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2012 Ex Post and Ex Ante Load Impact Evaluation of San Diego Gas & Electric Company's Summer Saver Program and Peak Time Rebate Program for Summer Saver Customers

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1 Executive Summary

San Diego Gas and Electric Company's (SDG&E) Summer Saver program is a demand response resource based on central air conditioner (CAC) load control. It is implemented through an agreement between SDG&E and Comverge Inc., and is currently scheduled to continue through 2016. SDG&E's Peak Time Rebate (PTR) program is a demand response resource available to nearly all residential and small commercial customers in SDG&E's territory. Under PTR, customers receive payments if they curtail loads on PTR event days as compared to a baseline.[1] This report provides ex post load impact estimates for the 2012 Summer Saver program and ex ante load impact forecasts for 2013 through 2023. This report also provides ex post and ex ante load impacts of PTR for Summer Saver Customers.

The Summer Saver program is available to residential customers and commercial facilities with average monthly peak demand up to a maximum of 100 kW over a 12-month period. The Summer Saver season runs from May 1 through October 31 and does not notify participating customers of an event. A Summer Saver event may be triggered if warranted by temperature and system load conditions.

There are four enrollment options each for both residential and commercial customers. Residential customers can choose to be cycled 50% or 100% of the time, and can have cycling occur only on weekdays or on weekends as well. Commercial customers have an option of choosing 30% or 50% cycling, on weekdays only or for seven days a week. The incentive paid for each option varies and is based on the number of CAC tons being controlled at each site.

As of the end of 2012 there were 27,699 premises enrolled in the program, which in aggregate have 142,283 tons of CAC capacity. About 83% of participants were residential customers, who account for 69% of the total tons of cooling in the program. Roughly 53% of residential participants are on the 100% cycling option. Approximately 66% of commercial customers have selected the 50% cycling option over the 30% option. Summer Saver enrollment is expected to stay roughly the same for the foreseeable future.

In 2012, the Summer Saver program provided an average of about 19 MW of demand response over 8 events.[2] Commercial customers provided an average of about 3 MW, and residential customers provided about 16 MW. Due to weather and seasonal conditions, events in 2012 did not provide the amount of demand response that might be expected under more severe heat. The average temperature during the average event was 88°F, as compared to ex ante event temperatures, which can be in the mid 90s. Under 1-in-10 September weather conditions (the hottest conditions currently modeled), it is expected that the program could provide up to 25 MW of demand response on average over a 1-6 PM event.

[1] PTR is available to residential customers receiving electric bundled service under a rate schedule that requires separate metering. PTR is available to small commercial customers on Schedule A – General Service. A full program description of PTR and analysis of the broader program can be found in the *2012 Load Impact Evaluation of SDG&E's Residential PTR Program* and the *2012 Load Impact Evaluation of SDG&E's Small Commercial PTR Program*, both by Christensen Associates.

[2] The average event reflects the average 2-hour event from 2-4 PM, omitting the August 10 event, which did not contain overlapping hours and the September 15 weekend event.

This is the second Summer Saver evaluation that has been performed using smart meter interval data exclusively. The prevalence of smart meters in the Summer Saver population allows for results to be more representative of the entire Summer Saver population because load data is available for a greater number of customers. Using smart meter data can also reduce the cost of evaluation because they do not require the installation of CAC load loggers. In this evaluation, the implementation of a treatment-control design in conjunction with the use of smart meter data provided for a streamlined evaluation process for residential customers. For these customers, ex post impact estimates were available as soon as the smart meter data became available. Due to the small size of the commercial customer sample and more variability in the data, more complicated analysis methods were used that rely on additional assumptions.

In 2012, the PTR program for Summer Saver customers did not produce statistically significant load impacts over seven events. While Summer Saver customers may respond to PTR events, the methods available for this evaluation are not sufficient to separate impacts from noise. However, an analysis of load impacts for residential Summer Saver customers who received PTR alerts did produce significant impacts. These 2,917 customers provided an estimated average load impact of about 1 MW across the 7 PTR event days, or 23% of the reference load. Enrollment in PTR alerts is expected to grow. By 2015, the forecast 4,156 enrolled customers are expected to provide approximately 1.8 MW of demand reductions under 1-in-10 weather conditions on a typical event day.

2 Introduction and Program Summary

SDG&E's Summer Saver program is a demand response resource based on CAC load control. It is implemented through an agreement between SDG&E and Alternative Energy Resources (AER), a subsidiary of Comverge Inc.,[3] and is currently scheduled to continue through 2016. This report provides ex post load impact estimates for 2012 for Summer Saver and for PTR for Summer Saver customers, as well as ex ante load impact forecasts for 2013 through 2023 for Summer Saver and PTR for Summer Saver Customers.

2.1 Program Overview

The Summer Saver program is available to residential customers and commercial facilities with average monthly peak demand up to a maximum of 100 kW over a 12-month period. For both residential and commercial customers enrolled in the program, events may be called between May 1 and October 31. Customers can elect to be eligible for events on weekdays only or on weekdays and weekends. Events must be between 2-hours and 4-hours in duration and cannot be called for more than 40 hours per month or 120 hours per year. Event days cannot include holidays or be called on more than three days in any calendar week.

Summer Saver is classified as a *day-of* demand response program and does not notify participating customers when an event is being called. SDG&E may call an event whenever the utility's electric system supply portfolio reaches resource dispatch equivalence of 15,000 Btu/kWh heat rate, or as utility system conditions warrant. A Summer Saver event may also be triggered as warranted by extreme system conditions, such as: special alerts issued by the California Independent System Operator; SDG&E system emergencies related to grid operations; conditions of high forecasted California spot market prices; or for testing or evaluation purposes.

There are four enrollment options each for residential and commercial customers. Residential customers can choose to be cycled 50% or 100% of the time during an event and can have cycling occur only on weekdays or on both weekdays and weekends. The incentive paid for each option varies; the 50% cycling option pays $11.50/ton of CAC capacity and the 100% cycling option pays $46/ton. The 7-day option pays an extra $10 compared to the weekday-only option. Thus, a residential customer with a 4-ton CAC (which is close to the average) would be paid the following under each option:

- $46 for the summer for the weekday, 50% cycling option;
- $56 for the 7-day, 50% cycling option;
- $184 for the weekday only, 100% cycling option; or
- $194 for the 7-day, 100% cycling option.

Commercial customers have an option of choosing 30% or 50% cycling, on weekdays only or for seven days a week. The incentive payment equals $9/ton for the 30% cycling option and $15/ton for the 50% cycling option. As for residential customers, the incremental payment for the 7-day a week

[3] SDG&E's contract with Comverge Inc. was amended in 2007 to reflect that the agreement is thereafter recognized to be between a subsidiary of Comverge Inc., AER and SDG&E. In this document, the company is referred to as Comverge Inc. for convenience.

option compared with the weekday-only option is $10. The average commercial participant has roughly nine enrolled tons of CAC (although some participants have significantly more). As such, the incentive payment for the average commercial customer under each enrollment option is as follows:

- $81 for the summer for the weekday, 30% cycling option;
- $91 for the 7-day, 30% cycling option;
- $135 for the weekday only, 50% cycling option; or
- $145 for the 7-day, 50% cycling option.

Enrollment in the Summer Saver program is summarized in Table 2-1. Total enrollment, as measured by number of customers, number of devices or enrolled tons, has decreased 6-7% since fall 2011. As of November 2012, there are 27,699 customers enrolled in the program, which in aggregate had 142,283 tons of CAC capacity. About 83% of participants were residential customers who accounted for 69% of the total tons of cooling subject to control under the program. About 53% of residential participants were on the 100% cycling option and roughly 66% of commercial customers were on the 50% cycling option. Summer Saver enrollment is expected to remain roughly constant in the immediate future.

Table 2-1: Summer Saver Enrollment, November 2012

Customer Type	Cycling Option	Enrolled Customers	Enrolled Control Devices	Enrolled Tons
Commercial	30%	1,621	4,031	15,091
	50%	3,150	7,635	29,026
	Total	4,771	11,666	44,117
Residential	50%	10,678	12,541	43,823
	100%	12,250	15,103	54,343
	Total	22,928	27,644	98,166
Grand Total		**27,699**	**39,310**	**142,283**

2.2 Ex Post Load Impact Estimates

Eight Summer Saver events were called in 2012. The events ranged in length from 2 to 4 hours and were called as early as 12 PM and as late as 4 PM. Table 2-2 shows the load impacts (averaged across each event hour) for each 2012 event day for residential customers and the ex post impact estimates from 2011 for comparison. In 2012, Summer Saver residential customers delivered an average aggregate load reduction over the 8 events of 16 MW. Residential impacts ranged from a low of 9 MW on September 15, to a high of 19 MW on August 13 and September 14. The September 15 event was only called for residential customers who are signed up for both weekday and weekend events, 6,381 customers, or about 28% of the residential Summer Saver population. There were 1,379 residential customers in the sample used to calculate ex post impacts.

Table 2-2: Summer Saver Residential Ex Post Impact Estimates

Year	Date	Impact			Temperature During Event
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2011	26-Aug-11	0.34	0.41	10	85
	7-Sep-11	0.64	0.77	19	90
	8-Sep-11	0.66	0.79	19	93
	9-Sep-11	0.2	0.24	6	73
	12-Oct-11	0.4	0.49	12	93
	13-Oct-11	0.62	0.74	18	89
	Average	0.48	0.57	14	87
2012	8-Aug-12	0.47	0.55	13	86
	10-Aug-12	0.55	0.65	15	82
	13-Aug-12	0.70	0.83	19	88
	17-Aug-12	0.62	0.73	17	87
	13-Sep-12	0.45	0.53	12	80
	14-Sep-12	0.69	0.81	19	100
	15-Sep-12	1.18	1.35	9	95
	1-Oct-12	0.54	0.64	15	86
	Average*	0.61	0.72	16	89

*reflects the average 2-hour event from 2-4 PM, omitting the Aug. 10 and Sept. 15 events.

Table 2-3 shows ex post load impact estimates for commercial customers for each 2012 event day and ex post estimates for 2011 events for comparison. Aggregate load impacts varied from a low of about 1 MW on August 8, September 13 and September 15 to a high of roughly 6 MW on August 17. The average event impact across all of the 2012 weekday events from 2-4 PM was 0.61 kW per premise, which translated to about 3 MW for the 4,771 customers in the commercial population. There were 393 commercial customers in the sample used to calculate ex post impacts.

Table 2-3: Summer Saver Commercial Ex Post Impact Estimates

Year	Date	Impact			Temperature During Event
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2011	26-Aug-11	0.34	0.89	4	82
	7-Sep-11	0.31	0.79	4	89
	8-Sep-11	0.38	0.98	5	91
	9-Sep-11	0.16	0.42	2	71
	12-Oct-11	0.29	0.75	4	92
	13-Oct-11	0.26	0.67	3	86
	Average	0.29	0.75	4	85
2012	8-Aug-12	0.14	0.29	1	84
	10-Aug-12	0.37	0.76	4	81
	13-Aug-12	0.26	0.53	3	86
	17-Aug-12	0.61	1.24	6	86
	13-Sep-12	0.06	0.13	1	78
	14-Sep-12	0.39	0.82	4	96
	15-Sep-12	0.70	1.34	1	95
	1-Oct-12	0.35	0.72	3	84
	Average*	0.30	0.62	3	86

*reflects the average 2-hour event from 2-4 PM, omitting the Aug. 10 and Sept. 15 events.

Table 2-4 shows ex post load impact estimates for the whole program for 2012.

Table 2-4: Summer Saver Program Ex Post Impact Estimates

Date	Impact			Temperature During Event
	Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
8-Aug-12	0.37	0.51	14	86
10-Aug-12	0.50	0.67	19	82
13-Aug-12	0.57	0.78	21	88
17-Aug-12	0.62	0.82	23	87
13-Sep-12	0.33	0.46	13	80
14-Sep-12	0.60	0.81	23	99
15-Sep-12	1.07	1.35	9	95
1-Oct-12	0.49	0.65	18	86
Average*	0.52	0.70	19	88

*reflects the average 2-hour event from 2-4 PM, omitting the Aug. 10 and Sept. 15 events.

2.3 Ex Ante Load Impact Estimates

Table 2-5 shows ex ante load impact estimates for residential Summer Saver customers. The values shown are averages over the CPUC Resource Adequacy window of 1-6 PM. Program enrollment is expected to remain stable for the future, so this table applies to the years 2013-2023, under the assumption that the program continues to operate under the same set of rules. The residential Summer Saver program is expected to produce an average of 14 MW of demand response over the course of a 1 PM to 6 PM event on a typical event day in a 1-in-10 weather year. The residential program is expected to produce considerably higher impacts under the much hotter conditions of a 1-in-10 September peak day. Under those conditions, the residential program is expected to produce 20 MW.

Table 2-5: Summer Saver Residential Ex Ante Impact Estimates

Day Type	Per CAC Unit Impact (kW)		Aggregate Impact (MW)	
	Weather Year		Weather Year	
	1-in-10	1-in-2	1-in-10	1-in-2
Typical Event Day	0.51	0.43	14	12
May Monthly Peak	0.38	0.15	11	4
June Monthly Peak	0.49	0.17	13	5
July Monthly Peak	0.50	0.44	14	12
August Monthly Peak	0.52	0.42	14	12
September Monthly Peak	0.71	0.56	20	16
October Monthly Peak	0.40	0.30	11	8

Table 2-6 shows ex ante impact estimates for commercial Summer Saver customers. Again, the values shown are averages over the CPUC Resource Adequacy window of 1-6 PM. Program enrollment for commercial customers is also expected to remain stable for the future, so this table applies to the years 2013-2023, under the assumption that the program continues to operate under the same set of rules. On a typical event day in a 1-in-10 year, the commercial Summer Saver program is expected to produce an average of 4 MW of demand response over the course of a 1 PM to 6 PM event. The commercial program is expected to produce higher impacts under the much hotter conditions of a 1-in-10 September peak day. Under those conditions, the commercial program is expected to produce 6 MW.

Table 2-6: Summer Saver Commercial Ex Ante Impact Estimates

Day Type	Per CAC Unit Impact (kW)		Aggregate Impact (MW)	
	Weather Year		Weather Year	
	1-in-10	1-in-2	1-in-10	1-in-2
Typical Event Day	0.36	0.30	4	4
May Monthly Peak	0.28	0.12	3	1
June Monthly Peak	0.33	0.13	4	2
July Monthly Peak	0.34	0.31	4	4
August Monthly Peak	0.36	0.30	4	3
September Monthly Peak	0.49	0.40	6	5
October Monthly Peak	0.29	0.22	3	3

2.4 Ex Post Load Impact Estimates of PTR for Summer Saver Customers

Seven PTR events were called in 2012. The events all lasted from 11 AM to 6 PM. Load impacts from PTR for the Summer Saver populations are not significantly different from zero. However, it is possible to calculate load impacts for residential Summer Saver customers who received PTR alerts. Table 2-7 shows the load impacts (averaged across each event hour) for each 2012 event day for the 2,917 residential customers enrolled on Summer Saver who received PTR alerts. These customers were notified of an upcoming PTR event by an e-mail, a text message, or both. In 2012, Summer Saver residential customers who received PTR alerts delivered an average aggregate load reduction over the 7 events of 1 MW. Impacts ranged from a low of 0.55 MW on August 21, to a high of 1.70 MW on September 15, a Saturday event with by far the highest temperature of any 2012 event day. There were 121 residential customers in the sample used to calculate these ex post impacts. The same analysis could not be completed for commercial customers because there were only seven customers in the commercial Summer Saver sample who received PTR alerts.

Table 2-7: PTR Ex Post Load Impact Estimates
Residential Summer Saver Customers Who Received PTR Alerts

Date	Impact		Temperature During Event (°F)
	Per Premise (kW)	Aggregate (MW)	
20-Jul-12	0.32	0.94	81
9-Aug-12	0.43	1.26	83
10-Aug-12	0.34	1.00	84
11-Aug-12	0.42	1.22	84
14-Aug-12	0.45	1.32	84
21-Aug-12	0.19	0.55	78
15-Sep-12	0.58	1.70	98
Average*	0.35	1.01	82

*reflects the average event, omitting the Aug. 11 and Sept. 15 weekend events.

2.5 Ex Ante Load Impact Estimates of PTR for Summer Saver Customers

Table 2-8 shows ex ante load impact estimates of PTR for residential Summer Saver customers who are forecast to receive PTR alerts. The values shown are averages over the event window of 11 AM to 6 PM. Program enrollment is expected to grow to 4,156 customers by 2015, at which time it is expected to stabilize. The aggregate MW load impacts in table 8-2 reflect the program in its steady state. In this state, residential Summer Saver customers enrolled in PTR alerts are expected to produce an average of about 1.8 MW of demand response over the course of an 11 AM to 6 PM event on a typical event day in a 1-in-10 weather year. Because there is only a brief history of events under PTR alerts, ex ante load impact estimates are capped according to the upper and lower values of the temperatures observed ex post.

Table 2-8: PTR Ex Ante Load Impact Estimates for 2015 Residential Summer Saver Customers Who Will Receive PTR Alerts

Day Type	Per Premise Impact (kW)		Aggregate Impact (MW)	
	Weather Year		Weather Year	
	1-in-10	1-in-2	1-in-10	1-in-2
Typical Event Day	0.42	0.41	1.76	1.69
January Monthly Peak	0.26	0.26	1.09	1.09
February Monthly Peak	0.26	0.26	1.09	1.09
March Monthly Peak	0.26	0.26	1.09	1.09
April Monthly Peak	0.26	0.26	1.09	1.09
May Monthly Peak	0.34	0.26	1.41	1.09
June Monthly Peak	0.42	0.26	1.76	1.09
July Monthly Peak	0.42	0.42	1.76	1.75
August Monthly Peak	0.42	0.39	1.76	1.61
September Monthly Peak	0.42	0.42	1.76	1.76
October Monthly Peak	0.36	0.26	1.50	1.09
November Monthly Peak	0.26	0.26	1.09	1.09
December Monthly Peak	0.26	0.26	1.09	1.09

2.6 Report Structure

The remainder of this report is organized as follows. Section 3 summarizes the data and methodologies that were used to develop the ex post and ex ante load impact estimates and the validation tests that were applied to assess their accuracy. Section 4 contains the ex post load impact estimates, an analysis of control device communication success and an analysis of the distribution of load impacts over customers. Section 5 presents the ex ante estimates. Section 6 summarizes the data and methodologies that were used to develop the ex post and ex ante load impact estimates of PTR for Summer Saver customers, including validation. Section 7 presents the ex post load impact estimates of PTR for Summer Saver customers. Section 8 presents the ex ante load impact estimates of PTR for Summer Saver customers.

3 Data and Methodology

This section summarizes the datasets and analysis methods that were used to estimate load impacts for each event in 2012 and for ex ante weather conditions. The residential ex post results were calculated using a control and treatment group design with an adjustment to the control loads to account for pre-existing differences between groups. The commercial ex post results were calculated using a panel model, which incorporates information from the control group and hot non-event days. The residential method is preferred because it doesn't rely on the assumption that we can adequately account for differences across days using a function of temperature. The relatively small commercial sample size (393 customers) necessitated an approach that made use of load variation both across customers and within customers to produce plausible results for commercial customers. For both the residential and commercial segments, the ex post results from the past three years are modeled as a function of temperature to produce the ex ante results.

3.1 Data

Eight Summer Saver events were called in 2012. Table 3-1 shows the date and day of week for each event, and the start and stop time for each event. All residential and commercial accounts were called for each weekday event, less a group of control customers that were held back for measurement and evaluation purposes. Control group customers were also held back on the weekend event, but the population size for this event was much smaller as only 6,381 residential customers and 470 commercial customers signed up for weekend events. Summer Saver events lasted two to four hours and began as early as 12 PM and as late as 4 PM.

Table 3-1: Summer Saver 2012 Event Summary

Date	Day of Week	Start Time	End Time
8-Aug-12	Wednesday	12:00 PM	4:00 PM
10-Aug-12	Friday	4:00 PM	6:00 PM
13-Aug-12	Monday	1:00 PM	5:00 PM
17-Aug-12	Friday	1:00 PM	5:00 PM
13-Sep-12	Thursday	2:00 PM	6:00 PM
14-Sep-12	Friday	1:00 PM	5:00 PM
15-Sep-12	Saturday	2:00 PM	6:00 PM
1-Oct-12	Monday	2:00 PM	6:00 PM

SDG&E provided FSC with samples of smart meter interval data for both the residential and commercial populations for summer 2012. The sample included data for 1,379 residential premises and 393 commercial premises. On each event day, approximately half of the customers in each sample (residential and commercial) did not receive an event signal. These customers provide the main source of information for reference loads, although for commercial customers, non-event days also provide reference load information.

Tables 3-2 and 3-3 show the distribution of CAC tonnage by cycling option and climate zone for the populations and samples of commercial and residential customers, respectively, as of November 2012. The differences between the fraction of residential customer tonnage in each sample cell and each population cell are small; there are only small differences across climate zones and cycling options. The differences between the fraction of commercial customers in each sample cell and each population cell are larger because the commercial sample was selected using an additional dimension – bins of usage during event-like conditions. Final results are weighted based on cycling option, climate zone, tonnage, and, for commercial customers, three bins of usage during event-like conditions.

Table 3-2: Distribution of AC Tonnage by Program Option and Climate Zone Residential Population

Cycling Option	Group	Climate Zone 1	Climate Zone 2	Climate Zone 3	Climate Zone 4	Total
50%	Population	3%	1%	0%	40%	45%
	Sample	4%	1%	0%	41%	45%
100%	Population	12%	1%	0%	43%	55%
	Sample	10%	1%	0%	44%	55%
Total	**Population**	**15%**	**2%**	**0%**	**83%**	**100%**
	Sample	**13%**	**1%**	**0%**	**85%**	**100%**

Table 3-3: Distribution of AC Tonnage by Program Option and Climate Zone Commercial Population

Cycling Option	Group	Climate Zone 1	Climate Zone 2	Climate Zone 3	Climate Zone 4	Total
30%	Population	14%	0%	0%	20%	34%
	Sample	15%	0%	0%	34%	49%
50%	Population	33%	0%	0%	32%	66%
	Sample	27%	0%	0%	24%	51%
Total	**Population**	**47%**	**1%**	**0%**	**53%**	**100%**
	Sample	**42%**	**0%**	**0%**	**58%**	**100%**

*The stratified sample was selected according to the above criteria as well as bins of usage during event-like conditions

3.2 Methodology

The primary task in estimating ex post event impacts is to estimate a reference load for each event. The reference load is a measure of what demand would have been in absence of the demand response event. The primary task in estimating ex ante event impacts (which are often of more practical concern) is to make the best use of available data on loads and load impacts to predict future program performance. The data and models used to estimate ex post impacts are typically major elements of the ex ante analysis.

The primary source of reference load information was load observed during event times for a control group of customers who were held back from receiving the event. Under this approach, a stratified, random load research sample of residential and commercial Summer Saver customers was created. During each event, half of the load research sample would be held back to provide reference load (i.e., those CAC units would not be controlled during the event). With the relatively large sample size available for residential customers (1,379 customers), the raw data from this design was sufficient to produce reliable impact estimates that only needed slight adjustment to be finalized. For commercial customers the sample was limited to 393 customers. Due to the inherent variability in commercial smart meter data, the control and treatment group method with adjustment was not sufficient to produce plausible ex post impacts for commercial customers. However, the control group data was useful in a panel model that also incorporated information from hot non-event days and produced load impact estimates that were similar to previous years' estimates, although based on stronger assumptions than the residential impact estimates.

In summary, the residential ex post impact estimates were developed using control group loads with a same-day adjustment, while commercial ex post impact estimates were developed using a panel regression model. Each is described below.

3.2.1 Residential Customer Ex Post Methodology

The methods used in the residential portion of the Summer Saver evaluation differ from those used in prior years. A joint effort among FSC, SDG&E and Comverge led to the implementation of a relatively large-scale experimental design for estimating residential ex post load impacts. Because smart meter data was available for a large sample of residential Summer Saver customers, the evaluation was based on a randomized experiment.

For each of the eight events during summer 2012, roughly half of the 1,379 customers in the residential sample received an event signal while the rest of the customers served as the control group. The group that received the event signal was alternated from event to event. Sample sizes of about 700 customers in each group eliminated the need for more complex regression methods, as were used in previous evaluations. This design has significant advantages in providing fast, reliable impact estimates if sample sizes are large enough.

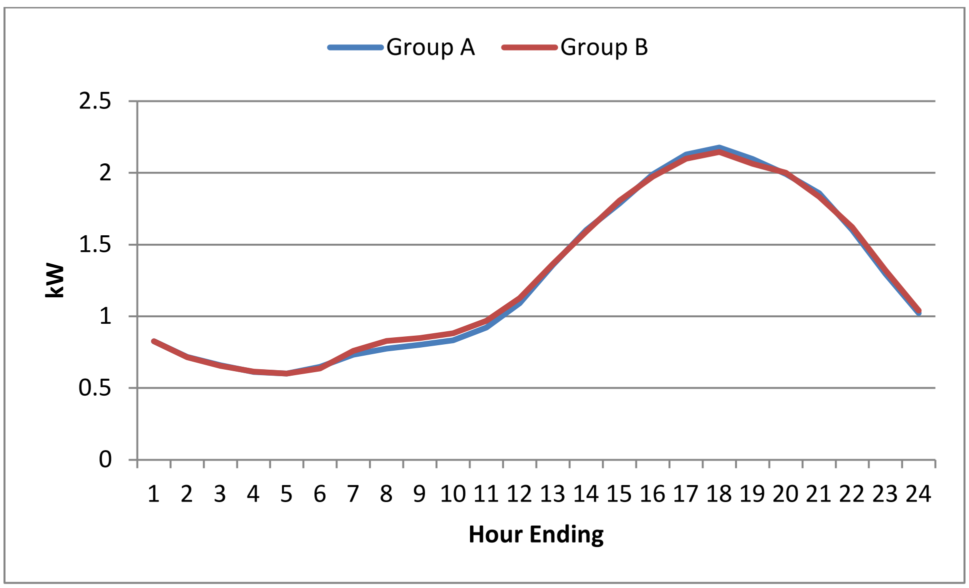
Ex post event impacts for each cycling option are estimated for each hour of each event by taking the average load in the group that received the event and subtracting it from the average adjusted load in the group that did not receive the event. The adjustment is based on the ratio of usage between the treatment and control groups for the five hours prior to the event start. For example, if the average usage in the treatment group during the five hours preceding an event is 1.2 kW, and the average usage in the control group is 1.3 kW, the ratio would be equal to 0.92 (1.2/1.3=0.92) and the control group load for the entire day would be multiplied by 0.92 to more closely match treatment group load. Impact estimates for the entire Summer Saver residential sample for each hour of each event are calculated by taking a weighted average of the impact estimates for each cycling option, with weights determined by the number of customers enrolled on each cycling option. Impacts for the average event day are calculated from unadjusted treatment and control group load shapes averaged across the six weekday events that contained the common hours of 2 to 4 PM.

3.2.2 Validity of Residential Ex Post Load Impact Estimates

Evidence for the validity of the residential ex post load impact estimates is available in the Excel-based load impact tables that accompany this document. As is typical for this type of evaluation, that file contains too many different individual tables to be reproduced in the primary document, but they constitute a necessary accompaniment in order to fully understand the results. In this case, the tables show raw and adjusted average loads for customers involved in each event, both those whose loads were controlled and those whose loads were not. Based on examining those loads in the pre- and post-event hours for each event, it is clear that the experimental method produced reference loads with little error for each event. Even at the cycling option level, reference loads appear reasonable in most cases.

Additionally, Figure 3-1 shows the average load within each group within the load research sample averaged over the five hottest non-event days of the summer. As the figure shows, the two groups are quite well-balanced in terms of average hourly usage, especially during the time period when events are likely to occur.

Figure 3-1: Residential A and B Group Comparison
Average Load on the Five Hottest Non-event Days



Finally, Table 3-4 shows the sample size of each group, average AC tonnage in each group, the fractions of each group that are on each cycling option and that are on the weekday-only option. Again, the groups are quite well balanced.

Table 3-4: Residential A and B Group Comparison Sample Size, Tonnage and Program Options

Group	Sample Size	Tonnage	%100% Cycling	% Weekday Only
A	696	2862	51%	70%
B	683	2882	56%	68%
Total	1379	5744	54%	69%

3.2.3 Commercial Customer Ex Post Methodology

The methods used in the commercial portion of the Summer Saver evaluation also differ from those used in prior years, as well as from the methods used for the residential evaluation this year. The commercial customer sample was limited to 393 customers, meaning that there were roughly 200 customers in the control and treatment groups on a given 2012 event day. Due to these small sample sizes and the inherent variability in commercial customer smart meter loads, the results produced using the residential ex post methodology were not plausible. It was instead necessary to use the control and treatment group data in a panel model that also incorporates information from hot non-event days.

A panel model approach to modeling event impacts is different than individual customer regressions in that data from all of the customers is used in a single regression model. Each hour of each event is included as the set of treatment variables in a model of kW usage that controls for temperature effects. Data from non-event days was included in the model estimation; however, this data was limited to the hours during which Summer Saver events occurred and days with maximum temperature equal to or above 80°F. Customer-level fixed effects were used to control for time-consistent characteristics at the customer level and the standard errors from the regression were corrected to account for correlation of observations from the same customer. Models were run separately by cycling option and for weekday and weekend events. A slightly different model that included each applicable event day, but modeled an average hourly effect from the common hours of 2 to 4 PM was used for estimation of average event impacts. In each case, the models included the full panel of data, that is, models were not run separately by hour.

Table 3-5 defines the variables in the regression models. The regression specification for estimating the weekday and weekend events is shown first, followed by the similar, but slightly different specification for modeling the average event.

$$kW_{it} = b_{1dt} * SSevent_{id}Xhour_t + b_{2t} * mean17_iXhour_t + e_{it} + a_i \quad (1)$$

$$kW_{it} = b_1 * SShr15_i + b_2 * SShr16_i + b_{3t} * mean17_iXhour_t + e_{it} + a_i \quad (2)$$

Table 3-5: Description of AC Load Regression Variables

Variable	Description
b_{ndt}	Estimated parameter coefficients, indicate the estimated coefficient for event day, d, at time interval, t
b_{nt}	Estimated parameter coefficients, indicate the estimated coefficient for a time interval, t
b_n	Estimated parameter coefficients
$SSevent_{id}Xhour_t$	Indicator variables representing whether or not a Summer Saver event occurred for customer, i, on event day, d, at time interval, t
$SShr15_i$	Indicator variable representing whether or not a Summer Saver event occurred for customer, i, during the hour from 2 to 3 PM
$SShr16_i$	Indicator variable representing whether or not a Summer Saver event occurred for customer, i, during the hour from 3 to 4 PM
$mean17_iXhour_t$	Average of the first 17 hourly temperature readings from each day, specific to each customer, i, with a value for each time interval, t, corresponding to the daily value
ε_{it}	Error term for each customer, i, for each time interval, t
a_i	Indicator variable for each customer, i, captures customer-level fixed effects

The estimated event coefficients for each event day and hour were taken as the commercial ex post impacts and the standard errors were used to construct confidence intervals. In the final step, reference loads for each event day and for the average event day were estimated to which the impacts were applied. This was to to complete the requirement of a load shape in the Excel-based load impact tables.

3.2.4 Validity of Commercial Ex Post Load Impact Estimates

In order for a model to be useful in the context of Summer Saver, it must make accurate predictions of CAC loads, primarily at high temperatures. Three methods of validation are used to assess this capability: in-sample testing, out-of-sample testing and evaluation of general plausibility of predictions.

In-sample Testing

The models must explain a large degree of the observed variation in household load during summer 2012. This is a test of the in-sample R-squared of the models, which is the simplest test for the models to pass and is a necessary, but not sufficient, condition for the models to be useful. A substantial body of evidence from previous evaluations by FSC and others demonstrate that weather and time variables in a regression model can explain a large amount of the variation in CAC load. Therefore, a model without an aggregate R-squared value of at least 70% would suggest a significant error and would bear significant investigation before being accepted.

The R-squared of a model can be inflated by including a very large number of variables. In this case, the model will appear to explain a large degree of the variation in load, but it may be highly inaccurate in predicting for conditions outside of the range of values for the data used to estimate the model. This is known as over-fitting. Diagnosing whether a model is over-fit inherently requires judgment. There are several metrics, such as adjusted R-squared, that attempt to penalize models for including many variables, but they are all based on arbitrary weightings of the number of variables as compared to the fit of the model. The method used here to guard against over-fitting is cross-validation (which is sometimes also referred to as out-of-sample testing), as described below. An over-fit model will not produce accurate predictions in cross-validation.

From an evaluation standpoint the focus is on how each panel regression performed. Therefore, the R-squared (goodness-of-fit) statistic is presented for each of the six models that were used to calculate the ex post results. Models were run separately by cycling option and for weekday and weekend events, as well as for the average event. Table 3-6 shows the R-squared values associated with each of these models.

Table 3-6: R-Squared Values by Model

Model	Cycling Option	R-squared
Weekday	30% Cycling	0.93
	50% Cycling	0.88
Weekend	30% Cycling	0.99
	50% Cycling	0.87
Average Event	30% Cycling	0.94
	50% Cycling	0.90

Cross Validation

The validity of the commercial panel models was tested by using similar model specifications as the ones used to produce the ex post impacts. More specifically, models with the same variables but slightly different data structure, were run by cycling option. The difference was that all Summer Saver event days were dropped from the data used to estimate the models and a set of five random days when no events occurred were chosen as the set of false treatment variables; with the A and B groups alternated between the five days. In this case, we would expect most of the coefficients on the false treatment variables to be insignificant since no events actually occurred on the days identified. The false events occurred from 1 PM to 5 PM and each hour of each false event is included in the models.

Table 3-7 shows the characteristics of the coefficients across the five false events. Coefficients can either be positive and significant, negative and significant or insignificant. In theory, about19 out of every 20 coefficients should be insignificant since no events actually occurred and since we are using a 5% significance test. A positive and significant coefficient means that usage in the treatment group is recognized by the model as being statistically significantly greater than usage in the control group, after accounting for unobservable customer characteristics. Zero of the coefficients are negative and significant and only two are positive and significant across both models. The rest are insignificant. This indicates that the models used to estimate commercial ex post load impacts probably do a reasonable job identifying event impacts.

Table 3-7: Significance of False Event Load Impact Estimates

Customer Type	Positive and Significant	Negative and Significant	Insignificant
30% Cycling	1	0	19
50% Cycling	1	0	19

*Significance measured at the 95% confidence level

Table 3-8 shows the sample size of each group, average AC tonnage in each group, the fractions of each group that are on each cycling option and that are on the weekday-only option. The groups are not quite as well balanced as the residential groups on tonnage, but otherwise they are well-balanced..

Table 3-8: Commercial A and B Group Comparison Sample Size, Tonnage and Program Options

Group	Count	Tonnage	50% Cycling	% Weekday Only
A	193	1757	50%	93%
B	200	1559	49%	95%
Total	393	3316	50%	94%

The final test of the model is one of general plausibility in predicting impacts during the event periods and for the ex ante weather conditions. This test is less well-specified but consists of producing reasonable household load patterns as a function of weather as compared to results in past years, results from other programs and general knowledge about how the program works. This reality-check test is a crucial way to test the assumptions that go into the model. The ex ante estimates that are presented in this report were carefully reviewed and generally display the expected patterns across event conditions and are consistent with other studies after judgmentally accounting for expected differences due to weather conditions and other factors.

3.3 Ex Ante Impact Estimation Methodology

In contrast to the ex post portion of this report, the same method was used to produce both residential and commercial ex ante results. Calculating the ex ante load impacts is a multi-step process, but is driven by a straightforward approach to modeling load impacts. In short, load impacts from the previous three years are modeled as a function of temperature and the parameters are used in a regression model to predict load impacts under ex ante weather conditions. Reference loads are developed and, for residential customers, snapback is added back into the load shapes for the Excel load impact tables. This section presents a detailed description of the ex ante methodology.

Ex ante load impacts are developed by using the available ex post data. For both residential and commercial customers, load impacts during the overlapping event hours from 2010, 2011 and 2012 from 2 to 4 PM are modeled as a function of the average temperature for the first 17 hours of each event day. Per ton load impacts are used so that load impacts are scalable to ex ante scenarios where the tonnage and number of devices per premise may be different. The models are run separately by customer type (residential or commercial) and cycling strategy and the parameters from the models are used to predict load impacts under 1-in-2 and 1-in-10 ex ante weather conditions. The final regression only includes one explanatory variable because more complicated models were not found to perform better in cross-validation.[4] The model that was used to predict average ex post impacts was:

$$impact_d = b_0 + b_1 \cdot mean17_{\mathrm{d}} + \varepsilon_d$$

[4] Weekend events are omitted, September 8, 2011, the day of a blackout in SDG&E's territory is omitted, and August 10, 2012, an event that does not contain the overlapping hours of 2 to 4 PM is omitted.

Table 3-9: Ex Ante Regression Variables

Variable	Description
$Impact_d$	Average per ton ex post load impact for each event day from 2 to 4 PM
b_0	Estimated constant
b_1	Estimated parameter coefficient
$mean17_d$	Average temperature over the 17 hours prior to the start of the event for each event day
ε_d	The error term for each day, d

Figures 3-4 through 3-7 show the ex post impacts from 2010 through 2012 by customer type and cycling strategy graphed against the ex ante predictions that are developed based on these load impacts. The ex ante estimates for residential customers follow from the ex post impacts and are quite plausible. While there is more noise in the commercial ex post estimates, the linear prediction through these estimates results in ex ante estimates that are conservatively in the middle of the range of ex post estimates. The figures also show that for each program segment, there is only one event day that has been observed where temperatures were similar to the hottest ex ante conditions. This indicates that the impact estimates under the hottest conditions—September 1-in-10—are particularly uncertain and should be expected to be sensitive to small amounts of additional data. This was the case this year, as is shown in Section 5. Most ex ante impact estimates were quite stable between 2011 and 2012, but September 1-in-10 changed the most, even though no events were observed under similar conditions in 2012.

Figure 3-4: Average 2 to 4 PM Ex Post Load Impacts and Ex Ante Predictions Residential 50% Cycling

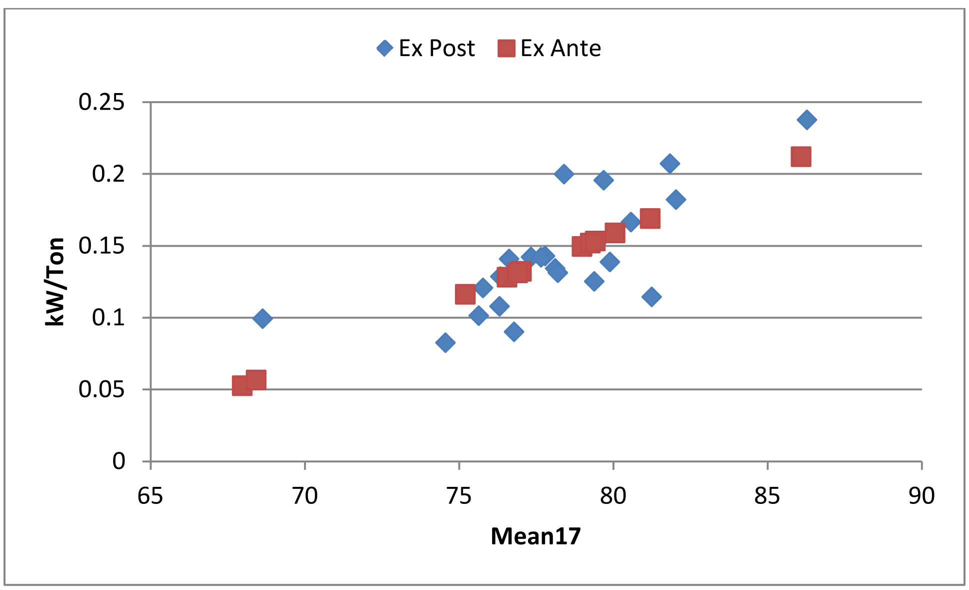


Figure 3-5: Average 2 to 4 PM Ex Post Load Impacts and Ex Ante Predictions Residential 100% Cycling

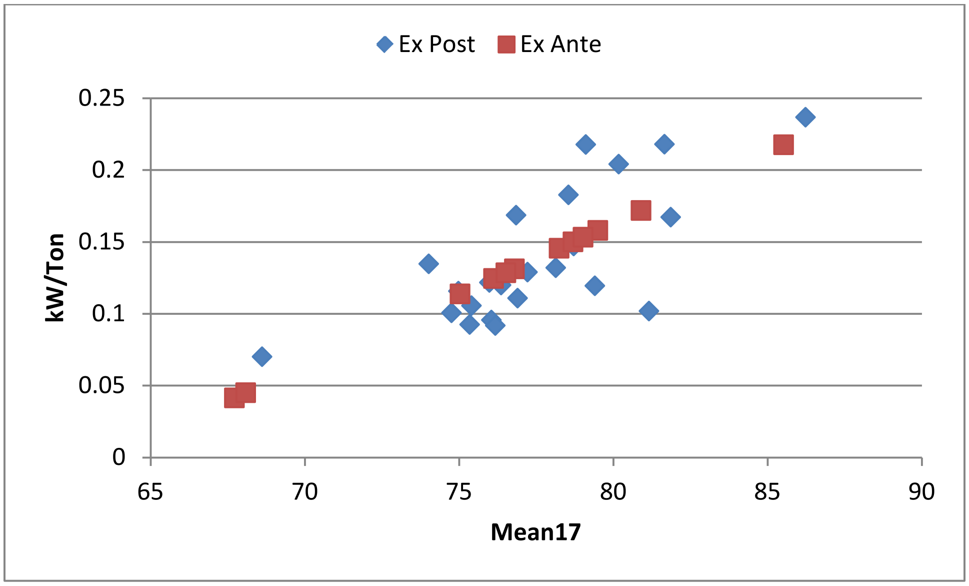


Figure 3-6: Average 2 to 4 PM Ex Post Load Impacts and Ex Ante Predictions Commercial 30% Cycling

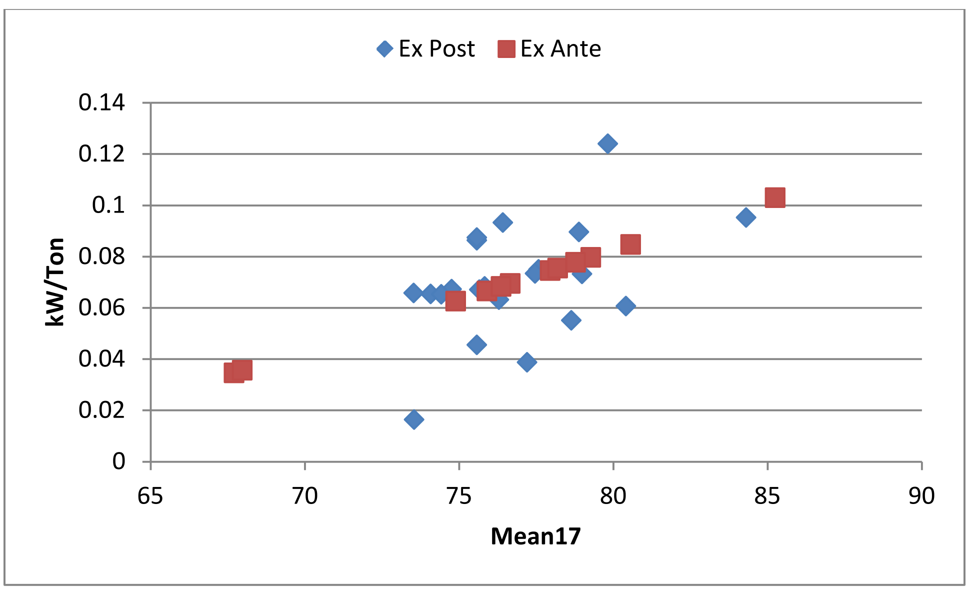
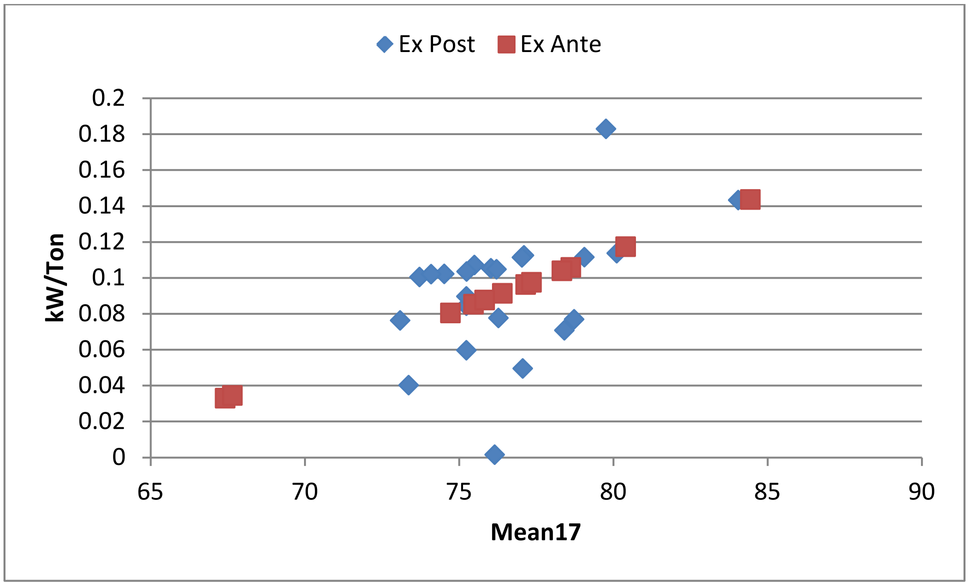


Figure 3-7: Average 2 to 4 PM Ex Post Load Impacts and Ex Ante Predictions Commercial 50% Cycling



The next step in estimating load impacts is to translate average impacts from 2 to 4 PM to hourly impacts over the entire range of time required for prediction, 1 to 6 PM. Hourly ex post impact estimates for each event in 2012 are expressed as a fraction of the average impact from 2 to 4 PM. Table 3-10 gives an example of this process. The first column of Table 3-10 shows how the average event impact for each hour of the five hour events compared to the average impact from 2 to 4 PM. This example is limited to customers in residential 100% cycling, but the methodology carries through for both customer classes and all cycling options. To illustrate, the second column shows the proportions in the first column multiplied by 0.13 kW/Ton, the average predicted impact from 2 to 4 PM for residential customers during a typical event day during a 1-in-2 weather year. To calculate the estimated impact for 1 to 2 PM, for example, 0.13 kW/Ton is multiplied by 84% to yield an impact of 0.11 kW/Ton. The same strategy is applied for all five hours of the event, as illustrated in Table 3-10.

Table 3-10: Hourly Impact Compared to Average Impact from 2-4 PM Residential 100% Cycling

Hour of Event	Hourly Impact/ Average 3–5 PM Impact (%)	Hourly Impact for Typical Event Day, 1-in-2 Weather (kW/Ton)
1-2 PM	84	0.11
2-3 PM	90	0.12
3-4 PM	1.10	0.14
4-5 PM	1.15	0.15
5-6 PM	87	0.11

This method constrains the relative size of event impacts across different hours to be the same for each event. Event impacts vary with weather, as usual, but in this model the ratio of the impact at 4 PM to the impact at 5 PM, for example, is always the same. A separate ex ante model could be used for each event hour separately. Such a strategy would have the virtue of independently identifying the effect of weather on event impacts at different times of day. However, where there are only a moderate number of events, that strategy risks fitting spurious trends to individual hours or trends across hours that conflict with one another unrealistically. Given the highly auto-correlated nature of the data, the differential impact of weather on different event hours is likely to be difficult to measure as compared to the primary effect of temperature on average event impacts.

Due to similar concerns, reference loads are calculated in much the same way as load impacts. As is the case with load impact estimation, models are run separately and reference loads are calculated separately by customer type and cycling strategy. The process can be expressed in a series of steps:

- Average control group usage during the 2 to 4 PM time period on 2012 event days is modeled as a function of mean17;
- The parameters from this regression are used to predict average usage during the 2 to 4 PM time period under ex ante weather conditions;
- A ratio between each ex ante prediction and average 2012 control group usage during the 2 to 4 PM time period across all 2012 event days is calculated; and
- Average control group load profiles for the entire average 2012 event day are adjusted by the ratio specific to each set of ex ante weather conditions to produce the final ex ante reference loads.

Because snapback is observed ex post, producing ex ante load impact tables in Excel requires adding in snapback. Like load impacts and reference loads, snapback for residential customers is calculated by cycling strategy. The calculation consists of the following steps:

1. Average the snapback values across the six hours after each ex post event.
2. Develop a ratio between snapback in each hour and snapback in the first hour.
3. Multiply the snapback value in the first hour by the ratios previously used to scale the ex post reference load to ex ante weather conditions.
4. Multiply the adjusted snapback values for each set of ex ante weather conditions by the snapback ratios to get snapback values for the six hours after each ex ante event.

Commercial snapback was estimated to be zero based on the available data.

4 Ex Post Load Impact Estimates

This section contains the ex post load impact estimates for program year 2012. Residential estimates are provided first, followed by commercial estimates. The section also contains an analysis on control device communication failure and an analysis of the distribution of impacts across customers.

4.1 Residential Ex Post Load Impact Estimates

Table 4-1 shows the ex post load impact estimates for residential Summer Saver customers for 2012. Summer Saver residential customers delivered an average aggregate load reduction over the eight events of 16 MW. Residential impacts ranged from a low of 9 MW on September 15, to a high of 19 MW on August 13 and September 14. Only 6,381 of the 22,928 residential customers were signed up for weekend events, which explains why the September 15 aggregate load reduction is the smallest of any event despite the fact that the per premise and per CAC unit results are the greatest of any event. These results also provide no evidence that program performance in 2012 deviated significantly from 2011 or 2010.

Table 4-1: Residential Ex Post Load Impact Estimates

Date	Impact			Temperature During Event (°F)
	Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
8-Aug-12	0.47	0.55	13	86
10-Aug-12	0.55	0.65	15	82
13-Aug-12	0.70	0.83	19	88
17-Aug-12	0.62	0.73	17	87
13-Sep-12	0.45	0.53	12	80
14-Sep-12	0.69	0.81	19	100
15-Sep-12	1.18	1.35	9	95
1-Oct-12	0.54	0.64	15	86
Average*	0.61	0.72	16	89

*reflects the average 2-hour event from 2-4 PM, omitting the Aug. 10 and Sept. 15 events.

4.2 Commercial Ex Post Load Impact Results

Table 4-2 shows the ex post load impact estimates for commercial Summer Saver customers for 2012. Summer Saver commercial customers delivered an average aggregate load reduction over the 6 events of 3 MW. Commercial impacts ranged from a low of 1 MW on August 8, September 13 and September 15 to a high of 6 MW on August 17. However, only 470 commercial customers are signed up for weekend events, which means that September 15 should not be included in this comparison. These results provide no evidence that program performance in 2012 deviated significantly from 2011 or 2010.

Table 4-2: Commercial Ex Post Load Impact Estimates

Date	Impact			Temperature During Event (°F)
	Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
8-Aug-12	0.14	0.29	1	84
10-Aug-12	0.37	0.76	4	81
13-Aug-12	0.26	0.53	3	86
17-Aug-12	0.61	1.24	6	86
13-Sep-12	0.06	0.13	1	78
14-Sep-12	0.39	0.82	4	96
15-Sep-12	0.70	1.34	1	95
1-Oct-12	0.35	0.72	3	84
Average*	0.30	0.62	3	86

*reflects the average 2-hour event from 2-4 PM, omitting the Aug. 10 and Sept. 15 events.

4.3 Load Impacts by Cycling Option

Table 4-3 shows load impacts per CAC unit and in aggregate by cycling option for residential and commercial customers. The average impact per unit is higher for the more intensive cycling options. This is in contrast to 2011 where within each segment, the average impact per unit was very close.

Table 4-3: Per CAC Unit Load Reductions by Cycling Option (kW)

	Per CAC (kW)				Aggregate (MW)			
	Cycling Option				Cycling Option			
	Residential		Commercial		Residential		Commercial	
Date	100	50	50	30	100	50	50	30
8-Aug-12	0.47	0.47	0.12	0.18	7	6	1	1
10-Aug-12	0.62	0.47	0.38	0.35	9	6	2	1
13-Aug-12	0.72	0.68	0.28	0.21	10	9	2	1
17-Aug-12	0.71	0.53	0.72	0.39	10	7	5	1
13-Sep-12	0.59	0.28	0.06	0.05	9	4	<0.5	<0.5
14-Sep-12	0.73	0.65	0.46	0.27	11	8	3	1
15-Sep-12	1.31	0.36	0.82	0.48	8	<0.5	<0.5	<0.5
1-Oct-12	0.54	0.54	0.39	0.27	8	7	3	1
Average*	0.70	0.51	0.34	0.24	10	6	2	1

*reflects the average 2-hour event from 2-4 PM, omitting the Aug. 10 and Sept. 15 events.

It is also important to note the significant differences in usage between cycling options that mask the difference in load impacts between cycling options, particularly for residential customers. Residential customers enrolled on 50% cycling used about 2.5 kW across the hours of 2 to 4 PM on the average event day, while residential customers enrolled on 100% cycling used roughly 2 kW during the same time period. Scaling the 100% cycling results to the 50% cycling loads, the impact for the average event for customers on 100% cycling would be about 0.90 kW. The difference in usage for commercial customers on 30% cycling and 50% cycling during this same time period is about 5%, with customers on the 30% cycling option using slightly more. This does not have a material impact on the results by cycling option for commercial customers.

4.4 Free Riders

One important issue for the cost-effectiveness of the program is the fraction of customers who sign up for the program, but who do not use their air conditioning much or at all. These customers are compensated for being on the program, but are likely to provide little load impact. To examine the fraction of possible free riders on the program, FSC used sub-metered data collected for contract settlement between AER and SDG&E to find the fraction of each population segment that had little AC usage. The sub-metered data was collected from a representative sample of residential and commercial AC units. The sample contained 620 AC units divided approximately evenly between the four combinations of percentage cycling option and residential/commercial. FSC calculated the fraction of AC units in each segment that had zero usage, averaged over all 11 AM-7 PM on days with high temperature above 80°F. FSC also calculated the same fraction for units with average usage below 0.05 kW over the same set of hours. The same calculations were also done dividing the population based on the weekday-only versus seven day event option. The results are shown in Tables 4-4 and 4-5. By both metrics, residential customers on 100% cycling are much more likely to use very little AC. The differences between the weekday only option and the all week option for residential customers is smaller, but there is a tendency for weekday only customers to be more likely to use very little AC. Commercial customers are generally much less likely to use very little AC, which makes sense. The differences between the commercial cycling options are fairly small in Table 4-6.

Table 4-4: Fraction of Residential AC Units with Small Average Usage on Warm Afternoons

Average Usage	Cycling Percentage		Cycle Plan	
	50%	100%	Weekday only	All Week
0 kW	5%	9%	5%	9%
<0.05 kW	13%	25%	22%	17%

Table 4-5: Fraction of Commercial AC Units with Small Average Usage on Warm Afternoons

Average Usage	Cycling Percentage		Cycle Plan	
	30%	50%	Weekday only	All Week
0 kW	1%	0%	0%	1%
<0.05 kW	6%	8%	6%	7%

4.5 The Distribution of Impacts Across Customers

Table 4-5 shows estimated event impacts for customers segmented into deciles of average load on hot, non-event days. In this procedure, each customer was placed into a decile category based on their average usage during the peak hours of 11 AM to 6 PM on hot non-event weekdays.

For residential customers, impact estimates were calculated separately for each decile using the average control and treatment group loads for each decile on the average event day. The commercial customer impact estimates by decile were calculated separately for each decile using a panel model for each decile and estimating the average event effect.

As Table 4-5 shows, non-event day loads are strongly predictive of average impacts. The table indicates that the top 30% of customers provide 68% and 52% of residential and commercial aggregate load impacts, respectively.

Table 4-5 also reports the standard errors of the estimates for each decile. It is important to note that while the overall trends in the table are consistent and likely reflect a true underlying pattern, the estimates at the decile level have fairly large standard errors. This is more pronounced for the commercial analysis since regression-based methods with more inherent variability were used. For example, the impact estimate for the highest decile for residential customers is statistically significantly different at the 5% level from the impact in all other deciles, but the impacts in the 7^{th} and 8^{th} deciles are not statistically significantly different from each other. For commercial customers, the impact estimates in some of the lowest deciles (1 and 2) are statistically significantly different from the impacts estimates in some of the highest deciles (8 and 9). However, impact estimates in neighboring deciles are not statistically significantly different from each other.

Table 4-6: Average Estimated Impacts within Deciles of Usage

Decile	Residential Customers			Commercial Customers		
	Average Impact (kW)	% of Total	Impact Standard Error (kW)	Average Impact (kW)	% of Total	Impact Standard Error (kW)
1	-0.04	-1%	0.05	0.08	1%	0.05
2	-0.04	-1%	0.03	0.19	3%	0.11
3	-0.02	0%	0.04	0.37	6%	0.14
4	0.13	2%	0.05	0.70	12%	0.17
5	0.41	7%	0.06	0.66	11%	0.19
6	0.54	9%	0.06	0.54	9%	0.30
7	0.89	15%	0.07	0.39	6%	0.21
8	1.01	17%	0.08	0.89	15%	0.32
9	1.32	22%	0.08	1.45	24%	0.46
10	1.72	29%	0.10	0.79	13%	0.64

5 Ex Ante Load Impact Estimates

The models described above were used to estimate load impacts based on ex ante event conditions and enrollment projections for the years 2013 through 2023. Enrollment is not expected to change in the future, so the tables in this section represent predictions for the whole period 2013 through 2023. FSC was provided with data by SDG&E that represents weather under 1-in-2 and 1-in-10 year conditions for each monthly system peak day.[5] The ex ante event window is from 1 to 6 PM, which is the CPUC resource adequacy window.

Tables 5-1 and 5-2 summarize the average and aggregate load impact estimates for residential and commercial customers, respectively. Aggregate impacts are based on steady enrollment levels equal to those as of fall 2012. Load impact estimates are presented for the average AC unit and for each customer segment as a whole.

For a typical event with 1-in-2 year weather conditions, the average impact per AC unit is 0.43 kW for residential customers. The 1-in-10 year typical event day estimate is 19% higher at 0.51 kW. The aggregate program load reduction potential for residential customers is 12 MW for a typical event day under 1-in-2 year weather conditions and 14 MW under 1-in-10 year weather conditions. September ex ante conditions are much hotter than typical conditions. The residential program is estimated to provide an average impact of 20 MW over a 5-hour event on a 1-in-10 September event day.

There is significant variation in load impacts across months and weather conditions. Based on 1-in-2 year weather, the low temperatures in May and June typically experienced in San Diego, result in small average and aggregate load impact estimates. The May and June 1-in-2 impacts for residential customers are only about 25% and 31% of the September estimate, respectively, which is the highest of any month in 1-in-2 year weather conditions. For residential customers, the May and June 1-in-10 year estimates are more than 2.5 times the 1-in-2 year estimates, which is a result of the 1-in-10 temperatures being much warmer than the 1-in-2 temperatures for May and June.

Commercial customers are estimated to provide lower per CAC unit impacts than residential customers. Due to the smaller number of commercial installations in the program, aggregate impacts for the commercial segment are much smaller than for residential customers. The commercial program is expected to provide the highest impact under 1-in-10 conditions in September, when its expected impact is 6 MW.

Tables 5-3 and 5-4 provide ex ante estimates on an hourly basis for residential and commercial customers, respectively. Residential impacts peak in the hours 3-5 PM, while commercial impacts are relatively flat over the event hours.

Table 5-5 provides program-level ex ante aggregate estimates for each hour. The program is expected to provide its highest impact under 1-in-10 conditions in September. Under those conditions, the average impact over the event window is expected to be 25 MW, with an hourly peak of 29 MW from 4 to 5 PM.

[5] The typical event day is an hourly average of the weather during the top 9 system load days in a 1-in-2 year and in a 1-in-10 year.

Table 5-1: Summer Saver Residential Ex Ante Impact Estimates

Day Type	Per CAC Unit Impact (kW)		Aggregate Impact (MW)	
	Weather Year		Weather Year	
	1-in-10	1-in-2	1-in-10	1-in-2
Typical Event Day	0.51	0.43	14	12
May Monthly Peak	0.38	0.15	11	4
June Monthly Peak	0.49	0.17	13	5
July Monthly Peak	0.50	0.44	14	12
August Monthly Peak	0.52	0.42	14	12
September Monthly Peak	0.71	0.56	20	16
October Monthly Peak	0.40	0.30	11	8

Table 5-2: Summer Saver Commercial Ex Ante Impact Estimates

Day Type	Per CAC Unit Impact (kW)		Aggregate Impact (MW)	
	Weather Year		Weather Year	
	1-in-10	1-in-2	1-in-10	1-in-2
Typical Event Day	0.36	0.30	4	4
May Monthly Peak	0.28	0.12	3	1
June Monthly Peak	0.33	0.13	4	2
July Monthly Peak	0.34	0.31	4	4
August Monthly Peak	0.36	0.30	4	3
September Monthly Peak	0.49	0.40	6	5
October Monthly Peak	0.29	0.22	3	3

Table 5-3: Aggregate Load Reductions by Day Type, Weather Year and Hour
All Residential Customers

Weather Year	Day Type	Hour of Day					Average
		1 to 2 PM	2 to 3 PM	3 to 4 PM	4 to 5 PM	5 to 6 PM	
1-in-2	Typical Event Day	12	12	14	13	9	12
	May Monthly Peak	4	4	5	5	3	4
	June Monthly Peak	5	5	5	5	3	5
	July Monthly Peak	12	12	14	13	9	12
	August Monthly Peak	11	12	13	13	9	12
	September Monthly Peak	15	16	18	17	12	16
	October Monthly Peak	8	8	10	9	6	8
1-in-10	Typical Event Day	14	14	16	16	11	14
	May Monthly Peak	10	10	12	12	8	11
	June Monthly Peak	13	13	15	15	10	13
	July Monthly Peak	13	14	16	15	11	14
	August Monthly Peak	14	14	17	16	11	14
	September Monthly Peak	19	20	23	22	15	20
	October Monthly Peak	11	11	13	12	8	11

Table 5-4: Aggregate Load Reductions by Day Type, Weather Year and Hour
All Commercial Customers

Weather Year	Day Type	Hour of Day					Average
		1 to 2 PM	2 to 3 PM	3 to 4 PM	4 to 5 PM	5 to 6 PM	
1-in-2	Typical Event Day	3	4	4	4	3	4
	May Monthly Peak	1	1	1	2	1	1
	June Monthly Peak	1	2	2	2	1	2
	July Monthly Peak	3	4	4	4	3	4
	August Monthly Peak	3	4	3	4	3	3
	September Monthly Peak	4	5	5	6	4	5
	October Monthly Peak	2	3	3	3	2	3
1-in-10	Typical Event Day	4	4	4	5	4	4
	May Monthly Peak	3	3	3	4	3	3
	June Monthly Peak	4	4	4	5	3	4
	July Monthly Peak	4	4	4	5	3	4
	August Monthly Peak	4	4	4	5	4	4
	September Monthly Peak	5	6	6	7	5	6
	October Monthly Peak	3	3	3	4	3	3

Table 5-5: Aggregate Load Reductions by Day Type, Weather Year and Hour
All Customers

Weather Year	Day Type	Hour of Day					Average
		1 to 2 PM	2 to 3 PM	3 to 4 PM	4 to 5 PM	5 to 6 PM	
1-in-2	Typical Event Day	15	15	17	17	12	15
	May Monthly Peak	6	6	6	6	4	6
	June Monthly Peak	6	6	7	7	5	6
	July Monthly Peak	15	16	18	18	12	16
	August Monthly Peak	14	15	17	17	12	15
	September Monthly Peak	19	20	23	23	16	20
	October Monthly Peak	11	11	12	12	9	11
1-in-10	Typical Event Day	17	18	20	21	14	18
	May Monthly Peak	13	14	15	16	11	14
	June Monthly Peak	17	17	19	20	14	17
	July Monthly Peak	17	18	20	20	14	18
	August Monthly Peak	18	19	21	21	15	19
	September Monthly Peak	24	25	28	29	20	25
	October Monthly Peak	14	14	16	16	11	14

6 Data and Methodology - PTR for Summer Saver Customers

This section summarizes the datasets and analysis methods that were used to estimate load impacts for each PTR event for Summer Saver customers in 2012. The load impacts from PTR for the Summer Saver population were found to be practically insignificant in a panel model that is meant to distinguish event days from non-event days. Load impacts from the analysis of residential Summer Saver customers who received PTR alerts were significant and were calculated using two methods: a matched control group and a panel model that uses information from hot non-event days, with the matched control group used for reporting.

6.1 Data

In 2012, seven PTR events were called. Table 6-1 shows the date of each event along with the start and stop time of each event. All residential and commercial accounts were called for each event. The samples used for the PTR load impact analysis for Summer Saver customers are exactly the same as those used for the Summer Saver load impact analysis; that is, a residential sample of 1,379 customers and a commercial sample of 393 customers. However, a smaller sample of 121 residential customers who received PTR alerts was used to calculate the load impacts for the subset of 2,917 residential customers in the Summer Saver population who received PTR alerts. The same analysis could not be carried out for commercial customers because only 7 commercial customers in the sample of 393 received PTR alerts. In 2012, PTR events lasted 7 hours, beginning at 11 AM and ending at 6 PM.

Table 6-1: PTR 2012 Event Summary

Date	Day of Week	Start Time	End Time
20-Jul-12	Friday	11:00 AM	6:00 PM
9-Aug-12	Thursday	11:00 AM	6:00 PM
10-Aug-12	Friday	11:00 AM	6:00 PM
11-Aug-12	Saturday	11:00 AM	6:00 PM
14-Aug-12	Tuesday	11:00 AM	6:00 PM
21-Aug-12	Tuesday	11:00 AM	6:00 PM
15-Sep-12	Saturday	11:00 AM	6:00 PM

Tables 3-2 and 3-3 in the Summer Saver methodology section show the distribution of CAC tonnage by cycling option and climate zone for the populations and samples of commercial and residential customers, respectively, as of November 2012. Table 6-2 shows the distribution of customers by cycling option and climate zone for the population and sample of residential Summer Saver customers who received PTR alerts. The differences between the fraction of residential customers in each sample cell and each population cell are small; there are only small differences across climate zones and cycling options. Final results are weighted based on cycling option, climate zone and tonnage – the same weights used for the analysis of Summer Saver load impacts.

Table 6-2: Distribution of Customers by Program Option and Climate Zone Residential Population

Alert Type	Group	Climate Zone 1	Climate Zone 2	Climate Zone 3	Climate Zone 4	Total
Email	Population	15%	0%	0%	49%	64%
	Sample	16%	1%	0%	51%	68%
Text	Population	3%	0%	0%	9%	12%
	Sample	2%	1%	0%	12%	15%
Both	Population	5%	0%	0%	18%	23%
	Sample	3%	0%	0%	14%	17%
Total	**Population**	**22%**	**1%**	**0%**	**76%**	**100%**
	Sample	**21%**	**2%**	**0%**	**78%**	**100%**

*2,917 customers in the SS Population received alerts, 121 of these customers are represented in the sample.

6.2 Methodology

The primary source of information available for the 2012 evaluation of PTR for Summer Saver customers is load observed during non-event times. Under this approach, the information from days comparable to event days is used as the basis for the reference load on an event day, usually with some sort of adjustment. This type of analysis was carried out for residential and commercial customers, but no load impacts from PTR could be detected. A similar type of analysis did produce detectable load impacts for residential customers who received PTR alerts. However, a better approach for modeling the load impacts associated with these customers that automatically accounts for Summer Saver event days is to use a matched control group of customers who did not receive PTR alerts. The matched control group method is not without some controversy since the customers in the control group were exposed to the PTR events. Results are provided for both methods, but the matched control group results are the results used for reporting.

In summary, residential and commercial ex post load impacts are shown to be implausible in a series of panel models that seek to distinguish event days from non-event days. Load impacts were modeled for residential customers who received PTR alerts using both a panel model and a matched control group of customers who did not receive PTR alerts, with the matched control group results used for reporting.

6.2.1 Residential and Commercial Customer Ex Post Methodology

Because information from a control group was not available for the analysis of PTR load impacts for the Summer Saver population, we instead used the available data in a series of panel models that incorporate information from hot non-event days and control for time-consistent customer characteristics that could be confounded with load impacts.

A panel model approach to modeling demand response events is different than individual customer regressions in that data from all of the customers is used in a single regression model. In this case, an indicator variable for the presence of a PTR event is used as the treatment variable in a model of kW usage that controls for daily temperature effects. The usage metric is average usage from 11 AM to 6PM (the time period corresponding to PTR events). Data from non-event days is included in the model estimation to determine if the indicator variable will pick up a negative and statistically significant effect on PTR event days. Customers are assumed to reduce usage on these days relative to days when no events are called. A number of different weather variables were tested and separate models were run with non-PTR days limited to days with maximum temperature equal to or above 75, 80, 85, or 90 degrees Fahrenheit, for a total of 12 models for both residential and commercial customers. Fixed effects estimation is used to control for time-consistent unobservable characteristics at the customer level and the standard errors from the regression are corrected to account for the correlation of observations from the same customer.

Table 6-3 defines the variables in the regression models. The regression specification was:

$$meankW11to6_{id} = b_1 * PTRevent_{id} + b_2 * weather_{id} + b_3 * weathersqr_{id} + e_{id} + a_i$$

Table 6-3: Description of PTR Regression Variables

Variable	Description
b_n	Estimated parameter coefficients
$PTRevent_{id}$	Indicator variables representing whether or not a PTR event occurred for customer, i, on day, d
$weather_{id}$	Weather variable specific to each customer, i, with a value for each day, d
$weathersqr_{id}$	Square of the weather variable specific to each customer, i, with a value for each day, d
ε_{id}	Error term for each customer, i, for each day, d
a_i	Indicator variable for each customer, i, captures customer-level fixed effects

The important output from these regressions is a coefficient on the indicator variable for a PTR event. If the coefficient is negative and statistically significant then there is evidence that PTR load impacts can be detected and that the analysis of PTR for residential and commercial Summer Saver customers is a fruitful analysis.

6.2.2 Residential PTR Alerts Ex Post Methodology

The load impacts for residential customers who received PTR alerts were calculated using two separate methods, a matched control group with an adjustment and a panel model, which adjusts hot non-event days to form a reference load. The matched control group method relies on a strong assumption that customers who did not receive PTR alerts, but who were otherwise enrolled in PTR, can be used as controls for customers who received PTR alerts. The load impacts calculated using the matched control group are greater than the load impacts calculated using the panel model, meaning that if this assumption is not true, then the matched control group estimates are still probably the more accurate estimates.

The method used to assemble the matched control group is designed to ensure that the control group has characteristics as similar as possible to the alerted PTR customers and therefore is likely to provide a valid counterfactual. The 121 customers in the residential Summer Saver sample who received PTR alerts were matched to customers in the sample who did not receive PTR alerts. This was done using a procedure known as propensity score matching. In this procedure, a probit model is used to estimate a score for each customer. In this case, the score was based on kW usage on a set of 10 hot non-event days. A probit model is a regression model designed to estimate probabilities – in this case, the probability that customers who did not receive PTR alerts have similar usage profiles to customers who did receive PTR alerts, absent an event. Each customer in the control group is matched to a customer who received PTR alerts. The impacts are calculated by taking the difference between the adjusted load shapes from the matched control group and the load shapes of the customers who received the PTR alerts. This method automatically accounts for Summer Saver events on days when both Summer Saver and PTR events were called because roughly the same proportion of customers in the control and treatment groups was subject to Summer Saver events.

The panel model approach to modeling load impacts for residential Summer Saver customers who received PTR alerts consists of estimating a predictive model of kW usage on hot non-event days and then applying the parameters from that model to the temperature characteristics of an event day to determine a reference load. This is a within-subjects method. The reference load is then adjusted based on the event-day load profiles during the five hours leading up to the PTR event, as discussed previously in this evaluation. This method is based on the strong assumption that usage on hot non-event days can effectively be matched to usage on event days based on temperature. However, as mentioned before, it is an essential validation check for the load impacts calculated with the matched control group.

Table 6-4 defines the variables in the regression model. The models were run separately by hour for a total of 24 models. The regression specification was:

$$kW_t = b_0 + b_1 * mean17_t + e_t$$

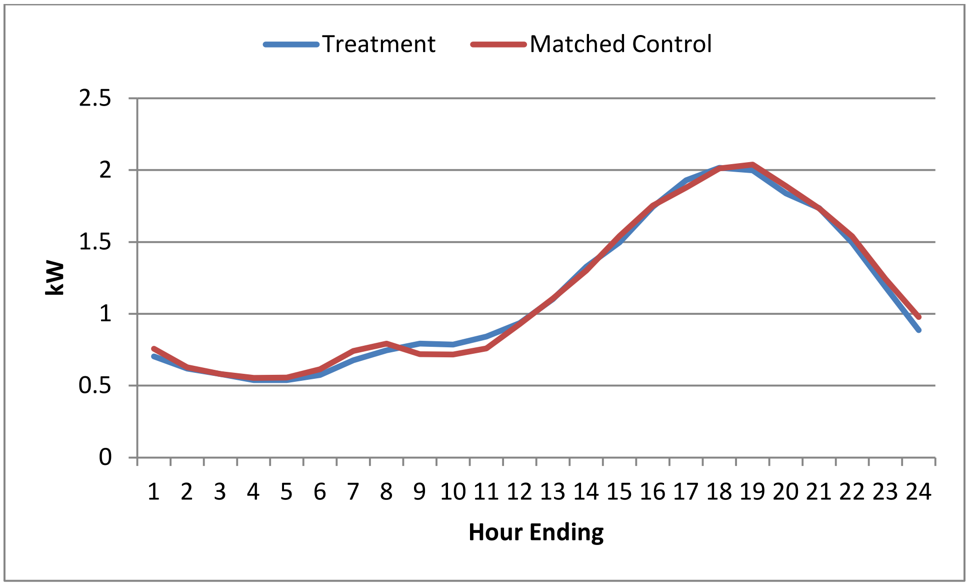
Table 6-4: Description of PTR Regression Variables

Variable	Description
b_0	Estimated constant
b_1	Estimated parameter coefficient
$mean17_t$	Average of the first 17 hourly temperature readings with a value for each time interval, t, corresponding to the daily value
ε_t	Error term for each time interval, t

6.2.3 Validity of Residential PTR Alerts Ex Post Load Impact Estimates

Figure 6-1 shows the average load within the treatment group and the matched control group averaged over the five hottest non-event days of the summer. As the figure shows, the two groups are quite well-balanced in terms of average hourly usage, especially during the time period when events are likely to occur.

Figure 6-1: Residential Treatment and Matched Control Group Comparison Average Load on the Five Hottest Non-event Days



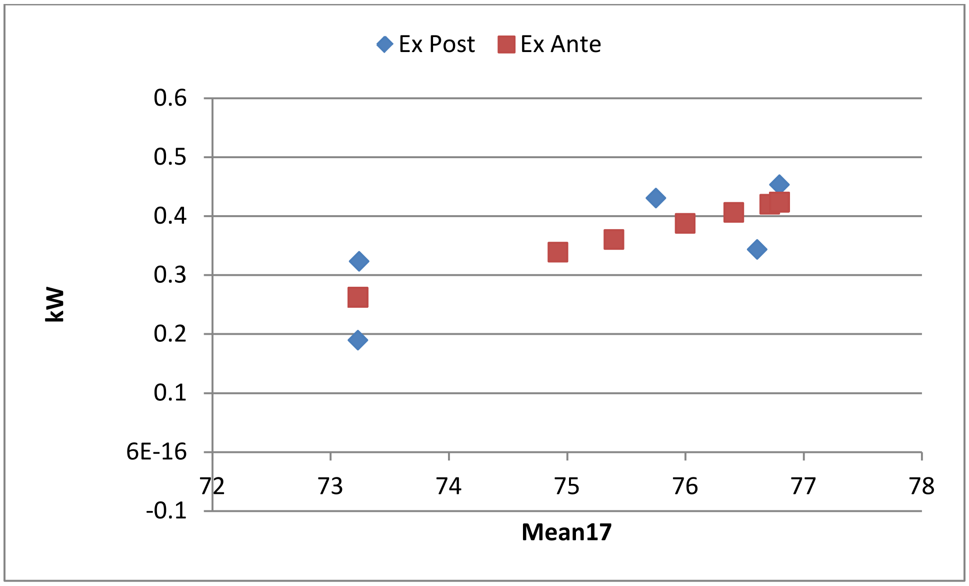
6.3 Residential PTR Alerts Ex Ante Impact Estimation Methodology

The same method used for the Summer Saver ex ante analysis was used to produce ex ante load impacts for residential customers who are forecast to receive PTR alerts. Similar to the Summer Saver ex ante analysis, load impacts from 2012 are modeled as a function of temperature and the parameters are used in a regression model to predict load impacts under ex ante weather conditions.[6] Reference loads are developed using the control group load profiles on event days in a regression model that relates usage to temperature. A detailed description of the ex ante methodology can be found in Section 3 of this report.

Figure 6-2 shows the ex ante impacts from 2012 graphed against the ex ante predictions that are developed based on those load impacts. The ex ante estimates for residential customers follow from the ex post impacts, however, the mean17 values used to predict the ex ante impacts are capped at the minimum and maximum values of the mean17 values observed ex post. With so few data points available, the model is quite sensitive to each data point. In this case, the linear trend is too strong to be plausible outside of the observable range. It can be inferred from Figure 6-2 that the model would start to predict negative load impacts at mean17 values below about 70^{0} Fahrenheit. The model fails this rudimentary check of general plausibility and is therefore not used for extrapolation to temperature conditions outside the bounds of the data from which the model was derived.

[6] Weekend events are omitted.

Figure 6-2: Average 11 AM to 6 PM Ex Post Load Impacts and Ex Ante Predictions Residential Summer Saver Customer Who Received PTR Alerts



7 Ex Post Load Impact Estimates - PTR for Summer Saver Customers

This section contains the ex post load impact estimates for program year 2012. Residential and commercial load impacts for the Summer Saver population are shown first, followed by load impacts for residential customers who received PTR alerts.

7.1 Residential and Commercial Ex Post Load Impact Estimates

Table 7-1 does not show ex post load impacts from PTR for residential and commercial Summer Saver customers. Instead, it shows the results from 12 different models that were designed to test whether PTR load impacts could be detected for the Summer Saver population. As discussed in the methodology section, 12 panel models were run for both residential and commercial customers, for a total of 24 models. The panel models include an indicator variable for PTR events in a function of usage that also controls for temperature. The models vary across two dimensions. Three different types of temperature variables were tested. Also, four different temperature thresholds were used to determine the characteristics of the dataset from which the parameters of each model were derived. The goal is to determine if PTR events can be detected with some regularity under a variety of plausible model specifications. If PTR events are detectable, the coefficient on the PTR event variable for most of the models should be negative and significant. Table 7-1 indicates how many coefficients fall into the categories of positive and significant, negative and significant, and insignificant across the 24 models. While a number of the coefficients on the PTR event variables are positive and significant, only one coefficient is negative and significant. A positive coefficient indicates that the model's estimated effect of PTR is an increase in load. This is implausible as a true outcome given the incentives a customer faces during a PTR event. This result indicates that the available reference days for modeling are not sufficient for detecting load impacts.

Table 7-1: Significance of Ex Post Load Impact Estimates

Customer Type	Positive and Significant	Negative and Significant	Insignificant
Residential	7	1	4
Commercial	6	0	6

*Significance measured at the 95% confidence level.

This test indicates that PTR load impacts cannot be reliably detected for the Summer Saver population. This analysis agrees with the broader PTR analysis, which was completed by Christensen Associates and documented in the *2012 Load Impact Evaluation of SDG&E's Residential PTR Program* and the *2012 Load Impact Evaluation of SDG&E's Small Commercial PTR Program*. Apart from customers who signed up for text messages and e-mail alerts, known as PTR Alerts, customers in the Summer Saver population receive no direct warning of an upcoming PTR event. Therefore, it is not surprising that across the population, customers do not respond to PTR events by reducing their usage.

7.2 Residential PTR Alerts Ex Post Load Impact Results

Table 7-2 shows the ex post load impact estimates for residential Summer Saver customers who received PTR alerts in 2012. Summer Saver residential customers who received PTR alerts delivered an average aggregate load reduction over the seven events of 1 MW. Residential impacts ranged from a low of 0.55 MW on August 21 to a high of 1.70 MW on September 15. The results of this analysis indicate that the PTR alerts significantly increase the likelihood that residential Summer Saver customers will respond to PTR events.

Table 7-2: Residential Summer Saver Customers Who Received PTR Alerts Matched Control Group Method

Date	Impact		Temperature During Event (°F)
	Per Premise (kW)	Aggregate (MW)	
20-Jul-12	0.32	0.94	81
9-Aug-12	0.43	1.26	83
10-Aug-12	0.34	1.00	84
11-Aug-12	0.42	1.22	84
14-Aug-12	0.45	1.32	84
21-Aug-12	0.19	0.55	78
15-Sep-12	0.58	1.70	98
Average*	0.35	1.01	82

*reflects the average event, omitting the Aug. 11 and Sept. 15 weekend events

These results are based on a matched control group methodology in which customers from the broader Summer Saver population are matched to customers who received PTR alerts. This method could be controversial since customers in the broader Summer Saver population were technically enrolled in PTR. This might tend to understate impacts if the control group customers actually responded. The best way to validate if the matched control group results can be trusted is to compare them with the results from a quasi-experimental design that uses non-event day information from customers who received PTR alerts.

Table 7-3 shows the ex post load impact estimates for residential Summer Saver customers who received PTR alerts in 2012. In contrast to the previous table, these results are calculated using a panel model that incorporates information from hot non-event days to come up with a reference load for event days. As discussed in the methodology section, usage is modeled as a function of temperature on hot non-event days and then the model parameters are applied to the temperature characteristics of event days to calculate the reference load. This approach relies on a strong assumption that the load profiles of hot non-event days can be accurately matched to what the load would have been on event days using only temperature. Under this method, Summer Saver residential customers who received PTR alerts delivered an average aggregate load reduction over the six events of 0.70 MW. Residential impacts ranged from a low of 0.39 MW on August 21 to a high of 1.27 MW on September 15.

Table 7-3: Residential Summer Saver Customers Who Received PTR Alerts
Panel Model Method

Date	Impact		Temperature During Event (°F)
	Per Premise (kW)	Aggregate (MW)	
20-Jul-12	0.26	0.75	81
9-Aug-12	0.29	0.86	83
10-Aug-12	0.28	0.82	84
11-Aug-12	0.23	0.66	84
14-Aug-12	0.23	0.67	84
21-Aug-12	0.13	0.39	78
15-Sep-12	0.44	1.27	98
Average*	0.24	0.70	82

*reflects the average event, omitting the Aug. 11 and Sept. 15 weekend events

Because the matched control group is selected from customers who could have participated in PTR events, a serious concern is that load impacts will be understated under the matched control group methodology. Since the results are actually about 30% lower on average under the panel model, there is no indication that the matched control group results are downward biased. In fact, it is more likely that the panel model results are downward biased due to a lack of hot non-event days for developing event day load profiles.

8 Ex Ante Load Impact Estimates - PTR for Summer Saver Customers

The model described above was used to estimate load impacts based on ex ante event conditions and enrollment projections for the years 2013 through 2023. Enrollment in PTR alerts amongst Summer Saver customers is expected to grow in the future. Table 8-1 shows the forecast enrollments by month and year. Currently, approximately 2,900 customers in the residential Summer Saver population receive PTR alerts. The number of customers receiving these alerts is expected to grow throughout 2013 and 2014 and stabilize at 4,156 accounts by October 2014.

Table 8-1: Forecast Enrollments
Residential Summer Saver Customers Who Will PTR Alerts

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	N/A	N/A	N/A	N/A	653	1,939	2,388	2,812	2,906	2,906	2,906	2,906
2013	2,906	2,906	2,906	2,906	2,906	3,121	3,546	3,694	3,834	3,865	3,865	3,865
2014	3,865	3,865	3,865	3,865	3,865	3,930	4,059	4,104	4,146	4,156	4,156	4,156
2015	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156
2016	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156
2017	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156
2018	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156
2019	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156
2020	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156
2021	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156
2022	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156
2023	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156	4,156

*There are small differences between these enrollments and the reported ex post enrollments because enrollments have changed since the ex post datasets were originally pulled

Table 8-2 summarizes the average and aggregate load impact estimates for residential Summer Saver customers receiving PTR alerts. Aggregate impacts are based on steady enrollment levels equal to those as of October 2015. For a typical event with 1-in-2 year weather conditions, the average impact per premise is 0.41 kW for these customers. The 1-in-10 year typical event day estimate is just barely higher at 0.42 kW. The aggregate program load reduction potential for residential customers on Summer Saver receiving PTR alerts is 1.7 MW for a typical event day under 1-in-2 year weather conditions and 1.8 MW under 1-in-10 year weather conditions.

Table 8-2: Average PTR Ex Ante Load Impact Estimates and Aggregate Estimates for 2015 Residential Summer Saver Customers Who Will Receive PTR Alerts

Day Type	Per Premise Impact (kW)		Aggregate Impact (MW)	
	Weather Year		Weather Year	
	1-in-10	1-in-2	1-in-10	1-in-2
Typical Event Day	0.42	0.41	1.76	1.69
January Monthly Peak	0.26	0.26	1.09	1.09
February Monthly Peak	0.26	0.26	1.09	1.09
March Monthly Peak	0.26	0.26	1.09	1.09
April Monthly Peak	0.26	0.26	1.09	1.09
May Monthly Peak	0.34	0.26	1.41	1.09
June Monthly Peak	0.42	0.26	1.76	1.09
July Monthly Peak	0.42	0.42	1.76	1.75
August Monthly Peak	0.42	0.39	1.76	1.61
September Monthly Peak	0.42	0.42	1.76	1.76
October Monthly Peak	0.36	0.26	1.50	1.09
November Monthly Peak	0.26	0.26	1.09	1.09
December Monthly Peak	0.26	0.26	1.09	1.09