being greater than $150,000. The income variable uses the midpoint of each category, with the lowest category coded as $15,000 and the highest as $200,000.

Population Weighted Values For The Explanatory Variables Used In The Regression Models[31]

Variable	Zone 1	Zone 2	Zone 3	Zone 4	State
Persons per household	3.14	2.96	3.37	3.51	3.16
# of Bedrooms	2.70	2.97	3.03	2.76	2.93
Central air conditioning	0.07	0.29	0.68	0.71	0.42
Income	76,596	71,409	66,897	48,281	68,293
Electric clothes dryer	0.33	0.38	0.30	0.40	0.35
Electric cooktop	0.34	0.39	0.34	0.36	0.36
Electric spa	0.01	0.08	0.07	0.05	0.06
Electric water heater	0.10	0.06	0.14	0.08	0.09
Home business	0.04	0.01	0.04	0.03	0.03
Own home	0.70	0.64	0.67	0.65	0.66
College education	0.55	0.48	0.46	0.20	0.45
Satisfied with utility	3.00	3.04	2.95	2.92	3.00
Swimming pool	0.01	0.06	0.10	0.15	0.08
Home computer use	0.60	0.54	0.60	0.36	0.55
# of freezers	0.17	0.16	0.29	0.32	0.22
# of dishwashers	0.62	0.61	0.67	0.57	0.63
# water pumps	0.02	0.10	0.03	0.10	0.07
# water beds	0.00	0.00	0.03	0.02	0.01

3.2.3 Weather Data

Weather is an important determinant of energy use and a key explanatory variable in the regression models. Although separate analysis has been done for each of four climate zones, there is still a wide variation in climate within each zone. Consequently, each control and treatment customer in the experiment was assigned by the relevant utility to a specific weather station located in close proximity to the customer, and weather data was gathered for that station. Data from 58 weather stations was used in the analysis. Table 3-4 lists the weather stations that were used and the corresponding customer population associated with each station. The population values were used to calculate climate-zone-specific averages for the weather variables. 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.

31 The values in this table represent the population in each climate zone. They are based on survey responses from control group customers (cells A01 through A04), properly weighted to reflect the population at large.

Table 3-4
Population By Weather Station Used To Calculate
Cooling Degree Hour Averages By Climate Zone

Utility	Station ID	Weather Area	Population	Zone 1	Zone 2	Zone 3	Zone 4
PG&E	P05	Concord	236,416		X	X	
PG&E	P06	Oakland	280,055	X	X		
PG&E	P07	San Ramon	81,199		X		
PG&E	P08	Colma	94,604	X	X		
PG&E	P09	Potrero	295,343	X			
PG&E	P10	Ukiah	44,668	X	X		
PG&E	P11	San Rafael	186,424	X	X		
PG&E	P12	Santa Rosa	161,644	X	X		
PG&E	P13	Sacramento	162,848			X	
PG&E	P14	Belmont	144,699	X	X		
PG&E	P15	Milpitas	491,164		X		
PG&E	P16	Santa Cruz	82,392	X			
PG&E	P17	Chico	84,998	X	X	X	X
PG&E	P18	Marysville	50,534		X	X	
PG&E	P19	Red Bluff	48,078	X			X
PG&E	P20	Auburn	124,617	X	X	X	
PG&E	P21	Angels Camp	65,661	X	X	X	X
PG&E	P22	Stockton	235,473			X	X
PG&E	P23	Paso Robles	31,116		X		
PG&E	P24	Salinas	114,703	X	X		
PG&E	P25	Santa Maria	107,566	X	X		
PG&E	P26	Eureka	57,284	X	X		
PG&E	P27	Bakersfield	159,010				X
PG&E	P28	Fresno	327,599	X			X
PG&E	P29	Cupertino	210,199	X	X		
SCE	E01	Tulare	124,357		X	X	
SCE	E02	Mammoth Lakes	10,797		X		
SCE	E03	San Dimas	211,541			X	
SCE	E04	Monterey Park	415,914		X	X	
SCE	E05	Ventura	115,460		X	X	
SCE	E06	Romoland	292,609			X	
SCE	E07	Rialto	353,505			X	
SCE	E08	Moorpark	141,237		X	X	
SCE	E09	Rimforest	44,072		X		X
SCE	E10	Valencia	77,528		X	X	
SCE	E12	Bishop	14,271		X		
SCE	E13	Goleta	66,229		X		
Utility	Station ID	Weather Area	Population	Zone 1	Zone 2	Zone 3	Zone 4
SCE	E14	El Segundo	206,231		X	X	

Utility	Station ID	Weather Area	Population	Zone 1	Zone 2	Zone 3	Zone 4
SCE	E15	Long Beach	321,292		X		
SCE	E16	Westminster	244,534		X		
SCE	E17	Santa Ana	713,691		X	X	
SCE	E18	Cathedral Cit	91,506				X
SCE	E19	Blythe	7,965				X
SCE	E20	Ridgecrest	25,362				X
SCE	E21	Barstow	14,645				X
SCE	E22	Lancaster	90,922				X
SCE	E23	Victorville	80,287				X
SCE	E24	Yucca Valley	23,239				X
SDG&E	S01	Lindbergh Field	254,600		X		
SDG&E	S02	Miramar	190,376		X	X	
SDG&E	S03	Montgomery Field	160,157		X	X	
SDG&E	S04	Oceanside Airport	74,951		X		
SDG&E	S05	Gillespie Field	162,609			X	
SDG&E	S06	Brown Field	40,693			X	
SDG&E	S07	Campo	2,930			X	
SDG&E	S08	Ramona	73,202		X	X	
SDG&E	S09	Carlsbad	123,367		X		

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[32] 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 have not been used to date.

The temperature data were used to calculate cooling 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.

32 Email from Ray Wong to Steve George dated 8/13/03 received at 12:47 pm.

3.2.5 PRICE DATA

The estimation of demand models requires development of price data. Given the complexity of electricity tariffs in general, and especially in California where tariffs currently have as many as five tiers, a key issue in the estimation of demand models is how best to represent the price to which customers respond. There is an extensive literature on this subject dating back to the mid-1970s, and many different price terms have been used, including current and lagged marginal price with and without infra-marginal price terms, price indices, average price and total bills, to name a few. Section 5.3 discusses the many options that were examined for the price variable to be used in this study.

As indicated in Section 5.3, the multiple pricing tiers in the experimental and control tariffs result in both average and marginal prices varying with usage level, utility, consumer income (e.g., CARE versus non-CARE customers), treatment, time of day and date (e.g., rate changes have occurred during the experiment, most significantly for SCE). The usage level at which customers move from one rate tier to another also varies by climate zone. Thus, although the experiment was designed to have three price levels for each treatment (e.g., a high and low treatment rate and the control group rate), there is, in fact, much more variation in price within the sample.

As discussed in section 5.3, the final decision on the price variable to be used in the demand models was the average price at the midpoint of the third tier. In order to calculate these prices, a composite tariff was constructed for each climate zone based on a population-weighted average of the baseline quantities associated with each of the baseline regions within each utility and climate zone. The resulting baseline quantities that were used to calculate average and marginal prices for each by utility, climate zone and season are contained in Table 3-5.

Table 3-5 **Average Baseline Quantities (kWh)** Used to Calculate Average and Marginal Prices					
Utility	**Season**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 4**
PG&E	Summer	264	384	485	548
PG&E	Winter	312	392	386	375
SCE	Summer	n/a	313	472	754
SCE	Winter	n/a	305	353	343
SDG&E[33]	Summer	n/a	315	313	n/a
SDG&E	Winter	n/a	327	347	n/a

Appendix 9 contains the prices that were calculated for use in the demand analysis. Both marginal and average prices are presented for each tier, as well as data on the ratio of treatment to control group prices, and the percentage and absolute differences between treatment and control prices. PG&E's prices have remained constant throughout the experimental period. SCE has had two price changes, with the most significant one going into effect on August 1 and the second on September 1. SDG&E has had three minor price changes since July 1, with effective dates of September 1, October 1 and October 7. Appendix 9 presents data for two pricing periods. Period 1 represents the prices that were in effect in early July, when most treatment customers were placed on the experimental rate. Period 2 reflects the August 1 price change for SCE and the September 1 price change for SDG&E (and the original prices for PG&E since PG&E's prices never change).

3.2.6 Miscellaneous Data

A variety of miscellaneous data was gathered in order to investigate potential selection bias and/or for possible use in the impact analysis. Each utility provided the following information for every customer that was chosen as part of the recruitment sample:[34]

33 Due to a discrepancy between data provided in calculating the SDG&E values and the baseline quantities that should have applied, the values Table 3-5 are not completely accurate. The summer values should have been 309 for Zone 2 and 358 for Zone 3. The winter value for Zone 2 is correct and the zone-3 value is off by 1 kWh. After the discrepancy was discovered, CRA recalculated the average prices to see if there would be any significant differences from the values used in the demand models. The differences occurred in the sixth decimal place, so the demand models were not re-estimated.

34 Recall from section 2 that multiple "clones" were drawn for each required sample. In the initial sample draw, SCE and SDG&E selected 10 clones for each slot while PG&E selected 20. In a few instances where all slots were not filled even after using the 10 clones, an additional 10 clones were drawn. In total, the sample database contains information on

- Average daily summer usage for the 2002 summer
- Weather station ID
- Housing type
- An indicator of whether or not a customer was contacted as part of the enrollment process
- An indicator of whether or not a contacted customer could be reached after the requisite number of attempts
- An indicator of a meter installation failure for customers that agreed to participate or for control customers
- An indicator that a contacted customer was ineligible due to plans to move within six months (a prerequisite for participation was that the customer was not planning to move within six months)
- An indicator of refusal to participate
- The customer's address.

For CPP-F and CPP-V customers who agreed to participate in the experiment, information was also obtained on their preferred optional notification methods.[35] For treatment customers participating in the SPP, information was also obtained on the number of times per day that each customer accessed their usage information via the experimental web site established for that purpose. This information will eventually be used to determine whether there is any correlation between web access and rate impacts.

As discussed in section 3.4 below, one approach to correcting for self-selection bias is to estimate an equation representing the choice to participate in the experiment. Developing a choice model requires having information both for customers who choose to participate as well as for those who were offered the choice to participate but declined. The ideal data for estimating a choice model would come from a survey among both customer groups. This survey would be similar in content to the survey that was conducted among those who chose to participate (as described in section 3.2.3). Time and budget constraints prevented such a survey from being conducted. As an alternative to the preferred approach, a decision was made to assess whether or not census information could be used to estimate a model for the probability of participation in the experiment.

Geocoding software was used to map each customer in the SPP sample into census groups. A census group consists of an aggregation of census blocks that varies in size between a few hundred and a few thousand households. Census group was chosen over census block because data on more variables is made available at the group level than at the block level. Roughly 90 percent of the customers who were contacted to enroll in the experiment were successfully mapped into the census groups based on the

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roughly 23,000 customers, of which roughly 15,000 are in PG&E's service territory, 3,800 are in SDG&E's service territory, and 3,400 are in SCE's service territory.

35 The primary notification for all customers is via a landline telephone. However, customers were given the option of having additional notification options, including an alternative landline, a cell phone, email and pager.

addresses provided by the utilities. Information on the following variables was obtained through this process:

- Census block population
- Average household size
- Percent of group households that are one-person households
- Percent of group households that are two-person households
- Percent of group households that are three-person households
- Percent of group households that rent
- Percent of group households where the native language is English
- Percent of group households that are linguistically isolated (e.g. no adult member of the household speaks English "very well")
- Percent of the population under the age of 18
- Percent of the population over the age of 65
- Median income
- Income per capita
- Percent of group households that are below the poverty line
- Percent of the population that is no Caucasian/white or Hispanic
- Percent of group households that have zero bedrooms
- Percent of group households that have one bedroom
- Percent of group households that have two bedrooms
- Percent of group households that have three bedrooms
- Percent of group households that have four or more bedrooms
- Percent of group households that have utility provided gas heating
- Percent of group households that have utility provided electric heating
- Percent of group households that heat with other fuels.

Section 3.4.2 explains how this data was used to estimate a probit model for customer participation.

3.3 C&I DATABASE SUMMARY

The data development process for the C&I sector was virtually identical to that of the residential sector for energy use and peak demand, CPP event information, weather[36] and miscellaneous experimental data. Consequently, a description of the development process for these databases will not be repeated. Price data have not yet been developed and no census information has been gathered for C&I customers.

As with the residential sector, a survey was conducted to obtain customer characteristics information for C&I customers. However, in the case of C&I customers, the survey was

36 The C&I sample was not segmented by climate zone so there was no need to map weather stations into climate zones for the C&I analysis.

much shorter. Appendix 8 contains the survey questionnaire. 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.

Table 3-6 shows the completion rates by cell for the C&I survey and Table 3-7 shows the percent of customers with load data that answered the structure size question on the survey. As seen, the survey completion rate for C&I customers was even higher than for residential customers, with an overall response rate of 95 percent. Structure size information was only obtained for roughly 79 percent of customers in the experiment.

Table 3-6
C&I Survey Completion Rates By Cell Id

		In Load Dataset [1]	In Survey Data [2]	In Both Load And Survey Data [3]	
CELLID	Cell Description	Count	Count	Count	Percent of Customers in Load
A17	Track A, C&I <20kW, Control (TOU)	47	43	43	91%
A18	Track A, C&I >20kW, Control (TOU)	48	45	45	94%
A19	Track A, C&I <20kW, CPP-V	13	12	11	85%
A20	Track A, C&I >20kW, CPP-V	28	31	28	100%
A21	Track A, C&I <20kW, TOU	54	55	53	98%
A22	Track A, C&I >20kW, TOU	53	57	53	100%
A27	Track A, C&I <20kW, Control (CPP-V)	47	45	45	96%
A28	Track A, C&I >20kW, Control (CPP-V)	44	44	44	100%
C03	Track C, C&I <20kW, Control	44	43	43	98%
C04	Track C, C&I >20kW, Control	47	43	43	91%
C05	Track C, C&I <20kW, CPP-V	58	61	54	93%
C06	Track C, C&I >20kW, CPP-V	89	87	80	90%
Total		572	566	542	95%

Table 3-7
Percent Of C&I Customers With Both Load And Structure Size Data

		In Load Dataset [1]	In Survey Data [2]	In Both Load And Survey Data [3]	
CELLID	Cell Description	Count	Count	Count	Percent of Customers in Load
A17	Track A, C&I <20kW, Control (TOU)	47	26	26	55%
A18	Track A, C&I >20kW, Control (TOU)	48	32	32	67%
A19	Track A, C&I <20kW, CPP-V	13	11	10	77%
A20	Track A, C&I >20kW, CPP-V	28	30	27	96%
A21	Track A, C&I <20kW, TOU	54	42	42	78%
A22	Track A, C&I >20kW, TOU	53	53	50	94%
A27	Track A, C&I <20kW, Control (CPP-V)	47	27	27	57%
A28	Track A, C&I >20kW, Control (CPP-V)	44	33	33	75%
C03	Track C, C&I <20kW, Control	44	39	39	89%
C04	Track C, C&I >20kW, Control	47	37	37	79%
C05	Track C, C&I <20kW, CPP-V	58	57	51	88%
C06	Track C, C&I >20kW, CPP-V	89	84	77	87%
Total		572	471	451	79%

3.4 SELECTION BIAS

A key issue in analyzing the impact of time-differentiated rates in the SPP is whether or not the results can be generalized to the target population. For CPP-F and TOU customers in Track A, the target population consists of the entire population in each climate zone and, ultimately throughout the state. If there are reasons to believe that the enrolled sample is not representative of the target population, it is important to test for and, if present, correct for any differences in energy use between the treatment and control customers that existed prior to the treatment going into affect. Such preexisting differences may result from self-selection (e.g., consumers who use less energy during the peak period might enroll at a higher rate), differences in sample selection, differences in the enrollment process, or any of a host of reasons. Regardless of the cause, throughout the remainder of this report, we refer to such differences as selection bias.

Given that participation in the SPP was voluntary and only 15-20% of the customers who were offered the opportunity to enroll actually did so, it is reasonable to suspect that selection bias may exist. Thus, it must be tested for and, if present, controlled for where possible when extrapolating to the target population. When testing and adjusting for selection bias, it is very important to distinguish between two types, one due to observable variables and the other due to unobservable variables. For example, assume that households that enroll in the experiment have higher usage than those that do not enroll, but this difference is due entirely to the fact that enrolled households have higher levels of air conditioner use. Assume also that, after accounting for these differential air conditioner saturation rates, the demand for electricity is the same between enrolled and non-enrolled households. Under these assumptions, if the saturations for each group are known, then adjustments can be made for the selection bias by controlling for differences in air conditioner saturation when estimating treatment impacts or demand models.

On the other hand, if the preexisting difference between enrolled and non-enrolled customers is due to factors that cannot be observed, adjustments must be made in the impact estimates or demand models. Intuitively, the reason is that the observed, treatment-period estimates and estimated price elasticities will reflect not only the true responsiveness of an individual household’s demand to price, but also the impact that the price treatment had on enrollment.

There are a number of ways to test for and adjust for selection bias. First, one can compare the characteristics of customers in the randomly chosen control groups and the voluntarily enrolled treatment groups (e.g., using the survey data described in Section 3.2.3). These characteristics include customer appliance holdings, socio-demographic factors, and attitudes toward the environment and the utility and household income. The results of such comparisons are presented in Section 3.4.1. Second, one can model the probability that a customer will choose to participate in the experiment, based on their observable characteristics. Section 3.4.2 presents the results of such choice modeling. Third, one can simply test whether or not there are systematic differences in electricity use by rate period between the treatment and control groups. Such tests are presented in Section 3.4.3. Fourth, one can estimate regression models that measure and explain any difference in usage patterns by rate period as a function of observable variables and test whether any remaining difference exists between treatment and control customers. Such models are discussed in Section 3.4.4.

Before continuing the discussion of selection bias and how it has been assessed, it is important to understand specifically what treatment and control groups are compared and what time periods are used for the various types of analyses that are presented later in this report. As the number of customers has evolved throughout the study, especially during the pretreatment period, it is also useful to obtain an understanding of the number of customers and number of customer days that underlie the various statistical comparisons and models that are presented later in this section and in sections 4 and 5.

Tables 3-9 through 3-12 summarize the relevant cells that are used for various analyses and the time periods that apply to the pretreatment and treatment periods in each case. As seen, data from the pretreatment period for CPP-F, TOU and CPP-V treatment customers on non-CPP days generally cover the period after which a customer's meter is installed and validated and prior to that customer going on the treatment rate. For the majority of customers, the treatment went into effect in early July. However, if a customer was recruited after July 15th, the treatment didn't go into effect until their next meter read date. Thus, the pretreatment period for some customers could extend significantly beyond July 1st. Indeed, for a handful of customers, the pretreatment period even extends into October.

The pretreatment data used for the CPP-day analysis for all treatments consists of the 12 maximum system load days in May and June. Five days occurred in May and seven in June. These warmer days were chosen because it was felt that the models estimated on these days would provide a much better match to the treatment period, CPP-day models.

The pretreatment and treatment period definitions are slightly different for Information Only customers than they are for the rate treatment customers. For rate treatment customers, there is a date certain after which they are billed according to the treatment rates, and this date is the correct dividing line between pretreatment and treatment periods. However, no such date exists for Information Only customers as they are on the same rate before and after the treatment goes into effect. Thus, the pretreatment period is defined as prior to July 1st for all customers, even though some customers were enrolled after that date.

Table 3-9
Data Summary For CPP-F Analysis

Treatment	**Climate Zone**	**Control Cell**	**Treatment Cell**	**Day Type**	**Pretreatment Definition**	**Treatment Definition**
CPP-F	1	A01	A05	CPP	12 maximum system load days in May & June	All CPP days after June 30 for control and after treatment goes into effect for each treatment customer
CPP-F	2	A02	A06	CPP	Same as above	Same as above
CPP-F	3	A03	A07	CPP	Same as above	Same as above
CPP-F	4	A04	A08	CPP	Same as above	Same as above
CPP-F	1	A01	A05	Non-CPP	All weekdays prior to July 1 for control customers and prior to treatment going into effect for each treatment customer	All non-CPP weekdays after June 30 for control and after treatment goes into effect for each treatment customer
CPP-F	2	A02	A06	Non-CPP	Same as above	Same as above
CPP-F	3	A03	A07	Non-CPP	Same as above	Same as above
CPP-F	4	A04	A08	Non-CPP	Same as above	Same as above

Table 3-10

Data Summary For TOU Analysis

Treatment	**Climate Zone**	**Control Cell**	**Treatment Cell**	**Day Type[37]**	**Pretreatment Definition**	**Treatment Definition**
TOU	1	A01	A13	CPP	Same as for CPP-F treatment	Same as for CPP-F treatment
TOU	2	A02	A14	CPP	Same as above	Same as above
TOU	3	A03	A15	CPP	Same as above	Same as above
TOU	4	A04	A16	CPP	Same as above	Same as above
TOU	1	A01	A13	Non-CPP	Same as for CPP-F treatment	Same as for CPP-F treatment
TOU	2	A02	A14	Non-CPP	Same as above	Same as above
TOU	3	A03	A15	Non-CPP	Same as above	Same as above
TOU	4	A04	A16	Non-CPP	Same as above	Same as above
TOU	1	A01	A13	All Weekdays	All weekdays prior to July 1 for control customers and prior to treatment going into effect for each treatment customer	All weekdays after June 30 and after treatment goes into effect for each treatment customer
TOU	2	A02	A14	All Weekdays	Same as above	Same as above
TOU	3	A03	A15	All Weekdays	Same as above	Same as above
TOU	4	A04	A16	All Weekdays	Same as above	Same as above

37 The analysis was done for the TOU rate on CPP and non-CPP days in order to compare responsiveness between customers on the CPP-F and TOU rates on the same day types. Unlike CPP-F customers, TOU customers do not receive any notification on CPP days.

Table 3-11
Data Summary For CPP-V Analysis

Treatment	Climate Zone	Control Cell	Treatment Cell	Day Type	Pretreatment Definition	Treatment Definition
CPP-V(ST)	3	C01 & C07	C02	CPP	Same as for CPP-F treatment	Same as for CPP-F treatment
CPP-V(ST)	3	C01 & C07	C02	Non-CPP	Same as for CPP-F treatment	Same as for CPP-F treatment
CPP-V(600)	3	A24	C02	CPP	Same as for CPP-F treatment	Same as for CPP-F treatment
CPP-V(600)	3	A24	C02	Non-CPP	Same as for CPP-F treatment	Same as for CPP-F treatment

Table 3-12
Data Summary For Information Only Treatment Analysis

Treatment	Climate Zone	Control Cell	Treatment Cell	Day Type	Pretreatment Definition	Treatment Definition
Info Only	23	A02	A11	CPP	Same as for CPP-F treatment	All CPP days after June 30 for both control and treatment customers
Info Only	3	A03	A12	Non-CPP	All weekdays prior to July 1 for both control and treatment customers	All non-CPP weekdays after June 30 for both control and treatment customers
Info Only	2	A02	A11	CPP	Same as for CPP-F treatment	All CPP days after June 30 for both control and treatment customers
Info Only	3	A03	A12	Non-CPP	All weekdays prior to July 1 for both control and treatment customers	All non-CPP weekdays after June 30 for control and treatment customers

Table 3-13 summarizes the number of customers and the number of customer days that exist for each of the time periods that were summarized in Tables 3-9 through 3-12 and that underlie the analysis in later sections of this report. As seen, in most instances, there is a reasonable balance between the number of customer days for treatment and control customers in the pretreatment period. This is universally true for CPP-day types, as the pretreatment period is constrained to the twelve maximum load days. For the non-CPP day comparisons, there are a number of instances where there is significantly more control group data than treatment group data. As discussed in Section 4, tests were run to see if constraining the pretreatment period to a time when there is greater balance between the treatment and control customers would lead to significantly different results. The analysis indicated that the bottom-line impact estimates did not change much.

Table 3-13
Customer Counts And Day Counts By Period

Rate	Day Type	Zone	Estimation Period	# of Customers		Customer Days	
				Control	Treatment	Control	Treatment
CPPF	Non-CPP	1	Pretreatment	38	38	2,193	869
			Treatment	42	45	2,964	3,193
		2	Pretreatment	70	133	2,518	2,834
			Treatment	70	147	5,076	10,040
		3	Pretreatment	73	150	2,327	2,701
			Treatment	76	162	5,353	10,966
		4	Pretreatment	63	86	2,816	1,894
			Treatment	63	97	4,514	6,438
CPPF	CPP	1	Pretreatment	38	38	437	294
			Treatment	41	45	437	463
		2	Pretreatment	70	114	643	871
			Treatment	70	144	824	1,548
		3	Pretreatment	73	130	624	852
			Treatment	75	158	867	1,645
		4	Pretreatment	63	80	627	597
			Treatment	63	92	734	939
TOU	Non-CPP	1	Pretreatment	38	37	2,193	1,035
			Treatment	42	48	2,964	3,434
		2	Pretreatment	70	32	2,518	780
			Treatment	70	38	5,076	2,628
		3	Pretreatment	73	43	2,327	792
			Treatment	76	42	5,353	2,735
		4	Pretreatment	63	42	2,816	1,013
			Treatment	63	47	4,514	3,186
TOU	CPP	1	Pretreatment	38	37	437	332
			Treatment	41	48	437	559
		2	Pretreatment	70	31	643	246

Table 3-13
Customer Counts And Day Counts By Period

Rate	Day Type	Zone	Estimation Period	# of Customers Control	# of Customers Treatment	Customer Days Control	Customer Days Treatment
			Treatment	70	38	824	428
		3	Pretreatment	73	34	624	245
			Treatment	75	42	867	444
		4	Pretreatment	63	40	627	340
			Treatment	63	47	734	517
TOU	All Weekdays	1	Pretreatment	38	37	2,193	1,035
			Treatment	42	48	3,401	3,993
		2	Pretreatment	70	32	2,518	783
			Treatment	70	38	5,900	3,056
		3	Pretreatment	73	43	2,327	811
			Treatment	76	42	6,220	3,179
		4	Pretreatment	63	42	2,816	1,017
			Treatment	63	47	5,248	3,703
CPPV (ST)	Non CPP		Pretreatment	66	76	2,592	759
			Treatment	66	85	3,044	5,492
CPPV (600)	Non CPP		Pretreatment	11	76	396	759
			Treatment	13	85	880	5,492
CPPV (ST)	CPP		Pretreatment	66	58	766	274
			Treatment	66	83	360	854
CPPV (600)	CPP		Pretreatment	11	58	122	274
			Treatment	12	83	144	854
INFO	Non CPP	2	Pretreatment	32	40	1,618	1,201
			Treatment	32	49	2,360	3,511
	Non CPP	3	Pretreatment	20	34	1,187	1,066
			Treatment	20	55	1,405	3,743
INFO	CPP	2	Pretreatment	32	40	342	368
			Treatment	32	49	381	570
	CPP	3	Pretreatment	20	34	238	325
			Treatment	20	55	223	613

3.4.1 Comparison of Customer Characteristics

Sample means between the control and treatment groups were compared for a total of 19 variables, the 18 variables listed in Table 3-3 plus one additional variable indicating environmental consciousness.[38] The comparisons were made for the Track A CPP-F and TOU treatments in each of four climate zones and for the Information Only treatments in climate zones 2 and 3. The t-test was used to determine whether or not differences in mean values were statistically significant. Table 3-14 lists the variables by treatment and climate zone where the difference in means is statistically significant. As seen, out of the 190 possible comparisons (e.g., 19 variables times 10 treatment/climate zone combinations), the mean values were statistically different at the 5% level of significance in only 14 cases (e.g., 7 percent of the time). That is, based on this simple test, the general conclusion is that there are relatively few cases in which there are statistically significant differences between the treatment and control groups based on these observable variables. Some of the differences that were found are interesting, however. These are reported in Table 3-14.

Table 3-14

Variables For Which Statistically Significant Differences Exist Between Treatment And Control Customers

Control Cell	Treatment Cell	Rate	Zone	Variable	Control Mean	Treat Mean	t-stat
A01	A05	CPP-F	1	Central Air conditioning	7.6	0	2.16
A02	A06	CPP-F	2	# of bedrooms Electric spa	3.2 11.3	2.9 5.2	2.06 1.96
A03	A07	CPP-F	3	# of water pumps	3.1	12.0	2.59
A04	A08	CPP-F	4	Green attitudes	1.2	9.5	2.43
A01	A13	TOU	1	None	-	-	-
A02	A14	TOU	2	Green attitudes	10.9	23.4	1.97
A03	A15	TOU	3	Satisfaction with utility # of water pumps	2.9 3.1	3.2 15.5	2.29 2.86
A04	A16	TOU	4	None	-	-	-
A02	A11	Info Only	2	Electric drier Electric cook top, # of dishwashers	54.3 54.4 66.0	81.2 88.3 87.3	3.18 4.40 2.66
A03	A12	Info Only	3	Electric dryer Electric cooktop # of water pumps	31.3 37.5 3.1	56.1 71.3 14.7	3.23 2.75 2.13

38 See the survey questionnaire in Appendix 5 and the coding instructions in Appendix 6 for a detailed explanation of this variable. In brief, the variable identifies consumers who strongly agreed with three environmentally favorable statements. This variable was not included in Table 3-3 because it did not prove statistically significant in most regression equations.

For example, in climate zone 1, people who chose to participate in the experiment are less likely to own central air conditioning than those in the control group. This is the type of selection bias that one would expect to find, as air conditioning owners are more likely to be negatively affected by the CPP-F rate in the absence of load shifting. However, it should be noted that the saturation and use of central air conditioning in this cool climate zone is very low. In fact, there are only four control group customers in the sample who have central air conditioning and no treatment customers have it. Thus, the impact of this statistically significant difference in means is likely to be very small in terms of explaining any significant differences in the average energy use between treatment and control customers in this climate zone.

For climate zone 2, CPP-F, there are statistically significant differences in the mean values for the number of bedrooms (a proxy for size of structure) and the saturation of electric spas. While statistically significant, the difference for number of bedrooms is only about 10 percent of the control group mean. With respect to spa saturation, treatment customers are half as likely to own an electric spa than control group customers. This result is somewhat counterintuitive in that spa usage is one of the more flexible loads, so one might expect, a priori, that customers with spas would be more likely to participate because they have greater potential to benefit from the new rate by shifting spa usage.

In climate zone 3, the only difference between treatment and control group customers is in the number of well pumps. Treatment customers are four times more likely to have a well pump than control customers. This result might suggest that customers with well pumps think they can shift load more easily than those without well pumps. It is interesting to note that the saturation of air conditioning in this climate zone (not shown in the table) is nearly identical for control and treatment customers (71.7 and 72.0 percent, respectively).

In zone 4, the hottest climate zone, customers who are more environmentally conscious are more likely to participate. It is also interesting to note that the difference in average income between treatment and control group households in zone 4 is statistically significant at the 90 percent level (t-statistic = 1.72). The average of $57,367 for control group customers is almost 20 percent larger than the average of $47,077 for treatment customers.

For the TOU treatment in climate zones 1 and 4, there are no variables for which the difference in means between control and treatment customers is statistically significant. In zone 4, however, the percent of households with a college degree is 40.7 for treatment customers and 25.9 for control customers, a difference that is statistically significant at the 90 percent confidence level (t-statistic = 1.84). In climate zone 2, the only variable with a statistically significant difference is the “green attitude” variable, where treatment customers display greater environmental consciousness (an average value of 23.4) than do control customers (an average value of 10.9). In climate zone 3, there are two variables where a significant difference is found, satisfaction with the utility and the number of well pumps.

The Information Only treatment groups have the greatest number of variables for which the difference between treatment and control customers is statistically significant, and the variables all have to do with the saturation of electric end uses. In climate zone 2, the saturation of electric driers is 81 percent for treatment customers and only 54 percent for control customers, a difference of roughly 50 percent. The difference for electric cook tops is even greater and the number of dishwashers is much higher for treatment than control group customers. Similar differences exist for electric driers and cook tops in climate zone 3. There is also a much greater saturation of well water pumps among treatment customers than among control customers in climate zone 3.

In summary, there are not a large number of differences in the means of various observable variables between the treatment and control customers. More significant differences exist for the Information Only treatment than for the rate treatments. The absence of differences in the means of the observable factors does not imply that there is no value in including observable factors such as appliance holdings and customer attitudes in the regression models, since there is inter-customer variation in these variables, and that variation can be very helpful in explaining inter-customer variation in customer consumption patterns.

3.4.2 MODELING THE LIKELIHOOD OF ENROLLMENT

A widely used method for dealing with the potential problem caused by self-selection bias in model estimation is due to Nobel laureate James Heckman. This method, called the Heckman correction, involves estimating a model to predict the probability of enrollment in an experiment and using that model to construct an auxiliary variable called the “inverse Mills ratio” or as part of a system of equations that also includes the demand equation of primary interest.[39] The intuition behind this approach is that the enrollment choice model will help to disentangle the two effects that cause observed demand to vary as observed prices vary by identifying and quantifying the changes in enrollment rates with variations in the explanatory factors that are used in the demand model.

For this method to work well, it is necessary that the choice model that explains enrollment/non-enrollment decisions yield good predictors of these choices and that it include explanatory factors that do not appear in the demand equation. If the model does not do a good job of distinguishing between enrollment/non-enrollment decisions, then it will do a poor job of quantifying the changing enrollment pattern component of the observed relationship between quantity and price. If the same explanatory factors appear in both the choice and demand models, then the choice model can only be identified by using alternative functional forms. Such distinctions in functional form are typically hard to justify or empirically verify, so the results are highly sensitive to untested or untestable assumptions.

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39 Jack Johnston and John DiNardo, Econometric Methods, Fourth Edition, Mc-Graw Hill, 1997.

It is difficult to lay out plausible a priori restrictions on enrollment decisions and electricity demand functions that would make some explanatory factors appear in the enrollment decision equation but not in the demand equation. Thus it is doubtful that one of the key criteria for deriving useful results from the Heckman approach would be satisfied. Nevertheless, several models were estimated to explain a customer's decision to enroll, since that would make it feasible to use the Heckman method. Given that the enrollment choice is binary, a probit model specification was used.[40]

The only demographic information readily available for all households that were randomly selected but did not choose to enroll in the experiment was their location, average daily summer usage from the previous summer, and dwelling type. As explained in Section 3.2.6, location was used to identify each customer's Census block group and then information was collected on economic and demographic factors at the block group level to proxy for these factors at the household level. These variables and the previous summer's average daily usage for each household were used as explanatory variables to estimate probit models of the enrollment decision.

The estimated probit models turned out to be uniformly poor. The variables that were included typically failed to be statistically significant and, in most cases, the regression as a whole was not statistically significant. Separate models were estimated for different experimental cells. It was found that even for the few variables that had statistically significant coefficients in one cell, the coefficients were often of a different sign or statistically insignificant for other experimental cells. Typical values of the McFadden R-squared (a measure of how much of the variation in enrollment choices is explained by the estimated equation) were 0.02 or less. Only three out of eleven McFadden R-squared values were as large as .04 and all these corresponded to relatively small sample sizes. In only one of the 11 cases was the probit model as a whole statistically significant at the 10% level. None were significant at the 5% level and most of the marginal significance levels were greater than 20%.[41]

A typical example of the poor performance of these models is illustrated by the results for the CPP-F rate in climate zone 3 shown in Table 3-15. In this model, the enrollment decision is expressed as a function of the households summer daily usage the previous year and a number of Census block group demographic factors including median household income, % renters, average household size, % of housing units with electric heat, % of housing units with 3 bedrooms, % of housing units with 4 or more bedrooms, % of households below the poverty level. For this model, the McFadden R-squared is only 0.0012 and the marginal significance or p-value for the Probit model is 0.115, indicating that the coefficients as a group were not statistically significantly different from 0 at the 10% level. None of the individual slope coefficients are statistically significant at

40 In a probit specification, the probability of enrollment is made a linear function of several "causal" variables such as appliance holdings, average daily usage, green attitudes and income. The results are used to estimate the inverse Mills ratio and this variable is introduced as a regressor in the demand model.

41 Overall significance was measured by the asymptotic likelihood ratio test for the slope parameters.

the 5% level and only one is statistically significant at the 10% level. Furthermore, the previous summer's usage variable is not only statistically insignificant, its coefficient is also extremely small indicating that actual usage patterns do not seem to be important in the enrollment decision.

Table 3-15
Summary Of Customer Enrollment Model
Results For CPP-F Zone 3

Dependent Variable: ENROLLED
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 12/03/03 Time: 14:48
Sample(adjusted): CELLID=A07
Included observations: 1128 after adjusting endpoints
Convergence achieved after 8 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.158746	0.430741	-2.690125	0.0071
INCOME_MED_HH	2.89E-06	3.21E-06	0.899215	0.3685
RENT_HH	0.217485	0.400836	0.542577	0.5874
ASUSE02	-0.004335	0.003080	-1.407706	0.1592
AVG_SIZE_HH	0.002283	0.081973	0.027854	0.9778
POVERTY_HH	0.335386	0.600340	0.558660	0.5764
BEDRM_3_HH	0.697770	0.414617	1.682924	0.0924
BEDRM_4P_HH	-0.520338	0.435613	-1.194497	0.2323
HEAT_ELEC_HH	-0.373190	0.356795	-1.045951	0.2956

Mean dependent var	0.177305	S.D. dependent var	0.382096
S.E. of regression	0.381196	Akaike info criterion	0.939074
Sum squared resid	162.6027	Schwarz criterion	0.979193
Log likelihood	-520.6380	Hannan-Quinn criter.	0.954233
Restr. log likelihood	-527.0943	Avg. log likelihood	-0.461559
LR statistic (8 df)	12.91261	McFadden R-squared	0.012249
Probability(LR stat)	0.114892		
Obs with Dep=0	928	Total obs	1128
Obs with Dep=1	200		

Results for all estimated probit models appear in Appendix 10. They are all uniformly poor and strongly suggest that enrollment decisions cannot be reliably modeled with any data that is readily available. Given the poor predictive performance of previous year's usage in the probit enrollment models, it is quite possible that the enrollment decision is not the source of any systematic differences in demand between treatment and control groups. An alternative explanation could be that the Census Group data is a poor proxy for customer-specific variation and is preventing the estimation of decent probit models. Better data can be obtained if a survey of those who declined to enroll is carried out in the future.

However, it is worth noting that other researchers who had customer specific data have not been able to estimate successful probit models in the context of TOU rates. While analyzing data from a voluntary TOU pricing experiment in Iowa, Baladi, Herriges and Sweeney (1998) estimated a probit model using explanatory variables such as appliance holdings, housing characteristics, socio-demographic factors and income. They found "little in the way of explanatory power in any of these variables either individually or jointly. In fact, we could not reject the hypothesis that they jointly had zero effect on the participation decision, using a 90% confidence interval." These authors also compared the saturation of major appliances between volunteers and non-volunteers and found just a single statistically significant difference pertaining to the ownership of swimming pools. They also found that baseline usage patterns played only a small role in self-selection, which is similar to the finding reported by Caves et al. (1989) and Train and Miraz (1994) dealing with the voluntary TOU project of Pacific Gas & Electric Company.[42]

The implications of these poor probit models for estimation of the Heckman correction for the demand equation is that the inverse Mills ratio will not vary appreciably over the sample, and will be close to a constant term. Thus, the estimated Heckman correction will be small and imprecisely measured and would not provide an economically or statistically meaningful adjustment for any potential self-selection bias in the sample. Thus, this line of research was not pursued.

3.4.3 Comparison of Mean Energy Consumption

For each of the various rate treatments, mean values for electric energy consumption by period (peak, off-peak and daily periods) were computed for the treatment and control groups in both the pretreatment and treatment periods. A t-test was used to determine if the means were statistically different from each other. Statistically significant differences between treatment and control customers in the pretreatment period would indicate the presence of selection bias and the need to correct for such differences when developing impact estimates during the treatment period. However, as previously discussed, any preexisting difference in usage may be correlated with the presence or absence of observable variables. Once the effect of those variables has been accounted for, one may find that there is no residual preexisting difference. The opposite may also be true. There may be no apparent pre-existing difference in the means but once the effects of appliance ownership or other factors are incorporated into the analysis, it may reveal a systematic difference in usage patterns between the treatment and control groups.

42 S. Mostafa Baladi, Joseph A. Herriges and Thomas A. Sweeney, " Residential response to voluntary time-of-use electricity rates," Resource and Energy Economics 20 (1998) 225-244; Caves, D., J Herriges and K. Kuester, "Load shifting under voluntary residential time-of-use rates," Energy Journal, 10 (1989), 83-99 and K. Train and G. Miraz, "Optimal time-of-use prices for electricity: econometric analysis of surplus and pareto impacts," RAND Journal of Economics, 25 (1994), 263-283.

Tables 3-16 through 3-24 summarize the comparison of means for the various treatments, time periods[43] and day types. Each table presents the mean values for each rate period and for daily usage, the difference in means and the t-statistics that determine whether or not the difference is statistically significant.

The CPP-F comparisons for non-CPP days are contained in Table 3-16 and the comparisons for CPP days are contained in Table 3-17. Looking first at non-CPP day results, one can see that, in climate zone 1, participants use significantly less electricity on a daily basis and during each rate period than do control customers. Daily energy use for treatment customers is 17 percent less than for control customers and peak period use is roughly 21 percent less for treatment customers.

The zone 1 results also clearly highlight the importance of controlling for preexisting differences. As seen in Table 3-16, the difference in peak-period mean values during the treatment period is significant, but it is actually less than the difference in the pretreatment period. Thus, a simple comparison of means based solely on treatment period data would indicate that zone 1 customers are reducing peak period energy use in response to the treatment. However, when the pretreatment difference is factored into the analysis, one would see that peak-period energy use actually increases more for the treatment customers than the control customers in the treatment period. That is, the difference between treatment and control customers in the treatment period is actually less than it is in the pretreatment period. Consequently, after adjusting for preexisting differences, one is led to conclude that the rate treatment either has no impact, or the impact is actually the opposite of what is expected. Clearly, a simple comparison of means that is carried out only in the treatment period would lead to the wrong conclusion.

The mean difference for treatment and control customers for the CPP-F treatment on non-CPP days shows a different pattern in zones 2, 3 and 4 than in zone 1. In all three of these zones, there is no statistically significant difference in daily or off-peak energy consumption. Importantly, the differences in mean values during the peak period are all statistically significant and show that treatment customers consume less energy on peak than do control customers. In zone 2, the difference equals 13 percent and in zones 3 and 4, it is 6 percent. These results are consistent with the classic self-selection bias behavior where one would expect customers who already use less energy during the high-priced period to participate at a higher rate than the average customer. They also indicate that a simple comparison of means in the treatment period would overstate response to the treatment by a minimum of 13 percent in zone 2 and 6 percent in zones 3 and 4. To the extent that the difference is weather sensitive, the bias in the

43 For this comparison, the pretreatment period was constrained to equal the month of June for both treatment and control customers. Thus, it is different from the pretreatment period summarized in Tables 3-9 through 3-14. This was done because a simple comparison does not allow one to control for weather or other conditioning factors. Thus, it is more important to constrain the data to represent the same days for both treatment and control customers than it is when a model-based approach is used that controls for differences in weather resulting from non-overlapping periods.

comparison of means estimate for the treatment period would actually be larger than these percentages because of the hotter temperatures in the treatment period.

Table 3-17 summarizes the comparison of means on CPP days. Recall that in this case, the pretreatment period consists of the 12 maximum system load days in the month of May and June. Here, the difference in means in climate zone 1 is quite similar to what it is on non-CPP days. Treatment customers use 14 percent less energy on the average day than control customers, and about 20 percent less during the peak period. For zones 2 and 3, the differences in peak period energy use are larger on these hotter days than they are on the cooler days used for the non-CPP day comparisons. In zone 2, peak period use is 19 percent less for treatment customers than for control customers, while in zone 3, it’s 20 percent less. In climate zone 4, the difference is still 6 percent during the peak period. In zone 3, daily energy use is 13 percent less for treatment customers than for control customers, and the difference is statistically significant. On cooler pretreatment days, there was no measurable difference in daily energy use in zone 3.

Table 3-18 presents the results for the TOU rate treatment on all weekdays. Tables 3-19 and 3-20 present the results for non-CPP days and CPP days, respectively. The non-CPP day and all weekday results are similar and will not be discussed separately. The non-CPP day and CPP day results are presented primarily so they can be compared with the CPP-F results. TOU customers do not receive any notification or different price signal on CPP days than on non-CPP days.

As seen in Table 3-18, as was true for the CPP-F rate, participants use more energy than do control customers, but the differences are smaller for the TOU treatment than for the CPP-F treatment. The difference in daily energy use is 6 percent, and the difference in peak-period use is 8 percent. For the CPP-F rate, the differences were 17 and 21 percent, respectively.

Climate zones 2 and 3 do not display the same selection bias that was found for the CPP-F rate. The difference in peak-period energy use is very small and statistically insignificant for the TOU rate in these zones. Indeed, in zone 3, average energy use for treatment and control customers is nearly identical in all time periods. Climate zone 4, on the other hand, shows a strong reflection of selection bias. The combination of a large (15 percent) and statistically significant difference in the peak period and a statistically insignificant difference in off-peak and daily use is a strong indication of selection bias. Importantly, the difference in the pretreatment period is roughly twice as large as the difference during the treatment period, indicating that a simple comparison of means in the treatment period would be very misleading.

Tables 3-21 and 3-22 contain results for the CPP-V rate treatment on non-CPP and CPP days, respectively. Recall that the treatment customers for this rate were all selected from volunteers for the AB 970 Smart Thermostat pilot that predates the SPP. Thus, they are not representative of the population as a whole and, as such, cannot be compared to a general population control group. Instead, one control group consists of similar volunteers for the Smart Thermostat pilot. The second control group consists of customers whose average monthly energy use during the summer exceeds 600 kWh. This group of customers is expected to have a higher saturation of air conditioning than the population at large, and therefore be a better match to the Smart Thermostat customers, all of whom have central air conditioning. As noted in Section 4, however, the survey data collected as part of the experiment indicates that less than half of the households in this second control group actually have central air conditioning, so that screening for use greater than 600 kWh was a crude proxy for the presence of central air conditioning. The model-based approach in Section 4 allows one to adjust for these differences but the simple comparison of means that is done here does not. Consequently, we would expect the differences in means to be greater for this second control group than for the first.

Table 3-21 presents the results of the comparison of means for non-CPP days. As expected, the differences are relatively small when using the Smart Thermostat control group. There is no statistically significant difference for daily use or off-peak use. Interestingly, the difference in means during the peak period shows that treatment customers use 8 percent more energy on peak than do control customers.

When compared with the other control group (e.g., customers who use more than 600 kWh per month), we see that treatment customers use significantly less energy during all periods than do control customers. This result is just the opposite of what was expected in light of the finding pointed out earlier that only half of these control customers have central air conditioning. One possible explanation for this result is that the treatment customers, by virtue of their having been in the Smart Thermostat pilot, have become very sensitive to energy costs and have found ways to use less during all periods. An alternative, and perhaps more likely explanation, is that the volunteers into the Smart Thermostat pilot, from which the treatment customers were selected, used much less energy overall than the average customer above 600 kWh a month. Either way, it suggests that impact estimates based on a comparison between the treatment customers and this second control group should be viewed with extreme caution.

Table 3-22 shows the comparison of means for the CPP-V rate on CPP days. When compared with the Smart Thermostat control group, the difference of means in the pretreatment period has the opposite sign for these hot days than for the cooler day comparison contained in Table 3-21. When using the whole month of June as the pretreatment period, the difference in daily energy use is statistically insignificant while the peak period energy comparison shows that treatment customer use 8 percent more energy. However, on the hottest days, treatment customers use significantly less (11 percent) energy in a day, and 16 percent less during the peak period than do control customers. It is difficult to imagine why this would be true given that both treatment and control customers are drawn from the same population of volunteers for the Smart Thermostat pilot, all have central air conditioning, and there is every reason to believe they would have much more similar usage patterns than are reflected in the mean values.

The final comparisons of means, representing the Information Only treatment group, are contained in Tables 3-23 and 3-24. In climate zone 2 on non-CPP days, the pretreatment difference shows that participants use 13 percent more energy during the peak period and 16 percent more energy overall than do control customers. However, in climate zone 3, there is no statistically significant difference between treatment and control customers in any time period. The same pattern is evident when the comparison is made for the 12 maximum load days in the pretreatment period. The most interesting thing to note about the comparisons for this treatment group is what happens during the treatment period on non-CPP days. Keeping in mind that these customers have exactly the same prices in the pretreatment and treatment period, and that these prices have no time-of-day variation, it is very difficult to understand why the difference in mean values changes so dramatically in the treatment period on non-CPP days. For example, in climate zone 3, treatment customers use 17 percent energy in a day than do control customers, and roughly 18 percent less energy during the peak period. In climate zone 2, treatment customers still use more energy daily than do control group customers, but the difference is only 5 percent rather than the 16 percent difference in the pretreatment period. During the peak period, treatment customers actually use about 4 percent less than control customers whereas before they used 16 percent more.

As seen in Table 3-24, the differences are even more significant in climate zone 3 during the treatment period on CPP days. While it is conceivable that there could be some change in behavior on these days in response to the notification customers receive to use less energy during peak periods, the magnitude of the change is suspicious. It is important to note that the differences in climate zone 3 apply to all three time periods (e.g., peak, off-peak and daily). Thus, these customers are showing signs of significant conservation rather than dramatic load shifting, the latter being the anticipated response. In light of these odd results, which were not eliminated by the more complex model specifications used in Section 4, impact estimates and demand models for Information Only customers have not been included in this report. The End-of-Summer survey of customers that is nearing completion as this report is written may shed light on these anomalous results.

It is clear from the discussion in this section that a simple comparison of mean differences in energy use between treatment and control customers during the treatment period would, in many instances, lead to incorrect conclusions and biased estimates of treatment impacts. At a minimum, preexisting differences in mean values must be netted out from the treatment period effects. However, as discussed elsewhere, to the extent that these preexisting differences can be explained by observable variables, one can adjust for the observable differences between treatment and control customers. By doing so, it may be possible to eliminate any remaining bias or, at least, to reduce it significantly. Furthermore, factoring in these observable variables allows one to more easily adjust for the impact of differences in weather in the pretreatment and treatment periods, and to extrapolate from the sample to the target population. The following subsection illustrates how impact estimates change as observable variables are factored into the analysis, and the last subsection describes in detail the model-based approach that was used to develop the impact estimates presented in Section 4.

Table 3-16
Comparison Of Means For The
CPP-F Treatment On Non-CPP Weekdays

	Period	Cell ID	Pretreatment Period N	Pretreatment Period Mean	Pretreatment Period t Value	Treatment Period N	Treatment Period Mean	Treatment Period t Value
CPP-F Non CPP Days								
	Peak	A01	892	3.007		3532	3.3246	
	Peak	A05	713	2.3691		4099	2.7837	
	Peak	**Diff (1-2)**		**0.6379**	**5.72**		**0.5409**	**9.95**
	Off Peak	A01	892	10.824		3532	11.431	
Zone 1	Off Peak	A05	708	9.14		4098	10.716	
	Off Peak	**Diff (1-2)**		**1.6843**	**5.42**		**0.7154**	**4.51**
	Daily	A01	892	13.831		3532	14.756	
	Daily	A05	708	11.518		4098	13.499	
	Daily	**Diff (1-2)**		**2.3128**	**5.78**		**1.2564**	**6.19**
	Peak	A02	1747	4.8047		6443	5.6638	
	Peak	A06	3000	4.1711		13634	4.2655	
	Peak	**Diff (1-2)**		**0.6335**	**4.53**		**1.3984**	**19.1**
	Off Peak	A02	1747	13.836		6443	15.171	
Zone 2	Off Peak	A06	2993	14.111		13633	14.704	
	Off Peak	**Diff (1-2)**		**-0.275**	**-0.89**		**0.4669**	**2.88**
	Daily	A02	1747	18.641		6443	20.835	
	Daily	A06	2993	18.286		13632	18.971	
	Daily	**Diff (1-2)**		**0.3548**	**0.83**		**1.864**	**8.46**
	Peak	A03	1745	6.9634		6490	8.4656	
	Peak	A7	2930	6.5622		13677	6.8053	
	Peak	**Diff (1-2)**		**0.4013**	**2.14**		**1.5308**	**16.35**
	Off Peak	A03	1745	17.074		6490	19.288	
Zone 3	Off Peak	A07	2927	17.511		13675	18.795	
	Off Peak	**Diff (1-2)**		**-0.438**	**-1.21**		**0.2003**	**2.97**
	Daily	A03	1745	24.037		6490	27.786	
	Daily	A07	2926	24.083		13674	25.625	
	Daily	**Diff (1-2)**		**-0.046**	**-0.09**		**1.7726**	**8.21**
	Peak	A04	1741	10.11		6207	10.457	
	Peak	A08	1864	9.4474		8422	8.5982	
	Peak	**Diff (1-2)**		**0.6629**	**2.34**		**1.8584**	**13.24**
	Off Peak	A04	1741	21.998		6206	23.496	
Zone 4	Off Peak	A08	1856	22.2		8421	22.74	
	Off Peak	**Diff (1-2)**		**-0.201**	**-0.39**		**0.7556**	**2.74**
	Daily	A04	1741	32.109		6206	33.951	
	Daily	A08	1856	31.645		8421	31.338	
	Daily	**Diff (1-2)**		**0.4632**	**0.61**		**2.6131**	**6.63**

Note: The pretreatment results in this table are calculated from all pretreatment data after May 31. The data in Table 3-25 are calculated with data from the entire pretreatment period and thus contain different results.

Table 3-17
Comparison Of Means For The
CPP-F Treatment On CPP Days

			Pretreatment Period			Treatment Period		
	Period	Cell ID	N	Mean	t Value	N	Mean	t Value
CPP-F CPP Days								
	Peak	A01	496	3.0415		522	3.3781	
	Peak	A05	391	2.436		583	2.6317	
	Peak	**Diff (1-2)**		**0.6054**	**4.02**		**0.7464**	**5.24**
	Off Peak	A01	496	10.864		522	11.429	
Zone 1	Off Peak	A05	386	9.4873		583	10.835	
	Off Peak	**Diff (1-2)**		**1.3764**	**3.32**		**0.5949**	**1.46**
	Daily	A01	496	13.905		522	14.807	
	Daily	A05	386	11.944		583	13.466	
	Daily	**Diff (1-2)**		**1.9616**	**3.67**		**1.3413**	**2.58**
	Peak	A02	805	5.8831		1047	6.1595	
	Peak	A06	1171	4.7734		2096	4.1059	
	Peak	**Diff (1-2)**		**1.1098**	**4.09**		**2.0536**	**10.55**
	Off Peak	A02	805	14.849		1047	15.859	
Zone 2	Off Peak	A06	1168	14.87		2096	15.195	
	Off Peak	**Diff (1-2)**		**-0.022**	**-0.04**		**0.6643**	**1.55**
	Daily	A02	805	20.732		1047	22.018	
	Daily	A06	1168	19.653		2096	19.301	
	Daily	**Diff (1-2)**		**1.0792**	**1.47**		**2.7178**	**4.68**
	Peak	A03	725	9.8792		1053	9.8749	
	Peak	A07	1038	7.9107		2037	6.6917	
	Peak	**Diff (1-2)**		**1.9684**	**5.42**		**3.1832**	**11.83**
	Off Peak	A03	725	20.821		1053	21.382	
Zone 3	Off Peak	A07	1037	18.839		2037	20.137	
	Off Peak	**Diff (1-2)**		**1.9817**	**3.14**		**1.2442**	**2.4**
	Daily	A03	725	30.7		1053	31.257	
	Daily	A07	1037	26.762		2037	26.829	
	Daily	**Diff (1-2)**		**3.9376**	**4.23**		**4.4274**	**6.06**
	Peak	A04	865	12.158		1007	11.812	
	Peak	A08	813	11.394		1245	8.718	
	Peak	**Diff (1-2)**		**0.7641**	**1.59**		**3.0938**	**8.22**
	Off Peak	A04	865	25.241		1007	25.704	
Zone 4	Off Peak	A08	808	24.21		1245	24.79	
	Off Peak	**Diff (1-2)**		**1.0314**	**1.22**		**0.9132**	**1.22**
	Daily	A04	865	37.4		1007	37.515	
	Daily	A08	808	35.614		1245	33.508	
	Daily	**Diff (1-2)**		**1.7857**	**1.41**		**4.007**	**3.76**

Table 3-18
Comparison Of Means For The
TOU Treatment On All Weekdays

			Pretreatment Period			***Treatment Period***		
	Period	**Cell ID**	**N**	**Mean**	**t Value**	**N**	**Mean**	**t Value**
TOU All Week Days								
	Peak	A01	892	3.007		4054	3.3315	
	Peak	A13	777	2.7526		4662	2.8754	
	Peak	**Diff (1-2)**		**0.2544**	**2.12**		**0.4561**	**8.84**
	Off Peak	A01	892	10.824		4054	11.431	
Zone 1	Off Peak	A13	777	10.299		4661	10.786	
	Off Peak	**Diff (1-2)**		**0.5255**	**1.58**		**0.6446**	**4.23**
	Daily	A01	892	13.831		4054	14.762	
	Daily	A13	777	13.053		4661	13.661	
	Daily	**Diff (1-2)**		**0.7778**	**1.8**		**1.1007**	**5.59**
	Peak	A02	1747	4.8047		7490	5.7331	
	Peak	A14	804	4.6729		4098	4.25	
	Peak	**Diff (1-2)**		**0.1318**	**0.62**		**1.4831**	**14.62**
	Off Peak	A02	1747	13.836		7490	15.267	
Zone 2	Off Peak	A14	804	15.459		4098	15.281	
	Off Peak	**Diff (1-2)**		**-1.623**	**-3.48**		**-0.013**	**-0.06**
	Daily	A02	1747	18.641		7490	21.001	
	Daily	A14	804	20.132		4098	19.531	
	Daily	**Diff (1-2)**		**-1.491**	**-2.34**		**1.4698**	**4.9**
	Peak	A03	1745	6.9634		7543	8.8264	
	Peak	A15	921	7.1315		4287	8.1963	
	Peak	**Diff (1-2)**		**-0.168**	**-0.63**		**0.6301**	**4.26**
	Off Peak	A03	1745	17.074		7543	19.854	
Zone 3	Off Peak	A15	920	16.779		4287	19.241	
	Off Peak	**Diff (1-2)**		**0.2949**	**0.63**		**0.6129**	**2.45**
	Daily	A03	1745	24.037		7543	28.681	
	Daily	A15	920	23.897		4287	27.438	
	Daily	**Diff (1-2)**		**0.14**	**0.2**		**1.243**	**3.34**
	Peak	A04	1741	10.11		7214	10.646	
	Peak	A16	855	8.6515		4279	9.8885	
	Peak	**Diff (1-2)**		**1.4588**	**4.18**		**0.7574**	**4.28**
	Off Peak	A04	1741	21.998		7213	23.804	
Zone 4	Off Peak	A16	854	22.366		4276	25.924	
	Off Peak	**Diff (1-2)**		**-0.368**	**-0.57**		**-2.121**	**-5.78**
	Daily	A04	1741	32.109		7213	34.449	
	Daily	A16	854	31.025		4276	35.816	
	Daily	**Diff (1-2)**		**1.0837**	**1.15**		**-1.368**	**-2.63**

Table 3-19
Comparison Of Means For The
TOU Treatment On Non-CPP Weekdays

	Period	Cell ID	*Pretreatment Period* N	Mean	t Value	*Treatment Period* N	Mean	t Value
TOU Non CPP Days								
	Peak	A01	892	3.007		3532	3.3246	
	Peak	A13	777	2.7526		4010	2.8736	
	Peak	**Diff (1-2)**		**0.2544**	**2.12**		**0.451**	**7.82**
	Off Peak	A01	892	10.824		3532	11.431	
Zone 1	Off Peak	A13	774	10.299		4009	10.798	
	Off Peak	**Diff (1-2)**		**0.5255**	**1.58**		**0.6332**	**3.85**
	Daily	A01	892	13.831		3532	14.756	
	Daily	A13	774	13.053		4009	13.671	
	Daily	**Diff (1-2)**		**0.7778**	**1.8**		**1.0843**	**5.11**
	Peak	A02	1747	4.8047		6443	5.6638	
	Peak	A14	799	4.6871		3524	4.1979	
	Peak	**Diff (1-2)**		**0.1176**	**0.55**		**1.4659**	**13.71**
	Off Peak	A02	1747	13.836		6443	15.171	
Zone 2	Off Peak	A14	799	15.493		3524	15.184	
	Off Peak	**Diff (1-2)**		**-1.656**	**-3.54**		**-0.013**	**-0.05**
	Daily	A02	1747	18.641		6443	20.835	
	Daily	A14	799	20.18		3524	19.382	
	Daily	**Diff (1-2)**		**-1.539**	**-2.41**		**1.4532**	**4.55**
	Peak	A03	1745	6.9634		6490	8.6563	
	Peak	A15	902	7.1094		3688	7.972	
	Peak	**Diff (1-2)**		**-0.146**	**-0.54**		**0.6842**	**4.37**
	Off Peak	A03	1745	17.074		6490	19.606	
Zone 3	Off Peak	A15	901	16.698		3688	18.999	
	Off Peak	**Diff (1-2)**		**0.376**	**0.8**		**0.607**	**2.28**
	Daily	A03	1745	24.037		6490	28.263	
	Daily	A15	901	23.794		3688	26.972	
	Daily	**Diff (1-2)**		**0.2436**	**0.35**		**1.2912**	**3.28**
	Peak	A04	1741	10.11		6207	10.457	
	Peak	A16	851	8.6638		3682	9.6961	
	Peak	**Diff (1-2)**		**1.4465**	**4.14**		**0.7605**	**4.04**
	Off Peak	A04	1741	21.998		6206	23.496	
Zone 4	Off Peak	A16	850	22.375		3679	25.567	
	Off Peak	**Diff (1-2)**		**-0.377**	**-0.58**		**-2.071**	**-5.3**
	Daily	A04	1741	32.109		6206	33.951	
	Daily	A16	850	31.046		3679	35.267	
	Daily	**Diff (1-2)**		**1.0627**	**1.13**		**-1.316**	**-2.38**

Table 3-20
Comparison Of Means For The
TOU Treatment On CPP Days

	Period	Cell ID	Pretreatment Period N	Mean	t Value	Treatment Period N	Mean	t Value
TOU CPP Days								
	Peak	A01	496	3.0415		522	3.3781	
	Peak	A13	404	2.8894		652	2.8864	
	Peak	**Diff (1-2)**		**0.152**	**0.9**		**0.4916**	**3.31**
	Off Peak	A01	496	10.861		522	11.429	
Zone 1	Off Peak	A13	401	10.328		652	10.715	
	Off Peak	**Diff (1-2)**		**0.5355**	**1.22**		**0.7142**	**1.76**
	Daily	A01	496	13.905		522	14.807	
	Daily	A13	401	13.229		652	13.602	
	Daily	**Diff (1-2)**		**0.6764**	**1.17**		**1.2058**	**2.3**
	Peak	A02	805	5.8831		1047	6.1595	
	Peak	A14	325	5.815		574	4.5698	
	Peak	**Diff (1-2)**		**0.0681**	**0.16**		**1.5896**	**5.2**
	Off Peak	A02	805	14.849		1047	15.859	
Zone 2	Off Peak	A14	325	17.644		574	15.874	
	Off Peak	**Diff (1-2)**		**-2.796**	**-3.38**		**-0.016**	**-0.02**
	Daily	A02	805	20.732		1047	22.018	
	Daily	A14	325	23.459		574	20.444	
	Daily	**Diff (1-2)**		**-2.728**	**-2.33**		**1.5741**	**1.84**
	Peak	A03	725	9.8792		1053	9.8749	
	Peak	A15	329	9.2388		599	9.5769	
	Peak	**Diff (1-2)**		**0.6404**	**1.19**		**0.2979**	**0.68**
	Off Peak	A03	725	20.821		1053	21.382	
Zone 3	Off Peak	A15	328	19.309		599	20.731	
	Off Peak	**Diff (1-2)**		**1.5114**	**1.67**		**0.6509**	**0.91**
	Daily	A03	725	30.7		1053	31.257	
	Daily	A15	328	28.517		599	30.308	
	Daily	**Diff (1-2)**		**2.1824**	**1.6**		**0.9489**	**0.87**
	Peak	A04	865	12.158		1007	11.812	
	Peak	A16	399	9.9597		597	11.075	
	Peak	**Diff (1-2)**		**2.1985**	**3.7**		**0.737**	**1.45**
	Off Peak	A04	865	25.241		1007	25.704	
Zone 4	Off Peak	A16	399	24.717		597	28.127	
	Off Peak	**Diff (1-2)**		**0.524**	**0.48**		**-2.423**	**-2.31**
	Daily	A04	865	37.4		1007	37.515	
	Daily	A16	399	34.677		597	39.202	
	Daily	**Diff (1-2)**		**2.7225**	**1.7**		**-1.685**	**-1.13**

Table 3-21
Comparison Of Means For The
CPP-V Treatment On Non-CPP Weekdays

	Period	Cell ID	Pretreatment Period N	Pretreatment Period Mean	Pretreatment Period t Value	Treatment Period N	Treatment Period Mean	Treatment Period t Value
CPPV Non CPP Days								
Smart Thermostat	Peak	C01,C07	1583	6.1101		3512	11.528	
	Peak	C02	965	6.6017		6808	7.6209	
	Peak	**Diff (1-2)**		**-0.492**	**-2.4**		**3.9074**	**26.01**
	Off Peak	C01,C07	1583	18.058		3515	23.155	
	Off Peak	C02	966	18.19		3808	20.815	
	Off Peak	**Diff (1-2)**		**-0.132**	**-0.33**		**2.3402**	**8.53**
	Daily	C01,C07	1582	24.177		3512	34.684	
	Daily	C02	965	24.802		3808	28.436	
	Daily	**Diff (1-2)**		**-0.625**	**-1.17**		**6.2476**	**16.01**
>600 kWh	Peak	A24	233	7.496		954	11.649	
	Peak	C02	965	6.6017		6808	7.6209	
	Peak	**Diff (1-2)**		**0.8942**	**2.22**		**4.0278**	**16.89**
	Off Peak	A24	233	22.042		954	29.56	
	Off Peak	C02	966	18.19		6808	20.815	
	Off Peak	**Diff (1-2)**		**3.8522**	**5.06**		**8.7447**	**18.38**
	Daily	A24	233	29.538		954	41.209	
	Daily	C02	965	24.802		6808	28.436	
	Daily	**Diff (1-2)**		**4.7357**	**4.42**		**12.772**	**19.12**

Table 3-22
Comparison Of Means For The
CPP-V Treatment On CPP Days

	Period	Cell ID	Pretreatment Period N	Pretreatment Period Mean	Pretreatment Period t Value	Treatment Period N	Treatment Period Mean	Treatment Period t Value
CPPV CPP Days								
Smart Thermostat	Peak	C01,C07	896	7.5078		419	7.5418	
	Peak	C02	343	6.2828		1062	5.0301	
	Peak	**Diff (1-2)**		**1.2249**	**3.32**		**2.5117**	**8.12**
	Off Peak	C01,C07	897	18.495		419	24.386	
	Off Peak	C02	343	16.951		1062	20.715	
	Off Peak	**Diff (1-2)**		**1.5439**	**2.63**		**3.6705**	**4.57**
	Daily	C01,C07	897	26.019		419	31.927	
	Daily	C02	343	23.234		1062	25.745	
	Daily	**Diff (1-2)**		**2.7846**	**3.32**		**6.1822**	**5.94**
>600 kWh	Peak	A24	134	8.9065		156	9.2657	
	Peak	C02	343	6.2828		1062	5.0301	
	Peak	**Diff (1-2)**		**2.6236**	**4.5**		**4.2357**	**9.48**
	Off Peak	A24	134	23.946		156	30.494	
	Off Peak	C02	343	16.951		1062	20.715	
	Off Peak	**Diff (1-2)**		**6.9973**	**6.55**		**9.7793**	**8.05**
	Daily	A24	134	32.852		156	39.76	
	Daily	C02	343	23.234		1062	25.745	
	Daily	**Diff (1-2)**		**9.6179**	**6.35**		**14.014**	**9.17**

Table 3-23
Comparison Of Means For The
Information Only Treatment On Non-CPP Weekdays

			Pretreatment Period			Treatment Period		
	Period	**Cell ID**	**N**	**Mean**	**t Value**	**N**	**Mean**	**t Value**
Info Only Non CPP Days								
	Peak	A02	810	5.5686		3066	5.8102	
	Peak	A11	1002	6.4078		4535	5.5763	
	Peak	**Diff (1-2)**		**-0.839**	**-2.8**		**0.2339**	**1.71**
	Off Peak	A02	810	13.983		3066	14.24	
Zone 2	Off Peak	A11	1001	16.308		4535	15.479	
	Off Peak	**Diff (1-2)**		**-2.325**	**-4.4**		**-1.239**	**-5.02**
	Daily	A02	810	19.552		3066	20.05	
	Daily	A11	1001	22.709		4535	21.055	
	Daily	**Diff (1-2)**		**-3.157**	**-4.04**		**-1.005**	**-2.8**
	Peak	A03	484	10.576		1735	9.7258	
	Peak	A12	750	10.381		4463	7.977	
	Peak	**Diff (1-2)**		**0.1956**	**0.42**		**1.7489**	**8.5**
	Off Peak	A03	484	22.671		1735	22.968	
Zone 3	Off Peak	A12	750	23.048		4461	19.168	
	Off Peak	**Diff (1-2)**		**-0.377**	**-0.51**		**3.8004**	**10.3**
	Daily	A03	484	33.247		1735	32.694	
	Daily	A12	750	33.429		4461	27.146	
	Daily	**Diff (1-2)**		**-0.181**	**-0.16**		**5.5481**	**9.8**

Table 3-24
Comparison Of Means For The
Information Only Treatment On CPP Days

			Pretreatment Period			Treatment Period		
	Period	**Cell ID**	**N**	**Mean**	**t Value**	**N**	**Mean**	**t Value**
Info Only CPP Days								
	Peak	A02	444	6.9327		496	6.9252	
	Peak	A11	484	7.7952		734	6.2158	
	Peak	**Diff (1-2)**		**-0.863**	**-1.73**		**0.7094**	**1.69**
	Off Peak	A02	444	15.261		496	15.526	
Zone 2	Off Peak	A11	483	18.434		734	15.996	
	Off Peak	**Diff (1-2)**		**-3.17**	**-3.94**		**-0.471**	**-0.69**
	Daily	A02	444	22.194		496	22.451	
	Daily	A11	483	26.217		734	22.212	
	Daily	**Diff (1-2)**		**-4.023**	**-3.26**		**0.2388**	**0.23**
	Peak	A03	275	13.954		277	11.969	
	Peak	A12	373	13.08		733	8.9803	
	Peak	**Diff (1-2)**		**0.8736**	**1.25**		**2.9884**	**5.15**
	Off Peak	A03	275	27.549		277	26.235	
Zone 3	Off Peak	A12	373	26.95		733	21.419	
	Off Peak	**Diff (1-2)**		**0.5993**	**0.53**		**4.8161**	**4.73**
	Daily	A03	275	41.503		277	38.204	
	Daily	A12	373	40.03	0.86	733	30.399	
	Daily	**Diff (1-2)**		**1.4729**			**7.8045**	**5.18**

3.4.3 A Model-Based Approach

As noted earlier, the presence of a difference in the means between control and treatment customers may be due to differences in observable, underlying drivers of electrical energy use. Inclusion of observable variables that are correlated with energy use may reduce any pre-existing difference.

This hypothesis can be tested through a model-based approach. A variety of different specifications are estimated, building up from a simple specification that includes an intercept term and a binary variable that has a value of 1 if a customer is in a treatment group cell and a value of 0 if a customer is in a corresponding control group cell. The coefficient on the binary variable would be expected to capture the difference in means between the treatment and control group and be similar in magnitude and statistical significance to the difference in means estimators presented in section 3.4.3. This specification is called Model 1.

Model 2 introduces a few additional explanatory variables to Model 1. Specifically, it includes a binary variable that has a value of 1 if a customer resides in a multi-family dwelling, another binary variable that has a value of 1 if a customer resides in a single family dwelling and is a high user, and a variable equal to cooling degree hours interacted with the presence of central air conditioning. With this specification, the coefficient on the treatment binary variable would be expected to differ from the coefficient in between Model1,since it is based on a more complete model specification.

Model 3 introduces several additional variables obtained through the survey of customer characteristics described in section 3.2.3. These variables are listed in the next section. The "high user" binary variable is dropped from the list of explanatory variables in this specification since its inclusion would make it difficult to infer the impact of several characteristics variables that have high values for high users. The coefficients on the treatment binary variables would be expected to differ even more between Models 3 and 1 because of the inclusion of even more variables that drive energy use.

Finally, Model 4 introduces interaction terms between the treatment dummy variable and several characteristics variables: presence of central air conditioning, presence of a swimming pool, and presence of electric cooking. This model allows the magnitude of the treatment effect to vary with differences in these end use saturations whereas the former models assume the impact is constant across all customers. With this more complex specification, the difference in usage between the treatment and control groups can no longer be inferred by reading the value of the coefficient on the treatment binary variable, since interaction effects are present. The treatment effect can be estimated, however, by adding the treatment binary variable coefficient to the sum of the product of the coefficients on the interaction variables times their mean values. If the mean values are based on the sample, one answer is obtained. For inter-modeling comparisons, this is the correct value to use. However, if the objective is to derive inferences for the population as a whole, the mean values should be based on population averages. These values of the self-selection bias are discussed in the next section but for completeness, are included in the table below. In Table 3-25, sample-based values are labeled 4-S and population based values are labeled 4-P in the table.

These four models were estimated for the CPP-F rate for non-CPP days during the pre-treatment period. The results are summarized in Table 3-25. The top panel of the table shows differences in means and the bottom panel shows the t-statistics. As expected, results from Model 1 are identical with the comparison of means results presented in the previous sub-section. Results begin to change as more explanatory variables are added in Models 2, 3 and 4.

For example, peak usage in Zone 1 shows a difference of -.8331 based on the difference of means. This difference is statistically significant, based on the t-statistic of –9.55 in the bottom panel of the table. Virtually identical results appear for Model 1, with a difference of -.82310 and a t-statistic of –9.4. Model 2 includes some explanatory variables, and this causes the difference in means to become more pronounced, at -.87403, with a t-statistic of –11.93. Model 3, which includes the survey variables, shows a smaller difference of -.45327 and a t-statistic of –5.2. This difference declines in Model 4, which has interaction terms. Model 4-S, with sample weights, has a value of -.33294 but it is still statistically significant with a t-statistic of –3.7. In this instance, the results for Model 4-P, with population weights, are very similar to those for Model 4-S.

Table 3-25
Variation In Self-Selection Estimates Across Models
CPP-F on Non-CPP Days

Zone	Period	*Difference of Means* [1]	Treatment Dummy Coefficients Model 1[2]	Model 2[3]	Model 3[4]	Model 4-S[5,6]	Model 4-P[5,7]
	Peak	-0.8331	-0.82310	-0.87403	-0.45327	-0.33294	-0.32311
1	Off Peak	-2.2388	-2.23878	-2.37540	-1.07013	-0.99406	-0.99515
	Daily	-3.0619	-3.06187	-3.25503	-1.52397	-1.32776	-1.31904
	Peak	-0.4892	-0.48243	-0.60268	-0.07370	-0.00592	0.03688
2	Off Peak	0.935	0.93456	0.80997	2.57701	2.34777	1.89997
	Daily	0.452	0.45213	0.19726	2.49847	2.39772	1.98031
	Peak	-0.0000327	0.00702	-0.09935	0.43907	-0.05580	0.02778
3	Off Peak	0.35	0.35451	0.62909	0.91529	0.56627	0.74078
	Daily	0.362	0.36153	0.49644	1.32287	0.50350	0.75347
	Peak	1.404	1.41870	0.26789	0.43014	0.05929	0.44762
4	Off Peak	2.225	2.22527	0.95680	1.96010	1.60885	2.12542
	Daily	3.644	3.64397	1.18267	2.34305	1.57533	2.48753

Zone	Period	*Difference of Means T-Stat*	Treatment T-Statistics Model 1	Model 2	Model 3	Model 4-S	Model 4-P
	Peak	-9.55	-9.4	-11.93	-5.2	-3.7	-3.6
1	Off Peak	-9.43	-9.43	-12.4	-4.7	-4.2	-4.2
	Daily	-9.95	-9.95	-13.42	-5.2	-4.4	-4.3
	Peak	-4.49	-4.42	-6.99	-0.69	-0.1	0.3
2	Off Peak	3.97	3.97	4.44	12.16	11.0	8.4
	Daily	1.4	1.4	0.82	8.8	8.3	6.5
	Peak	0	0.05	-0.77	3.03	-0.4	0.2
3	Off Peak	1.19	1.19	2.74	3.62	2.2	2.8
	Daily	0.86	0.86	1.57	3.73	1.4	2.1
	Peak	7.2	7.25	1.55	2.1	0.3	2.2
4	Off Peak	6.18	6.18	3	5.35	4.2	5.7
	Daily	6.88	6.94	2.63	4.43	2.9	4.7

Notes

1. Treatment minus control means. The pretreatment results in this table are calculated from the entire pretreatment period. The data in Table 3-16 are calculated with all pretreatment data after May 31 and thus contain different results.
2. Model 1 has the following explanatory variables: Treatment Dummy
3. Model 2 has the following explanatory variables: Treatment Dummy, MFU Dummy, HighUser Dummy,
4. Model 3 has the following explanatory variables: Treatment Dummy, MFU Dummy, HighUser Dummy, Weather*CAC interaction term, Survey Variables
5. Models 4-P and 4-S have the following explanatory variables: Treatment Dummy, MFU Dummy, HighUser Dummy, Weather*CAC interaction term, Survey Variables, Treatment*Pool, Treatment*MFU, Treatment*ECOOK
6. Model 4-S coefficient is calculated as the treatment coefficient added to each of the interaction terms*sample weights
7. Model 4-P coefficient is calculated as the treatment coefficient added to each of the interaction terms*population weights

A review of this information suggests that simple comparisons of means can be misleading for assessing self-selection bias. They ignore the influence of various underlying factors on customer usage, such as appliance holdings, socio-demographic factors, income, and attitudes toward green energy and their utility. The only way to account for the influence of these factors on customer usage is to use a model-based approach that allows self-selection bias to be estimated net of the differences in "observable" factors such as those discussed above. Models that include more observable factors should provide better estimates of self-selection bias. In other words, Model 4 would give more credible estimates than Models 1, 2 or 3. Thus, it was decided to use Model 4 as the basis for estimating impacts net of self-selection bias. The approach is described in the next section.

3.5 OVERVIEW OF THE IMPACT ESTIMATION METHODOLOGY

This subsection summarizes in detail the model-based methodology that was used to develop the impact estimates presented in Section 4 of this report. As previously discussed, in the absence of selection bias, the treatment impact could be estimated by calculating the difference in the mean usage by rate period between control and treatment customers in the treatment period. If selection bias exists, this difference would not accurately reflect the impact of the treatments, because it would result not only from the treatment impact but also from any difference in usage between treatment and control group customers that predated the implementation of the treatment (that is, differences that are likely due to self-selection bias). As illustrated in subsection 3.4.3, selection bias is evident for many of the treatments in many climate zones.

At the most fundamental level, the impact estimation methodology is based on the following three equations.

$$\Delta_1 = T_1 - C_1 \quad (1)$$
$$\Delta_2 = T_2 - C_2 \quad (2)$$
$$\Delta = \Delta_2 - \Delta_1 \quad (3)$$

where

T_1 = average, period-specific usage for treatment customers in the pretreatment period

C_1 = average, period-specific usage for control group customers in the pretreatment period

T_2 = average, period-specific usage for treatment customers in the treatment period

C_2 = average, period-specific usage for control group customers in the treatment period following implementation of the treatment

Δ = the difference between two values.

Equations 1 through 3 could be used as is to estimate impacts if there was no difference in weather between the pre- and post-treatment periods (or if weather were not a key driver of energy use) and if the control and treatment groups represented the population at large. Neither of these assumptions is valid. Thus we must correct for differences in weather between the pre- and post treatment periods and for differences in the characteristics of the estimating sample and the population at large. Furthermore, we have a variety of information that allows us to adjust for any differences between treatment and control customer energy use that results from differences in observable variables. All of the above adjustments are accomplished using the following six steps.

1. Estimate the following regression model for each treatment type and climate zone using data for the pretreatment period. Separate models are estimated for peak usage, off-peak usage and daily usage.

kWh = A
+ B∗(treatment binary variable)
+ C∗(multi-family binary variable)
+ D∗(cooling degree hours)(central air conditioning binary variable)
+ E∗(persons per household)
+ F∗(number of bedrooms)
+ G∗(electric dryer binary variable)
+ H∗(electric cooking binary variable)
+ I∗(electric spa binary variable)
+ J∗(electric water heater binary variable)
+ K∗(home business binary variable)
+ L∗(college graduate binary variable)
+ M∗(continuous variable representing satisfaction with utility)
+ N∗(swimming pool binary variable)
+ O∗(number of stand-alone freezers)
+ P∗(number of well water pumps)
+ Q∗(number of water beds)
+ R∗(household income)
+ S∗(home computer use binary variable)
+ T∗(treatment binary variable)∗(multi-family binary variable)
+ U∗(treatment binary variable)∗(swimming pool binary variable)
+ V∗(treatment binary variable)∗(electric cooking binary variable)
+ W∗(treatment binary variable)∗ (cooling degree hours)∗(central air conditioning binary variable).

The dependent variable in the above equation, kWh, represents energy consumption in the relevant period (e.g., peak, off-peak or daily). The cooling degree hour values used in the right-hand-side of the equation correspond to the same time period. The pretreatment period used to estimate these models for each treatment was described previously and is summarized in Tables 3-9 through 3-14.

Use the models estimated in step 1 to predict what both treatment and control customers would use in each rate period based on treatment-period weather and adjusting for differences between the sample weights and the population weights. This is done by multiplying the regression coefficients (e.g., coefficients B through W) by the average values for each variable for the target population and, where relevant, the cooling degree hour values for the treatment period. The average values for each variable for the target population in each climate zone were presented earlier in Table 3-3.

Calculate the difference between the estimated values for the control and treatment customers produced in step 2. This difference equals Δ_1 in equations 1 and 3. It is an estimate of the difference between treatment and control customer energy use by rate period assuming treatment-period weather conditions and after adjusting for all observable differences between the two groups.

This step is identical to step 2, except that the regression models are estimated using treatment-period data rather than pretreatment-period data. Once the regressions are estimate, the same average values for each right-hand-side variable that were used in step 2 are multiplied by the regression coefficients because the goal is to estimate what the treatment impact is for the target population, not the estimating sample.

This step is the same as step 3, except the difference calculated here is based on the predicted values from step 4. This difference represents Δ_2 in equations 2 and 3.

The final step in the process is to calculate delta (Δ), the "difference of differences," in equation 3. This equals the difference calculated in step 5 minus the difference calculated in step 3. It represents an unbiased estimate of the treatment impact after adjusting for all observable differences between treatment and control group customers and for any remaining, preexisting difference between these two groups of customers.

4. Residential Sector Impact Analysis

This section of the report presents estimates of the impact of the SPP treatments on residential energy use by rate period, by day and at the hour of system peak. Section 4.1 discusses the results for the CPP-F rate, section 4.2 focuses on the TOU rate and section 4.3 on the CPP-V rate. A brief comparison of the results across the various rate treatments is contained in section 4.4, while section 4.5 briefly summarizes how rate impacts vary with customer characteristics.

4.1 IMPACT ESTIMATES FOR THE CPP-F RATE

Before reviewing the impacts of the CPP-F rate, it is useful to recall that the peak period is five hours long, beginning at 2 pm and ending at 7 pm. The off-peak period is 19 hours long, covering the time from midnight to 2 pm and 7 pm to midnight. For each tariff, all weekend and holiday hours are also charged at the off-peak rate, but these hours have been excluded from the analysis in this report.

The impacts for the CPP-F rate are presented in Table 4-1. The table is divided into four primary sections. The first section, labeled Delta 1, shows the difference in average energy use by time period between treatment and control customers based on the analysis approach described in section 3.5 of this report. Recall that these differences are derived using the regression equations estimated from pre-treatment period data but using treatment period weather and average values for the target population for all other explanatory variables.[44] In judging the statistical significance of results, a confidence level of 95 percent is used to assess the significance of parameter values.

Estimates of the pre-existing differences between treatment and control group customers could be due to self-selection bias or simply due to random differences between the groups. The time period over which the Delta 1 regression equations have been estimated begins in early April, when the first load data began to be collected. In the early part of the pretreatment period, data was only collected on control group customers since they were the first ones to have meters installed. Thus, there are more control group customers than treatment group customers in much of April and early May.

44 The regression equations have been estimated using ordinary least squares in the SAS software package. The panel nature of the dataset has made it difficult to adjust for the presence of heteroskedasticity (HS) or autocorrelation (AC) in the error term. Even though HS may be present in the error terms of the regression equations that are used to estimate the differences in means (normalized for the effects of observables such as appliance holdings), it is unlikely to have much effect on these "difference of means" estimates. HS should have roughly similar effects on the treatment and control groups because the pattern of such HS should be similar across the two groups. HS is a concern largely when the individual unit variability is appreciably correlated with the explanatory variable of interest—in that case, the average variability may be a poor approximation to the variability of the parameter being estimated.

4. Residential Sector Impact Analysis

In order to assess whether the imbalance in the number of observations for treatment and control customers in the pretreatment period introduces significant error into the impact estimates, separate estimates of Delta 1 were developed for the CPP-F rate based on both the entire pretreatment period and a truncated pretreatment period that excluded observations collected prior to June 1. While there were differences in several of the regression coefficients, the impact on the Delta 1 estimates was small. The all zone average went from .032 kWh (with a t-statistic of .435) to .029 kWh (with a t-statistic of .324). The change was negligible and both estimates are statistically insignificant. The difference in the estimates varied across climate zones, but, in general, the impact values and their statistical significance do not change -substantially. Thus, it was decided to use the entire pre-treatment sample in the estimation of Delta 1.

Table 4-1
Impact Estimates For Residential CPP-F Rate On Non-CPP Weekdays[45]

Delta 1-Treatment Minus Control, *Pretreatment Period Model, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-F Z1	**-0.323**	**-0.995**	**-11.55%**	**-9.63%**	0.091	0.237	-3.560	-4.199	**-1.32**	**-10.04%**	0.305	-4.321
CPP-F Z2	0.037	**1.900**	0.88%	**16.23%**	0.115	0.226	0.321	8.399	**1.98**	**12.45%**	0.305	6.501
CPP-F Z3	0.028	**0.741**	0.40%	**4.48%**	0.151	0.260	0.184	2.848	**0.75**	**3.21%**	0.367	2.051
CPP-F Z4	**0.448**	**2.125**	**5.64%**	**11.57%**	0.205	0.373	2.184	5.696	**2.49**	**9.42%**	0.533	4.665
All Zones	0.032	**1.220**	0.62%	**8.92%**	0.075	0.141	0.435	8.654	**1.26**	**6.66%**	0.000	6.517

Delta 2-Treatment Minus Control, *Treatment Period Model, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-F Z1	**-0.403**	**-0.626**	**-13.36%**	**-6.03%**	0.055	0.143	-7.359	-4.363	**-1.02**	**-7.62%**	0.185	-5.519
CPP-F Z2	**-0.561**	0.105	**-12.97%**	0.80%	0.076	0.154	-7.391	0.682	-0.33	-1.94%	0.207	-1.616
CPP-F Z3	**-0.504**	**1.110**	**-6.63%**	**6.16%**	0.106	0.177	-4.753	6.261	**0.62**	**2.43%**	0.255	2.440
CPP-F Z4	-0.241	**2.096**	-2.84%	**10.46%**	0.151	0.271	-1.588	7.732	**1.78**	**6.25%**	0.389	4.585
All Zones	**-0.491**	**0.521**	**-8.82%**	**3.49%**	0.051	0.096	-9.657	5.424	0.09	0.42%	0.132	0.646

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-F Z1	-0.080	0.369	-2.66%	3.56%	0.106	0.277	-0.758	1.332	0.30	2.21%	0.357	0.830
CPP-F Z2	**-0.598**	**-1.795**	**-13.82%**	**-13.73%**	0.138	0.274	-4.344	-6.559	**-2.31**	**-13.39%**	0.368	-6.286
CPP-F Z3	**-0.532**	0.369	**-7.00%**	2.05%	0.185	0.315	-2.882	1.173	-0.13	-0.52%	0.447	-0.295
CPP-F Z4	**-0.688**	-0.030	**-8.13%**	-0.15%	0.255	0.461	-2.701	-0.065	-0.70	-2.47%	0.660	-1.068
All Zones	**-0.524**	**-0.699**	**-9.40%**	**-4.68%**	0.090	0.171	-5.799	-4.096	**-1.17**	**-5.74%**	0.234	-5.011

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
CPP-F Z1	2.797	10.336	3.021	10.374
CPP-F Z2	4.189	11.710	4.328	13.074
CPP-F Z3	6.872	16.551	7.602	18.017
CPP-F Z4	7.942	18.377	8.466	20.026
All Zones	5.206	13.675	5.571	14.935

Treatment Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
CPP-F Z1	2.474	9.341	2.617	9.748
CPP-F Z2	4.226	13.610	3.767	13.179
CPP-F Z3	6.899	17.292	7.098	19.128
CPP-F Z4	8.390	20.503	8.225	22.121
All Zones	5.238	14.895	5.080	15.456

45 In all of the tables presented in this report, impacts that are statistically significant are in **bold** font and those that are not significant are in normal font. Also, the impact estimates and the period-specific usage estimates at the bottom of each table pertain to the rate period, which differs in length between the peak and off-peak periods. Thus, the values for the peak-period represent energy use or the change in energy use for a five-hour time period, and the off-peak estimates represent values for a nineteen-hour time period. All values in the tables are adjusted for population weights and normalized for treatment-period weather.

4. Residential Sector Impact Analysis

Referring to Table 4-1, the Delta 1 estimates for peak period energy consumption for the CPP-F rate group is statistically significant only in climate zones 1 and 4. The differences in off-peak and daily energy consumption are statistically significant in all four climate zones. In zones 2, 3, and 4, treatment customers use between 3 and 13 percent more energy on a daily basis than do control group customers, while in zone 1, they use 10 percent less energy than control customers on non-CPP days.

The second section in Table 4-1, labeled Delta 2, contains the estimated difference between treatment and control group customers based on regressions run on treatment period data and average values for treatment period weather and for the target population for all explanatory variables. These estimated differences reflect both the impact of the treatment variable as well as any preexisting differences between treatment and control customers.

The third section in Table 4-1, labeled "Delta-Difference in Differences," presents the estimated impacts of the CPP-F rate after adjusting for preexisting differences in observable variables between the treatment and control groups and normalizing for treatment period weather. This difference equals Delta 2 minus Delta 1.

The fourth section of Table 4-1 contains estimated total energy use for the control and treatment groups during the pretreatment and treatment periods. These estimates are the predicted values from the regression models based on treatment period weather and target population values for all explanatory variables.
As seen in Table 4-1, on non-CPP days, the CPP-F rate induced a statistically significant reduction in peak-period energy consumption in climate zones 2, 3 and 4 at the 95 percent confidence level.[46] In the off-peak period, the impact is only statistically significant in zone 2. Over the entire day, in zone 2, the net effect of the CPP-F rate on non-CPP days is a reduction in average daily energy consumption of about 13.4 percent, with the percentage reduction being roughly the same in both the peak and off-peak period. The peak-period reduction in energy consumption is smallest (and statistically insignificant) in absolute terms in the coolest climate zone (zone 1) and largest in the hottest climate zone (zone 4). In the most populated zone (zone 2), the reduction in peak-period energy use on non-CPP days equals almost 0.60 kWh. The population-weighted, statewide average reduction is 0.524 kWh per customer, which equals a reduction of 9.4 percent. Figure 4-1 compares the rate-period-specific load curves (expressed as average kWh/hour) for treatment and control group customers, averaged across all zones. It shows an average hourly reduction in energy consumption of -.11 kWh/hr during the five-hour long period.

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46 A t-statistic of 1.96 represents a statistically significant difference at the 95% confidence level for large sample sizes (a t-statistic of 1.98 corresponds to the 95% confidence interval for a sample of 120).

Figure 4-1
Average Hourly Energy Use By Time Period
All-Zone Average For CPP-F Customers On Non-CPP Weekdays

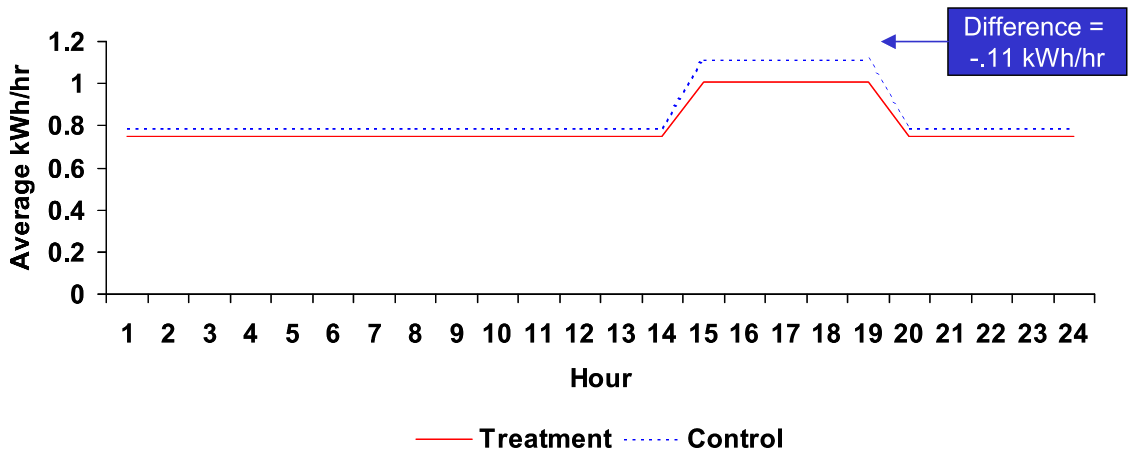


Table 4-2 presents the average impact estimates associated with the CPP-F rate on the twelve CPP days that were implemented during the four-month treatment period. Recall from Section 3 that the data used to estimate the pretreatment period models in this case came from the 12 maximum system load days in May and June. As seen in the table, there is no statistically significant, pretreatment difference between treatment and control customers during the peak period in any of the climate zones. Indeed, there is only a difference in zones 2 and 3 for off-peak energy use and in zone 2 for daily energy use.

The bottom-line impact of the CPP-F rate during the peak period on CPP days is statistically significant in all four climate zones, ranging from a low of -.394 kWh in zone 1 to a high of –1.9 kWh in zone 3. The percent reduction ranges from 122.5 percent in zone 4 to 26.4 percent in zone 2. The population-weighted impact across all climate zones is –1.31 kWh, or -22 percent of the control group energy use in the treatment period. The CPP-day estimates are between two and four times larger than the reductions on non-CPP days in zones 2, 3 and 4. Clearly, customers respond much more on CPP days than on non-CPP days.

The change in off-peak energy use on CPP days is statistically significant only in zone 2. Interestingly, off-peak energy use in zone 4 increases by 2.4 kWh, or 11.1 percent, suggesting that customers in this zone are shifting load from the peak to the off-peak period. The change in daily energy use is statistically significant in zone 2, showing a moderate conservation effect. Figure 4-2 contains the stylized load shape for control and treatment customers, based on treatment-period weather and adjusted for population weights. It shows an average reduction of .26 kWh/hr in peak period energy consumption, or about two and a half times larger than during the non-CPP days.

Table 4-2
Impact Estimates For Residential CPP-F Rate On CPP Days[47]

Delta 1-Treatment Minus Control, *Pretreatment Period Model: 12 Max Load Days, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-F Z1	-0.161	-0.273	-5.91%	-2.75%	0.147	0.400	-1.096	-0.682	-0.44	-3.45%	0.511	-0.851
CPP-F Z2	0.175	**1.713**	4.09%	**14.26%**	0.270	0.466	0.648	3.672	**1.94**	**11.94%**	0.661	2.938
CPP-F Z3	0.226	**1.088**	2.92%	**6.20%**	0.349	0.556	0.648	1.957	1.32	5.22%	0.820	1.608
CPP-F Z4	-0.195	-0.291	-2.12%	-1.45%	0.612	0.991	-0.318	-0.293	-0.52	-1.78%	1.503	-0.346
All Zones	0.110	**1.071**	1.95%	**7.52%**	0.178	0.299	0.618	3.582	**1.20**	**6.07%**	0.432	2.789

Delta 2-Treatment Minus Control, *Treatment Period Model: CPP Days Only, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-F Z1	**-0.555**	-0.641	**-18.18%**	-6.14%	0.139	0.363	-3.993	-1.763	**-1.19**	**-8.80%**	0.462	-2.570
CPP-F Z2	**-1.027**	0.059	**-22.52%**	0.44%	0.199	0.399	-5.155	0.147	-0.87	-4.88%	0.534	-1.633
CPP-F Z3	**-1.678**	**1.069**	**-19.44%**	**5.54%**	0.269	0.470	-6.243	2.273	-0.60	-2.14%	0.662	-0.900
CPP-F Z4	**-1.372**	**2.107**	**-14.56%**	**9.76%**	0.412	0.729	-3.328	2.892	0.63	2.04%	1.043	0.606
All Zones	**-1.198**	0.486	**-19.66%**	3.11%	0.132	0.251	-9.066	1.934	**-0.67**	**-3.10%**	0.343	-1.957

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-F Z1	-0.394	-0.368	-12.90%	-3.53%	0.202	0.540	-1.946	-0.682	-0.75	-5.58%	0.689	-1.092
CPP-F Z2	**-1.202**	**-1.654**	**-26.35%**	**-12.35%**	0.335	0.614	-3.584	-2.693	**-2.81**	**-15.75%**	0.849	-3.312
CPP-F Z3	**-1.904**	-0.019	**-22.06%**	-0.10%	0.440	0.728	-4.323	-0.026	-1.91	-6.87%	1.054	-1.817
CPP-F Z4	-1.178	2.398	-12.50%	11.11%	0.738	1.230	-1.597	1.949	1.15	3.72%	1.829	0.630
All Zones	**-1.308**	-0.585	**-21.96%**	-5.16%	0.392	0.703	-3.335	-0.831	**-1.88**	**-8.65%**	0.552	-3.401

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
CPP-F Z1	2.729	9.895	3.053	10.440
CPP-F Z2	4.275	12.011	4.562	13.392
CPP-F Z3	7.735	17.557	8.632	19.301
CPP-F Z4	9.172	20.085	9.424	21.589
All Zones	5.623	14.241	6.093	15.638

Treatment Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
CPP-F Z1	2.568	9.622	2.498	9.799
CPP-F Z2	4.449	13.724	3.535	13.451
CPP-F Z3	7.961	18.645	6.954	20.370
CPP-F Z4	8.978	19.794	8.051	23.697
All Zones	5.733	15.311	4.894	16.125

47 In general, the standard errors for delta 2 are lower due to the larger sample size available during the treatment period.

Figure 4-2
Average Hourly Energy Use By Time Period
All-Zone Average For CPP-F Customers On CPP Days

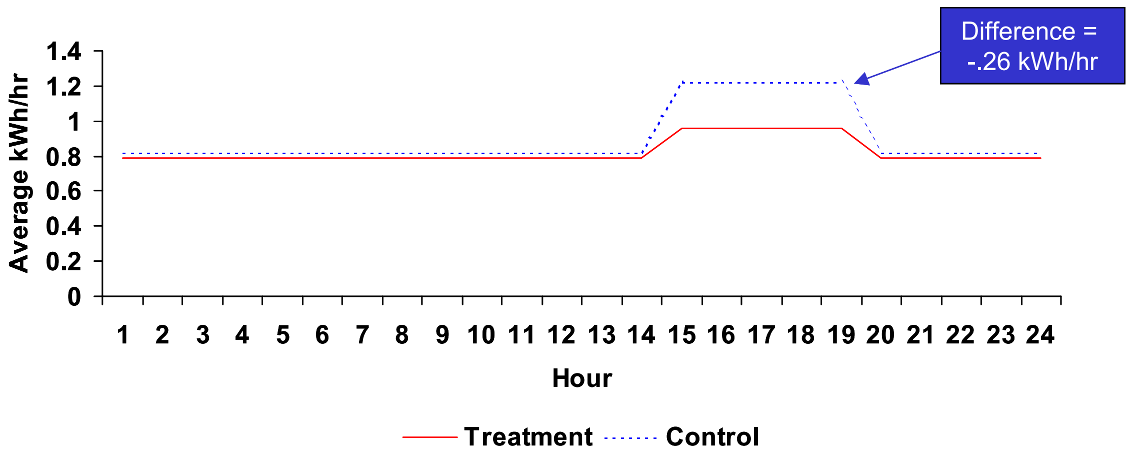


Table 4-3 presents the estimates of the average impact of the CPP-F rate on coincident peak demand on CPP days. The Delta 1 estimates for this treatment indicate that there was no statistically significant, preexisting difference between control and treatment customers after adjusting for difference in observable variables.[48]

The population-weighted, statewide average coincident peak impact reduction due to the CPP-F rate is 0.221 kWh/hour, or 19.5 percent. The per-customer reduction in coincident peak demand use is only statistically significant in climate zones 2 and 3. The impacts range from a low of -.018 kWh/hour in zone 1 to a high of -.273 in zone 3. The percentage reduction in zone 2 is 303 percent and in zone 3 is 16.7 percent.

48 Similar to the CPP-day analysis, the coincident peak demand analysis is based on a pretreatment period consisting of the 12 maximum load days in the pretreatment period.

Table 4-3
Coincident Peak Demand Impact Estimates
For Residential CPP-F Customers

Delta 1-Treatment Minus Control, *Pretreatment Period Model: 12 Max Load Days, 07/08/09/10 Weather*

	$kWh/hour_{cp}$	% $kWh/hour_{cp}$	SE $kWh/hour_{cp}$	T-Stat $kWh/hour_{cp}$
CPP-F Z1	-0.067	-13.18%	0.039	-1.723
CPP-F Z2	0.062	8.23%	0.062	1.003
CPP-F Z3	-0.062	-4.21%	0.081	-0.775
CPP-F Z4	0.003	0.16%	0.137	0.020
All Zones	0.003	0.27%	0.041	0.069

Delta 2-Treatment Minus Control, *Treatment Period Model: CPP Days Only, 07/08/09/10 Weather*

	$kWh/hour_{cp}$	% $kWh/hour_{cp}$	SE $kWh/hour_{cp}$	T-Stat $kWh/hour_{cp}$
CPP-F Z1	**-0.085**	**-15.79%**	0.034	-2.522
CPP-F Z2	**-0.191**	**-22.85%**	0.045	-4.214
CPP-F Z3	**-0.335**	**-20.49%**	0.063	-5.329
CPP-F Z4	-0.167	-9.56%	0.095	-1.765
All Zones	**-0.218**	**-19.27%**	0.030	-7.166

Delta-Difference in Differences (Delta 2 - Delta 1)

	$kWh/hour_{cp}$	% $kWh/hour_{cp}$	SE $kWh/hour_{cp}$	T-Stat $kWh/hour_{cp}$
CPP-F Z1	-0.018	-3.35%	0.051	-0.351
CPP-F Z2	**-0.253**	**-30.25%**	0.077	-3.302
CPP-F Z3	**-0.273**	**-16.67%**	0.102	-2.667
CPP-F Z4	-0.170	-9.72%	0.167	-1.020
All Zones	**-0.221**	**-19.52%**	0.051	-4.345

*% Change from Treatment Period Control Customer Values

Control Group kWh/hour

	Pretreatment Period Model $kWh/hour_{cp}$	Treatment Period Model $kWh/hour_{cp}$
CPP-F Z1	**0.507**	**0.537**
CPP-F Z2	**0.754**	**0.837**
CPP-F Z3	**1.482**	**1.635**
CPP-F Z4	**1.672**	**1.750**
All Zones	**1.036**	**1.132**

Treatment Group kWh/hour

	Pretreatment Period Model $kWh/hour_{cp}$	Treatment Period Model $kWh/hour_{cp}$
CPP-F Z1	**0.440**	**0.452**
CPP-F Z2	**0.816**	**0.646**
CPP-F Z3	**1.420**	**1.300**
CPP-F Z4	**1.675**	**1.583**
All Zones	**1.038**	**0.914**

4.2 IMPACT ESTIMATES FOR TOU RATES

Tables 4-4, 4-5 and 4-6 present the impact estimates for the TOU rate on all weekdays, non-CPP weekdays, and CPP weekdays, respectively. TOU customers are not notified about CPP days, nor do their rates change on these days. The only reason impacts are presented for different day types is to allow comparability with the CPP-F rate impact estimates. The impacts on all weekdays and non-CPP weekdays are generally similar. Figure 4-3 presents the all-zone, stylized load shape for TOU customers.

As seen in Table 4-4, the pretreatment difference in daily energy use between treatment and control customers is statistically significant at the 95 percent confidence level in zones 1, 2 and 4. In zone 1, treatment customers use 10.3 percent less energy than control group customers, while in zones 2 and 4, they use 10.1 and 5.6 percent more energy. In the peak period, the differences are statistically significant in zones 1 and 2, with zone 1 treatment customers using less than control customers during the peak period and zone 2 treatment customers using more.

The statewide, population-weighted average reduction in energy use induced by TOU rates equals roughly 0.9 kWh in both the peak and off-peak periods. This represents –16% of peak period consumption and –5.8 percent of off-peak consumption. The peak period reduction is largest in zone 3 and smallest in zone 4. Zone 1 actually shows an increase in energy consumption compared to the control group in both the peak and off-peak period. Conservation is apparent in zones 2 and 3, with reductions in daily energy consumption of 13.3 percent and 11.2 percent respectively. The impacts on non-CPP days, presented in Table 4-5, are similar to those for all weekdays.

As seen in Table 4-6, the overall reduction in peak period energy consumption for TOU rate customers on CPP days is 1.2 kWh verses .9 kWh on non-CPP days, and the corresponding percentage reductions are 20.8 percent and 16.2 percent. On these CPP days, conservation is statistically significant only in zone 3, where daily consumption declines by 4.1 kWh, or 14.7 percent. In zones 1 and 4, the reduction in peak-period energy use is more than offset by the increase in energy use in the off-peak period. Over all zones, daily consumption declines by 2 kWh, or 9.4%

4. Residential Sector Impact Analysis

Table 4-4
Impact Estimates For Residential TOU Rate On All Weekdays

Delta 1-Treatment Minus Control, ***Pretreatment Period Model, 07/08/09/10 Weather***

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	**-0.326**	**-0.957**	**-12.38%**	**-9.71%**	0.077	0.204	-4.246	-4.697	**-1.28**	**-10.26%**	0.260	-4.935
TOU Z2	**0.551**	**0.929**	**13.35%**	**7.92%**	0.211	0.411	2.613	2.259	**1.60**	**10.09%**	0.552	2.895
TOU Z3	-0.243	-0.631	-3.50%	-3.89%	0.222	0.370	-1.097	-1.703	-0.95	-4.08%	0.530	-1.790
TOU Z4	-0.267	**1.871**	-3.26%	**10.03%**	0.270	0.524	-0.991	3.570	**1.50**	**5.56%**	0.734	2.044
All Zones	0.120	0.330	2.31%	2.43%	0.123	0.232	0.976	1.423	0.47	2.52%	0.317	1.497

Delta 2-Treatment Minus Control, ***Treatment Period Model, 07/08/09/10 Weather***

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	**-0.124**	**0.520**	**-4.31%**	**5.15%**	0.048	0.128	-2.603	4.070	**0.38**	**2.93%**	0.162	2.354
TOU Z2	**-0.449**	-0.255	**-10.38%**	-1.96%	0.111	0.221	-4.025	-1.156	**-0.69**	**-4.02%**	0.294	-2.362
TOU Z3	**-1.625**	**-2.248**	**-21.15%**	**-12.46%**	0.152	0.227	-10.657	-9.880	**-3.83**	**-14.90%**	0.338	-11.320
TOU Z4	**-0.620**	**1.807**	**-6.97%**	**8.97%**	0.199	0.385	-3.120	4.698	1.00	3.43%	0.546	1.824
All Zones	**-0.776**	**-0.535**	**-13.81%**	**-3.59%**	0.073	0.132	-10.644	-4.057	**-1.31**	**-6.42%**	0.182	-7.215

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	**0.202**	**1.477**	**7.04%**	**14.64%**	0.090	0.241	2.241	6.141	**1.66**	**12.80%**	0.306	5.433
TOU Z2	**-1.000**	**-1.184**	**-23.13%**	**-9.07%**	0.239	0.467	-4.191	-2.537	**-2.29**	**-13.28%**	0.626	-3.666
TOU Z3	**-1.381**	**-1.617**	**-17.98%**	**-8.96%**	0.269	0.434	-5.133	-3.722	**-2.88**	**-11.21%**	0.629	-4.576
TOU Z4	-0.352	-0.064	-3.96%	-0.32%	0.335	0.650	-1.051	-0.099	-0.50	-1.73%	0.914	-0.550
All Zones	**-0.896**	**-0.865**	**-15.95%**	**-5.80%**	0.143	0.267	-6.253	-3.243	**-1.79**	**-8.74%**	0.365	-4.895

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
TOU Z1	2.636	9.857	2.874	10.093
TOU Z2	4.128	11.728	4.321	13.065
TOU Z3	6.960	16.201	7.682	18.044
TOU Z4	8.203	18.657	8.889	20.153
All Zones	5.210	13.549	5.618	14.917

Treatment Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
TOU Z1	2.309	8.900	2.750	10.614
TOU Z2	4.679	12.657	3.873	12.809
TOU Z3	6.717	15.570	6.058	15.797
TOU Z4	7.935	20.528	8.269	21.960
All Zones	5.331	13.879	4.842	14.381

4. Residential Sector Impact Analysis

Table 4-5
Impact Estimates For Residential TOU Rate On Non-CPP Weekdays

Delta 1-Treatment Minus Control, *Pretreatment Period Model, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	**-0.324**	**-0.958**	**-12.32%**	**-9.72%**	0.077	0.204	-4.224	-4.702	**-1.28**	**-10.26%**	0.260	-4.934
TOU Z2	**0.535**	**0.833**	**13.04%**	**7.12%**	0.212	0.413	2.527	2.017	**1.49**	**9.40%**	0.555	2.680
TOU Z3	-0.162	-0.657	-2.35%	-4.09%	0.224	0.375	-0.720	-1.753	-0.89	-3.85%	0.537	-1.653
TOU Z4	-0.264	**1.842**	-3.25%	**9.95%**	0.270	0.523	-0.979	3.525	**1.47**	**5.51%**	0.732	2.012
All Zones	0.138	0.273	2.67%	2.03%	0.124	0.233	1.110	1.172	0.44	2.33%	0.319	1.368

Delta 2-Treatment Minus Control, *Treatment Period Model, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	-0.092	**0.604**	-3.24%	**6.03%**	0.051	0.140	-1.792	4.316	**0.48**	**3.71%**	0.176	2.720
TOU Z2	**-0.473**	-0.255	**-11.00%**	-1.96%	0.117	0.236	-4.029	-1.082	**-0.71**	**-4.13%**	0.313	-2.269
TOU Z3	**-1.564**	**-2.158**	**-20.71%**	**-12.06%**	0.162	0.243	-9.666	-8.898	**-3.67**	**-14.46%**	0.359	-10.212
TOU Z4	**-0.607**	**1.811**	**-6.89%**	**9.06%**	0.211	0.409	-2.882	4.429	1.02	3.54%	0.580	1.758
All Zones	**-0.764**	**-0.498**	**-13.74%**	**-3.36%**	0.077	0.141	-9.914	-3.534	**-1.26**	**-6.21%**	0.194	-6.503

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	**0.232**	**1.562**	**8.15%**	**15.60%**	0.092	0.247	2.511	6.319	**1.76**	**13.64%**	0.313	5.610
TOU Z2	**-1.008**	**-1.088**	**-23.43%**	**-8.36%**	0.242	0.476	-4.164	-2.288	**-2.20**	**-12.77%**	0.637	-3.449
TOU Z3	**-1.402**	**-1.501**	**-18.57%**	**-8.39%**	0.277	0.447	-5.069	-3.361	**-2.78**	**-10.96%**	0.646	-4.304
TOU Z4	-0.343	-0.031	-3.89%	-0.16%	0.342	0.664	-1.001	-0.047	-0.45	-1.58%	0.934	-0.486
All Zones	**-0.902**	**-0.771**	**-16.22%**	**-5.20%**	0.146	0.272	-6.171	-2.831	**-1.70**	**-8.36%**	0.373	-4.550

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
TOU Z1	2.634	9.858	2.849	10.013
TOU Z2	4.102	11.706	4.303	13.015
TOU Z3	6.872	16.083	7.551	17.890
TOU Z4	8.121	18.512	8.811	19.988
All Zones	5.163	13.489	5.559	14.820

Treatment Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
TOU Z1	2.309	8.900	2.757	10.616
TOU Z2	4.637	12.539	3.830	12.760
TOU Z3	6.710	15.425	5.987	15.732
TOU Z4	7.856	20.355	8.204	21.799
All Zones	5.301	13.762	4.795	14.322

Table 4-6
Impact Estimates For Residential TOU Rate On CPP Days

Delta 1-Treatment Minus Control, ***Pretreatment Period Model: 12 Max Days Only, 07/08/09/10 Weather***

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	-0.159	-0.527	-6.20%	-5.60%	0.130	0.339	-1.224	-1.556	-0.71	-5.90%	0.432	-1.635
TOU Z2	**1.043**	0.673	**25.33%**	5.63%	0.498	0.934	2.095	0.721	1.82	11.33%	1.281	1.419
TOU Z3	0.001	-0.852	0.01%	-4.92%	0.593	0.907	0.001	-0.939	-0.79	-3.16%	1.366	-0.577
TOU Z4	-1.146	0.715	-11.87%	3.39%	0.753	1.333	-1.521	0.537	-0.59	-1.91%	1.958	-0.301
All Zones	0.355	0.075	6.39%	0.53%	0.305	0.538	1.164	0.140	0.48	2.42%	0.760	0.628

Delta 2-Treatment Minus Control, ***Treatment Period Model: CPP Days Only, 07/08/09/10 Weather***

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	-0.242	0.313	-8.20%	3.05%	0.125	0.339	-1.945	0.924	0.05	0.38%	0.426	0.120
TOU Z2	-0.283	-0.190	-6.32%	-1.42%	0.337	0.625	-0.841	-0.304	-0.49	-2.74%	0.845	-0.576
TOU Z3	**-1.990**	**-2.868**	**-23.21%**	**-14.97%**	0.446	0.650	-4.463	-4.412	**-4.86**	**-17.54%**	0.980	-4.957
TOU Z4	-0.651	1.929	-6.71%	8.95%	0.580	1.114	-1.123	1.731	1.05	3.37%	1.587	0.663
All Zones	**-0.824**	-0.702	**-13.61%**	-4.51%	0.217	0.375	-3.801	-1.872	**-1.56**	**-7.22%**	0.525	-2.967

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
TOU Z1	-0.084	0.841	-2.83%	8.18%	0.180	0.480	-0.465	1.753	0.76	5.72%	0.607	1.248
TOU Z2	**-1.326**	-0.863	**-29.60%**	-6.45%	0.601	1.124	-2.207	-0.768	-2.30	-12.97%	1.534	-1.501
TOU Z3	**-1.990**	-2.017	**-23.22%**	-10.52%	0.742	1.116	-2.684	-1.807	**-4.07**	**-14.69%**	1.681	-2.420
TOU Z4	0.495	1.214	5.11%	5.63%	0.950	1.737	0.521	0.699	1.64	5.25%	2.520	0.651
All Zones	-1.179	-0.777	-20.75%	-4.58%	0.627	1.105	-1.880	-0.703	**-2.04**	**-9.44%**	0.924	-2.203

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
TOU Z1	2.558	9.417	2.953	10.277
TOU Z2	4.119	11.951	4.480	13.372
TOU Z3	7.667	17.326	8.572	19.167
TOU Z4	9.658	21.103	9.692	21.546
All Zones	5.558	14.191	6.051	15.565

Treatment Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
TOU Z1	2.399	8.890	2.711	10.591
TOU Z2	5.162	12.624	4.197	13.182
TOU Z3	7.667	16.474	6.582	16.299
TOU Z4	8.512	21.819	9.041	23.475
All Zones	5.914	14.266	5.228	14.863

Figure 4-3
Average Hourly Energy Use By Time Period
All-Zone Average For TOU Customers On All Weekdays

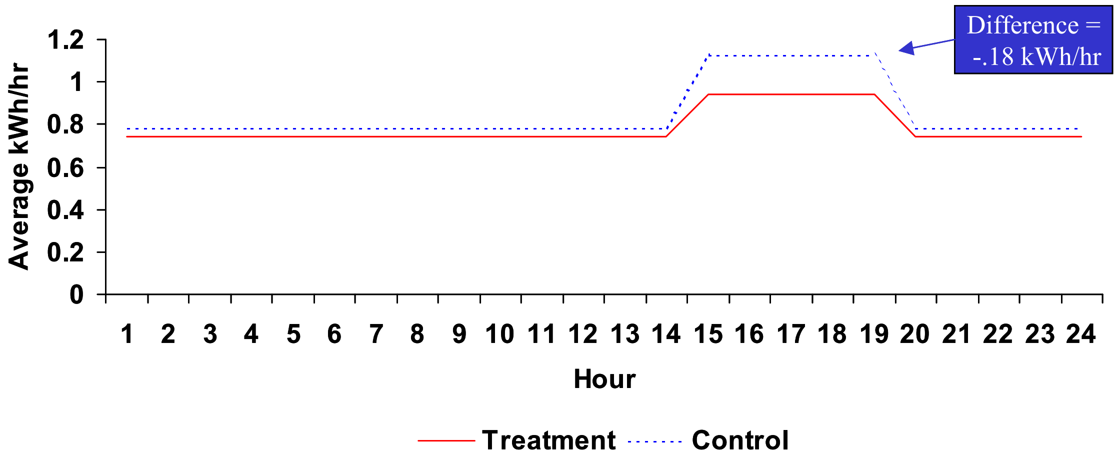


Table 4-7 presents estimates of the impact of TOU rates on coincident peak demand on CPP days. Delta 1 is statistically significant only in climate zone 2, indicating that treatment customers have larger coincident peak demands than do control group customers absent the influence of the TOU rate. The population-weighted, statewide average impact of the rate on coincident peak demand is estimated to equal -.263 kWh/hour, which represents a 23.4 percent reduction in demand at the hour of system peak. In zones 1 and 4, the rate impact is statistically insignificant, while in zones 2 and 3, the impacts are significant and equal to roughly 37 and 27 percent respectively.

Table 4-7
Coincident Peak Demand Impact Estimates For The Residential TOU Rate

Delta 1-Treatment Minus Control, *Pretreatment Period Model, 07/08/09/10 Weather*

	$kWh/hour_{cp}$	% $kWh/hour_{cp}$	SE $kWh/hour_{cp}$	T-Stat $kWh/hour_{cp}$
TOU Z1	-0.048	-10.38%	0.033	-1.445
TOU Z2	**0.317**	**44.37%**	0.115	2.742
TOU Z3	0.061	4.15%	0.135	0.453
TOU Z4	-0.110	-6.19%	0.167	-0.658
All Zones	**0.151**	**14.80%**	0.070	2.149

Delta 2-Treatment Minus Control, *Treatment Period Model, 07/08/09/10 Weather*

	$kWh/hour_{cp}$	% $kWh/hour_{cp}$	SE $kWh/hour_{cp}$	T-Stat $kWh/hour_{cp}$
TOU Z1	-0.015	-3.02%	0.030	-0.510
TOU Z2	0.009	1.05%	0.077	0.112
TOU Z3	**-0.372**	**-22.91%**	0.108	-3.449
TOU Z4	-0.040	-2.23%	0.132	-0.304
All Zones	**-0.113**	**-10.03%**	0.051	-2.225

Delta-Difference in Differences (Delta 2 - Delta 1)

	$kWh/hour_{cp}$	% $kWh/hour_{cp}$	SE $kWh/hour_{cp}$	T-Stat $kWh/hour_{cp}$
TOU Z1	0.032	6.37%	0.045	0.725
TOU Z2	**-0.308**	**-37.45%**	0.139	-2.220
TOU Z3	**-0.433**	**-26.66%**	0.172	-2.512
TOU Z4	0.070	3.93%	0.213	0.330
All Zones	**-0.263**	**-23.45%**	0.086	-3.045

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model	Treatment Period Model
	$kWh/hour_{cp}$	$kWh/hour_{cp}$
TOU Z1	**0.461**	**0.509**
TOU Z2	**0.714**	**0.822**
TOU Z3	**1.469**	**1.624**
TOU Z4	**1.783**	**1.790**
All Zones	**1.019**	**1.123**

Treatment Group kWh

	Pretreatment Period Model	Treatment Period Model
	$kWh/hour_{cp}$	$kWh/hour_{cp}$
TOU Z1	**0.413**	**0.494**
TOU Z2	**1.030**	**0.831**
TOU Z3	**1.530**	**1.252**
TOU Z4	**1.673**	**1.750**
All Zones	**1.169**	**1.010**

4. Residential Sector Impact Analysis

4.3 IMPACT ESTIMATES FOR THE CPP-V RATE

This section presents the impact estimates for the CPP-V tariff on non-CPP days. Recall that these customers were selected from a group of customers who had previously volunteered for the AB970 Residential Smart Thermostat pilot program. The estimates in Table 4-8 are based on a comparison with control customers who also were participants in the AB970 pilot. Thus, both treatment and control customers represent the same population of volunteers from an already established pilot program. All of these customers have central air conditioning and smart thermostats. Consequently, the impact estimates presented here are not directly comparable to the estimates for the other rate treatments.

As seen in Table 4-8, the response of CPP-V customers on non-CPP days relative to the Smart Thermostat control group is large and highly significant. The reduction in peak-period energy use equals 3.7 kWh (or 28 percent) and the off-peak reduction equals 5.5 kWh (or 23.7 percent). The reduction of 26.6 percent in daily energy consumption shows a strong conservation effect, which may suggest that participants used the energy saving tips in the Welcome Package quite seriously.

Table 4-8
Impact Estimates For Residential CPP-V Rate On Non-CPP Weekdays
(Smart Thermostat Control Group)

Delta 1-Treatment Minus Control, *Pretreatment Period Model, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-V ST	0.344	**2.647**	3.94%	**14.67%**	0.458	0.514	0.751	5.150	**3.373**	**12.73%**	0.901	3.742

Delta 2-Treatment Minus Control, *Treatment Period Model, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-V ST	**-3.310**	**-2.896**	**-25.40%**	**-12.40%**	0.218	0.224	-15.211	-12.914	**-6.366**	**-17.41%**	0.375	-16.967

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-V ST	**-3.654**	**-5.543**	**-28.04%**	**-23.73%**	0.507	0.561	-7.207	-9.884	**-9.739**	**-26.64%**	0.976	-9.975

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
CPP-V ST	8.731	18.043	13.031	23.357

Treatment Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
CPP-V ST	9.075	20.690	9.721	20.461

Table 4-9 contains impact estimates for the CPP-V rate on non-CPP days based on a comparison between the same treatment group and a group of customers whose average summer usage exceeded 600 kWh per month. This threshold was believed to be a reasonably accurate screen for the presence or absence of central air conditioning. As such, this control group was believed to be more representative of the same population targeted for the AB970 Smart Thermostat pilot. In reality, less than half of the households in this control group have central air conditioning, based on the customer characteristics survey that was completed as part of this study. To adjust for this deficiency in the control group sample, the impact estimates were based on model predictions assuming 100 percent saturation of central air conditioning for the control group rather than the actual saturation of 43 percent.

Table 4-9
Impact Estimates For Residential CPP-V Rate On Non-CPP Weekdays
(>600 kWh Control Group)

Delta 1-Treatment Minus Control, *Pretreatment Period Model, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-V 600	**-10.282**	**-16.623**	**-61.24%**	**-54.58%**	1.636	1.661	-6.285	-10.005	**-22.585**	**-51.29%**	2.282	-9.895

Delta 2-Treatment Minus Control, *Treatment Period Model, 07/08/09/10 Weather*

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-V 600	**-13.612**	**-17.933**	**-60.69%**	**-50.04%**	0.542	0.548	-25.096	-32.727	**-25.246**	**-52.23%**	0.757	-33.368

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh_p	kWh_o	% kWh_p	% kWh_o	SE kWh_p	SE kWh_o	T-Stat kWh_p	T-Stat kWh_o	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}	T-Stat kWh_{Day}
CPP-V 600	-3.330	-1.310	-14.85%	-3.65%	1.723	1.749	-1.932	-0.749	-2.661	-5.51%	2.405	-1.107

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
CPP-V 600	16.791	30.456	22.429	35.841

Treatment Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh_p	kWh_o	kWh_p	kWh_o
CPP-V 600	6.509	13.832	8.817	17.908

As seen in Table 4-9, the bottom-line difference in energy consumption in the peak period on non-CPP days using this alternative control group is quite similar to the estimate using the Smart Thermostat control group, but the interim calculations leading to that estimate are quite different and the estimate itself (a reduction of 3.3 kWh/hr or 14.9 percent) is statistically insignificant at the 95 percent confidence level (but significant at the 90 percent level). The standard error of the estimate in this instance is much larger than the standard error for the Smart Thermostat control group analysis, reflecting the very large difference between the treatment and control group in both the Delta 1 and Delta 2 calculations. As seen in the table, the pre-existing difference between the control and treatment groups in this case is quite large, with the difference in daily usage exceeding 50 percent. In other words, even after adjusting for the difference in air conditioning saturations between treatment and control customers, it does not appear that this control group is well matched to the treatment group and any impact estimates based on this comparison should be used with extreme caution, if at all.

It should be noted that the impact estimates for the CPP-V rate on non-CPP days represent the change in energy consumption over the entire peak and off-peak periods, as was true for all tables included in sections 4.1 and 4.2. However, the estimates on CPP days, contained in Tables 4-10 and 4-11, represent the change in energy use/hour during each rate period on CPP days. The reason for this difference in approach is that, with the CPP-V rate, the length of the peak period varies on CPP days, while it is fixed at five hours on non-CPP days. In order to pool the data across CPP days, it was necessary to use the average load per hour (measured in kWh/hr) as the dependent variable in the regression equations.[49]

The CPP-V rate has a larger average impact during the peak period on CPP days than on non-CPP days regardless of which control group the analysis is based on. As seen in Table 4-10, there is no statistically significant difference between the treatment group and the Smart Thermostat control group prior to the implementation of the treatment. However, during the treatment period, the difference is highly significant, equaling –1.2 kWh/hour (43.3 percent) in the peak period and -.24 kWh/hour (17.20 percent) in the off-peak period. If this impact could be sustained throughout the entire five-hour peak period, the reduction in energy use would equal 5.5 kWh, or almost 75 percent more than the peak period reduction on non-CPP days.

Table 4-10
Impact Estimates For Residential CPP-V Rate On CPP Days
Smart Thermostat Control Group
(Impacts are reported in kWh/hour)

Delta 1-Treatment Minus Control, *Pretreatment Period Model: 12 Max Load Days, 07/08/09/10 Weather*

	kWh/ hour$_p$	kWh/ hour$_o$	% kWh/ hour$_p$	% kWh/ hour$_o$	SE kWh/ hour$_p$	SE kWh/ hour$_o$	T-Stat kWh/ hour$_p$	T-Stat kWh/ hour$_o$	kWh$_{Day}$	% kWh$_{Day}$	SE kWh$_{Day}$
CPP-V ST	-0.126	-0.003	-7.22%	-0.34%	0.162	0.045	-0.778	-0.072	-0.674	-2.50%	1.494

Delta 2-Treatment Minus Control, *Treatment Period Model: CPP Days Only, 07/08/09/10 Weather*

	kWh/ hour$_p$	kWh/ hour$_o$	% kWh/ hour$_p$	% kWh/ hour$_o$	SE kWh/ hour$_p$	SE kWh/ hour$_o$	T-Stat kWh/ hour$_p$	T-Stat kWh/ hour$_o$	kWh$_{Day}$	% kWh$_{Day}$	SE kWh$_{Day}$
CPP-V ST	**-1.198**	**-0.244**	**-43.30%**	**-17.27%**	0.120	0.039	-9.999	-6.269	**-8.509**	**-23.10%**	1.051

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh/ hour$_p$	kWh/ hour$_o$	% kWh/ hour$_p$	% kWh/ hour$_o$	SE kWh/ hour$_p$	SE kWh/ hour$_o$	T-Stat kWh/ hour$_p$	T-Stat kWh/ hour$_o$	kWh$_{Day}$	% kWh$_{Day}$	SE kWh$_{Day}$
CPP-V ST	**-1.072**	**-0.241**	**-38.75%**	**-17.04%**	0.201	0.059	-5.326	-4.065	**-7.835**	**-21.27%**	1.827

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model		Treatment Period Model	
	kWh/hour$_p$	kWh/hour$_o$	kWh/hour$_p$	kWh/hour$_o$
CPP-V ST	1.742	0.965	2.767	1.415

Treatment Group kWh

	Pretreatment Period Model		Treatment Pe
	kWh/hour$_p$	kWh/hour$_o$	kWh/hour$_p$
CPP-V ST	1.616	0.961	1.569

The rate impact is even larger when compared with the alternative control group of consumers whose usage exceeds 600 kWh. As seen in Table 4-11, the estimated impact equals –1.98 kWh/hour (35.1 percent) during the peak period. It should be kept in mind, however, that this estimate is based on the assumption that all control group customers have central air conditioning (e.g., by setting the air conditioning saturation equal to 1 in the forecast equation). If the actual control group saturation of air

49 A reasonable comparison between impacts on CPP and non-CPP days can be made by dividing the non-CPP day values by 5 or multiplying the CPP values by 5. This has been done in Section 4.4.

conditioning (equal to only 43 percent) is used in the analysis, the estimated difference is -.769 kWh/hour, or just less than 4 kWh over the entire peak period.

Table 4-11
Impact Estimates For Residential CPP-V Rate On CPP Days
>600 kWh Control Group
(Impacts are reported in kWh/hour)

Delta 1-Treatment Minus Control, ***Pretreatment Period Model: 12 Max Load Days, 07/08/09/10 Weather***

	kWh/ $hour_p$	kWh/ $hour_o$	% kWh/ $hour_p$	% kWh/ $hour_o$	SE kWh/ $hour_p$	SE kWh/ $hour_o$	T-Stat kWh/ $hour_p$	T-Stat kWh/ $hour_o$	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}
CPP-V 600	**-2.336**	**-1.135**	**-63.69%**	**-64.02%**	0.436	0.126	-5.356	-8.994	**-27.048**	**-57.35%**	3.081

Delta 2-Treatment Minus Control, ***Treatment Period Model: CPP Days Only, 07/08/09/10 Weather***

	kWh/ $hour_p$	kWh/ $hour_o$	% kWh/ $hour_p$	% kWh/ $hour_o$	SE kWh/ $hour_p$	SE kWh/ $hour_o$	T-Stat kWh/ $hour_p$	T-Stat kWh/ $hour_o$	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}
CPP-V 600	**-4.311**	**-1.289**	**-76.50%**	**-55.18%**	0.292	0.100	-14.751	-12.930	**-28.092**	**-56.49%**	1.879

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh/ $hour_p$	kWh/ $hour_o$	% kWh/ $hour_p$	% kWh/ $hour_o$	SE kWh/ $hour_p$	SE kWh/ $hour_o$	T-Stat kWh/ $hour_p$	T-Stat kWh/ $hour_o$	kWh_{Day}	% kWh_{Day}	SE kWh_{Day}
CPP-V 600	**-1.975**	-0.153	**-35.05%**	-6.56%	0.525	0.161	-3.763	-0.953	-1.045	-2.10%	3.609

*% Change from Treatment Period Control Customer Values

Control Group kWh/hour

	Pretreatment Period Model		Treatment Period Model	
	kWh/$hour_p$	kWh/$hour_o$	kWh/$hour_p$	kWh/$hour_o$
CPP-V 600	3.668	1.774	5.635	2.336

Treatment Group kWh/hour

	Pretreatment Period Model		Treatment P
	kWh/$hour_p$	kWh/$hour_o$	kWh/$hour_p$
CPP-V 600	1.332	0.638	1.324

Table 4-12 presents coincident peak demand impact estimates for the CPP-V rate when compared with the Smart Thermostat control group, while Table 4-13 presents impact estimates based on the >600 kWh control group.[50] The reduction in peak demand on CPP days equals 1.4 kWh (49.4 percent) when compared with the Smart Thermostat control group and 2.8 kWh (50 percent) when compared with the alternative control group. The latter estimate assumes that all treatment and control households have air conditioning. The impact estimate based on the average central air conditioning saturation of the control group, equal to 43 percent, is –1.49. The percentage reduction of 50 percent in coincident peak demand is consistent with other experiments where enabling technology has been used in combination with critical peak pricing.

Table 4-12

50 There is the possibility that the hour of System-wide Coincident Peak may not coincide with the CPP-V period, which is being used to estimate the CPP-V models. However, this turns out to be a minor problem in the SPP. On 9 of the 12 CPP days, the two periods coincide with each other. In the remaining three days, they are within an hour of each other.

Coincident Peak Demand Impact Estimates For Residential CPP-V Rate On CPP Days
Smart Thermostat Control Group
(Impacts are reported in kWh/hour)

Delta 1-Treatment Minus Control, ***Pretreatment Period Model: 12 Max Load Days, 07/08/09/10 Weather***

	kWh/hour$_{cp}$	% kWh/hour$_{cp}$	SE kWh/hour$_{cp}$	T-Stat kWh/hour$_{cp}$
CPP-V ST	-0.066	-4.06%	0.195	-0.338

Delta 2-Treatment Minus Control, ***Treatment Period Model: CPP Days Only, 07/08/09/10 Weather***

	kWh/hour$_{cp}$	% kWh/hour$_{cp}$	SE kWh/hour$_{cp}$	T-Stat kWh/hour$_{cp}$
CPP-V ST	**-1.486**	**-51.70%**	0.137	-10.810

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh/hour$_{cp}$	% kWh/hour$_{cp}$	SE kWh/hour$_{cp}$	T-Stat kWh/hour$_{cp}$
CPP-V ST	**-1.420**	**-49.41%**	0.238	-5.959

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model kWh/hour$_{cp}$	Treatment Period Model kWh/hour$_{p}$
CPP-V ST	**1.622**	**2.873**

Treatment Group kWh

	Pretreatment Period Model kWh/hour$_{cp}$	Treatment Period Model kWh/hour$_{cp}$
CPP-V ST	**1.556**	**1.388**

Table 4-13
Coincident Peak Demand Impact Estimates For Residential CPP-V Rate On CPP Days
>600 kWh Control Group
(Impacts are reported in kWh/hour)

Delta 1-Treatment Minus Control, ***Pretreatment Period Model: 12 Max Load Days, 07/08/09/10 Weather***

	kWh/hour$_{cp}$	% kWh/hour$_{cp}$	SE kWh/hour$_{cp}$	T-Stat kWh/hour$_{cp}$
CPP-V 600	**-1.598**	**-55.45%**	0.554	-2.887

Delta 2-Treatment Minus Control, ***Treatment Period Model: CPP Days Only, 07/08/09/10 Weather***

	kWh/hour$_{cp}$	% kWh/hour$_{cp}$	SE kWh/hour$_{cp}$	T-Stat kWh/hour$_{cp}$
CPP-V 600	**-4.350**	**-79.11%**	0.311	-13.966

Delta-Difference in Differences (Delta 2 - Delta 1)

	kWh/hour$_{cp}$	% kWh/hour$_{cp}$	SE kWh/hour$_{cp}$	T-Stat kWh/hour$_{cp}$
CPP-V 600	**-2.751**	**-50.04%**	0.635	-4.331

*% Change from Treatment Period Control Customer Values

Control Group kWh

	Pretreatment Period Model kWh/hour$_{cp}$	Treatment Period Model kWh/hour$_{p}$
CPP-V 600	**2.883**	**5.498**

Treatment Group kWh

	Pretreatment Period Model kWh/hour$_{cp}$	Treatment Period Model kWh/hour$_{cp}$
CPP-V 600	**1.284**	**1.149**

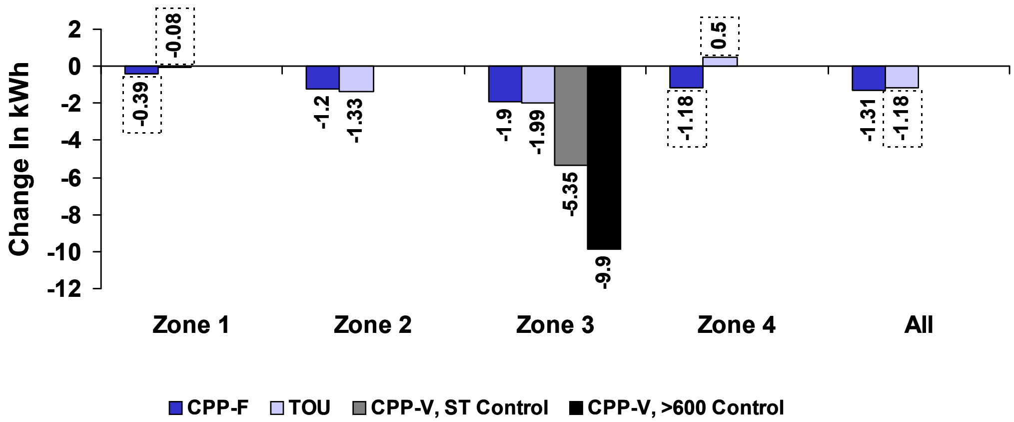
4.4 A Comparison Of Impact Estimates Across Rate Treatments

Figures 4-4, 4-5, and 4-6 summarize the impact estimates for each rate treatment and rate period. When examining these figures, it must be kept in mind that the CPP-V impacts are not directly comparable to the other rate treatments in that both the treatment and control group households differ in several ways from the general population. Not only do the CPP-V treatment customers represent volunteers based on an "opt-in" marketing strategy for an unrelated pilot, but also they are also all single-family dwellings with central air conditioning.

As previously discussed, both of the dynamic rates show much larger impacts on CPP days than on non-CPP days. This is to be expected, since the rates are much higher on these days. The TOU impact is also larger on CPP days than on non-CPP days, even though the rate doesn't change on CPP days. This also is expected, as CPP days are much hotter than non-CPP days and, at least for those customers with air conditioners, the same pattern of behavior on both day types will result in different absolute responses.

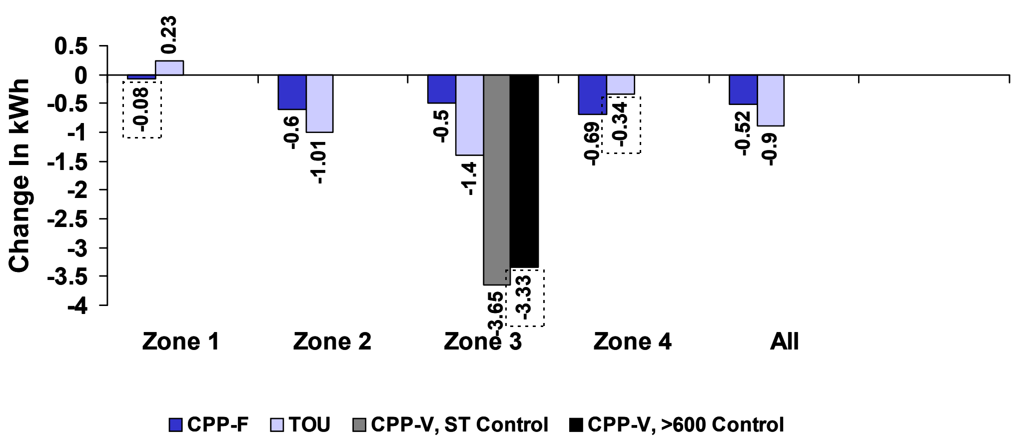
The most surprising result by far is the estimated impact of the TOU rate. Not only is the magnitude of the impact larger than expected but it is also slightly greater than the CPP-F rate impact on CPP days in zones 2 and 3, which together account for more than three-quarters of the state's population. This is completely counter-intuitive in light of the much larger peak-period price facing CPP-F customers on CPP days compared with TOU customers. Collectively, the results show that prices certainly influence energy use during the peak period, and the CPP-F rates by themselves show that higher prices reduce demand more than lower prices, even on very hot days. But the TOU results indicate that, on CPP days and when compared with the same control groups, the lower TOU prices produce larger reductions than do the higher CPP-F rates. The End-of-Summer report that will soon be available may shed light on these anomalous results.

Figure 4-4
Peak-Period Impact Of Rate Treatments On CPP Days*



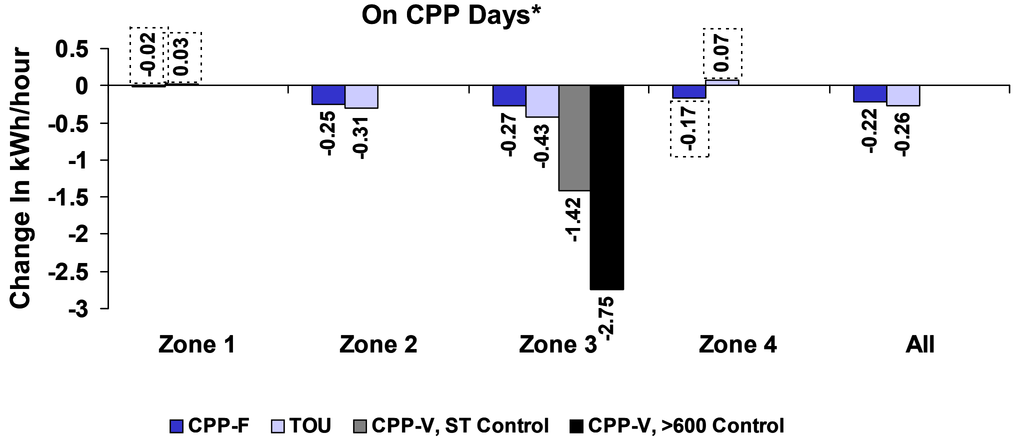
*The figures in dotted boxes are not statistically significant at the 95% confidence level. The impacts for the CPP-V rate represent households with central air conditioning and are not directly comparable to the other impact estimates.

Figure 4-5
Peak-Period Impact Of Rate Treatments On Non-CPP Weekdays*



*The figures in dotted boxes are not statistically significant at the 95% confidence level. The impacts for the CPP-V rate represent households with central air conditioning and are not directly comparable to the other impact estimates.

Figure 4-6
Coincident Peak Demand Impact Of Rate Treatments On CPP Days*



*The figures in dotted boxes are not statistically significant at the 95% confidence level. The impacts for the CPP-V rate represent households with central air conditioning and are not directly comparable to the other impact estimates.

4.5 A Comparison of Impact Estimates Across Customer Types

One of the potential advantages of the model-based approach is that it allows one to estimate treatment impacts for target populations other than those of the estimating samples or the population at large. If the model specification includes terms representing the interaction between customer characteristics and the treatment variable, the model can be used to estimate treatment effects based on variation in customer characteristics. For example, a customer who has a central air conditioner (CAC) would be expected to show greater responsiveness to time-varying prices than one who does not have a CAC. Similar impact variations would be expected with the presence or absence of other major electric-intensive appliances.

After testing a wide variety of interaction terms, the final models used in this section allow impacts to vary with three major appliances: CAC, swimming pools and electric cooking. Table 4-14 shows how impact estimates vary with appliance ownership for several rate types. In general, the results move as expected. For example, as seen in the first column of the table, the average impact of the CPP-F rate on non-CPP days across all zones is -.524 kWh. This rises to -.909 kWh for households with CAC and falls to -.321 for households without CAC. Similarly, the impact rises to –1.761 kWh for households with a swimming pool and falls to -.449 for households without pools. The composite impact for households with all three appliances is –2.065 kWh (or 400 percent of the average household's impact) and impact is only -.301 kWh (or 57 percent of the average household's impact) for households with none of the three appliances.

Table 4-14 Comparison of Impact Estimates Across Customer Types All Zone Peak Period kWh Impact							
Customer Type	CPP-F (Non-CPP Days)	CPP-F (CPP Days)	TOU (Non-CPP Days)	TOU (CPP Days)	TOU All Weekdays	CPP-V (>600) (CPP Days)	CPP-V (>600) (Non-CPP Days)
Average	**-0.524**	**-1.308**	**-0.092**	**-1.179**	**-0.896**	**-3.845**	**-0.617**
A/C	-0.909	-2.03	-1.252	-1.648	-1.238	-9.875	-1.832
No A/C	-0.321	-0.679	-1.062	-1.184	-1.098	0.645	0.289
Pool	-1.761	-2.83	-3.034	-2.441	-3.079	-6.905	-1.223
No Pool	-0.449	-1.215	-0.719	-1.117	-0.711	-3.525	-0.552
A/C, Pool, and Electric Cooking	-2.065	-3.456	-3.536	-2.615	-3.3635	-10.125	-1.849
No A/C, Pool, or Electric Cooking	-0.301	-0.635	-0.79	-1.249	-0.787	-1.475	-0.16

A similar pattern is observed for the CPP-F rate on CPP days. The average impact is –1.308 kWh. For households with all three appliances, the impact rises to –3.456 kWh (or about 264 percent of the average household's impact), and for households with none of the three appliances, it falls to -.635 kWh (or 49 percent of the average household's impact). The next three columns present the impact of TOU rates on the three day types and show how the impacts vary by appliance ownership. The last two columns show impacts for the CPP-V rate on CPP and non-CPP days, measured against the control group with greater than 600 kWh. In general, impacts are 200 to 300 percent higher when households have all three appliances and lower by varying percentage amounts when they don't have any of the three appliances.

A careful examination of the predicted values in Table 4-14 shows that the relative magnitude of impacts across customer types does not always move as expected for all rate treatments. For example, the impact for TOU customers on all weekdays is larger for households with no central air conditioning than it is for the average household. The most likely reason for these unexpected results is that the experiment was not designed to ensure statistically valid estimates for households with different appliance holdings. Thus, the ability to develop appliance-specific impact estimates is an empirical matter and largely dependent on a combination of a large enough sample and enough variation across appliance holdings within that sample. A priori, one would expect that the existing samples would likely support this type of analysis for the CPP-F treatment in climate zone 2. For example, where the sample size is large and there is significant variation in appliance ownership (especially air conditioning and pool ownership) within the sample. On the other hand, for the TOU rate in climate zone 1, it would not be surprising to find statistically insignificant coefficients on these interaction terms, since the sample sizes are much smaller and there is much less variation in ownership within the sample in this zone.

5 Residential Demand Models And Price Elasticity Estimates

5.1 INTRODUCTION

An important goal of the SPP is to estimate demand models and price elasticities that can be used to evaluate the cost-effectiveness of alternative tariffs. This section discusses how factors that determine the demand for electricity by time-period—such as the price of electricity, socio-demographic factors, appliance holdings, income and weather conditions—have been identified and their impact quantified through the specification, testing and estimation of what are called "demand models" in the economics literature.[51] The choice of variables is based on the application of economic theory to consumer decision-making regarding the use of electricity. Multiple regression analysis has been used to estimate separate demand models for peak and off-peak period energy consumption on CPP and non-CPP weekdays for the CPP-F, CP-V and TOU rate treatments. Coincident peak demand models are also estimated.

The past quarter century of research in econometrics has shown that carefully estimated demand models provide the best method of estimating the impact of new rates on energy consumption and peak demand. Economic theory does not provide a single representation of demand models and thus the best model must be found through empirical analysis.

Demand models yield summary statistics known as price elasticities of demand. These are dimensionless quantities that equal the ratio of the percent change in the demand for electricity to the percent change in price. Price elasticities provide a "first-order" approximation for predicting the impact of new rates on energy consumption and peak demand. A variety of price elasticities have been computed from the SPP database, including own-price elasticities for coincident peak demand and critical peak, peak and off-peak energy use and the associated cross-price elasticities.[52]

This report section discusses the specification of demand models, the measurement of price, the estimation of demand models and the derivation of price elasticities. It concludes with a simulation of impacts using the demand models that have been estimated.

As noted earlier in this report, a key feature of the SPP design is the inclusion of two price pairs (peak and off-peak prices) within each tariff type (e.g., TOU, CPP-F and CPP-V). When data from both price pairs are combined with the standard price faced by

51 An overview of demand models is provided in Robert A. Pollak and Terence J. Wales, *Demand System Specification & Estimation*, Oxford University Press, 1992. Many applications from the literature on consumer marketing can be found in Gary L. Lilien, Philip Kotler and K. Sridhar Moorthy, *Marketing Models*, Prentice Hall, 1992.

control group customers, three price pairs are available for the estimation of demand functions. If only a single price were tested with each tariff type, it would not be possible to estimate demand functions.

It is important to develop demand functions in order to allow policymakers to estimate the impact of price levels that were not explicitly tested in the pilot. For example, if the SPP only included a TOU rate with a single price pair where the peak/off-peak price ratio was, say, 2/1, the analysis could only estimate the energy and demand impacts of customers who faced this specific price ratio. However, if the pilot includes customers who face price ratios of, say 3/1 and 1.5/1, and also includes control group customers who implicitly face a price ratio of 1/1, the differential response by customers facing these various price ratios can be used to estimate a mathematical equation that relates energy consumption in the peak period to peak and off-peak prices. Subsequently, this demand function can be used to estimate the impact of an alternative tariff that was not tested (e.g., one with a price ratio of 2.5/1, 2/1, 1.75/1, etc.).

5.2 SPECIFICATION OF DEMAND MODELS

Consumer demand for electricity is derived from the satisfaction or "utility" that consumers obtain from the services that flow from electricity, such as space cooling, refrigeration and hot water. Consumers seek to maximize their utility from consuming various goods and services, subject to their income constraint and their preferences for the services that derive from these goods and services. Thus, the amount of a given good or service consumers will use depends on the prices of each good or service, consumer income, and the nature of their utility function.

Solving this constrained maximization problem yields demand functions that express the amount a consumer will purchase of a particular good, such as electricity, as a function of the price of electricity, the prices of all other goods and services, and the consumer's income. Demand curves for specific goods can be derived from the demand functions by varying the price of that good and holding all other factors constant. For example, by allowing the price to rise along a demand curve, one would observe a reduction in the quantity demanded, provided the consumer's income is held constant along with the prices of all other goods and services. Changes in income and the price of other goods will shift the entire demand curve either toward the origin or away from it.

The SPP has collected detailed data on electricity consumption by pricing period but, like most electricity pricing experiments, it has collected minimal information on the consumption of non-electricity goods and services. Consequently, to operationalize the

52 A good overview of pertinent elasticity concepts is contained in R. G. D. Allen, *Mathematical Analysis for Economists*, St. Martin's Press, 1964.

theory described above, it would be necessary to separate the consumer's decision problem into electricity and non-electricity goods and services. This is a fairly common procedure in empirical work dealing with time-varying pricing. Under this approach, a consumer's utility function, (U), is assumed to be separable into two sub-functions, one dealing with electricity (U_1) and the other dealing with non-electricity (U_2). U_1 can be thought of as being an index of aggregate electricity consumption. Optimization of U_1 yields a set of electricity-related demand functions that relate electricity consumed in the various pricing periods to electricity prices in each of the periods and total expenditures on electricity (rather than consumer income). In addition, recognizing that consumers who differ in socio-demographic characteristics and appliance holdings are likely to use electricity differently, it is common practice to include explanatory variables on the right hand side that reflect these variables. Finally, since weather conditions have a major impact on electricity consumption, it is also necessary to include weather as an explanatory variable. As seen in earlier sections, the SPP has collected data on such variables.

A series of demand models for peak and off-peak energy consumption on CPP and non-CPP weekdays were estimated through regression analysis using metered usage data, weather data and customer characteristics survey data. These models were estimated using the double-logarithmic functional form that is popular in such research because it has the advantage of instantly yielding estimates of the price elasticities of demand. This model specification has been widely used to estimate demand systems for a wide variety of consumer goods and services, largely because of its simplicity of interpretation and ease of estimation. In addition, the equations can be estimated through ordinary least squares. Examples include the analysis of data from the Los Angeles Department of Water and Power TOU pricing experiment by Jan Acton and Bridger Mitchell (1979) and the analysis of Swiss electricity data by Massimo Filippini (1995).[53] In addition, another functional form that yields elasticities of substitution was also estimated. This provides another means of validating the results of the SPP with other studies in the vast literature on time-varying pricing.

Separate demand models were estimated for each rate type, climate zone and day type (e.g., CPP and non-CPP days). In a typical equation, the natural logarithm of electricity use is a function of the natural logarithm of peak and off-peak prices and other relevant variables such as appliance holdings, household demographics and weather. The coefficient of the peak period price in the equation for peak period usage is the own-price elasticity of demand for on-peak usage, and the coefficient of the off-peak price in the same equation is the cross-price elasticity between on-peak usage and off-peak

53 Acton, Jan Paul and Bridger M. Mitchell, "Evaluating Time-of-day Electricity Rates For Residential Customers," RAND R-2509-DWP, November 1979; Filippini, Massimo, "Swiss residential demand for electricity by time-of-use," *Resource and Energy Economics*, 1995.

price. With this specification, all own-price and cross-price elasticities are constant across various price levels.

5.3 PRICE SPECIFICATION

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 by various analysts, including current and lagged marginal price with and without infra-marginal price terms, price indices, current and lagged average price and total bills. [54] Before discussing the different methods for measuring the price of electricity, it is useful to discuss three criteria by which the methods should be evaluated.

The first criterion is that the method be econometrically sound. That is, it should not create estimation problems that would lead to biased, inconsistent or inefficient estimates of the regression coefficients and ultimately impair estimation of the price elasticities of demand. A problem that is commonly encountered in demand models is simultaneity between price and usage. This occurs if the underlying rate design is either declining block or inverted block. In the SPP case, the rate design is inverted block. The more electricity a customer uses in a time period, the higher the price the customer pays. Thus, if average price was used as the price term in the demand model, not only would usage depend on price, but the magnitude of price would depend on the customer's usage. This simultaneous determination of both price and quantity can cause biased estimates of the coefficient on the price term.

A variety of methods can be used to address this problem, including two-stage least squares estimation procedures or indirect least squares requiring the use of instrumental variables. Another option is to use lagged price terms (e.g., average price from the previous billing period), but this can lead to loss of data.[55] Another option for reducing,

54 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 on 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.

55 In the current instance, we would need to eliminate all of the July data from the demand models so that we could use it to calculate lagged prices.

although not completely eliminating, the simultaneity problem is to use the marginal price corresponding to the final tier that the customer is in.[56]

The second criterion is that the price term should bear some relationship to what most customers actually perceive. Focus group research conducted as part of the SPP has indicated that, while California customers have a general idea of what they are paying for electricity and understand the concept of time-varying rates, they are not aware of the actual prices (expressed in cents/kWh) they pay. It is important to strike a reasonable balance between accuracy in the price calculation and the likely perceptions that customers have about the prices they are charged. That is, it may be a mistake to use precisely accurate prices if they have little to do with what customers actually perceive.

The third criterion is that the method be computationally parsimonious. Computationally intensive methods can be error prone, time consuming, opaque and expensive without yielding any obvious payoffs in improved parameter estimates.

Within the context of the SPP, there are a variety of methods that could be used to measure price, including the following:

- One approach is to use the prices that were communicated to customers in the Welcome Package they received after enrolling in the SPP. Prices using this approach would 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. For example, for the CPP-F rate in SDG&E territory, the current average rate was stated to be 15.5 cents/kWh. The SPP treatment rate was stated to be 10.8 cents/kWh off-peak for 85% of the hours in the year, 27.6 cents/kWh on-peak for 14% of the hours of the year and 76.8 cents/kwh super peak for 1% of the hours of the year. The chart also indicated the specific times for the peak and off-peak periods. This approach is by far the easiest to implement.

- A second approach would begin with development of a composite tariff schedule by climate zone equal to a population-weighted average of the tariffs that exist within each climate zone and service territory. Next, each customer's average daily usage (ADUs) from the previous summer would be used to assign customers to specific tiers with each zone. Finally, average or marginal prices would be computed for the super-peak, peak, and off-peak periods based on the midpoint of each tier by utility, rate type, rate level and climate zone. This assignment of prices would stay constant for an entire season. With this method,

56 The marginal price varies with usage only when customers move across tiers. For any usage within a tier, the marginal price is constant. The average price, on the other hand, changes with each additional kWh usage even within a tier.

there is some variation in average prices across customers within a season due to the assignment of customers to different tiers based on their historical usage but the simultaneity should be less than with other options because the energy consumption used to calculate prices is fixed, based on historical (e.g., year-old) values.

- A third method is similar to the second except that it allows prices to vary with changes in energy consumption by calendar month. With this approach, average or marginal prices would be determined by assigning each customer to a tier based on usage in the current calendar month. The price for all customers assigned to a tier would be the same and equal to the average price based on usage equal to the mid-point of the assigned tier. For example, if a tier ran from 400 kWh to 700 kWh, and the customers usage in July equaled 600 kWh, the average price for this customer, and for all customers whose usage fell in that tier, would be based on assumed usage of 550 kWh (e.g., the midpoint of the tier).

- A fourth method would take each customer's usage by calendar month and compute their actual, customer-specific prices rather than using the mid-point of the tier (i.e., each customer's usage would be run through the bill calculator that was developed at the beginning of the project to establish the SPP rate designs). If marginal prices were used in the two methods rather than average prices, this method and the previous one would result in the same values. However, with average prices, the result would be different. The advantage of this approach over the following one is that it avoids the need to grapple with billing cycle issues. Dealing with billing cycles as opposed to calendar months is much more complex computationally and also introduces additional econometric issues.

- A final option would use the average price paid by customers based on their actual billing cycle energy consumption, lagged one period. It should be noted that this option would result in the exclusion of the July data from the regression analysis, as the approach only makes sense under the assumption that customers base their usage decisions in a billing cycle on the price information received in the previous bill.

After evaluating the options described above, an initial decision was made to pursue option 3. This option appeared to strike a reasonable compromise between accuracy, computational ease and minimization of econometric problems. Unfortunately, in practice, option 3 did not fare well. It yielded positive and statistically significant estimates of the price elasticities of demand across all rate types and day types. On further examination, it became clear that the regression results were being dominated by the simultaneity problem described above. The coefficients on the price terms did not represent the negative slope of the demand curve but reflected instead the upward slope of the inverted five-tier rate schedule.

This was confirmed when the data were subdivided into five tiers and separate regression models estimated for each tier. This “Option 6” yielded satisfactory estimates of price elasticities within each tier for most rate types. However, since the sample was not designed to produce meaningful results at the tier level, an alternative approach was pursued.

First, two-stage least squares (2SLS) was used to estimate the demand models. This involved estimating an “instrumental variable” model in which price is regressed on factors other than usage. Variables used in the first stage included appliance holdings, household socio-demographic characteristics, weather and binary variables representing climate zone, utility and CARE/non-CARE pricing. The predicted value of price obtained from the instrumental variable regression was then used as the price term in the demand function. Unfortunately, the results from this approach were largely unsatisfactory (e.g., statistically insignificant, wrong signs, etc.), confirming that the problem of simultaneity was sufficiently strong that even the 2SLS procedure failed to remove it.

Second, a variant of Option 1 was explored, where prices for all customers were set equal to the Tier 3 average price based on the midpoint of the tier. This approach approximates Option 1 except that prices were allowed to vary as general rate adjustments occurred for each utility over the treatment period. The prices also reflect whether or not a customer receives the CARE discount. With this approach, prices primarily reflect the experimental design and do not vary with customer usage, essentially making them ideal instruments for the demand models.

Satisfactory results (described below) were obtained using the Tier 3 prices. To test the sensitivity of the results, models were also estimated using Tier 1 and Tier 2 prices. The results were quite robust across the three price sets.[57] 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 is usually a Tier 3 customer, a decision was made to stick with results obtained using Tier 3 prices.

57 Separate demand models were estimated using Tier 1, Tier 2 and Tier 3 prices. The results were generally similar, in terms of the overall goodness of fit of the regressions, as measured by the R-square values, and the magnitude and statistical significance of the price elasticities of demand. A decision was made to use Tier 3 prices since the "typical" customer for each utility lies in Tier 3.

5 Residential Demand Models And Price Elasticity Estimates

Demand models were also estimated using both average and marginal, Tier 3 prices. The results varied little[58] and 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.

An illustrative set of prices from PG&E in Zone 2 are contained in Table 5-1. The prices used in the regression models appear in Appendix 9.

Table 5-1
CPP-F Illustrative Average Prices (PG&E, Zone 2, Tier 3 Customer)

Rate Level	Daily Price (¢/kWh)	Critical Peak Price (¢/kWh)	Peak Price (¢/kWh)	Off Peak Price (¢/kWh)
High Summer Ratio	12.15	73.77	24.50	6.20
Low Summer Ratio	14.30	54.43	22.43	9.08
High Summer Ratio (CARE)	8.00	57.29	17.88	3.25
Low Summer Ratio (CARE)	9.72	41.82	16.22	5.55

5.4 PRICE ELASTICITY ESTIMATES

The estimated demand models included most of the same variables that were used in the treatment impact models described in Section 4 except that the treatment variable used there was replaced with the natural log of peak and off-peak prices in each equation and no interaction terms were used in the current demand models. The demand equation for climate zone 2 for the critical peak period on CPP days is provided below.

In (Peak Period Usage) = -0.77

-0.24 [In (CPP Price)]

-0.34 [In(Off Peak Price)]

-0.31 (multi-family binary variable)

58 For example, with the CPP-F rate on CPP days, the price elasticities for zones 1 through 4, respectively, based on the average price were -.142, -.240, -.337 and -.249. When marginal

+0.10 (persons per household)

+0.14 (number of bedrooms)

+0.01(cooling degree hours)(central air conditioning binary variable)

+0.13 (electric drier binary variable)

+0.15 (electric cooking binary variable)

+0.12 (electric spa binary variable)

+0.29 (electric water heater binary variable)

+0.33 (home business binary variable)

-0.14 (college graduate binary variable)

-0.03 (continuous variable representing satisfaction with utility)

+0.45 (swimming pool binary variable)

+0.11 (number of stand-alone freezers)

-0.24 (number of well water pumps)

-0.30 (number of water beds)

+0.00079 (household income)

+.04 (home computer use binary variable)

The own and cross-price elasticities obtained from this specification equal the coefficients of the natural log of peak and off-peak period prices, respectively. In the above example, the own-price elasticity equals -.24 and the cross-price elasticity equals -.34. A positive cross-price elasticity means that peak and off-peak energy consumption are substitutes—that is, as the peak period price increases, off-peak energy consumption increases. If the cross-price elasticity is negative, peak and off-peak energy consumption are complementary—that is, as the peak-period price increases, off-peak energy consumption will fall (along with peak period energy consumption).

Tables 5-2 through 5-8 present the estimated elasticities for each of the estimated models. Values that are statistically significant are shown in **bold**. The price elasticities in the tables are generally consistent with estimates reported in the literature, which suggests that price elasticities lie in a range between 0 and -.4, with most values lying

price is used instead of average price, the elasticity values are -.119, -.250, -.319 and -.263. The difference between the simple average of the four elasticities is less than 2 percent.

between -.1 and -.3. Summaries of the literature on price elasticities are contained in King and Chatterji (2003) and Faruqui and George (2002).[59]

Table 5-2
Price Elasticities of Demand
CPP-F Rate on CPP Days

Climate Zone	Peak Period		Off Peak Period	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Zone 1	-0.14	-0.28	-0.32	-0.13
Zone 2	-0.24	**-0.34**	**-0.24**	-0.01
Zone 3	**-0.34**	**-0.52**	**-0.37**	-0.07
Zone 4	**-0.25**	**-0.32**	**-0.27**	-0.04

Table 5-3
Price Elasticities of Demand
CPP-F Rate on Non-CPP Weekdays

Climate Zone	Peak Period		Off Peak Period	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Zone 1	**-0.21**	**-0.21**	**-0.22**	-0.25
Zone 2	**-0.26**	**-0.11**	**-0.19**	+0.02
Zone 3	**-0.50**	**-0.37**	**-0.32**	-0.17
Zone 4	**-0.25**	**-0.11**	**-0.16**	**-0.05**

As seen in tables 5-2 and 5-3, all of the estimates of the own-price elasticity of demand for peak and off-peak energy consumption for the CPP-F rate are negative and statistically significant. For peak period energy consumption, the lowest values are in zone 1 and the highest in zone 3. The elasticities in zones 2 and 4 are quite similar, with values roughly equal to -.25 on both CPP and non-CPP days. In zones 1 and 3, the elasticity estimates on non-CPP days are higher than on CPP days. This is not surprising given the much larger percentage increase in prices on CPP days relative to

59 Chris King and Sanjoy Chatterjee, "Predicting California Demand Response: How Do Customers Respond to Hourly Prices," *Public Utilities Fortnightly*, July 1, 2003; Faruqui, Ahmad and Stephen S. George. "The Value of Dynamic Pricing of Electricity in Mass Markets," *The Electricity Journal*, July 2002.

non-CPP days. It suggests that average responsiveness diminishes as prices increase significantly and suggests caution when applying elasticity values based on moderate, non-CPP pricing to predict changes in energy demand associated with price ratios that typically apply on CPP days.

The peak and off-peak, own-price elasticities are comparable in magnitude in zones 2, 3 and 4 on CPP days. On non-CPP days in zones 2 through 4, the off-peak elasticities are roughly two-thirds the size of the peak-period elasticities.

Estimates for the cross-price elasticity of demand for peak period energy consumption relative to changes in the off-peak price are all negative and statistically significant for the CPP-F rate, indicating that the dominant effect is complementarity rather than substitutability. That is, if off-peak prices increase, both peak and off-peak energy consumption decline. Most of the cross-price elasticities for off-peak energy consumption relative to a change in peak period prices are also negative, although three out of eight are not statistically significant and those that are significant tend to be much smaller in magnitude than the peak-period, cross-price effect.

Tables 5-4 and 5-5 contain price elasticity estimates for the CPP-V rate. Recall from Section 4 that the CPP-V rate was used only in climate zone 3 in the SDG&E service territory. Thus, it should be compared most closely with the zone 3 estimate for the CPP-F rate. Recall also that these estimates are based on a comparison with the AB970 Smart Thermostat control group rather than the population at large.[60] Thus, they are not directly comparable to the CPP-F estimates. As seen in the tables, the own-price elasticity of demand for peak-period energy consumption is nearly twice as large on non-CPP days as on CPP days. This suggests that the percent change in energy use is smaller for very large price changes than it is for smaller price changes. That does not mean, however, that the absolute change in energy use is less on CPP days than on non-CPP days. The cross-price elasticity of peak period energy consumption relative to a change in off-peak prices is statistically insignificant on both CPP and non-CPP days. The own-price elasticity of demand for off-peak energy consumption is also statistically insignificant, although the cross-price elasticity of demand is statistically significant and negative.

Table 5-4
Price Elasticities of Demand
CPP-V Rate on CPP Days

	Peak Period	Off Peak Period

60 As described in Section 4, an alternative control group is available for estimation of demand models using the CPP-V rate. However, as discussed in Section 3.4.3, this control group is not well matched to the treatment group and such a comparison may not be valid. Consequently, we did not estimate demand models based on this control group.

Climate Zone	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Smart Thermostat control group	-0.39	-0.03	+0.07	-0.12

Table 5-5
Price Elasticities of Demand
CPP-V Rate on Non-CPP Weekdays

Climate Zone	Peak Period		Off Peak Period	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Smart Thermostat control group	-0.66	+0.13	+0.08	-0.27

Tables 5-6 through 5-8 contain elasticity estimates for the TOU rate on CPP, non-CPP and all weekdays, respectively. Estimates of the own-price elasticity of demand for peak period energy consumption are either small and statistically significant, or insignificant in zones 1 and 2, indicating limited responsiveness to the peak-period price signal in these zones. The zone three estimate, on the other hand, is quite large in all cases. Indeed, it is larger than the peak period elasticity for the CPP-F rate. This odd result is consistent with the similarly odd finding reported in Section 4, where the zone 3 impact is larger for the TOU rate than for the much higher CPP-F rate. We suspect some form of bias in both estimates but so far we have been unable to identify the potential cause of these anomalies.[61]

The positive and statistically significant cross-price elasticities in zone 2 on non-CPP days and all weekdays is the only indication of strong substitutability between peak and off-peak energy consumption across all rate treatments. However, the magnitude of the cross-price effect for the peak period, especially relative to the own-price effect, is much larger than expected and could suggest some spurious factors.

Table 5-6
Price Elasticities of Demand
TOU Rate on CPP Days

	Peak Period	Off Peak Period

61 As indicated in Section 4, we hope that information gained through the End-of-Summer survey will shed light on these anomalies.

Climate Zone	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Zone 1	-0.06	-0.19	-0.22	-0.08
Zone 2	-0.20	+0.31	+0.12	+0.02
Zone 3	-0.72	-0.47	-0.37	-0.47
Zone 4	**-0.20**	**-0.35**	**-0.44**	+0.07

Table 5-7
Price Elasticities of Demand
TOU Rate on Non-CPP Weekdays

Climate Zone	Peak Period		Off Peak Period	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Zone 1	+0.05	**-0.17**	**-0.24**	-0.01
Zone 2	**-0.11**	**+0.39**	**+0.15**	**+0.08**
Zone 3	**-0.57**	**-0.29**	**-0.28**	**-0.36**
Zone 4	**-0.28**	**-0.26**	**-0.36**	+0.01

Table 5-8
Price Elasticities of Demand
TOU Rate on All Weekdays

Climate Zone	Peak Period		Off Peak Period	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Zone 1	+0.03	**-0.18**	**-0.24**	-0.02
Zone 2	**-0.13**	**+0.38**	**+0.15**	**+0.07**
Zone 3	**-0.59**	**-0.31**	**-0.29**	**-0.38**
Zone 4	**-0.27**	**-0.28**	**-0.37**	+0.02

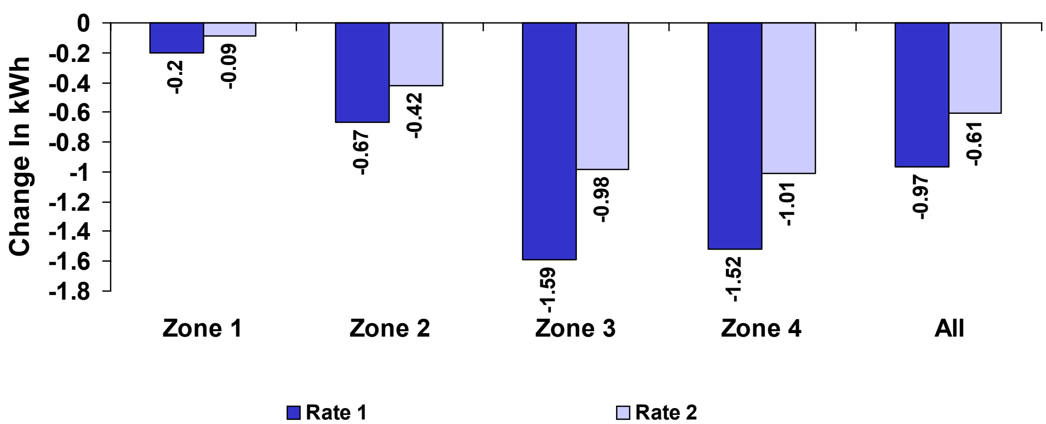
5.5 IMPACT SIMULATIONS

With the estimation of demand models, it is possible not only to measure the responsiveness of consumers to the specific prices that were tested in the pilot, but also to simulate how energy consumption would change in response to alternative prices. This simulation capability allows policy makers and utility managements to conduct a number of "what if" scenarios that can be used to determine the cost-effectiveness of alternative pricing policies. In this section, illustrative simulations are presented with the experimental rates that were used in the SPP and with alternative rates.

Figure 5-1 shows the impact of two different CPP-F rates on energy usage in the peak period on CPP days and Figure 5-2 shows the corresponding impacts on non-CPP days. The two rates are not designed to be revenue neutral in this illustrative example.

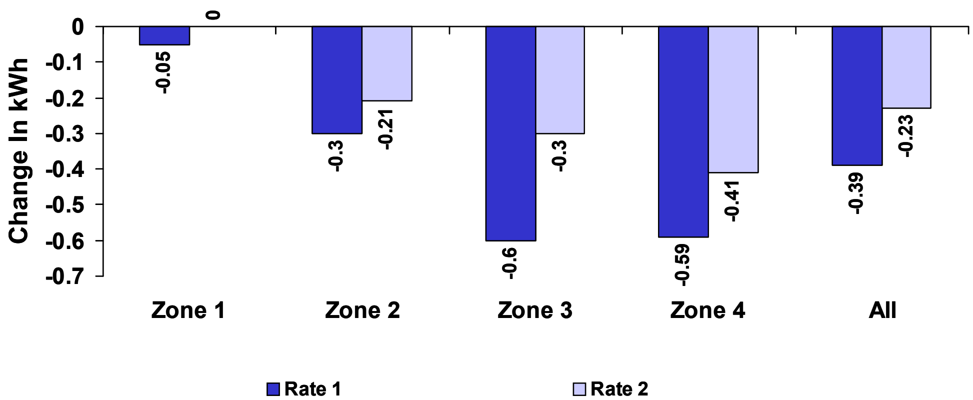
In Figure 5-1, rate 1 represents one of the experimental rates. The price during the critical peak period equals 74.17 cents/kWh and equals 8.17 cents/kWh during the off-peak period. The second rate has a lower critical peak price of 50 cents/kWh and the same off-peak rate. As expected, the impact is smaller in all four zones with the second rate. The all zone average is -.97 kWh (-21.71%) with rate 1 and -.61 (-13.45%) with rate 2.

Figure 5-1
Peak-Period Impact of Rate Treatments on CPP Days



In Figure 5-2, the first rate is the experimental rate, with a peak period price of 24.9 cents/kWh and an off-peak price of 8.17 cents/kWh. The second rate has a lower peak period price of 22 cents/kWh and the same off-peak rate. As expected, the impact is smaller in all four zones with the second rate. The all zone average is -.39 kWh (-9.37%) with rate 1 and -.23 kWh (-5.69%) with rate 2.

Figure 5-2
Peak-Period Impact of Rate Treatments on Non-CPP Days



5.6 ELASTICITY OF SUBSTITUTION MODELS

The double-log formulation presented in the previous sections is the most widely used functional form for estimating demand models and own-price and cross-price elasticities of demand. However, an alternative formulation based on the concept of the elasticity of substitution is also fairly common in the literature on customer impacts of time-differentiated rates. The elasticity of substitution measures the shape of the indifference curves that underlie the consumer's utility function. It is closely related to the own-price and cross-price elasticities of demand through the well-known Slutsky equation.[62]

The most commonly used functional form for estimating the elasticity of substitution is called the Constant-Elasticity-Of-Substitution (CES). The CES functional form was developed jointly in 1961 by four economists (Kenneth Arrow, Hollis Chenery, Bagicha Minhas, and Robert Solow). Arrow and Solow were subsequently awarded the Nobel Prize in Economics, partly for their research on the CES functional form. The CES model has been widely used in the empirical literature in economics, for modeling consumer and producer behavior.

62 This was put forward in 1915 by a Russian economist, E. E. Slutsky. It states that the own-price elasticity of demand equals the compensated own-price elasticity of demand plus the product of the income elasticity of demand and the budget share of the commodity in question.

For the two-part TOU rate, this functional form expresses the natural log of the ratio of peak and off-peak energy consumption as a function of an intercept term, the natural log of the ratio of peak and off-peak prices and all the non-price terms mentioned above. The coefficient on the price ratio is the elasticity of substitution, which is related to the own-price and cross-price elasticities of demand. The intercept term is the ratio of peak and off-peak usage in the control group.

This functional form has been used previously in the analysis of TOU experiments. For example, it was used in the analysis of the Southern California Edison and Wisconsin experiments, and in EPRI's analysis of the top five pricing experiments (Connecticut, Los Angeles, North Carolina, Southern California, and Wisconsin).[63] The CES function has the advantage of being fully consistent with the neoclassical theory of utility maximization discussed earlier.

CES regression equations were estimated for the CPP-F and TOU models for non-CPP days. The results are shown in Table 5-9. Specifically, two sets of equations were estimated. The first one regressed the natural log of the ratio of peak and off-peak energy consumption on an intercept term, the natural log of the ratio of peak and off-peak energy prices and the other variables listed in Section 5.4. The coefficient of the price ratio term is the elasticity of substitution. The second equation regressed the natural log of daily energy consumption on an intercept term, the natural log of daily energy price and the other variables. The second equation yields an estimate of the own-price elasticity of daily energy consumption. It is needed to obtain the levels of energy consumption in the peak and off-peak periods since the first equation by itself only yields the ratio of energy consumption in the rate periods.

Satisfactory results were obtained that are consistent with the empirical literature. The elasticity of substitution is insignificant in Zone 1 for both rate types, but that zone does display significant daily price elasticities for both rate types. All other elasticity of substitution estimates are significant and lie between -0.11 and -0.25. The median value is -0.14 (zone 3), which is very close to the value found by EPRI researchers. With one exception, the daily price elasticities lie between -0.22 and -0.62, with a median value of -0.40 (zone 4).[64] These elasticities show that customers in the SPP are definitely price responsive.

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63 Caves, Douglas W. and Laurits R. Christensen, "Consistency of residential customer response in time-of-use electricity pricing experiments," *Journal of Econometrics*, 1984.

64 The one exception is the positive value of .26 for the TOU rate for zone 2. This value is also statistically significant. Further tests are being done on this estimate.

Table 5-9
Elasticities of Substitution and Daily Energy Consumption
CPP-F and TOU Rates on Non-CPP Days

Climate Zone	CPP-F Rate		TOU Rate	
	Elasticity of Substitution	Own-Price Elasticity of Daily Energy Consumption	Elasticity of Substitution	Own-Price Elasticity of Daily Energy Consumption
Zone 1	0.02	**-0.44**	0.01	**-0.34**
Zone 2	**-0.19**	**-0.22**	**-0.20**	**0.26**
Zone 3	**-0.14**	**-0.62**	**-0.11**	**-0.41**
Zone 4	**-0.12**	**-0.27**	**-0.25**	**-0.40**

Table 5-10 contains the elasticities of substitution and daily energy consumption for the CPP-F and TOU models on CPP days. Again, all the elasticities of substitution are significant, with the exception of zone 1. The other elasticities range from -0.10 to -0.24. The own-price elasticity of daily energy consumption is significant in all cases except for the TOU rate in zone 2. These elasticities range from -0.29 to -0.61, with a median value of -0.46.

Table 5-10
Elasticities of Substitution and Daily Energy Consumption
CPP-F and TOU Rates on CPP Days

Climate Zone	CPP-F Rate		TOU Rate	
	Elasticity of Substitution	Own-Price Elasticity of Daily Energy Consumption	Elasticity of Substitution	Own-Price Elasticity of Daily Energy Consumption
Zone 1	-0.02	**-0.46**	0.00	**-0.33**
Zone 2	**-0.16**	**-0.29**	**-0.20**	0.17
Zone 3	**-0.16**	**-0.61**	**-0.10**	**-0.55**
Zone 4	**-0.15**	**-0.46**	**-0.24**	**-0.46**

Table 5-11 contains the elasticities of substitution and the own-price elasticity for daily energy consumption for the CPP-V rate based on the Smart Thermostat control group on non-CPP days and CPP days only. The elasticity of substitution is higher on CPP days than on non-CPP days, but both estimates are large and statistically significant. Neither of the own-price elasticity estimates for daily energy consumption is statistically significant perhaps because the data comes from one utility and climate zone and there is insufficient price variation in the daily price.

Table 5-11
Elasticities of Substitution and Daily Energy Consumption
CPP-V (Smart Thermostat Control Group)

	Non-CPP Days		CPP Days Only	
	Elasticity of Substitution	Own-Price Elasticity of Daily Energy Consumption	Elasticity of Substitution	Own-Price Elasticity of Daily Energy Consumption
Smart Thermostat control group	**-0.26**	0.03	**-0.39**	0.07

5.7 COINCIDENT PEAK DEMAND MODELS

A set of models for explaining the behavior of coincident peak demand were estimated using the double-log formulation. The natural log of coincident peak demand was regressed on an intercept term, the natural log of peak and off-price prices, and the other variables listed in Section 5.4. Since the concept of coincident peak demand only has meaning on critical peak days, these regressions were only performed on CPP days. Results that are generally similar to those for peak period energy consumption were found. The adjusted R-Squares were slightly lower. Tables 5-12 and 5-13 summarize these results.

Table 5-12
Price Elasticities of Coincident Peak Demand
CPP-F and TOU Rates on CPP Days

Climate Zone	CPP-F Rate		TOU Rate	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Zone 1	**-0.17**	**-0.41**	**-0.02**	**-0.30**
Zone 2	**-0.22**	**-0.29**	**-0.13**	**0.43**
Zone 3	**-0.37**	**-0.57**	**-0.51**	-0.17
Zone 4	**-0.25**	**-0.41**	**-0.28**	**-0.52**

As seen in Table 5-12, all of the estimates of the own-price elasticity of demand for peak and off-peak energy consumption for the CPP-V rate on non-CPP days are negative and statistically significant. They are generally similar to the values for peak energy consumption shown in Table 5-2. For peak period energy consumption, the lowest elasticity values are in zone 1 and the highest elasticity values are in zone 3. The elasticities in zones 2 and 4 are quite similar.

Three of the eight price elasticities for the TOU rate are not significant. These include two own-price elasticities for zones 1 and 2 and the cross-price elasticity for zone 3. As has been seen elsewhere, for zone 3, the price elasticity for the TOU rate is much higher compared to the price elasticity for the CPP-F rate.

Table 5-13
Price Elasticities of Coincident Peak Demand
CPP-V Rate on CPP Days

Climate Zone	Peak Period		Off Peak Period	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Smart Thermostat control group	-0.51	-0.24	N/a	N/a

Table 5-13 contains price elasticity estimates for the CPP-V rate on CPP days. As noted earlier, these estimates are not directly comparable to the CPP-F estimates because they apply to a special group of customers who have volunteered into the AB 970 Smart Thermostat pilot program. The own-price elasticity is large and statistically significant while the cross-price elasticity is not statistically significant. The value of -.51404 for the own-price elasticity of demand for coincident peak demand exceeds the value of -0.39 noted earlier in Table 5-11 for peak period energy consumption, showing that customer demand at the hour coincident with system peak responds more than energy consumption over the five-hour long peak period.