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2011 Impact Evaluation of San Diego Gas & Electric's Peak-Time Rebate Pilot Program

Ex-Post and Ex-Ante Report

CALMAC Study ID SDG 0255

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ABSTRACT

This study evaluates the changes in electricity usage of customers participating in San Diego Gas and Electric Company's (SDG&E) Peak Time Rebate (PTR) pilot in 2011. The pilot was undertaken to gain experience on the operational aspects of and customer response to such a program, with a view toward expanding to system-wide PTR (also referred to as "Reduce Your Use Rewards"), with automatic enrollment of approximately 1.2 million residential customers in 2012. Under PTR, consumers receive bill credits for reducing usage during certain hours on a limited number of event days, which are announced on the day prior, but face no financial penalties if they decide not to, or are unable to respond. This report describes an evaluation conducted to measure the extent that participating customers succeeded in reducing their event-period usage during the pilot.

Features of the PTR pilot

SDG&E selected a sample of approximately 3,000 residential customers for the pilot, including about 100 customers who were also participants in SDG&E's Summer Saver (SS) air conditioner cycling program. Selected PTR pilot participants remained on their standard residential commodity rate, but were eligible to receive bill credits ($0.75 per kWh for PTR-only participants, and $1.25 per kWh for those also on Summer Saver) for all measured reductions in energy usage during PTR event periods. A comparable control group sample was selected using the same sampling approach. These customers were selected after all events had taken place, and were not informed of their selection.

The SDG&E PTR pilot differs from most previous PTR pilots in that participants were randomly selected and assigned to the program rather being asked to volunteer. Pilot participants were chosen by SDG&E so as to be representative of all residential customers in the service area. Participants were informed of their selection and given information on the pilot and on ways that they might benefit by reducing usage when events were called.

Due to weather conditions in 2011, the five PTR events that SDG&E called occurred on nearly every unusually hot day in the two climate zones (Coastal and Inland) in which

most residential customers reside. Furthermore, two of the events were called on hot days in mid-October, by which time customers' average on-peak usage was substantially lower than in August and September, likely due to less frequent use of air conditioning. These features of the PTR pilot events in 2011 created analytical challenges to estimating participating customers' reductions in usage, due to a lack of comparable days to use in comparing their consumption data (*e.g.*, comparing usage on an event day to usage on comparably hot non-event days). Fortunately, the available control group allowed side-by-side event-day comparisons and greatly aided the analysis.

Study findings

Overall, the study found that those PTR pilot participants who were not also enrolled in Summer Saver reduced their electricity usage by about 1 percent to 5 percent across the five PTR events compared to control-group customers, after adjusting for other differences between the two groups. PTR participants reduced their usage by 4.5 percent on September 7, the most "typical" summer weekday event of 2011. This translates into an *average hourly* reduction over the seven-hour event of 0.06 kWh per hour per customer. Information on the statistical precision of the estimated usage reductions indicates that an eighty percent confidence interval around the estimated 4.5 percent reduction on September 7 ranges from 2.6 percent to 6.4 percent.

The study projects that once SDG&E has expanded PTR system-wide, with automatic enrollment of approximately 1.2 million residential customers in 2012, average event-hour usage reductions on monthly system peak days in 2014, under typical weather conditions, will range from about 27 MW in May and June, to a maximum of approximately 46 MW in September.

EXECUTIVE SUMMARY

This study evaluates the changes in electricity usage of customers participating in San Diego Gas and Electric Company's (SDG&E) Peak Time Rebate (PTR) pilot in 2011. SDG&E is a regulated public utility that provides energy service to 3.5 million consumers through 1.4 million electric meters and more than 850,000 natural gas meters in San Diego and southern Orange counties. The utility's area spans 4,100 square miles. SDG&E's 2011 system peak was 4,327 MW, which occurred at 2:00 p.m. on September 7th. The majority of SDG&E residential customers are enrolled on an inverted block rate with four tiers and the average residential rate is $0.17.

The pilot was undertaken to gain experience on the operational aspects of and customer response to such a program, with a view toward expanding to system-wide PTR, with automatic enrollment of approximately 1.2 million residential customers in 2012. Under PTR, consumers receive bill credits for reducing usage during certain hours on a limited number of event days, which are announced on the day prior, but face no financial penalties if they decide not to, or are unable to respond. This report describes an evaluation conducted to measure the extent that participating customers succeeded in reducing their event-period usage during the pilot.

ES.1 Features of the Pilot

PTR pilot program

The SDG&E PTR pilot differs from most previous PTR pilots in that participants were randomly selected and assigned to the program rather being asked to volunteer. Pilot participants were chosen by SDG&E so as to be representative of all residential customers in the service area. Participants were informed of their selection and given information on the pilot and on ways that they might benefit by reducing usage when events were called.

In most other pilots, mailings are typically sent to target customers, asking them to volunteer to participate. Through this process, those who agree to participate may differ from the average customer, such as having some expectation that they are likely to benefit from the bill credits by taking actions to reduce usage on event days.[1] In contrast, participants in the SDG&E pilot were given information *after* they were selected and assigned to the pilot about ways that they might benefit by reducing consumption during PTR events, but they may have had little interest in doing so.

The PTR pilot had the following features:

- Up to 9 events could be called, where the event window was 11 a.m. to 6 p.m.[2]
- Enrolled customers were notified on the day prior to events by automated phone messaging, and could also request notification through email or text message. They were encouraged to sign up through a website to receive electronic notification.
- The bill credits that participants were eligible to receive depended on whether they used automated enabling technology installed through a SDG&E program.[3] The basic rebate level was $0.75 per kWh, with a premium level of $1.25 / kWh for customers with enabling technology.
- Each participant received one of two types of introductory educational packages; one emphasized the *financial benefits* ("rewards") of reducing usage during PTR events, while the other emphasized the potential *environmental benefits* associated with such reductions in consumption.
- Reductions in energy consumption for rebate calculations were measured relative to a customer-specific reference level (CRL) that was based on an average of their consumption during the same period on previous days.[4]

[1] The only other pilot of which we are aware that assigned customers to a PTR program through a sampling process rather than recruiting volunteers is the Customer Applications Pilot undertaken in 2010 by Commonwealth Edison Company in Illinois. Results from that pilot have been published by EPRI.
[2] SDG&E's planned full-scale program will have no limits on the number of events, but will target 9 events for the year.
[3] The only available automated enabling technology was the air conditioner cycling devices already installed for Summer Saver (SS) participants.
[4] Specifically, usage reductions during event hours were measured relative to a customer-specific reference level (CRL) defined as consumption during the event window hours averaged over the highest 3 out of the most recent 5 similar non-event weekdays. The highest days are defined to be the days with the highest total consumption between 11 AM and 6 PM. The similar days exclude weekends, holidays, and other PTR event days, and exclude other demand response program event days for customers participating in multiple demand response programs. The CRL for a weekend or holiday event is defined as the

PTR participants

SDG&E selected a sample of approximately 3,000 residential customers for the pilot, including about 100 customers who were also participants in SDG&E's Summer Saver (SS) air conditioner cycling program. Selected PTR pilot participants remained on their standard residential commodity rate, but were eligible to receive bill credits for all measured reductions in energy usage during PTR event periods. A comparable control group sample was selected using the same sampling approach. These customers were selected after all events had taken place, and were not informed of their selection.

The participant sample was drawn approximately equally from four *climate zones*: Coastal, Mountain, Desert, and Inland; and was further distributed across three *size categories*: Low, Medium, and High, based on summer average daily usage.[5] Average hourly usage ranged from approximately 0.25 to 0.30 kWh per hour for the low-usage categories, 0.6 to 1.0 kWh per hour for the medium-usage categories, and 1.5 to 2.0 kWh per hour for the high-use categories. Throughout the evaluation we distinguish results by PTR participants and control group customers who were also SS participants (denoted as PTR-SS and Control-SS) from those that had no such enabling technology (denoted as PTR-NT and Control-NT).

PTR events

Five PTR events were called in 2011. Four of the five PTR event days (September 7 and 8, and October 12 and 13) were also SS event days, although the SS events applied only to the relatively small subset of PTR-SS and Control-SS customers. Only one PTR-only event was called (August 28, a Sunday). All PTR events spanned the seven-hour period from 11 a.m. to 6 p.m., while all SS events were four hours in duration, covering the period of either 1 p.m. to 5 p.m. or 2 p.m. to 6 p.m. Of note, a system-wide outage began between 3 and 4 p.m. during the September 8 event, which caused all customers' loads to drop to zero for the remaining event hours. While results for the hours prior to the outage

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consumption during the PTR event period for the highest day from within the immediately preceding three (3) weekend days.

[5] While sample sizes were approximately equal across climate zones, population weights were applied to sample averages by climate zone and usage level to appropriately account for the relatively larger populations in the Coastal and Inland areas.

are included in the study, they are not discussed in detail. Two of the events were called on hot days in mid-October, by which time customers' average on-peak usage was substantially lower than in August and September, likely due to less frequent use of air conditioning. SDG&E usually calls demand response events on weekdays in the months of July, August and September, therefore the PTR event on September 7th was the only "typical" demand response event.

ES.2 Study Findings

Overall, the study found that those PTR pilot participants *without* enhanced technology (*i.e.*, PTR-NT) reduced their electricity usage by about 1 percent to 5 percent across the five PTR events compared to Control-NT customers, after adjusting for other differences between the two groups. These findings are summarized in Table ES-1, which shows average temperatures, event hours, percentage load impacts, and average hourly load impacts per customer. For the most "typical" summer weekday event (September 7), PTR participants reduced their usage by 4.5 percent, which translates into an *average hourly* reduction over the seven-hour event of 0.06 kWh per hour per customer. Information on the statistical precision of the estimated load impact coefficients indicates that an 80 percent confidence interval around the estimated 4.5 percent reduction in energy usage on September 7 ranges from 2.6 percent to 6.4 percent.

Table ES-1: Overall PTR-NT Estimated Load Impacts and Event Characteristics

	Event Date				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Ave. Temp. (11am - 6pm)	83.7	92.7	91.6	93.5	89.5
Event Hours (Hour Ending)	12-18	12-18	12-15[1]	12-18	12-18
Estimated Load Impact (%)	2.5%	4.5%	5.1%	3.3%	1.2%
Ave. Hourly LI (kW)	0.031	0.056	0.057	0.027	0.011

[1]Event truncated by outage

These usage reduction findings may be viewed in the context of a survey conducted as part of a process evaluation of the pilot, which found that about 63 percent of participants surveyed were *aware* that they had been selected for the pilot program, and about the same percentage recalled receiving at least one event notification.

A limited sample size for the subset of joint PTR-SS participants prohibited a comprehensive analysis of their usage changes across all climate zones. Analysis of the medium and high-usage customers in the Inland area, where most of the sample participants were located, confirmed that they reduced their usage substantially during SS event hours, as expected. However, when compared to the loads of the Control-SS customers on days for which both PTR and SS events were called, estimates of incremental changes in usage in the non-SS hours within the PTR event window varied substantially across events.

Finally, we conducted a high-level comparison of SDG&E's estimates of pilot program usage reductions (calculated using the CRL baseline approach), which were used for computing customers' bill credits, to regression-based estimates from customer-level regression analysis used in this study.[6] We found a moderate degree of correlation (0.51) between the two sets of estimates and the following percentages regarding differences between cases in which participants were found by the two methods to have *reduced* or *increased* usage during event-periods:

- Regression and CRL baseline both indicate a usage Reduction 28%
- Regression indicates Reduction, but CRL indicates Increase 30%
- Regression indicates Increase, but CRL indicates Reduction 6%
- Regression and CRL baseline both indicate a usage Increase 35%.

These results suggest that the baseline loads implied by the regression-based method are higher than those produced by the CRL baseline method, and thus estimate usage reductions more frequently and in greater amounts than does the CRL baseline method.

ES.3 Methodology

The objective of this evaluation is to provide estimates of usage changes for the PTR pilot participants using a methodology that is widely recognized as more accurate than the customer-specific reference level (CRL) method used by SDG&E for the purposes of

[6] These customer-level analyses were used to examine differences in usage changes across customers; however, pilot-level estimates of usage reductions were obtained through an analysis of usage differences between averages for *groups* of participant and control customers, as described in the methodology section below.

calculating bill credits. The merit of the CRL method's estimates of usage changes lies in its utilization of information that is available for participating customers shortly after each event and therefore can be used to calculate bill credits in a timely manner. However, the evaluation methods used in this report make use of information not available in the few days following each event, such as hourly load data for all participant and control group customers spanning the entire summer season, as well as hourly weather data from relevant weather stations. These additional data provide the opportunity to estimate load reductions for each pilot event with greater accuracy.

The availability of the control group data allowed comparisons of differences between PTR participant and control group loads on event days and non-event days, and contributed greatly to the ability to illustrate and measure pilot program load impacts. That is, after adjusting for persistent differences in usage patterns and weather sensitivity between the two groups on non-event days, event-day usage levels for the control group customers effectively serve as reference loads for the participant groups (*i.e*., an estimate of what their usage pattern would have been in the absence of the event).

The availability of the control group was particularly valuable in this evaluation of the 2011 pilot because of the fact that PTR events were called on essentially every hotter than normal day, which limited our ability to estimate participants' usage reductions by comparing their own usage on comparably hot event and non-event days.[7]

To obtain load impact estimates at the needed level of detail (*e.g*., by climate zone and in total), the study applied statistical analysis to differences between the usage of the average participant and control-group customer in each climate and usage-level group. Specifically, the statistical models are equations designed to explain *differences* between the hourly loads of participant and control-group customers, by means of a series of explanatory factors such as time of day, day of week, weather conditions, and occurrence

[7] That is, it is difficult to statistically disentangle the *positive* effect of hot temperatures on consumers' energy consumption in afternoon hours, from the potential *negative* effect of any actions that they may have taken to reduce usage during PTR event hours.

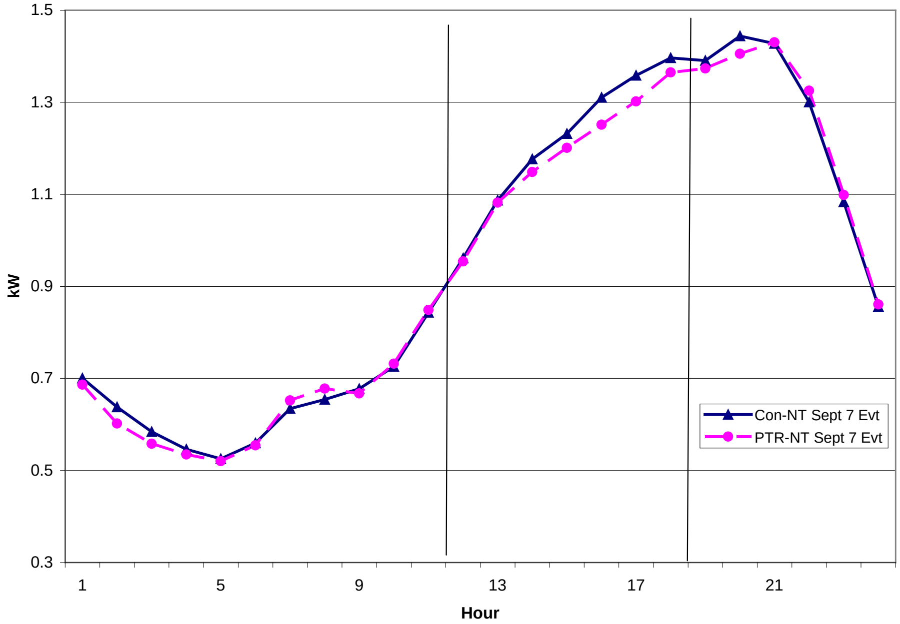
of PTR events.[8] The effect of each factor is reflected in the estimated coefficient associated with the factor.

Importantly, the coefficients on the factors, or variables, that indicate hours on an event day represent estimates of the effect of the event on the difference between participant and control group usage. We then sum the estimated usage reductions across size group and region (using appropriate sample weights) to obtain overall estimates of pilot-level usage reductions. This methodology represents a classic evaluation approach of estimating program impacts by comparing differences between treatment (participant) and control groups in the variable of interest (*e.g.*, hourly electricity consumption during event hours), after accounting for other measurable differences between the groups.

Figure ES-1 illustrates the evaluation methodology and a key pilot finding using observed data on the overall average hourly load profiles of the PTR participants and control group customers for the September 7 event day. The average participant load (dashed line) tracks the average control group load (solid line) quite closely during the morning hours, before dipping below the control group load during most of the event period hours. Similar load comparisons for *non-event* days, shown in the body of the report, indicate that average participant usage typically *exceeds* average control-group usage during the afternoon hours in which events apply. The statistical analysis described above takes into account these persistent differences in participant and control-group usage on non-event days when measuring the differences in usage on *event* days that were presented above (*e.g.*, the estimated 4.5 percent usage reduction on the September 7 event).

[8] The model needs to account for weather conditions and day-type characteristics (such as day of week) to account for any systematic differences between PTR and control-group loads on *non-event* days due to normal sample variability. While these differences may be small (e.g., less than 2 percent during weekday afternoon hours), they are relevant for measuring the magnitude of load impacts on PTR *event* days.

Figure ES-1: Overall PTR-NT and Control Group Load Profiles –
September 7 Event



ES.4 Anticipated Future Usage Reductions

As noted in the introduction to this summary, SDG&E plans to expand PTR system-wide, with automatic enrollment of approximately 1.2 million residential customers in 2012. The final element of this study involved developing a forecast of anticipated usage reductions of residential customers who are informed of their enrollment in PTR and notified when events, referred to as "Reduce Your Use" days, are scheduled to occur. Developing these estimates of future PTR usage reductions involved combining information on the usage reductions found in the pilot for 2011, described above; findings on awareness of those customers enrolled in the pilot, from process evaluation surveys; and SDG&E forecasts of residential customers.

Based on these information sources, the study projects that average event-hour usage reductions on monthly system peak days in 2014, under typical weather conditions, will range from about 27 MW in May and June, to a maximum of approximately 46 MW in September.

ES.5 Conclusions

The findings of the load impact evaluation of SDG&E's PTR pilot program for 2011 may be summarized in the following high-level points:

- The average PTR participant without enabling technology (*i.e.*, who was not also enrolled in SDG&E's Summer Saver air conditioner cycling program) reduced electricity usage during the five PTR events by amounts ranging from about 1 percent to 5 percent compared to the average control-group customer, including 4.5 percent on the one event that represents a typical summer weekday.
- The estimated PTR usage reductions for the pilot are somewhat smaller than the estimates from a number of other pilots undertaken in recent years throughout the U.S.[9] The difference in outcomes is likely due largely to different pilot designs. That is, SDG&E's pilot simulates an automatic enrollment design; participants were selected at random from the general population and assigned to the pilot. In contrast, most other pilots have recruited volunteers from a target population, often requiring contacts with up to 20 customers for each successfully enrolled participant. These volunteers might be expected to be more aware of and favorably disposed toward the program than a customer selected at random and assigned to the pilot. In addition, several of the pilots have featured bill credits that are greater than the $0.75 per kWh-reduced in the SDG&E pilot, where the larger credits provide greater incentives to reduce usage.
- The subset of PTR-SS participants reduced load substantially during SS event hours as expected. However, their usage changes relative to Control-SS customers, in PTR hours outside of SS event hours, varied considerably by event, and were not statistically significant for the two mid-October events.

[9] Estimates of percent reductions in peak load for other PTR pilots have typically ranged from 10 to 20 percent for customers without enabling technologies.

1. Introduction and Purpose of the Study

This report describes the results of a load impact evaluation of San Diego Gas and Electric Company's (SDG&E) Peak Time Rebate (PTR) pilot program for the 2011 program year. Under PTR, consumers receive bill credits for reducing usage during certain hours on a limited number of event days, which are announced on the day prior, but face no financial penalties if they do not reduce. During the pilot, participants were automatically notified of events by phone, but were encouraged to also sign up for notification by email or text. The impact evaluation analysis includes estimation of *ex post* load impacts for each PTR event, and the allocations of those impacts by climate zone and customer type.

An important feature of the SDG&E PTR pilot that differentiates it from most previous PTR pilots is that potential participants were not recruited and asked to volunteer to participate. Instead, participants in the PTR pilot were randomly selected by SDG&E and assigned to the pilot.[10] Participating customers were informed of their selection and given information on the pilot and on ways that they might benefit by reducing usage when events were called. In addition, a control group of comparable customers was selected using the same sample design.

This pilot design differs sharply from most of the dynamic pricing pilots that have been conducted in recent years around the U.S., whose results have been reported in a number of forums. In those pilots, customers who volunteer to participate logically have some expectation that they are willing or able to take actions such as reducing usage on event days, which will allow them to benefit from the features of the pilot.[11] In contrast, participants in the SDG&E pilot are given information after their selection about ways that they might benefit by reducing consumption during PTR events, but they may have little interest in doing so.

The primary objective of this evaluation is to estimate the *ex post* load impacts of the PTR pilot, including:

- Total pilot and average participant hourly load reductions on each event day, differentiated if possible by climate zone; and
- Incremental hourly load reductions related to air conditioner cycling.

Additional objectives include examination of potential differences in load impacts between participants who received alternative educational materials, and for those participants who requested additional means of event notification.

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[10] The pilot sample was selected on the basis of a stratified random sample design (using summer average daily usage as the stratifying variable and differentiated by four climate zones), and as such it is representative of all residential customers in the service area.

[11] The only other pilot of which we are aware that assigned customers to a PTR program through a sampling process rather than recruiting volunteers is the Customer Applications Pilot undertaken in 2010 by Commonwealth Edison Company in Illinois. The report for that pilot may be obtained from EPRI at http://my.epri.com/portal/server.pt?Abstract_id=000000000001023644.

The report is organized as follows. Section 2 describes the PTR program, the enrolled customers, and the events called; Section 3 describes the analysis methods used in the study; Section 4 contains the *ex post* load impact results; Section 5 contains an assessment of the validity of the results; and Section 6 provides recommendations.

2. Description of Resources Covered in the Study

2.1 Program Description

The PTR pilot was designed to study how residential customers would respond to a default program that offers only upside opportunities; customers may receive rebate payments for event-period reductions in consumption, but face no financial penalties if they decide not to respond.

The PTR pilot included the following features:

- Load reductions for rebate purposes were measured relative to a customer-specific reference level (CRL) based on an average of the highest three out of the most recent five similar non-event days.[12]
- Two rebate levels were available – a basic level of $0.75 / kWh, or a premium level of $1.25 / kWh for customers who use automated enabling technology installed through a SDG&E program.[13]
- Five events were called, with an event window of 11 a.m. to 6 p.m.
- Enrolled customers were notified on the day prior to events by automated phone messaging, and could also request notification through email or text message. They were encouraged to sign up through a website to receive electronic notification.
- Each participant received one of two types of educational packages; one emphasized the financial benefits ("rewards") of reducing usage during PTR events, while the other emphasized the potential environmental benefits associated with such reductions in consumption.

2.2 Participant and control group characteristics

Approximately 3,000 SDG&E residential customers were selected for the pilot, about 100 of whom also participated in SDG&E's Summer Saver (SS) air conditioner cycling program.[14] Selected PTR pilot customers remained on their standard residential commodity rate, but were eligible to receive rebate payments for all reductions in energy

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[12] Specifically, usage reductions during event hours were measured relative to a customer-specific reference level (CRL) defined as consumption during the event window hours averaged over the highest 3 out of the most recent 5 similar non-event weekdays. The highest days are defined to be the days with the highest total consumption between 11 AM and 6 PM. The similar days exclude weekends, holidays, and other PTR event days, and exclude other demand response program event days for customers participating in multiple demand response programs. The CRL for a weekend or holiday event is defined as the consumption during the PTR event period for the highest day from within the immediately preceding three (3) weekend days.

[13] The only available automated enabling technology for the pilot was the air conditioner cycling devices already installed for Summer Saver participants.

[14] Due to normal customer turnover, approximately 100 premises experienced a change in occupant. Those premises were kept in the pilot and the new occupants were provided with information on the pilot.

usage during PTR event periods, measured relative to their CRL. A comparable control group sample was selected using the same sample frame. These customers were selected after all events had taken place, and were not informed of their selection.

Table 2-1 summarizes the characteristics of the PTR pilot participant sample. The first column designates sample groups, or cells, differentiated by *climate zone*: 1 (Coastal), 2 (Mountain), 3 (Desert), and 4 (Inland) and *size* category: Low (L), Medium (M), and High (H).[15] The next two columns show the sample sizes for the subsets of the pilot sample participants that did *not* have enabling technology (PTR-NT) in the form of Summer Saver load control devices, and those that that were joint participants in the PTR pilot and the SS program (PTR-SS). The next two columns show summer average hourly usage (kW) for those two sample subsets. The last two columns show the total population of residential customers in the indicated climate zone/usage cell, and overall sample weights, which may be used to calculate sample-weighted averages and sums for the entire sample. As in a typical stratified random sample design, high-usage customers are sampled in greater proportion relative to their population shares than customers in other size groups. Thus, in calculating average results for the entire sample, their loads and load impacts are given lower weights than, for example, low-usage customers in order to avoid over-stating program results.

Finally, the two rows at the bottom of the table provide sample-weighted averages and sums for the usage metric. That is, the sample average hourly summer usage was 0.63 kW for PTR-NT customers and nearly the same for PTR-SS customers. However, the total load for the PTR-NT portion of the sample is substantially greater than that for the PTR-SS portion due to the much larger number of sample points.

[15] The pilot terminology refers to cells by code in the form of R_Z_S, where *Z* indicates one of the four indicated climate zones (1-4) and *S* indicates one of the three indicated size categories (S,M,L).

Table 2-1: Characteristics of the PTR pilot program *participant* sample

Sample cell	Premise count		Summer Average Hourly Usage (kWh/hr)			
	PTR-NT	PTR-SS	PTR-NT	PTR-SS	Group population	Overall weight
Coastal, High Use	310	2	1.52	1.75	69,280	5.61%
Coastal, Medium Use	232	4	0.64	0.70	360,520	29.19%
Coastal, Low Use	97	0	0.25		270,769	21.92%
Total Coastal	639	6	0.58	0.36	700,569	56.73%
Mountain, High Use	407	10	1.96	1.80	2,399	0.19%
Mountain, Medium Use	169	3	0.99	1.00	6,449	0.52%
Mountain, Low Use	139	1	0.31	0.40	5,545	0.45%
Total Mountain	715	14	0.89	0.90	14,393	1.17%
Desert, High Use	129	0	1.99		481	0.04%
Desert, Medium Use	231	0	0.90		1,169	0.09%
Desert, Low Use	157	1	0.25	0.36	1,242	0.10%
Total Desert	517	1	0.80	0.00	2,892	0.23%
Inland, High Use	438	40	1.48	1.42	77,778	6.30%
Inland, Medium Use	307	21	0.77	0.73	228,989	18.54%
Inland, Low Use	291	4	0.33	0.42	210,384	17.04%
Total Inland	1,036	65	0.69	0.71	517,151	41.87%
Total Premises	**2,907**	**86**			**1,235,005**	**100.00%**
Sample Wtd Average			0.63	0.51		
Sample Wtd Total			1,829.8	43.8		

Table 2-2 summarizes information on the control group sample. The two groups have similar distributions across climate zone and usage level, with one major difference. That is that the control group with no enabling technology (Control-NT) has far fewer high-usage customers in the Mountain and Desert climate zones than does the participant sample. Similar to the PTR-SS sample, the Con/SS sample is sparse, with most sample points located in the Inland climate zone.

Table 2-2: Characteristics of the PTR pilot program *control group* sample

Sample cell	Premise count		Summer Average Hourly Usage (kWh/hr)			
	Con-NT	Con-SS	Con-NT	Con-SS	Group population	Overall weight
Coastal, High Use	308	4	1.53	1.68	69,280	5.61%
Coastal, Medium Use	237	0	0.61	0.0	360,520	29.19%
Coastal, Low Use	97	0	0.23	0.0	270,769	21.92%
Total Coastal	642	4	0.56	1.68	700,569	56.73%
Mountain, High Use	5	7	1.82	1.86	2,399	0.19%
Mountain, Medium Use	164	8	1.03	1.01	6,449	0.52%
Mountain, Low Use	134	6	0.35	0.41	5,545	0.45%
Total Mountain	303	21	0.90	0.92	14,393	1.17%
Desert, High Use	5	0	2.65	0.0	481	0.04%
Desert, Medium Use	140	2	0.95	1.1	1,169	0.09%
Desert, Low Use	103	0	0.25	0.00	1,242	0.10%
Total Desert	248	2	0.93	0.00	2,892	0.23%
Inland, High Use	448	31	1.56	1.49	77,778	6.30%
Inland, Medium Use	309	19	0.75	0.72	228,989	18.54%
Inland, Low Use	290	6	0.32	0.45	210,384	17.04%
Total Inland	1,047	56	0.69	0.73	517,151	41.87%
Total Premises	**2,240**	**83**			**1,235,005**	**100.00%**
Sample Wtd Average			0.62	1.27		
Sample Wtd Total			1,386.5	105.0		

2.3 Events

The dates and times of events for the PTR pilot and the SS program in 2011 are shown in Table 2-3, along with the average temperature during the PTR event window.[16] Two SS-only events were called (August 26 and September 9), and only one PTR-only event was called (August 28, a Sunday). Both event types were called on the other days, although the SS event hours varied somewhat by event. In particular, all PTR events spanned the seven-hour period from hours-ending 12 (noon) to 18 (6 p.m.), while all SS events were four hours in duration, covering either hours-ending 14 to 17 or 15 to 18. Of note, a system-wide outage began during HE 16 on the September 8 event, which caused all customers' loads to drop to zero for the remaining event hours.

[16] The average temperature values shown are weighted averages of the temperatures for the KSDM (Brown Field Municipal Airport) and KSEE (Gillespie Field Airport) weather stations, which were the most common stations for the customers in the important Inland climate zone.

Table 2-3: Peak Time Rebate and Summer Saver Events in 2011

Event date	Day of Week	Program	Event hours (hours ending)	Ave. Temp.[1] (HE 12-18)
26-Aug	Friday	SS	15 - 18	84.7
28-Aug	Sunday	PTR	12 - 18	83.7
7-Sep	Wednesday	PTR	12 - 18	92.7
		SS	15 - 18	
8-Sep [2]	Thursday	PTR	12 - 15	91.6
		SS	14 - 15	
9-Sep	Friday	SS	15 - 18	73.6
12-Oct	Wednesday	PTR	12 - 18	93.5
		SS	14 - 17	
13-Oct	Thursday	PTR	12 - 18	89.5
		SS	14 - 17	

[1]Weighted average for KSDM and KSEE
[2]Events truncated by outage

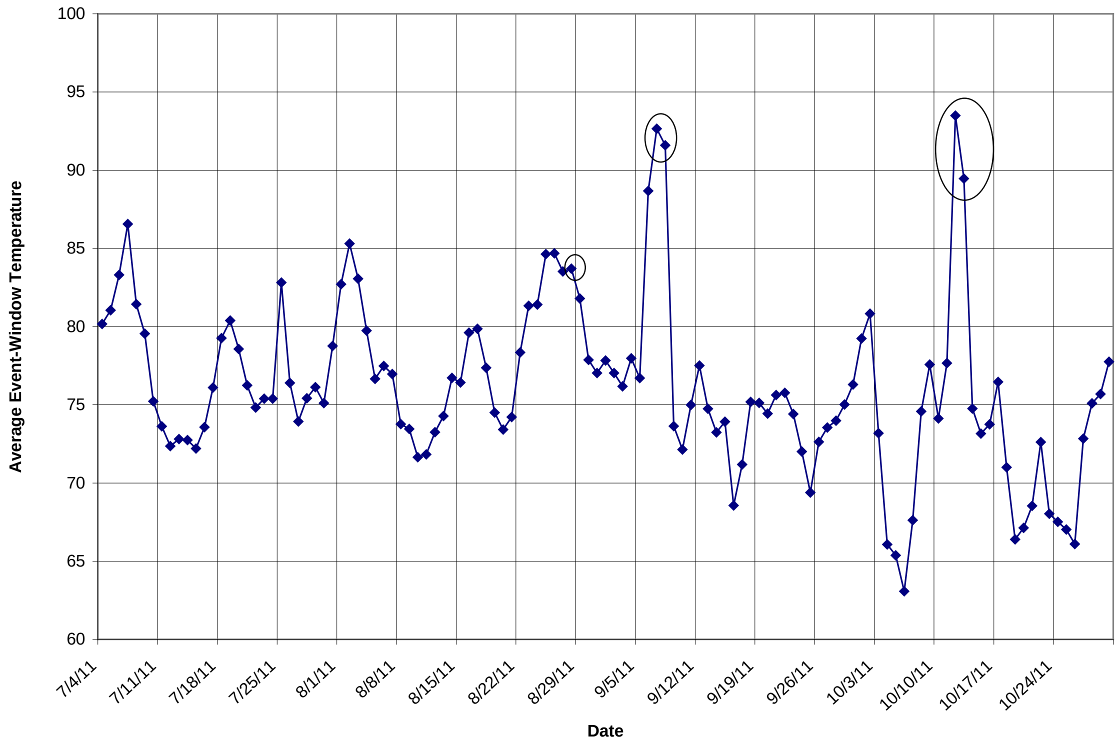
The relatively small number of events and their characteristics created challenges for estimating both PTR *ex post* load impacts and the incremental load impacts associated with joint participation in SS. Most of the unique features of the events relate to day-of-week and weather conditions. For example, the sole PTR-only event occurred on a Sunday, and no other weekend events were called, thus complicating attempts to measure incremental PTR load impacts for combined PTR-SS participants. That is, all joint PTR and SS events occurred on weekdays, while there were no weekday PTR-only events. In addition, the weather conditions differed substantially between the early-September events and the mid-October events.[17] That factor, combined with the outage on September 8, leaves September 7 as the only "typical" mid-summer weekday PTR event.[18]

Finally, events were called on nearly every hot day in the summer of 2011. Figure 2-1 shows daily average temperatures during the PTR event window (HE 12 – 18) for July 4 through October 31 for the Inland climate zone.[19] Event days, which are indicated by circles, may be seen to have occurred on nearly every unusually hot day of the period.[20] This factor severely limits the ability to identify comparable non-event days for purposes of measuring PTR-NT load impacts from participant data alone. It also emphasizes the

[17] For most customers, the two October event days were isolated hot days following nearly four weeks of mild weather, which resulted in substantially lower loads than during the mid-summer period.
[18] However, even the September 7 event day occurred during the week of Labor Day. The fact that the event occurred during a holiday week raises the possibility that its load impacts are not typical of a summer weekday during a non-holiday week.
[19] As noted in a previous footnote, the temperature values represent a weighted average of the temperatures for the KSDM and KSEE weather stations.
[20] Temperatures on September 6 were relatively low entering the event-window hours, and then rose quickly to reach the highest maximum value of the summer, at about 4 p.m. Thus, customers' loads for that day tend to have a different, late-peaking profile than on the other hot days.

importance of the availability of the control group data, which allows side-by-side comparison of participant and control group loads on event days.

Figure 2-1: Average Event-Window (HE 12-18) Temperatures:
July 4 – October 31, 2011



2.4 Observed Participant and Control Group Loads – Selected Day-types

This sub-section lays the groundwork for estimating PTR pilot load impacts by providing the reader with examples of observed PTR participant and control group load profiles for selected event and non-event days. We focus first on the PTR-NT customers who were not also participants in the Summer Saver program. We then show load profiles for the joint PTR-SS customers. The load profiles and directly calculated load differences are indicative of the PTR pilot load impacts. However, the formal estimates of *ex post* load impacts designed to meet the Protocols are produced by the regression-based methodology described in Section 3, and are presented in Section 4.

2.4.1 PTR-NT load profiles

To illustrate the degree of comparability of the PTR-NT participant and control groups, Figure 2-2 compares overall PTR-NT and Control-NT load profiles for the average non-event weekday for two specific time periods: July 5 – 8, representing a series of moderately hot days (top two lines); and July through September 15, representing the mid-summer period in which the September 7 event occurred (lower two lines).[21] Due to sampling variability, the overall loads for the participant and control group samples differ somewhat. In this case, the overall average participant loads exceed the average control group loads during the event-window hours for both day-types by a small amount (2.5% and 3.1% for the top and bottom pairs of loads in the figure).

Figure 2-2: Overall PTR-NT and Control-NT Load Profiles –
Selected Average Non-Event Weekdays

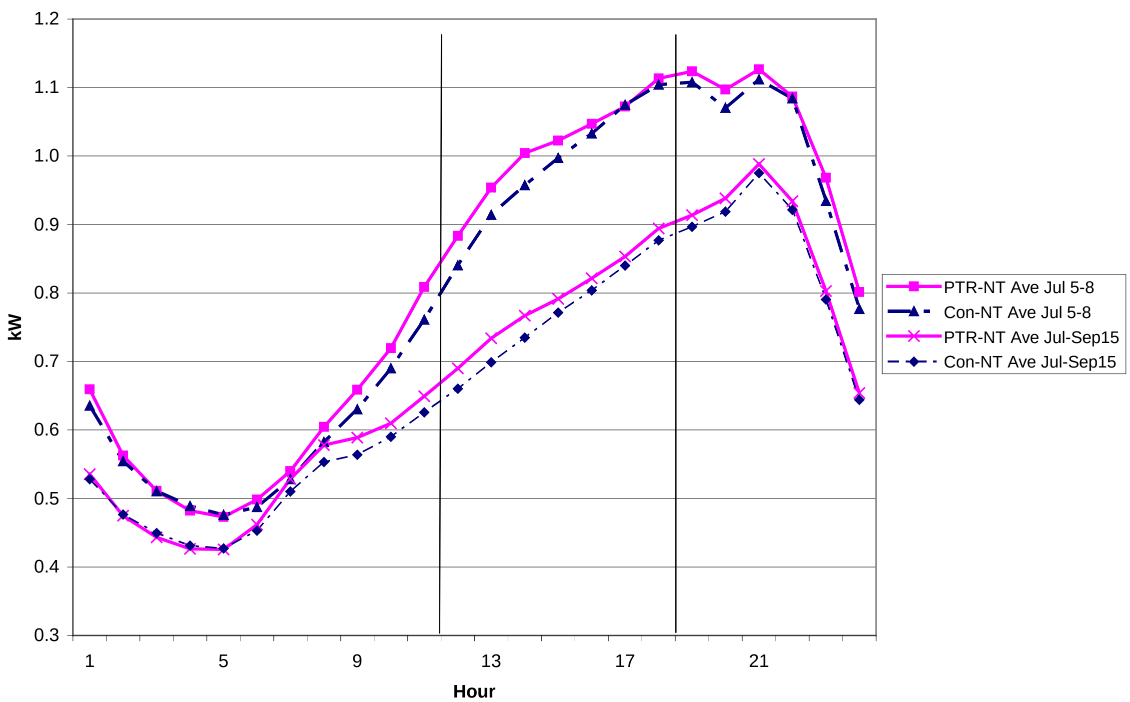


Figure 2-3 compares PTR-NT and Control-NT loads for the Sunday, August 28 event and for the average Sunday for July through September 15. The overall participant load is somewhat higher than the control group load on the average Sunday (lower two lines). The two loads are nearly identical during the August 28 event hours. However, the participant load appears to be rising somewhat faster than the control group load just prior to the Sunday event (consistent with the pattern on the average Sunday), suggesting a reduction in consumption during the event period. Applying a difference-in-differences concept to the two sets of loads suggests a modest PTR event-period load reduction in the range of 3%.[22]

[21] The overall average loads are obtained by applying the appropriate population weights to the average loads for each of the twelve climate-zone/usage-level cells.

[22] A difference-in-differences evaluation approach compares the difference between participant and control group values during the period of interest (*e.g.*, event hours on an event-day) to their difference during a comparable period (*e.g.*, event-window hours on non-event day).

Figure 2-3: Overall PTR-NT and Control-NT Load Profiles –
August 28 Event

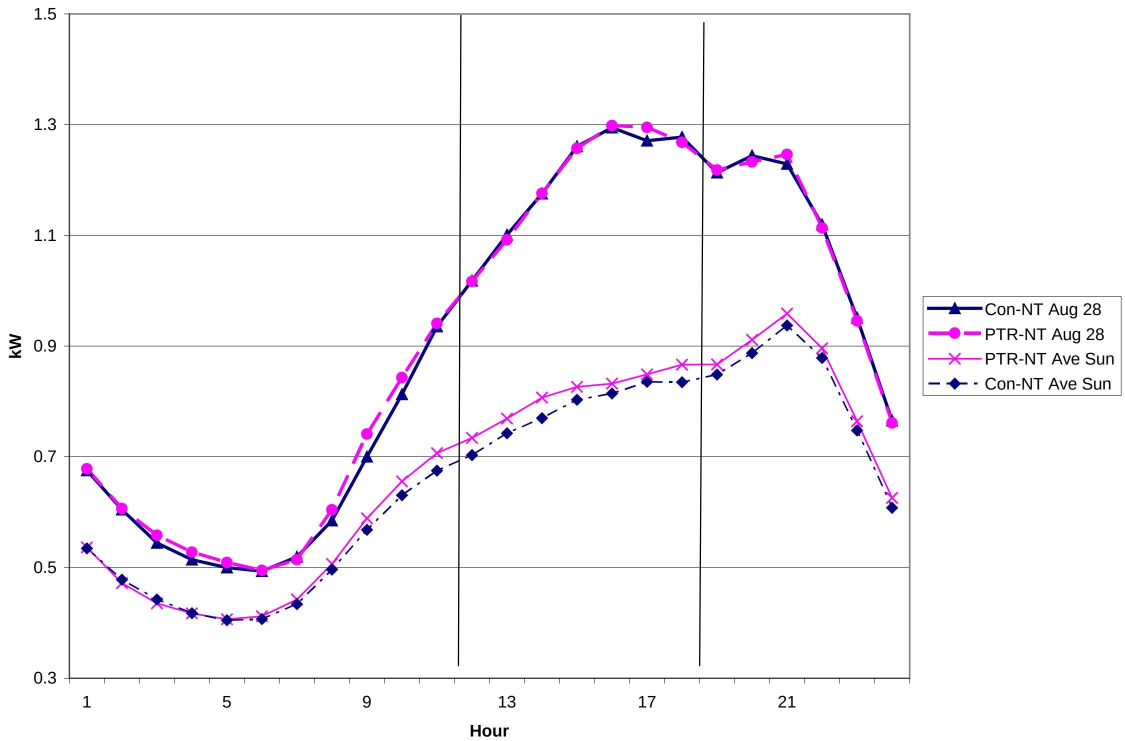
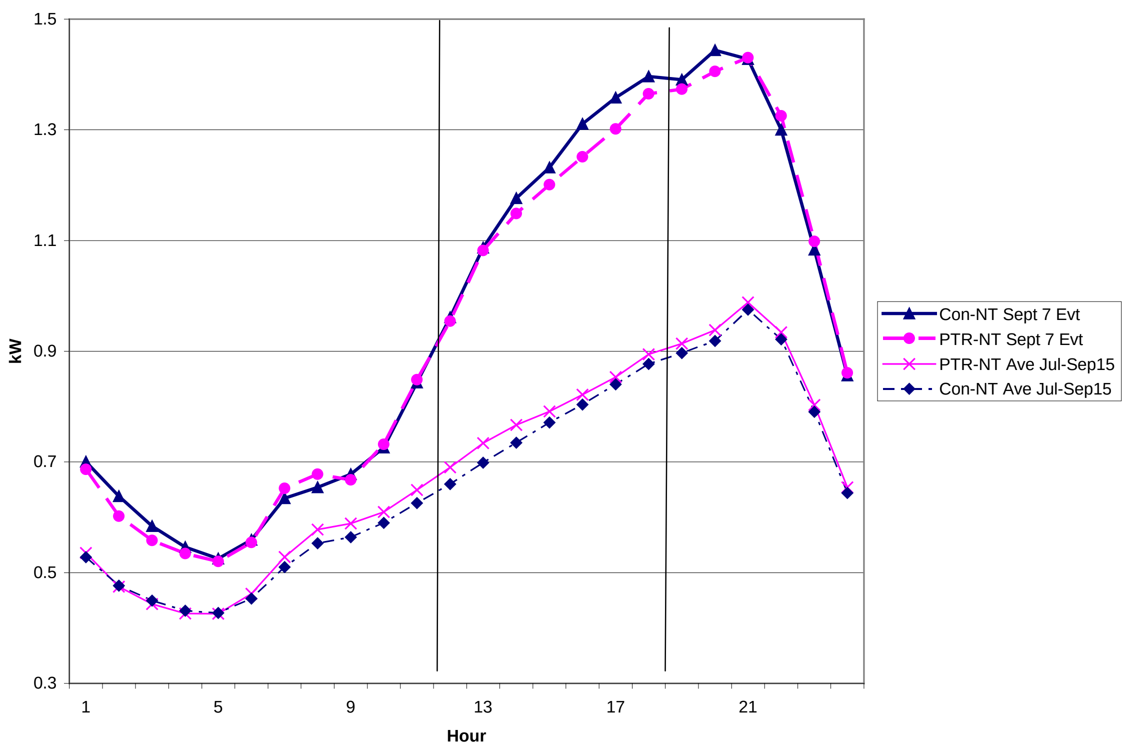


Figure 2-4 compares PTR-NT participant and Control-NT control group loads for the September 7 event. Also shown for comparison purposes are the loads for the average non-event weekday for July through September 15. Focusing first on the latter set of loads (bottom two lines), the participant load is somewhat (*i.e.*, 3.1%) higher than the control group load for the average weekday. In contrast, the participant load lies *below* the control group load (by 2.6%) on the September 7 event. Again using a difference-in-differences approach relative to the average non-event weekday loads, an estimate of the overall PTR load impact on September 7 is about 5.6% (*i.e.*, 2.6% + 3.1%).

Figure 2-4: Overall PTR-NT and Control-NT Load Profiles –
September 7 Event



Figures 2-5 and 2-6 compare PTR-NT participant and control group loads for the events on October 12 and 13 respectively. Also shown in each figure are the loads for the average non-event weekday in the period September 16 through October 31. As in the earlier figures, the participant load is somewhat higher than the control group load for the average late-summer weekday (bottom two lines). Both loads are substantially lower (by about 0.2 kW, or more than 20%) in the middle of the event window than they are for the mid-summer period (which were shown in Figure 2-2), suggesting less air conditioning load during this period than in the mid-summer period. During the October 12 event, the participant load begins slightly higher than the control group load, and then falls somewhat below it. During the October 13 event, the participant load begins below the control group load, but then rises above it. A difference-in-differences approach relative to the average non-event weekday loads suggests overall PTR load impacts of about 2.5% and 1.8% for the October 12 and 13 events respectively.

Figure 2-5: Overall PTR-NT and Control-NT Load Profiles –
October 12 Event

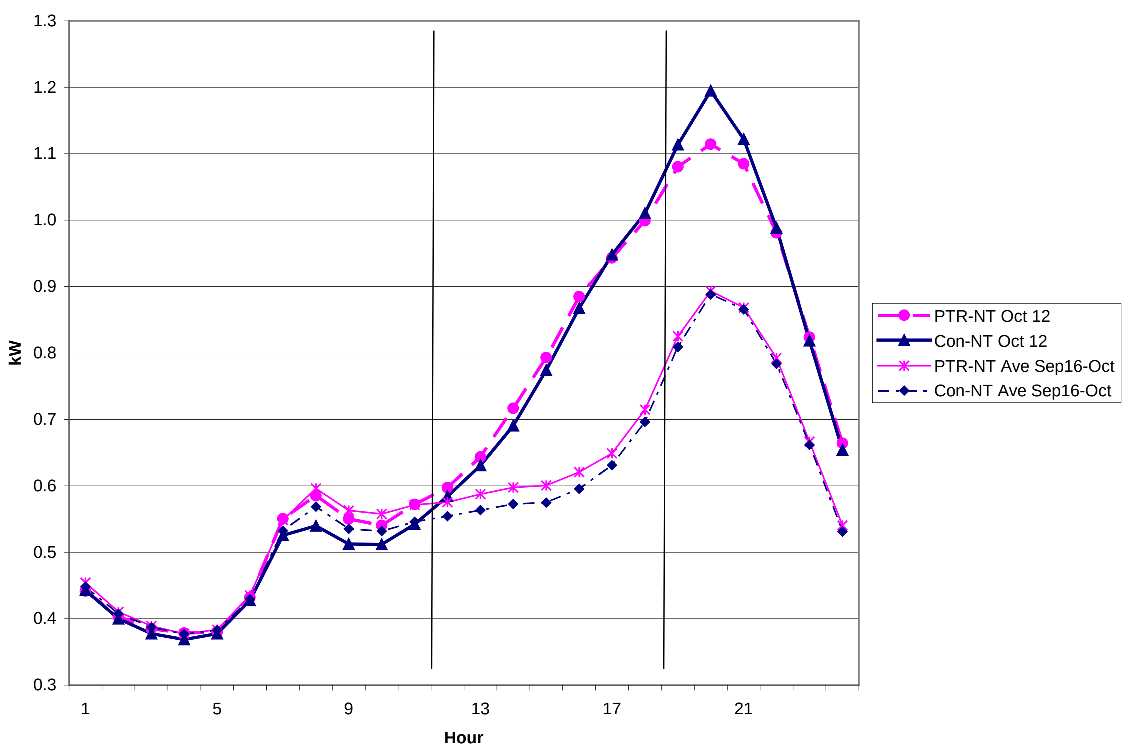
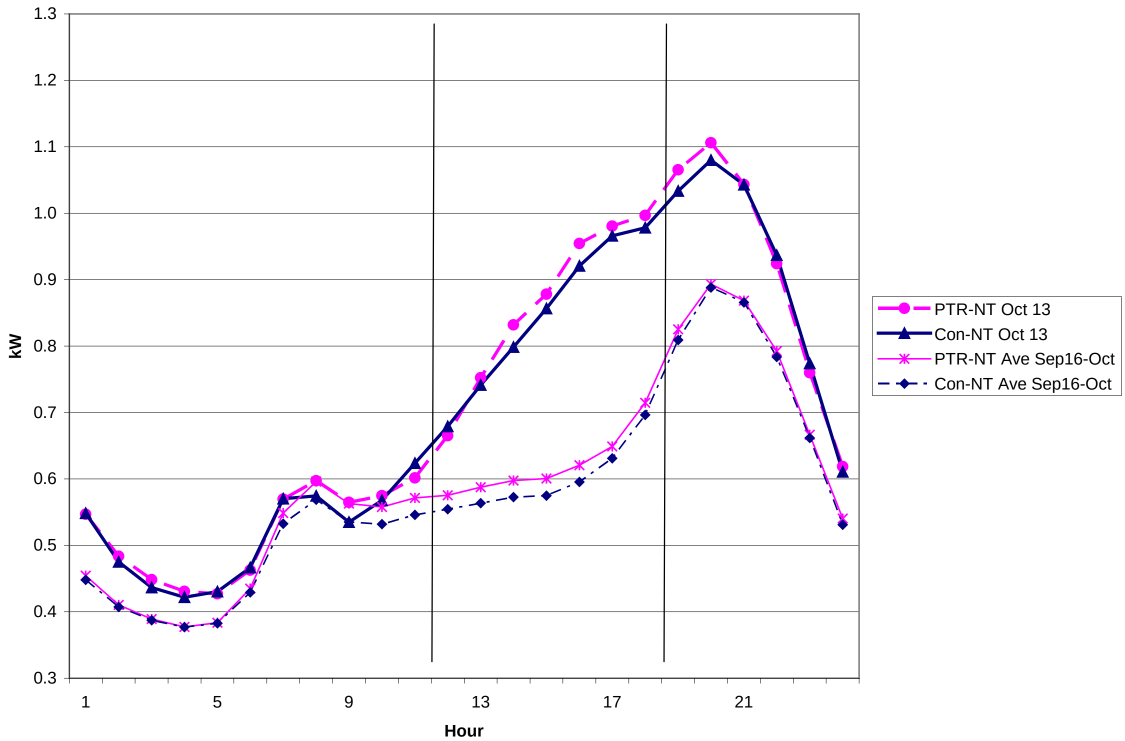


Figure 2-6: Overall PTR-NT and Control-NT Load Profiles –
October 13 Event



The above figures illustrate some of the features of the PTR events described in Section 2. One is that the event-day loads were substantially higher than loads on typical non-event days (both Sundays and weekdays), thus indicating both the weather sensitivity of residential customer loads and the substantially hotter temperatures on the few event days. An additional important factor suggested by the figures is that the magnitude of overall average PTR-NT load impacts is likely to be relatively small, ranging from 2% to 5%. Given the inherent variability of residential customer loads, such relatively small expected load impacts pose a challenge to any estimation method.

2.4.2 PTR-SS load profiles

This section shows load profiles for the subset of PTR participants who are jointly enrolled in the Summer Saver air conditioner cycling program (PTR-SS). To illustrate the comparability of the participant and control group customers in that subset, Figure 2-7 compares overall PTR-SS and control group (Control-SS) load profiles for non-event weekdays in the mid-summer and late-summer periods.[23] The participant loads are about 7 percent higher than the control group loads during the PTR event window for both time periods, which is a somewhat greater difference than for the PTR-NT and Control-NT case. Differences are due to sampling variability, which likely is greater for the PTR-SS

[23] These overall average loads represent a weighted average of only two of the twelve climate zone/usage level cells, due to the very small sample sizes for some of the cells. The selected cells are the high- and medium-use cells in the Inland zone.

and Control-SS subsets of the overall samples due to their smaller size (*e.g.*, approximately 90 PTR-SS customers overall, and 61 in the Inland zone, compared to 2,900 for PTR-NT).

Figure 2-7: Overall PTR-SS Participant and Control-SS Load Profiles – *Non-Event Weekdays*

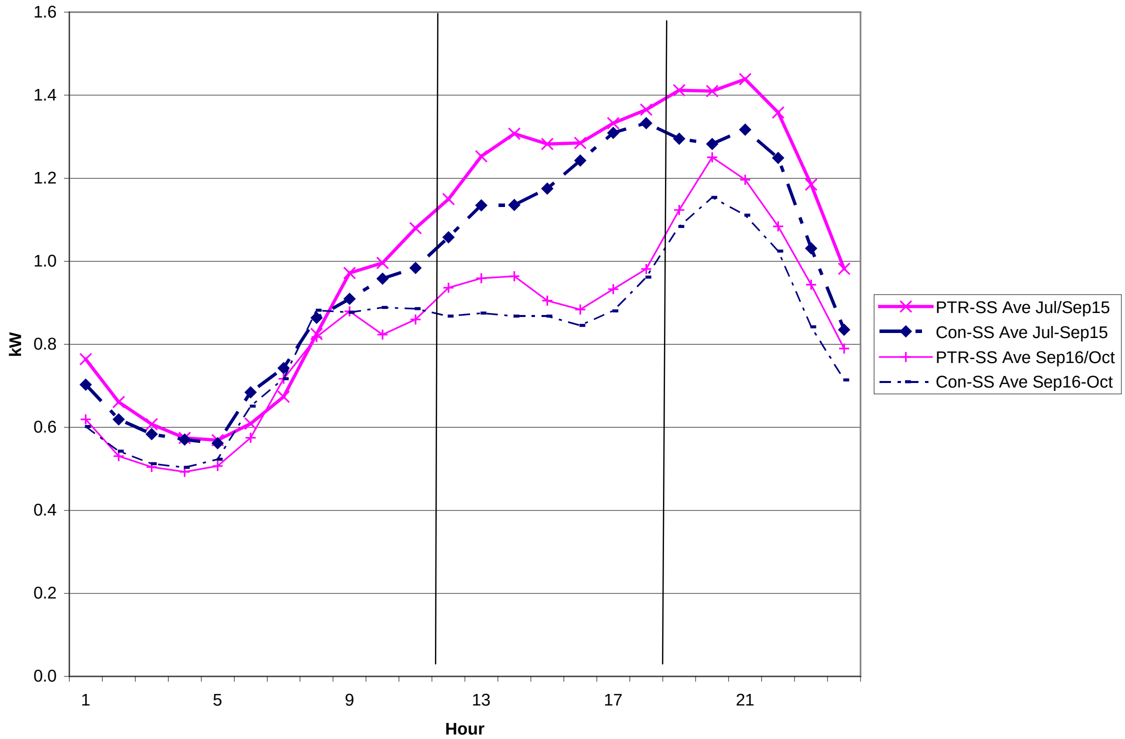
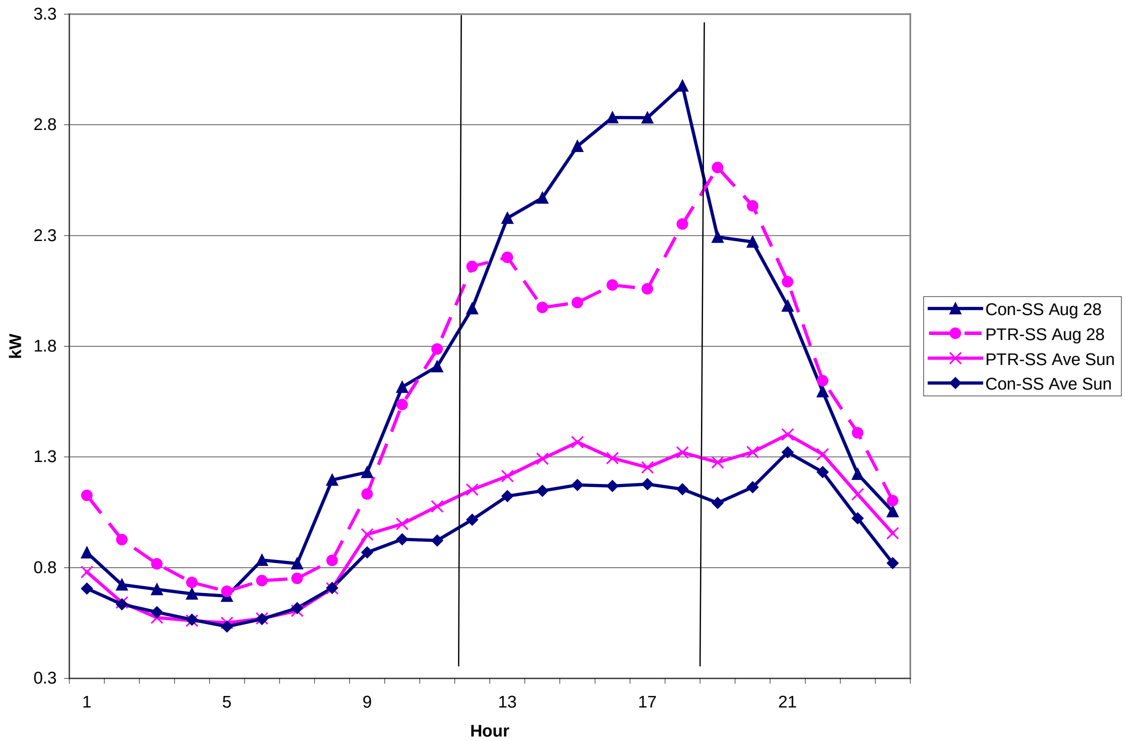


Figure 2-8 compares overall PTR-SS participant and Control-SS loads for the Sunday, August 28 PTR-only event, and for the average Sunday in the July through September 15 period. On the average Sunday in that period, the participant load is nearly 12 percent higher than the control group load during the event window hours. On the August 28 PTR event-day, the two loads are quite similar in the hours leading up to the event, but the participant load drops substantially during the event, while the control group load continues to rise.[24] The statistical analysis described below, which compares PTR-SS data to Control-SS data, confirms the significant usage reduction shown in the figure.

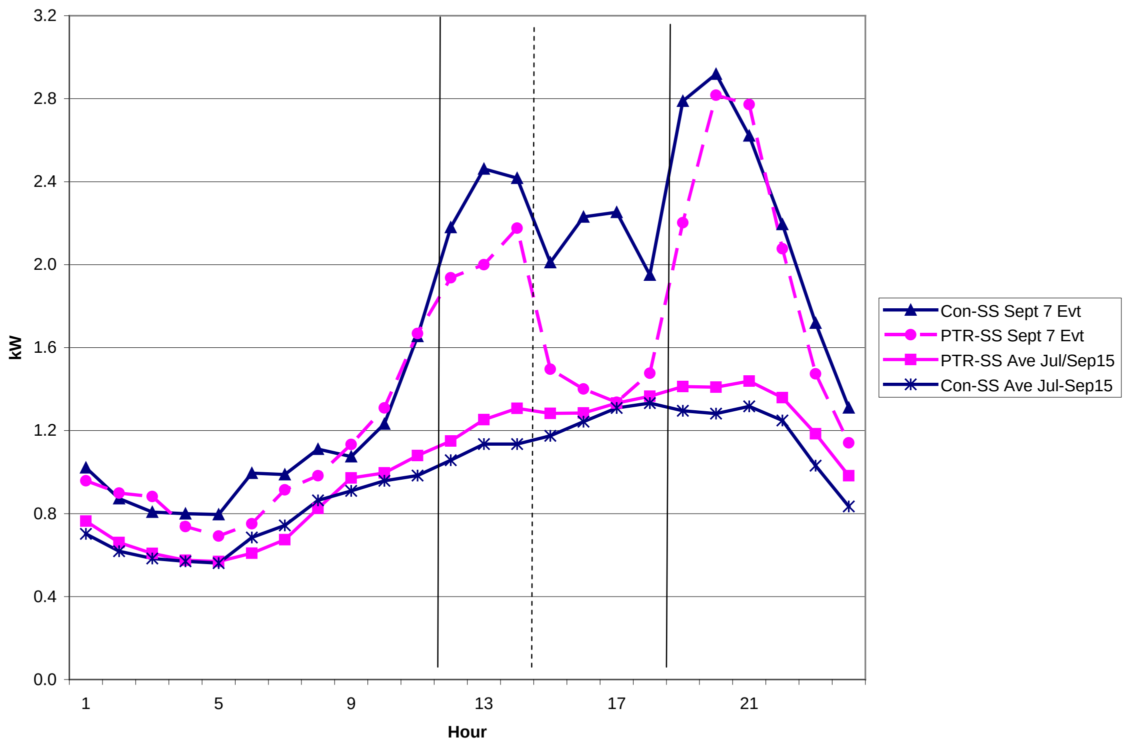
Figure 2-8: Overall PTR-SS and Control-SS Load Profiles –
Average Mid-Summer Sunday, and August 28 Event



[24] In aggregate, the PTR-SS load reduction appears to take on the shape of a four-hour air conditioner load control episode in HE 14 to 17, though no SS event was called on that day. Closer inspection of the underlying customer data indicates that the four-hour dip in load was confined to the Inland medium-use cell, and was comprised of a variety of individual participant load changes, only some of which reflected the four-hour dip, that averaged to the shape shown.

Figure 2-9 compares PTR-SS and Control-SS loads for the September 7 event and for the average non-event weekday in the period from July through September. As shown in Figure 2-7, the participant load is about 7 percent higher than the control group load on typical mid-summer weekdays. However, on the combined PTR and SS event on September 7, it lies below the control group load during the entire PTR event window. Both loads show four-hour "notches" during the SS event. Both groups rebound to higher load levels in the hour following the end of the PTR and SS events, reaching the same load level in the second hour following the events. The statistical analysis described below finds significant PTR-SS usage reductions relative to Control-SS customers in both SS and non-SS hours.

Figure 2-9: Overall PTR-SS and Control-SS Load Profiles –
Average Mid-Summer Weekday, and September 7 Event



Figures 2-10 and 2-11 compare PTR-SS and Control-SS loads for the Inland high- and medium-use cells for the October 12 and 13 events. The load profiles for the October events, which occurred on two isolated hot days after a period of moderate weather, are much lower than on comparably hot days in August and early September. The level and shape of the profiles suggests less air conditioning load than on a mid-summer weekday with comparable temperatures. As a result, the four-hour load impacts during the SS events are smaller and less well-defined than for the September 7 event. The nature of the load impacts appears to vary substantially between the two events. In particular, on the October 12 event, the PTR-SS Inland high-use load shows only a minor reduction during the SS event hours, while the PTR-SS Inland medium-use load reflects a more familiar notch, at least in the last 3 hours of the event. In contrast, on the October 13 event, the Inland high-use load shows a definitive SS reduction, while the Inland medium-use load tails off at a relatively flat level during and after the SS event. The statistical analysis reported below reflects these variable usage changes, finding no statistically significant load impacts.

Figure 2-10: PTR-SS and Control-SS Cell-Level Load Profiles –
October 12 Event

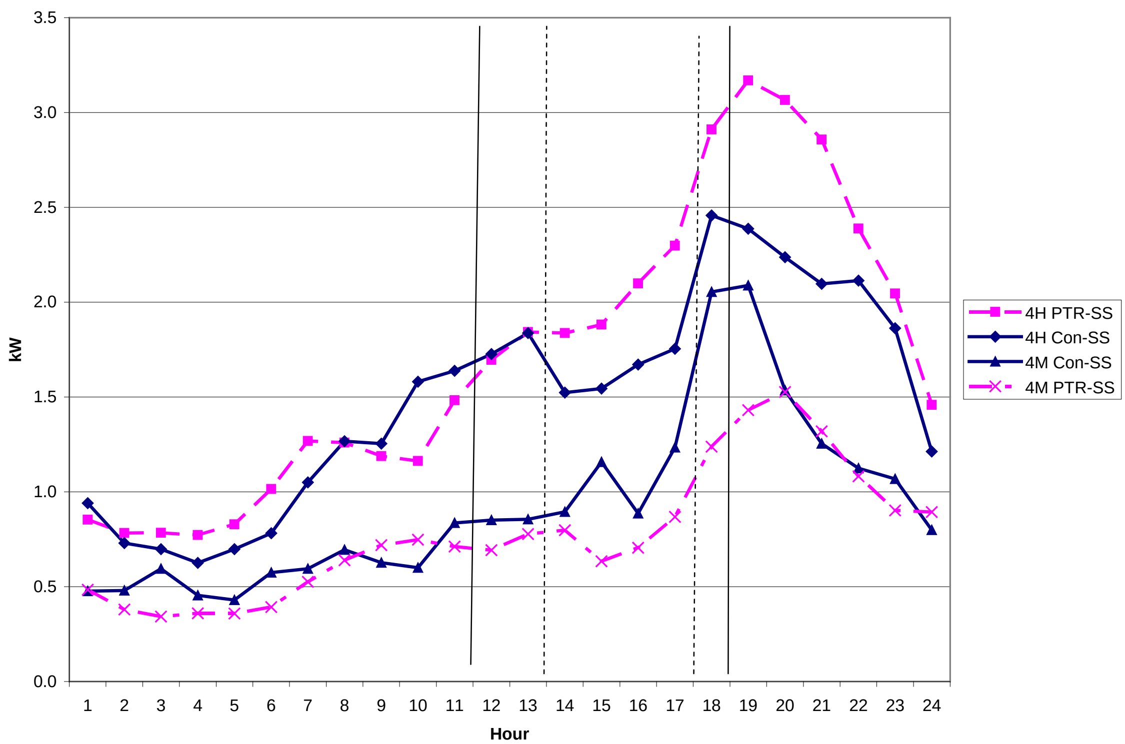
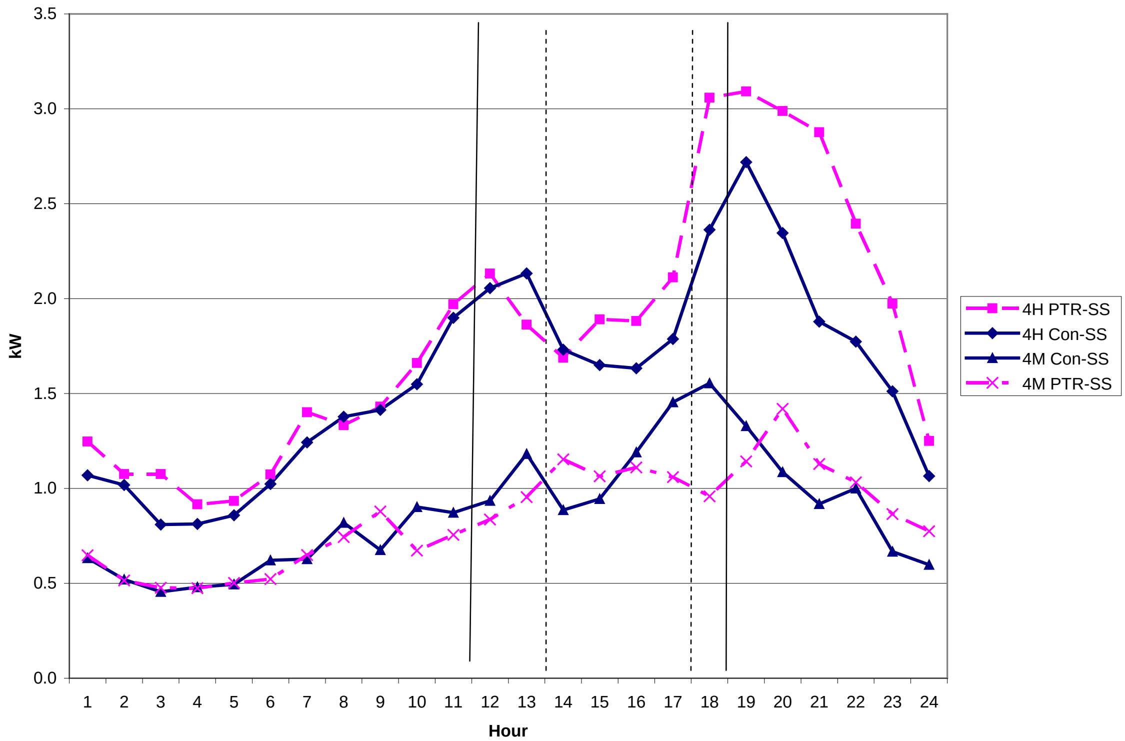


Figure 2-11: PTR-SS and Control-SS Cell-Level Load Profiles –
October 13 Event



3. Study Methodology

3.1 Overview

The overall goals of the *ex post* load impact evaluation were summarized in Section 1. Placed in the traditional DR evaluation terminology, the load impact evaluation of the PTR pilot for 2011 includes the following activities:

1. Estimate pilot-wide (aggregate) and per-called customer hourly load impacts and average daily load impacts for each PTR event day in 2011;
2. Estimate the uncertainty-adjusted range of load impacts, on an aggregate and per-called customer basis;
3. Estimate the *distribution* of hourly and average daily impacts provided by different customer segments for the *average event* (*e.g.*, "X" percent of the load impact was provided by "Y" percent of the enrolled customers).

The data to be used in the load impact analysis consist of hourly integrated load data for the pilot participants and control group customers, hourly observations on appropriate weather variables for relevant weather stations, information on relevant customer characteristics, and information on the timing of events.

Estimation of customer load impacts for the SDG&E PTR pilot proved challenging, for two primary reasons. One, as mentioned above, is that PTR events were called on virtually all of the limited number of unusually hot days in the summer of 2011. This condition creates difficulty in disentangling weather effects (*e.g., increases* in usage during the afternoon event window on very hot days) from event effects (*e.g., reductions* in usage during event hours on those same hot days). The other primary complicating factor is that average PTR-NT load impacts are relatively small (*e.g.*, on the order of 1% to 4.5%), which makes it difficult to isolate from the "noise" of normal customer load variability across hours and days.

These two factors emphasize the value of an available control group in estimating program load impacts. In particular, since the control group customers who were not joint SS participants (Control-NT) faced the same weather conditions as the PTR-NT participants, their usage patterns on PTR event days can help account for weather effects on event days, thus allowing separate estimation of PTR pilot program load impacts. It should be noted in advance, however, that the average load profile of the control group sample is not identical to that of the sample of participants, even though it was drawn in the same way and from the same sample frame. In practice, each sample draw represents one of many possible outcomes. Sampling variability may cause the average loads for the participant and control group samples to differ in some way. One challenge for the impact evaluation is to account for those differences on non-event days so as to make the most appropriate use of the control group data in estimating participant load impacts on event days.

3.2 Description of methods

3.2.1 Background

Given the above evaluation challenges, we have applied estimation methods that differ in certain ways from the methods that have been used in recent impact evaluations of non-residential dynamic pricing and demand response programs in California. Those methods have generally involved conducting customer-level regression analysis using hourly load data for participants only, and have developed program-level load impacts by adding up the estimated load impacts of each participating customer account. Some incorrectly signed load impacts (*i.e.*, load increases during event hours) are nearly always obtained for some customers due to our inability to fully explain each customer's load variability given limited available information.[25] However, the relatively large magnitude of estimated load impacts for many customers, and consistency between aggregations of customer-level results and load impacts estimated from aggregated data have provided confidence in the evaluation findings.

The conditions for the PTR pilot, however, appear to differ from non-residential dynamic pricing and demand response programs in California. In particular, PTR pilot load impacts appear generally smaller in percentage terms than most non-residential programs.

[25] This condition is technically referred to as omitted variable bias; we lack information on, and thus omit variables that might otherwise be used to explain residential customers' load profiles (e.g., their regular schedule of hours spent outside of the home, or their typical air conditioner thermostat set point).

In addition, the 2011 event characteristics described above complicated the isolation of event effects from weather effects using participant data alone. Fortunately, control group data were available to assist in controlling for weather effects on event days.

We tested several alternative customer-level regression models, including a panel approach for each climate zone/usage level zone cell, which included load data for all participant and control group customers from each cell. Based on these tests, we concluded that the most straightforward and appropriate approach to obtaining load impact estimates at the needed level of detail (*e.g.*, by climate zone and in total) was to estimate separate aggregate-level models for each of the twelve climate zone/usage level cells (*i.e*., using load data for the average customer in each cell), using data for both participant and control group customers. We then aggregate those cell-level results to the climate-zone and overall program level using appropriate sample weights.

For the PTR-SS portion of the pilot, sufficient sample sizes were available for only two cells within the Inland area, which is important in terms of the population.[26] As a result, estimated load impacts for PTR-SS are reported only for that climate zone.

The modeling decisions just described were made for three primary reasons: 1) the relatively long processing time needed to estimate cell-level panel regression models that contain hourly data for hundreds of PTR and control-group customers, 2) the complications of designing appropriate methods for incorporating the control group customers to adjust estimated participant load impacts on a customer-level basis,[27] and 3) the small sample sizes for the PTR-SS participant and control groups for most of the climate zone/usage cells.

3.2.2 *Ex post* load impact regression models

The models that were used to produce the estimated load impact results described in Section 4.2 below are specified in terms of *differences* between hourly loads averaged over the relevant participant and control group sample customers in each climate-zone/usage-level cell. That is, the *dependent* variable in the regression is the above difference in the hourly load of the participant and control groups, rather than the *level* of usage of participants, which is the more common approach that has been used in previous California load impact evaluations.

[26] Our understanding is that the samples were not designed to be representative of the SS customers in the population. Instead, SS customers were included in the samples as selected at random, with the constraint that no more than 100 SS customers were included in the samples. As drawn, the SS customers selected were largely concentrated in three cells: R2H, R4H and R4M. That is, they were largely customers in the Mountain and Inland climate zones with higher than average usage levels. In addition, the R2H cell has a very low weight due to its relatively small population, which implies that results for that cell have little effect on overall results.

[27] The classic participant *vs*. control group evaluation approach compares energy consumption for the *average* customer in each group. More complicated designs attempt to match individual participants and control group customers along observable characteristics. However the PTR control group was not designed with this approach in mind; it was drawn from the same sample frame (see following footnote), with the objective of achieving overall comparability of the participant and control samples.

We use similar types of explanatory variables as in a typical *ex post* load impact regression, including hourly indicator variables interacted with each event day, weather variables, load shape variables, and day-type and month indicator variables. Using this design, the estimated event-day coefficients represent direct estimates of participant load impacts that account for estimated differences between the loads of participant and control group customer groups. This approach effectively amounts to a standard "difference-in-differences" evaluation approach. That is, estimated load impacts are represented by differences between participant and control group loads on event days, while controlling for estimated differences between the load profiles of the two samples under non-event day conditions.

The general form of the *ex post* load impact difference model is the following:

$$
\begin{aligned}
DQ_t &= a + \sum_{Evt=1}^{E} \sum_{i=1}^{24} (b_{i,Evt} \times h_i \times PTR_t) + \sum_{SSEvt=1}^{SSE} \sum_{i=1}^{24} (b_i^{SS} \times h_i \times SS_t) + \sum_{i=1}^{24} (b_i^{CDH} \times h_i \times CDH_t) \\
&+ \sum_{i=1}^{24} (b_i^{WECDH} \times h_i \times WECDH_t) + \sum_{i=1}^{24} (b_i^{CDH2} \times h_i \times CDH^2{}_t) + \sum_{i=1}^{24} (b_i^{LagCDH} \times h_i \times LagCDH_t) \\
&+ \sum_{i=2}^{24} (b_i^{MON} \times h_i \times MON_t) + \sum_{i=2}^{24} (b_i^{FRI} \times h_i \times FRI_t) + \sum_{i=2}^{24} (b_i^{h} \times h_i) + \sum_{i=2}^{24} (b_i^{WE} \times h_i \times WE_t) \\
&+ \sum_{i=2}^{7} (b_i^{DTYPE} \times DTYPE_{i,t}) + \sum_{i=6}^{10} (b_i^{MONTH} \times MONTH_{i,t}) + e_t
\end{aligned}
$$

In this equation, DQ_t represents the difference between the average hourly usage in time period t of the participants and control group samples for a particular climate zone/usage level cell; the b's are estimated parameters; h_i is an indicator variable for hour i; PTR_t is an indicator variable for PTR event days (and takes on a value of 1 only for participants); CDH_t is cooling degree hours;[28] $WECDH_t$ is cooling degree hours interacted with an indicator variable for weekends; CDH^2_t is cooling degree hours squared; $LagCDH_t$ is cooling degree hours from the same hour in the previous day; MON_t, FRI_t, and WE are indicator variables for Monday, Friday, and weekend days respectively, where the interaction with the hourly indicators allows estimation of different load shapes for those day types (an additional set of hourly indicators not interacted with other variables is included to represent the load profile for Tuesday through Thursday)[29]; $DTYPE_{i,t}$ is a series of indicator variables that allow constant adjustments for each day of the week; $MONTH_{i,t}$ is a series of indicator variables for each month; and e_t is the error term.

[28] Cooling degree hours are defined relative to a reference temperature of 60 degrees. In all cases, customer-specific weather variables are calculated using data for the appropriate climate zone.
[29] Note that the hour indices for some sets of interacted variables include all 24 hours, while the hourly indicator variables (including those interacted with day type) exclude hour 1. Excluding one of the hourly variables is required in these cases in order to avoid perfect multicollinearity among the included variables (*e.g.*, when an hourly regression equation includes a constant term, it cannot also distinguish between an exhaustive list of all hours; one must be excluded).

The term with the double summation signs is the component of the equation that allows estimation of *hourly load impacts* (the $b_{i,Evt}$ coefficients) for each event day. It does so via the hourly indicator variables h_i interacted with the event variables (indicated by PTR_t), where the coefficients reflect hourly differences between the participant and control group loads on event days (with that convention, participant event-day load reductions below control group levels would be represented by negative coefficients). The remaining terms in the equation are designed to control for weather and other periodic factors (*e.g.*, hours, days, and months) that determine the difference between PTR and control-group customer loads. The interaction of Monday, Friday and weekend indicators with the hourly indicators is designed to account for potentially different hourly load profiles on the first and last days of the workweek, and on weekends.

3.2.3 Customer-level regression models to identify "responders"

While the cell-level difference models are appropriate for estimating PTR-NT and PTR-SS program effects, customer-level models represent the only method for investigating the distribution of individual PTR pilot participants' responsiveness to event calls. To provide an efficient and straightforward method for identifying consistent PTR event responders, we applied a simplified version of a customer-level participant-only model.

Two simplifications were made. One was to compress the hourly data, and estimate *daily* models (rather than hourly), using average hourly load during PTR event-window hours (11 a.m. to 6 p.m.) for each day as the variable to be explained. Explanatory variables included indicator variables for PTR and SS event days, weather variables (*e.g.*, CDD interacted with weekday and weekend, and also interacted with pre- and post-September 15 time periods, to account for an observed difference in weather responsiveness in late-September and October), and day-of-week indicators, including weekends, and month indicators.

The other simplification was to include only two PTR event variables: one that indicated both the August 28 and September 7 events (the September 8 outage event day was excluded from this analysis), and another that indicated both of the two October events. With this design, the two estimated event-day coefficients represent the average hourly load impact across the two pairs of events, and the standard errors provide indicators of the significance of the response.[30] This more parsimonious model facilitated the estimation and interpretation of the customer-level models. For example, we could categorize a "responder" based on the sign and significance of a single variable, which would not have been possible in an hourly model.

[30] We initially intended to include only a single event variable. However, customers' response to the October events appears to have differed substantially from that for the earlier events, so it appeared important to distinguish the two sets of events.

With these changes, the customer-level regression model is the following:

$$Q_t = a + b^{PTRa} \times PTR_t^a + b^{PTRb} \times PTR_t^b + \sum_{i=1}^{4}(b_i^{SS} \times SS_{i,t}) + b^{CDD} \times CDD_t + b^{LagCDD} \times LagCDD_t$$
$$+ b^{WECDD} \times WE_t \times CDD_t + b^{SumCDD} \times Summer \times CDD_t + b^{SumLagCDD} \times Summer \times LagCDD_t$$
$$+ b^{SumWECDD} \times Summer \times WE_t \times CDD_t + \sum_{i=2}^{7}(b_i^{DTYPE} \times DTYPE_{i,t}) + \sum_{i=7}^{10}(b_i^{MONTH} \times MONTH_{i,t}) + e_t$$

In this equation, Q_t represents the average hourly usage during the event-window on day *t* for a particular customer; the *b*'s are estimated parameters; $PTR^a{}_t$ and $PTR^b{}_t$ are indicator variables for the two categories of PTR event days; $SS_{i,t}$ indicates SS events[31]; CDD_t is cooling degree days[32]; $LagCDD_t$ is cooling degree days on the previous day; WE_t is an indicator variable for weekend days; $Summer_t$ is an indicator variable for dates from June 1 through September 15; $DTYPE_{i,t}$ is a series of indicator variables that allow constant adjustments for day of the week; $MONTH_{i,t}$ is a series of indicator variables for each month; and e_t is the error term.

The first two terms allow estimation of *average hourly load impacts* (the $b_{i,Evt}$ coefficients) for the two sets of event days. The "*a*" coefficient indicates the average hourly load impact for the August 28 and September 7 events, while the "*b*" coefficient indicates the average hourly load impact for the October 12 and 13 events.

3.2.4 Development of Uncertainty-Adjusted Load Impacts

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. In the case of *ex post* load impacts, the parameters that constitute the load impact estimates are not estimated with certainty. Therefore, we base the uncertainty-adjusted load impacts on the variances associated with the estimated load impact coefficients.

Specifically, we add the variances of the estimated cell-level load impact coefficients across climate zones (using appropriate sample weights), and then take the square root to produce an overall standard deviation around the overall estimated load impact coefficients. The uncertainty-adjusted values are developed under the assumption that each hour's load impact is normally distributed with the mean equal to the above weighted sum of the estimated load impacts and the standard deviation equal to the square root of the weighted sum of the variances of the errors around the estimates of the load impacts. Hourly results for the 10th, 30th, 70th, and 90th percentile assumptions are generated from these distributions for inclusion in the Protocol tables.

[31] The SS variables apply only to the PTR-SS sub-sample. Four different variables were actually included to differentiate days that were SS-only, PTR-only, or both PTR and SS (differentiating between September 7 and the October 12 and 13 events).

[32] As described above, several CDD variables were used in the model, including CDD interacted with a weekend indicator, and CDD interacted with a "summer" variable (June through September 15), to distinguish weather response during that period from the late-summer period (September 16 – October 31).

4. Detailed Study Findings

This section presents the formal estimated *ex post* load impacts for the PTR pilot that are produced from the regression analysis described in the methodology section above. Overall, the study found that those PTR pilot participants *without* enhanced technology (*i.e*., PTR-NT) reduced their electricity usage by about 1 percent to 5 percent across the five PTR events, compared to Control-NT customers, after adjusting for other differences between the two groups. These findings are summarized in Table 4-1, which shows average temperatures, event hours, percentage load impacts, and average event-hour load impacts per customer.

For the most "typical" summer weekday event (September 7), PTR participants reduced their usage by 4.5 percent, which translates into an *average hourly* reduction over the seven-hour event of 0.06 kWh per hour per customer. Information on the statistical precision of the estimated load impact coefficients indicates that an 80 percent confidence interval around the estimated 4.5 percent reduction in energy usage on September 7 ranges from 2.6 percent to 6.4 percent, as illustrated below.

Table 4-1: Overall PTR-NT Estimated Load Impacts and Event Characteristics

	Event Date				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Ave. Temp. (11am - 6pm)	83.7	92.7	91.6	93.5	89.5
Event Hours (Hour Ending)	12-18	12-18	12-15[1]	12-18	12-18
Estimated Load Impact (%)	2.5%	4.5%	5.1%	3.3%	1.2%
Ave. Hourly LI (kW)	0.031	0.056	0.057	0.027	0.011

[1]Event truncated by outage

These usage reduction findings may be viewed in the context of a survey conducted as part of a process evaluation of the pilot, which found that about 63 percent of participants surveyed were *aware* that they had been selected for the pilot program, and about the same percentage recalled receiving at least one event notification.

Turning to the more detailed findings, Section 4.1 summarizes average estimated event-hour load impacts by event and climate zone. Selected tables of *hourly* load impacts are presented in Section 4.2 in the format required by the Load Impact Protocols adopted by the California Public Utilities Commission (CPUC) in Decision (D.) 08-04-050 (Protocols). The tables include uncertainty-adjusted load impacts at different probability levels. The values in the tables are also represented in figures that illustrate the PTR event-day loads and load impacts. Protocol table generator spreadsheet files are provided separately, as indicated in the appendix.

4.1 Average Event-Hour PTR Load Impacts

Section 2.4 above illustrated selected average overall load profiles for PTR participants and control group customers. This section summarizes the estimated *ex post* load impacts for each event, where the estimates were obtained using the formal regression-based methodology of load-differences between the participant and control group samples described in section 3.2.2. The load impacts in this section are presented in the form of values averaged across the event hours.

4.1.1 PTR-NT average event-hour load impacts

Tables 4-2 and 4-3 summarize the estimated load impacts for the PTR participants without enabling technology (PTR-NT), on a per-customer and pilot-level basis respectively. The first panel in each table reports average hourly estimated load impacts for each PTR event and for each climate zone.[33] By convention, *positive values represent load reductions*. The second panel reports percentage load impacts relative to the estimated reference loads.[34] The third panel reports the estimated change in *total energy usage* (kWh) over the event period. The climate zone and total results are calculated by applying appropriate overall population weights to cell-level regression results. Overall percentage load impacts for the PTR-NT portion of the pilot sample, shown in the last line of the second panel, range from about 1 percent to 5 percent across all events, as summarized in Table 4-1 above. Greater variation occurs across climate zones.

Table 4-2: Estimated PTR-NT Load Impacts – *Customer-Level*
(Positive values reflect <u>reductions</u> in load or energy usage)

	Average Hourly Load Impact (kW)				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Coastal	0.026	0.041	0.054	0.016	-0.009
Mountain	0.112	0.102	0.137	-0.032	-0.075
Desert	-0.070	-0.008	0.011	0.158	0.058
Inland	0.037	0.077	0.058	0.044	0.039
Total	**0.031**	**0.056**	**0.057**	**0.027**	**0.011**

	Average Hourly Load Impact (% of Reference Load)				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Coastal	3.0%	4.9%	6.7%	2.5%	-1.3%
Mountain	4.8%	5.2%	8.5%	-3.2%	-7.1%
Desert	-3.9%	-0.5%	0.7%	16.6%	6.2%
Inland	2.2%	4.3%	3.8%	4.1%	3.3%
Total	**2.5%**	**4.5%**	**5.1%**	**3.3%**	**1.2%**

	Total Energy Change During Event Hours (kWh)				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Coastal	0.2	0.3	0.2	0.1	-0.1
Mountain	0.8	0.7	0.5	-0.2	-0.5
Desert	-0.5	-0.1	0.0	1.1	0.4
Inland	0.3	0.5	0.2	0.3	0.3
Total	**0.2**	**0.4**	**0.2**	**0.2**	**0.1**

[33] Load impacts for the September 8 event are averaged only over hours-ending 12 – 15, because the outage appears to have begun part way through hour 16 (*i.e.*, 3 p.m. to 4 p.m.).
[34] Reference loads during the event period are estimated by adding the amount of the estimated load impact in a given hour to the *observed load* in that hour.

It is worth noting that the estimated overall percentage load impacts are generally consistent with the characterization of the load impacts implied by the figures in Section 2.4. This is as expected since the regression-based estimates are based on the same load data that is illustrated in the figures.

Figure 4-1 illustrates confidence intervals around the estimated percent load impacts shown in the middle panel of Table 4.2. The heights of the bars represent the magnitudes of the estimated percent load impacts while the dark lines illustrate 90/10 confidence intervals around those estimates based on the standard errors of the estimated load impact coefficients. It is evident that the load impact for the September 7 event has the smallest confidence interval relative to the magnitude of the load impact, while the estimated load impacts for the two October events have relatively large confidence intervals.

Figure 4-1: Percent Load Impacts and Ninety Percent Confidence Intervals

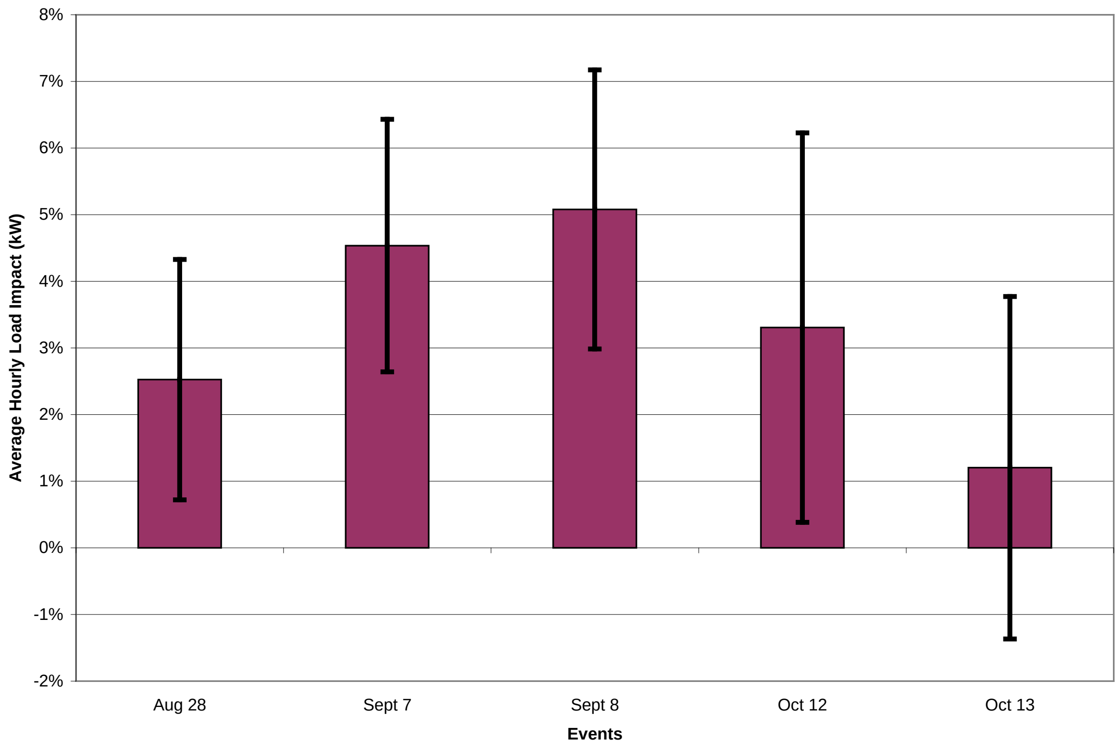


Table 4-3 aggregates the estimated load impacts in Table 4-2 to the *pilot program level* using appropriate sample weights and scaling to the total number of PTR-NT participants.

Table 4-3: Estimated PTR-NT Load Impacts – *Pilot Level*
(Positive values reflect reductions in load or energy usage)

	Average Hourly Load Impact (kW)				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Coastal	42.2	67.3	89.3	25.7	-14.4
Mountain	3.8	3.5	4.7	-1.1	-2.6
Desert	-0.5	-0.1	0.1	1.1	0.4
Inland	44.8	93.2	70.9	53.5	47.1
Total	**90.4**	**163.9**	**164.9**	**79.2**	**30.6**

	Average Hourly Load Impact (% of Reference Load)				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Coastal	3.0%	4.9%	6.7%	2.5%	-1.3%
Mountain	4.8%	5.2%	8.5%	-3.2%	-7.1%
Desert	-3.9%	-0.5%	0.7%	16.6%	6.2%
Inland	2.2%	4.3%	3.8%	4.1%	3.3%
Total	**2.5%**	**4.5%**	**5.1%**	**3.3%**	**1.2%**

	Total Energy Change During Event Hours (kWh)				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Coastal	295.6	471.1	357.4	180.2	-100.6
Mountain	26.6	24.2	18.6	-7.6	-17.9
Desert	-3.3	-0.4	0.3	7.5	2.8
Inland	313.9	652.1	283.4	374.2	330.0
Total	**632.8**	**1,147.1**	**659.7**	**554.4**	**214.3**

4.1.2 Differences in PTR-NT load impacts by type of mailer

Upon selection for the pilot, participants were randomly assigned one of two introductory mailings. One focused on potential financial benefits, or *rewards*, of reducing usage during events, while the other focused on the *environmental benefits* of such reductions in consumption. To explore potential differences in PTR load impacts by the two groups, we constructed separate average loads by cell for participants in each of the two groups, and then re-estimated the cell-level difference models, using the same average control group loads in each case.

Results for the "Reward" and "Environmental" subsets of the pilot participants are shown in Table 4-4, in the form of estimated percentage load impacts for the average event hour, as in the middle panel of Table 4-2 for overall PTR-NT participants. Focusing first on the Reward participants, the estimated percent load impacts for the first three events are slightly larger than those for all PTR-NT customers (shown in Table 4-2), while the load impacts for the two October events are smaller. In the case of the Environmental participants, estimated load impacts for the first two events are smaller than the overall average, while those for the two October events are larger. Perhaps importantly, the results for the most "typical" event on September 7 do not differ materially.

While the differences in estimated load impacts are somewhat intriguing, it is difficult to draw any strong overall conclusion regarding the differential effects of the two types of introductory material, particularly given the problematic nature of the two October events. These findings are generally consistent with the process evaluation of the pilot, which found few differences in attitudes or performance between the two groups of participants who received the different educational mailers.

Table 4-4: Average Event-Hour Percentage Load Impacts – *“Reward” and “Environmental” Mailers*

"Reward"	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Coastal	3.8%	6.9%	12.2%	1.9%	-0.9%
Mountain	6.2%	6.9%	5.2%	-5.8%	-8.0%
Desert	-3.1%	0.2%	2.7%	14.5%	6.9%
Inland	3.0%	4.8%	5.8%	1.1%	-2.7%
Total	**3.4%**	**5.6%**	**8.4%**	**1.4%**	**-2.0%**

"Environmental"	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Coastal	2.2%	3.0%	1.0%	3.2%	-1.7%
Mountain	3.0%	3.2%	12.6%	0.0%	-6.3%
Desert	-5.0%	-0.5%	-0.5%	18.6%	4.8%
Inland	1.4%	4.0%	2.1%	6.6%	8.7%
Total	**1.7%**	**3.6%**	**1.8%**	**5.1%**	**4.2%**

4.1.3 PTR-SS average event-hour load impacts

Estimated load impacts for the PTR participants who were also Summer Saver customers (PTR-SS) are shown in Tables 4-5 and 4-6. These estimated load impacts are based on the models of differences in loads between the treatment and control group customers described in Section 3. Table 4-5 shows results on a per-customer basis, and differentiates between the Inland high-use and medium-use customers. Table 4-6 expands the per-customer results to the total number of PTR-SS participants in the Inland climate zone (61) that were included in the analysis.

The three panels in Table 4-5 show estimated load impacts, percentage load impacts, and changes in total energy consumption, respectively. The results are differentiated by hours within PTR events which were also SS event hours, and the remaining non-SS PTR hours. The August 28 PTR-only event does not include any SS hours, and the September 8 joint event includes only two non-SS and two SS hours before the outage began. All other events contained four SS hours and three non-SS PTR hours. The results are discussed after presenting information on the confidence intervals associated with the load impact estimates.

Table 4-5: Estimated PTR Load Impacts per Customer – *Joint PTR-SS (Inland Climate Zone Sub-Sample)*
(Positive values reflect reductions in load or energy usage)

		Average Hourly Load Impact (kW)				
Sample Cell	Event hours	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Inland, High use	SS Hrs	n/a	0.387	0.262	-0.229	-0.007
	Non-SS Hrs	0.762	0.677	0.527	0.086	0.082
Inland, Medium use	SS Hrs	n/a	0.392	0.661	-0.118	-0.166
	Non-SS Hrs	0.505	0.212	-0.042	0.173	0.249
Total Inland	SS Hrs	n/a	0.391	0.560	-0.146	-0.126
	Non-SS Hrs	0.570	0.330	0.102	0.151	0.207

		Average Hourly Load Impact (% of Reference Load)				
Sample Cell	Event hours	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Inland, High use	SS Hrs	n/a	12.2%	9.2%	-11.9%	-0.3%
	Non-SS Hrs	17.3%	19.6%	14.2%	3.8%	3.5%
Inland, Medium use	SS Hrs	n/a	23.5%	38.4%	-16.9%	-19.5%
	Non-SS Hrs	24.0%	14.3%	-2.7%	17.5%	19.6%
Total Inland	SS Hrs	n/a	21.5%	27.9%	-15.7%	-10.8%
	Non-SS Hrs	21.2%	13.9%	4.9%	11.0%	13.9%

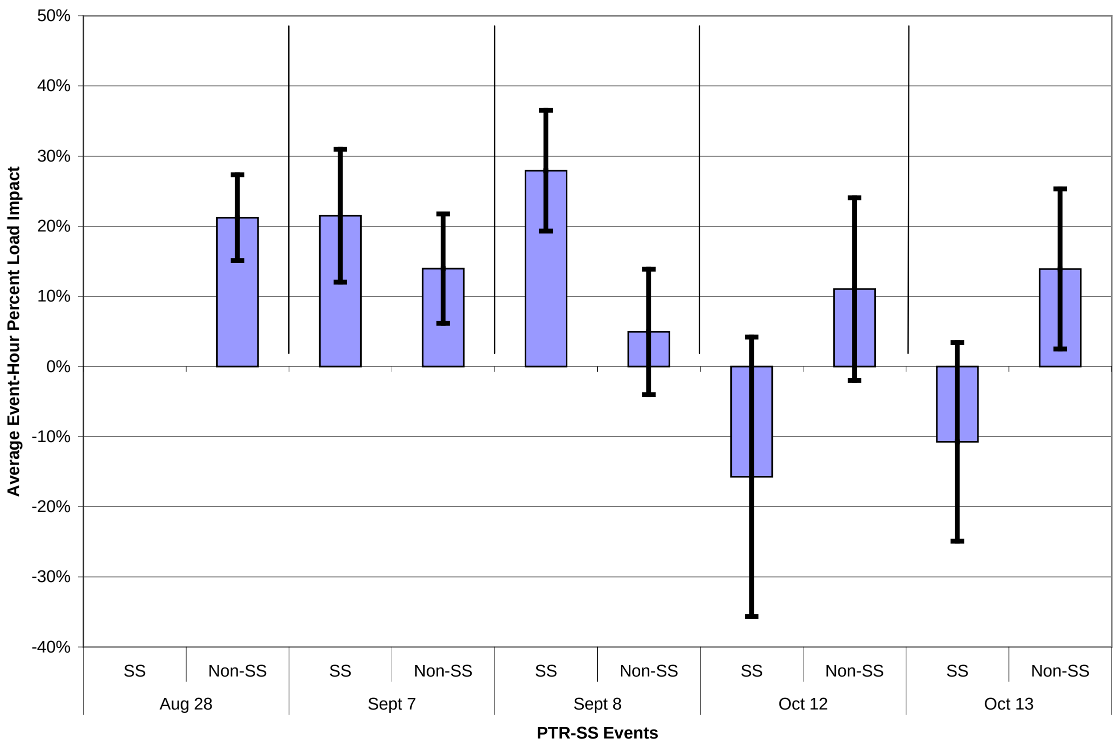
		Total Energy Change During Event Hous (kWh)				
Sample Cell	Event hours	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Inland, High use	SS Hrs	n/a	1.55	0.52	-0.92	-0.03
	Non-SS Hrs	5.34	2.03	1.05	0.26	0.25
Inland, Medium use	SS Hrs	n/a	1.57	1.32	-0.47	-0.67
	Non-SS Hrs	3.54	0.64	-0.08	0.52	0.75
Total Inland	SS Hrs	n/a	1.56	1.12	-0.58	-0.50
	Non-SS Hrs	3.99	0.99	0.20	0.45	0.62

Table 4-6: Estimated PTR Load Impacts (Pilot Level) – *Joint PTR-SS (Inland Climate Zone Sub-Sample)*
(Positive values reflect reductions in load or energy usage)

		Inland Climate Zone (4)				
	Event hours	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Ave Hrly LI (kWh/hr)	SS Hrs	n/a	23.83	34.16	-8.91	-7.69
	Non-SS Hrs	34.79	20.14	6.24	9.22	12.62
% LI	SS Hrs	n/a	21.5%	27.9%	-15.7%	-10.8%
	Non-SS Hrs	21.2%	13.9%	4.9%	11.0%	13.9%
kWh Chg	SS Hrs	n/a	95.3	68.3	-35.6	-30.8
	Non-SS Hrs	243.5	60.4	12.5	27.7	37.8

Figure 4-2 illustrates confidence intervals around the total Inland estimated percent load impacts shown in the middle panel of Table 4-5. Values are shown separately for SS and non-SS hours in each event. The bars represent the magnitudes of the estimated percent load impacts, while the dark lines illustrate 10th and 90th percentile bounds on confidence intervals around those estimates based on the standard errors of the estimated load impact coefficients. As with the case for PTR-NT, load impacts are estimated more precisely for the first two events than for the last two events.

Figure 4-2: Percent Load Impacts and 10th & 90th Percentile Confidence Intervals – *PTR-SS*



As shown in the figures in Section 2.4 above, the PTR-SS participants clearly reduced usage during SS events as expected, though in varying amounts across events. However, when compared statistically to the loads of the Control-SS customers through the regression analysis, the patterns of estimated PTR load impacts vary substantially across events. On September 7, the one joint PTR/SS event that might be considered "typical", the PTR-SS participants reduced usage during both SS and non-SS event hours by statistically significant amounts, as reflected in the relatively narrow confidence intervals. The average usage reduction on the PTR-only event on Sunday, August 28, also has a narrow confidence interval. For the two October events, however, incremental load impacts relative to the Control-SS customers are negative (higher usage) during SS hours, and positive (lower usage) during non-SS hours, and confidence intervals are wide.

4.1.4 Distribution of customer-level load impacts

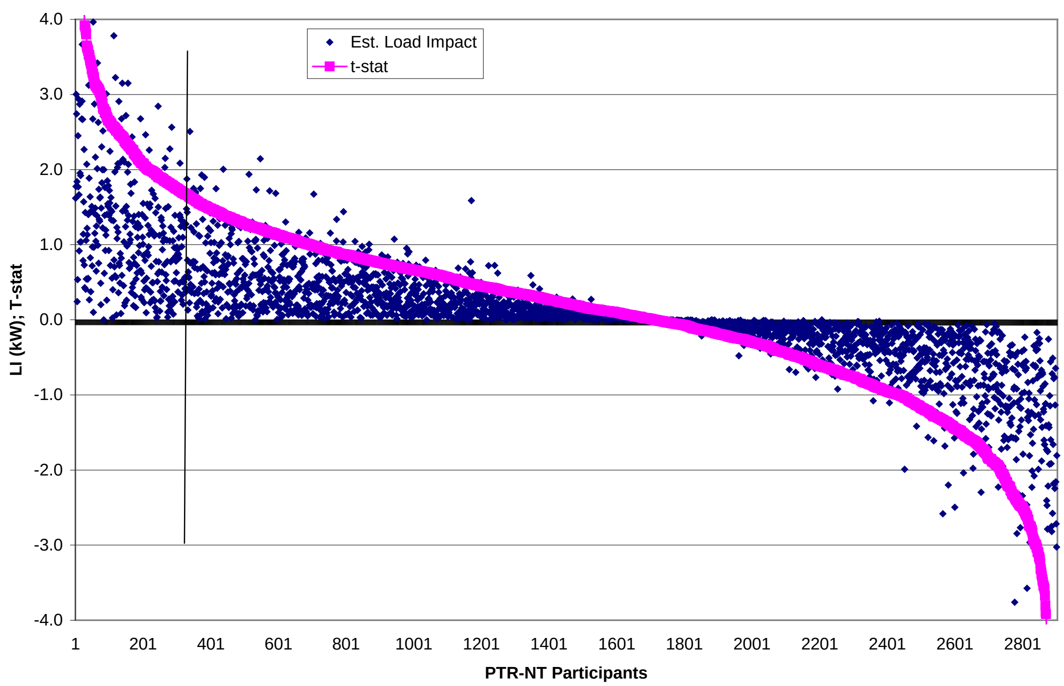
Customer-level regression models based on daily observations of average hourly usage in the event window hours, as described in Section 3.2.4 above, were estimated for all PTR participant and control group customers. We focus here on estimated load impact results for the PTR-NT participants for the average of the August 28 and September 7 events.[35]

[35] The estimated load impacts for the two October events were not nearly as well-defined as those for the first two events. Only about 100 customers had significant correctly-signed load impact coefficients, and

Figure 4-3 shows two values for each PTR-NT participant arrayed across the x-axis. One is their estimated average hourly PTR load impact (using the convention that positive values indicate load *reductions*) for the first two events combined. The other is the associated *t*-statistic for that estimate.

The two sets of values are sorted by the *t*-statistic values, which make up the smooth *S*-shaped curve. Each point scattered around that curve represents the estimated load impact associated with a given customer's *t*-statistic. A 90 percent confidence level for the *t*-statistic of approximately 1.65 is indicated by the vertical line that lies somewhat to the right of the left axis. This line implies that all load impact estimates that lie to the left of the line represent statistically significant load *reductions*. These represent approximately 330 PTR-NT participants (about 11 percent of the total), who reduced their usage during the first two PTR events by a statistically significant amount. Note that more than half of the participants are estimated to have reduced usage during those two events, even if not by a statistically significant amount.

Figure 4-3: PTR-NT Customer-Level Estimated Load Impacts and *t*-Statistics – ***Average of August 28 and Sept. 7 Events***



Curves of this type showing the range of estimated load impacts across customers have been reported in a number of load impact evaluations in California and elsewhere. Some evaluations show relatively larger or smaller proportions of estimated load *reductions*

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these were often very large. We expect that the customer-level participant-only model cannot successfully distinguish between the weather effects of the isolated hot late-summer days and the October PTR events that were called on those same days. This result is in contrast to the cell-level difference models that are able to leverage off of information on control group loads on those isolated days to assist in estimating PTR event effects.

relative to estimated load *increases*. There has been considerable discussion of the reasons underlying the significant load *increases* that are often estimated for some portion of customers. In the case of the PTR pilot in 2011, we expect that a major reason for the numerous estimated load increases has to do with the fact that the two events represented in the figure were called on unusually hot days, and the load increases represent the effect of weather and other unexplained changes in usage.

For completeness, the same form of customer-level daily model was also estimated for each of the control group customers. That is, PTR event-day indicators were included in their regressions, even though the control customers received no request to reduce usage during the event window on event days (in fact they were not selected until after all events had taken place). The resulting distribution of estimates of customer-level average event-period load impacts has a similar pattern to that of the PTR participants shown above. That is, similar to the 11 percent of responders among PTR participants, about 10 percent of the control group customers had statistically significant estimates of average event-hour load reductions across the first two PTR events. However, as shown below, their overall reduction in usage during event hours was less than that of the participant "responders," particularly on the September 7 event day, for which it was half as large. These somewhat puzzling findings are discussed in more detail below.

4.1.5 Estimated load impacts by event-responders

After flagging the customers identified as "event responders" on the basis of the significance test described above, we calculated average event-hour load impacts by sample cell, and then an overall weighted average. The overall event-hour load impact for the PTR-NT responders for the average of the August 28 and September 7 events is 0.73 kW per customer, or 41 percent of their overall estimated reference load. In contrast, the estimated overall load impact for *all* PTR-NT participants as reported in Table 4-1 is less than 0.10 kW, representing about 3.5 percent of the estimated reference load averaged across the two events. Scaling the estimated load impacts to the total number of responders produces a total load impact of approximately 394 kW.

To illustrate the pattern of event-day loads for the PTR-NT responders, we constructed cell-level and overall weighted-average loads for those customers flagged as demonstrating significant event-day load reductions. Figure 4-4 compares load profiles for the overall average PTR-NT and average Control-NT customer (top two lines) to the average PTR-NT *responder* (dark dashed line) for the Sunday, August 28 event. As indicated earlier, the overall average PTR-NT participant load differs little from the average control group load.[36] However, the average PTR-NT responder shows a substantial load reduction during the event window, and a recovery of load following the event.

[36] As shown in Section 2.4, the average participant load is somewhat higher than the average control group load on the typical Sunday, which implies that the small difference between the two loads on the event day is consistent with a small PTR load reduction.

Figure 4-4: PTR-NT Responders, All PTR-NT, and All Control-NT Loads –
Average Sunday and August 28 Event

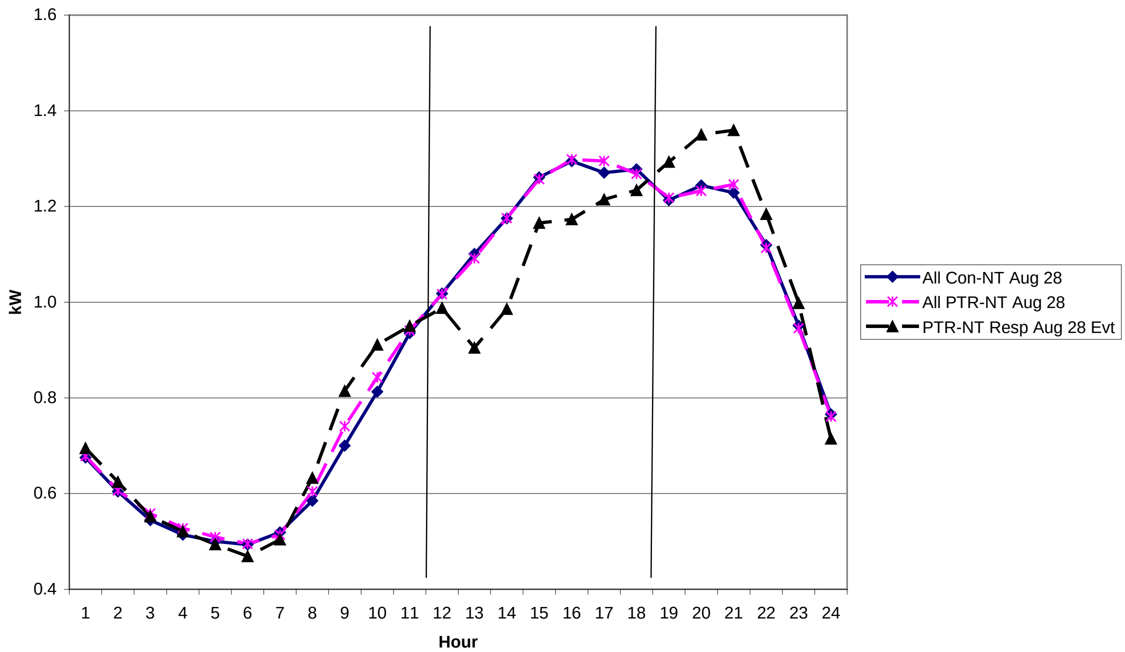


Figure 4-5 illustrates a similar comparison for apparent responders found in the control group. The control group responder profile indicates an event-period load reduction similar to the participant responder profile, except that that the post-event load increase (or "rebound") is not present for the control group customers. For this event, the average load reduction compared to all control group customers is somewhat smaller for the control-group responders, at 7.8 percent, versus 8.7 percent for the PTR responders.

Figure 4-5: Control-NT Responders and All Control-NT Loads –
Average Sunday and August 28 Event

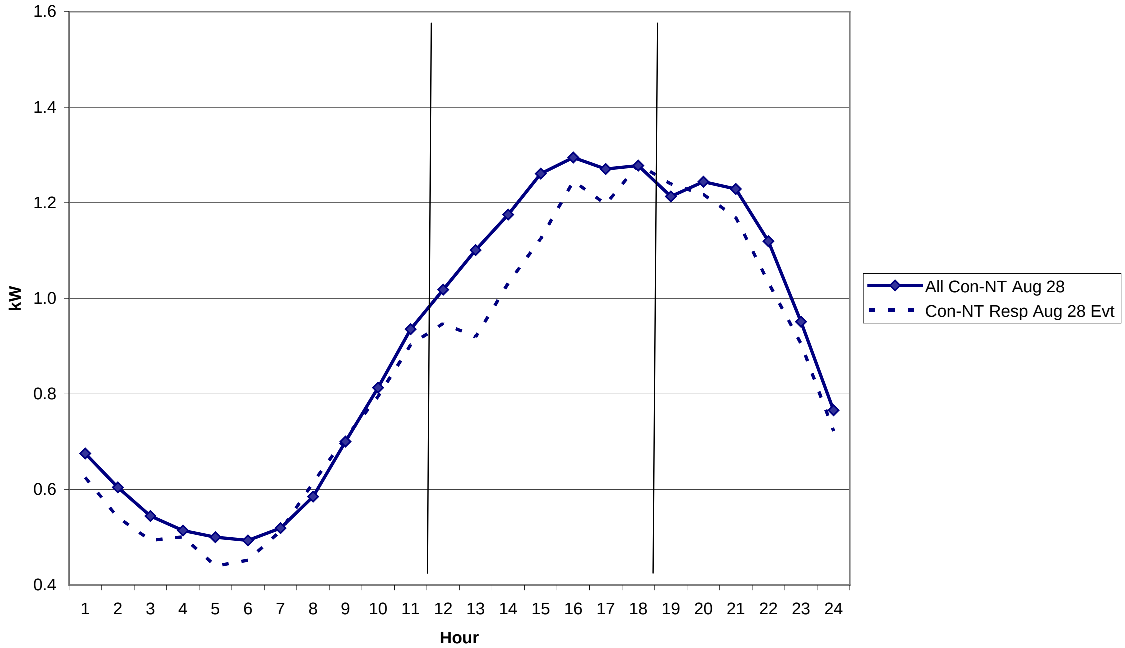


Figure 4-6 and 4-7 show comparable information for the September 7 event day. The top two lines of Figure 4-6 show the same overall average PTR-NT participant and Control-NT loads that were shown earlier in Section 2.4. In contrast to the overall participant load, the PTR-NT *responder* load again shows a definitive reduction in usage during the event window, after tracking the other two event-day loads quite closely in the pre-event hours.

Finally, Figure 4-7 shows the load profile for the apparent event-responders found in the control group, along with the overall average control group profile. While there is a similar pattern compared to the participant responders (load reductions relative to all customers during event hours, and with some rebound effect), the average load reduction (relative to the entire control group) is only 8.9 percent for the control responders versus 19.5 percent for the PTR responders, less than half as much.

Figure 4-6: PTR-NT Responders, All PTR-NT, and All Control-NT Loads –
September 7 Event

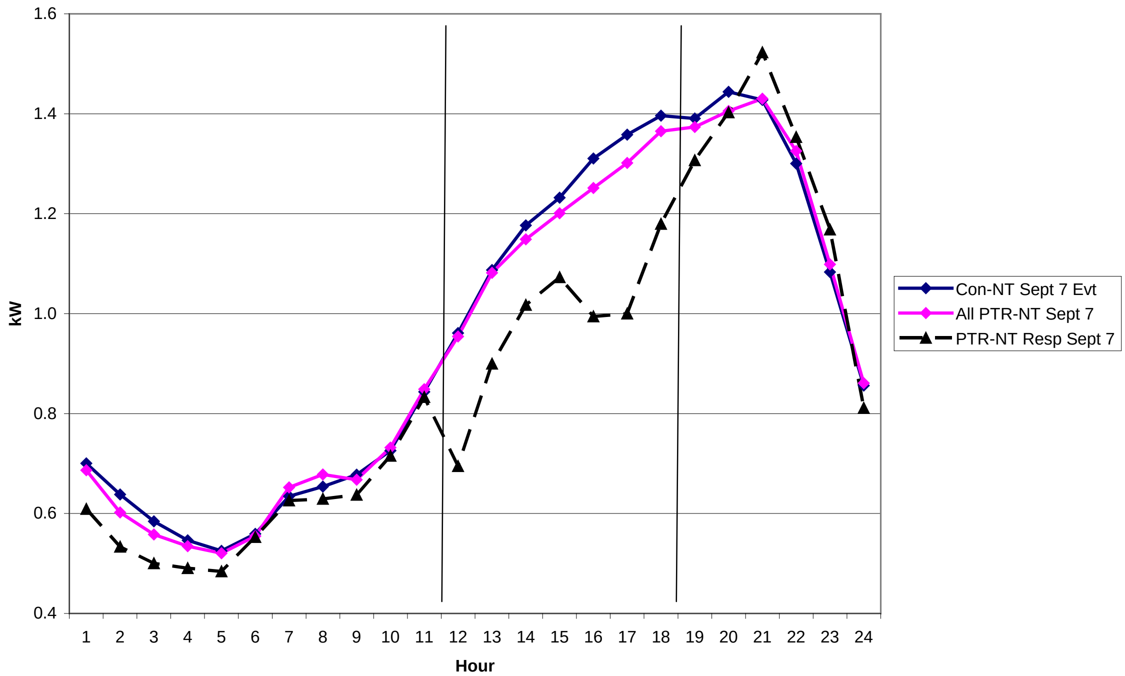
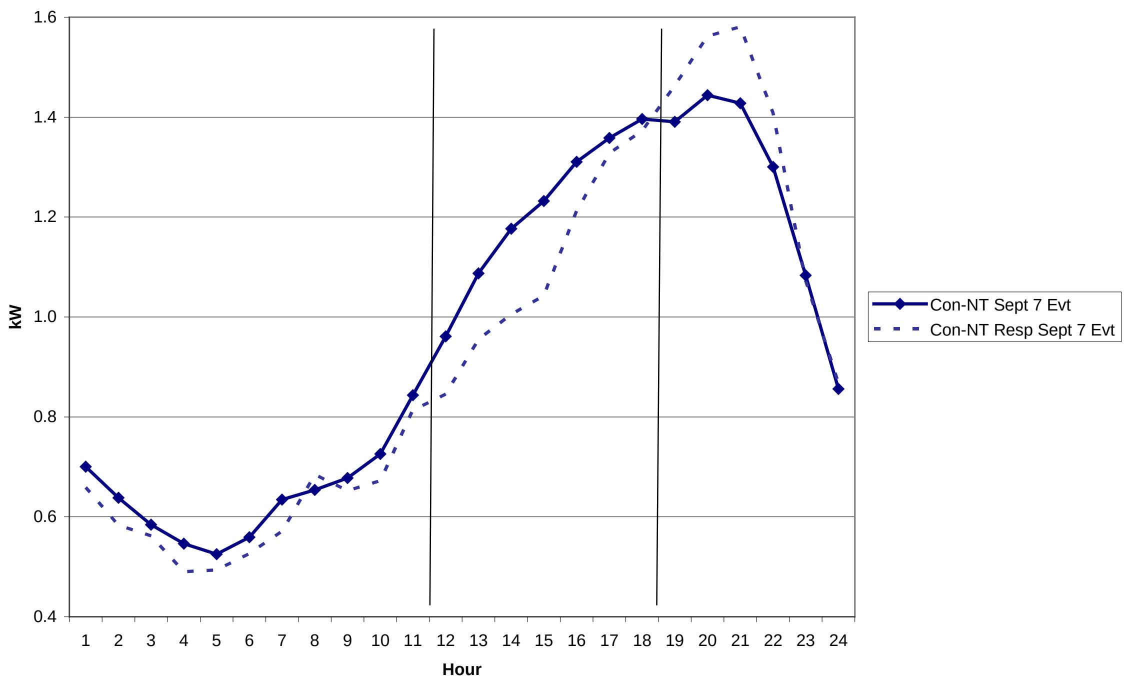


Figure 4-7: Control-NT Responders All Control-NT Loads –
September 7 Event



We conclude that a subset of approximately 11 percent of the PTR-NT participants responded to the PTR event notification by reducing usage by statistically significant amounts during the first two PTR events, resulting in average usage reductions of about 40 percent. These participants are likely the primary source of the 2.5 and 4.5 percent overall load reductions that were estimated for those events for the entire PTR-NT pilot sample. A parallel analysis conducted for the control-group customers found a similar share of apparent "responders", but with lower levels of usage reductions than were found for responders among the PTR pilot participants.

We can offer two possible explanations for these findings regarding participant and control group responders. One possibility is that the estimated PTR-NT responder load impacts represent something other than customers reducing usage during event periods. For example, the customer-level models estimated a broad distribution of event-day load impacts, and the method used to identify responders from among participants and control group customers may have simply captured the "tail" of a distribution of load changes that is bound to be found regardless of whether customers actually responded to the event. However, the fact that the "notching" of their load (*i.e.*, reductions only during event hours) is more pronounced for the PTR participant responders than for the control group "responders" provides some reason to doubt this explanation. It is difficult to develop alternative explanations (other than event response) for why the "responders" have lower loads only during event hours on event days. For example, if the method of identifying responders were simply capturing customers who were on vacation during both events, we might expect loads to be lower throughout the day, and not just during the event hours.[37]

The second explanation has to do with possible reasons for finding control group "responders" that actually reduced usage during afternoon hours on event days. That is, the similarity of PTR and control-group responder findings could be consistent with the findings of the process evaluation of the pilot, which indicated some confusion on the part of PTR participants about whether they should "reduce their use" during peak hours on every day, on days that are unusually hot, or only on days on which they are informed that PTR events are called. Part of the reason for this confusion may have to do with the extensive publicity in California in recent years regarding the importance of reducing usage on hot days that strain the power system. Both the PTR pilot participants and control group customers have been exposed to those messages. Perhaps a subset of control group customers was responding to the occurrence of unusually high temperatures on the PTR event days and previous communications from SDG&E about the importance of reducing peak-period usage on such days, but without being aware of the fact that PTR events were called.

4.1.6 Effect of optional event notification on estimated load impacts

In addition to default notification by phone, PTR participants were encouraged to sign up to receive electronic notification of events through email, text or cell phone. One

[37] Also, for example, customers who set back their thermostat every day during hours ending 12 through 18 (the event window) would not be categorized as "responders" using our method, as there would be no difference between event-day and non-event day loads.

hundred forty-nine pilot participants signed up to receive event notifications. To examine potential effects of choice of event notification on participants' usage reductions, or load impacts, we combined customer-level information on dates of signing up for notification with the customer-level estimated load impacts described in Section 4.1.4.

The measure of estimated load impact was the coefficient on the variable indicating the August 28 and September 7 events. Given those dates, we restricted the list of "notified" customers to those PTR-NT participants who signed up prior to the August 28 event. This resulted in a total of 110 notified customers. Of those, 19, or about 17 percent appeared in our list of "event-responders" to those two events. Using information on estimated load impacts and observed loads during the event periods, we find that the 19 customers who requested notification and were classified as event-responders reduced event-period usage by 46 percent relative to the reference load. This is in contrast to the 41 percent load reduction by the overall responder group. Given the small numbers, it is difficult to draw a definitive conclusion regarding whether the small subset of customers who requested optional methods of notification were more or less likely to be classified as event-responders or to have reduced usage by a significantly greater amount than the typical responder.[38]

4.1.7 Assessment of CRL-based estimated load impacts

This section contains an assessment of the relationship between load impacts as estimated by the PTR program CRL baseline method, and as estimated by the *ex post* evaluation regression methods. We begin by summarizing the PTR pilot load impacts and bill credits as calculated by SDG&E. Table 4-7 provides a range of relevant statistics for each event, and across events. As shown, each row in the main body contains results for one of the five PTR events. The three rows at the bottom show totals or averages, as appropriate, across three different sets of events: All five events; all events excluding the September 8 outage event; and the average of the first two events, which is useful in comparing results to our customer-level regression analysis.

[38] The process evaluation found little difference between the notified customers and other customers in terms of their event performance or their recollections about receiving notifications.

The columns of the table show the following information:[39]

- The sum of estimated usage reductions during PTR event hours, across all customers for whom the usage changes relative to the CRL implied reductions rather than increases;
- The number of participants who were found to have reduced usage during the event;
- The amount of reduced usage as a percentage of the CRL baseline load estimate;
- Total bill credits, calculated as $0.75 times the reduced usage in the first column;
- Bill credits per "reducer";
- The percentage of "reducers" relative to the total number of PTR-NT participants;
- Reduced use per "reducer"; and
- Reduced use per participant.

Table 4-7: PTR-NT Usage Reductions and Bill Credits by CRL Calculations

Event	Reduced Usage per CRL (kWh)	Num. of Reducers	% Reduced Usage	Total Bill Credits	Bill Credit per Reducer	Reducers as % of Partic.	Reduced Use per Reducer (kWh)	Reduced Use per Partic. (kWh)
28-Aug-11	3,013	961	28%	$ 2,260	$ 2.35	34%	3.1	1.1
07-Sep-11	3,801	1,201	27%	$ 2,851	$ 2.37	42%	3.2	1.3
08-Sep-11	12,478	2,452	39%	$ 9,358	$ 3.82	86%	5.1	4.4
12-Oct-11	3,119	1,428	28%	$ 2,339	$ 1.64	50%	2.2	1.1
13-Oct-11	3,919	1,564	30%	$ 2,939	$ 1.88	54%	2.5	1.4
Total/Ave.	26,330	7,606	32%	$ 19,747	$ 2.60	53%	3.5	1.8
Total/Ave. (Excl 9/8)	13,852	5,154	28%	$ 10,389	$ 2.02	45%	2.7	1.2
Average for 8/28, 9/7	3,407	1,081	28%	$ 2,555	$ 2.36	38%	3.2	1.2

The estimated amount of reduced usage and the bill credits are fairly consistent across events, with the exception of the September 8 event, for which the outage caused large usage reductions relative to the CRL levels. Of note are the relatively small average usage reductions and bill credits per reducer, which average $2.00 per event, or $2.36 for the first two events.

Also important to keep in mind is that these values represent simple sums or averages across pilot participants, without regard to their sample weights. As such, they represent the observed pilot-level usage reductions and bill credits. However, they are not representative of the population from which the sample was drawn, as the sample contains relatively more high-usage customers and customers in the sparsely populated Mountain and Desert climate zones than their proportion in the population. As a result, the values in the table likely overstate the usage reductions and bill credits that would apply to the actual population. For that reason, we also calculated population-weighted results for a subset of the factors shown in the table. These are shown in Table 4-8.

[39] As described below, the values in this table represent simple sums or averages across pilot participants, without regard to sample weights. Following the discussion of the table, we provide selected values that are adjusted for population weights.

Table 4-8: Alternative Estimates of PTR-NT Usage Reductions

	Reduced Usage	Reduced Usage per Partic.
CRL-based (Unweighted)	3,407	1.20
CRL-based (Weighted)	2,059	0.72
Cust-level Regression (Wtd)	3,143	1.10
Cell-level Regression (Wtd)	890	0.31

Three sets of population-weighted usage changes are shown, along with un-weighted values from the last line of Table 4-7, which are repeated in the first row. The two metrics shown are total estimated reduced usage for the average of the first two PTR events, and reduced usage per participant for those events. The second row in the table shows usage reductions obtained by applying appropriate sample weights to the same CRL-based estimates that were used as the basis for the values in Table 4-7. As expected, the population-weighted usage reductions are smaller than the un-weighted values. The third row contains sample-weighted values based on the customer-level regressions described in the previous sub-section. These usage reductions are about fifty percent larger than those estimated by the CRL baseline. The values in both of these rows include results only for those participants who are estimated to have reduced usage during the two events, where that determination is made by the relevant estimation method (*i.e.*, CRL baseline for the second row, and customer-level regression for the third row).

Finally, the last row shows comparable usage reduction estimates based on the cell-level regressions specified in the form of differences between participant and control groups, which were used to develop the *ex post* load impacts described earlier. These are also sample-weighted. However, they implicitly include usage changes for *all* participants, including those who increased usage during PTR events. It is therefore not surprising that the usage changes are smaller than for the cases where only usage reductions were included.

We were also asked to undertake a high-level comparison of the customer-level usage reductions estimated by the PTR program CRL method and those estimated by the customer-level regression methods. Given the nature of the customer-level analysis using daily observations on average hourly usage during the event window, the most readily available metric for comparing the alternative sources of load impact methods is the average event-hour load impact for the average of the August 28 and September 7 events. Values for the CRL method are calculated from the SDG&E pilot program database, and values for the regression-based estimates are drawn from our customer-level regression model results.

Figure 4-8 shows both metrics, sorted by the load impact values based on the CRL baseline method, where positive values represent load reductions. Two values are shown for each participant, whose results are arrayed across the horizontal axis. The scattered points (squares) that surround the smooth curve of program estimates represent load impacts estimated by our customer-level regression models. There is some degree of apparent correlation between the two sources of load impact estimates, which is investigated further in the next figure.

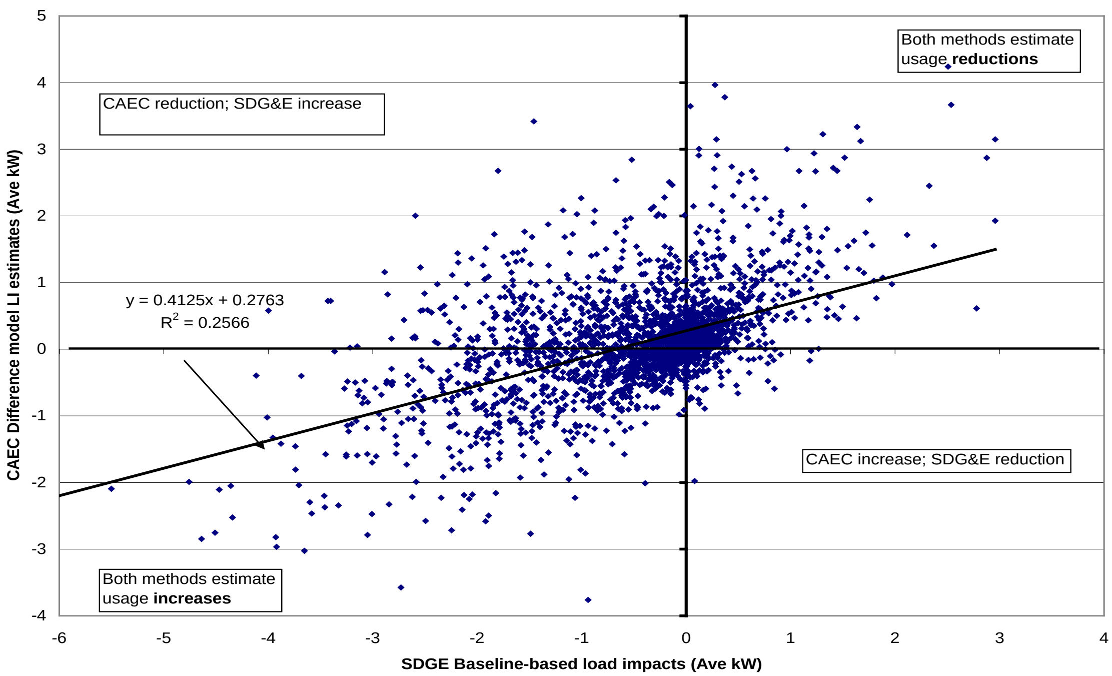
Figure 4-8: Relationship between PTR-NT load impacts as estimated by program method and M&E *ex post* evaluation – *Average of August 28 and Sept. 7 Events*

Figure 4-9 shows the same data points as in Figure 4-8, but in a scatter diagram that better clarifies the relationship between the two sets of estimated load impacts. Labels in the four quadrants of the figure indicate agreement or disagreement between the estimated load reductions (positive values) and load increases (negative values). The correlation between the two measures of load impacts is 0.51, which is reflected in the upward-sloping line in the figure. That is, it tends to be the case that when the program measurement indicates a usage reduction, the *ex post* estimate does as well. A comparison of the percentage of cases of agreement and disagreement between the two measures of usage changes produces the following results:

Regression and CRL baseline both indicate usage Reduction	28%
Regression indicates Reduction, but CRL indicates Increase	30%
Regression indicates Increase, but CRL indicates Reduction	6%
Regression and CRL baseline both indicate Increase	35%.

In summary, the regression method finds usage reductions for the average of the August 28 and September 7 events for about 58 percent of PTR participants. In about half of those cases, the CRL baseline also indicates a reduction, but in the other half it indicates a usage increase. Finally, in most of the remainder of cases, in which the regression method finds usage increases, the CRL baseline shows the same result. These results, combined with the aggregate usage reductions shown in Table 4-8, suggest that the baseline loads implied by the regression-based method are higher than those produced by the CRL baseline method, and thus estimate usage reductions more frequently and in greater amounts than does the CRL baseline method.

Figure 4-9: Scatter plot of PTR-NT load impacts as estimated by PTR program method and M&E *ex post* evaluation – *Average of August 28 and Sept. 7 Events*



4.2 Hourly PTR Load Impacts

The following tables and figures illustrate hourly estimated load impacts for the PTR-NT and PTR-SS participants for selected events, in the format required by the Protocols. Spreadsheet-based table generators that display loads and load impacts for each event and climate zone, on a per-customer and aggregate basis, are included as appendices. Table 4-9 shows results for the August 28 Sunday event, while Table 4-10 shows results for the September 7 event, which can be considered a "typical" mid-summer weekday event. The tables show estimated reference loads, observed loads and estimated load impacts, temperature, and uncertainty-adjusted load impacts. PTR event hours are shaded.

Figures 4-10 and 4-11 illustrate the tabular results in graphic form, where load impacts are shown against the right vertical axis, and positive values represent load reductions. PTR event hours are indicated by the vertical lines. As reported above, the estimated load impacts over the seven-hour PTR events averaged 2.5 percent of the reference load for the August 28 event, and 4.5 percent for the September 7 event.

Table 4-9: Hourly Pilot-Level PTR-NT Loads and Load Impacts –
August 28 Event

Hour Ending	Estimated Reference Load (kWh/hour)	Observed Event Day Load (kWh/hour)	Estimated Load Impact (kWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (kWh/ hr)- Percentiles				
					10th%ile	30th%ile	50th%ile	70th%ile	90th%ile
1	1,969	1,972	-2	70	-75	-32	-2	28	71
2	1,736	1,762	-26	70	-98	-56	-26	3	45
3	1,553	1,623	-70	70	-142	-100	-70	-41	2
4	1,455	1,534	-79	69	-149	-108	-79	-50	-8
5	1,417	1,480	-62	68	-131	-90	-62	-34	7
6	1,424	1,438	-14	68	-84	-43	-14	14	55
7	1,517	1,495	22	69	-45	-5	22	49	89
8	1,732	1,757	-24	72	-92	-52	-24	3	43
9	2,108	2,154	-46	75	-112	-73	-46	-18	21
10	2,482	2,450	32	78	-33	5	32	58	96
11	2,819	2,735	84	80	20	58	84	110	147
12	3,052	2,956	96	80	33	70	96	122	159
13	3,359	3,174	186	83	121	159	186	212	250
14	3,539	3,417	121	83	56	95	121	148	186
15	3,769	3,654	114	83	49	87	114	141	180
16	3,816	3,774	41	82	-23	15	41	68	106
17	3,730	3,765	-35	80	-99	-61	-35	-9	29
18	3,796	3,687	109	78	45	83	109	136	174
19	3,584	3,541	43	75	-21	17	43	69	107
20	3,646	3,583	63	72	-3	36	63	89	128
21	3,631	3,622	9	71	-56	-18	9	36	74
22	3,295	3,237	58	70	-7	31	58	85	123
23	2,818	2,749	68	69	3	42	68	95	134
24	2,284	2,212	72	68	7	46	72	99	137
	Reference Energy Use (kWh)	Estimated Event Day Energy Use (kWh)	Change in Energy Use (kWh)	Cooling Degree Hours (Base 75 oF)	Uncertainty Adjusted Impact (kWh/ hour) - Percentiles				
					10th	30th	50th	70th	90th
Daily	64,531	63,771	760	52.2	n/a	n/a	n/a	n/a	n/a

Figure 4-10: Hourly Pilot-Level PTR-NT Loads and Load Impacts –
August 28 Event

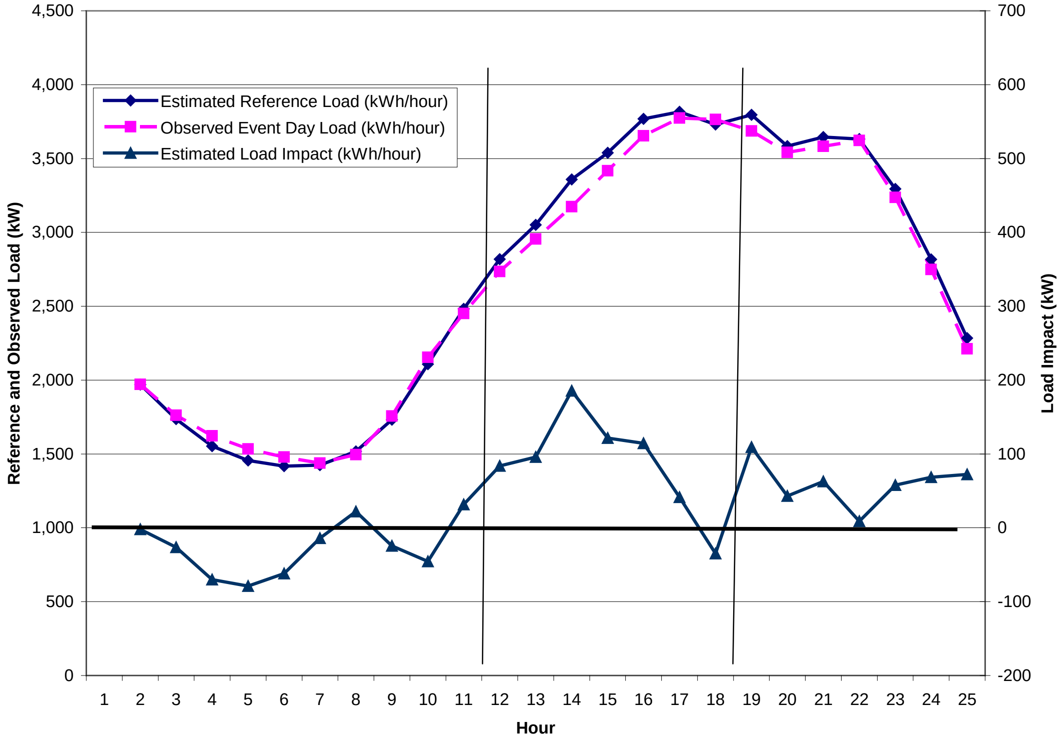


Table 4-10: Hourly Pilot-Level PTR-NT Loads and Load Impacts – *September 7 Event*

Hour Ending	Estimated Reference Load (kWh/hour)	Observed Event Day Load (kWh/hour)	Estimated Load Impact (kWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (kWh/ hr)- Percentiles				
					10th%ile	30th%ile	50th%ile	70th%ile	90th%ile
1	2,075	1,996	80	72	0	47	80	113	160
2	1,846	1,750	96	72	22	66	96	127	170
3	1,682	1,622	60	72	-16	29	60	91	137
4	1,546	1,554	-8	71	-83	-39	-8	23	67
5	1,504	1,513	-8	70	-83	-39	-8	22	67
6	1,623	1,612	10	70	-60	-18	10	39	80
7	1,869	1,896	-27	71	-93	-54	-27	0	39
8	1,953	1,971	-18	77	-91	-48	-18	12	55
9	2,031	1,940	91	82	20	62	91	120	162
10	2,217	2,128	89	87	16	59	89	119	162
11	2,573	2,467	105	89	37	77	105	134	174
12	2,925	2,774	151	90	80	122	151	180	222
13	3,322	3,145	177	89	109	149	177	205	245
14	3,518	3,339	179	89	111	151	179	206	246
15	3,630	3,491	139	87	73	112	139	166	205
16	3,860	3,638	222	88	156	195	222	250	289
17	3,954	3,784	170	88	99	141	170	199	240
18	4,077	3,968	109	86	39	81	109	138	180
19	4,072	3,993	80	83	8	50	80	109	151
20	4,232	4,086	146	81	63	112	146	180	228
21	4,227	4,157	69	79	-20	33	69	106	158
22	3,775	3,853	-78	78	-163	-113	-78	-43	7
23	3,213	3,193	20	74	-51	-9	20	49	91
24	2,526	2,503	23	71	-43	-4	23	50	89
	Reference Energy Use (kWh)	Estimated Event Day Energy Use (kWh)	Change in Energy Use (kWh)	Cooling Degree Hours (Base 75 oF)	Uncertainty Adjusted Impact (kWh/ hour) - Percentiles				
					10th	30th	50th	70th	90th
Daily	68,252	66,374	1,877	146.7	n/a	n/a	n/a	n/a	n/a

Figure 4-11: Hourly Pilot-Level PTR-NT Loads and Load Impacts – ***September 7 Event***

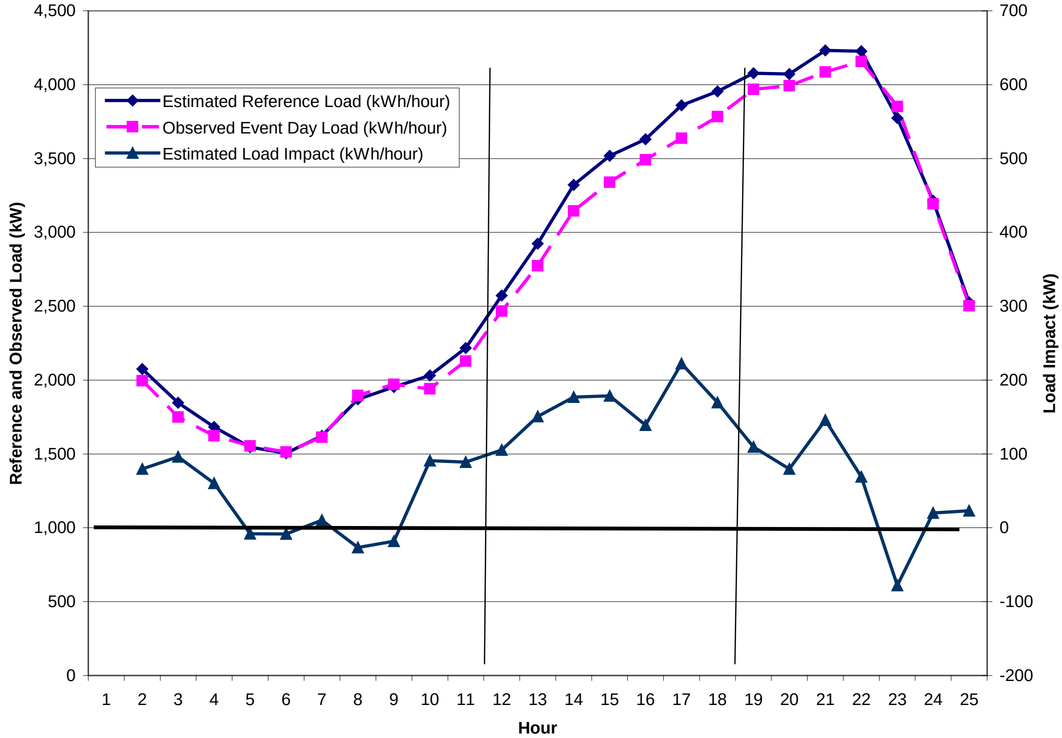


Table 4-11 shows loads and load impacts for the PTR-SS participants in the Inland climate zone for the August 28 PTR-only event, while Table 4-12 shows results for the September 7 joint PTR and SS event. Figures 4-12 and 4-13 illustrate the tabular results in graphic form.

Table 4-11: Hourly Pilot-Level PTR-SS Loads and Load Impacts (Inland) –
August 28 Event

Hour Ending	Estimated Reference Load (kWh/hour)	Observed Event Day Load (kWh/hour)	Estimated Load Impact (kWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (kWh/ hr)- Percentiles				
					10th%ile	30th%ile	50th%ile	70th%ile	90th%ile
1	62	69	-7	69	-19	-12	-7	-2	6
2	49	57	-7	69	-19	-12	-7	-2	5
3	48	50	-2	68	-14	-7	-2	3	10
4	45	45	0	67	-12	-5	0	5	12
5	45	42	3	68	-9	-2	3	8	16
6	51	45	6	68	-7	1	6	11	19
7	51	46	5	69	-7	0	5	10	16
8	77	51	26	72	15	22	26	31	37
9	76	69	7	78	-4	3	7	11	18
10	107	94	14	80	4	10	14	18	24
11	122	109	13	83	2	8	13	17	23
12	131	132	-1	83	-10	-5	-1	3	9
13	148	134	14	88	4	10	14	18	24
14	158	120	38	87	28	34	38	42	48
15	166	122	44	88	34	40	44	48	54
16	180	127	53	86	43	49	53	57	63
17	182	126	56	84	46	52	56	60	66
18	183	143	39	81	29	35	39	43	49
19	140	159	-19	77	-29	-23	-19	-15	-9
20	137	148	-11	74	-22	-16	-11	-7	-1
21	116	128	-11	72	-22	-15	-11	-7	-1
22	100	100	0	69	-10	-4	0	4	10
23	83	86	-3	69	-13	-7	-3	1	8
24	77	67	10	67	-1	5	10	14	20
	Reference Energy Use (kWh)	Estimated Event Day Energy Use (kWh)	Change in Energy Use (kWh)	Cooling Degree Hours (Base 75 oF)	Uncertainty Adjusted Impact (kWh/ hour) - Percentiles				
					10th	30th	50th	70th	90th
Daily	2,534	2,268	266	89.7	n/a	n/a	n/a	n/a	n/a

Figure 4-12: Hourly Pilot-Level PTR-SS Loads and Load Impacts (Inland) – *August 28 Event*

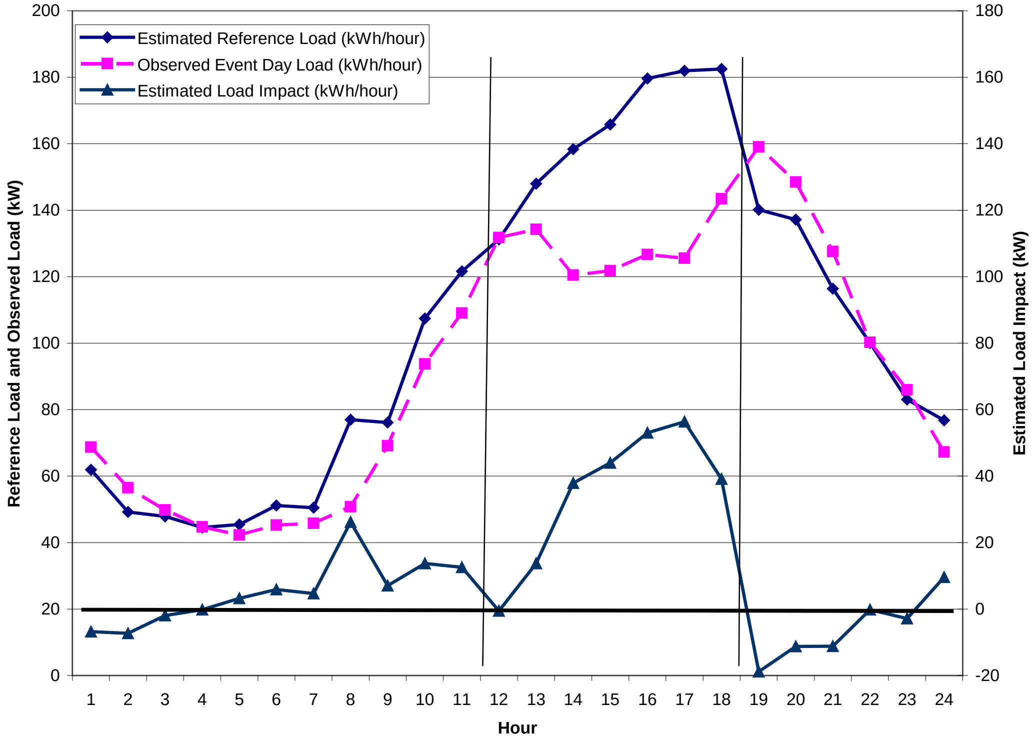
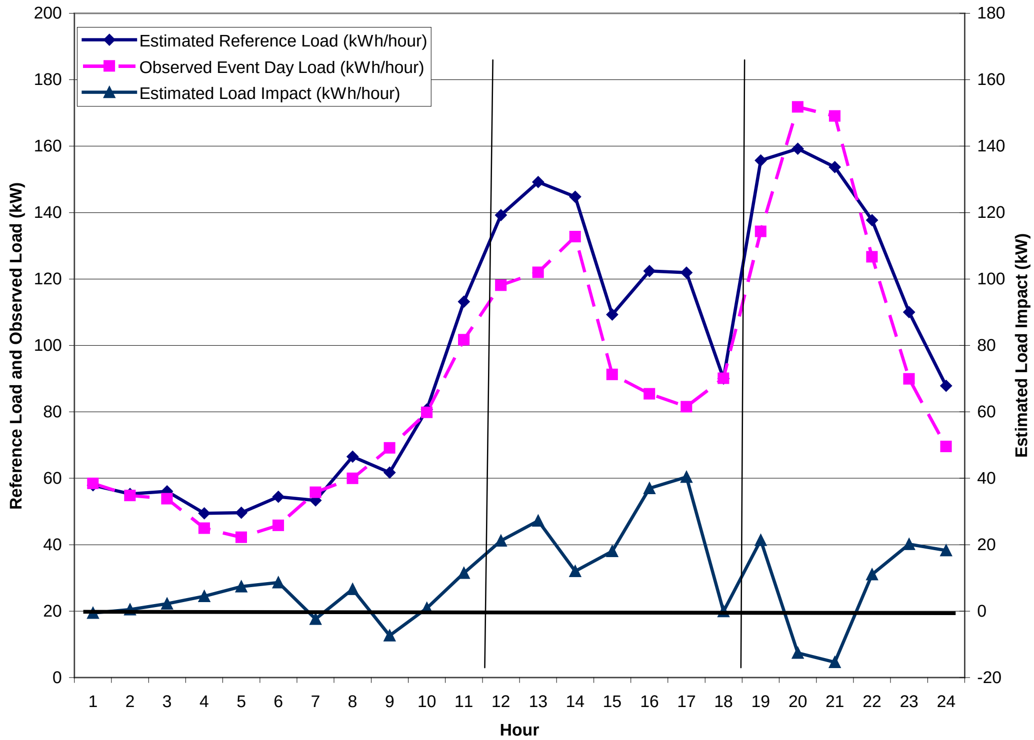


Table 4-12: Hourly Pilot-Level PTR-SS Loads and Load Impacts (Inland) – *September 7 Event*

Hour Ending	Estimated Reference Load (kWh/hour)	Observed Event Day Load (kWh/hour)	Estimated Load Impact (kWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (kWh/ hr)- Percentiles				
					10th%ile	30th%ile	50th%ile	70th%ile	90th%ile
1	58	58	-1	71	-13	-6	-1	5	12
2	55	55	0	71	-11	-4	0	5	12
3	56	54	2	71	-10	-3	2	7	15
4	49	45	5	70	-8	-1	5	10	17
5	50	42	7	70	-6	2	7	13	21
6	54	46	9	68	-3	4	9	13	20
7	53	56	-2	70	-13	-7	-2	2	8
8	67	60	7	77	-4	2	7	11	17
9	62	69	-7	83	-18	-12	-7	-3	4
10	81	80	1	89	-11	-4	1	6	13
11	113	102	11	92	0	7	11	16	23
12	139	118	21	96	9	16	21	26	33
13	149	122	27	95	16	23	27	32	38
14	145	133	12	95	1	8	12	16	23
15	109	91	18	93	8	14	18	22	28
16	122	85	37	92	27	33	37	41	47
17	122	82	40	91	30	36	40	45	51
18	90	90	0	88	-11	-4	0	4	11
19	156	134	21	82	11	17	21	26	32
20	159	172	-13	80	-24	-17	-13	-8	-1
21	154	169	-15	77	-27	-20	-15	-11	-4
22	138	127	11	76	-1	6	11	16	23
23	110	90	20	74	9	16	20	25	31
24	88	70	18	69	8	14	18	22	29
	Reference Energy Use (kWh)	Estimated Event Day Energy Use (kWh)	Change in Energy Use (kWh)	Cooling Degree Hours (Base 75 oF)	Uncertainty Adjusted Impact (kWh/ hour) - Percentiles				
					10th	30th	50th	70th	90th
Daily	2,379	2,149	230	181.9	n/a	n/a	n/a	n/a	n/a

Figure 4-13: Hourly Pilot-Level PTR-SS Loads and Load Impacts (Inland) – *September 7 Event*



5. Validity Assessment

We examined several methods for estimating *ex post* load impacts. First, we estimated the typical customer-level regression models in which each customer's non-event day loads (controlling for differences in day-type and weather conditions) serve as the event-day reference loads. Because of the absence of hot non-event days, this approach produced results that were not reasonable based on our review of the raw observed load data. The presence of a control group gave us the flexibility to try alternative approaches. We first examined whether we could estimate load impacts by simply comparing PTR and control-group customer loads. Because of some persistent differences in non-event day loads between the two groups, we determined that this approach was not ideal.

In our implemented approach, we estimate load impacts based on the difference between PTR and control-group customer loads, controlling for differences in usage levels and patterns across day types, months, and varying weather conditions. The remainder of this section describes the performance of these models.

Table 5-1 shows the R-squared values for each of the cell-level models used to estimate *ex post* load impacts. Many of these values appear somewhat low compared to the R-squared values obtained in models of the *level* of customer usage. In those models, the daily patterns and effects of weather are somewhat regular, so R-squared values in excess of 0.95 are common. In this case, where we estimate drivers of the *difference* between the level of treatment and control usage, the effects are less regular. Even so, it is clear from the results that the models are effective in controlling for differences between PTR and control-group usage patterns, as the R-squared value (averaged across cells using population weights) is 0.346 with the non-event variables included, but 0.063 with only the event variables in the model.

Table 5-1: R-squared Values from *Ex post* Load Impact Regression Models of Differences between Participant and Control Group Loads

Sample Cell	R^2, NT Model	R^2, SS Model
Coastal, High Use	0.535	n/a
Coastal, Medium Use	0.249	n/a
Coastal, Low Use	0.345	n/a
Mountain, High Use	0.499	n/a
Mountain, Medium Use	0.280	n/a
Mountain, Low Use	0.269	n/a
Desert, High Use	0.740	n/a
Desert, Medium Use	0.327	n/a
Desert, Low Use	0.753	n/a
Inland, High Use	0.328	0.396
Inland, Medium Use	0.419	0.373
Inland, Low Use	0.343	n/a

We conducted additional tests in order to demonstrate the predictive accuracy of the regression models. To do so, we selected five hot non-event days to serve as proxies for event days.[40] That is, the ability of the model to accurately predict the difference between PTR and control-group loads on these days may be indicative of its ability to perform well on event days (for which we do not have the "true" answer).

For each cell (of which there are 12 for NT and 2 for SS), we estimate five models. In each of these models, one of the five "test" days is withheld from the sample, and the estimated model parameters are used to predict the usage difference (*i.e.*, the dependent variable) for that day. The difference between the observed value and the predicted value for the test days provides a means of assessing the model's accuracy.

Figure 5-1 graphs the predicted versus actual values for differences between PTR-NT and Control-NT (*i.e.*, non-Summer Saver) customers, where the results are averaged across the five test days and all cells (using sample weights). The same information is presented in tabular form in Table 5-2. The average prediction error during the event window is 0.003 kW. This error is quite small compared to the average estimated load impact from September 7 of 0.056 kW.

[40] The selected days are: July 7, July 25, August 1, August 2, and August 25. As noted in Section 2.3, the hottest days were all event days, so these "test" days were selected from the next-hottest group of days.

Figure 5-1: Predicted versus actual difference between PTR and control-group usage, NT customers

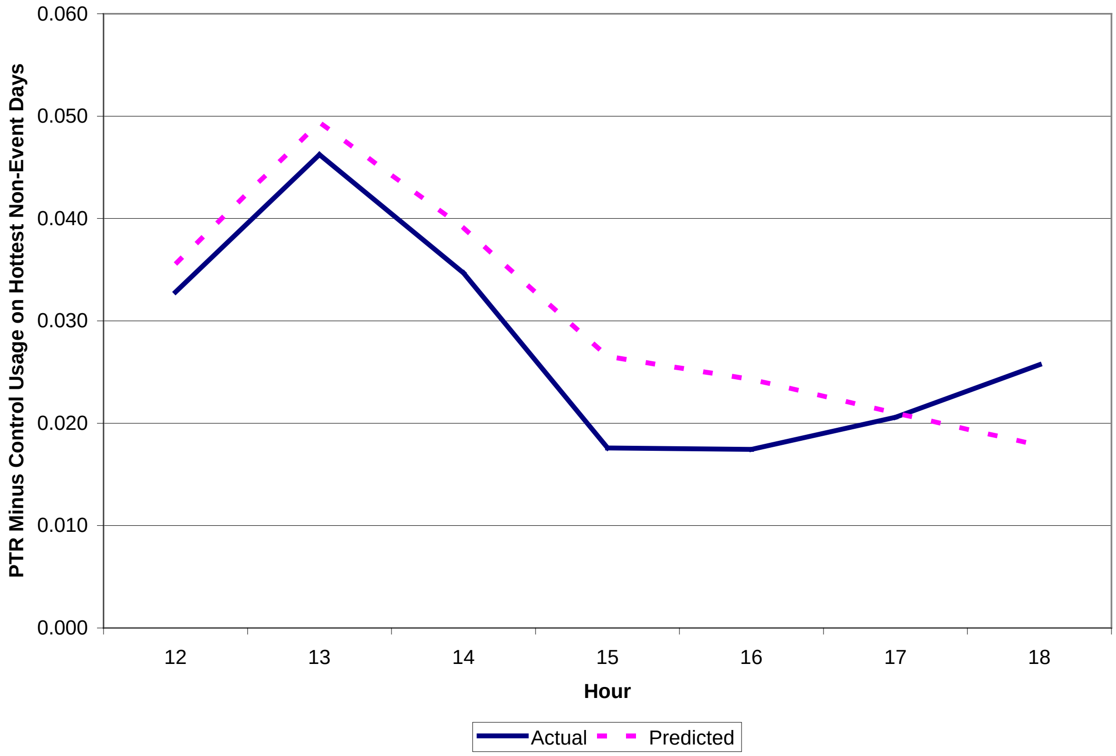


Table 5-2: Predicted versus actual difference between PTR and control-group usage, NT customers

Hour Ending	Observed	Predicted
12	0.033	0.036
13	0.046	0.049
14	0.035	0.039
15	0.018	0.027
16	0.017	0.024
17	0.021	0.021
18	0.026	0.018
Average	**0.028**	**0.031**
Number of customers by group: PTR-NT = 2,907 Control-NT = 2,240		

Figure 5-2 presents the results for the medium- and high-use Summer Saver customers in the Inland region. The same information is presented in tabular form in Table 5-3. In this case, the results indicate a larger error rate during the event window of 0.029 kW. However, the average error is still low compared to the estimated load impact on September 7 of 0.36 kW. In addition, a substantial portion of the error appears to be due to a bad prediction on only one of the test days (August 2). In the absence of this day, the average event-hour error is reduced to 0.006 kW.

Figure 5-2: Predicted versus actual difference between PTR and control-group usage, SS customers

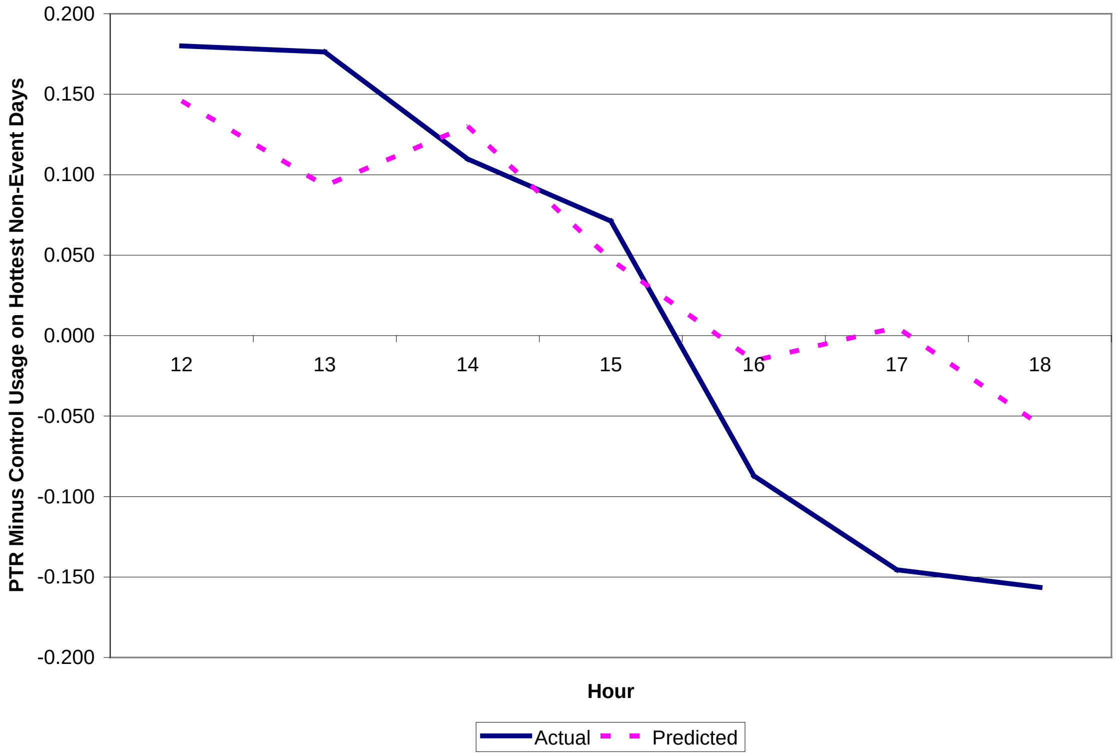


Table 5-3: Predicted versus actual difference between PTR and control-group usage, SS customers

Hour Ending	Observed	Predicted
12	0.180	0.146
13	0.176	0.093
14	0.110	0.130
15	0.071	0.047
16	-0.087	-0.016
17	-0.145	0.005
18	-0.156	-0.055
Average	**0.021**	**0.050**
Number of customers by group: PTR-SS = 61 Control-SS = 50		

The specification tests described in this section indicate that the methods used to estimate the *ex post* load impacts are reliable.

6. *Ex Ante* Load Impact Forecasts

The ex-ante forecast for PTR in 2011 is unique due to SDG&E's plans to automatically enroll all of its approximately 1.2 million residential customers (with limited exceptions) in the program beginning in June 2012, under the name "Reduce Your Use Rewards." In this first *ex ante* forecast for the program, SDG&E is assuming that half of the enrolled customers will become *aware* of the program, and thus be likely to reduce usage when events are called. This section provides load impact forecasts under those assumptions, using information from the ex post evaluation and, in some cases, the California Statewide Pricing Pilot (SPP) conducted in 2003 and 2004. This section describes the *ex ante* load impact requirements, methods used, assumptions made, and the resulting load impact forecasts.[41]

6.1 Ex Ante Load Impact Requirements

The DR Load Impact Evaluation Protocols require that hourly load impact forecasts for event-based DR resources must be reported at the program level and by Local Capacity Area (LCA)[42] for the following scenarios:

- For a typical event day in each year; and
- For the monthly system peak load day in each month for which the resource is available;

under both:

- 1-in-2 weather-year conditions, and
- 1-in-10 weather-year conditions.

at both:

- the program level (*i.e.*, in which only the program in question is called), and
- the portfolio level (*i.e.*, in which all demand response programs are called).

6.2 Description of Methods

This section describes the methods used to develop reference loads for the relevant customer base and event day-types, and to develop percentage load impacts for a typical event day.

6.2.1 Development of Reference Loads and Load Impacts

Reference loads and load impacts for all of the required factors were developed in the following series of steps:

1. Define data sources

[41] Ex ante load impacts are provided only for PTR-NT customers due to the small number of PTR-SS customers that participated in the pilot, and the fact that a separate evaluation of Summer Saver is conducted.
[42] SDG&E's entire service area is considered to be one LCA.

2. Estimate ex ante regressions and simulate reference loads by cell and scenario
3. Calculate percentage load impacts by cell
4. Apply percentage load impacts to the reference loads
5. Scale the reference loads using enrollment forecasts

Each of these steps is described below.

Define data sources
Reference loads are developed using data for customers enrolled in the PTR pilot during 2011. The percentage load impacts that are applied to the reference loads to create hourly load impacts are based upon a combination of the *ex post* load impacts from the 2011 ex post evaluation and simulations using the SPP load impact models.[43]

Simulate reference loads
In order to develop reference loads, we first re-estimated regression equations for the average customer in each cell defined by climate zone. Separate equations were estimated for the summer months of May through October, and for the remaining non-summer months. These equations were then used to simulate reference loads by customer type under the various scenarios required by the Protocols (*e.g.*, the typical event day in a 1-in-2 weather year).

For the summer months, the re-estimated regression equations were similar in design to the *ex post* load impact equations described in Section 3.2, except that they were estimated for levels of hourly usage by participants rather than for differences relative to control group customers.

Because PTR events may be called in any month of the year, we estimated separate regression models to allow us to simulate non-summer reference loads. The non-summer model is shown below.

$$Q_t = a + \sum_{i=1}^{24}(b_i^{CDD} \times h_{i,t} \times CDD_t) + \sum_{i=1}^{24}(b_i^{HDD} \times h_{i,t} \times HDD_t) + \sum_{i=2}^{24}(b_i^{MON} \times h_{i,t} \times MON_t) + \sum_{i=2}^{24}(b_i^{FRI} \times h_{i,t} \times FRI_t)$$
$$+ \sum_{i=2}^{24}(b_i^{h} \times h_{i,t}) + \sum_{i=2}^{7}(b_i^{DTYPE} \times DTYPE_{i,t}) + \sum_{i=1-5,12}(b_i^{MONTH} \times MONTH_{i,t}) + e_t$$

In this equation, Q_t represents the demand in hour t for a customer enrolled in PTR prior to the last event date; the b's are estimated parameters; $h_{i,t}$ is a dummy variable for hour i; CDD_t is cooling degree days; HDD_t is heating degree days;[44] MON_t is a dummy variable for Monday; FRI_t is a dummy variable for Friday; $DTYPE_{i,t}$ is a series of dummy

[43] The California SPP included a voluntary CPP rate for residential and small commercial customers, as well as a TOU rate, an information-only component, and a residential enabling technology component. Customers' price response was modeled by a demand model for which an elasticity of substitution and overall elasticity were estimated. In this study, we used the relevant model for voluntary CPP.
[44] Heating degree days (HDD) was defined as MAX[0, 60 – (MaxT + MinT) / 2], where MaxT is the daily maximum temperature and MinT is the daily minimum temperature, both expressed in degrees Fahrenheit. Customer-specific HDD values are calculated using data from the most appropriate weather station.

variables for each day of the week; $MONTH_{i,t}$ is a series of dummy variables for each month; and e_t is the error term.

Once these models were estimated, we simulated 24-hour load profiles for each required scenario. The typical event day was assumed to occur in August. Much of the differences across scenarios can be attributed to varying weather conditions.

Calculate forecast percentage load impacts
The primary basis for the ex ante percentage load impacts is the ex post load impacts from the September 7th event day. This event day is most representative of our expectation for future event days. The other event days were unusual for various reasons (occurring on a weekend, during an outage, or during an unusually hot period in October).

To account for the effect of changing weather conditions and seasons on customer price responsiveness, we varied the hourly percentage load impacts from September 7th using the estimated elasticity of substitution equations from the SPP. In those equations, the elasticity of substitution varies with the weather conditions (the difference between peak and off-peak cooling degree hours), the central air conditioning saturation rate, and season (summer, winter, and "inner" winter).

Using these SPP equations, we simulated the elasticity of substitution for the September 7th event day using the conditions from that day. We then performed the same calculation for each of the Protocol scenarios. The hourly percentage load impacts for each Protocol scenario were then calculated as the ex post September 7th percentage load impacts multiplied by the ratio of the SPP elasticity of substitution for the Protocol day divided by the value for September 7th.

In addition, the percentage load impacts were adjusted to account for differences in historical and forecast customer awareness. To do this, we multiplied the percentage load impact by the ratio of forecast awareness (which is 50 percent throughout the forecast period) to the awareness rate of 63 percent estimated by Research Into Action in the process evaluation of the pilot.

In equation form:

$$\%LI_h^P = (\varepsilon_s^P / \varepsilon_s^{Sep7}) \text{ x } (Aware^F / Aware^{2011}) \text{ x } \%LI_h^{Sep7}$$

In this equation, $\%LI_h^P$ is the percentage load impact in hour h of Protocol scenario P; ε_s^P is the elasticity of substitution calculated from the SPP for Protocol scenario P; ε_s^{Sep7} is the elasticity of substitution calculated from the SPP for the conditions on the September 7th event day; $Aware^F$ is the forecast awareness rate; $Aware^{2011}$ is the awareness rate estimated for 2011; and $\%LI_h^{Sep7}$ is the ex post percentage load impact estimated for hour h of the September 7th event day. During the summer months, the adjustment factor (ε_s^P / ε_s^{Sep7}) ranges from 0.777 to 1.032. During the non-summer months, it ranges from 0.258 to 0.559.

The uncertainty-adjusted scenarios of load impacts were developed directly from the ex post load impacts scenarios from the September 7th event. That is, the percentage load impacts for each of the 10th, 30th, 50th, 70th, and 90th scenarios from that event day were adjusted using the ε_s ratio method described above.

Finally, the percentage load impacts are shifted to account for the event windows required by the Protocols, which are 1:00 to 6:00 p.m. from April through October and 4:00 to 9:00 p.m. in all other months. The event window is reduced from the historical window of seven hours to the forecast window of five hours as follows: the 2nd and 3rd hours of the historical window are averaged together to form the 2nd hour of the forecast window; and the 4th and 5th hours of the historical window are averaged together to form the 3rd hour of the forecast window. To account for the timing of the window, the load impacts are shifted back two hours (for April through October) to four hours (for all other months), with zero load impact values inserted at the beginning of the day.

Apply percentage load impacts to reference loads for each event scenario. In this step, the percentage load impacts were applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts.

Apply forecast enrollments to produce program-level load impacts. SDG&E provided enrollment forecasts representing the eligible residential customers who will be automatically enrolled in PTR, and assumptions regarding the percentage of “aware” customers (50%). Program-level results were obtained by aggregating results across cells.

6.3 Enrollment Forecasts

Table 6-1 shows enrollment forecasts provided by SDG&E, which represent forecasts of numbers of residential customers. The following section describes the resulting reference loads and ex ante load impact forecasts. Detailed tables of all results required by the Protocols are provided in associated appendices.

Table 6-1: PTR Enrollment Forecast

Year	Residential Customers	Awareness forecast PTR	Aware Customers
2012	1,242,221	50%	621,111
2013	1,253,235	50%	626,617
2014	1,267,145	50%	633,572
2015	1,282,580	50%	641,290
2016	1,298,021	50%	649,010
2017	1,313,097	50%	656,549
2018	1,327,797	50%	663,898
2019	1,342,345	50%	671,173
2020	1,356,822	50%	678,411
2021	1,371,138	50%	685,569

6.4 Reference Loads and Load Impacts

We provide the following illustrative information regarding the load impact forecasts, including the hourly profile of reference loads and load impacts for typical event days; and the pattern of estimate load impacts across months. Figure 6-1 shows estimated reference load, event-day load, and load impacts (right axis) for the average enrolled PTR customer on the August peak day in 2014 in the 1-in-2 weather scenario. Following the pattern of *ex post* load impacts, the estimated load reductions extend somewhat beyond the *ex ante* event window of 1 p.m. to 6 p.m. (shown by the vertical lines).

Figure 6-1: PTR Reference Load and Load Impacts per Enrolled Customer –
(August Peak Day; 2014; 1-in-2 Weather Scenario)

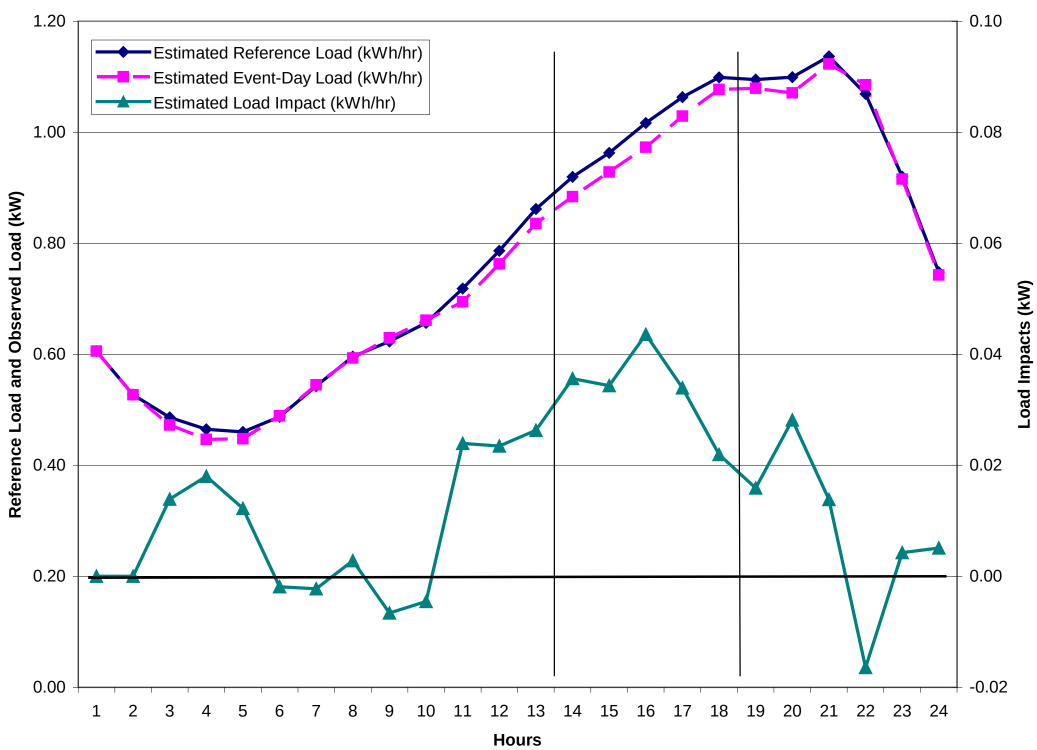
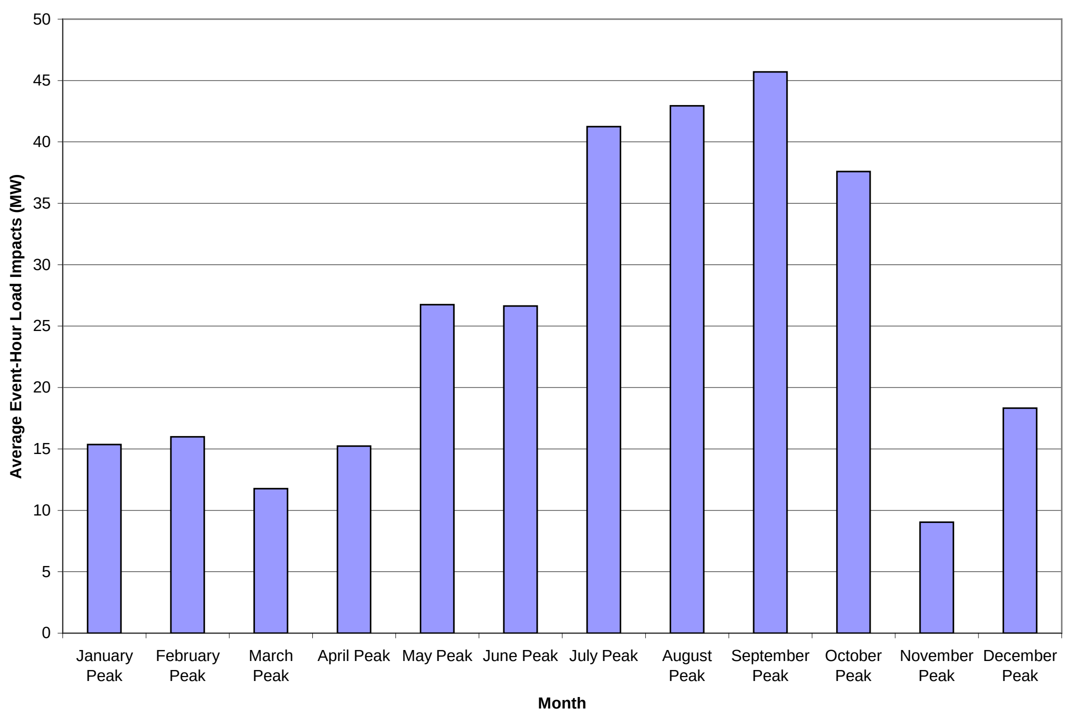


Table 6-2 reports program-level average event-hour usage reductions by month and year, for 1-in-2 weather years, in units of MW. Usage reductions are greatest during the summer months set off by the top two horizontal lines.[45] Aggregate usage reductions grow somewhat over time along with numbers of residential customers. Figure 6-2 illustrates the pattern of average event-hour load impacts across months in 2014 in a 1-in-2 weather year. As noted above, estimated load impacts are greatest during summer months, reaching their highest level in September.

Table 6-2: PTR Program-Level Average Event-Hour Load Impacts -- by Month and Year; *1-in-2 Weather Scenario (MW)*

Month / Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
January Peak	15.0	15.1	15.3	15.5	15.7	15.8	16.0	16.2	16.4	16.5
February Peak	15.8	16.0	16.1	16.3	16.5	16.7	16.9	17.1	17.3	17.5
March Peak	11.6	11.7	11.8	11.9	12.1	12.2	12.4	12.5	12.6	12.8
April Peak	14.4	14.5	14.7	14.9	15.1	15.2	15.4	15.6	15.7	15.9
May Peak	26.2	26.5	26.7	27.1	27.4	27.7	28.0	28.3	28.6	28.9
June Peak	26.1	26.3	26.6	27.0	27.3	27.6	27.9	28.2	28.5	28.8
July Peak	40.4	40.8	41.2	41.7	42.2	42.7	43.2	43.7	44.2	44.6
August Peak	42.1	42.5	42.9	43.5	44.0	44.5	45.0	45.5	46.0	46.5
September Peak	44.8	45.2	45.7	46.3	46.8	47.4	47.9	48.4	48.9	49.5
October Peak	36.8	37.2	37.6	38.0	38.5	38.9	39.4	39.8	40.2	40.7
November Peak	8.8	8.9	9.0	9.1	9.2	9.3	9.4	9.5	9.6	9.7
December Peak	18.0	18.2	18.4	18.6	18.9	19.1	19.3	19.5	19.7	19.9
Typical Event Day	41.4	41.8	42.2	42.7	43.3	43.8	44.3	44.7	45.2	45.7

Figure 6-2: PTR Program-Level Average Event-Hour Load Impacts: by Monthly Peak Day *(2014; 1-in-2 Weather Scenario)*[46]



[45] Averages are taken over hours 1 p.m. to 6 p.m. in summer months, and 4 p.m. to 9 p.m. in non-summer months.

[46] *Ex ante* event hours are 1 p.m. – 6 p.m. in summer and 4 p.m. – 9 p.m. in non-summer months.

All of the tables required by the DR Protocols are provided in an Appendix.

7. Conclusions and Recommendations

This evaluation was complicated by the unusual characteristics of the five 2011 PTR event days. For example, events were called on essentially all of the hot days of the summer; one of the events that would otherwise have provided useful data was interrupted by a system-wide outage; and two of the events were called in mid-October, when air conditioning use patterns appear to differ substantially from those of the core summer months. On the positive side, the evaluation was greatly facilitated by the presence of a representative control group of customers similar to the PTR participants, which provided valuable information on what PTR loads likely would have been on the high-temperature event days had the events not been called.

Some of these factors do not lead directly to recommendations for future program years. For example, we do not recommend that SDG&E call its event days in such a way as to facilitate *ex post* load impact evaluations (*e.g.*, by not calling events on some of the very hot days). At the same time, under different weather patterns at least some non-event days may be available that are more similar to the event days than in 2011. In addition, it may be difficult or impossible to maintain a control group in future years as PTR is rolled out as an automatic enrollment program. Any customers withheld from PTR would likely become aware of event-days given SDG&E's need to notify all of its residential customers, thus limiting their value as members of an unaffected control group.

It is quite possible that the issues we encountered this year will not be present in future program years. For example, as more customers are added to PTR, the precision of the estimated load impacts will improve, thus allowing for the estimation of even relatively small impacts. In addition, the magnitude of the load impacts themselves may be expected to improve as awareness and education levels are increased over time. Either of these conditions would facilitate the estimation of future *ex post* load impacts.

Finally, based on the results of the comparisons of usage changes that are estimated by the regression-based approach and by the program CRL baseline method, we suggest that it would be useful to conduct a separate study of the baseline issue for measuring PTR usage changes. This would involve a more detailed investigation of the usage patterns of the PTR pilot customers than was possible within the time and resources of this evaluation, and an evaluation of alternative baseline methods, including day-of adjustments, that might more accurately measure usage changes.

Appendices

The following Appendices accompany this report. Each is a Microsoft Excel file that can produce the *ex post* tables required by the Protocols.

Appendix A: *Ex post* Load Impact Tables (PTR-NT)
Appendix B: *Ex post* Load Impact Tables (PTR-SS)
Appendix C: *Ex ante* Load Impact Tables