REPORT

San Diego Gas and Electric Company Summer Saver 2014 Program Evaluation

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Prepared for

San Diego Gas and Electric Co.

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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. This report provides ex post load impact estimates for the 2014 Summer Saver program and ex ante load impact forecasts for 2015–2025.

The Summer Saver program is available to residential and nonresidential customers 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. A Summer Saver event may be triggered by temperature or system load conditions and customers are not automatically notified when an event occurs, however, customers can sign up to receive event notification.

There are two enrollment options each for both residential and nonresidential customers. Residential customers can choose between 50% or 100% cycling and nonresidential customers can choose between 30% and 50% cycling. The incentive paid for each option varies and is based on the number of CAC tons being controlled at each site.

At the end of 2014 there were 27,816 customers enrolled in the program with a total cooling capacity of 142,488 tons, representing a 2.3% decrease over 2013 enrolled customers and a 2.5% decrease in enrolled tons. About 83% of participants were residential customers, who accounted for 69% of the total tons of cooling in the program. Roughly 54% of residential participants were on the 100% cycling option and 72% of nonresidential customers selected the 50% cycling option over the 30% option. Summer Saver enrollment is projected to stay constant over the forecast horizon.

Eight Summer Saver events were called in 2014 and each one lasted four hours. Three of the six events were from 2 to 6 PM, with the others going from 12 to 4 PM, 3 to 7 PM, and 4 to 8 PM. For the three events with the same event hours, the average aggregate demand reduction for residential customers from 2 to 6 PM equaled 11.2 MW. The average per household load reduction equaled 0.42 kW. The aggregate load reduction for nonresidential customers equaled roughly 3.2 MW, or 0.69 kW per premise. In aggregate, the average reduction for the entire Summer Saver program across the three event days with common hours from 2 to 6 PM equaled 14.4 MW. These aggregate load reductions represent load control events called during relatively cool weather; the average temperature during the three 2 to 6 PM events was only 85°F for the residential program segment and 84°F for the nonresidential segment, which has greater enrollment in the coastal area than the residential segment.

Ex ante load impacts are intended to represent weather conditions under normal (1-in-2 year) and extreme (1-in-10 year) conditions, defined for two scenarios: one representing weather conditions expected when the SDG&E system peaks and another representing weather conditions when the CAISO system peaks. The event window for ex ante impacts is 1 to 6 PM, which differs from the typical 2014 ex post event window from 2 to 6 PM. On a typical event day under 1-in-2 year SDG&E-specific peaking conditions, aggregate load impacts are projected to equal 9.4 MW for residential customers and 2.7 MW for nonresidential customers, for a total program load reduction equal to 12.1 MW. Summer Saver load impacts increase with temperature, and load impacts for the hotter 1-in-2 year SDG&E-specific

September monthly system peak day are estimated to be 12.1 MW for residential customers and 3.2 MW for nonresidential customers, for a total load reduction potential of 15.3 MW.

Under 1-in-10 year SDG&E-specific peaking conditions, estimated impacts on the typical event day are forecasted to equal 14.6 MW and 3.7 MW for residential and nonresidential customers, respectively, or 18.3 MW in total. This is about 50% greater than on a typical event day under 1-in-2 year weather conditions. On the much hotter September SDG&E monthly system peak day for a 1-in-10 weather year, estimated impacts equal 17.9 MW and 4.3 MW respectively, for a total load reduction of 22.2 MW for the entire program.

As Summer Saver enters its tenth year of operation as an important demand resource in the San Diego region, Nexant recommends that SDG&E consider the following changes to the program's operational and measurement and evaluation activities going forward:

- The increasing number of years of Summer Saver event history has begun to accumulate a significant collection of ex post load impact observations since 2010. The 2015 evaluation plan should include scope to conduct model testing to determine if ex ante load impact models that incorporate more information can outperform the current model that was developed for optimal use with a more limited number of data points.
- A comparison of the ex post analysis between the 2013 and 2014 program years indicates that the RCT approach for the nonresidential segment may be unviable if sample sizes are desired that will support more comparable randomly-selected control groups. Hourly loads are more variable for the nonresidential program segment than for the residential segment. Larger sample sizes can be determined with power analysis for the nonresidential program segments, however, they are likely to be so large as to be impractical and costly to use. Any customers that are held back from load control to provide the basis for estimating reference load are not generating load impacts, which diminishes the demand response resource actually delivered for the sake of evaluation. With a relatively small number of nonresidential program participants enrolled in the program to begin with, sample sizes larger than those used for this evaluation would tax the segment's load impact contribution severely. We recommend that the nonresidential analysis return in 2015 to the quasi-experimental approach of selecting a matched control group for the entire nonresidential customer program segment.
- As of 2013, a small number of customers have begun to opt-in to receive notice of Summer Saver events by telephone. Nearly all of these customers are from the residential program segment. If SDG&E's customer program strategy evolves to further encourage event notification, and specifically to encourage participants to pre-cool their home before the event, the Summer Saver evaluator should work with SDG&E to determine if a different analysis approach should be used; alternatives to the same-day adjustment exist and are used effectively in evaluating load control programs similar to Summer Saver that utilize thermostats that feature automated pre-cooling strategies.

2 Introduction and Program Summary

The Summer Saver program is a San Diego Gas and Electric Co. (SDG&E) demand response resource based on central air conditioning (CAC) load control. It is implemented through an agreement between SDG&E and Alternative Energy Resources (AER), a subsidiary of Comverge, Inc.,[1] and is expected to continue to be implemented at SDG&E through 2016. This report provides 2014 ex post load impact estimates and ex ante load impact estimates for an 11-year forecast horizon (2015–2025).

The Summer Saver program is available to both residential and nonresidential customers, where eligible nonresidential customers are subject to a demand limit; only those nonresidential customers with average monthly peak demand up to a maximum of 100 kW over a 12-month period may participate. Summer Saver events may only be called during the months of May through October. Load control events must run for at least two hours but may also not run for more than four hours. Participants' air conditioners cannot be cycled for more than four hours in any event day and events cannot be triggered for more than 40 hours per month or 120 hours per year. Load control events can occur on weekends but not on holidays and cannot be called more than three days in any calendar week. These program rules apply to both residential and nonresidential customers alike.

Summer Saver is classified as a day-of demand response program. SDG&E may call an event whenever the utility's electric system supply portfolio reaches a resource dispatch equivalence of 15,000 Btu/kWh heat rate or as utility system conditions warrant. A Summer Saver event may also be triggered by extreme system conditions, such as special alerts issued by the California Independent System Operator (CAISO), SDG&E system emergencies related to grid operations, conditions of high forecasted California spot market prices, or for testing or evaluation purposes.

There are two enrollment options for both residential and nonresidential participants. Residential customers can choose to have their CAC units cycled 50% or 100% of the time during an event. The incentive paid for each option varies; the 50% cycling option pays $11.50 per ton per year of CAC capacity and the 100% cycling option pays $38 per ton per year. A residential customer with a four-ton CAC unit would be paid the following in the form of an annual credit on their SDG&E bill:

- $46 for 50% cycling; or
- $152 for 100% cycling.

Nonresidential customers have the option of choosing 30% or 50% cycling. The incentive payment for 30% cycling is $9 per ton per year and $15 per ton per year for the 50% cycling option. A nonresidential customer with five tons of air conditioning would be paid the following in the form of an annual credit on their SDG&E bill:

- $45 for 30% cycling; or
- $75 for 50% cycling.

[1] 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 the remainder of this document, the company is referred to as Comverge.

Prior to 2013, Summer Saver offered two additional options regarding the days of the week when an event can be called—only weekdays or both on weekdays and weekends. In 2013, all participants taking the five-day option were converted to the seven-day option.

In 2013, SDG&E began offering Summer Saver participants the option of receiving notification of load control events by telephone. A letter announcing the availability of telephone notification was sent to program participants in 2013. As of February 2015, 1,429 residential participants and 6 nonresidential participants had signed up for event notification, representing 6.2% and 0.1% of the program population, respectively.

Enrollment in the Summer Saver program as of October 2014 is summarized in Table 2-1.
Total enrollment, as measured by number of customers, number of devices, and air conditioning capacity (measured in tons) has decreased since fall 2013. As of October 2014, there were 27,816 customers enrolled in the program, which in aggregate represents 142,488 tons of CAC capacity. This is a 2.3% decrease in enrolled customers and a 2.5% decrease in enrolled tons relative to 2013. About 83% of participants were residential customers who accounted for 69% of the total tons of cooling subject to control under the program. About 54% of residential participants chose 100% cycling and 72% of nonresidential customers chose 50% cycling. While the percentage of residential customers taking the 100% cycling option has remained steady at roughly 50% since 2010, the percentage of nonresidential customers taking the 50% cycling option has consistently increased from 60% in 2010 to 72% in 2014. Overall, Summer Saver enrollment is expected to remain roughly constant for the remaining life of the program.

Table 2-1: Summer Saver Enrollment, October 2014

Customer Type	Cycling Option	Enrolled Customers	Enrolled Control Devices	Enrolled Tons
Nonresidential	30%	1,337	3,651	14,185
	50%	3,452	7,671	29,752
	Total	4,789	11,322	43,937
Residential	50%	12,332	14,424	50,620
	100%	10,695	13,205	47,931
	Total	23,027	27,629	98,552
Grand Total		**27,816**	**38,951**	**142,488**

2.1 Report Structure

The remainder of this report is organized as follows. Section 3 summarizes the data and methods that were used to develop 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 and Section 5 presents the ex ante estimates. Section 5 also provides details concerning differences between ex post and ex ante load impacts.

3 Data and Methodology

This section describes the datasets and analysis methods used to estimate load impacts for each event in 2014 and for ex ante weather and event conditions. Ex post results were calculated using control and treatment groups. For both residential and nonresidential program segments, the treatment and control group samples equaled approximately 740 customers, with each group further segmented by cycling strategy. The groups were randomly selected from the Summer Saver population. However, the treatment and control groups were not established before the May events. May ex post load impacts were estimated using statistically matched control groups in which load shape and usage characteristics were used to match Summer Saver participants to similar non-Summer Saver customers. The ex post results from 2010 through 2014 were used to estimate models relating temperature to load reductions that were then used in conjunction with ex ante weather data to estimate ex ante load impacts.

3.1 Data

Eight Summer Saver events were called in 2014. Table 3-1 shows the date, day of week, and the start and stop time for each event. All residential and nonresidential participants were called for each event, except for a group of control customers that were held back for measurement and evaluation purposes during non-May event days. No weekend events were called in 2014. Summer Saver events all lasted four hours in 2014, with some events starting as early as noon and others as late as 4 PM.

Table 3-1: Summary of 2014 Summer Saver Events

Date	Day of Week	Start Time	End Time
5/14/2014	Wednesday	4:00PM	8:00PM
5/15/2014	Thursday	4:00PM	8:00PM
5/16/2014	Friday	12:00PM	4:00PM
7/29/2014	Tuesday	3:00PM	7:00PM
8/27/2014	Wednesday	2:00PM	6:00PM
9/15/2014	Monday	2:00PM	6:00PM
9/16/2014	Tuesday	3:00PM	7:00PM
9/17/2014	Wednesday	2:00PM	6:00PM

Tables 3-2 and 3-3 show the distribution of CAC tonnage by cycling option and climate zone for the participant population as of October 2014 and for the samples of residential and nonresidential customers used for analysis purposes. The differences between the fraction of residential customer tonnage in the residential sample and population cells are small; there are only small differences across climate zones and cycling options. The differences across nonresidential sample and population cells are larger. Sample weights were applied during the analysis so that average load impacts reflect the program's enrollment across climate zones for each cycling strategy.

Table 3-2: Distribution of CAC 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	5%	1%	0%	46%	51%
	Sample	5%	0%	0%	43%	48%
100%	Population	11%	1%	0%	37%	49%
	Sample	10%	0%	0%	42%	52%
Total	**Population**	**15%**	**2%**	**0%**	**83%**	**100%**
	Sample	**15%**	**0%**	**0%**	**85%**	**100%**

Table 3-3: Distribution of CAC Tonnage by Program Option and Climate Zone Nonresidential Population

Cycling Option	Group	Climate Zone 1	Climate Zone 2	Climate Zone 3	Climate Zone 4	Total
30%	Population	14%	0%	0%	18%	32%
	Sample	23%	0%	0%	30%	53%
50%	Population	35%	0%	0%	33%	68%
	Sample	22%	0%	0%	25%	47%
Total	**Population**	**49%**	**0%**	**0%**	**50%**	**100%**
	Sample	**46%**	**0%**	**0%**	**54%**	**100%**

3.2 Methodology

The primary task in developing ex post load impacts is to estimate a reference load for each event. The reference load is a measure of what participant demand would have been in the absence of the CAC cycling during an event. The primary task in estimating ex ante load impacts (which is often of more practical concern) is to make the best use of historical data on loads and load impacts to predict future program performance. The data and models used to estimate ex post impacts are typically the key inputs to the ex ante analysis.

The primary source of reference load information used here was load observed during event times for a control group of customers who did not experience the load control event. Under this approach, random samples of Summer Saver customers were selected for each program segment (residential and nonresidential) and cycling strategy. During each event, half of the sample did not have their CAC units cycled so that these customers could be used to provide a reference load for those who did have their units cycled. This research design is referred to as a randomized control trial (RCT). For the events occurring in May, when no customers were withheld as a control group, a statistically matched control

group was used to estimate load impacts. Since the RCT provides the primary research framework, the methodology used to select a matched control group for the May events is described in Appendix A.

3.2.1 RCT Ex Post Methodology

An RCT is an experimental research approach where customers are randomly assigned to treatment and control conditions so that the only difference between the two groups, other than random chance, is the existence of the treatment condition. In this context, for each of the five non-May events this year, roughly half of the 1,512 customers in the residential sample and half of the 1,475 customers in the nonresidential sample had their CAC unit cycled while the remaining customers served as the control group. The group that received the event signal alternated from event to event. 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 were 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 of the group that did not receive the event. The adjustment was based on the ratio of usage between the treatment and control groups for the hour prior to the event start. For example, if the average usage in the treatment group during the hour preceding an event is 1.2 kW and the average usage in the control group is 1.3 kW, the ratio would equal 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. This adjustment is referred to as a “same-day adjustment” and is an effective way of accounting for small differences in load that can arise between randomly assigned treatment and control groups. Such an adjustment is appropriate in this setting because the vast majority of customers were not notified of Summer Saver events prior to the events’ initiation. As mentioned in Section 2, event notification became an option starting in 2013 but only about 6% of residential participants are signed up to receive notification by telephone and a very small fraction of a percent of nonresidential participants receive notification. Since Summer Saver is a day-of demand response program, the notification occurs within hours of the actual event. To the extent that this group of customers engaged in pre-cooling prior to the event, it would be reflected in both the treatment and control groups.

Hourly impact estimates for the residential and nonresidential Summer Saver population were calculated by taking a weighted average of the impact estimates for each cycling option, with weights determined by the number of tons enrolled on each cycling option. Similar weighting was done to calculate cycle percentage level impacts. For cycle percentage level impacts, weights were determined by the number of tons enrolled in each climate zone. Impacts for the average event day were calculated from treatment and control group load shapes averaged across the three events that lasted from 2 to 6 PM.

3.2.2 RCT Ex Post Validation Analysis

Tables 3-4 and 3-5 compare the sample size, average CAC tonnage, and cycling option for the two randomly chosen test groups for residential and nonresidential participants, respectively. As seen, the two groups are very similar along the dimensions of CAC tonnage and cycling option.

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

Group	Sample Size	Average CAC Tonnage per Premise	% of Customers on 50% Cycling
A	754	4.1	50%
B	758	4.2	50%
Total/Average	1,512	4.2	50%

Table 3-5: Nonresidential A and B Group Comparison Sample Size, Tonnage, and Cycling Options

Group	Sample Size	Average CAC Tonnage per Premise	% of Customers on 50% Cycling
A	740	9.6	50%
B	735	9.4	50%
Total/Average	1,475	9.5	50%

Even though random assignment should produce two groups with similar characteristics, it is still important to compare the two groups based on electricity consumption when Summer Saver events are not in effect since, in the absence of very large samples, differences in energy consumption between two randomly selected samples can still occur due to chance. Prior evaluations have used residential sample sizes similar in size to those used for this evaluation and differences between the A and B groups have ranged between 1 and 5%. In 2014, differences between the residential A and B groups on hot nonevent days are at the high end of that range, around 5%. For nonresidential customers, a sample of approximately 1,500 customers was randomly assigned to A and B groups. The A group used approximately 6% more electricity during peak hours. Figures 3-1 and 3-2 illustrate these differences on 10 hot nonevent days in 2014. As the figures show, the two groups are quite similar with respect to load shape but indicate the magnitude differences alluded to above. Figures 3-3 and 3-4 show the comparison of groups A and B further segmented by cycling option, which represents sample sizes of approximately 370 customers each. At the cycling level, residential A and B groups show some difference for both the cycling options—the difference is larger for 50% cycling than for 100%. The nonresidential A and B groups for the 50% and 30% cycling options show much larger differences in consumption, especially for the 50% option group. These larger differences between A and B groups are attributable to the greater variability in electricity consumption for nonresidential customers than residential customers. For these nonresidential segments, larger sample sizes would be required to reliably produce randomly assigned A and B groups with smaller differences in peak hourly electricity consumption. These relatively large differences between treatment and control groups result in greater reliance on the same-day adjustment than is desired.

Figure 3-1: Residential A and B Group Comparison Average Load on 10 Hot 2014 Non-event Days[2]

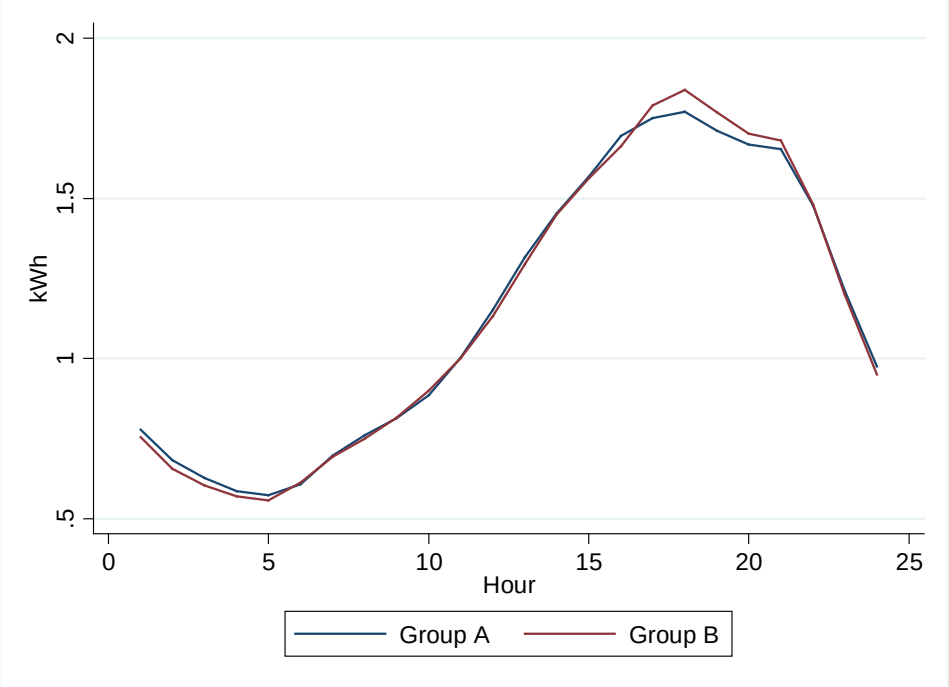
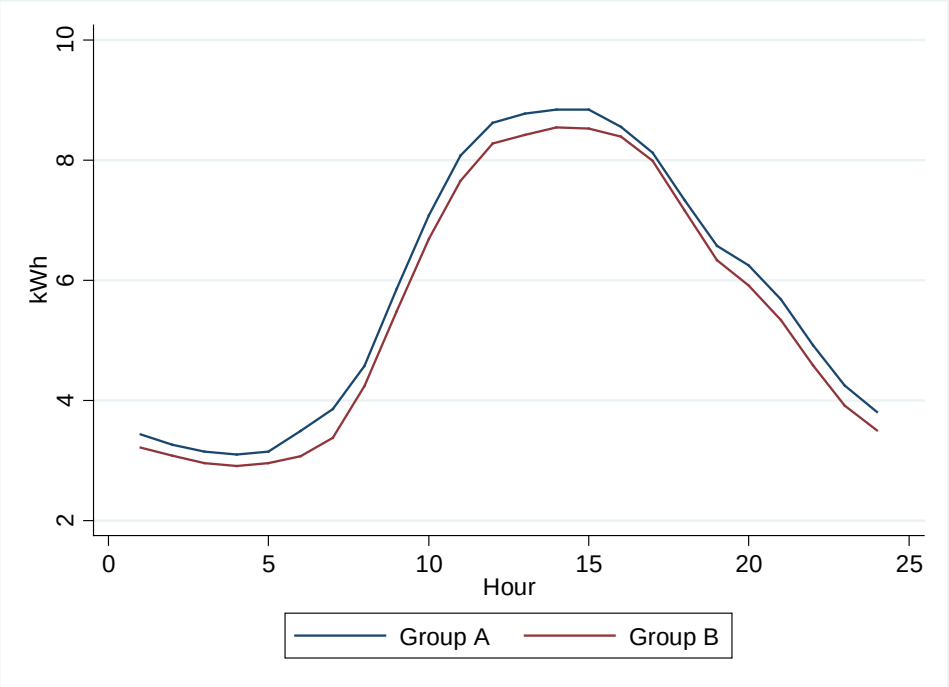


Figure 3-2: Nonresidential A and B Group Comparison Average Load on the 10 Hottest 2014 Non-event Days



[2] The 10 non-event days used for this analysis are 4/29, 4/30, 5/1, 5/2, 5/13, 8/28, 9/7, 9/8, and 9/14/14.

Figure 3-3: Residential A and B Group Comparison
Average Load on 10 Hot 2014 Non-event Days by Cycling Option

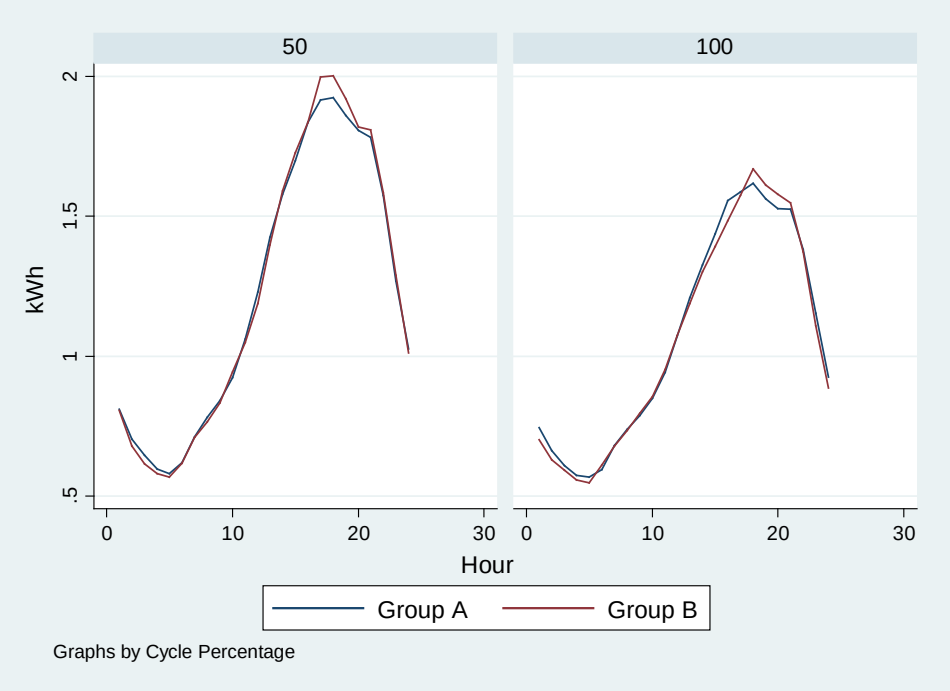
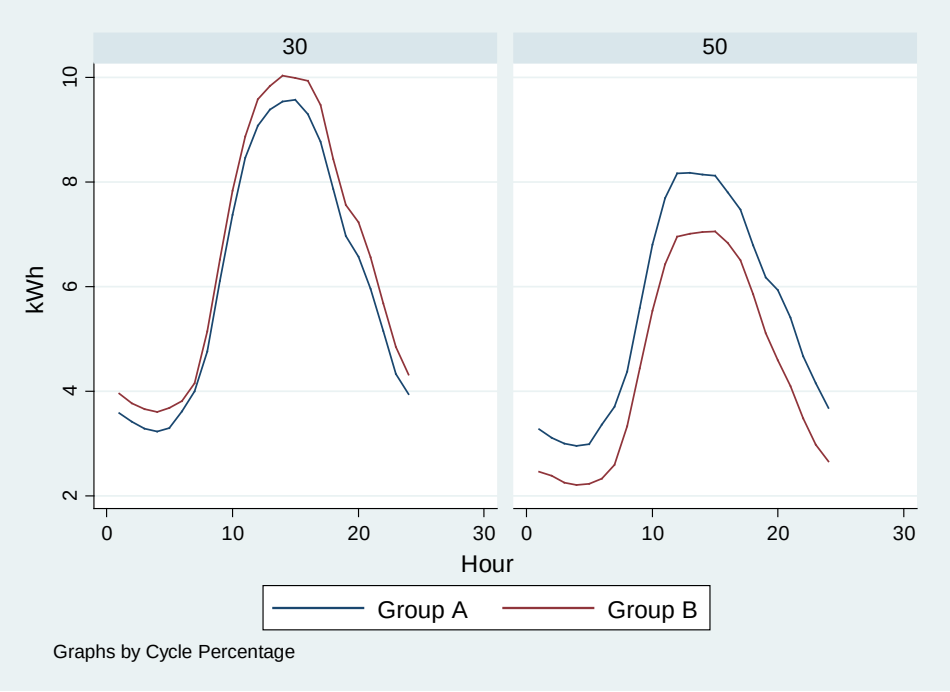


Figure 3-4: Nonresidential A and B Group Comparison
Average Load on 10 Hot 2014 Non-event Days by Cycling Option



3.3 Ex Ante Impact Estimation Methodology

Calculating the ex ante load impacts is a multi-step process, but is driven by a straightforward approach to modeling load impacts as a function of weather. Briefly, load impacts from the previous five years of Summer Saver events were modeled as a function of temperature and then applied to ex ante weather conditions to predict ex ante load impacts. This section presents a detailed description of the ex ante methodology.

Ex ante load impacts were developed by using the available ex post data. For both residential and nonresidential customers, load impacts for a common set of hours across all ex post events from 2010 through 2014 were used in the estimation database for developing the ex ante model. Only the hours from 2 to 5 PM were used for the analysis because these hours were common across the greatest number of ex post event days. Certain prior Summer Saver event days were not used in the ex ante regression analysis because of atypical circumstances surrounding the event. September 8 and 9, 2011 were excluded as they were associated with a regional system outage. September 15, 2012 was excluded because it was a Saturday. August 10, 2012 was excluded because the event only had one hour during the period 2 to 5 PM. The May 2014 events were excluded because of wildfires in the San Diego region in addition to unusually high temperatures, attributable to Santa Ana wind conditions, that were recorded during those events which were further coupled with unusually low load impacts.

The average load reduction from 2 to 5 PM was modeled as a function of the average temperature for the first 17 hours of each event day, midnight to 5 PM, (mean17). This 17-hour average was used to capture the impact of heat buildup leading up to and including the event hours. Per ton load impacts were used so that the load impacts would be scalable to ex ante scenarios where the tonnage and number of devices per premise may be different. The models were run separately by customer type (residential and nonresidential) and cycling strategy. The estimated parameters from the models were used to predict load impacts under 1-in-2 and 1-in-10 year ex ante weather conditions. The final regressions only included one explanatory variable because more complicated models were not found to perform better in cross-validations done in previous Summer Saver evaluations. The model that was used to predict average ex post impacts was:

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

Table 3-6: Ex Ante Regression Variables

Variable	Description
$Impact_d$	Average per ton ex post load impact for each event day from 2 to 5 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 3-5 through 3-8 show the ex post impacts from 2010 through 2014 by customer type and cycling strategy as a function of mean17. The figures also contain the ex ante predictions that were developed

based on the regression model of ex post impacts as a function of mean17. The ex ante estimates for residential customers, shown in Figures 3-5 and 3-6, follow from the ex post impacts and are quite plausible. While there is more noise in the nonresidential ex post estimates, shown in Figures 3-7 and 3-8, the linear prediction through these estimates produce ex ante estimates that are conservatively in the middle of the range of ex post estimates. It is also worth noting how the load impacts at a given value of mean17 are quite similar for the two residential cycling options. As discussed in the next section, customers who chose the 100% cycling option have much lower reference loads than those on the 50% cycling option so the average, absolute impacts for the two groups are quite similar in spite of the very different cycling strategies. This is not the case with nonresidential customers, where the difference in load impacts across the two cycling options is much greater. This is logical since residential customers have more discretion in their use of air conditioning (especially those who are not home during the day) and there is much more potential for selection effects to differ across those choosing the two different cycling options. Nonresidential customers have less discretion in how they operate their air conditioning during business hours so selection effects correlated with cycling options are less prevalent for this customer segment.

Figure 3-5: Average Ex Post Load Impacts and Ex Ante Predictions from 2 to 5 PM for Residential 50% Cycling Participants

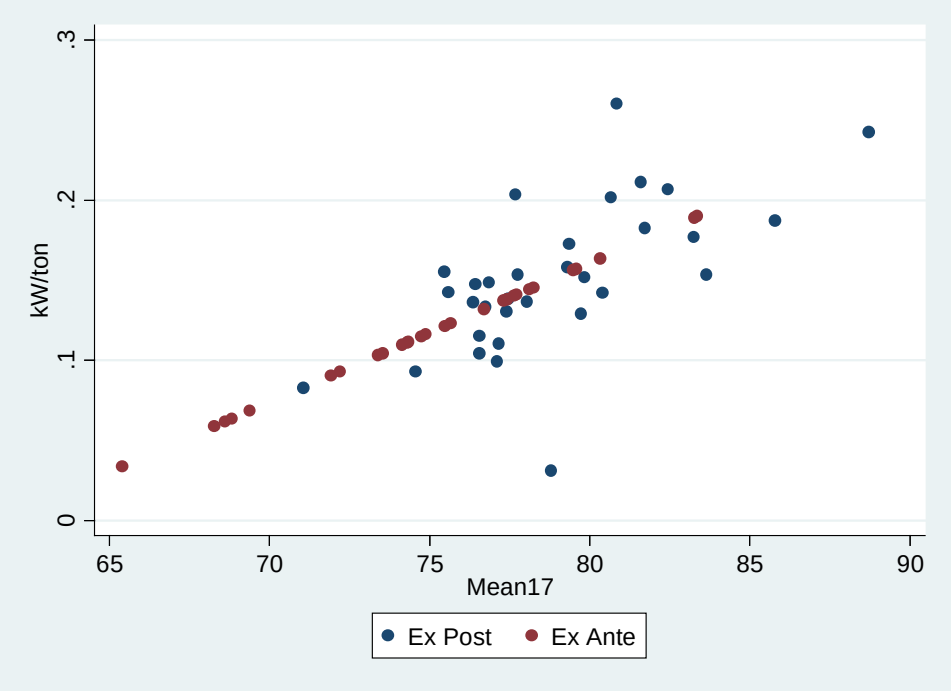


Figure 3-6: Average Ex Post Load Impacts and Ex Ante Predictions from 2 to 5 PM for Residential 100% Cycling Participants

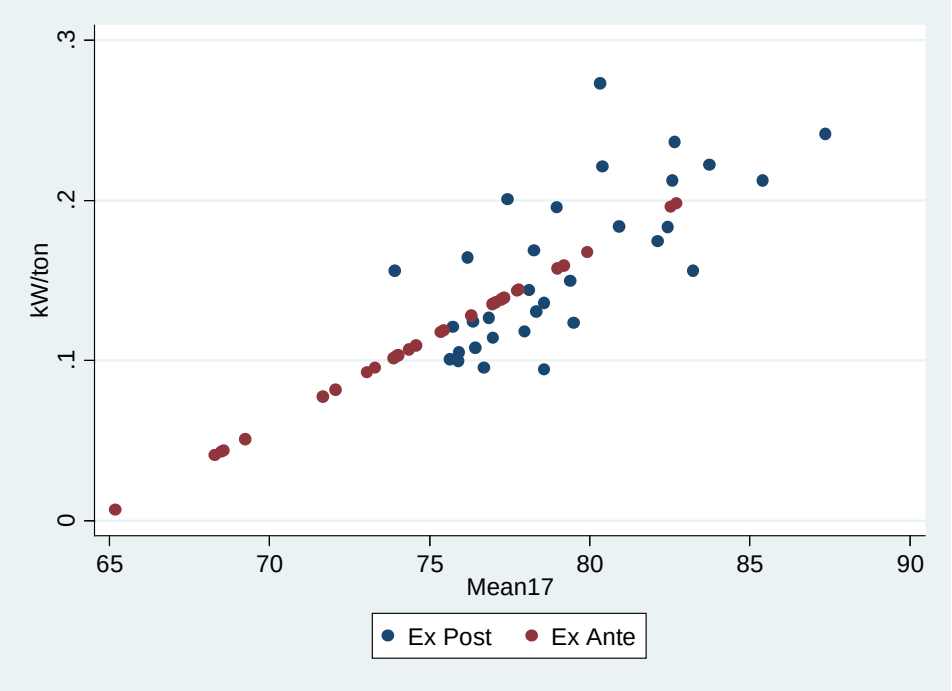


Figure 3-7: Average Ex Post Load Impacts and Ex Ante Predictions from 2 to 5 PM for Nonresidential 30% Cycling Participants

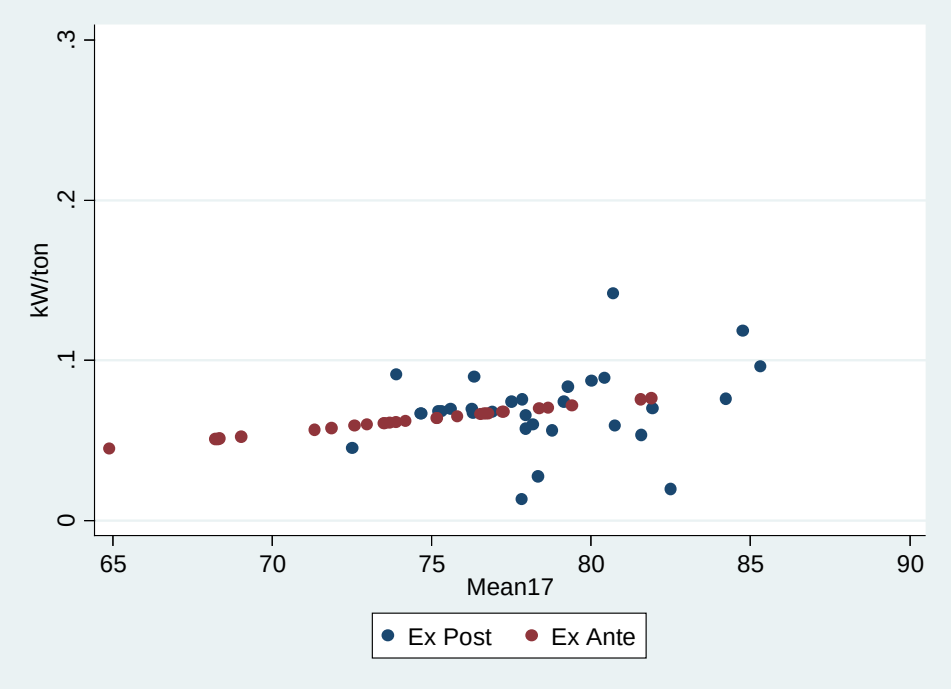
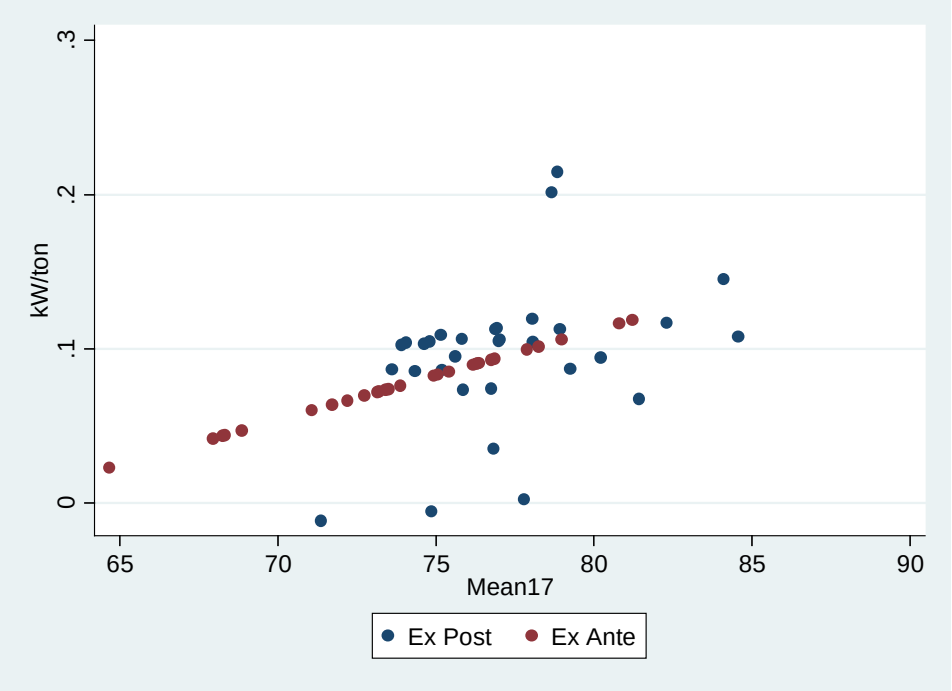


Figure 3-8: Average Ex Post Load Impacts and Ex Ante Predictions from 2 to 5 PM for Nonresidential 50% Cycling Participants



After the ex ante impacts have been estimated for the 2 to 5 PM period, the next step is to predict impacts for the additional hours covered by the CPUC resource adequacy window from 1 to 6 PM. Hourly ex post impact estimates for each event from 2010 to 2014 were expressed as a fraction of the average impact from 2 to 5 PM. Table 3-7 shows the average of these ratios for the hours 1 to 6 PM for the 100% residential cycling group. The first column of Table 3-7 shows how the average event impact for each hour compares with the average impact from 2 to 5 PM. To illustrate further, the second column shows the proportions in the first column multiplied by 0.10 kW/ton, which is the average predicted impact from 2 to 5 PM for residential customers during a typical event day under 1-in-2 year weather conditions. To calculate the estimated impact for 1 to 2 PM, for example, 0.10 kW/ton is multiplied by 0.70 to yield an impact of 0.07 kW/ton. The same strategy was applied for all five hours of the ex ante event window for each cycling option and customer class.

Table 3-7: Hourly Load Impacts Compared to Average Impact from 2 to 5 PM Residential 100% Cycling

Hour of Event	Hourly Impact/ Average 2-5 PM Impact*	Hourly Impact for Typical CAISO Event Day, 1-in-2 Weather (kW/ton)	Hourly Impact for Typical SDG&E Event Day, 1-in-2 Weather (kW/ton)
1–2 PM	0.70	0.07	0.07
2–3 PM	0.85	0.09	0.08
3–4 PM	1.02	0.11	0.10
4–5 PM	1.12	0.12	0.11
5–6 PM	1.04	0.11	0.10

*Multiyear dataset from 2010–2014

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, when there are only a moderate number of events and, for some hours, many fewer events than for other hours, that strategy risks fitting spurious trends to individual hours or trends across hours that conflict with one another. 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 compared with the primary effect of temperature on average event impacts.

As discussed above, average ex ante load impacts were estimated directly based on ex post impacts. However, the CPUC Load Impact Protocols[3] require that ex ante reference loads also be estimated even though they may not always be necessary for load impact estimation, as is true here. To meet this requirement, reference loads were estimated in a manner similar to the approach used for ex ante impact estimation. Models for estimating reference loads were estimated separately by customer type and cycling strategy. The following steps were used:

- Average control group usage during the 2 to 5 PM time period on 2011–2014[4] event days was modeled as a function of mean17;
- The parameters from this regression were used to predict average usage from 2 to 5 PM under ex ante weather conditions;
- A ratio between each ex ante prediction and average 2013 control group usage from 2 to 5 PM across all days was calculated; and

[3] See CPUC Rulemaking 07-01-041 Decision (D.) 08-04-050, "Adopting Protocols for Estimating Demand Response Load Impacts" and Attachment A, "Protocols."

[4] Data for the year 2010 was excluded from the reference load estimation process because the evaluation was based on end-use, rather than whole-premise, interval data.

- Average control group load profiles for the entire average event day 2011–2014 were adjusted by the ratio specific to each set of ex ante weather conditions to produce the final ex ante reference loads.

Finally, estimates of the ex ante snapback effect were developed in a similar manner. Snapback refers to the increase in load following termination of a load control event as a result of the increased temperature that occurs in buildings when air conditioning is cycled. Like load impacts and reference loads, snapback for residential customers was calculated by cycling strategy. The calculation consisted 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; and
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.

Nonresidential snapback was assumed to be zero as there is little prior evidence of CAC snapback after Summer Saver events for nonresidential participants.

4 Ex Post Load Impact Estimates

This section contains the ex post load impact estimates for program year 2014. Residential load impacts are presented first, followed by nonresidential load impacts.

4.1 Residential Ex Post Load Impact Estimates

Summer Saver program events were triggered eight times in 2014 and each event lasted four hours. The hours covered by each event varied, but three of the eight events lasted from 2 to 6 PM. Two events were called late in the day, from 4 to 8 PM. Table 4-1 presents ex post load impacts for the residential program segment for 2014 and 2013, for comparison. Aggregate load impacts ranged from a low of 6.0 MW on May 16, 2014 to a high of 19.5 MW on September 16, 2014. The three events that occurred from 2 to 6 PM produced, on average, 11.2 MW of load reduction. These load impacts represent some of the lowest estimated load impacts in recent years. Two factors may explain these low impacts. First, there were three events called in the month of May during a Santa Ana weather event in the San Diego region. These three events are the first time that Summer Saver has been dispatched in the month of May. Such early events may reflect reduced air conditioning load due to the fact that many HVAC systems were not set to cooling mode yet. Second, the Summer Saver events called in 2014 were called during historically cool weather conditions—on average, the temperatures observed during the event hours are the lowest observed since 2010.

Table 4-1: Summer Saver Residential Ex Post Load Impact Estimates

Year	Date	Impact			Avg. Temperature During Event (°F)
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2013	8/28/2013	0.48	0.52	12	84
	8/29/2013	0.46	0.51	12	88
	8/30/2013	0.68	0.78	18	91
	9/3/2013	0.58	0.65	15	88
	9/5/2013	0.57	0.63	14	89
	9/6/2013	0.84	0.90	21	92
	Average*	0.66	0.74	17	90
2014	14-May-14	0.26	0.31	6.9	85
	15-May-14	0.41	0.49	10.9	87
	16-May-14	0.22	0.27	6.0	93
	29-Jul-14	0.45	0.54	12.2	80
	27-Aug-14	0.23	0.27	6.1	85
	15-Sep-14	0.68	0.81	18.2	88
	16-Sep-14	0.73	0.87	19.5	89
	17-Sep-14	0.53	0.64	14.3	83
	Average**	0.42	0.50	11.2	85

*Reflects the average 1–5 PM 2013 Summer Saver event

**Reflects the average 2–6 PM 2014 Summer Saver event

Table 4-2 shows the estimated load impacts for residential participants on each event day segmented by cycling option. On a per premise basis, load impacts for 100% cycling range from a high of 1.05 kW to a low of 0.43 kW. Load impacts for 50% cycling range from 0.85 kW to 0.11 kW per premise. Across the three days with the same event times, load impacts for 100% cycling are 35% higher than for 50% cycling, despite the fact that the cycling percentage differs by a factor of two. This is primarily due to the fact that average reference load for customers taking the 50% cycling option is about 40% higher than for those taking the 100% option. Put another way, customers that use their CAC units more are less likely to take the 100% cycling options.

In the case of two event days—July 29, 2014 and September 15, 2014—reference loads for 100% cycling customers are in fact much higher, which is also when load impacts for 100% cycling are actually lower than 50% cycling. While the differences between the estimated load impacts for 50% and 100% cycling are not statistically significant, on both of these days, reference loads for customers on the 50% cycling option are about 60% higher than for customers on the 100% option. Similar outcomes have been observed in prior evaluations of the Summer Saver program, but given the relatively small sample sizes at the cycling option level of aggregation, this result may just be due to random fluctuation. There may also have been slightly different weather patterns for the two groups that caused the larger reference load increase for the 50% cycling customers on these days (100% cycling customers are more highly concentrated in the moderate coastal climate zone than are 50% cycling customers, so there are small differences in average weather for the two groups).

Table 4-2: Summer Saver Residential Average (kW per Premise) and Aggregate (MW) Load Impacts by Cycling Option

Event Date	Average Load Impact per Premise (kW)		Aggregate Load Impact (MW)	
	100%	50%	100%	50%
5/14/2014	0.45	0.19	4.8	2.2
5/15/2014	0.58	0.41	6.1	4.8
5/16/2014	0.43	0.12	4.5	1.5
7/29/2014	0.56	0.54	5.9	6.3
8/27/2014	0.44	0.11	4.6	1.3
9/15/2014	0.80	0.85	8.5	10.0
9/16/2014	1.05	0.69	11.2	8.1
9/17/2014	0.68	0.63	7.3	7.4
Average*	0.58	0.43	6.2	5.0

*Reflects the average 2-6 PM 2014 Summer Saver event

Table 4-3 shows estimated event impacts for residential customers segmented by usage quintiles. Each customer was placed into one of five quintiles based on their average usage during the peak hours from 11 AM to 6 PM on hot non-event weekdays in 2014. Impact estimates were calculated separately for

each quintile using the treatment group loads for each quintile during the average event hour of the average 2 to 6 PM 2014 Summer Saver event.

Table 4-3 shows both the average impact as well as the standard error of the estimates for each quintile. Load impacts increase across the quintiles, likely truly reflecting an underlying pattern, but the estimates at the quintile level have fairly large standard errors. For example, the impact estimate for the highest quintiles for residential customers with 50% cycling are significantly different at the 95% level of confidence from the impact in all other quintiles, but the impacts in the other quintiles are not statistically significantly different from each other.

Table 4-3: Summer Saver Residential Average per Premise Estimated Impacts by Usage Quintile and Cycling Option

Quintile	50% Cycling		100% Cycling	
	Average* Per Premise Load Impact (kW)	Load Impact Standard Error (kW)	Average* Per Premise Load Impact (kW)	Load Impact Standard Error (kW)
1	0.05	0.08	0.07	0.06
2	0.07	0.09	0.29	0.06
3	0.31	0.12	0.51	0.09
4	0.49	0.15	0.72	0.13
5	1.21	0.21	1.30	0.17

*Reflects the average 2-6 PM 2014 Summer Saver event

4.2 Nonresidential Ex Post Load Impact Estimates

Table 4-4 presents ex post load impact estimates for nonresidential customers for each 2014 event day and on average across the three Summer Saver events in 2014 with common event hours from 2 to 6 PM, in addition to the 2013 ex post load impacts for comparison. Nonresidential customers represent 17% of total Summer Saver participants and 31% of enrolled CAC tonnage. Nonresidential aggregate impacts varied from a low of 0.5 MW on July 29 to a high of 4.0 MW on September 16. While both nonresidential and residential load impacts peaked on the same day, nonresidential and residential load impacts were at their lowest in 2014 on different days. Nonresidential load impacts were extremely low on July 29, but not unprecedentedly so. The average temperature observed on this day for nonresidential customers during the event was 78°F, which is the lowest observed average event temperature since the same average event temperature was observed during an event in 2012. Per premise load impacts for this event (on September 13, 2012) were estimated at 0.13 kW, similar to the 0.10 kW per premise estimated for July 29, 2014. Like the residential program segment, the nonresidential segment saw relatively low load impacts for the first event day during the May Santa Ana weather event, but unlike the residential segment, the nonresidential segment returned to the typical range of load impacts for nonresidential participants on hot summer days.

Table 4-4: Summer Saver Nonresidential Ex Post Load Impact Estimates

Year	Date	Impact			Avg. Temperature During Event (°F)
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2013	8/28/2013	0.20	0.50	2	82
	8/29/2013	0.28	0.69	3	87
	8/30/2013	0.34	0.83	4	90
	9/3/2013	0.34	0.84	4	85
	9/5/2013	0.34	0.83	4	86
	9/6/2013	0.38	0.94	4	90
	Average*	0.35	0.86	4	88
2014	5/14/2014	0.16	0.37	1.7	85
	5/15/2014	0.25	0.60	2.8	86
	5/16/2014	0.33	0.79	3.7	91
	7/29/2014	0.04	0.10	0.5	78
	8/27/2014	0.31	0.74	3.5	84
	9/15/2014	0.24	0.56	2.6	86
	9/16/2014	0.36	0.85	4.0	89
	9/17/2014	0.32	0.76	3.5	82
	Average**	0.29	0.69	3.2	84

*Reflects the average 1–5 PM 2013 Summer Saver event

**Reflects the average 2–6 PM 2014 Summer Saver event

A comparison of average impacts per CAC unit in Tables 4-1 and 4-4 shows that the impact for nonresidential customers is roughly 70% of the value for residential customers. Much of this difference is certainly due to the lower average cycling options used for nonresidential customers, but per CAC unit load impacts can be compared for residential and nonresidential participants on the same cycling strategy to determine if other factors may be at play.

Prior Summer Saver evaluations have found larger overall differentials between residential and nonresidential load impacts and have also found that they are accompanied by a differential in residential and nonresidential load impacts for the 50% cycling strategy. In 2014, the overall difference between load impacts per CAC unit is not as large, and no clear directional difference in load impacts is observed between residential and nonresidential 50% cycling, as shown in Table 4-5.

Table 4-5: Comparison of Residential and Nonresidential Summer Saver 50% Cycling Load Impacts

Event Date	Average Load Impact per CAC Unit (kW)	
	Residential 50%	Nonresidential 50%
5/14/2014	0.16	0.22
5/15/2014	0.35	0.33
5/16/2014	0.11	0.37
7/29/2014	0.46	0.05
8/27/2014	0.10	0.37
9/15/2014	0.73	0.28
9/16/2014	0.59	0.32
9/17/2014	0.53	0.44
Average*	0.37	0.35

Table 4-6 shows the estimated load impacts for nonresidential participants on each event day segmented by cycling strategy. On a per premise basis, load impacts for 50% cycling range from 0.98 kW to 0.11 kW. Per premise load impacts for 30% cycling range from 1.12 kW to 0.10 kW. Across the three days with the same event times, load impacts for 50% cycling are 72% higher than load impacts for 30% cycling,

Table 4-6: Summer Saver Nonresidential Average (kW per Premise) and Aggregate (MW) Load Impacts by Cycling Option

Event Date	Average Load Impact per Premise (kW)		Aggregate Load Impact (MW)	
	50%	30%	50%	30%
5/14/2014	0.49	0.10	1.62	0.14
5/15/2014	0.73	0.29	2.43	0.38
5/16/2014	0.83	0.67	2.77	0.90
7/29/2014	0.11	0.07	0.37	0.09
8/27/2014	0.83	0.56	2.77	0.75
9/15/2014	0.62	0.47	2.06	0.63
9/16/2014	0.73	1.12	2.42	1.49
9/17/2014	0.98	0.23	3.25	0.30
Average*	0.79	0.46	2.64	0.61

*Reflects the average 2-6 PM 2014 Summer Saver event

Table 4-7 shows the load impacts for nonresidential customers by usage quintiles, determined in the same manner as for residential customers as discussed above. For nonresidential customers, load

impacts generally increase across the quintiles, but the estimates by quintile are considerably noisier than the residential quintile estimates; the nonresidential load impact estimates are not distinguishable between quintiles at the 95% level of confidence.

Table 4-7: Summer Saver Nonresidential Average per Premise Estimated Impacts by Usage Quintile and Cycling Option

Quintile	30% Cycling		50% Cycling	
	Average* Per Premise Load Impact (kW)	Load Impact Standard Error (kW)	Average* Per Premise Load Impact (kW)	Load Impact Standard Error (kW)
1	0.11	0.13	0.24	0.10
2	0.27	0.25	0.43	0.21
3	0.59	0.41	0.71	0.33
4	0.44	0.71	0.50	0.58
5	0.85	3.56	2.05	2.42

4.3 Free Riders

An important issue for the cost-effectiveness of the Summer Saver program is the fraction of customers who sign up for the program but who do not use their CAC unit much or at all. These customers are compensated for their enrollment in the program, but are likely to provide little load impact. Sub-meter data can be used to estimate the fraction of each program segment that had little CAC usage in 2014. Sub-metered data was collected from a sample of 307 residential and 309 nonresidential CAC units divided approximately evenly among cycling options.

Table 4-8 shows the fraction of CAC units with zero or small CAC usage. A first check for customers with sub-metered usage equal to 0 kW across the entire summer considered all non-event days in the summer of 2014. The residential program segment shows more than five times the incidence of 0 kW usage than the nonresidential program segment.

A second check for customers with sub-metered usage equal to nearly 0 kW (thresholds of 0.02 kW and 0.05 kW were used) on hot non-event days[5] was also made. Residential 100% cycling participants are more likely to show very low CAC usage than 50%, but nonresidential participants in the 30% cycling segment are about as likely to have very low CAC usage as nonresidential participants in the 50% cycling segment. These outcomes reflect the fact that nonresidential cooling needs and preferences are usually less flexible than those of residential customers, likely leading to less selection between cycling options for nonresidential customers than residential customers.

[5] Hot non-event days in 2014 were selected for analysis if the average temperature between 11 AM and 6 PM was greater than 80°F.

Table 4-8: Fraction of CAC Units with Low Average Usage Sub-meter Sample – Hot Non-event Days in 2014

Average Usage	Residential		Nonresidential	
	50%	100%	30%	50%
0 kW	6%	11%	1%	2%
< 0.02 kW	11%	23%	10%	11%
< 0.05 kW	15%	30%	14%	14%

4.4 Control Device Communications Failure

Summer Saver load control switches rely on radio signals for activating load control during program events. If the switch is broken, if the signal is blocked, or if the signal is sent on a frequency that the device is not set up to receive, then load control will not occur for that device. This is referred to as control device communication failure.

There was no direct verification of control device communication for the 2014 evaluation. However, the sub-sample of Summer Saver participants (see Section 4.3) with sub-metered data is available to provide some limited information on the prevalence of control device communication failure. The sub-sample includes 157 participants on the 100% cycling option. The sub-metered data from these customers[6] on event days should show load reductions very close to 100%, otherwise they can be presumed to be affected by communication failure. Since there is no obvious reason why customers on 100% cycling should have different communication failure rates from residential customers on other cycling options, so this analysis probably reflects communication across the residential Summer Saver population. Commercial Summer Saver customers may have different rates of communication failure due to differing building types and switch locations.

As shown in Table 4-9, an analysis of the number of customers in the 100% cycling group that had non-zero load during each event hour of 2014 revealed that communication failure was variable in 2014, but averaged 19% after the first hour of the event. The higher percentage of non-zero loads in the first hour can be attributed to the fact that for each customer, events actually begin sometime in the first half-hour of the event, rather than immediately at the top of the hour.

[6] About half of these 157 customers are held back from load control during each event, so the number of sub-metered CAC units available for this analysis is about half that for each event.

Table 4-9: Percentage of Premises on 100% Cycling with Non-zero Load during Each Event Hour in 2014

Event Date	Event Hour			
	1	2	3	4
5/14/2014	25%	16%	16%	17%
5/15/2014	30%	27%	26%	21%
5/16/2014	16%	15%	17%	17%
7/29/2014	22%	20%	18%	14%
8/27/2014	20%	14%	12%	11%
9/15/2014	35%	25%	23%	24%
9/16/2014	32%	16%	18%	17%
9/17/2014	34%	23%	22%	21%
Average	**27%**	**20%**	**19%**	**18%**

Communications failure did not affect the same customers for each event; only 3 customers (1.9% of sampled customers) showed failure for all of the events for which they were called. Approximately 85% of sampled customers failed less than half of the time they were called. Forty-six customers (29% of sampled customers) showed no failure for all event hours.

5 Ex Ante Load Impact Estimates

This section presents ex ante load impact estimates for SDG&E's Summer Saver program. Residential ex ante estimates are provided first, followed by estimates for nonresidential customers. The last subsection provides a detailed discussion of the differences between ex post and ex ante estimates.

5.1 Ex Ante Estimates

The model described in Section 3 was used to estimate load impacts based on ex ante event weather conditions and enrollment projections for the years 2015–2025. Enrollment in the Summer Saver program is not expected to change over the forecast horizon so the tables in this section represent predictions for the entire 11 years from 2015 to 2025.

The Protocols require that ex ante load impacts be estimated assuming weather conditions associated with both normal and extreme utility operating conditions. Normal conditions are defined as those that would be expected to occur once every two years (1-in-2 conditions) and extreme conditions are those that would be expected to occur once every 10 years (1-in-10 conditions). Since 2008, the California IOUs have based the ex ante weather conditions on system operating conditions specific to each individual utility for estimating demand response load impacts. However, ex ante weather conditions could alternatively reflect 1-in-2 and 1-in-10 year operating conditions for the CAISO rather than the operating conditions for each IOU. While the protocols are silent on this issue, a letter from the CPUC Energy Division to the IOUs dated October 21, 2014 directed the utilities to provide impact estimates under two sets of operating conditions starting with the April 1, 2015 filings: one reflecting operating conditions for each IOU and one reflecting operating conditions for the CAISO system.

In order to meet this new requirement, California's IOUs contracted with Nexant to develop ex ante weather conditions based on the peaking conditions for each utility and for the CAISO system. The previous ex ante weather conditions for Pacific Gas and Electric Co. and Southern California Edison Co. were developed in 2009; the previous ex ante weather conditions were developed in 2012 for SDG&E. These scenarios were updated this year along with the development of the new CAISO-based conditions. Both sets of estimates used a common methodology, which is documented in a report delivered to the IOUs.[7]

The extent to which utility-specific ex ante weather conditions differ from CAISO ex ante weather conditions largely depends on the correlation between individual utility and CAISO peak loads. Based on CAISO and SDG&E system peak loads for the top 25 CAISO system load days each year from 2006 to 2013, the correlation coefficient for SDG&E is 0.56, indicating that there are many days on which the CAISO system loads are high while SDG&E loads are more modest. This correlation for SDG&E tends to be weakest when CAISO loads have been below 46,000 MW. CAISO loads often reach 43,000 MW when loads in the Los Angeles area are extreme but San Diego loads are moderate (or vice-versa). However, whenever CAISO loads have exceeded 45,000 MW, loads typically have been high across all three IOU's.

[7] See *Statewide Demand Response Ex Ante Weather Conditions*. Nexant, Inc. January 30, 2015.

Table 5-1 shows the Summer Saver enrollment-weighted average temperature from midnight to 5 PM (mean17) for the typical event day and the monthly system peak day under the four sets of weather conditions for which load impacts are estimated. The differences in mean17 values based on SDG&E peak conditions and CAISO peak conditions, and also based on normal and extreme weather, can be quite large. There are also large differences across months. As seen later, even small differences in the value of mean17 can have large impacts on aggregate load impacts.

Table 5-1: Summer Saver Enrollment-weighted Ex Ante Weather Values (mean17)

Customer Type	Cycle	Day Type	CAISO-based Weather (°F)		SDG&E-based Weather (°F)	
			1-in-2	1-in-10	1-in-2	1-in-10
Nonresidential	30%	Typical Event Day	74	77	73	78
		May Peak Day	65	74	68	77
		June Peak Day	69	74	68	74
		July Peak Day	72	74	73	79
		August Peak Day	77	77	75	79
		September Peak Day	77	82	76	82
		October Peak Day	68	75	71	77
	50%	Typical Event Day	73	76	73	78
		May Peak Day	65	73	68	76
		June Peak Day	69	73	68	73
		July Peak Day	72	74	72	78
		August Peak Day	76	77	75	79
		September Peak Day	77	81	75	81
		October Peak Day	68	75	71	76
Residential	50%	Typical Event Day	74	78	74	79
		May Peak Day	65	74	69	77
		June Peak Day	69	74	69	75
		July Peak Day	72	75	73	80
		August Peak Day	77	78	75	80
		September Peak Day	78	83	77	83
		October Peak Day	68	76	72	78
	100%	Typical Event Day	74	77	73	79
		May Peak Day	65	74	69	77
		June Peak Day	69	74	68	74
		July Peak Day	72	75	73	79
		August Peak Day	77	78	75	80
		September Peak Day	78	83	76	83
		October Peak Day	68	75	72	77

While Summer Saver events can be called any time between noon and 8 PM, ex ante load impacts reported here represent the average load impact across the hours from

1 to 6 PM, reflecting the peak period as defined by the CPUC for determining resource adequacy requirements.

Tables 5-2 and 5-3 summarize the average and aggregate load impact estimates per premise under SDG&E-specific peaking conditions and CAISO peaking conditions, respectively. For a typical event day in a 1-in-2 year, SDG&E-specific weather conditions, the impact per premise is 0.41 kW for residential customers. The 1-in-10 year typical event day estimate is 56% higher at 0.64 kW. Under 1-in-2 CAISO peak conditions, the typical event day residential load impact per premise is 0.44 kW; for the 1-in-10 scenario, it is 0.56 kW, or 27% higher. These large differences are driven by the larger differences in mean17, which vary by 5 or 6 degrees across some of the above conditions. A difference of 5 degrees on average over 17 hours represents a very large difference in temperature conditions and air conditioning requirements.

Nonresidential Summer Saver load impacts for the typical event day are 0.57 kW per premise under 1-in-2 SDG&E-specific peak conditions, and 0.77 kW for 1-in-10. Under CAISO peak conditions, nonresidential typical event day load impacts are 0.59 kW per premise for 1-in-2 and 0.71 kW per premise for 1-in-10 weather. The 1-in-2 to 1-in-10 increase in load impacts is 35% for SDG&E-specific peak conditions and 20% for CAISO peak conditions.

The aggregate program load reduction potential for residential customers is 9.4 MW for a typical event day under SDG&E-specific 1-in-2 year weather conditions and 14.6 MW under SDG&E-specific 1-in-10 year weather conditions. Residential aggregate load impacts for 1-in-2 CAISO peaking conditions are 10.0 MW and 13.0 MW for the 1-in-10 weather scenario. For SDG&E peaking conditions, nonresidential aggregate program load reduction potential is 2.7 MW under the 1-in-2 scenario and 3.7 MW under the 1-in-10 scenario for the typical event day. For CAISO peaking conditions, the nonresidential typical event day load impacts for 1-in-2 and 1-in-10 conditions are similar: 2.8 MW and 3.4 MW, respectively.

Comparison of Ex Ante Load Impacts by Month

September ex ante conditions are much hotter than typical event day conditions. The residential program is estimated to provide an average impact of 17.9 MW over the 5-hour event window from 1 to 6 PM on a 1-in-10 September monthly system peak day and 12.1 MW on the September monthly system peak day under 1-in-2 year weather conditions for SDG&E-specific peaking conditions. Under CAISO peak conditions, residential aggregate load reduction on a September monthly system peak day is 13.5 MW for 1-in-2 and 18.1 MW for 1-in-10.

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 impacts. The May and June 1-in-2 year impacts for residential customers are only about 40% of the September estimate, which is the highest of any month under 1-in-2 year weather conditions. For residential customers, the May and June 1-in-10 year estimates are 1.5 times greater than the 1-in-2 year estimates as a result of the 1-in-10 year temperatures being much warmer than the 1-in-2 year temperatures for May and June.

For the residential segment of Summer Saver, the May 2014 ex post load impacts are quite a bit larger than the 1-in-2 ex ante load impacts for May, attributable to the fact that the Santa Ana weather event created temperature conditions far from the norm for San Diego in May. The two midsummer events' ex post load impacts on average are similar to 1-in-2 typical event day load impacts, while the three September events' ex post load impacts are closer to the 1-in-10 September monthly peak day ex ante estimate than the 1-in-2.

The nonresidential segment's ex post reflects the same general relationship with the ex ante load impacts: the May 2014 events' ex post load impacts far exceed the May 1-in-2 ex ante estimate, most likely due to the Santa Anas. The midsummer events are on average lower than even the 1-in-2 ex ante estimate for the typical event day, and this outcome is strongly influenced by the very low load impacts observed on July 29, 2014—one of the coolest Summer Saver events in recent years. The September 2014 events' load impacts are generally in between the 1-in-2 and 1-in-10 ex ante load impacts.

On a per premise basis, the nonresidential segment provides more load impacts than residential customers. But in aggregate, the residential segment provides far more MW of load reduction due to the much greater numbers of residential participants than nonparticipants.

Table 5-2: Summer Saver Ex Ante Load Impact Estimates by CAISO and SDG&E-specific Weather and Day Type (1 to 6 PM, 1-in-10 Conditions)

Customer Type	Day Type	Per Premise Impact (kW)		Aggregate Impact (MW)	
		CAISO	SDGE	CAISO	SDGE
Residential	Typical Event Day	0.56	0.64	13.0	14.6
	May Monthly Peak	0.44	0.55	10.0	12.7
	June Monthly Peak	0.43	0.45	9.9	10.4
	July Monthly Peak	0.46	0.64	10.5	14.8
	August Monthly Peak	0.58	0.67	13.4	15.4
	September Monthly Peak	0.79	0.78	18.1	17.9
	October Monthly Peak	0.49	0.57	11.3	13.1
Non-Residential	Typical Event Day	0.71	0.77	3.4	3.7
	May Monthly Peak	0.58	0.70	2.8	3.4
	June Monthly Peak	0.59	0.60	2.8	2.9
	July Monthly Peak	0.61	0.79	2.9	3.8
	August Monthly Peak	0.73	0.82	3.5	3.9
	September Monthly Peak	0.91	0.89	4.3	4.3
	October Monthly Peak	0.65	0.71	3.1	3.4

Table 5-3: Summer Saver Ex Ante Load Impact Estimates by CAISO and SDG&E-specific Weather and Day Type (1 to 6 PM, 1-in-2 Conditions)

Customer Type	Day Type	Per Premise Impact (kW)		Aggregate Impact (MW)	
		CAISO	SDGE	CAISO	SDGE
Residential	Typical Event Day	0.44	0.41	10.0	9.4
	May Monthly Peak	0.09	0.22	2.0	5.1
	June Monthly Peak	0.24	0.21	5.6	4.9
	July Monthly Peak	0.36	0.40	8.2	9.2
	August Monthly Peak	0.56	0.48	12.8	11.2
	September Monthly Peak	0.59	0.53	13.5	12.1
	October Monthly Peak	0.20	0.34	4.7	7.9
Non-Residential	Typical Event Day	0.59	0.57	2.8	2.7
	May Monthly Peak	0.25	0.38	1.2	1.8
	June Monthly Peak	0.41	0.39	2.0	1.9
	July Monthly Peak	0.53	0.55	2.5	2.6
	August Monthly Peak	0.71	0.66	3.4	3.2
	September Monthly Peak	0.73	0.67	3.5	3.2
	October Monthly Peak	0.39	0.50	1.9	2.4

Tables 5-4 and 5-5 provide ex ante impact estimates on an hourly basis for residential and nonresidential customers, respectively. The hours reflect the peak period as defined by the CPUC resource adequacy requirements, 1 to 6 PM. Residential impacts peak in the hour from 4 to 5 PM, while nonresidential impacts are relatively flat across these hours.

Table 5-4: Summer Saver Ex Ante Load Impact Estimates (MW) by Weather Year, Day Type and Hour – Residential Customers – SDG&E Peaking Conditions

Weather Year	Day Type	Hour of Day					Average (MW)
		1 to 2 PM (MW)	2 to 3 PM (MW)	3 to 4 PM (MW)	4 to 5 PM (MW)	5 to 6 PM (MW)	
1-in-2	Typical Event Day	7.5	8.8	10.1	10.7	9.7	9.4
	May Monthly Peak	4.1	4.8	5.5	5.8	5.2	5.1
	June Monthly Peak	4.0	4.7	5.3	5.6	5.1	4.9
	July Monthly Peak	7.4	8.6	9.9	10.5	9.5	9.2
	August Monthly Peak	9.0	10.5	12.1	12.8	11.5	11.2
	September Monthly Peak	9.8	11.4	13.1	13.9	12.6	12.1
	October Monthly Peak	6.4	7.4	8.5	9.0	8.1	7.9
1-in-10	Typical Event Day	11.8	13.7	15.8	16.7	15.2	14.6
	May Monthly Peak	10.2	11.9	13.7	14.5	13.2	12.7
	June Monthly Peak	8.4	9.7	11.2	11.8	10.7	10.4
	July Monthly Peak	11.9	13.8	15.9	16.9	15.3	14.8
	August Monthly Peak	12.4	14.5	16.7	17.7	16.0	15.4
	September Monthly Peak	14.4	16.8	19.4	20.5	18.6	17.9
	October Monthly Peak	10.5	12.3	14.1	14.9	13.5	13.1

Table 5-5: Summer Saver Ex Ante Load Impact Estimates (MW) by Weather Year, Day Type and Hour - Nonresidential Customers – SDG&E Peaking Conditions

Weather Year	Day Type	Hour of Day					Average (MW)
		1 to 2 PM (MW)	2 to 3 PM (MW)	3 to 4 PM (MW)	4 to 5 PM (MW)	5 to 6 PM (MW)	
1-in-2	Typical Event Day	2.7	3.0	2.9	2.9	2.0	2.7
	May Monthly Peak	1.8	2.0	1.9	1.9	1.3	1.8
	June Monthly Peak	1.9	2.0	2.0	2.0	1.4	1.9
	July Monthly Peak	2.6	2.9	2.8	2.8	1.9	2.6
	August Monthly Peak	3.2	3.4	3.4	3.4	2.3	3.2
	September Monthly Peak	3.3	3.5	3.5	3.5	2.4	3.2
	October Monthly Peak	2.4	2.6	2.6	2.6	1.8	2.4
1-in-10	Typical Event Day	3.7	4.0	4.0	4.0	2.7	3.7
	May Monthly Peak	3.4	3.7	3.6	3.6	2.5	3.4
	June Monthly Peak	2.9	3.1	3.1	3.1	2.1	2.9
	July Monthly Peak	3.8	4.1	4.1	4.1	2.8	3.8
	August Monthly Peak	3.9	4.3	4.2	4.2	2.9	3.9
	September Monthly Peak	4.3	4.7	4.6	4.6	3.1	4.3
	October Monthly Peak	3.4	3.7	3.7	3.7	2.5	3.4

Table 5-6 provides program-level ex ante aggregate estimates for each hour. The program is expected to provide its highest impact under 1-in-10 year conditions in September. Under those conditions, the average impact over the event window is expected to be 22.2 MW, with an hourly peak of 25.2 MW from 4 to 5 PM.

Table 5-6: Summer Saver Ex Ante Load Impact Estimates (MW) by Weather Year, Day Type and Hour – All Customers – SDG&E Peaking Conditions

Weather Year	Day Type	Hour of Day					Average (MW)
		1 to 2 PM (MW)	2 to 3 PM (MW)	3 to 4 PM (MW)	4 to 5 PM (MW)	5 to 6 PM (MW)	
1-in-2	Typical Event Day	10.3	11.8	13.0	13.6	11.7	12.1
	May Monthly Peak	6.0	6.8	7.4	7.7	6.5	6.9
	June Monthly Peak	5.9	6.7	7.3	7.6	6.4	6.8
	July Monthly Peak	10.0	11.5	12.7	13.3	11.4	11.8
	August Monthly Peak	12.2	13.9	15.4	16.2	13.9	14.3
	September Monthly Peak	13.0	14.9	16.6	17.4	14.9	15.4
	October Monthly Peak	8.8	10.0	11.1	11.6	9.9	10.3
1-in-10	Typical Event Day	15.5	17.8	19.8	20.7	17.9	18.3
	May Monthly Peak	13.6	15.6	17.4	18.2	15.7	16.1
	June Monthly Peak	11.3	12.9	14.3	14.9	12.8	13.2
	July Monthly Peak	15.7	18.0	20.0	21.0	18.1	18.5
	August Monthly Peak	16.3	18.7	20.9	21.9	18.9	19.3
	September Monthly Peak	18.7	21.5	24.0	25.2	21.7	22.2
	October Monthly Peak	14.0	16.0	17.8	18.6	16.0	16.5

5.2 Comparison of 2013 Ex Ante Load Impacts to 2014 Ex Ante Load Impacts

The ex ante impacts summarized above are lower for both residential and nonresidential Summer Saver program segments compared to the ex ante estimates developed in the 2013 load impact evaluation. Average per premise load impacts for residential customers on the typical event day under 1-in-2 conditions are 26% lower than estimated in 2013 and about 4% lower under 1-in-10 year conditions.

Enrollment has also decreased by 2.4% since the 2013 evaluation. Together these decreases in average per premise load impact and enrollment produce a 28% decrease in aggregate load impacts for the 1-in-2 year scenario and a 6.8% decrease in load impacts for the 1-in-10 year scenario. These estimates assume SDG&E-specific peaking conditions. Under CAISO peaking conditions, the change in per premise load impacts is smaller for the 1-in-10 scenario and larger for the 1-in-2 scenario; aggregate load impacts for 1-in-2 CAISO peak conditions on the typical event day are 23% lower than projected in 2013 and 17% lower for the 1-in-10 scenario.

The nonresidential program segment shows smaller changes relative to the 2013 load impact evaluation. Under SDG&E-specific peaking conditions, average per premise load impacts fell by 18% for 1-in-2 conditions and by 1% for 1-in-10 conditions. Nonresidential enrollment also decreased less, by 1.7% since 2013, which is much less than the change in residential enrollment. Altogether, aggregate nonresidential load impacts under the 1-in-2 year scenario decreased by roughly 20% under 1-in-2 conditions and 2.7% under 1-in-10 conditions, assuming SDG&E-specific peaking conditions. Under CAISO peaking conditions, 2014 aggregate load impacts for the typical event day are 16% lower than in 2013 for the 1-in-2 scenario and 11% lower for the 1-in-10 scenario.

While year-to-year fluctuations in a mature load control program such as Summer Saver are not unusual (for example, 2013 enrollments were 3% greater than 2012 enrollments), significant changes in per premise load impacts are of interest. The decreases in ex ante per premise load impacts are attributable to two primary factors: the relatively low load impacts estimated for the 2014 events and the change in standard ex ante weather conditions relative to the prior standard ex ante weather conditions.

Figures 5-1 through 5-4 illustrate the ex post load impacts from 2010 through 2014 that were used to model the relationship between load impact and temperature. The y-axis represents average ex post load impacts (kW) per ton for the 2 to 5 PM period. The x-axis represents mean17 temperatures (average temperature from midnight to 5 PM). Ex post load impacts are color-coded in the graphs to illustrate how load impacts vary across years. Load impacts for 2014 are denoted with dark blue, diamond-shaped markers. The purple line represents the linear relationship of load impacts with mean17 temperature that is used to determine load impacts under ex ante temperature conditions.

Figure 5-1: Summer Saver Ex Post Load Impacts (kW/ton) vs. mean17 Residential 100% Cycling

Figure 5-2: Summer Saver Ex Post Load Impacts (kW/ton) vs. mean17 Residential 50% Cycling

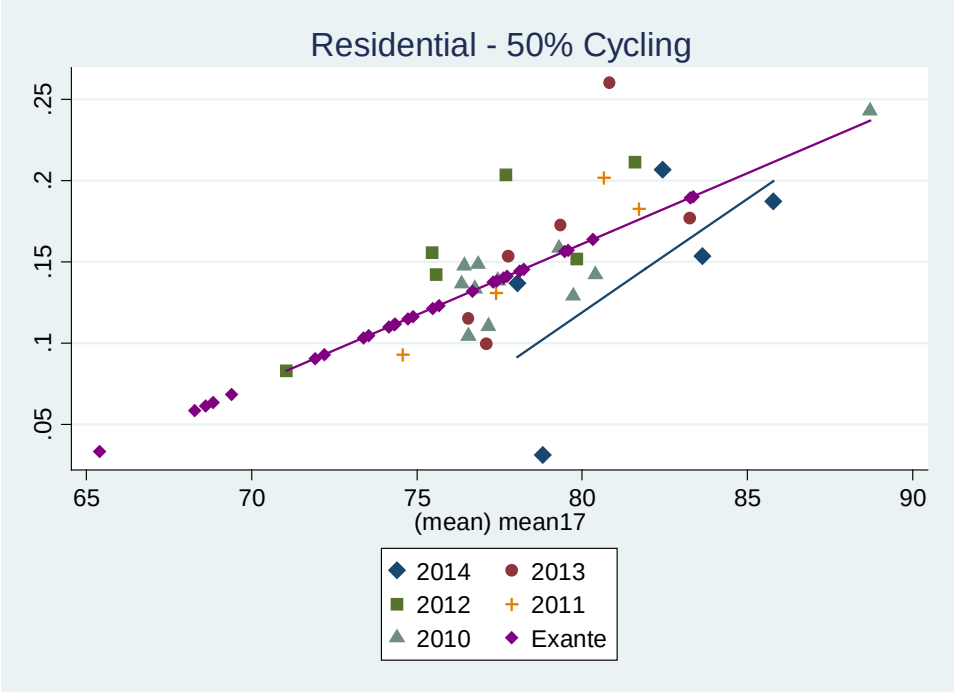


Figure 5-3: Summer Saver Ex Post Load Impacts (kW/ton) vs. mean17 Nonresidential 50% Cycling

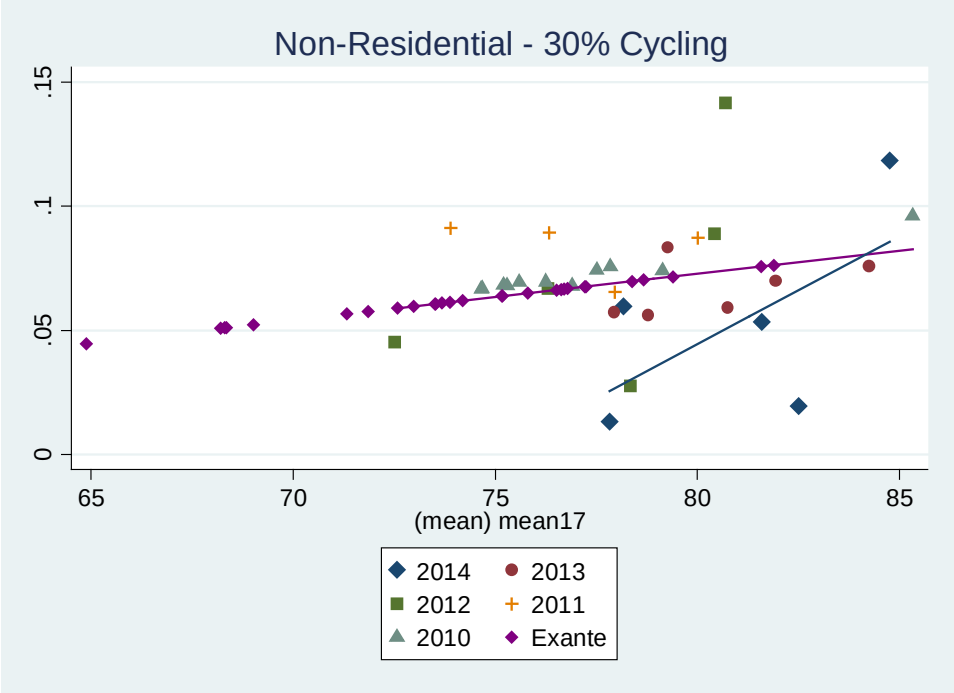
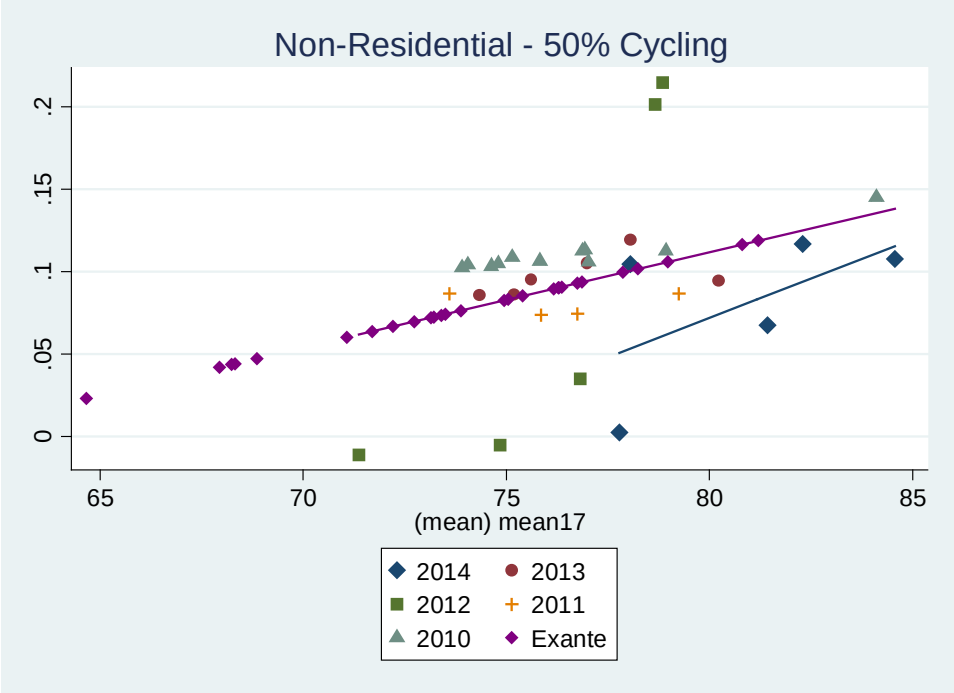


Figure 5-4: Summer Saver Ex Post Load Impacts (kW/ton) vs. mean17 Nonresidential 30% Cycling



The first thing evident about 2014 load impacts is that they are, on the whole, lower than the other years' load impacts at the same temperatures. The lower trend is least evident in the residential 50% program segment but more pronounced in the other segments. At the same time, the lower 2014 load impacts occurred in what are seen to be relatively typical temperature ranges. While from a mean17 perspective the 2014 Summer Saver events occurred under conditions typical for the program over the past few years, as noted in Section 3, the temperatures observed during the events were low. Specifically, the ratio of average event temperature to mean17 is at its lowest point in 2014 than in any other year in the period from 2010 to 2014. While the use of mean17 is a useful strategy to guard against over-predicting load impacts due to isolated hot hours that may occur in the afternoon, the 2014 events present a different case: relatively high overnight temperatures paired with moderated temperatures during event hours. The 2014 ex post load impacts indicate that while overnight heat buildup is an important predictor of CAC load control load impacts, the heat during event hours may also be important.

Another important change concerns the newly adopted ex ante weather conditions. Table 5-7 presents enrollment-weighted, mean17 temperatures for the new CAISO and SDG&E-weather and for the old ex ante weather file (which was SDGE-based only). As seen, the old and new SDG&E-based weather differs in some important ways. First, for the average event day, while the 1-in-10 weather is relatively unchanged, the new SDG&E based 1-in-2 weather is 3 degrees cooler than the old SDG&E-based weather. For the September monthly system peak day, both 1-in-2 and 1-in10 weather year conditions are lower in the new weather file with the largest decreases occurring in the 1-in-2 weather year. For September 1-in-10 weather, which is the month and weather year combination with the highest potential for Summer Saver load impacts, per premise load impacts would be 0.89 kW for the residential segment under the old weather conditions. Under the new weather conditions, the same estimate is 0.78 kW. A similar effect for the nonresidential segment is also present: 1.02 kW per premise with the old weather and 0.89 kW per premise with the new weather.

Table 5-7: Comparison of Summer Saver Enrollment-weighted Temperatures (mean17) across Weather Scenarios

Customer Type	Cycle	Day Type	CAISO-based Weather		SDG&E-based Weather		Old Weather	
			1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Nonresidential	30%	Typical Event Day	74	77	73	78	76	79
		May Peak Day	65	74	68	77	68	75
		June Peak Day	69	74	68	74	68	76
		July Peak Day	72	74	73	79	77	78
		August Peak Day	77	77	75	79	76	79
		September Peak Day	77	82	76	82	81	85
		October Peak Day	68	75	71	77	73	76
	50%	Typical Event Day	73	76	73	78	76	78
		May Peak Day	65	73	68	76	67	75
		June Peak Day	69	73	68	73	68	76
		July Peak Day	72	74	72	78	77	77
		August Peak Day	76	77	75	79	76	78
		September Peak Day	77	81	75	81	81	84
		October Peak Day	68	75	71	76	72	76
Residential	50%	Typical Event Day	74	78	74	79	77	80
		May Peak Day	65	74	69	77	68	76
		June Peak Day	69	74	69	75	68	77
		July Peak Day	72	75	73	80	77	80
		August Peak Day	77	78	75	80	77	79
		September Peak Day	78	83	77	83	82	86
		October Peak Day	68	76	72	78	74	77
	100%	Typical Event Day	74	77	73	79	76	79
		May Peak Day	65	74	69	77	68	76
		June Peak Day	69	74	68	74	68	77
		July Peak Day	72	75	73	79	77	79
		August Peak Day	77	78	75	80	77	79
		September Peak Day	78	83	76	83	82	85
		October Peak Day	68	75	72	77	74	77

5.3 Relationship between Ex Post and Ex Ante Estimates

Ex post and ex ante load impacts may differ for a variety of reasons, including differences in weather conditions, the timing and length of the event window, and other factors. Tables 5-8 and 5-9 show how aggregate load impacts for residential participants change as a result of differences in the factors underlying ex post and ex ante estimates. Table 5-6 pertains to residential customers in the 50% cycling option and Table 5-7 pertains to 100% cycling participants.

Columns A through D describe the particular circumstances of each 2014 Summer Saver load control event. Each event is denoted by its date, shown in Column A. Column B shows the time of the event window, and column C shows the temperature for each event day, as measured by mean17 (the enrollment-weighted temperature averaged across the hours midnight to 5 PM). Column C reflects the temperatures reported in Section 3 of this report and in the ex post table generators. These temperatures reflect averages across seven weather stations in the San Diego region for which weather data is available in 2014. Column D reflects the mean17 temperature for each event using only two weather stations—San Diego International Airport (KSAN) and Miramar Marine Corps Air Station (KNKX). This is the first difference between the ex post and ex ante load impacts: ex ante load impacts are estimated using weather conditions determined by only these two weather stations; so the first step in the comparison process is to translate the ex post temperatures using seven weather stations to ex post temperatures based on two weather stations. Given the geographic distribution of Summer Saver enrollment, this adjustment should typically lower ex post mean17 values. This is because some of the five weather stations omitted from the ex ante weather conditions typically record significantly hotter peak temperatures than KSAN or KNKX. As seen below, the atypical Santa Ana weather event in May 2014 shows the opposite outcome.

Column F presents the load impacts that the ex ante model predicts for the ex post event window (Column B) and for the ex post weather conditions (Column E). Column G makes a final adjustment to the predicted load impacts shown in Column F by recalculating the predicted load impacts for the ex ante event window, which is always 1 to 6 PM. By comparing Columns D and G, one can observe that relative to the historic relationship between load impacts and mean17 temperatures, the 2014 load impacts are below average. This relationship can also be seen in Figures 5-1 through 5-4: most of the blue diamonds, which represent 2014 load impacts, fall below the purple regression line. A year with hotter than average load impacts would show Column D with values usually greater than Column G.

Columns H and I compare Column G with the ex ante load impact estimate given the SDG&E-specific ex ante weather conditions for 1-in-2 and 1-in-10 year system peaking scenarios. Columns H and I are divided into three rows: orange, blue, and purple. The orange rows represent the May monthly system peak day ex ante estimates, which is appropriate to compare with the values in Column G for the May events. The blue rows show the typical event day ex ante estimates, which are most representative of the July and August events. Finally, the purple rows show the September monthly peak day ex ante estimates, for comparison with the September event load impacts shown in Column G.

Columns J through K, like Columns H and I, show ex ante load impacts for 1-in-2 and 1-in-10 year conditions, but for CAISO peaking conditions rather than SDG&E peaking conditions.

Tables 5-10 through 5-11 show similar outcomes for the nonresidential participants: first, the May events in 2014 were accompanied by temperatures that far exceeded the typical temperatures seen in the month of May in San Diego. This is evident in how the predicted load impacts (Column G) exceed the ex ante load impacts for the May day types: the May day types assume much lower temperatures.

Second, the predicted load impacts (Column G) for two events in July and August fall between the 1-in-2 and 1-in-10 ex ante estimates for the typical event day, in the neighborhood of what is expected. The

values in Column G for the three September events are closest to the 1-in-10 load impacts in Column I. This is due to the temperatures observed ex post exceeding the temperatures expected under both the 1-in-2 and 1-in-10 SDG&E September peaking conditions, an outcome that was observed in many prior Summer Saver evaluations and that warrants future investigation.

Table 5-8: Differences in Ex Post and Ex Ante Load Impacts Due to Key Factors
Residential 50% Cycling

Date	2014 Ex Post				2014 Ex Ante Model					
	Event Window	Mean17 (°F)	Ex Post Aggregate Impact (MW)	Mean17 using KSAN KNKX Only (°F)	Ex Ante Impact with Ex Post Event Window and Weather (MW)	Ex Ante Impact (1PM-6PM) using Ex Post Weather (MW)	Ex Ante Impact SDG&E 1-in-2 (MW)	Ex Ante Impact SDG&E 1-in-10 (MW)	Ex Ante Impact CAISO 1-in-2 (MW)	Ex Ante Impact CAISO 1-in-10 (MW)
A	B	C	D	E	F	G	H	I	J	K
5/14/2014	4-8 pm	82	2.2	82	9	8.6	3.0 (69°F)	6.6 (77°F)	1.6 (65°F)	5.3 (74°F)
5/15/2014	4-8 pm	84	4.8	86	10.5	10.1				
5/16/2014	12-4 pm	82	1.5	83	8.7	8.9				
7/29/2014	3-7 pm	80	6.3	78	7.3	6.9	5.0 (74°F)	7.5 (79°F)	5.3 (74°F)	6.7 (78°F)
8/27/2014	2-6 pm	79	1.3	79	7.5	7.2				
9/15/2014	2-6 pm	84	10	82	9	8.7	6.3 (77°F)	9.1 (83°F)	7.0 (78°F)	9.1 (83°F)
9/16/2014	3-7 pm	86	8.1	86	10.7	10.1				
9/17/2014	2-6 pm	86	7.4	84	9.6	9.2				

Table 5-9: Differences in Ex Post and Ex Ante Impacts Due to Key Factors
Residential 100% Cycling

Date	2014 Ex Post				2014 Ex Ante Model					
	Event Window	Mean17 (°F)	Ex-Post Aggregate Impact (MW)	Mean17 using KSAN KNKX Only (°F)	Ex Ante Impact with Ex Post Event Window and Weather (MW)	Ex-Ante Impact (1PM-6PM) using Ex Post Weather (MW)	Ex Ante Impact SDG&E 1-in-2 (MW)	Ex Ante Impact SDG&E 1-in-10 (MW)	Ex Ante Impact CAISO 1-in-2 (MW)	Ex Ante Impact CAISO 1-in-10 (MW)
A	B	C	D	E	F	G	H	I	J	K
5/14/2014	4-8 pm	82	4.8	82	9.9	8.6	2.0 (69°F)	6.1 (77°F)	0.3 (65°F)	4.7 (74°F)
5/15/2014	4-8 pm	84	6.1	85	11.8	10.3				
5/16/2014	12-4 pm	82	4.5	83	8.1	8.9				
7/29/2014	3-7 pm	79	5.9	78	7.4	6.6	4.3 (73°F)	7.1 (79°F)	4.7 (74°F)	6.3 (77°F)
8/27/2014	2-6 pm	79	4.6	79	7.4	6.9				
9/15/2014	2-6 pm	83	8.5	82	9.3	8.7	5.8 (76°F)	8.9 (83°F)	6.5 (78°F)	9.0 (83°F)
9/16/2014	3-7 pm	85	11.2	85	11.6	10.3				
9/17/2014	2-6 pm	85	7.3	83	9.8	9.2				

Table 5-10: Differences in Ex Post and Ex Ante Impacts Due to Key Factors
Nonresidential 30% Cycling

Date	2014 Ex Post				2014 Ex Ante Model					
	Event Window	Mean17 (°F)	Ex-Post Aggregate Impact (MW)	Mean17 using KSAN KNKX Only (°F)	Ex Ante Impact with Ex Post Event Window and Weather (MW)	Ex-Ante Impact (1PM-6PM) using Ex Post Weather (MW)	Ex Ante Impact SDG&E 1-in-2 (MW)	Ex Ante Impact SDG&E 1-in-10 (MW)	Ex Ante Impact CAISO 1-in-2 (MW)	Ex Ante Impact CAISO 1-in-10 (MW)
A	B	C	D	E	F	G	H	I	J	K
5/14/2014	4-8 pm	82	0.1	82	0.9	1	0.7 (69°F)	0.9 (77°F)	0.6 (65°F)	0.8 (74°F)
5/15/2014	4-8 pm	84	0.4	85	1	1.1				
5/16/2014	12-4 pm	81	0.9	82	1.1	1				
7/29/2014	3-7 pm	79	0.1	78	0.9	0.9	0.8 (74°F)	0.9 (79°F)	0.8 (74°F)	0.9 (78°F)
8/27/2014	2-6 pm	78	0.7	78	0.9	0.9				
9/15/2014	2-6 pm	82	0.6	82	1	1	0.9 (77°F)	1.0 (83°F)	0.9 (78°F)	1.0 (83°F)
9/16/2014	3-7 pm	85	1.5	85	1	1.1				
9/17/2014	2-6 pm	84	0.3	83	1	1				

Table 5-11: Differences in Ex Post and Ex Ante Impacts Due to Key Factors
Nonresidential 50% Cycling

Date	2014 Ex Post				2014 Ex Ante Model					
	Event Window	Mean17 (°F)	Ex Post Aggregate Impact (MW)	Mean17 using KSAN KNKX Only (°F)	Ex Ante Impact with Ex Post Event Window and Weather (MW)	Ex Ante Impact (1PM-6PM) using Ex Post Weather (MW)	Ex Ante Impact SDG&E 1-in-2 (MW)	Ex Ante Impact SDG&E 1-in-10 (MW)	Ex Ante Impact CAISO 1-in-2 (MW)	Ex Ante Impact CAISO 1-in-10 (MW)
A	B	C	D	E	F	G	H	I	J	K
5/14/2014	4-8 pm	82	1.6	82	3.1	3.3	1.1 (69°F)	2.5 (77°F)	0.6 (65°F)	2.0 (74°F)
5/15/2014	4-8 pm	84	2.4	85	3.5	3.9				
5/16/2014	12-4 pm	81	2.8	82	3.5	3.3				
7/29/2014	3-7 pm	78	0.4	78	2.6	2.7	1.9 (73°F)	2.7 (79°F)	2.0 (74°F)	2.5 (77°F)
8/27/2014	2-6 pm	78	2.8	78	2.7	2.7				
9/15/2014	2-6 pm	82	2.1	81	3.3	3.3	2.3 (76°F)	3.2 (83°F)	2.5 (78°F)	3.3 (83°F)
9/16/2014	3-7 pm	84	2.4	85	3.7	3.8				
9/17/2014	2-6 pm	83	3.3	82	3.4	3.4				

Appendix A Selection of Matched Control Groups for May Events

The methods used to estimate reference load for the three 2014 Summer Saver events that occurred in the month of May differ from that used for the remainder of the events. An experimental protocol was put into place for a sample of Summer Saver participants that allow estimation of ex post reference load with an RCT, but the protocol had not been initiated at the time of the May events. As a result, for the three May events, there were no Summer Saver customers that did not experience the load control events that could provide the basis for estimating the reference load for those events.

A matched control group was selected for all four program segments using propensity score modeling. The pool of control group customers was comprised of SDG&E customers who do not participate in the Summer Saver program but have observable characteristics similar to Summer Saver customers.

The matched control group method used for this analysis is superior to a within-subjects analysis because there is a large population of non-Summer Saver customers to use as a pool for matching and because it eliminates the problem of model misspecification.[8] Any reference load model based on loads observed at non-event times requires the modeler to make assumptions about the relationships between load, time, and temperature. If this assumed function does not reflect the true relationships between load, time, and temperature, then the model can produce incorrect results. Accurately estimating such a model is particularly difficult when there are relatively few non-event days with similar characteristics to event days. This is often the case in SDG&E's service territory where the number of hot days each summer is small and events are called on the hottest days. The matched control group methodology eliminates the need to model such relationships by assuming that customers who behave similarly to Summer Saver customers during non-event periods would also behave similarly during event periods. This eliminates the need to specify load as a function of weather.

The control groups were selected using a propensity score match to find non-Summer Saver customers who had similar load shapes and characteristics as the nonresidential Summer Saver participants. Conducting propensity score matching using customer characteristics such as load shape requires the use of hourly interval data, in particular, hourly interval data for the hottest event-like days. In the case of selecting a matched control group for the three May events, interval data for a selection of non-event days from the months of April through September 2014 (there was a spate of unusually warm weather at the end of April and early May in addition to the warm weather that accompanied the May Summer Saver events). This interval data was not available for SDG&E's entire population of small commercial and residential customers. A preliminary selection step was necessary: monthly billing data for 2014 was made available for every small commercial customer and for a very large random sample of residential customers (n = 350,000), in addition to customer characteristics such as peak time rebate (PTR) enrollment and climate zone. The Summer Saver sample customers were binned according to June 2014 average daily usage of width 10 kWh, where usage bins were created separately for a number of segments: PTR enrollment (for residential customers only), climate zone, and customer type. Ten control pool customers were chosen for each treatment customer for each usage/PTR/climate zone/customer

[8] For a comparison of results using various research methods, including RCT/RED designs, statistical matching and within-subjects regression analysis, see the interim report on Sacramento Municipal Utility District's Smart Pricing Options pilot: https://www.smartgrid.gov/sites/default/files/MASTER_SMUD%20CBS%20Interim%20Evaluation_Final_SUBMITTED%20TO%20TAG%2020131023.pdf

type bin. If there were too few control pool customers to completely fill a bin, customers were used from adjacent usage bins. Hourly interval data was then received for this “10x” control group pool.

Once the interval data was received for the control group pool, the matching process began, which starts with model selection for the propensity score model. Six matching models were tested. They all used different combinations of total load and percentage of load across different times of day in order to capture load shape and usage levels. Model selection was conducted separately by segment—customer type, industry (for nonresidential customers), PTR enrollment (for residential customers, climate zone, and usage bin, where the usage bins were consolidated versions of the usage bins used to select a control pool.

Models were selected based on the best performance with respect to bias and precision with out-of-sample testing, that is, by comparing the treatment groups’ average hourly load shape with the matched control group’s load shape on non-event days that were not used in the matching process. In conducting out-of-sample testing, it became apparent that the Santa Ana weather event that accompanied the May Summer Saver events were unusual. When hot non-event days were used from other months (i.e., September), out-of-sample testing performance fell dramatically. Figure A-1 shows hourly temperature and humidity for the three May 2014 event days (red lines), for three similar April and May non-event days (green lines), and the two hottest non-event days outside of April and May 2014 (blue lines). In the end, the propensity score models were estimated using average hourly usage for the three April and May hot nonevent days. Improved matching performance was sought by adding the two hottest non-April, non-May nonevent days into the analysis, but when they were included the matching performance suffered. Both the hourly temperature and humidity profiles indicate why this may be the case: the weather conditions on the April and May nonevent days were much more similar to the May event days than the September day, both with respect to overnight and peak period conditions.

Figure A-1: Temperature (°F) and Humidity on May 2014 Summer Saver Event Days Nonevent Days

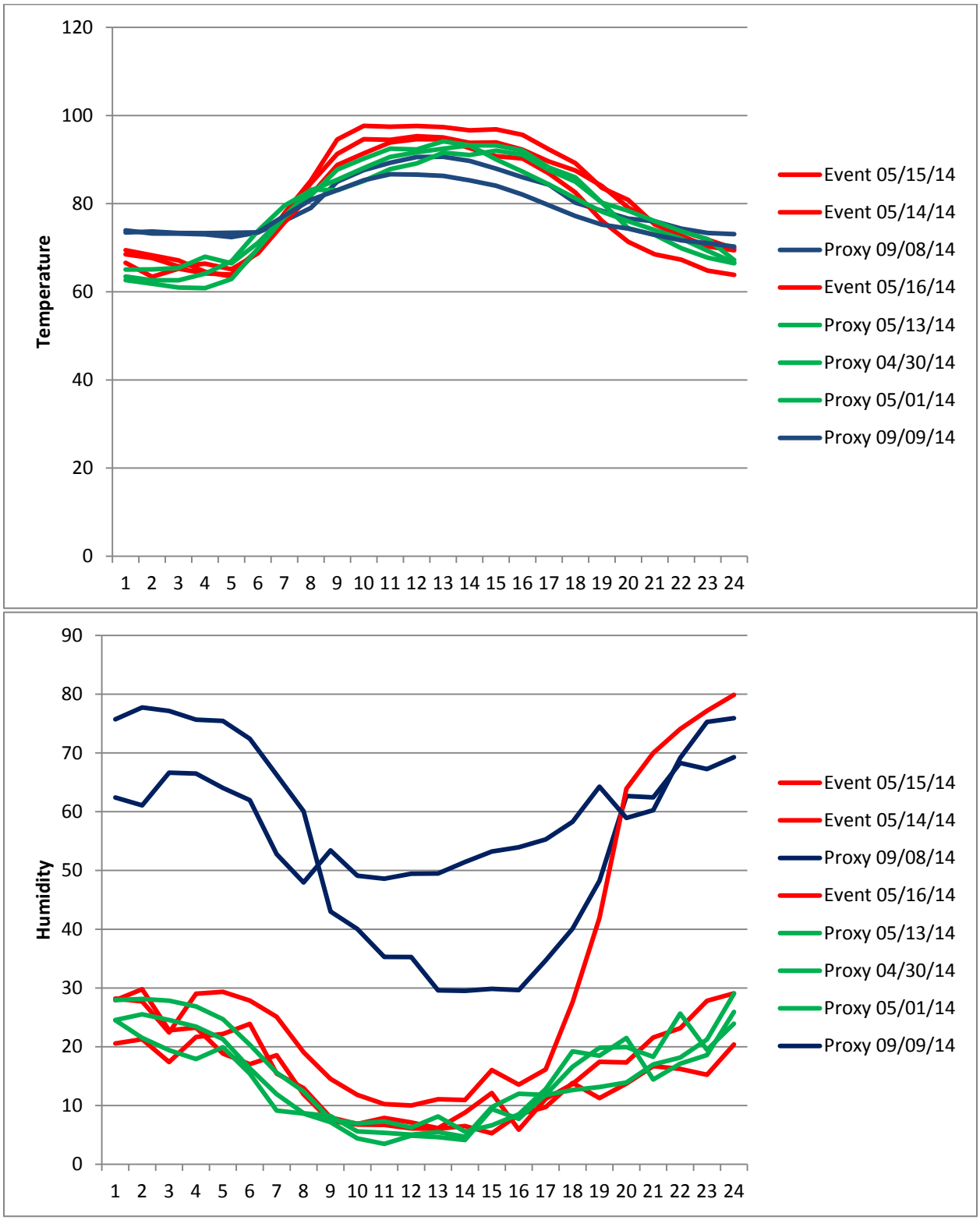


Table A-1 shows the p-values from tests of significance for the difference of means across a number of variables on three hot non-event days that were not used in the matching process (April 29, May 2, and May 12, 2014). Values under 5% would indicate that the treatment and matched control groups are statistically different from each other with respect to that variable with 95% certainty.

Table A-1: p-values from Tests of Significance

Variable	Nonresidential		Residential	
	30%	50%	50%	100%
kwh 1	53%	65%	94%	79%
kwh 2	56%	68%	85%	96%
kwh 3	57%	69%	84%	88%
kwh 4	58%	77%	94%	87%
kwh 5	53%	70%	97%	80%
kwh 6	80%	84%	44%	35%
kwh 7	74%	79%	21%	87%
kwh 8	45%	95%	34%	63%
kwh 9	46%	89%	8%	81%
kwh 10	58%	75%	21%	39%
kwh 11	71%	66%	39%	33%
kwh 12	81%	65%	38%	62%
kwh 13	95%	67%	34%	92%
kwh 14	93%	81%	43%	52%
kwh 15	97%	90%	77%	37%
kwh 16	94%	95%	63%	12%
kwh 17	98%	96%	36%	23%
kwh 18	78%	87%	48%	94%
kwh 19	64%	92%	53%	82%
kwh 20	40%	95%	75%	75%
kwh 21	38%	67%	88%	84%
kwh 22	49%	64%	57%	93%
kwh 23	54%	85%	45%	85%
kwh 24	51%	89%	83%	41%
total kwh	93%	99%	52%	77%
total kwh (Night)	63%	74%	96%	98%
total kwh (Morning)	61%	77%	19%	69%
total kwh (Afternoon)	93%	92%	45%	39%
total kwh (Evening)	47%	88%	68%	79%
peak kwh (12-6PM)	93%	92%	45%	39%
pct peak usage	31%	13%	93%	18%
climate	97%	75%	93%	95%
PTR			77%	93%
industry	100%	100%		

Figures A-2 and A-3 show comparisons of hourly usage for the treatment and matched control groups, averaged across April 29, May 2, and May 12, 2014. The matched control groups perform reasonably well, considering the paucity of non-event days in the early summer months of 2014 with similar weather conditions; absolute differences between hourly load are generally under 5% during peak hours.

Figure A-2: Residential Matched Control and Treatment Group Comparison Average Load on Three Proxy Event Days

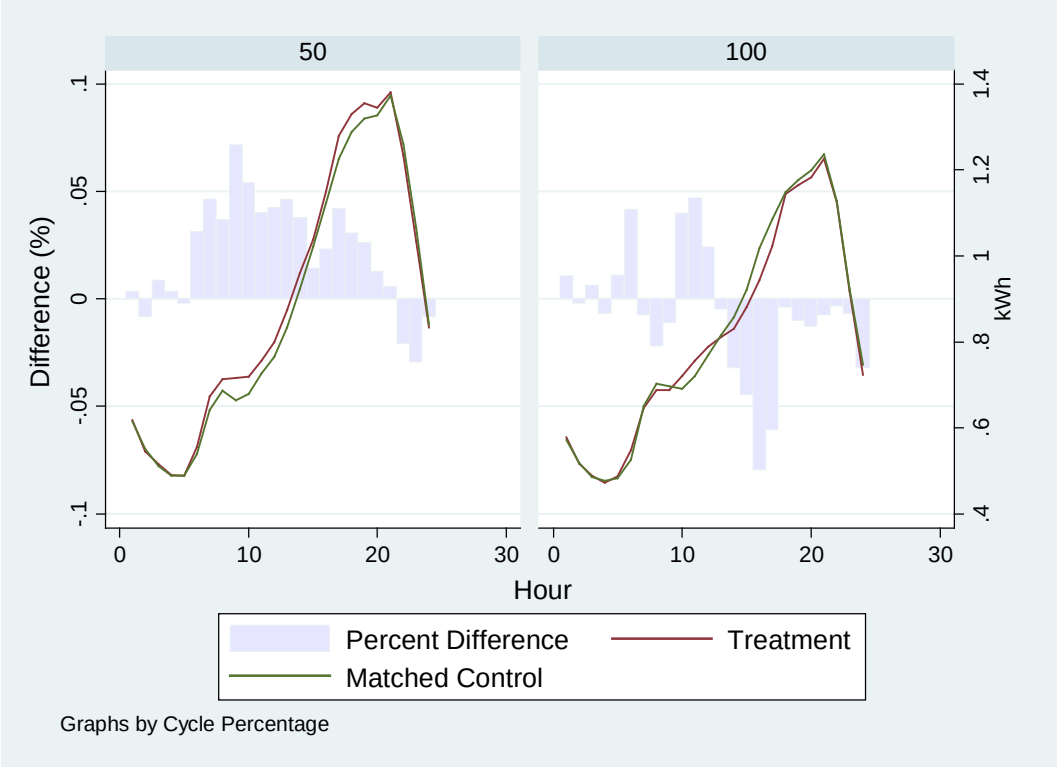
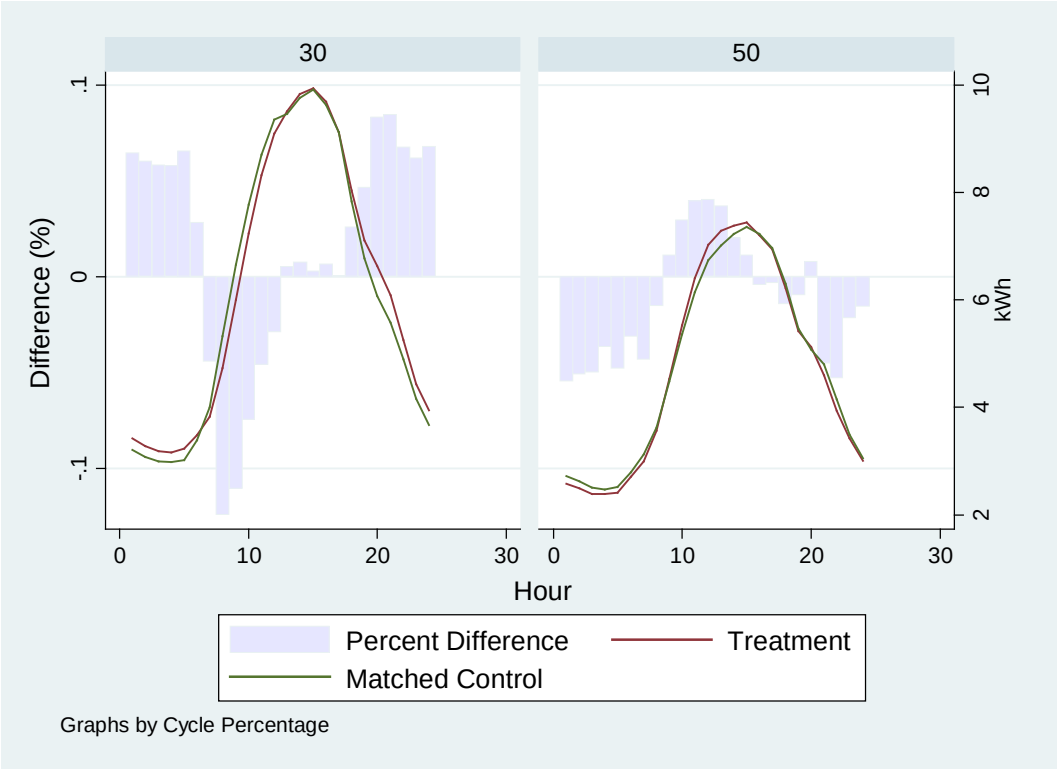



Figure A-3: Nonresidential Matched Control and Treatment Group Comparison Average Load on Three Proxy Event Days