San Diego Gas and Electric Co. Summer Saver 2013 Program Evaluation

Final Report

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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 2013 Summer Saver program and ex ante load impact forecasts for 2014–2024.

The Summer Saver program is available to residential customers and nonresidential premises 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 and system load conditions and customers are not notified when an event occurs.

There are two enrollment options each for both residential and nonresidential customers. Residential customers can choose to be cycled 50% or 100% of the time 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 2013 there were 28,472 premises enrolled in the program with a total cooling capacity of 146,184 tons. This is roughly a 3% increase over 2012 enrollment. About 83% of participants were residential customers, who accounted for 69% of the total tons of cooling in the program. Roughly 48% of residential participants were on the 100% cycling option. Approximately 70% of nonresidential customers selected the 50% cycling option over the 30% option. Summer Saver enrollment is projected to stay constant over the forecast horizon.

Six Summer Saver events were called in 2013 and each one lasted four hours. Four of the six events were from 1 to 5 PM, with the remaining two going from 2 to 6 PM and 3 to 7 PM. For the four events with common hours, the average aggregate demand reduction for residential customers from 1 to 5 PM equaled 16.8 MW. The average per household load reduction equaled 0.74 kW. The average reduction for nonresidential customers equaled roughly 4.0 MW, or 0.86 kW per premise. In aggregate, the average reduction for the entire Summer Saver program across the four event days with common hours from 1 to 5 PM equaled 20.8 MW.

Ex ante load impacts are intended to represent weather conditions under normal (1-in-2 year) and extreme (1-in-10 year) conditions. The event window for ex ante impacts is 1 to 6 PM, which differs from the typical 2013 ex post event window from 1 to 5 PM. On a typical event day under 1-in-2 year weather conditions, aggregate load impacts are forecasted to equal 13.0 MW for residential customers and 3.2 MW for nonresidential customers, for a total program load reduction equal to 16.2 MW. On the annual peak day (which is predicted to be in September), ex ante impacts are estimated to equal 17.6 MW for residential customers and 4.0 MW for nonresidential customers, for a total load reduction potential of 21.6 MW. This is slightly more than what was observed across the typical 2013 event window.

Under 1-in-10 year weather conditions, estimated impacts on the typical event day are forecasted to equal 15.7 MW and 3.7 MW for residential and nonresidential customers, respectively, or 19.4 MW in total. This is about 20% greater than on a typical event day under 1-in-2 year weather conditions. On the much hotter September system peak day for a 1-in-10 weather year, estimated impacts equal 22.6 MW and 4.8 MW respectively, for a total load reduction of 27.4 MW for the entire program.

2013 is the third 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 it does 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 nonresidential customer sample and more variability in the data, more complicated analysis methods were used that rely on additional assumptions.

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.,[1] and is expected to continue to be implemented at SDG&E through 2016. This report provides 2013 ex post load impact estimates as well as ex ante load impact estimates for a ten-year forecast horizon (2014–2024).

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. Events must run for at least 2 hours and no more than 4 hours and cannot be called 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 rules apply to both residential and nonresidential customers alike.

Summer Saver is classified as a day-of demand response program. The program does not notify participating customers when an event is called. 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, 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 on an annual basis under each option:

- $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 a nine-ton CAC unit would be paid the following on an annual basis under each option:

- $81 for 30% cycling; or
- $135 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 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.

Enrollment in the Summer Saver program is summarized in Table 2-1. Total enrollment, as measured by number of customers, number of devices and air conditioning capacity (measured in tons), increased since fall 2012. As of October 2013, there were 28,472 customers enrolled in the program, which in aggregate represents 146,184 tons of CAC capacity. This is a 3% increase compared with 2012 enrollment. About 83% of participants were residential customers who accounted for 69% of the total tons of cooling subject to control under the program. About 48% of residential participants chose 100% cycling and roughly 70% of nonresidential customers chose 50% cycling. Summer Saver enrollment is expected to remain roughly constant for the remaining life of the program.

Table 2-1: Summer Saver Enrollment, October 2013

Customer Type	Cycling Option	Enrolled Customers	Enrolled Control Devices	Enrolled Tons
Nonresidential	30%	1,469	3,911	15,148
	50%	3,401	7,684	29,863
	Total	4,870	11,595	45,011
Residential	50%	12,158	14,290	50,033
	100%	11,444	14,108	51,140
	Total	23,602	28,398	101,173
Grand Total		**28,472**	**39,993**	**146,184**

2.1 Report Structure

The remainder of this report is organized as follows. Section 3 summarizes the data and methodologies 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 ant load impacts.

3 Data and Methodology

This section describes the datasets and analysis methods used to estimate load impacts for each event in 2013 and for ex ante weather and event conditions. Residential ex post results were calculated using a control and treatment group; both approximately 730 customers in size. The groups were randomly selected from the residential Summer Saver population. Nonresidential customers also had a control group that was held back during events, but due to its small size of roughly 300 customers, nonresidential ex post load impacts were not estimated using the same methods that were used to estimate residential impacts. Nonresidential ex post impacts were estimated using a matched control group. Load shape and usage variables were used to match nonresidential Summer Saver customers to similar non-Summer Saver customers. For both the residential and nonresidential segments, the ex post results from 2010 through 2013 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

Six Summer Saver events were called in 2013. 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 weekday event, except for a group of control customers that were held back for measurement and evaluation purposes. No weekend events were called in 2013. Unlike in 2012, there is no longer a distinction between customers who do and do not sign up for weekend events – all customers can now be called on weekends. This year's Summer Saver events all lasted four-hours; some events began as early as 1 PM and others as late as 3 PM.

Table 3-1: Summer Saver 2013 Event Summary

Date	Day of Week	Start Time	End Time
28-Aug-13	Wednesday	3:00 PM	7:00 PM
29-Aug-13	Thursday	2:00 PM	6:00 PM
30-Aug-13	Friday	1:00 PM	5:00 PM
3-Sep-13	Tuesday	1:00 PM	5:00 PM
5-Sep-13	Thursday	1:00 PM	5:00 PM
6-Sep-13	Friday	1:00 PM	5:00 PM

Table 3-2 shows the distribution of CAC tonnage by cycling option and climate zone for the participant population as of October 2013 and the sample of residential customers used for analysis purposes. The differences between the fraction of residential customer tonnage in each sample and population cell are small; there are only small differences across climate zones and cycling options.

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

Cycling Option	Group	Climate Zone Coastal	Climate Zone Mountain	Climate Zone Desert	Climate Zone Inland	Total
50%	Population	4%	1%	0%	44%	49%
	Sample	3%	1%	0%	44%	48%
100%	Population	11%	1%	0%	39%	51%
	Sample	10%	1%	0%	42%	52%
Total	**Population**	**15%**	**2%**	**0%**	**83%**	**100%**
	Sample	**13%**	**2%**	**0%**	**85%**	**100%**

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 the 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 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 were held back from receiving the event. Under this approach, a stratified, random sample of residential and nonresidential Summer Saver customers was created. During each event, half of the sample did not have their air conditioners cycled so that these customers could be used as a reference load for those who did have their units cycled. With the relatively large sample size available for residential customers (1,489 customers), the data from this research design was sufficient to produce reliable impact estimates that only needed small same-day adjustments. For nonresidential customers, the sample was limited to 427 customers. Due to the inherent variability in hourly nonresidential electricity usage patterns, the control and treatment group method with adjustment was not sufficient to produce plausible ex post impacts for nonresidential customers.

In summary, the residential ex post impact estimates were developed using an experimental treatment and control group that was randomly picked from the Summer Saver population. Nonresidential ex post impact estimates were developed using a control group selected from non-Summer Saver customers using statistical matching based on usage and load shape factors. Each method is described further below.

3.2.1 Residential Customer Ex Post Methodology

The residential customer ex post methodology involved a relatively large-scale experiment design known as a randomized control trial (RCT). With an RCT experiment, 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 six events during summer 2013, roughly half of the 1,489 customers in the residential sample received an event signal while the remaining customers served as the control group. The group that received the event signal was alternated from event to event. Sample sizes of about 740 customers in each group eliminated the need for more complex regression methods. 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 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. 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 customers were not notified of Summer Saver events prior to the events’ initiation. Impact estimates for the entire Summer Saver residential sample for each hour of each event were 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 were calculated from treatment and control group load shapes averaged across the four events that lasted from 1 to 5 PM.

3.2.2 Residential Ex Post Validation Analysis

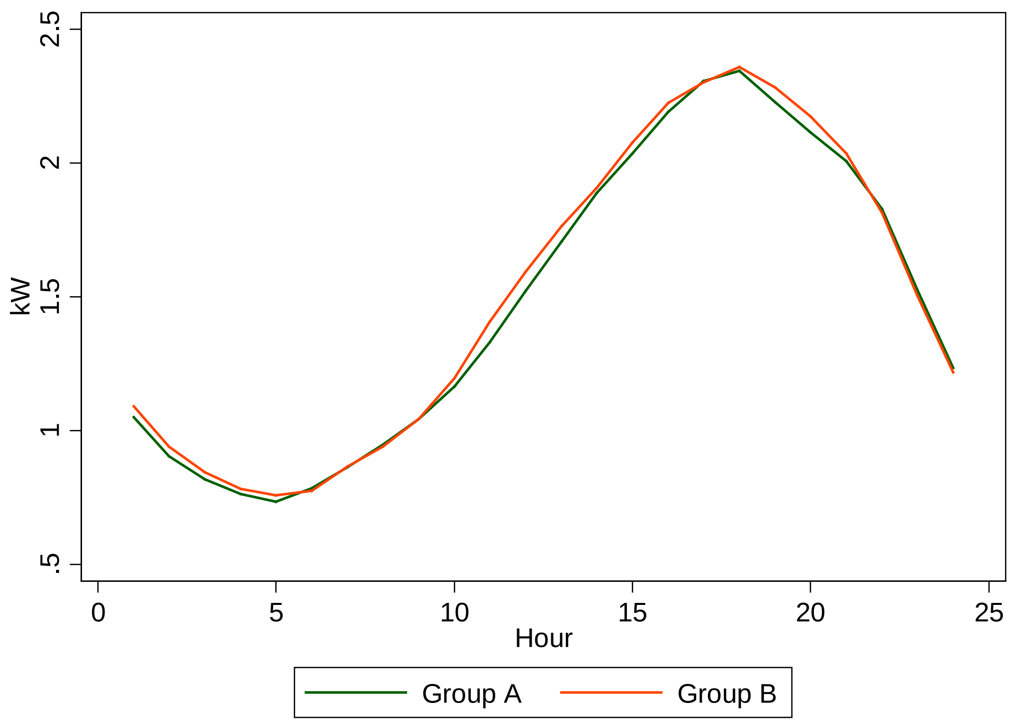
Even though random assignment should produce two groups with very similar characteristics, it is still important to compare the two groups based on observable characteristics since, in the absence of very large samples, differences can still occur due to chance. Table 3-3 compares the sample size, average CAC tonnage and cycling option for the two randomly chosen test groups. As seen, the two groups are very similar on the two important dimensions of CAC tonnage and cycling option.

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

Group	Sample Size	Average CAC Tonnage per Household	% of Population on 50% Cycling
A	733	4.23	48%
B	756	4.25	47%
Total/Average	1,489	4.24	48%

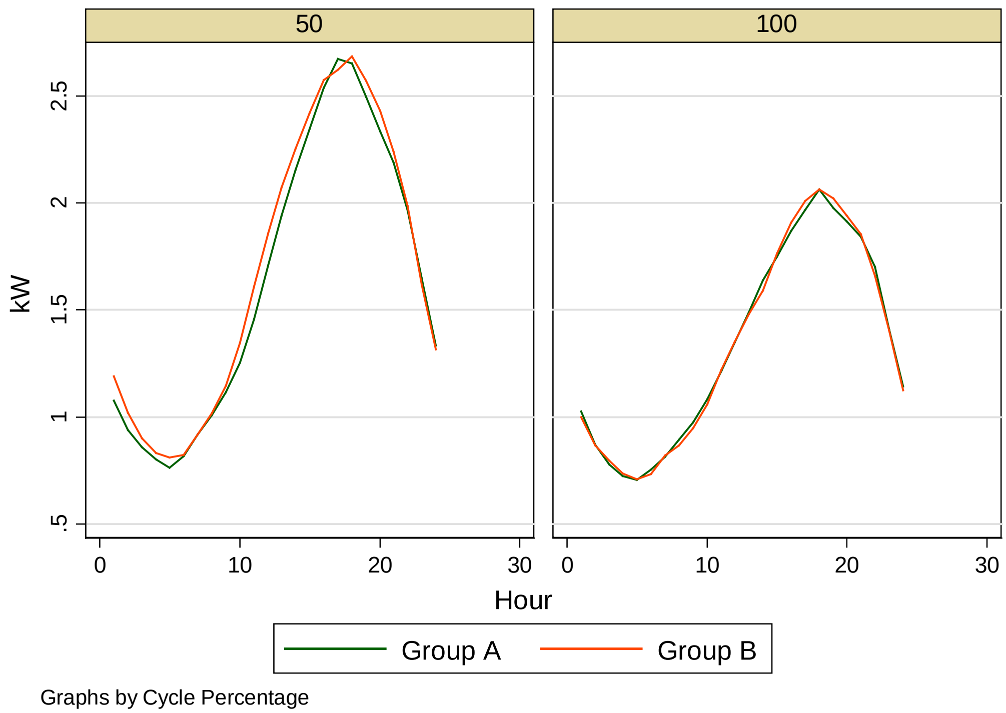
Figure 3-1 shows the average load for each of the two test groups on the five hottest, non-event days in 2013. As the figure shows, the two groups are quite similar. Figure 3-2 shows the average hourly load for each test group segmented by cycling option. Even at the cycling option level, the two test groups remain comparable. It is worth noting in Figure 3-2 how different the loads are for the two cycling options. The peak load for customers who chose the 50% cycling option is roughly 2.7 kW whereas the peak load for the 100% cycling group is approximately 2.0 kW, roughly 25% less. On average, customers who chose the 100% cycling option are less intensive users of air conditioning than those that chose the milder cycling option. As seen later, this explains why the difference in average load impacts for 50% and 100% cycling customers is not as large as one might expect based on the difference in cycling alone.

Figure 3-1: Residential A and B Group Comparison Average Load on the Five Hottest 2013 Non-event Days[2]



[2] The five hottest, non-event days used for this analysis occurred on 10/17/2012, 5/13/2013, 8/31/2013, 9/4/2013, 9/7/2013.

Figure 3-2: Residential A and B Group Comparison
Average Load on the Five Hottest 2013 Non-event Days[2] by Cycling Option



3.2.3 Nonresidential Customer Ex Post Methodology

The methods used to analyze the nonresidential portion of the Summer Saver program in 2013 differ from those used in prior years, as well as from the methods used for the residential evaluation this year. The nonresidential customer research sample was limited to less than 500 customers. Due to these small sample sizes and the inherent variability in nonresidential customer hourly loads, producing nonresidential load impacts using the same approach that was used to estimate residential load impacts was not appropriate. Instead, propensity score matching was used to develop a control group comprised of non-Summer Saver customers with observable characteristics similar to nonresidential 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.[3] 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

[3] 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

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 nonresidential 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 group was 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. In this procedure, a probit model was used to estimate a score for each customer based on a set of observable variables such as load shape, percent of usage that occurs on peak and average usage. A probit model is a regression model designed to estimate probabilities – in this case, the probability that a customer would behave like a specific Summer Saver customer. The propensity score can be thought of as a summary variable that includes all the relevant information on the observable variables about a Summer Saver customer's daily load. Each customer in the treatment population is matched with a customer in the non-Summer Saver population with the closest propensity score.

With the matched control group in hand, ex post event impacts for each nonresidential 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, exactly like the residential load impacts were calculated. The adjustment is based on the ratio of usage between the treatment and control groups for the hour prior to the event start.

3.2.4 Nonresidential Ex Post Validation Analysis

Figure 3-3 shows the hourly load for the nonresidential group averaged over the five proxy days represented by the five highest, non-event system load days. As Figure 3-3 shows, the two groups are well-balanced in terms of average hourly usage. Most important of all is the load shape, because the same-day adjustment will remove differences in scale between the control and treatment groups. This is the same adjustment that was applied to residential control loads based on the ratio of usage in the hour prior to the event. Figure 3-4 shows the average load for the nonresidential Summer Saver customers and the matched control customers, but it is split up by cycling option. Even at the cycling option level, reference loads match reasonably well.

Figure 3-3: Nonresidential Matched Control and Treatment Group Comparison Average Load on Five Proxy Event Days[4]

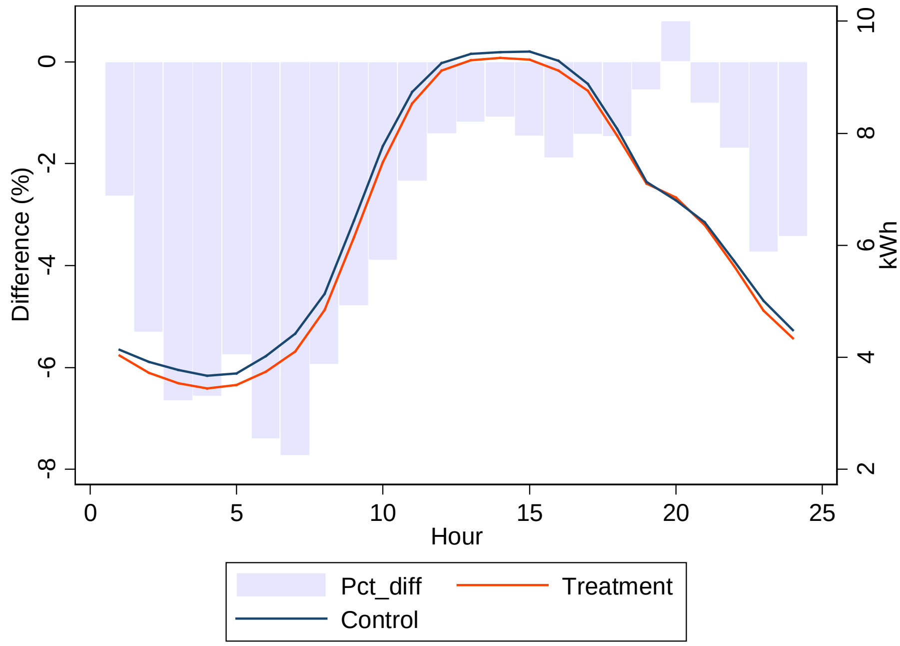
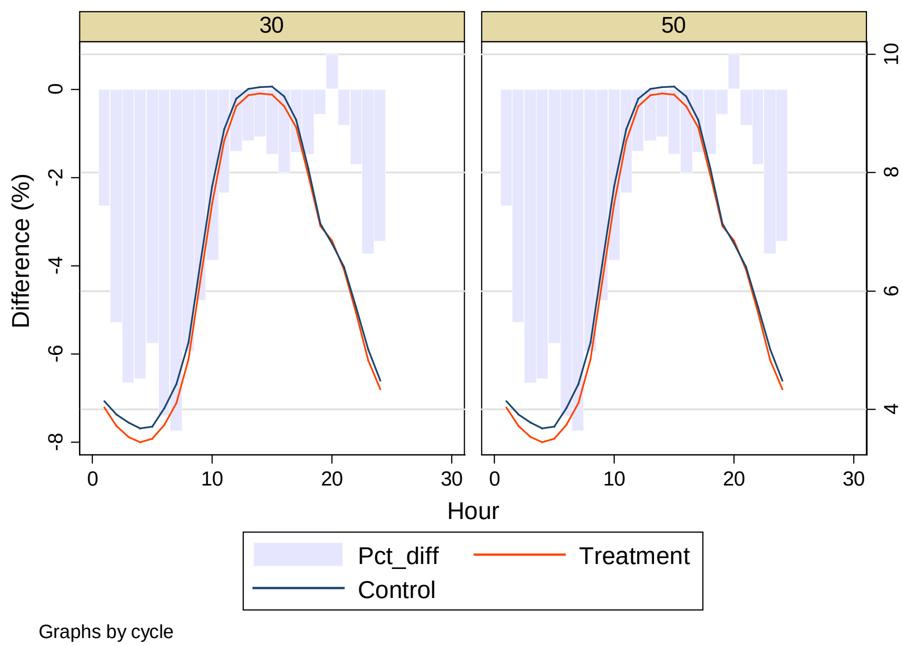


Figure 3-4: Nonresidential Matched Control and Treatment Group Comparison Average Load on Five Proxy Event Days[4] by Cycle Percentage



[4] The five highest, non-event system load days occurred on 8/26/2013, 8/27/2013, 8/31/2013, 9/7/2013, 9/16/2013

3.3 Ex Ante Impact Estimation Methodology

In contrast to the ex post analysis where different methods were applied, the same method was used to produce both residential and nonresidential ex ante load impacts. 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 four 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 2013. Only the hours from 2 to 4 PM were used for the analysis because these hours were common across the greatest number of ex post event days. The average load reduction across these hours was modeled as a function of the average temperature for the first 17-hours of each event day. 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 3-4: 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 3-5 through 3-8 show the ex post impacts from 2010 through 2013 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 results in 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 previously, 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 between 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 option are less prevalent for this customer segment.

Figure 3-5: Average Ex Post Load Impacts and Ex Ante Predictions from 2 to 4 PM for Residential 50% Cycling Participants

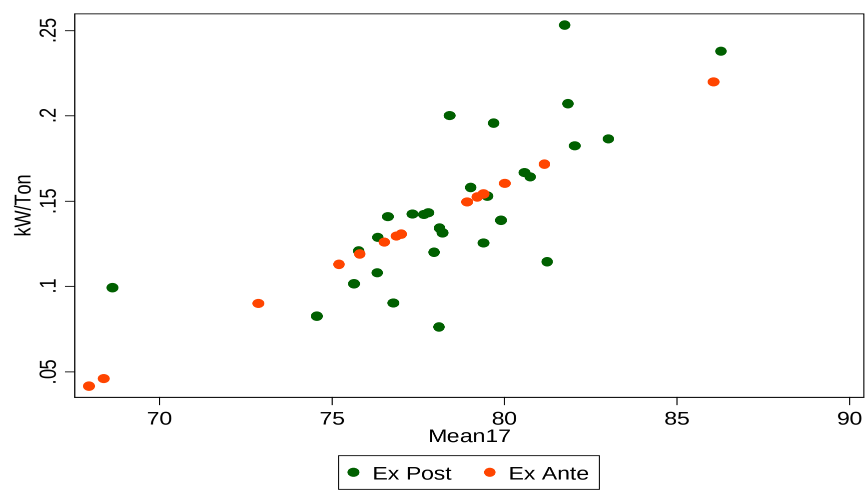


Figure 3-6: Average Ex Post Load Impacts and Ex Ante Predictions from 2 to 4 PM for Residential 100% Cycling Participants

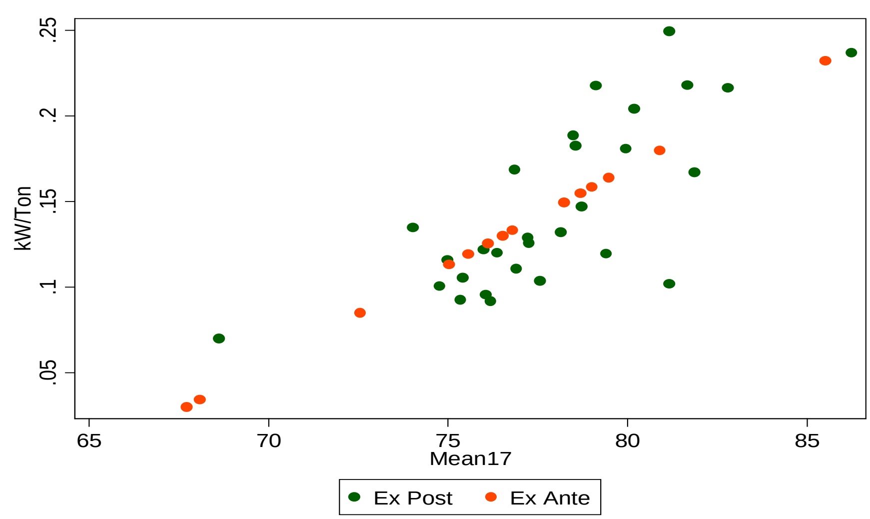


Figure 3-7: Average Ex Post Load Impacts and Ex Ante Predictions from 2 to 4 PM for Nonresidential 30% Cycling Participants

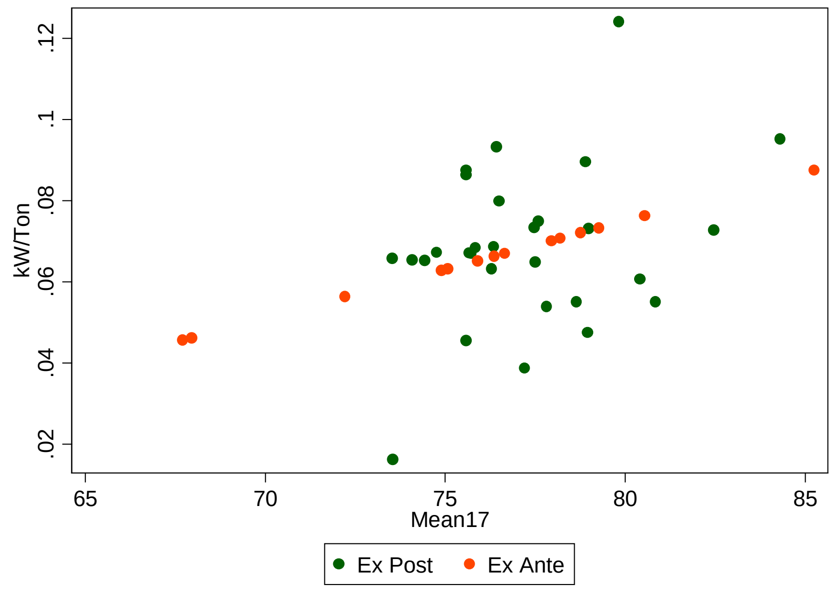
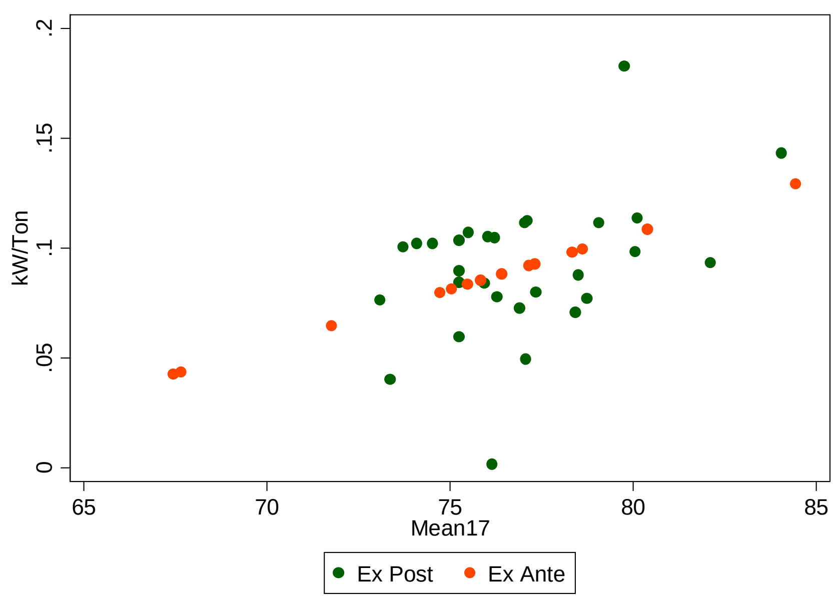


Figure 3-8: Average Ex Post Load Impacts and Ex Ante Predictions from 2 to 4 PM for Nonresidential 50% Cycling Participants



The next step in estimating load impacts is to translate the average impacts for the common hours from 2 to 4 PM to hourly impacts over the ex ante resource adequacy event window from 1 to 6 PM. Hourly ex post impact estimates for each event in 2013 were expressed as a fraction of the average impact from 2 to 4 PM. Table 3-5 shows these ratios for the 100% residential cycling group. The first column of

Table 3-5 shows how the average event impact for each hour compares with the average impact from 2 to 4 PM. To illustrate further, the second column shows the proportions in the first column multiplied by 0.13 kW/ton, which is the average predicted impact from 2 to 4 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, 0.13 kW/ton is multiplied by 0.74 to yield an impact of 0.10 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 3-5: Hourly Impact Compared to Average Impact from 2 to 4 PM
Residential 100% Cycling

Hour of Event	Hourly Impact/Average Impact from 2 to 4 PM	Hourly Impact for Typical Event Day, 1-in-2 Year Weather (kW/Ton)
1–2 PM	0.74	0.10
2–3 PM	0.95	0.12
3–4 PM	1.05	0.14
4–5 PM	1.29	0.17
5–6 PM	1.03	0.13

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 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 very similar manner 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 4 PM time period on 2013 event days was modeled as a function of mean17;
- The parameters from this regression were used to predict average usage from 2 to 4 PM under ex ante weather conditions;

- A ratio between each ex ante prediction and average 2013 control group usage from 2 to 4 PM across all 2013 event days was calculated; and
- Average control group load profiles for the entire average 2013 event day 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 done 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;
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 2013. Residential estimates are discussed first, followed by nonresidential estimates.

4.1 Residential Ex Post Load Impact Estimates

Six Summer Saver events were called in 2013 and each one lasted four hours. Four of the six events were from 1 to 5 PM, with the remaining two going from 2 to 6 PM and 3 to 7 PM. For the four events with common hours, the average aggregate demand reduction for residential customers equaled 16.8 MW. The average reduction per household equaled 0.74 kW. Residential impacts ranged from a low of 11.8 MW on August 29 to a high of 20.6 MW on September 6.

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

Date	Event Timing	Impact			Temperature During Event (°F)[5]
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
8/28/2013	3 to 7 PM	0.48	0.52	12.0	84
8/29/2013	2 to 6 PM	0.46	0.51	11.8	88
8/30/2013	1 to 5 PM	0.68	0.78	17.8	91
9/3/2013	1 to 5 PM	0.58	0.65	14.8	88
9/5/2013	1 to 5 PM	0.57	0.63	14.5	89
9/6/2013	1 to 5 PM	0.84	0.9	20.6	92
Average*	1 to 5 PM	0.66	0.74	16.8	90

*Average for the four event days with common hours from 1 to 5 PM

Table 4-2 shows the estimated load impacts for residential participants on each event day segmented by cycling option. Overall, the average impact for the four event days with a common set of hours (the last four days in the table) differs by roughly 15% across the two cycling options even though the cycling percentage differs by a factor of 2. As discussed previously, this is primarily due to the fact that the average reference load for customers on the 50% cycling option is much higher than for those on the 100% cycling option. It can also be noted that the difference between the two cycling options varies significantly across event days, with large differences on some days and virtually none on others. On September 6, the impact for the 100% cycling group is slightly less than for the 50% cycling option, although this difference is definitely not statistically significant. A closer look at this particular day shows that the reference load for the 50% cycling group is almost 50% higher than for the 100% cycling group. Given the relatively small sample sizes at the cycling option level of aggregation, this result may just be due to random fluctuation or there may have been slightly different weather patterns for the two groups that caused the reference load to increase on this day (100% cycling customers are more

[5] Residential population weighted temperature.

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: Residential Average (per CAC unit) and Aggregate Load Impacts by Cycling Option

Event Date	Average Impact per CAC Unit (kW)		Aggregate Impact (MW)	
	100%	50%	100%	50%
8/28/2013	0.67	0.29	8.2	3.6
8/29/2013	0.49	0.44	5.9	5.9
8/30/2013	0.81	0.56	10.6	7.0
9/3/2013	0.62	0.53	8.0	6.7
9/5/2013	0.61	0.53	7.6	6.8
9/6/2013	0.83	0.85	10.3	10.3
Average*	0.71	0.61	9.1	7.6

*Average for the four event days with common hours from 1 to 5 PM

Table 4-3 shows estimated event impacts for residential customers segmented by usage deciles. Each customer was placed into a decile category based on their average usage during the peak hours from 11 AM to 6 PM on hot non-event weekdays. Impact estimates were calculated separately for each decile using the average control and treatment group loads for each decile on the average event day.

Table 4-3 shows both the average impact as well as the standard error of the estimates for each decile. It is important to note that while the overall trend across deciles generally increase as expected and likely reflects a true underlying pattern, the estimates at the decile level have fairly large standard errors. For example, the impact estimate for the highest two deciles for residential customers with 50% cycling is statistically significantly different at the 5% level from the impact in all other deciles but the impacts in the 7th and 8th deciles are not statistically significantly different from each other.

Table 4-3: Average Estimated Impacts by Usage Decile and Cycling Option for Residential Participants

Decile	50% Cycling		100% Cycling	
	Average Impact (kW)	Standard Error	Average Impact (kW)	Standard Error
1	-0.23	0.08	-0.13	0.05
2	0.15	0.04	0.28	0.03
3	0.06	0.06	0.23	0.03
4	0.07	0.06	0.72	0.04
5	0.20	0.07	0.86	0.05
6	0.75	0.06	0.92	0.06
7	0.70	0.07	1.17	0.06
8	0.87	0.07	1.81	0.07
9	1.42	0.06	1.83	0.08
10	1.41	0.08	2.68	0.10

4.2 Nonresidential Ex Post Load Impact Estimates

Table 4-4 shows ex post load impact estimates for nonresidential customers for each 2013 event day and for the average across the four days with common event hours from 1 to 5 PM. Nonresidential customers constitute roughly 17% of total participants and about 30% of enrolled CAC tonnage. Average impacts per customer for the four days with common hours equaled 0.35 kW per CAC unit and 0.86 kW per premise. Aggregate impacts varied from a low of about 2.3 MW on August 28 to a high of 4.4 MW on September 6.

Table 4-4: Nonresidential Ex Post Load Impact Estimates

Date	Event Timing	Impact			Temperature During Event (°F)[6]
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
28-Aug-13	3 to 7 PM	0.20	0.50	2.3	82
29-Aug-13	2 to 6 PM	0.28	0.69	3.2	87
30-Aug-13	1 to 5 PM	0.34	0.83	3.9	90
3-Sep-13	1 to 5 PM	0.34	0.84	3.9	85
5-Sep-13	1 to 5 PM	0.34	0.83	3.9	86
6-Sep-13	1 to 5 PM	0.38	0.94	4.4	90
Average*	1 to 5 PM	0.35	0.86	4.0	88

*Average for the four event days with common hours from 1 to 5 PM

[6] Commercial population weighted temperature.

A comparison of average impacts per CAC unit in Tables 4-1 and 4-4 shows that the impact for nonresidential customers is roughly half the value for residential customers. While some of this difference is due to the lower average cycling options used for nonresidential customers, a closer look suggests that other factors are also at work. Table 4-5 shows the average ex post load impacts for nonresidential participants by cycling strategy. Comparing the load impacts for residential 50% cycling participants in Table 4-2 with those for nonresidential 50% cycling participants in Table 4-4 shows that the nonresidential impacts are about one third less per CAC unit even under the same cycling option. The same comparison based on impact per ton of air conditioning shows that nonresidential impacts per ton are almost 45% lower than residential impacts based on 50% cycling for both customer segments. There are several possible explanations for the lower impacts for nonresidential customers. One is that nonresidential buildings may have excess cooling capacity compared with residential buildings, which would lead to lower duty cycles and lower impacts for the same cycling option. Another possibility is that not all air conditioners on nonresidential buildings are enrolled in the program so that when enrolled units are cycled, other units work harder to make up for the drop in cooling. A third possibility is that there are differential communication success rates for nonresidential control devices compared with residential devices. It is likely that some combination of all three of these factors, or perhaps others, explains this observed difference in load impacts across customers segments.

Table 4-5: Nonresidential Average (per CAC unit) and Aggregate Load Impacts by Cycling Option

	Average Impact per CAC Unit (kW)		Aggregate Impact (MW)	
Event Date	**50%**	**30%**	**50%**	**30%**
8/28/2013	0.22	0.16	1.8	0.6
8/29/2013	0.32	0.19	2.6	0.7
8/30/2013	0.35	0.30	2.9	1.0
9/3/2013	0.35	0.32	2.8	1.1
9/5/2013	0.39	0.24	3.1	0.8
9/6/2013	0.44	0.28	3.5	0.9
Average*	0.38	0.28	3.1	1.0

Table 4-6 shows the load impacts for nonresidential customers by usage deciles, determined in the same manner as for residential customers as discussed above. For nonresidential customers with 30% cycling, the impact estimates in some of the lowest deciles (1 and 2) are statistically significantly different from the impact estimates in the higher deciles (5 to 10). However, impact estimates in neighboring deciles are not statistically significantly different from each other. As seen, load impacts for customers in the lowest usage deciles are very “noisy” in a statistical sense, with standard errors that are much greater than the estimated impacts.

Table 4-6: Average Estimated Impacts by Usage Decile and Cycling Option for Nonresidential Participants

Declie	30% Cycling		50% Cycling	
	Average Impact (kW)	Standard Error	Average Impact (kW)	Standard Error
1	0.00	0.12	0.01	0.07
2	-0.05	0.10	0.05	0.08
3	0.13	0.10	0.08	0.07
4	0.06	0.10	0.26	0.07
5	0.28	0.11	0.43	0.07
6	0.47	0.10	0.56	0.07
7	0.60	0.10	0.78	0.07
8	0.65	0.11	0.94	0.08
9	0.88	0.13	1.38	0.09
10	1.57	0.30	2.39	0.24

5 Ex Ante Load Impact Estimates

This section contains 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 conditions and enrollment projections for the years 2014–2024. Enrollment is not expected to change over the forecast horizon so the tables in this section represent predictions for the ten-year period from 2014 to 2024. Nexant 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.[7] The ex ante event window is from 1 to 6 PM, which is the same as the CPUC Resource Adequacy window.

Tables 5-1 and 5-2 summarize the average and aggregate load impact estimates per CAC unit for residential and nonresidential customers, respectively. For a typical event day with 1-in-2 year weather conditions, the impact per CAC unit is 0.46 kW for residential customers. The 1-in-10 year typical event day estimate is 20% higher at 0.55 kW. The aggregate program load reduction potential for residential customers is 13.0 MW for a typical event day under 1-in-2 year weather conditions and 15.7 MW under 1-in-10 year weather conditions. September ex ante conditions are much hotter than typical event day conditions. The residential program is estimated to provide an average impact of 22.6 MW over the 5-hour event window from 1 to 6 PM on a 1-in-10 September peak day and 17.6 MW on the system peak day under 1-in-2 year weather conditions.

It should be noted that the ex ante impact estimates for the typical event day under both 1-in-2 and 1-in-10 year weather conditions are less than the ex post values discussed in Section 4. This is because the ex ante weather is cooler than the average weather in 2013. The values of mean17, which are the basis for the ex ante load impacts, equal 77°F and 79°F for the typical event day under 1-in-2 and 1-in-10 year weather conditions, respectively. Both of these values are lower than the average mean17 value for 2013, which equaled 80.1°F. We have recommended to SDG&E that they revisit the development of ex ante weather conditions prior to the 2014 evaluation to determine whether the weather may understate the likely ex ante conditions and the true potential of the Summer Saver program.

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 22% 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 more than 2.5 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.

[7] 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.

Nonresidential customers are estimated to provide lower per CAC unit impacts than residential customers. Possible explanations for these lower impacts were discussed in Section 4.2. Due to the smaller number of nonresidential installations in the program, aggregate impacts for the nonresidential segment are much smaller than for residential customers. The nonresidential program is expected to provide the highest impact under 1-in-10 year conditions in September, when its estimated impact is 4.8 MW.

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	0.55	0.46	15.7	13.0
May Monthly Peak	0.40	0.13	11.3	3.6
June Monthly Peak	0.53	0.14	15.0	4.0
July Monthly Peak	0.54	0.47	15.4	13.2
August Monthly Peak	0.57	0.44	16.2	12.6
September Monthly Peak	0.80	0.62	22.6	17.6
October Monthly Peak	0.42	0.31	11.9	8.8

Table 5-2: Summer Saver Nonresidential 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	0.32	0.28	3.7	3.2
May Monthly Peak	0.26	0.15	3.0	1.8
June Monthly Peak	0.30	0.16	3.5	1.8
July Monthly Peak	0.30	0.29	3.5	3.3
August Monthly Peak	0.32	0.27	3.7	3.2
September Monthly Peak	0.41	0.35	4.8	4.0
October Monthly Peak	0.27	0.22	3.1	2.5

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

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

Weather Year	Day Type	Hour of Day					Average
		1–2 PM	2–3 PM	3–4 PM	4–5 PM	5–6 PM	
1-in-2	Typical Event Day	10.4	12.4	13.9	15.4	12.9	13.0
	May Monthly Peak	2.9	3.4	3.9	4.2	3.6	3.6
	June Monthly Peak	3.2	3.8	4.3	4.7	4.0	4.0
	July Monthly Peak	10.5	12.6	14.1	15.7	13.2	13.2
	August Monthly Peak	10.1	12.0	13.4	15.0	12.5	12.6
	September Monthly Peak	14.0	16.8	18.8	20.9	17.5	17.6
	October Monthly Peak	7.0	8.4	9.4	10.4	8.7	8.8
1-in-10	Typical Event Day	12.5	14.9	16.7	18.6	15.6	15.7
	May Monthly Peak	9.0	10.8	12.1	13.5	11.3	11.3
	June Monthly Peak	12.0	14.3	16.0	17.8	14.9	15.0
	July Monthly Peak	12.3	14.7	16.4	18.3	15.3	15.4
	August Monthly Peak	12.9	15.5	17.3	19.3	16.2	16.2
	September Monthly Peak	18.0	21.6	24.1	26.9	22.6	22.6
	October Monthly Peak	9.5	11.4	12.7	14.2	11.9	11.9

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

Weather Year	Day Type	Hour of Day					Average
		1–2 PM	2–3 PM	3–4 PM	4–5 PM	5–6 PM	
1-in-2	Typical Event Day	3.0	3.5	3.7	3.5	2.6	3.2
	May Monthly Peak	1.7	1.9	2.0	1.9	1.4	1.8
	June Monthly Peak	1.7	1.9	2.0	1.9	1.4	1.8
	July Monthly Peak	3.1	3.6	3.8	3.6	2.6	3.3
	August Monthly Peak	3.0	3.4	3.6	3.4	2.5	3.2
	September Monthly Peak	3.8	4.3	4.6	4.3	3.2	4.0
	October Monthly Peak	2.4	2.7	2.9	2.7	2.0	2.5
1-in-10	Typical Event Day	3.4	3.9	4.2	3.9	2.9	3.7
	May Monthly Peak	2.8	3.2	3.5	3.2	2.4	3.0
	June Monthly Peak	3.3	3.7	4.0	3.7	2.7	3.5
	July Monthly Peak	3.3	3.8	4.0	3.7	2.8	3.5
	August Monthly Peak	3.5	4.0	4.3	4.0	2.9	3.7
	September Monthly Peak	4.4	5.1	5.4	5.1	3.8	4.8
	October Monthly Peak	2.9	3.3	3.5	3.3	2.4	3.1

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 year conditions in September. Under those conditions, the average impact over the event window is expected to be 27.4 MW, with an hourly peak of 32.0 MW from 4 to 5 PM.

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

Weather Year	Day Type	Hour of Day					Average
		1–2 PM	2–3 PM	3–4 PM	4–5 PM	5–6 PM	
1-in-2	Typical Event Day	13.4	15.8	17.6	18.9	15.5	16.2
	May Monthly Peak	4.6	5.3	5.9	6.1	5.0	5.4
	June Monthly Peak	5.0	5.8	6.4	6.6	5.4	5.8
	July Monthly Peak	13.7	16.2	17.9	19.3	15.8	16.6
	August Monthly Peak	13.0	15.4	17.1	18.3	15.1	15.8
	September Monthly Peak	17.8	21.1	23.4	25.3	20.7	21.6
	October Monthly Peak	9.4	11.1	12.2	13.1	10.7	11.3
1-in-10	Typical Event Day	15.9	18.8	20.9	22.5	18.5	19.3
	May Monthly Peak	11.9	14.0	15.6	16.7	13.7	14.4
	June Monthly Peak	15.2	18.0	20.0	21.5	17.7	18.5
	July Monthly Peak	15.6	18.4	20.4	22.0	18.1	18.9
	August Monthly Peak	16.4	19.4	21.6	23.3	19.1	20.0
	September Monthly Peak	22.5	26.6	29.6	32.0	26.3	27.4
	October Monthly Peak	12.4	14.7	16.3	17.5	14.3	15.0

The ex ante impacts summarized above are somewhat higher for residential customers and lower for nonresidential customers compared with the ex ante estimates developed in conjunction with the 2012 evaluation. Average impacts for residential customers on the typical event day under 1-in-2 year conditions are roughly 7% higher based on the 2013 analysis compared with the 2012 analysis and about 8% under 1-in-10 year weather conditions. This higher average impact combined with an increase in forecasted enrollment of about 3% produces an overall increase of roughly 12% in the aggregate impact estimate for typical event day conditions. For nonresidential customers, both average and aggregate estimated ex ante impacts are lower by roughly 12% in this year's evaluation compared with the 2012 evaluation.

5.2 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 number of customers dispatched, the timing and length of the event window, and other factors. Tables 5-6 and 5-7 and Figure 5-1 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. The figure graphs the average values at the bottom of each table.

As seen in columns B through D in Table 5-6, the event window and mean17 values vary across ex post event days but the percent of the resource dispatched (Column D) is constant at 97%. Column E shows the aggregate impacts for the percent of the program dispatched, whereas Column F represents what the load reduction would have been under historical weather conditions and event window timing and length if all customers had been dispatched.

Columns G through J incorporate the influence of ex ante assumptions about weather and the event window as well as differences in the methodology used to estimate ex post and ex ante impacts. Column G uses the ex ante model to predict what the impacts would have been under ex post weather conditions and event duration and timing. This reflects the influence of the change in methodology from the RCT-based ex post estimates to the regression-based ex ante estimates. For 50% cycling, the regression model over predicts the ex post values by about 13% (from 6.9 MW to 7.8 MW as seen in columns F and G in Table 5-6). The regression model for 100% cycling under predicts the ex post values by about 1% (from 8.7 MW to 8.6 MW as seen in columns F and G in Table 507). Column H shows the effect of changing from the actual event window to the standardized resource adequacy window (from 1 to 6 PM). This did not change impacts much for either cycling option. The last two columns, I and J, show the impact of changing from ex post weather conditions to 1-in-2 and 1-in-10 year weather conditions. Shifting from ex post to ex ante 1-in-2 year weather for a typical event day decreased aggregate impacts by about 20% for both cycling options and shifting to 1-in-10 year weather conditions decreased the impacts by nearly 5% compared with ex post conditions. As previously discussed, the ex ante numbers are lower because mean17 for the typical event day under 1-in-2 and 1-in-10 year weather conditions equals about 77°F and 79°F, respectively. Both of these temperatures are lower than the average mean17 for 2013, which equaled 80.1°F.

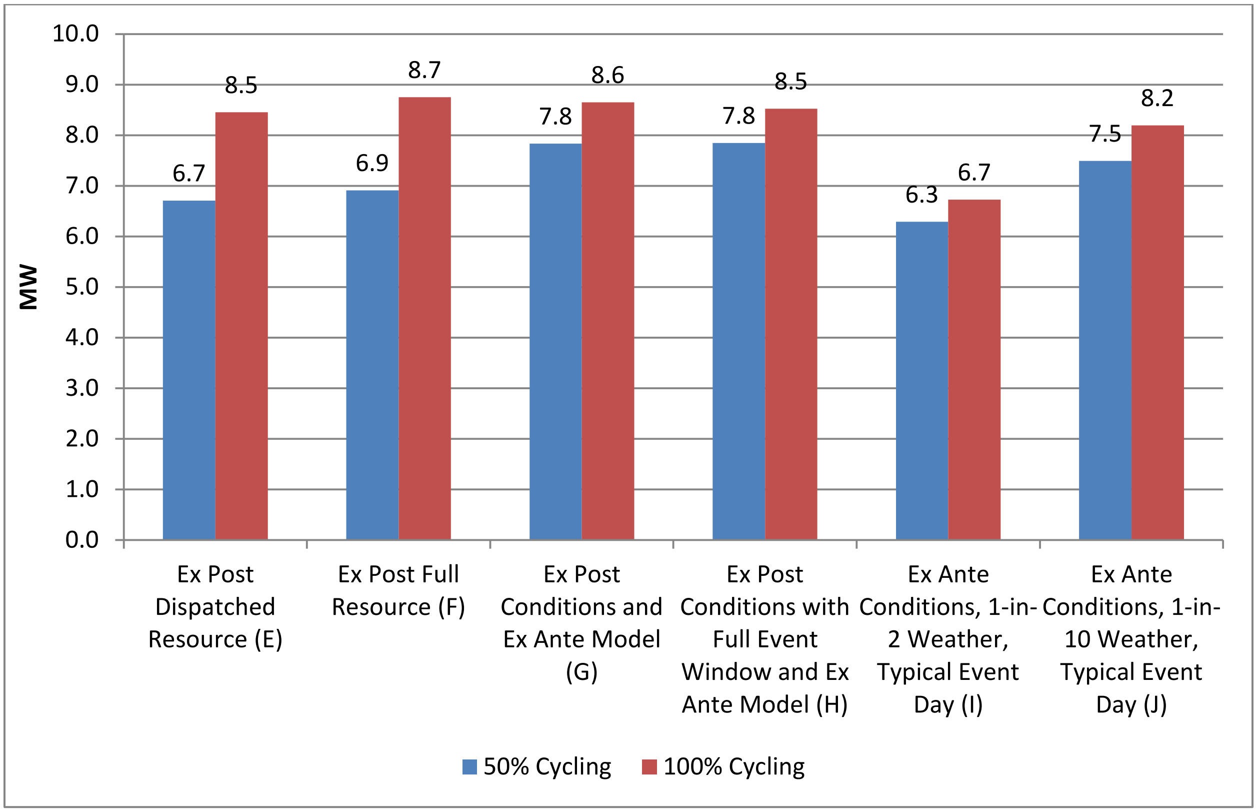
Table 5-6: Differences in Ex Post and Ex Ante Load Impacts Due to Key Factors for 50% Cycling Participants – Residential Customers

Date	2013 Ex Post Aggregate Estimates					Aggregate Estimates Based on the Ex Ante Model			
	Event Window	Mean17 (°F)	% of Resources Dispatched	Aggregate Reduction (MW)	Aggregate Reduction if All Participants are Controlled (MW)	Historical Window & Weather (MW)	Historical Weather & Standardized Event Window (MW)	1-in-2 Year Weather, Forecast Enrollment (MW)	1-in-10 Year Weather, Forecast Enrollment (MW)
A	B	C	D	E	F	G	H	I	J
28-Aug-13	3-7 pm	78.0	97%	3.6	3.8	6.3	6.8	6.3	7.5
29-Aug-13	2-6 pm	78.1	97%	5.9	6.1	7.1	6.9		
30-Aug-13	1-5 pm	83.0	97%	7.0	7.2	9.3	9.2		
3-Sep-13	1-5 pm	79.0	97%	6.7	6.9	7.4	7.3		
5-Sep-13	1-5 pm	80.8	97%	6.8	7.0	8.2	8.2		
6-Sep-13	1-5 pm	81.8	97%	10.3	10.6	8.7	8.6		
Average		**80.1**	**97%**	**6.7**	**6.9**	**7.8**	**7.8**		

Table 5-7: Differences in Ex Post and Ex Ante Impacts Due to Key Factors for 100% Cycling Participants – Residential Customers

Date	2013 Ex Post Aggregate Estimates					Aggregate Estimates Based on the Ex Ante Model			
	Event Window	Mean17 (°F)	% of Resources Dispatched	Aggregate Reduction (MW)	Aggregate Reduction if All Participants are Controlled (MW)	Historical Window & Weather (MW)	Historical Weather & Standardized Event Window (MW)	1-in-2 Year Weather, Forecast Enrollment (MW)	1-in-10 Year Weather, Forecast Enrollment (MW)
A	B	C	D	E	F	G	H	I	J
28-Aug-13	3-7 pm	77.3	97%	8.2	8.5	7.6	7.2	6.7	8.2
29-Aug-13	2-6 pm	77.6	97%	5.9	6.1	7.9	7.4		
30-Aug-13	1-5 pm	82.8	97%	10.6	11.0	10.4	10.4		
3-Sep-13	1-5 pm	78.5	97%	8.0	8.3	7.9	7.9		
5-Sep-13	1-5 pm	80.0	97%	7.6	7.9	8.7	8.8		
6-Sep-13	1-5 pm	81.2	97%	10.3	10.7	9.4	9.5		
Average		**79.6**	**97%**	**8.5**	**8.7**	**8.6**	**8.5**		

Figure 5-1: Differences in Residential Ex Post and Ex Ante Impacts Due to Key Factors



To better understand the possible reason for the difference in ex post and ex ante estimates based on the ex ante model using ex post weather and event conditions (columns F and G in Tables 5-6 and 5-7), we replicated those tables while constraining the impact values to the two hours from 2 to 4 PM. As discussed in Section 2, these are the hours used in the regression model that is the basis for the ex ante forecasts because they were most common across all ex post event days. Tables 5-8 and 5-9 show the relationship between ex post and ex ante estimates using just the hours from 2 to 4 PM. A comparison of columns F and G in Table 5-8 shows that ex post and ex ante estimates match almost perfectly for 50% cycling participants but now the ex ante model under predicts by about 8% using ex post weather for the 100% cycling group as seen in Table 5-9.

The above analysis suggests that some of the difference between ex post and ex ante estimates stems from the process used to produce load impacts for hours outside the 2 to 4 PM window. Recall from Section 3 that estimates for the hours from 1 to 2 PM and from 4 to 6 PM are based on the ratio of load impacts in those hours relative to the hours from 2 to 4 PM. These ratios, shown previously in Table 3-5, were based only on data from 2013 whereas the regression model was based on data from 2010 through 2013. It's possible that using ratios based on data from all four years could improve the match between ex post and ex ante estimates, although a simple comparison of the ratios based on all four years with the ratios from 2013 suggests that any difference in ex ante estimates would be small and that the differences between ex post and ex ante might still exist.

Table 5-8: Differences Ex Post and Ex Ante Impacts for 50% Cycling Customers Using Only the Hours from 2 to 4 PM – Residential Customers

<table>
<tr><th rowspan="2">Date</th><th colspan="5">2013 Ex Post Aggregate Estimates</th><th colspan="4">Aggregate Estimates Based on the Ex Ante Model</th></tr>
<tr><th>Analysis Window</th><th>Mean17 (°F)</th><th>% of Resources Dispatched</th><th>Aggregate Reduction (MW)</th><th>Aggregate Reduction if All Participants are Controlled (MW)</th><th>Historical Window & Weather (MW)</th><th>Historical Weather & Standardized Event Window (MW)</th><th>1-in-2 Year Weather, Forecast Enrollment (MW)</th><th>1-in-10 Year Weather, Forecast Enrollment (MW)</th></tr>
<tr><td>A</td><td>B</td><td>C</td><td>D</td><td>E</td><td>F</td><td>G</td><td>H</td><td>I</td><td>J</td></tr>
<tr><td>28-Aug-13</td><td>2-4 pm</td><td>78.0</td><td>97%</td><td>5.8</td><td>6.0</td><td>7.0</td><td>6.8</td><td rowspan="7">6.3</td><td rowspan="7">7.5</td></tr>
<tr><td>29-Aug-13</td><td>2-4 pm</td><td>78.1</td><td>97%</td><td>3.7</td><td>3.8</td><td>7.1</td><td>6.9</td></tr>
<tr><td>30-Aug-13</td><td>2-4 pm</td><td>83.0</td><td>97%</td><td>9.0</td><td>9.3</td><td>9.5</td><td>9.2</td></tr>
<tr><td>3-Sep-13</td><td>2-4 pm</td><td>79.0</td><td>97%</td><td>7.7</td><td>7.9</td><td>7.5</td><td>7.3</td></tr>
<tr><td>5-Sep-13</td><td>2-4 pm</td><td>80.8</td><td>97%</td><td>8.0</td><td>8.2</td><td>8.4</td><td>8.2</td></tr>
<tr><td>6-Sep-13</td><td>2-4 pm</td><td>81.8</td><td>97%</td><td>12.3</td><td>12.7</td><td>8.9</td><td>8.6</td></tr>
<tr><td colspan="2">Average</td><td>80.1</td><td>97%</td><td>7.8</td><td>8.0</td><td>8.1</td><td>7.8</td></tr>
</table>

Table 5-9: Differences in Ex Post and Ex Ante Impacts for 100% Cycling Customers Using Only the Hours from 2 to 4 PM – Residential Customers

Date	2013 Ex Post Aggregate Estimates					Aggregate Estimates Based on the Ex Ante Model			
	Analysis Window	Mean17 (°F)	% of Resources Dispatched	Aggregate Reduction (MW)	Aggregate Reduction if All Participants are Controlled (MW)	Historical Window & Weather (MW)	Historical Weather & Standardized Event Window (MW)	1-in-2 Year Weather, Forecast Enrollment (MW)	1-in-10 Year Weather, Forecast Enrollment (MW)
A	B	C	D	E	F	G	H	I	J
28-Aug-13	2-4 pm	77.3	97%	6.2	6.4	7.1	7.2	6.7	8.2
29-Aug-13	2-4 pm	77.6	97%	5.2	5.3	7.3	7.4		
30-Aug-13	2-4 pm	82.8	97%	10.7	11.1	10.3	10.4		
3-Sep-13	2-4 pm	78.5	97%	9.4	9.7	7.8	7.9		
5-Sep-13	2-4 pm	80.0	97%	9.0	9.2	8.7	8.8		
6-Sep-13	2-4 pm	81.2	97%	12.4	12.8	9.4	9.5		
Average		**79.6**	**97%**	**8.8**	**9.1**	**8.4**	**8.5**		

Exploring this issue even further, Figures 5-2 and 5-3 show the impacts that went into the regression (on a per ton of air conditioning capacity basis) for 50% and 100% cycling, respectively. The red squares represent load impacts for the 2013 events and the blue diamonds show the load impacts from 2010 through 2012. As seen in Figure 5-2, three of the six 2013 events lie almost perfectly on the regression line that is fit to data from all four years and the September 6 outlier is more or less offset by the combination of the two events on August 28 and 29. Given this, it is not surprising that the ex post and ex ante estimates based on only the hours from 2 to 4 PM match quite well. Figure 5-3 shows the same data for the 100% cycling group. Here, four of the six 2013 events are above the regression line, two of them significantly so. As such, it is not surprising that the ex ante model under predicts impacts based on 2013 ex post weather.

Figure 5-2: 50% Cycling Ex Ante Regression Model and 2010-2013 Impacts from 2-4 PM – Residential Customers

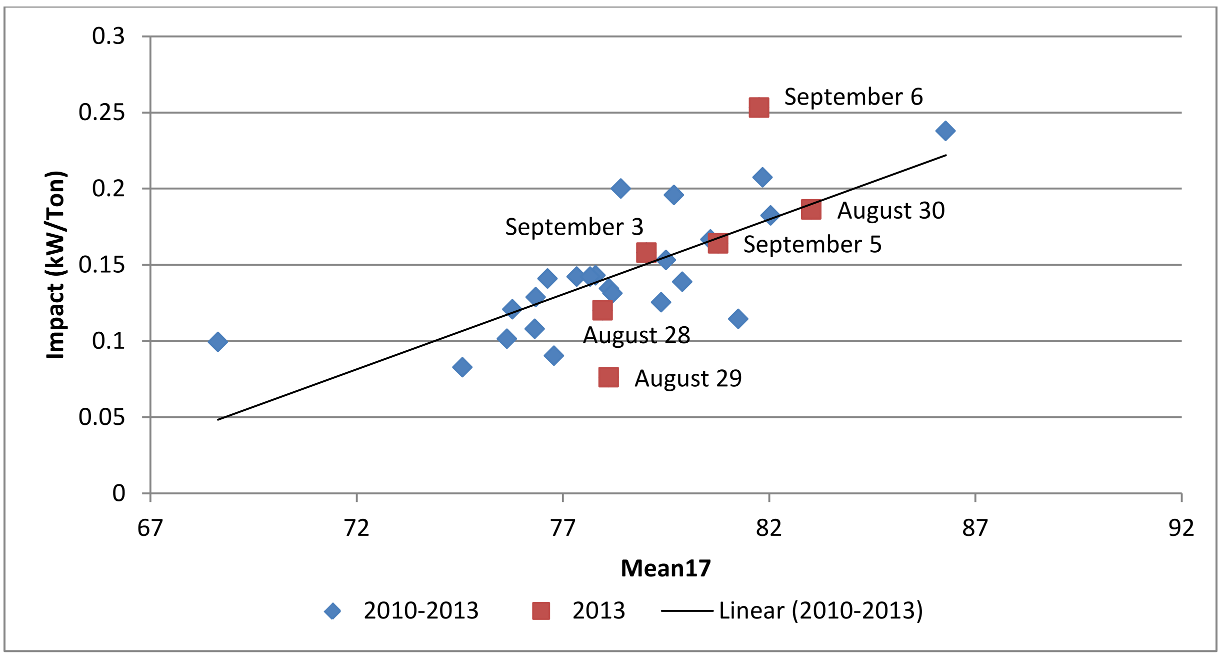
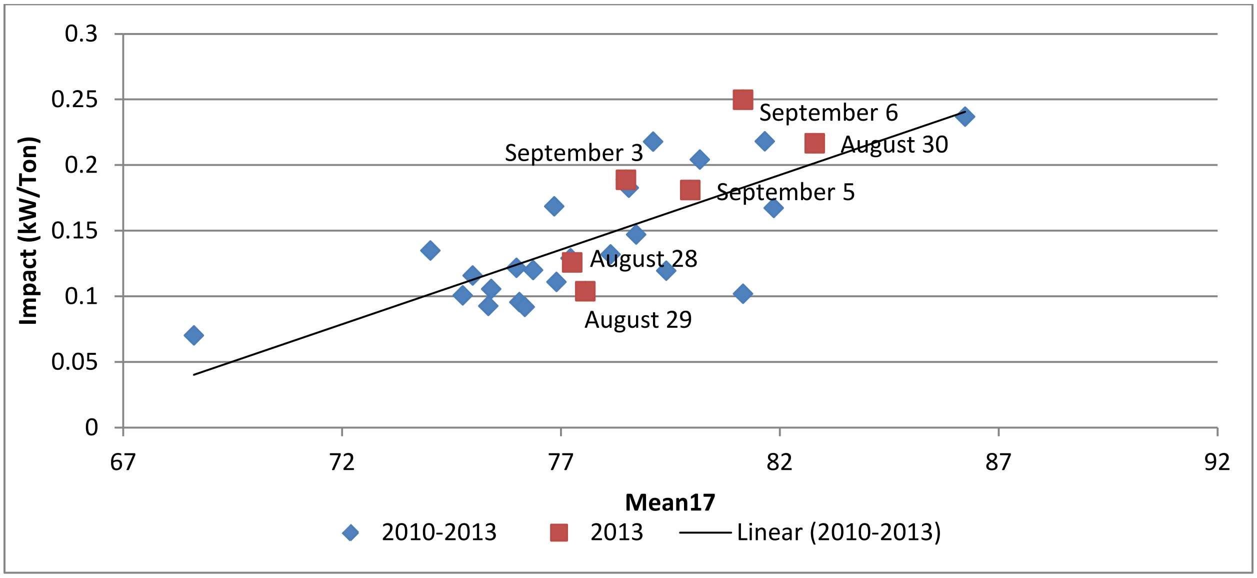


Figure 5-3: 100% Cycling Ex Ante Regression Model and 2010-2013 Impacts from 2 to 4 PM – Residential Customers



The differences between ex post and ex ante estimates for nonresidential customers are very similar to what was discussed for residential customers. Tables 5-10 and 5-11 and Figure 5-4 show how aggregate load impacts change as a result of differences in the factors underlying ex post and ex ante estimates. Table 5-10 covers the impacts for 30% cycling participants and Table 5-11 does the same for 50% cycling. The figure graphs the average values at the bottom of each table.

Going from Column F to G in Tables 5-10 and 5-11, again reflects the influence of the change in methodology from the RCT-based ex post estimates to the regression-based ex ante estimates. For 30% cycling, the regression model over predicts the ex post values by about 7% (from 0.9 MW to 1.0 MW in Table 5-10). The regression model for 50% cycling under predicts the ex post values by about 6% (from 2.9 MW to 2.7 MW in Table 5-11). The last two columns, I and J, show the impact of changing from ex post weather conditions to 1-in-2 and 1-in-10 year weather conditions. Shifting from ex post to ex ante 1-in-2 year weather decreased aggregate impacts by about 9% for 30% cycling and 14% for 50% cycling. Shifting to 1-in-10 year weather conditions decreased the impacts by about 1% compared with ex post conditions. As discussed previously, these ex ante numbers are lower because mean17 is lower under ex ante weather on a typical event day than under 2013 weather conditions. The 1-in-10 year conditions show impacts that are 9% higher than 1-in-2 year conditions for 30% cycling and nearly 15% higher for 50% cycling.

Table 5-10: 30% Cycling Ex Ante Regression Model and 2010-2013 Impacts from 2-4 PM – Non Residential Customers

Date	2013 Ex Post Aggregate Estimates					Aggregate Estimates Based on the Ex Ante Model			
	Event Window	Mean17 (°F)	% of Resources Dispatched	Aggregate Reduction (MW)	Aggregate Reduction if All Participants are Controlled (MW)	Historical Window & Weather (MW)	Historical Weather & Standardized Event Window (MW)	1-in-2 Year Weather, Forecast Enrollment (MW)	1-in-10 Year Weather, Forecast Enrollment (MW)
A	B	C	D	E	F	G	H	I	J
28-Aug-13	3-7 pm	76.5	93%	0.6	0.6	0.7	0.9	0.9	1.0
29-Aug-13	2-6 pm	77.5	93%	0.7	0.7	0.9	0.9		
30-Aug-13	1-5 pm	82.5	93%	1.0	1.1	1.1	1.1		
3-Sep-13	1-5 pm	77.8	93%	1.1	1.2	1.0	0.9		
5-Sep-13	1-5 pm	79.0	93%	0.8	0.9	1.0	1.0		
6-Sep-13	1-5 pm	80.8	93%	0.9	1.0	1.1	1.0		
Average		**79.6**	**93%**	**0.9**	**0.9**	**1.0**	**1.0**		

Table 5-11: 50% Cycling Ex Ante Regression Model and 2010-2013 Impacts from 2-4 PM – Non Residential Customers

Date	2013 Ex Post Aggregate Estimates					Aggregate Estimates Based on the Ex Ante Model			
	Event Window	Mean17 (°F)	% of Resources Dispatched	Aggregate Reduction (MW)	Aggregate Reduction if All Participants are Controlled (MW)	Historical Window & Weather (MW)	Historical Weather & Standardized Event Window (MW)	1-in-2 Year Weather, Forecast Enrollment (MW)	1-in-10 Year Weather, Forecast Enrollment (MW)
A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**
28-Aug-13	3-7 pm	75.9	97%	1.8	1.8	1.8	2.3	2.3	2.7
29-Aug-13	2-6 pm	76.9	97%	2.6	2.7	2.5	2.5		
30-Aug-13	1-5 pm	82.1	97%	2.9	2.9	3.4	3.2		
3-Sep-13	1-5 pm	77.4	97%	2.8	2.9	2.7	2.5		
5-Sep-13	1-5 pm	78.5	97%	3.1	3.2	2.8	2.7		
6-Sep-13	1-5 pm	80.1	97%	3.5	3.6	3.1	2.9		
Average		**78.5**	**97%**	**2.8**	**2.9**	**2.7**	**2.7**		

Figure 5-4: Differences in Nonresidential Ex Post and Ex Ante Impacts Due to Key Factors