



2013 Load Impact Evaluation for Pacific Gas and Electric Company's SmartAC Program

Pacific Gas and Electric Company

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1 Executive Summary

> *PG&E's SmartAC program had roughly 160,000 customers enrolled at the end of 2013. It can deliver peak period load reductions of roughly 100 MW under normal weather conditions and more than 120 MW under 1-in-10 year weather conditions.*

This report documents the ex post and ex ante load impact evaluation of PG&E's SmartAC™ program. The SmartAC™ program is an air conditioning cycling program that involves the installation of control devices (primarily switches) on central air conditioners (CACs) at residential and small and medium business (SMB) premises. The program formerly also offered programmable communicating thermostats (PCTs); a large number of those are still in operation. When a SmartAC event is called, the control devices limit the duty cycles of CAC units, thereby reducing demand.

SmartAC events can be called under a variety of conditions when peak demand reductions are needed, including for testing purposes to support measurement and evaluation (M&E) of the program. Events can be called at any time of day between May 1 and October 31, up to 6-hours per event, for a maximum of 100-hours per season. Events can be called at any time of day, but are most likely to be called at times near system peak demand, which typically occur in the late afternoon on hot summer days. No system wide events were called in 2013. Four emergency events were called in selected sub-LAP[1] regions. Two test events were called for subsets of the population as discussed in detail throughout this report.

Residential customer enrollment at the end of summer 2013 was roughly 168,000 control devices on approximately 151,000 different premises. SMB customer enrollment was around 9,000 control devices on 5,800 premises. Nearly 39,000 customers with roughly 43,000 devices were dually enrolled in SmartAC and PG&E's critical peak pricing tariff known as SmartRate. Prior to 2012, dually enrolled customers were a small enough fraction of the program (about 4,000 residential customers) that they could effectively be ignored during evaluation. In 2012 and 2013, the SmartRate program expanded substantially, with a major emphasis on enrolling SmartAC customers. For this reason, the dually enrolled population must now be evaluated as a separate group from customers enrolled only on SmartAC. Since, historically, SmartAC and SmartRate events have overlapped substantially, ex post impact estimates for dually enrolled customers are reported in the evaluation of the SmartRate program rather than included in this report. However, dually enrolled customers are included in the aggregate ex ante estimates for SmartAC contained in this report since including them represents the maximum capability of SmartAC for hours when the program is called and SmartRate is not.

1.1 Residential SmartAC Ex Post Load Impact Summary

In 2013, M&E test events were called on July 1 and September 9. On July 1, PG&E called a series of one-hour test events, using different control and test groups for each hour, spanning the hours from 10 AM to 8 PM. A key focus of this test day was to estimate impacts for hours outside the 1 to 6 PM resource

[1] A sub-LAP is a load aggregation point. There are 16 sub-LAPs within PG&E's service territory. A sub-LAP map is contained in Section 4.4.

adequacy window. On September 9, a one-hour test event was called between 2 and 3 PM. In addition, four localized emergency events were called on other days, one in each of four sub-LAP regions.

In 2013, for the first time, PG&E called SmartAC during morning and evening hours. Average impacts were much lower in the morning than in the afternoon, but evening impacts were higher than the average impact between 1 and 6 PM.

Table 1-1 shows the estimated load impact from 2 to 3 PM for the two 2013 test events. The table focuses on 2 to 3 PM because that hour was common to both events, which makes the estimated load impacts comparable with each other without confounding time-of-day effects with other reasons for impact variability. The overall average impact from 2 to 3 PM was 0.41 kW per customer, or about 17% of the whole house load. The average aggregate impact for the test population that was called (about 10% of the total program population) was roughly 5 MW.

Table 1-1: Ex Post Loads, Impacts and Temperatures from 2 to 3 PM on 2013 Event Days

Event Date	Event Hours	Average Whole-Building Reference Load (kW)	Average Event Impact (kW)	Percent Impact	Aggregate Impact (MW)	Average Temperature 2 to 3 PM (°F)
7/1/2013	2 to 3 PM	2.84	0.54	19.0%	6.34	98.9
9/9/2013	2 to 3 PM	2.00	0.28	14.0%	3.50	94.7
Average	2 to 3 PM	2.42	0.41	16.5%	4.92	96.8

Table 1-2 shows the average impact in each hour for the multiple test events held on July 1. As seen, the average impacts in the hours leading up to the resource adequacy window are significantly less than the impacts between 1 and 6 PM. For example, the impact between 10 and 11 AM, 0.13 kW, is only 1/6th as large as the peak hourly impact of 0.79 kW, which occurred between 5 and 6 PM. The impact of 0.32 kW in the hour just prior to the resource adequacy window is roughly half the average impact of 0.62 kW across the five-hour resource adequacy window. On the other hand, average impacts in the evening hours, from 6 to 8 PM, are quite high and, indeed, are higher than the average value from 1 to 6 PM. The load reductions across the 10-hours from 10 AM to 8 PM range from a low of 8% of total building load to a high of 23%. The average percent reduction during the resource adequacy window from 1 to 6 PM is 20%.

Table 1-2: Ex Post Loads,[2] Impacts and Temperatures for the July 1, 2013 Event Day (Average Impact per Device for SmartAC-only customers)

Hour Ending	Treatment Group	Reference	Average Impact per Device	Percent	Aggregate Impact[3]	Average Temperature
11	1	1.63	0.13	8%	1.55	87
12	2	1.93	0.21	11%	2.48	91
13	3	2.25	0.32	14%	3.76	94
14	4	2.56	0.40	16%	4.74	96
15	5	2.84	0.54	19%	6.34	99
16	6	3.12	0.61	20%	7.22	99
17	7	3.34	0.76	23%	8.96	100
18	8	3.51	0.79	23%	9.35	100
19	9	3.55	0.77	22%	9.03	97
20	0	3.39	0.69	20%	8.07	94
Average	**N/A**	**2.81**	**0.52**	**18%**	**6.15**	**96**

1.2 Residential SmartAC Ex Ante Load Impact Summary

Ex ante load impact estimates are meant to represent the expected average and aggregate load impacts for the SmartAC program if all customers are called simultaneously under normal weather conditions (e.g., 1-in-2 year weather) and extreme weather conditions (e.g., 1-in-10 year weather). Table 1-3 shows the average ex ante impact estimates for the residential SmartAC population over the resource adequacy window from 1 to 6 PM. These estimates include the contribution of dually enrolled customers. For the 1-in-2 weather year, the highest estimated impact is on the July peak day, with an average load reduction of 93 MW and a peak hourly impact of 109 MW. The July peak day also shows the highest impacts for the 1-in-10 weather year. The mean impact over the five-hour event window under 1-in-10 year conditions is 117 MW and the peak hourly impact is 133 MW.

[2] Reference loads are whole-building loads.

[3] It should be noted that these aggregate impacts represent only roughly 10% of SmartAC-only customers which, in turn, are only about 75% of total enrolled customers, with remainder being dually enrolled in SmartAC and SmartRate. The impacts in this table are not directly comparable to the ex ante impacts contained in Table 1-3 because those impacts include dually enrolled customers and assume that all enrolled customers are dispatched.

Table 1-3: 2014 Residential SmartAC Ex Ante Load Impact Estimates By Weather Year and Day Type (Event Period 1 to 6 PM)

Weather Year	Day Type	Mean Hourly Per Customer Impact (kW)	Max. Hourly Per Customer Impact (kW)	Aggregate Mean Hourly Impact (MW)	Aggregate Max Hourly Impact (MW)
1-in-2	Typical Event Day	0.48	0.58	75	90
	May Peak Day	0.32	0.40	50	61
	June Peak Day	0.40	0.49	62	77
	July Peak Day	0.60	0.70	93	109
	August Peak Day	0.46	0.56	72	87
	September Peak Day	0.47	0.56	72	87
	October Peak Day	0.24	0.32	38	49
1-in-10	Typical Event Day	0.64	0.74	98	114
	May Peak Day	0.53	0.64	83	98
	June Peak Day	0.59	0.70	91	108
	July Peak Day	0.76	0.86	117	133
	August Peak Day	0.67	0.77	104	119
	September Peak Day	0.53	0.64	83	99
	October Peak Day	0.46	0.56	71	87

1.3 SMB SmartAC Ex Ante Load Impact Summary

The SMB segment of the SmartAC program is currently closed to new customers. No M&E test events were called for this group during summer 2013 and the number of SMB customers located in the sub-LAPs where emergency events were called was too small to use for impact estimation. The ex ante estimates presented in this report are based on the average impacts per device estimated in the 2011 evaluation, adjusted for attrition and changes in the enrollment forecast.

Table 1-4 shows the average ex ante load reductions for the SMB population for the resource adequacy window of 1 to 6 PM. For the 1-in-2 weather year, the highest estimated impact is on the July peak day, with an average impact of 3.5 MW and a peak hourly impact of 4.1 MW. The July peak day also shows the highest impacts for the 1-in-10 weather year. The mean impact over the five-hour event window is almost 4.0 MW and the peak hourly impact is 4.6 MW.

Table 1-4: 2014 SMB SmartAC Ex Ante Load Impact Estimates By Weather Year and Day Type (Event Period 1 to 6 PM)

Weather Year	Day Type	Mean Hourly Per Customer Impact (kW)	Max. Hourly Per Customer Impact (kW)	Aggregate Mean Hourly Impact (MW)	Aggregate Max Hourly Impact (MW)
1-in-2	Typical Event Day	0.55	0.65	2.8	3.3
	May Peak Day	0.37	0.45	1.9	2.2
	June Peak Day	0.47	0.56	2.3	2.8
	July Peak Day	0.69	0.81	3.5	4.1
	August Peak Day	0.55	0.65	2.7	3.2
	September Peak Day	0.51	0.61	2.6	3.0
	October Peak Day	0.32	0.39	1.6	1.9
1-in-10	Typical Event Day	0.72	0.85	3.6	4.2
	May Peak Day	0.63	0.74	3.2	3.7
	June Peak Day	0.66	0.78	3.3	3.9
	July Peak Day	0.79	0.93	4.0	4.6
	August Peak Day	0.76	0.88	3.8	4.4
	September Peak Day	0.61	0.72	3.0	3.6
	October Peak Day	0.50	0.59	2.5	2.9

1.4 Recommendations

The ex post event day on which events were called for different groups across the hours from 10 AM to 8 PM produced very useful input regarding the magnitude of the demand response resource in the late morning and early evening hours. With increasing attention to the role that demand response resources can play as a complement to variable supply resources such as wind and solar, it is important to gain insights regarding the magnitude of the resource across a broader number of hours than the traditional afternoon, CAC intensive period. As such, we recommend that PG&E include similar M&E events in the operational plan for SmartAC in 2014. We also recommend calling several test events on days when SmartRate is not also called so that it will be possible to produce better estimates of the load impacts for dually enrolled customers on SmartAC-only days.

2 Overview of SmartAC Program and Evaluation Plan

PG&E's SmartAC™ program currently installs direct load control switches on central (or packaged) air conditioners at residential and SMB premises. Formerly, the program also offered PCTs as a load control option and many of these are still operational. When a SmartAC event is called, the control devices limit the duty cycles of CAC units, thereby reducing demand. Three device types are currently used by PG&E to control air conditioners and each has different functional capabilities. LCR5000 and LCR5200 are both load control receivers (referred to hereafter as switches), which attach directly to the premise near or on the CAC unit. They control the duty cycle of the CAC unit directly using one of several different algorithms.[4] UtilityPro and ExpressStat are PCTs that can control the CAC unit using either duty cycle control, like a switch, or by adjusting thermostat temperatures.

Duty cycle control, not temperature control, was used exclusively in 2012 and 2013 for all control devices. The exact type of cycling varied depending on the control device and type of customer, as shown in Table 2-1. As the table shows, there are two basic kinds of cycling, indexed by a percentage value. Under simple cycling, the CAC compressor's duty cycle is capped at the percentage value for each hour. For example, under 50% simple cycling, a unit's compressor could run for no more than half a given hour. With this simple cycling approach, if the duty cycle was less than 50%, cycling would not result in any load reduction. Under the adaptive cycling algorithm known as TrueCycle2, a baseline methodology is used to limit the compressor to run no more than the given percentage of what it would have been expected to run without switch activation. For example, under 50% TrueCycle2, a compressor is constrained to run for no more than 50% of its duty cycle. All else equal, TrueCycle2 will produce larger load reductions than simple cycling.

Table 2-1: Control Strategies by Segment and Device Type

Segment	Control Device		
	LCR (Switch)	UtilityPRO	Express Stat
Residential	50% TrueCycle2	50% TrueCycle2	50% Simple Cycling
SMB	33% TrueCycle2	33% TrueCycle2	33% Simple Cycling

In 2013, no system wide events were called. M&E test events were called on July 1 and September 9. On July 1, PG&E called a series of one-hour test events spanning the hours from 10 AM to 8 PM. Different control and test groups were used for each hour. A key focus of this test day was to estimate impacts for hours outside the 1 to 6 PM resource adequacy window. On September 9, a one-hour test event was called between 2 and 3 PM. In addition, four localized emergency events were called, one in each of four sub-LAP [5]regions. All resources within each sub-LAP were called for these events rather than holding back a control group for purposes of impact estimation. As such, different methodologies for impact estimation were used for the two test events and the four localized emergency events.

[4] Duty cycle is the fraction of time that an air conditioning compressor is active. Duty cycles vary significantly with temperature. The hotter the temperature across the hours of a day, the longer the duty cycle.

[5] A sub-LAP is a load aggregation point. There are 16 sub-LAPs within PG&E's service territory. A sub-LAP map is contained in Section 3.

Table 2-2 shows the number of enrolled control devices by customer type, device type and local capacity area (LCA) near the end of the 2013 program year.

Table 2-2: SmartAC Active Control Devices as of September 9, 2013

Customer Class	Local Capacity Area	Enrolled Customers	PCTs	Switches	Total Devices
Residential – SmartAC-only	Greater Bay Area	38,719	5,418	38,423	43,841
	Greater Fresno	20,393	4,786	17,743	22,529
	Kern	4,638	1,205	3,998	5,203
	Northern Coast	7,459	1,032	6,934	7,966
	Other	18,943	3,058	17,426	20,484
	Sierra	12,605	1,480	13,019	14,499
	Stockton	9,882	1,508	9,159	10,667
	Total	**112,639**	**18,085**	**107,104**	**125,189**
Residential – Dually Enrolled (SmartAC and SmartRate)	Greater Bay Area	14,893	1,887	15,007	16,894
	Greater Fresno	5,321	1,302	4,599	5,901
	Kern	1,775	860	1,150	2,010
	Northern Coast	2,373	301	2,219	2,520
	Other	6,287	964	5,812	6,776
	Sierra	4,536	451	4,758	5,209
	Stockton	3,614	538	3,369	3,907
	Total	**38,799**	**6,221**	**36,996**	**43,217**
SMB	Greater Bay Area	1,989	3,387	210	3,597
	Greater Fresno	838	1,601	195	1,796
	Kern	246	413	28	441
	Northern Coast	672	952	108	1,060
	Other	1,146	2,089	191	2,280
	Sierra	447	729	75	804
	Stockton	440	729	148	877
	Total	**5,778**	**9,905**	**950**	**10,855**
All	**Total**	**157,216**	**33,262**	**145,999**	**179,261**

It is important to distinguish between enrolled customers and enrolled devices, as many customers, especially SMB customers, have multiple CAC units and, therefore, multiple control devices. Some accounts even have both kinds of control device associated with separate CAC units. Residential customer enrollment at the end of summer 2013 was 151,438 accounts and SMB customer enrollment was 5,778 accounts. There were 168,406 active installed devices among residential accounts and 10,855 devices for SMB accounts. Nearly 39,000 residential customers with roughly 43,000 devices were dually enrolled in SmartRate and SmartAC, leaving about 125,000 devices on 113,000 premises in the SmartAC-only population for which the ex post impacts are reported.

The majority of SmartAC devices are associated with residential households. Indeed, the residential segment comprises 95% of all SmartAC devices, 99% of switches and 74% of PCTs. Among residential customers, the majority of devices are switches, while among SMB customers the majority are PCTs. SMB accounts have roughly 1.9 devices per premise, whereas residential accounts average 1.1 devices per premise.

2.1 SmartAC Analytical Overview

At the core of the ex post load impact evaluation for test events is a randomized control trial, the gold standard of evaluation methodologies.

Detailed discussions of the ex post and ex ante methodologies are contained in Sections 3 and 5, respectively. As in the prior two ex post evaluations of the SmartAC program, this year's analysis for test events was based on a randomized control trial (RCT) in which the participant population was divided into 10 randomly selected groups. For each test event, one group has their devices activated and the others do not. If a system wide event had been called, one group would have been held back from activation. The load impacts are estimated by calculating the difference in loads for the group(s) whose devices are activated and the group(s) whose devices are not activated. The advantages of this evaluation design are discussed extensively in the 2011 evaluation.[6] Briefly, this method removes virtually all uncertainty from the ex post half of the evaluation. The groups are large and random within the SmartAC population, which means that reference loads, estimated loads during events, and ex post load impacts are measured with very small variance and no selection bias or model specification bias.

As previously mentioned, load impacts for the emergency sub-LAP events were necessarily estimated using a different methodology since all customers within each sub-LAP were called during the event. As such, reference loads could not be based on a control group of participants that did not have their devices activated. A comparison group was developed using statistical matching techniques that selected customers with usage patterns similar to those that were subjected to the emergency events but that were not subject to device activation. Once these groups were selected, impacts were estimated using the same differencing methodology as with the RCT groups.

Ex ante estimates are based on a model that relates the variation in ex post load impacts to variation in event day weather. The regression model is based on ex post load impacts from 2011, 2012 and 2013. Load impacts from 4 to 5 PM are modeled as a function of the average temperature from midnight to 5

[6] See "2011 Load Impact Evaluation for Pacific Gas & Electric's SmartAC Program" prepared by FSC. Available at http://fscgroup.com/reports/2011-pge-smartac-evaluation.pdf

PM on each event day, and this model is used to predict ex ante load impacts from 4 to 5 PM under ex ante weather conditions. Ex ante impacts for the remaining resource adequacy hours from 1 to 4 PM and 5 to 6 PM are then modeled as proportions of the 4 to 5 PM impacts based on a model of the relative size of load impact across event hours as a function of weather. The details of these models are discussed in Section 5.

2.2 Report Organization

The remainder of this report is organized as follows. Section 3 describes the ex post evaluation design and the methods used to calculate ex post impact estimates for test events. Section 4 presents residential ex post load impact results for the test events and also explains the approach and results for estimating impacts for the sub-LAP emergency events. Section 5 describes the methods used to estimate ex ante load impacts and Section 6 summarizes those results, as well as ex ante results for SMB customers. Section 7 concludes with a summary and recommendations. Following the main body of the paper are two appendices that discuss how the impact of isolated power outages were treated in the analysis and the approach to estimating ex ante reference loads.[7]

[7] The methodology used to estimate ex ante load impacts does not require estimation of a reference load. However, the load impact protocols that guide this evaluation require reporting reference loads along with load impacts. As such, it is necessary to produce a reference load even though it is not required to obtain load impacts. The approach to dealing with this is discussed in the appendix.

3 Evaluation Design and Ex Post Methods

This section details the evaluation design and numerical methods used to estimate ex post load impacts for residential customers for the 2013 program year. As discussed in the prior section, there were only two M&E test days this year, with a single one-hour event on one of the days and separate events for each of the hours from 10 AM to 8 PM on the other day. In addition, there were four emergency events that occurred in four different sub-LAP areas. The methodology used for test and emergency events was different. This section discusses the methodology used for estimating impacts for test events, which is conceptually identical to the method used in the prior two evaluations. The approach to estimating impacts for the sub-LAP events is discussed in Section 4.3, where the sub-LAP impact estimates are presented.

3.1 Residential Experimental Design and Operations

As in the prior two years, the research design for ex post estimation involved an RCT. The SmartAC-only population was randomly assigned to 1 of 10 groups with each group consisting of roughly 12,000 devices. For any given test, the devices in one or more groups were activated and the devices in remaining groups were not. Load impacts for each event are estimated as the difference in loads for the activated and non-activated groups during the event period and in the hours following the event to capture any snapback effect.

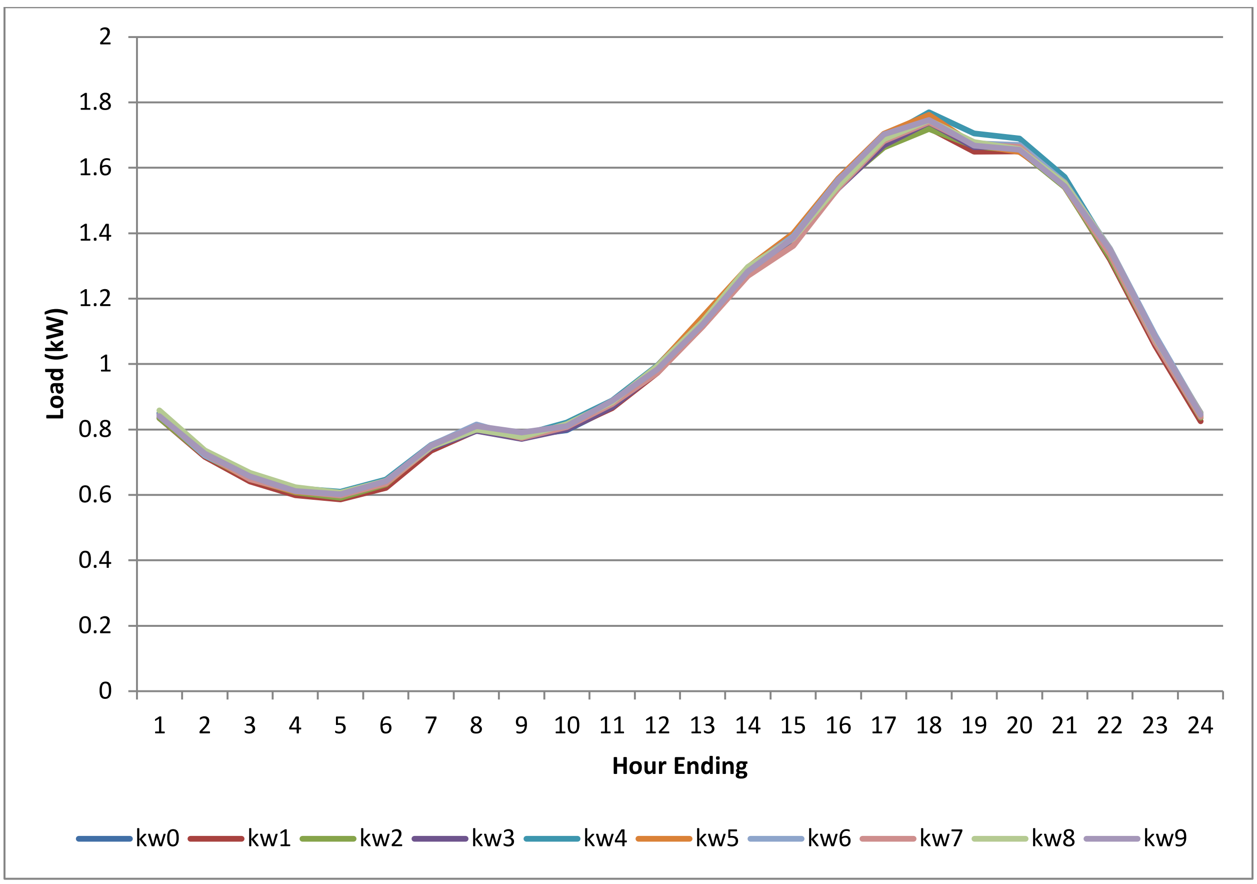
The RCT design combined with large samples sizes for test and control groups produces extremely accurate ex post load impact estimates for the SmartAC-only customer segment.

Table 3-1 shows how well matched the M&E groups are along two important dimensions: location (LCA) and mean daily usage. Figure 3-1 shows how well the hourly loads match across groups for a non-event day (September 10, 2013). Figure 3-2 illustrates visually how the load impacts were estimated by comparing an activated group with the remaining, non-activated groups for a 2012 event several hours in length.

Table 3-1: Comparison of Randomized Groups

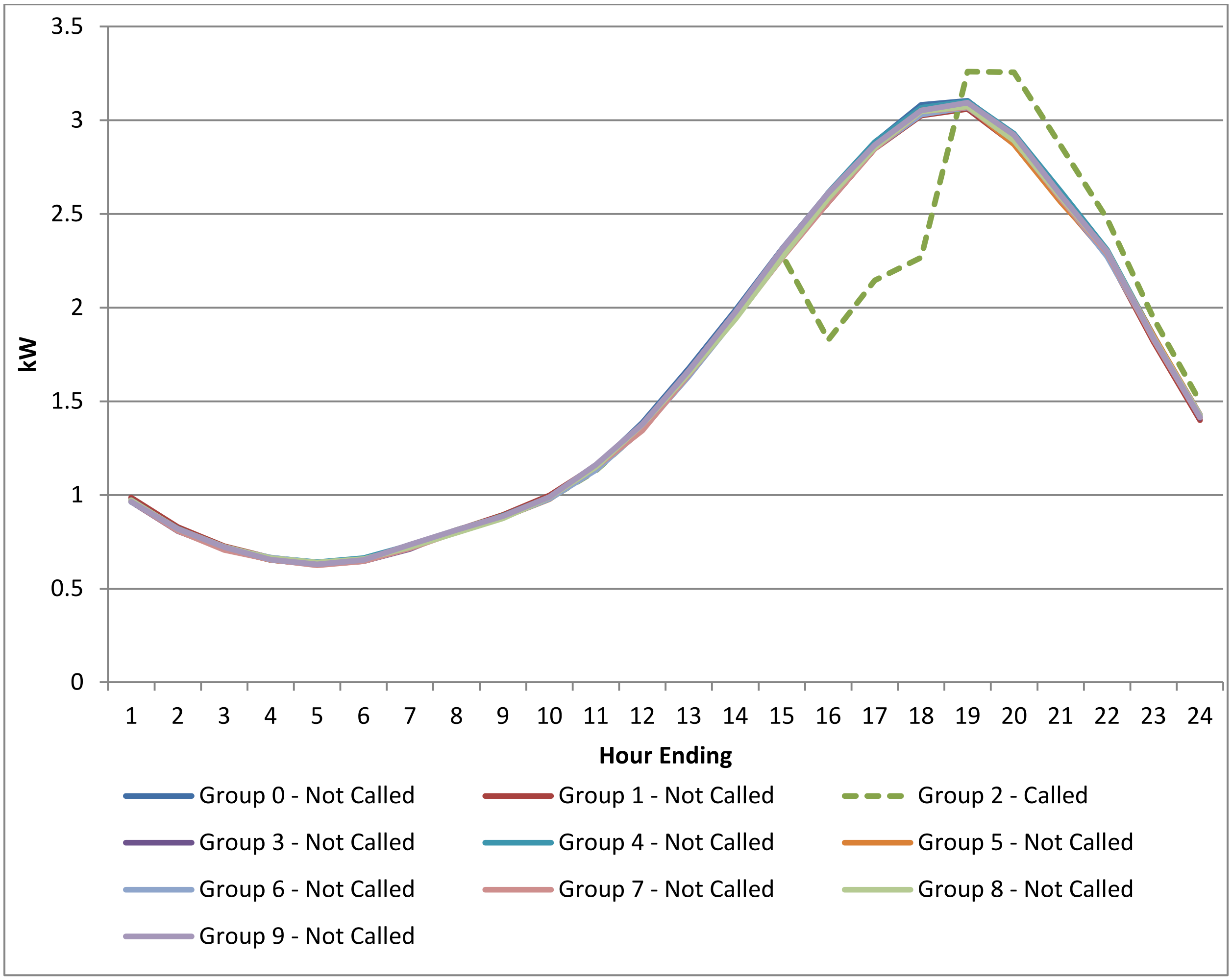
Randomized Group	Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	Mean Daily Usage (kWh)[8]
0	38%	12%	1%	5%	6%	17%	11%	25.9
1	39%	12%	1%	5%	6%	17%	11%	25.7
2	39%	12%	1%	5%	6%	17%	11%	25.8
3	38%	12%	0%	5%	6%	17%	11%	25.9
4	38%	13%	1%	5%	6%	17%	11%	26.3
5	39%	13%	1%	5%	6%	17%	11%	26.0
6	38%	13%	1%	4%	6%	17%	11%	26.1
7	38%	13%	1%	5%	5%	17%	11%	25.8
8	38%	13%	1%	5%	6%	17%	11%	26.1
9	39%	13%	1%	5%	6%	17%	11%	26.0

Figure 3-1: Comparison of Loads for Randomized Groups on a Non-event Day (September 10, 2013)



[8] Calculated on September 10, 2013 – a non-event day

Figure 3-2: Comparison of Loads for Randomized Groups on a 2012 Event Day



On July 1, each test group was called once at a different hour of the day from 10 AM to 8 PM. Devices were activated 30-minutes prior to the hour of interest so that all devices were under control at the start of the hour.[9] There can also be a snapback effect at the end of each hour. Because of these pre- and post-event effects, in order to estimate impacts for the test group in each hour, groups that were called in the prior two hours or that were scheduled to be called in the subsequent hour cannot be used as controls. Table 3-2 shows the groups that were used as controls for each of the hourly tests. Figure 3-3 shows the reference loads for each test group. The extreme similarity across the reference loads indicates that all of the groups provide highly accurate reference loads for each test. Figure 3-4 shows the load impacts and snapback effect for each hourly test. As seen, both the reference loads and load impacts increase significantly from the morning to the afternoon and evening hours.

[9] A typical operation ramps in device activation over a 30-minute period so that not all devices come off of the control condition at the end of the control period, which could create instability in grid operations. In order to capture the full effect of each test group for the full test hour, the ramping for these tests was started 30-minutes before the hour.

Table 3-2: Groups used as Reference Loads for Randomized Groups on the July 1, 2013 Event Day

Test for Hour Ending	Control Groups
11	3,4,5,6,7,8,9,0
12	4,5,6,7,8,9,0
13	5,6,7,8,9,0
14	1,6,7,8,9,0
15	1,2,7,8,9,0
16	1,2,3,8,9,0
17	1,2,3,4,9,0
18	1,2,3,4,5,0
19	1,2,3,4,5,6
20	1,2,3,4,5,6,7

Figure 3-3: Comparison of Reference Loads for Randomized Groups on the July 1, 2013 Event Day

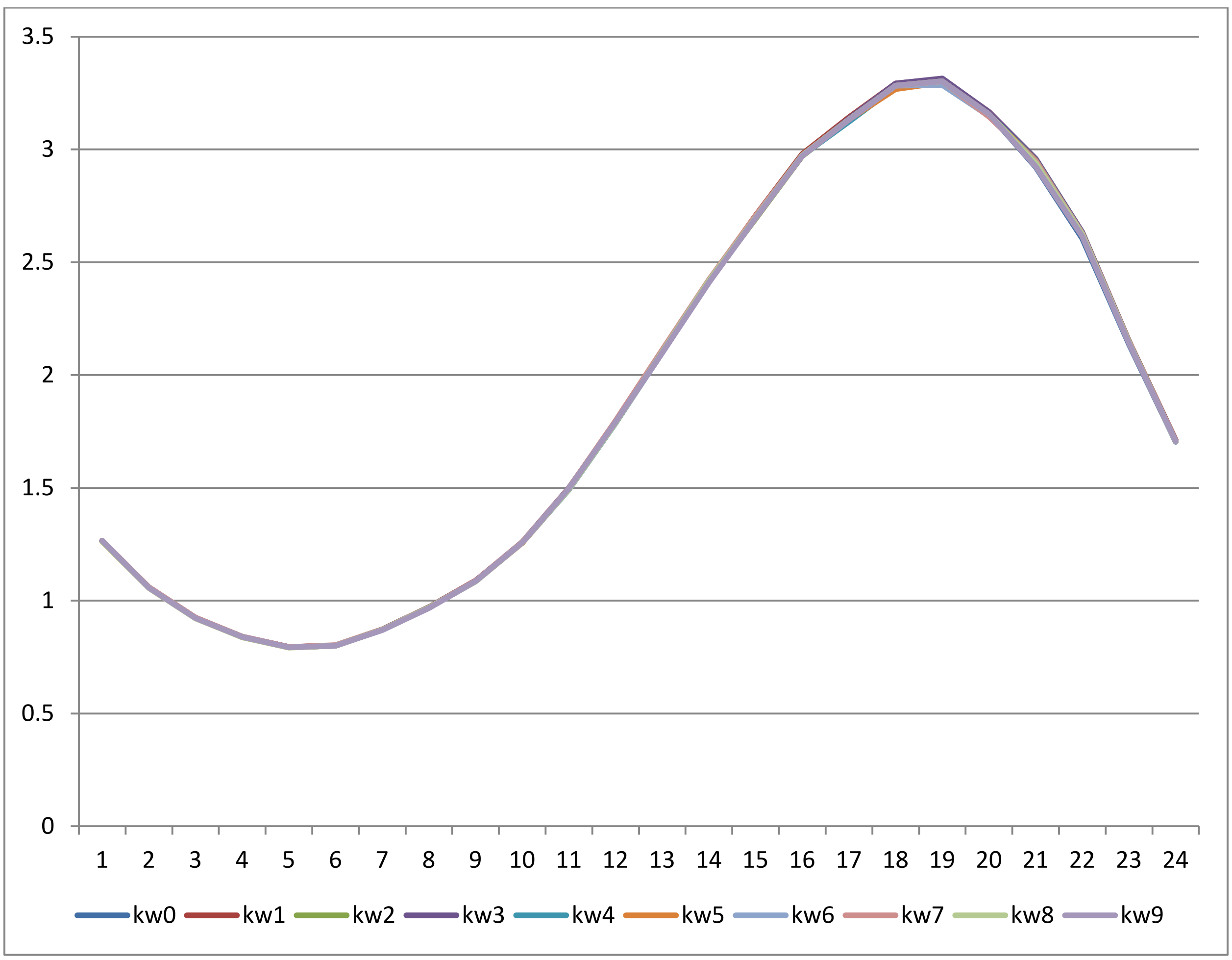
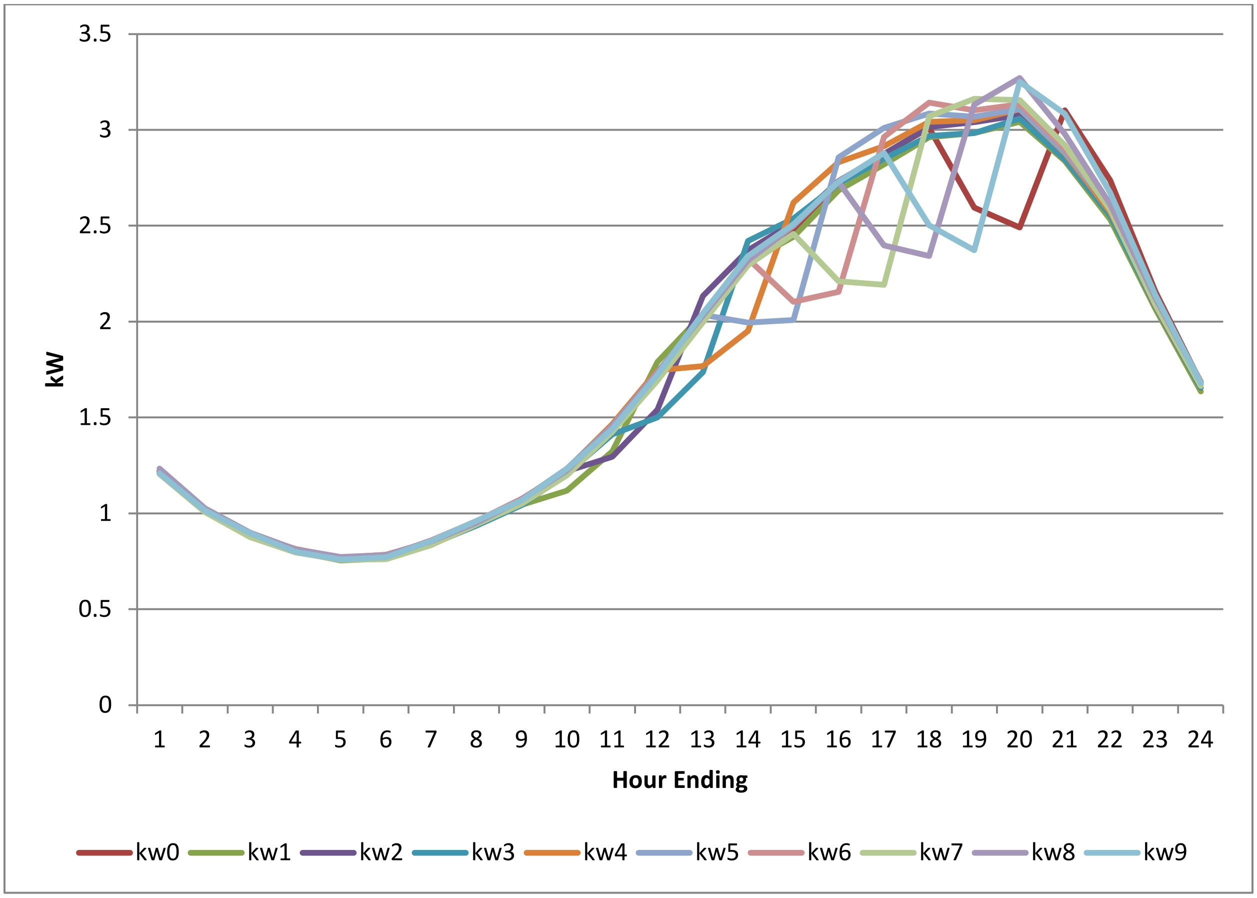


Figure 3-4: Comparison of Treatment Loads for Randomized Groups on the July 1, 2013 Event Day



3.2 Dually Enrolled Participants

Of the residential customers enrolled in the SmartAC program in 2013, 38,799 customers with 43,217 devices were also enrolled in PG&E's SmartRate program. These customers have their CAC units cycled on SmartRate days and the ex post impacts for these days are estimated as part of the SmartRate evaluation. In hours when the SmartAC program is called and SmartRate is not, these customers will also have their control devices activated. However, the average load reduction for these customers may differ from that of the typical SmartAC participant. Indeed, as discussed in Section 5, the average reference load for dually enrolled customers is less than for SmartAC customers. As such, even if the percent reductions for SmartAC-only and dually enrolled customers were the same, the absolute impacts for dually enrolled participants would be less than for SmartAC-only customers. In 2013, there were no SmartAC test events on days when SmartRate was not called. While the sub-LAP emergency events that were called in 2013 included some hours during which SmartAC control was in effect but SmartRate was not, these events involved relatively small populations of dually enrolled customers, which undermine the ability to estimate load impacts for this subpopulation. As such, this report does not contain ex post impact estimates for dually enrolled customers.

3.3 Households with Multiple CAC Units

There are more than 14,000 SmartAC residential customers with more than one control device in their homes (just under 10% of the population). In past years, these houses were omitted from the primary analysis because over 95% of customers with multiple CAC units had control devices in different randomized groups, meaning that one control device might be called for one event while another device in the house might be called for a different event. In a situation like this, the whole-house load impact would not necessarily represent the true effect of a SmartAC event on that household, since during a system wide, non-test event, both units would be controlled. Secondary analysis of multi-device premises was undertaken in 2012 and showed that these premises do not provide higher impacts than single-device premises. There are at least two possible explanations for this result. One is that both CAC units may not be set to run simultaneously during event hours (e.g., one might cool the downstairs during the day and the other the upstairs at night). Another possibility is that both units are operating simultaneously and when one unit is controlled during an event, the duty cycle on the other increases significantly to compensate. In past years, these multi-device households were excluded from the aggregate impact estimates. This year, they have been included in the primary ex post results, thereby lowering the average load impact per device, but increasing the number of devices used to calculate the aggregate impact.

4 Residential Ex Post Load Impact Estimates

This chapter presents the ex post SmartAC program load impacts for the 2013 program year. Across the two event days that were called, the average ex post impact per customer for participants that are only enrolled in the SmartAC program equaled 0.41 kW during the hour from 2 to 3 PM, which was the only hour common to the two events.[10]

This chapter is divided into three main sections. Section 4.1 summarizes the ex post impact results for the two 2013 test events. Section 4.2 provides impact estimates for participants segmented by LCA and average usage decile, which provides an estimate of the distribution of impacts across the population. Section 4.3 compares ex post estimates for 2013 with those from prior evaluations and Section 4.4 summarizes the methodology used and results for the four sub-LAP emergency events that were called. Appendix A is also relevant to the ex post evaluation. It addresses how a couple of power outages impacted analysis of some of the sub-LAP events and what was done analytically to account for these outages.

4.1 SmartAC Primary Test Event Results

2013 was the first year in which test events were held for morning and evening hours outside the resource adequacy window from 1 to 6 PM. Morning impacts were much lower than afternoon impacts but evening impacts were comparable.

Table 4-1 shows the average impact per device for the first test event, July 1, 2013, along with average temperature over the event period for the residential SmartAC population not enrolled in SmartRate. The table also shows the standard errors of the estimates which, given the large sample sizes, are quite small relative to the estimated impact. As discussed in Section 3, this test day involved a series of one-hour tests involving different test groups in each hour. A primary interest in this series of tests was to estimate the impact of the SmartAC program outside the normal hours associated with the resource adequacy window from 1 to 6 PM. Of particular interest, therefore, are the hours from 10 AM to 1 PM and from 6 to 8 PM (e.g., see the Hour Ending column from rows 11 to 13 and from rows 19 to 20 in Table 4-1).

As seen in Table 4-1, the average impacts in the hours leading up to the resource adequacy window are significantly less than the impacts between 1 and 6 PM. For example, the impact between 10 and 11 AM, 0.13 kW, is only 1/6th as large as the peak hourly impact of 0.79 kW, which occurred between 5 and 6 PM. The impact of 0.32 kW in the hour just prior to the resource adequacy window is roughly half the average impact of 0.62 kW across the five-hour resource adequacy window. On the other hand, average impacts in the later evening hours, from 6 to 8 PM, are quite high and, indeed, are higher than the resource adequacy average value. The load reductions range from a low of 8% of total building load to a

[10] During the July 1st, 2013 event many customers in Sierra experienced an interruption in service due to a large fire. These customers were removed from the analysis since their loads do not truly reflect the impacts of the SmartAC event. This issue is further discussed in Appendix A.

high of 23% across the 10-hours tested on this event day. The average percent reduction between 1 and 6 PM is 20%.

Importantly, the values in Table 4-1 do not reflect dually enrolled SmartRate customers since the two test days, July 1 and September 9, were both SmartRate days. These customers were controlled from 2 to 7 PM under that program. The impacts for those customers are included in PG&E's SmartRate evaluation report. Dually enrolled customers have smaller average impacts on days when only SmartAC is called because they tend to have smaller average loads than SmartAC-only customers.

Table 4-1: Ex Post Loads,[11] Impacts and Temperatures for the July 1, 2013 Event Day (Average Impact per Device for SmartAC-only Customers)

Hour Ending	Treatment Group	Reference	Impact	Standard Error of Impact	Percent	Aggregate Impact	Average Temperature
11	1	1.63	0.13	0.015	8%	1.55	87
12	2	1.93	0.21	0.016	11%	2.48	91
13	3	2.25	0.32	0.018	14%	3.76	94
14	4	2.56	0.40	0.020	16%	4.74	96
15	5	2.84	0.54	0.020	19%	6.34	99
16	6	3.12	0.61	0.021	20%	7.22	99
17	7	3.34	0.76	0.021	23%	8.96	100
18	8	3.51	0.79	0.021	23%	9.35	100
19	9	3.55	0.77	0.022	22%	9.03	97
20	0	3.39	0.69	0.021	20%	8.07	94
Average	**N/A**	**2.81**	**0.52**	**0.020**	**18%**	**6.15**	**96**

Table 4-2 shows the aggregate event impacts on July 1, 2013, still excluding the effect of SmartRate customers. Importantly, the aggregate ex post impacts only represent about 10% of the SmartAC-only population since only one test group was called in each hour. As such, the aggregate impact estimates in the table are not at all representative of the load reduction potential for the SmartAC program. Aggregate impacts range from 1.6 MW to 9.4 MW.

[11] Reference loads are whole-building loads.

Table 4-2: Total Devices Called and Aggregate Ex Post Impacts for July 1, 2013 (Note: Impacts are for test groups only and do not represent total program potential)

Hour Ending	Treatment Group	Aggregate Impact	N Called[12]
11	1	1.55	11,676
12	2	2.48	11,630
13	3	3.76	11,614
14	4	4.74	11,803
15	5	6.34	11,712
16	6	7.22	11,807
17	7	8.96	11,864
18	8	9.35	11,805
19	9	9.03	11,670
20	0	8.07	11,706
Average	**N/A**	**6.15**	**11,729**

The second event called, on September 9, 2013 was more similar to prior years. Only one group was called that day for one hour, from 2 to 3 PM. The results of that event are summarized in Table 4-3. The impact per device equaled 0.27 kW, or 13% of total building load. The aggregate impact for the 12,531 devices that were called totaled 3.5 kW.

Table 4-3: Average Residential per Device Reference Load, Impact and Temperature for September 9, 2013 Event Day

Hour Ending	Reference	Impact	Percent	Average Temperature
15	2.0	0.28	14%	95

Impacts can also be broken down by type of control device. Table 4-4 shows the per-premise impacts by device type for residential SmartAC customers. Customers with switches provide average impacts that are more than 50% greater than the average for PCT customers. This difference is not due to systematic temperature or building-size differences between houses with different device types, as shown in Table 4-5. In fact, premises with PCTs tend to be in hotter areas and have somewhat higher reference loads than those with switches, indicating that the performance gap is even larger than Table 4-4 indicates. As was shown in past reports, PCTs have worse signal reception than switches. This probably accounts for the majority of the performance gap.

12 This excludes those 631 Sierra customers dropped from the analysis due to a fire-related power outage. This is discussed further in Appendix A.

Table 4-4: Average Residential Impacts per Customer by Device Type

Date	Hour Ending	PCT	Switch
1-Jul-13	11	0.06	0.14
	12	0.09	0.23
	13	0.17	0.34
	14	0.42	0.41
	15	0.39	0.57
	16	0.26	0.69
	17	0.44	0.79
	18	0.49	0.83
	19	0.46	0.80
	20	0.41	0.74
9-Sep-13	15	0.17	0.28
Average	**N/A**	**0.31**	**0.53**

Load reductions are much greater for switches, which constitute the majority of devices in the field, than for PCTs, due to lower communication success rates for the indoor PCTs.

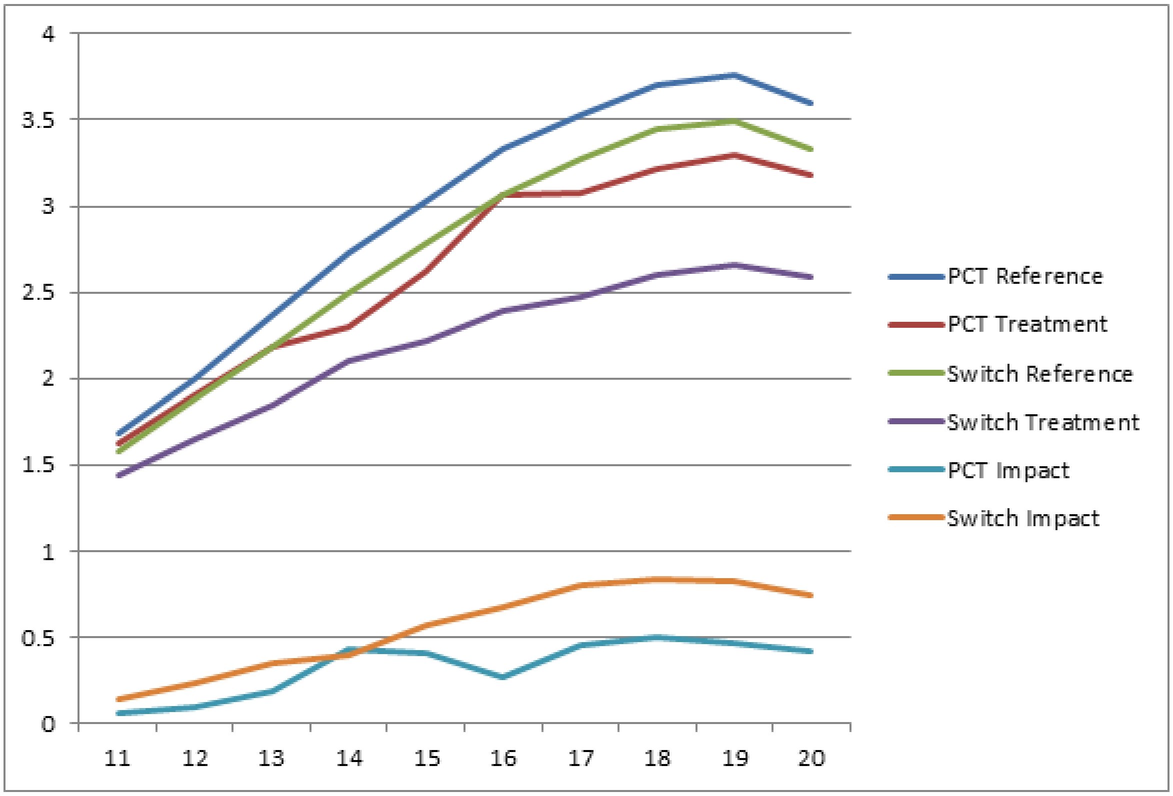
Table 4-5: Comparison of Device Type Groups by LCA

Device Type	Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	Mean Daily Usage (kWh)[13]
Switch	39%	12%	4%	6%	17%	12%	10%	25.6
PCT	32%	19%	7%	5%	19%	8%	9%	28.1

Table 4-4 shows one hour where the load impacts for PCTs and switches were essentially the same whereas in every other hour there are significant differences. This odd result was investigated further and found to be correct, although it is hard to understand why this would occur. Figure 4-1 shows the reference and treatment loads for each hour when events were called on July 1, and the difference between the treatment and control loads for PCTs and switches. The top four lines are the average loads for each group based on the raw data. As seen, there is an unusual notch in the PCT treatment curve in the hour ending 14. There is also a small uptick in the switch reference load in the same hour. These two unusual fluctuations combined produce the odd result in hour 14, which can also be seen in the lower two lines that depict the difference between treatment and control groups. The two impact curves essentially merge at that hour, which is the result shown for hour 14 in Table 4-4.

[13] Calculated on September 10, 2013 (non-event day)

Figure 4-1: Reference and Treatment Loads for Customers with PCTs and Switches on July 1, 2013



4.2 Distribution of Impacts Across Customers

This section summarizes an analysis of the distribution of impacts across two different dimensions: LCA and usage decile. Table 4-6 shows the average load impact from 2 to 3 PM for the two event days by LCA. As will be discussed in Section 6.2, event response appears to follow essentially the same trend with respect to temperature, regardless of LCA. As such, it is not surprising that the average impacts in Table 4-6 are highly correlated with the average temperature at the same time period. Kern and Greater Fresno are the hottest LCAs and also provide two of the three highest load impacts, while the Greater Bay Area and Northern Coast are the coolest and provide two of the three smallest average impacts. However, this correlation is not perfect, as Sierra, which is much warmer than the Bay Area and the North Coast, has an average impact similar to those two regions. Clearly there are other factors besides weather that vary across LCAs. These might include differences in housing types, lifestyle patterns and economic conditions.

Table 4-6: Average Event Impacts from 2 to 3 PM by LCA

Local Capacity Area	Impact (kW)	Average Temperature (°F)
Greater Bay Area	0.34	94
Greater Fresno	0.46	100
Kern	0.53	100
Northern Coast	0.36	93
Other	0.45	99
Sierra	0.35	98
Stockton	0.49	99

Table 4-7 shows the load impact from 2 to 3 PM averaged across both event days for customers grouped by usage decile. Customers were divided into deciles based on average monthly usage from June to September 2013. Customers in the lowest decile had an average monthly usage of 204 kWh compared to 1,818 kWh for customers in the highest decile of usage.[14] As expected, customers with higher average usage showed greater absolute impacts but not necessarily greater percent reductions relative to the whole house reference load. Customers in the highest usage decile had average impacts almost 12 times larger than customers in the lowest usage decile but the percent load reduction in the highest usage decile was only about twice as large as in the lowest decile. These findings highlight the importance of targeting higher use customers for program enrollment.

Load impacts for customers in the highest usage decile, based on average summer usage, are almost 12 times larger than for customers in the lower usage decile, highlighting the importance of targeting large users to enhance program performance and cost effectiveness.

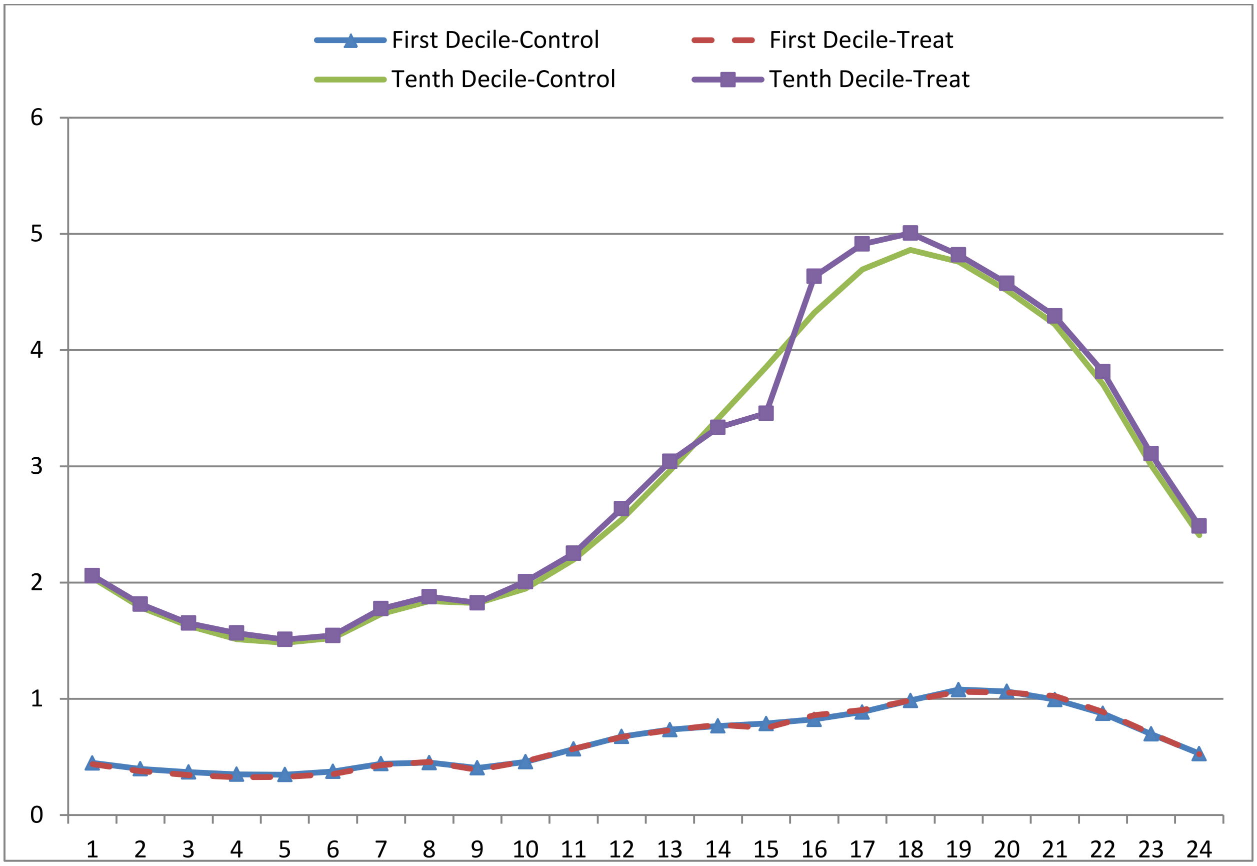
[14] Usage deciles could also be calculated using daily SmartMeter data instead of monthly billing data.

Table 4-7: Average Event Impacts by Usage Decile

Monthly Usage Decile	Average Monthly Usage (kWh)	Average Impact from 2 to 3 PM (kW)	Average Percent Impact from 2 to 3 PM
1	204	0.06	7%
2	393	0.16	14%
3	502	0.26	17%
4	601	0.36	19%
5	700	0.38	18%
6	808	0.48	20%
7	928	0.49	18%
8	1076	0.54	17%
9	1284	0.56	16%
10	1818	0.71	15%

Figure 4-2 further illustrates how different impacts and usage are from the first to the tenth decile. The solid purple line with square markers and solid green line represent the treatment and control group loads on the September 9 event for customers in the tenth percentile. The red dashed line and the blue solid line with triangle markers show the treatment and control usages for customers in the first decile. These findings suggest that PG&E could increase program impacts by focusing marketing efforts on customers with higher-than-average monthly usage.

Figure 4-2: Impacts for September 9, 2013 Event – 1st and 10th Usage Deciles



4.3 Comparison of Ex Post Impacts Across Years

The ex post load impacts for 2013 were similar to impacts found in prior years after adjusting for differences in weather. There is only one hour that is common to most events in 2011, 2012 and 2013, from 4 to 5 PM. Table 4-8 shows the average load reduction per device for each event and the average event for the three years from 2011 to 2013 for the common hour. The table also shows *mean17* for each hour. As seen, the load impacts vary significantly across events and are generally correlated with *mean17*. The *mean17* value 83.3°F for the common hour in 2013 was the highest of any event across the three years. The estimated impact for that hour is 0.76 kW. The hour with the *mean17* value closest to the value in 2013 was on June 21, 2011, when *mean17* equaled 82.2°F and the load impact was also 0.76 kW. The next two closest values for *mean17* occurred on July 11 and August 13, 2012, with *mean17* values between 80 and 81°F, and load impact estimates equal to roughly 0.66 kW per device.

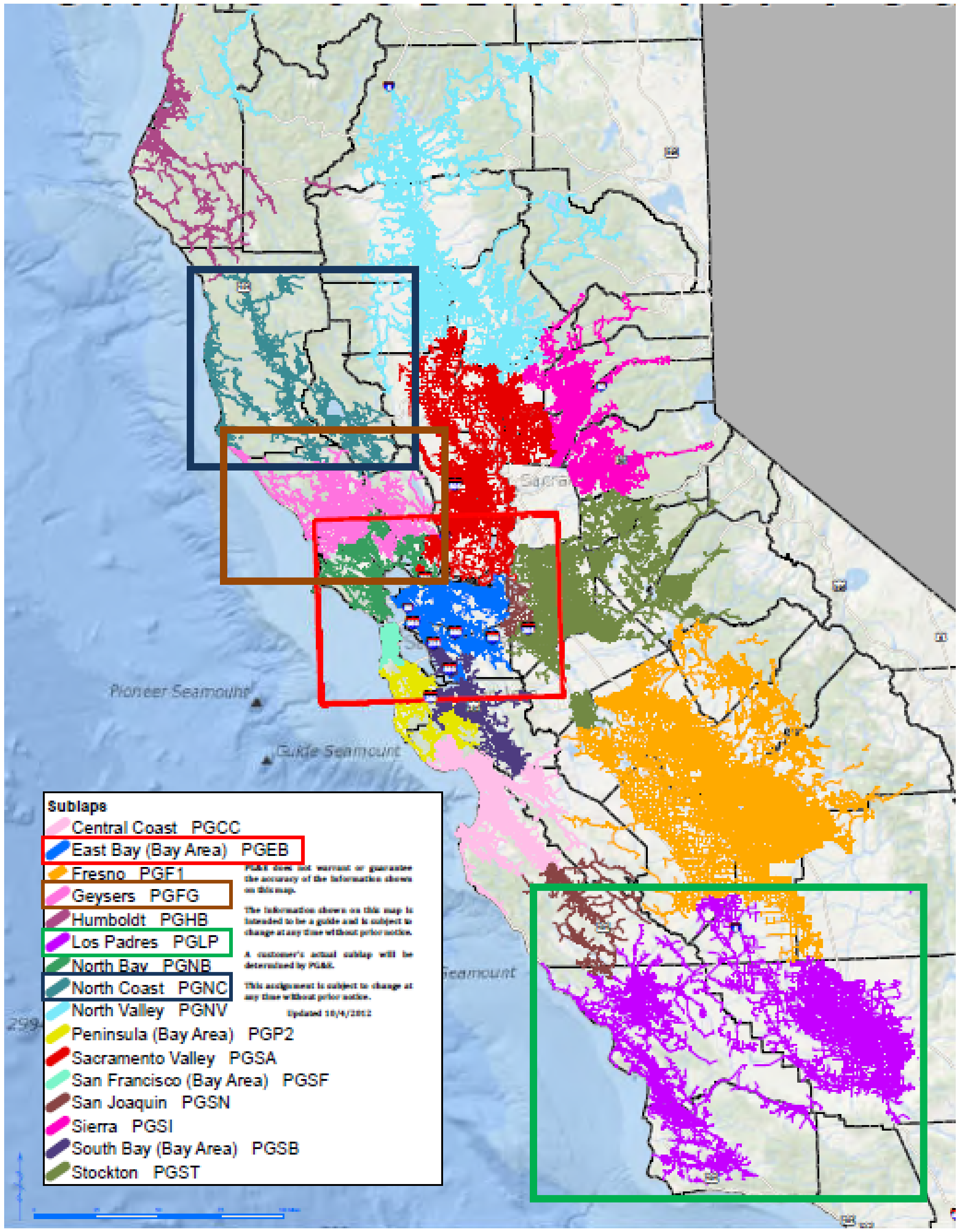
Table 4-8: Load Impact per Device from 4 to 5 PM for Each Ex Post Event in 2011, 2012 and 2011

Date	*Mean17* (°F)	Load Reduction from 4 to 5 PM (kW)
2011		
15-Jun-11	77.1	0.33
21-Jun-11	82.2	0.76
22-Jun-11	79.9	0.57
24-Aug-11	78.6	0.67
6-Sep-11	72.9	0.38
7-Sep-11	76.6	0.52
8-Sep-11	74.3	0.47
Average 2011	77.4	0.53
2012		
9-Jul-12	72.5	0.44
10-Jul-12	76.0	0.63
11-Jul-12	80.1	0.65
12-Jul-12	79.9	0.63
2-Aug-12	76.23	0.60
13-Aug-12	80.9	0.67
13-Sep-12	74.4	0.44
14-Sep-12	73.2	0.29
1-Oct-12	75.6	0.34
1-Oct-12	75.6	0.49
Average 2012	76.5	0.52
2013		
1-Jul-13	83.3	0.76

4.4 Impacts for Emergency Sub-LAP Events

In addition to the M&E test events, several events were called at the sub-LAP level in response to local emergency conditions. Figure 4-3 illustrates the location of the 16 sub-LAP regions in PG&E's service territory. Events were called in four different sub-LAPs in 2013: East Bay on June 7, 2013; Los Padres on July 2, 2013; Geysers on July 3, 2013; and Northern Coast also on July 3, 2013.

Figure 4-3: PG&E's Sub-LAPs by Geography



All program participants were called within each sub-LAP for these emergency events. As such, there weren't any control groups to use for purposes of estimating load impacts and an alternative approach was required. A statistical matching process, known as propensity score matching, was used to select a group of customers that had similar load patterns during non-event times as those of customers that had their air conditioners controlled during the event. The matching process involved several steps.

First, candidate proxy days were chosen for each emergency event and sub-LAP based on similarities in cooling degree hours (CDH) on event days and candidate proxy days. Table 4-9 shows possible proxy days for each event. All possible days were within 10% of the cooling degree hours (CDH) of the event except for the case of Los Padres where days with CDH within 15% of the event day were considered. The East Bay is such a large sub-LAP with differing temperature profiles that it was divided into two groups for matching purposes – East Bay Hot (Concord and San Ramon) and East Bay Cool (Milpitas and Oakland). Different proxy days were chosen for these two groups. Only non-holiday weekdays were considered. July 5 was excluded because it was between the July 4 holiday and the weekend. The dates highlighted in light blue are the chosen proxy days.

Table 4-9: Potential Proxy Days to be Used for Matching on Sub-LAP Emergency Events

Sub-LAP	Event	Event CDH	Potential Proxy Date	Proxy CDH	Proxy Day of Week	Chosen?	Reason for Exclusion
East Bay - Hot	7-Jun-13	189	1-Jun-13	198	Saturday	No	Weekend
			27-Jun-13	190	Thursday	Yes	
			9-Jul-13	191	Tuesday	Yes	
			24-Jul-13	182	Wednesday	Yes	
East Bay - Cool	7-Jun-13	78	4-May-13	78	Saturday	No	Weekend
			14-Jun-13	75	Friday	Yes	
			26-Jun-13	75	Wednesday	Yes	
			9-Jul-13	76	Tuesday	Yes	
			24-Jul-13	71	Wednesday	No	Too cool
Los Padres	2-Jul-13	471	8-Jun-13	405	Saturday	No	Weekend
			29-Jun-13	428	Saturday	No	Weekend
			30-Jun-13	437	Sunday	No	Weekend
			1-Jul-13	407	Monday	Yes	
			3-Jul-13	419	Wednesday	Yes	
			4-Jul-13	449	Thursday	No	Holiday
			5-Jul-13	433	Friday	No	Between Holiday and Weekend
Geysers	3-Jul-13	129	1-May-13	126	Tuesday	No	Too early
			2-May-13	132	Thursday	No	Too early
			3-May-13	126	Friday	No	Too early
			20-May-13	138	Monday	Yes	
			31-May-13	123	Friday	Yes	
			7-Jun-13	117	Friday	No	Too cool
			14-Jun-13	117	Friday	No	Too cool
			22-Jun-13	126	Saturday	No	Weekend

Sub-LAP	Event	Event CDH	Potential Proxy Date	Proxy CDH	Proxy Day of Week	Chosen?	Reason for Exclusion
			2-Jul-13	126	Tuesday	Yes	
Northern Coast	3-Jul-13	233	8-Jun-13	239	Saturday	No	Weekend
			29-Jun-13	218	Saturday	No	Weekend
			2-Jul-13	247	Monday	Yes	

Once the proxy dates were chosen, the possible control group pool needed to be limited by geographic area. After looking at the CDH for each weather station on the proxy days, several weather stations were chosen to represent each sub-LAP. These weather stations are summarized in Table 4-10.

Table 4-10: Weather Stations Used for Matching

Sub-LAP	Weather Station	Chosen Weather Stations
East Bay	CONCORD	Remainder[15] of Concord, Remainder of San Ramon, Stockton, Sacramento
	SAN RAMON	
	MILPITAS	Remainder of Milpitas, Remainder of Oakland
	OAKLAND	
Los Padres	BAKERSFIELD	Remainder of Bakersfield, Remainder of Fresno, Remainder of Paso Robles, Remainder of Santa Maria
	FRESNO	
	PASO ROBLES	
	SANTA MARIA	
Geysers	SAN RAFAEL	Remainder of San Rafael, Remainder of Santa Rosa (not in Northern Coast), Red Bluff
	SANTA ROSA	
Northern Coast	SANTA ROSA	Remainder of Santa Rosa (not in Geysers), Remainder of Ukiah, Red Bluff
	UKIAH	

Once the above steps were completed, control group customers were chosen based on statistical matching within each group of weather stations listed in Table 4-10 based on load shape, daily use, SmartRate enrollment, and CARE enrollment. All of the 4,813 Los Padres customers were matched.[16] Instead of matching all 21,125 of the customers in the hot East Bay sub-LAP, we chose to randomly sample 20% of these customers for matching and 4,225 customers were successfully matched. All but 1 of the 3,413 cool East Bay customers was matched with a control customer. Over 99% of the 3,829

15 By “remainder” we mean customers assigned to each weather station that were located outside of the sub-LAP.

16 Customers in the candidate control group population could be chosen more than once as the best match for treatment customers. This is referred to as “matching with replacement.”

Geyser customers and 929 Northern Coast customers were successfully matched. Due to a power outage, 114 Northern Coast customers were excluded from the match. This is discussed in more detail in Appendix A.

Figure 4-4 shows the treatment and reference (or control) group loads on the average proxy day for the hot East Bay sub-LAP. This represents the loads of the two groups on July 9 and July 24. The lines are quite similar in nearly all hours but there is a small difference in mid-afternoon. A difference-in-differences calculation was used to adjust for this difference.

Figure 4-4: Control and Treatment Groups on the Average Proxy Day for Hot East Bay Sub-LAP

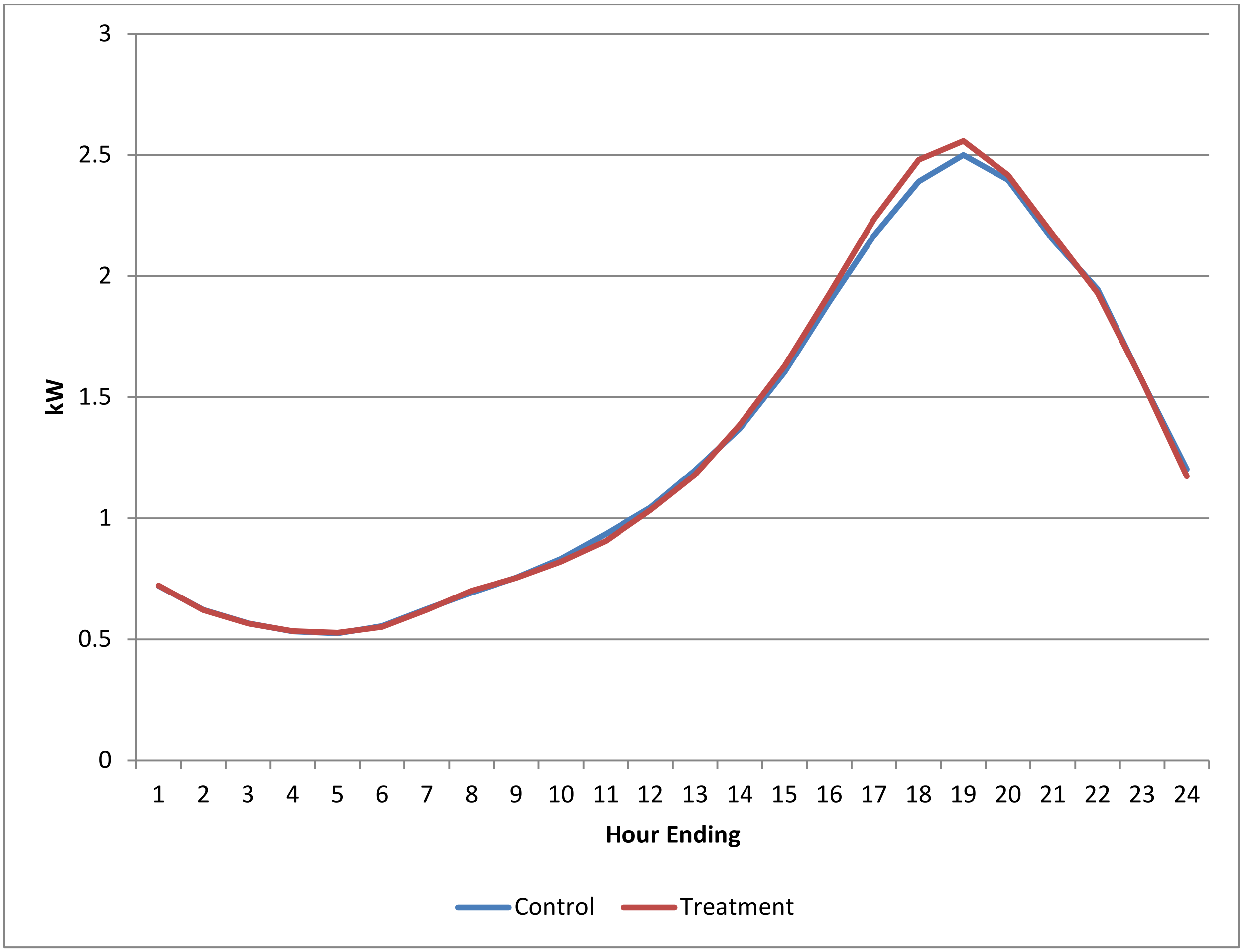


Figure 4-5 shows the treatment and matched control group loads on the East Bay event day, June 7 for the hot East Bay region. Applying a difference-in-differences calculation, there is an average impact of 0.10 kW across the three-hour event from 7 to 10 PM.

Figure 4-5: Control and Treatment Groups of the Hot East Bay Sub-LAP for the June 7, 2013 Event Day

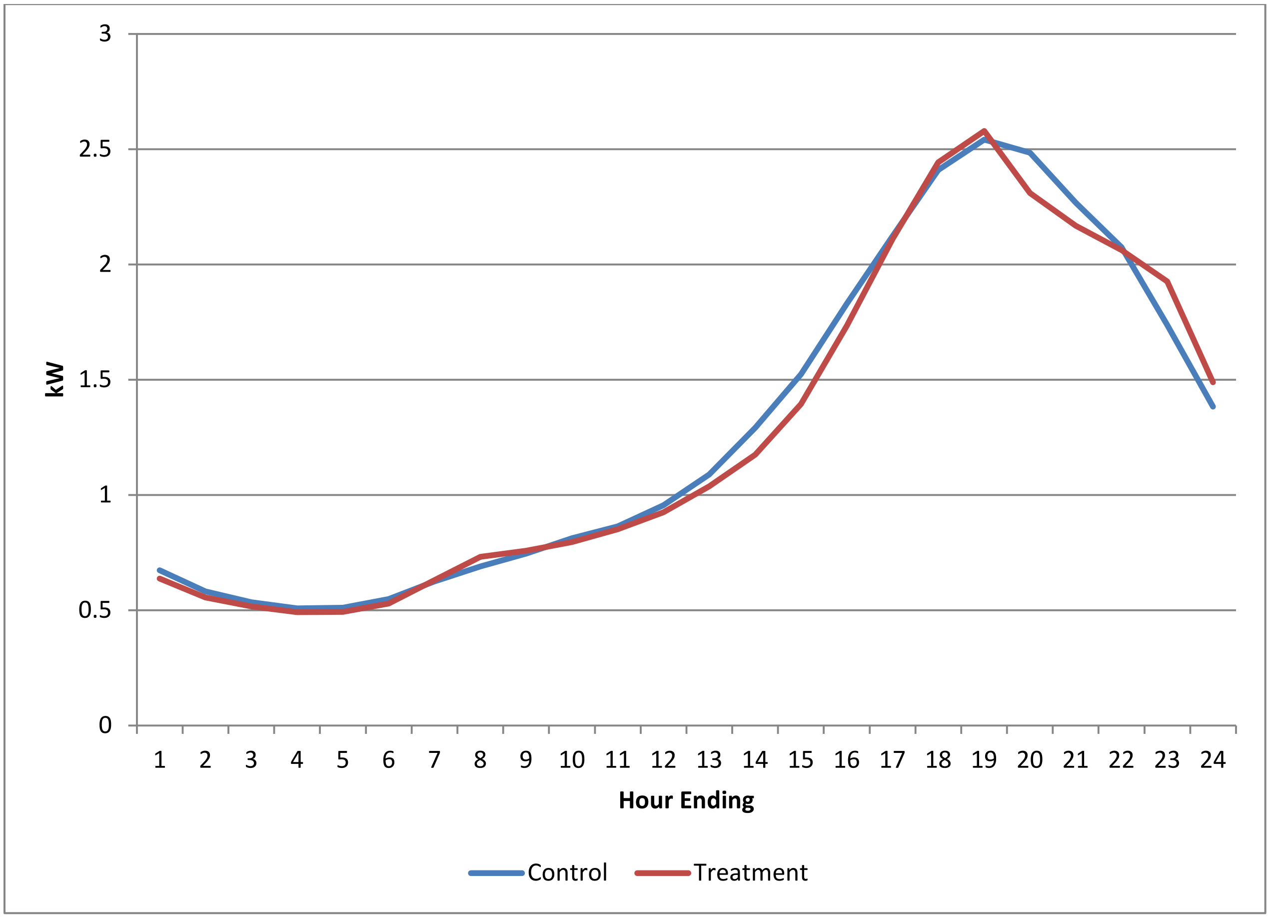


Table 4-11 summarizes the impact estimates for the events in each of the four sub-LAP regions. The East Bay had the largest aggregate impact with 4.1 MW in hour 20 on June 7, 2013. Los Padres had the largest impact per device at 0.54 kW during hour 20 on July 2, 2013. The East Bay impacts combine the separate estimates for the hot and cool East Bay regions, although the average impacts are dominated by the hotter region. This average masks significant variation across hours, ranging from 0.17 kW between 7 and 8 PM to 0 between 9 and 10 PM when air conditioning loads typically drop off in the East Bay as the much cooler evening breezes often take effect. The variation across hours is much less in the Los Padres and Geysers regions. No impact was observed in the Northern Coast region where a power outage had occurred earlier in the day. Indeed, the estimates show that customers that were controlled have higher loads during the event period than customers used for the reference load. This could be due to errors in the matching process, random fluctuation due to small sample sizes (this group was much smaller than in the other sub-LAPs, especially when the customers who had experienced the power outage were removed from the analysis)), or some combination of the two.

Table 4-11: Sub-LAP Emergency Event Impacts

Sub-LAP	Date	Hours	Devices	Hour Ending	Average (kW)	Aggregate (MW)
East Bay	7-Jun-13	7:00 - 10:00 PM	24,695	20	0.17	4.1
				21	0.10	2.6
				22	0.00	-0.1
				Average	0.09	2.2
Los Padres	2-Jul-13	6:50 - 10:50 PM	4,840	20	0.54	2.6
				21	0.33	1.6
				22	0.28	1.4
				23	0.16	0.8
				Average	0.33	1.6
Geysers	3-Jul-13	5:50 - 9:50 PM	3,861	19	0.47	1.8
				20	0.34	1.3
				21	0.23	0.9
				22	0.17	0.6
				Average	0.30	1.2
Northern Coast	3-Jul-13	5:45 - 9:45 PM	1,032	19	-0.11	-0.1
				20	-0.15	-0.2
				21	-0.23	-0.2
				22	-0.25	-0.3
				Average	-0.19	-0.2

5 Residential SmartAC Ex Ante Methodology

Ex ante load impacts were estimated based on statistical analysis of ex post load impact estimates from 2011, 2012 and 2013, which were pooled across local capacity areas. This approach provides a rich database containing ex post values under a wide range of weather conditions.

This section explains the steps used to predict ex ante load impacts for residential SmartAC customers. Ex ante estimates rely on ex post impacts as a starting point. Since only two test events were called in 2013, the ex ante modeling was based on ex post estimates for three years, 2011, 2012 and 2013. Estimates from the sub-LAP emergency events could not be used as input to ex ante estimation because the populations in the sub-LAPs are not representative of the broader SmartAC population.

Two key issues had to be addressed during most of the ex ante estimates. First, the weather observed during events in 2011 to 2013 is different from the weather conditions used to represent ex ante conditions. Second, the hours over which each test or system wide event occurred in the past often do not match the entire resource adequacy window of 1 to 6 PM, for which ex ante impacts must be estimated.

At a high level, the modeling steps used to produce ex ante impact estimates consisted of the following:

- First, a regression model was developed that relates the change in load reductions to differences in weather conditions leading up to during the hour from 4 to 5 PM. This is the hour that is most common across all ex post events. As in 2012, this model was estimated based on data pooled across all of the LCAs rather than estimating separate models for each LCA.
- The model was used to estimate average impacts from 4 to 5 PM for the two sets of ex ante weather conditions representing a normal (1-in-2) and extreme (1-in-10) weather year. The estimates of the average impact from 4 to 5 PM were then converted to hourly impacts from 1 to 6 PM using a scaling factor based on load impacts observed during longer historical events.
- Next, whole-house reference loads from 4 to 5 PM were predicted for each set of ex ante weather conditions based on the loads observed over the summers of 2011 through 2013. Load shapes were estimated by taking the average load for each hour of the day, by LCA.[17]
- Finally, a similar regression model was developed and used to estimate snapback effects during the hours immediately following the end of the event period.

The first two steps, which produce estimated load impacts, are described in detail below. The steps used to predict whole-house loads and snapback are described in Appendix B.

As explained previously, while the ex post estimates for 2013 excluded dually enrolled customers (because these impacts are estimated in the SmartRate program evaluation), ex ante estimates for the SmartAC program must include dually enrolled customers in order to estimate the full potential of the program. To do this, prior to estimating the regression model described in Step 1 above, the average

[17] With this approach, ex ante load impacts are estimated directly from ex post impacts and reference loads are not required to develop the impact estimates. However, the load impact protocols require producing reference loads and this step was necessary to meet that requirement.

SmartAC-only impact estimates from 2011 to 2013 were adjusted to reflect the weighted average impacts for SmartAC-only and dually enrolled customers.

In 2012, three SmartAC test events were called on days when SmartRate was not called. In the 2012 evaluation, ex post impacts for dually enrolled customers were included in the ex ante analysis by using the ratio of load impacts for the dually enrolled population to that of the SmartAC-only population on these three days to produce weighted average impacts for all ex post events days for use in the ex ante modeling. However, after the 2012 report was completed, it was discovered that many control devices for dually enrolled customers were not properly addressed in the operating system used to implement event control for participating households. As such, the estimates for dually enrolled customers relative to SmartAC-only customers on those days understate, perhaps significantly, the impacts associated with dually enrolled customers on SmartAC-only days. For this year's evaluation, ratios were instead calculated, again at the local capacity area, using the reference loads of the SmartAC-only customers and dually enrolled customers during the common hour of the three 2012 events when only SmartAC was called. Assuming the dually-enrolled and the SmartAC-only customers provide the same *percent* load reduction, we multiplied the *percent* load reduction of SmartAC-only customers by the reference load of dually enrolled customers (which is lower than that of the average SmartAC-only customer) to obtain the absolute load impacts of the dually-enrolled customers. An average weighted by the population numbers in each LCA was then used in the ex ante regression model.

Table 5-1 shows the ratios used to calculate the new impacts as well as the distribution of SmartAC-only and dually enrolled customers. For example, on July 10, 2012 in the Stockton LCA, we observed an impact of 0.62 kW for the SmartAC-only customers. We then found the expected impact for dually enrolled customers by multiplying this impact by 0.85, the ratio for Stockton in Table 5-1, giving an impact of 0.53 kW. We then weighted each impact by their respective percentages before adding them for the final adjusted impact of 0.60. The impacts of all three years were adjusted by these ratios and the dually enrolled population percentages from 2013. The ex ante model assumes that these percentages will not change in the forecasted years.

Table 5-1: 2013 Reference Load Ratios Between Residential SmartAC and Dually Enrolled Customer's for the Hour from 4 to 5 PM

Local Capacity Area	Ratio	Percent Dually Enrolled	Percent SmartRate-only
Greater Bay Area	0.71	28	72
Greater Fresno	0.87	23	77
Kern	0.89	29	71
Northern Coast	0.78	25	75
Other	0.82	24	76
Sierra	0.87	27	73
Stockton	0.85	28	72

Having adjusted the ex post impacts to reflect the contribution of dually enrolled customers, the next step is to model ex post load impacts as a function of temperature.

The ex ante model specification was developed through a systematic process of testing using cross validation analysis to determine the best model from a wide variety of weather variables and functional forms.

5.1 Regression Modeling

As explained in last year's report, to determine the best regression to use for ex ante estimation, 64 different models were estimated and assessed using out-of-sample testing to determine which one was most accurate at predicting ex post impacts for 2011 and 2012 for the hour 4 to 5 PM. Since there was only one event in 2013 that included the common hour from 4 to 5 PM, this cross validation analysis was not repeated and the same model specification was used this year as in 2012. The regression coefficients differ because the ex post estimates used for estimation are different due to differences in the mix of customers between SmartAC and dually enrolled customers. The model specification is summarized below.

$$Impact_c = a + b \cdot mean17_c + \boldsymbol{\varepsilon_c}$$

Table 5-2: Definition of Load Impact Regression Model Variables

Variable	Description
$Impact_c$	Average per customer ex post load impact for each event day from 4 to 5PM
a	Estimated constant
b	Estimated parameter coefficient
$mean17$	Average temperature over the 17 hours prior to the start of the event
$\boldsymbol{\varepsilon_t}$	The error term, assumed to be a mean zero and uncorrelated with any of the independent variables

The average temperature over the 17 hours from midnight to 5 PM was chosen as the weather variable for modeling based both on its predictive accuracy and because all values came from the same 24-hour period rather than from prior days. Models using hours from prior days were tested and some performed similarly,[18] but using them for ex ante estimation would require additional assumptions about weather in the day prior to each ex ante day. Using the previous 17 hours makes full use of the available ex ante weather information without requiring additional assumptions and without sacrificing model accuracy.

[18] Models using temperature as far back as 48 hours prior to the event were tested, but were not found to perform better than the model using 17 hours.

In 2011, modeling was done separately for most LCAs.[19] In 2012, it was found that the relationship between load impacts and weather followed essentially the same trend with respect to *mean17* in nearly all LCAs. As such, the estimating database used for development of the ex ante model uses data pooled across all LCAs. This approach reduces the need to estimate impacts outside of the observed values when developing ex ante estimates for weather conditions that occur rarely in selected LCAs. In Figure 5-1, the adjusted impacts from 4 to 5 PM for 2011, 2012 and 2013 are graphed against *mean17*.

Figure 5-1: Average Event Impacts From 4 to 5 PM Versus *Mean17* Across All LCAs

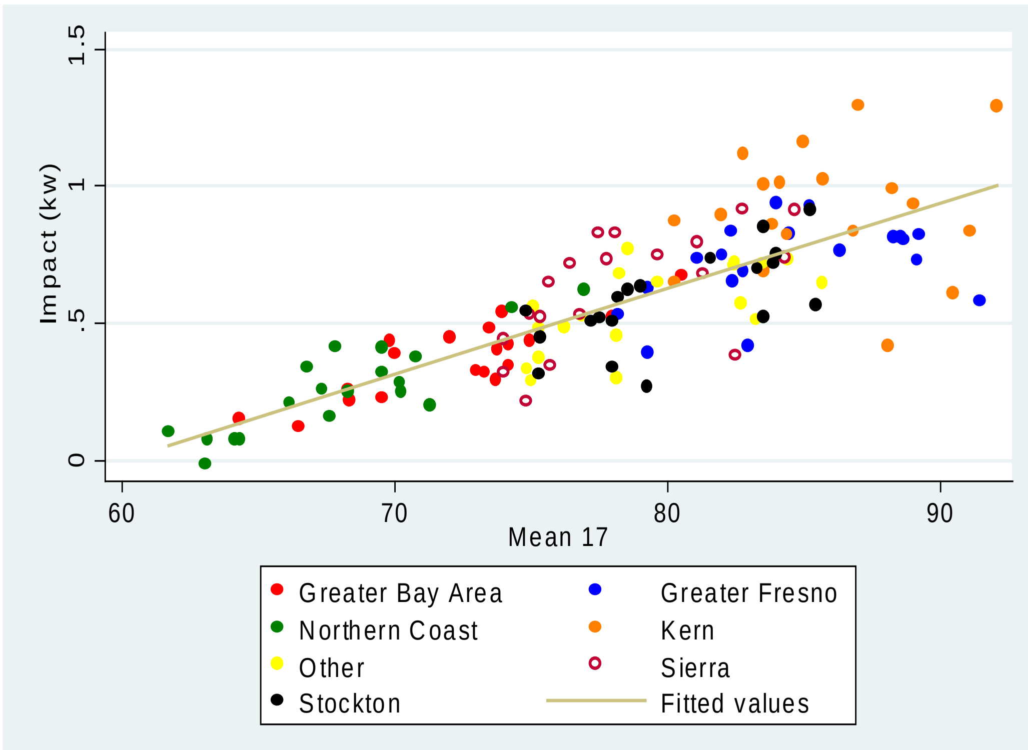
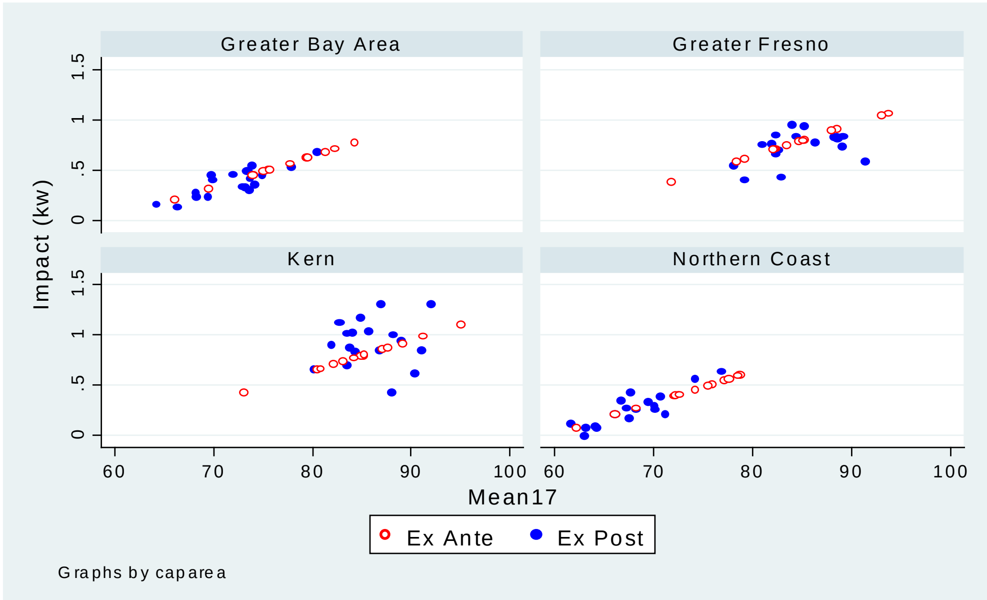
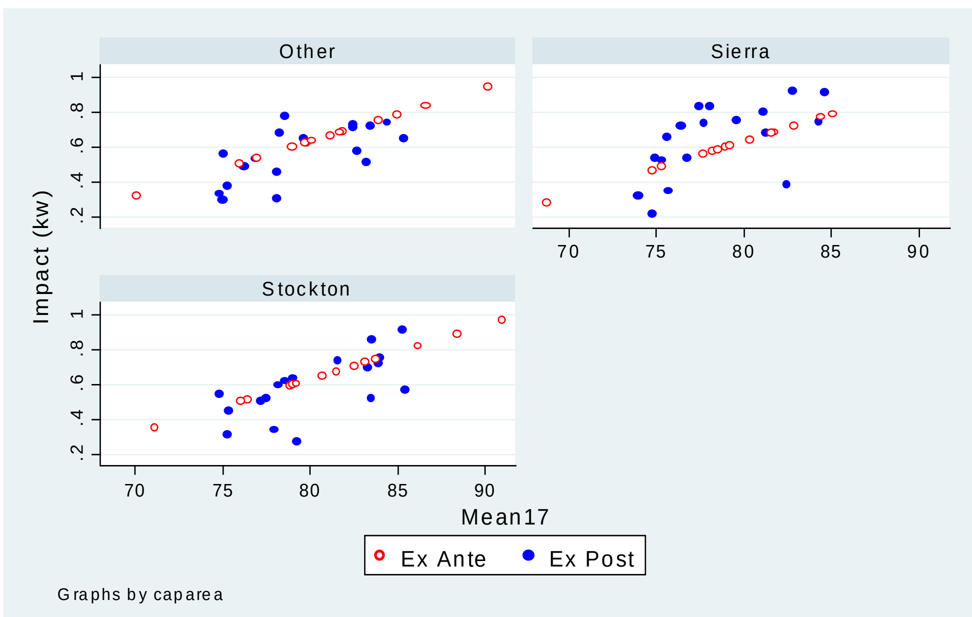


Figure 5-2 displays the final ex ante and ex post estimates graphed against *mean17* for each LCA. The solid blue circles represent ex post impacts and the hollow red circles are ex ante estimates. By graphing both ex ante and ex post results on the same plot, the figure shows that the ex ante results follow the same trend as the ex post results for each LCA even though the model is based on ex post results across all LCAs. It also illustrates how often ex ante weather conditions exceed the ex post conditions within many LCAs, which is a key benefit of using this pooled approach for model development. If separate models had been estimated for each LCA, ex ante values would have required extrapolating outside of the range of historical experience for many LCAs.

[19] Data was pooled across some LCAs in cases where ex ante temperatures exceeded temperatures observed in a particular LCA, as described in the 2011 evaluation report.

Figure 5-2: Ex Post and Ex Ante Impacts Versus *Mean17* by LCA





The last step in estimating load impacts was to translate average impacts from 4 to 5 PM to hourly impacts over the entire range of time required for prediction, 1 to 6 PM. Using ex post impact estimates from all of the events that included any hours between 1 and 6 PM, the average impact for each hour from 1 to 6 PM was expressed as a fraction of the average impact from 4 to 5 PM. Then, for each hour, separate models were developed of this fraction as a function of *mean17*, using the same specification as was used to model impact magnitudes from 4 to 5 PM above. The results of this modeling are shown in Figures 5-3 and 5-4. Figure 5-3 shows how this modeling works for each hour. Each graph in the figure contains a scatter plot of the ratios between the ex post impact estimates for that hour and the ex post impact estimates for 4 to 5 PM against *mean17*. The graphs include all such ratios calculated for each LCA over all events for 2011 and 2012. The graphs also show the trend line for each hour, which is used to provide estimates of each hour's respective ratio under each set of ex ante conditions. Figure 5-4 shows the trend lines together on one graph.

Figure 5-3: Impact Ratios for Each Hour Compared to Hour 17 (4 to 5 PM) as a Function of *Mean17*

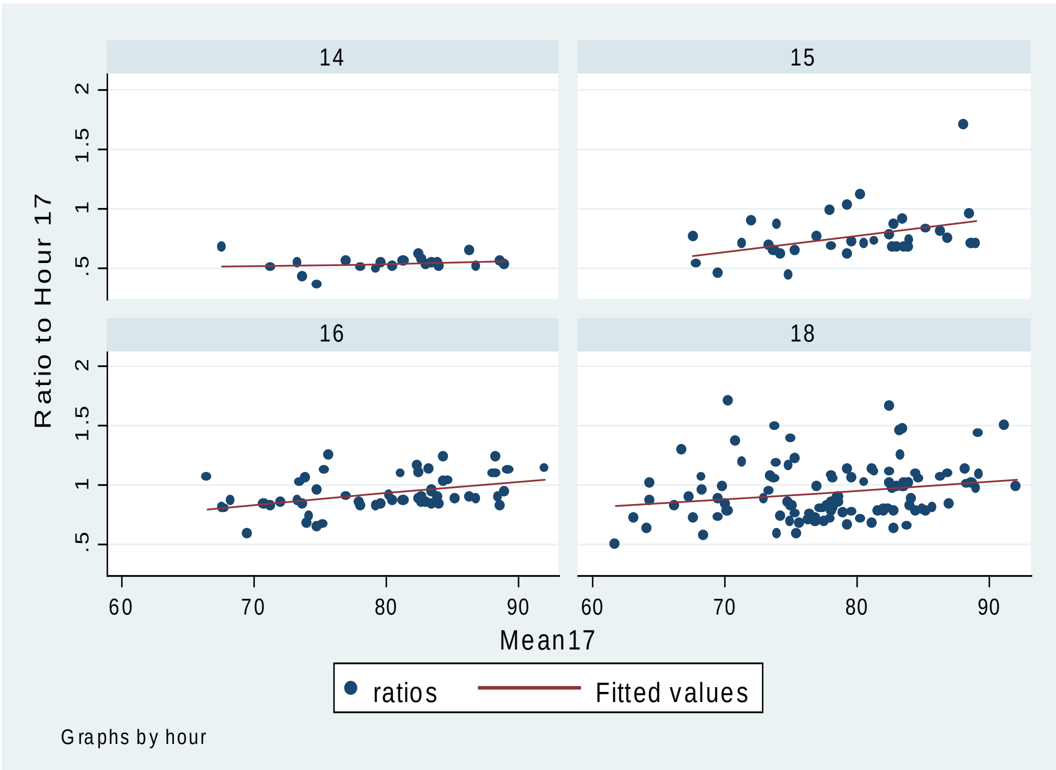
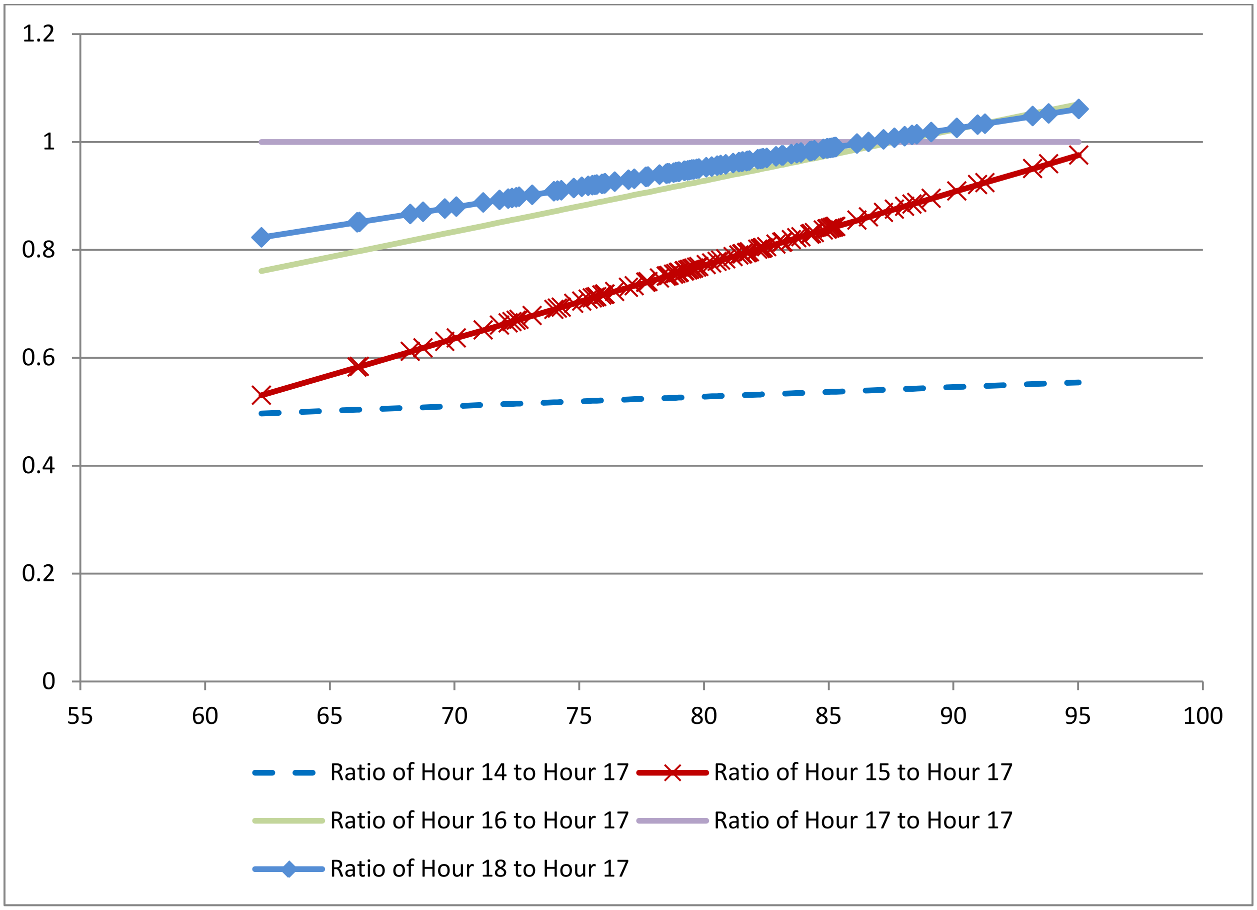


Figure 5-4: Impact Ratios for Each Hour to Hour 17 as a Function of *Mean17*



The regression functions underlying the trend lines were then used to estimate impacts as fractions of the impact from 4 to 5 PM for each set of ex ante weather conditions for each LCA. These fractions were multiplied by the already-predicted impacts from 4 to 5 PM to produce impact estimates for each set of ex ante weather conditions over the period 1 to 6 PM.

The advantage of this strategy for estimating impacts across all hours is that it forces load impacts across all hours to make sense with respect to each other. A common alternative in load impact evaluations is to model each hour completely independently. In cases with modest amounts of data or modest variation in observed conditions and impacts (as is frequently the case) this can lead to unreasonable results where, for example, the function that determines impacts from 4 to 5 PM is quite different from the function that determines impacts from 5 to 6 PM. This can lead to implausible impact estimates for particular hours. In the approach used here, the fundamental relationship between event impact and temperature is allowed to be determined completely by the data, but we enforce a certain amount of uniformity on the relative load impacts across hours, recognizing that we lack the data to model each hour completely independently.

6 SmartAC Ex Ante Load Impact Results

The SmartAC program is intended to alleviate system stress during times of high demand. The primary purpose of this evaluation is to predict load impacts during such conditions. These ex ante predictions cover a pre-chosen set of temperature profiles meant to mimic what could be expected for monthly system peak days that might occur every other year and every tenth year. Aggregate estimates of load impacts combine estimates of per customer load impacts developed in this report with estimates of program enrollment developed in a separate effort by PG&E.

PG&E's SmartAC program had roughly 160,000 residential and SMB customers enrolled at the end of 2013. It can deliver peak period load reductions of roughly 100 MW under normal weather conditions and more than 120 MW under 1-in-10 year weather conditions.

Enrollment projections for residential customers by local capacity area as of August of each year are presented in Table 6-1. These estimates were developed by PG&E. These projections reflect modest growth over the enrollment of 151,000 customers that existed at the end of summer 2013.

Table 6-1: Projected Residential Enrollment for August of Each Year (1000s of Customers)

LCA	2014	2015 to 2024
Greater Bay Area	54.4	54.8
Greater Fresno	17.8	17.9
Kern	6.8	6.8
Northern Coast	8.8	8.9
Other	37.3	37.6
Sierra	17.2	17.4
Stockton	14.5	14.6
Total	**156.8**	**158.0**

Ex ante load impact estimates are shown for residential customers in Table 6-2, including dually enrolled customers. The first column shows the average hourly ex ante load impact estimates per customer over the event period from 1 to 6 PM and the second column shows the maximum per customer hourly impact. The third and fourth columns show the corresponding estimated aggregate load impacts. The first set of rows corresponds to 1-in-2 weather conditions while the second set covers 1-in-10 weather conditions. For the 1-in-2 weather year, the highest estimated impact is on the July peak day, with an average impact of 93 MW and a peak hourly impact of 109 MW. The impact for the typical event day under 1-in-2 year weather conditions is 75 MW. Under 1-in-10 year weather conditions, the estimated July peak day impact equals 117 MW and the peak hourly impact is 133 MW. The impact on the typical event day under 1-in-10 year conditions is 98 MW.

Table 6-2: 2014 Residential SmartAC Ex Ante Load Impact Estimates By Weather Year and Day Type (Event Period 1 to 6 PM)

Weather Year	Day Type	Mean Hourly Per Customer Impact (kW)	Max. Hourly Per Customer Impact (kW)	Aggregate Mean Hourly Impact (MW)	Aggregate Max Hourly Impact (MW)
1-in-2	Typical Event Day	0.48	0.58	75	90
	May Peak Day	0.32	0.40	50	61
	June Peak Day	0.40	0.49	62	77
	July Peak Day	0.60	0.70	93	109
	August Peak Day	0.46	0.56	72	87
	September Peak Day	0.47	0.56	72	87
	October Peak Day	0.24	0.32	38	49
1-in-10	Typical Event Day	0.64	0.74	98	114
	May Peak Day	0.53	0.64	83	98
	June Peak Day	0.59	0.70	91	108
	July Peak Day	0.76	0.86	117	133
	August Peak Day	0.67	0.77	104	119
	September Peak Day	0.53	0.64	83	99
	October Peak Day	0.46	0.56	71	87

The SMB segment of the SmartAC program is currently closed to new enrollment. No M&E test events were called for this group during summer 2013 and no ex post impacts were estimated. Therefore, no new load impact information is available to use for updating the per-device ex ante estimates from 2011. The operations of the SMB segment have not changed since 2011, and so the per device ex ante values for this segment are the same as in the 2011 evaluation. The only source of change in ex ante load impact estimates for SMB customers is a decline in enrollment. Enrollment projections for SMB customers by local capacity area as of August of each year are presented in Table 6-3. These estimates were provided by PG&E.

Table 6-3: Projected SMB Enrollment for August of Each Year

LCA	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Greater Bay Area	1,710	1,664	1,618	1,574	1,531	1,490	1,449	1,409	1,371	1,334	1,297
Greater Fresno	514	500	486	473	460	447	435	423	412	401	390
Kern	42	41	40	39	38	37	36	35	34	33	32
Northern Coast	285	278	270	263	256	249	242	235	229	223	216
Other	525	511	497	484	470	458	445	433	421	410	399
Sierra	1,115	1,084	1,055	1,026	998	971	945	919	894	869	846
Stockton	375	365	355	345	336	327	318	309	301	292	284
Total	4,984	4,848	4,716	4,588	4,462	4,341	4,223	4,107	3,996	3,887	3,781

Table 6-4 shows the per-customer and aggregate ex ante impact estimates for the SMB population. For the 1-in-2 weather year, the highest aggregate mean hourly impact occurs on the July peak day, with an impact of 3.5 MW. The highest individual hourly impact during a 1-in-2 year is also the July value – 4.1 MW. The July peak day also shows the highest impacts for the 1-in-10 weather year. The largest aggregate impact over the five-hour event is 4.0 MW and highest individual hour provides an estimated impact of 4.6 MW.

Table 6-4: 2014 SMB SmartAC Load Impact Estimates By Weather Year and Day Type (Event Period 1 to 6 PM)

Weather Year	Day Type	Mean Hourly Per Customer Impact (kW)	Max. Hourly Per Customer Impact (kW)	Aggregate Mean Hourly Impact (MW)	Aggregate Max Hourly Impact (MW)
1-in-2	Typical Event Day	0.55	0.65	2.8	3.3
	May Peak Day	0.37	0.45	1.9	2.2
	June Peak Day	0.47	0.56	2.3	2.8
	July Peak Day	0.69	0.81	3.5	4.1
	August Peak Day	0.55	0.65	2.7	3.2
	September Peak Day	0.51	0.61	2.6	3.0
	October Peak Day	0.32	0.39	1.6	1.9
1-in-10	Typical Event Day	0.72	0.85	3.6	4.2
	May Peak Day	0.63	0.74	3.2	3.7
	June Peak Day	0.66	0.78	3.3	3.9
	July Peak Day	0.79	0.93	4.0	4.6
	August Peak Day	0.76	0.88	3.8	4.4
	September Peak Day	0.61	0.72	3.0	3.6
	October Peak Day	0.50	0.59	2.5	2.9

6.1 Comparison of 2012 and 2013 Ex Ante Estimates

The residential ex ante impacts for 2013 are roughly 10% lower than the estimates provided in 2012. This difference is due to two factors. First, in 2012, ex post impacts in the first hour of each event were grossed up to adjust for the ramping in of devices. This assumption was dropped in 2013, which lowered the ex post impacts used for modeling. Second, the percent of SmartAC customers that are dually enrolled continued to increase in 2013 and this drives down the overall average impact per customer as dually enrolled customers have smaller reference loads and therefore smaller load impacts on SmartAC-only days.

The biggest difference between ex post and ex ante aggregate load impact estimates results from the fact that almost all ex post events only dispatched a small share of the total SmartAC resource. Differences in the timing and length of the event window and weather conditions account for most of the remaining difference.

6.2 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, differences in the number of customers dispatched, differences in the event window, and others. Table 6-5 lists all of the possible factors that might cause ex post and ex ante impacts to differ and indicates the expected influence of each factor on this difference. As seen, the fact that only about 10% of the program was dispatched for all but one of the ex post events is the most significant reason why ex post and ex ante aggregate impacts differ so much. Including dually enrolled customers in the ex ante aggregate estimates is also an important differentiating factor. Differences in weather and the length and timing of the event window can also be influential, while differences in methodology should have a relatively small impact since the ex ante model takes ex post impacts as input.

Table 6-5: Summary of Factors Underlying Differences Between Ex Post and Ex Ante Impacts for the Residential SmartAC Program

Factor	Ex Post	Ex Ante	Expected Impact
Weather	72.6 < *mean17* < 82.8 (event day) Average event day *mean17* = 77.4	*Mean17* for the 1-in-2 typical event day = 78.5 *Mean17* for the 1-in-10 typical event day = 83.6	1-in-2 year typical event day impact will be slightly higher than the average ex post event due to differences in weather 1-in-10 year typical event day impacts will be significantly higher due to weather
Event window	This varies significantly between events, from 1 to 5 hours over the hours 1 to 6 PM	Common ex ante event window is 5 hours, from 1 to 6 PM	Could have significant impact since most ex post events occurred during the highest load hours and a longer event window will include lower load hours
% of resource dispatched	10% of the group is dispatched for each event, with the other 90% acting as the control group for the evaluation	Assumes 100% dispatch	Biggest impact of all factors
Enrollment	The number of dually enrolled SmartRate/SmartAC customers continued to increase from very small in 2011 to more than 20% in 2013. As discussed in Section 4, the ex post impacts represent SmartAC-only customers whereas the ex ante impacts include dually enrolled customers	Assumed the percent of dually enrolled SmartRate customers is the same as at the end of summer 2013	Average impacts are lower for dually enrolled customers than for SmartAC-only customers. However, incorporating dually enrolled customers into the aggregate program estimate increases the value significantly compared with the ex post estimates that do not include this customer segment
Methodology	Impacts based on RCT with large sized treatment and control groups	Regression of ex post impacts against *mean17* for common hours using three years' worth of ex post impacts	Small impact expected

Table 6-6 and Figure 6-1 show how aggregate load impacts change as a result of differences in the factors underlying ex post and ex ante estimates. Table 6-6 covers events from both 2012 and 2013 since there was only one event in 2013 used in the ex ante model. The figure graphs the average values at the bottom of the table.

As seen in columns B and C in Table 6-6, the event window and *mean17* vary significantly across ex post event days, but the percent of the resource dispatched (Column D) is nearly constant at 10% except for the system wide event day on August 10, 2012 when all devices were called. 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 SmartAC-only customers had been dispatched. Column G scales the aggregate impacts up further to include the impacts that dually enrolled customers would have had if none of the historical events had been on SmartRate days. This represents the maximum impact that could have been achieved under ex post weather and event window conditions if the whole program had been called and SmartRate was not called at the same time.

Columns H through L incorporate the influence of ex ante assumptions about weather, the event window and forecasted enrollment, and also differences due to the methodology used to estimate ex ante impacts. Column H 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. The regression model under predicts the ex post values by less than 5% (from 81.7 MW to 77.9 MW). This small under prediction is partly attributable to the fact that the impacts from 2011 through 2013 go into creating the ex ante model, while the table only shows 2012 and 2013 events. Figure 6-2 shows all of the impacts on a kW per customer basis that are used to create the model, with 2012and 2013 in red. The green line depicts the ex ante model that was used for this evaluation and the orange line represents what the ex ante predictions would have been if 2011 data was not included. Though it is very close, the 2011-2013 line predicts lower impacts than the line based on data from 2012-2013 when the value of mean17 is less than 83°F.

A much more influential factor underlying the difference between ex post and ex ante impacts is the change in the event window from the typically short ex post window that covered the hottest hours in the day to the longer resource adequacy window that includes lower load hours in the early afternoon. As seen in column I, shifting from the ex post to the ex ante event window reduced the aggregate impacts by about 13% (from 77.9 MW to 67.7 MW).

Column J shows the influence of the modest increase in projected enrollment between the end of summer 2013 to the projected enrollment in 2014. This factor increases aggregate impacts by about 4%.

The last two columns, K and L, 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 increased aggregate impacts by about 6% and shifting to 1-in-10 year weather conditions increased the impacts by nearly 40% compared with ex post conditions. The 1-in-10 year conditions show impacts that are 32% higher than 1-in-2 year impacts.

Table 6-6: Differences in Ex Post and Ex Ante Impacts Due to Key Factors

Date	2012 Ex Post Aggregate Estimates						Aggregate Estimates Based on Ex Ante Model				
								Standardized Event Window			
	Event Window	*Mean17*	% of Resources Dispatched	Aggregate Reduction of SmartAC-only (MW)	Scaled to SmartAC-only Population Reductions	Scaled Up to include Dually enrolled	Historical Window, Weather & Enrollment	Historical Weather & Enrollment	Historical Weather, Forecast Enrollment	1-in-2 Year Weather, Forecast Enrollment	1-in-10 Year Weather, Forecast Enrollment
A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**
9-Jul-12	4-6 pm	72.6	10%	5.5	55.1	64.7	56.3	47.6	49.9		
10-Jul-12	4-6 pm	76.1	10%	7.9	78.9	92.5	72.1	61.3	64.3		
11-Jul-12	3-6 pm	80.2	10%	9.1	91.4	107.3	90.5	79.0	82.7		
12-Jul-12	2-5 pm	80	10%	7.6	76.0	89.2	84.6	78.4	82.1		
2-Aug-12	4-6 pm	76.3	10%	7.1	71.1	83.3	73.9	62.9	65.2		
10-Aug-12	4-6 pm	80.7	100%	77.8	77.8	91.2	95.2	82.4	85.1		
13-Aug-12	3-6 pm	80.9	10%	9.3	93.3	109.3	95.8	83.9	86.7	74.6	98.5
13-Sep-12	4-6 pm	74.4	10%	5.0	50.4	59.0	65.5	55.3	56.7		
14-Sep-12	3-5 pm	73.3	10%	4.6	46.1	53.9	59.5	51.1	52.4		
1-Oct-12	2-5 pm	75.6	10%	4.1	41.2	48.2	64.2	59.8	61.4		
1-Oct-12	4-6 pm	75.6	10%	5.6	56.4	66.0	71.0	59.8	61.4		
1-Jul-13	4-5 pm	82.8	10%	9.0	90.4	115.7	106.0	91.4	96.1		
Average		77.4	10%	6.8	69.0	81.7	77.9	67.7	70.3		

Figure 6-1: Differences in Ex Post and Ex Ante Impacts Due to Key Factors

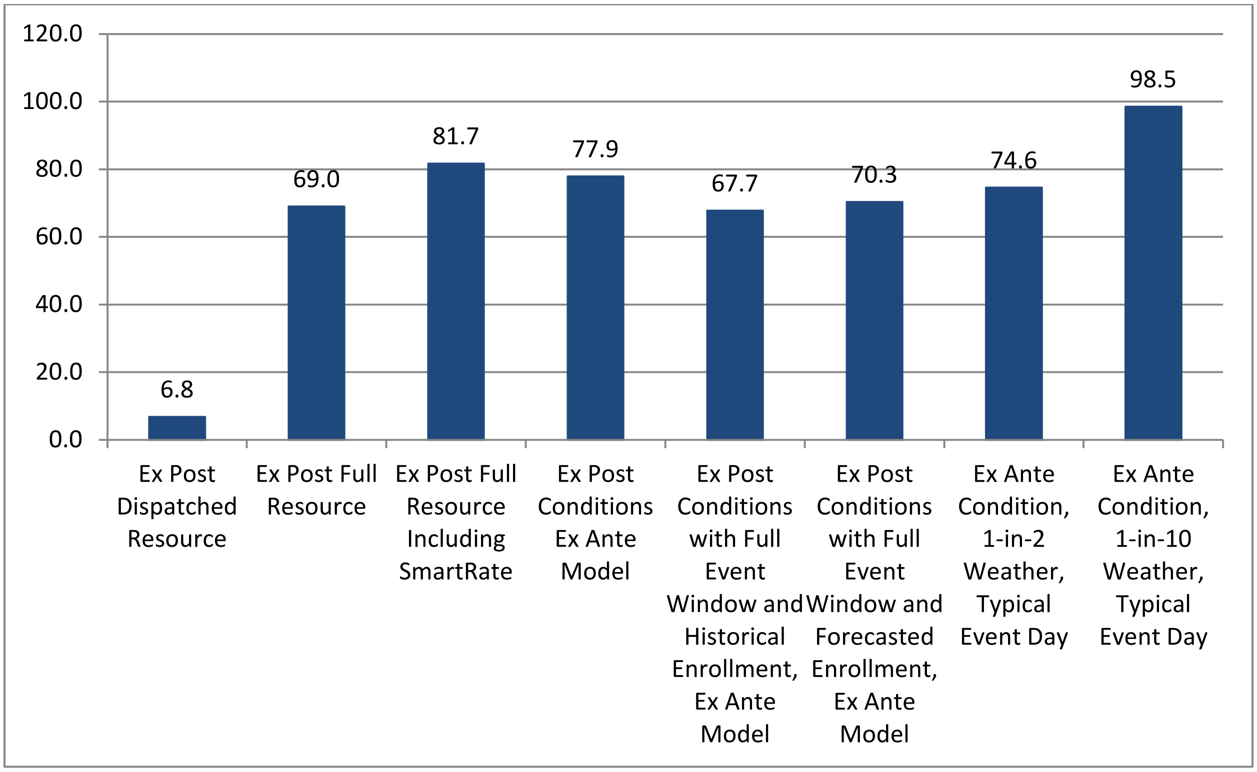
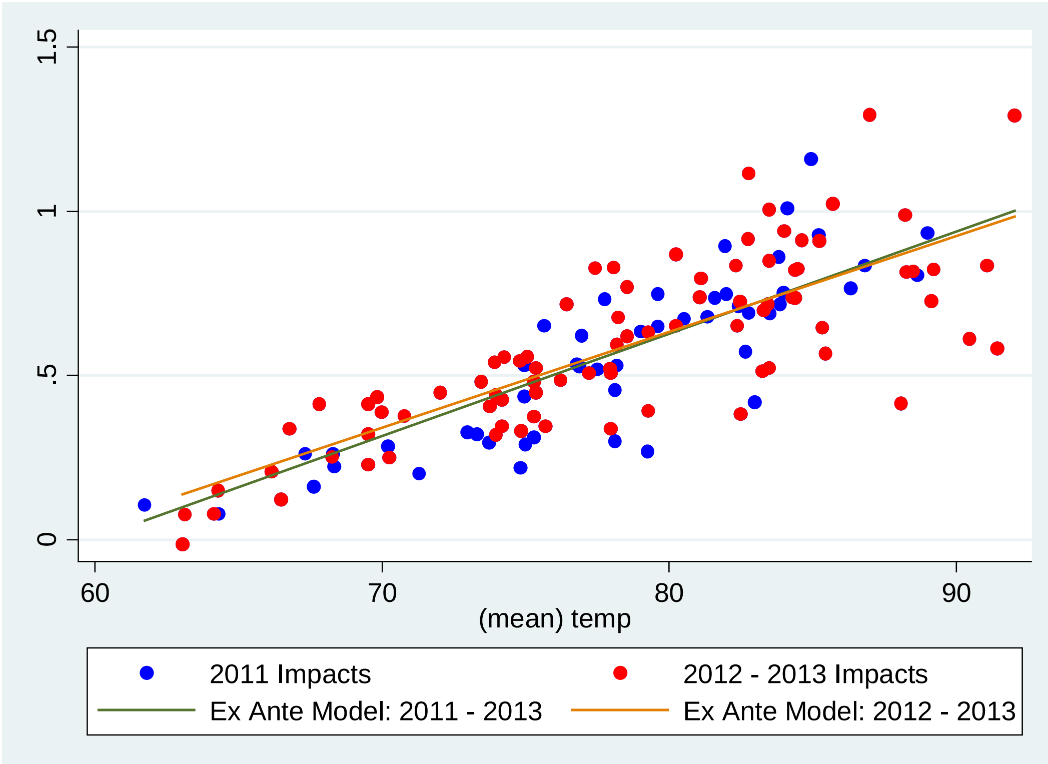


Figure 6-2: Impacts from 4 to 5 PM Used For Ex Ante Model



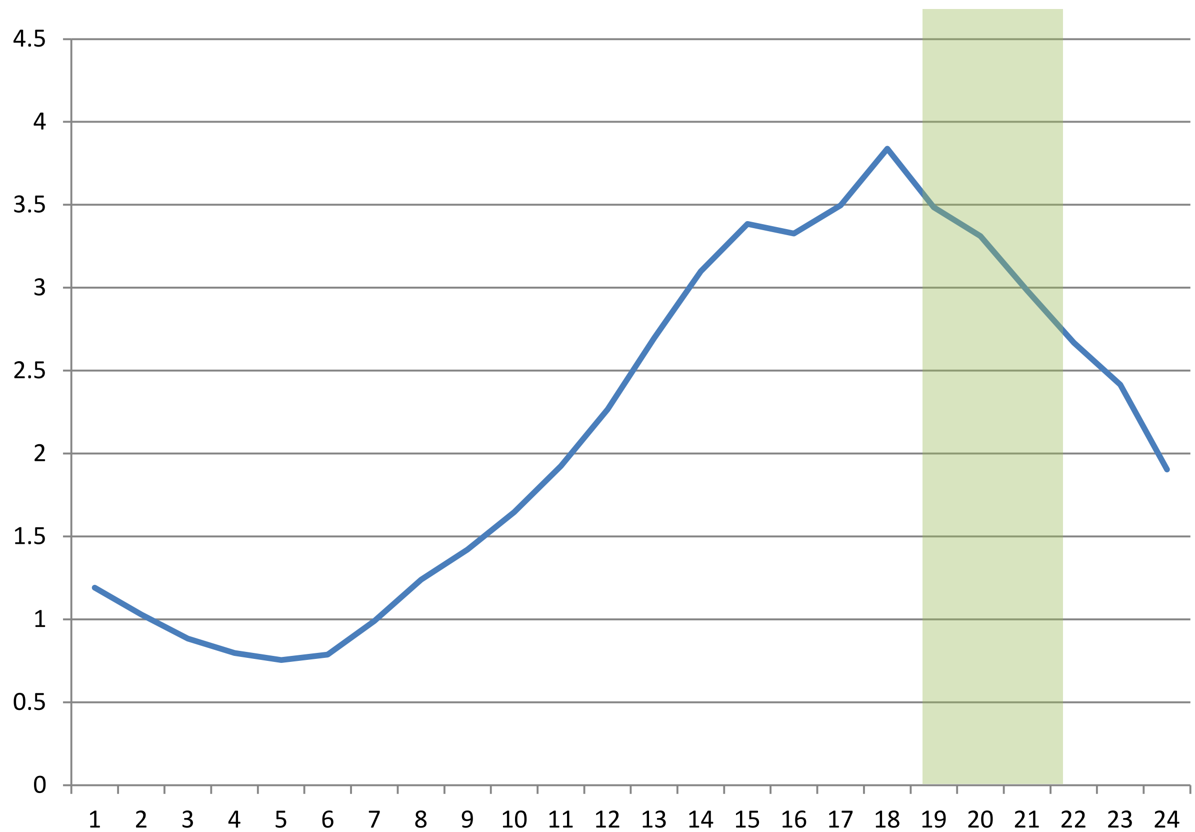
7 Recommendations

The 2013 ex post event day on which multiple events were called for different groups across the hours from 10 AM through 8 PM produced very useful input regarding the magnitude of the demand response resource in the late morning and early evening hours. With increasing attention to the role that demand response resources can play as a complement to variable supply resources such as wind and solar, it is important to gain insights regarding the magnitude of the resource across a broader number of hours than the traditional afternoon, CAC intensive period. As such, we recommend that PG&E include similar M&E events in the operational plan for SmartAC in 2014. We also recommend calling several test events on days when SmartRate is not also called so that it will be possible to produce better estimates of the load impacts for dually enrolled customers on SmartAC-only days.

Appendix A Accounting for Power Outages

Power outages typically affect such a small number of customers as to be negligible in the overall analysis. However, this year the smaller emergency sub-LAP events allowed a closer look at this phenomenon. Figure A-1 shows the load of the treatment customers in the Northern Coast LCA on July 3, 2013. It looks like there is some sort of event called around 3 PM but the event was scheduled to begin at 5:45 PM.

Figure A-1: Load of Treatment Customers During the Northern Coast LCA Event on July 3, 2013



The event being called early was ruled out by examining the Yukon logs but outage data revealed that 114 Northern Coast customers experienced a power outage from 3:15 to 4:17 PM. Figure A-2 shows the load for the customers affected by the power outage. As seen, there is a very significant load drop during the period when the outage occurred. Figure A-3 represents the load of the sub-LAP with these customers removed. The load shape is as expected and ex-post impacts were calculated for these customers much in the same way as for the other sub-LAPs in Section 4.3.

Figure A-2: Load of Treatment Customers Who Experienced a Power Outage in Northern Coast LCA

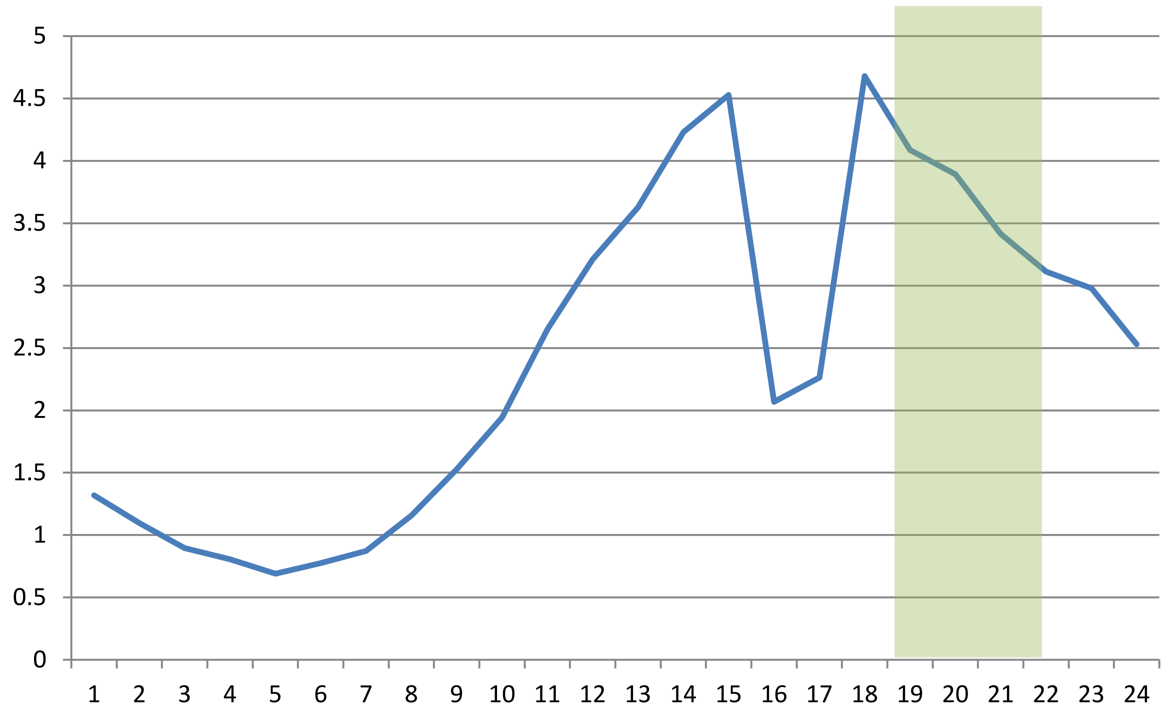
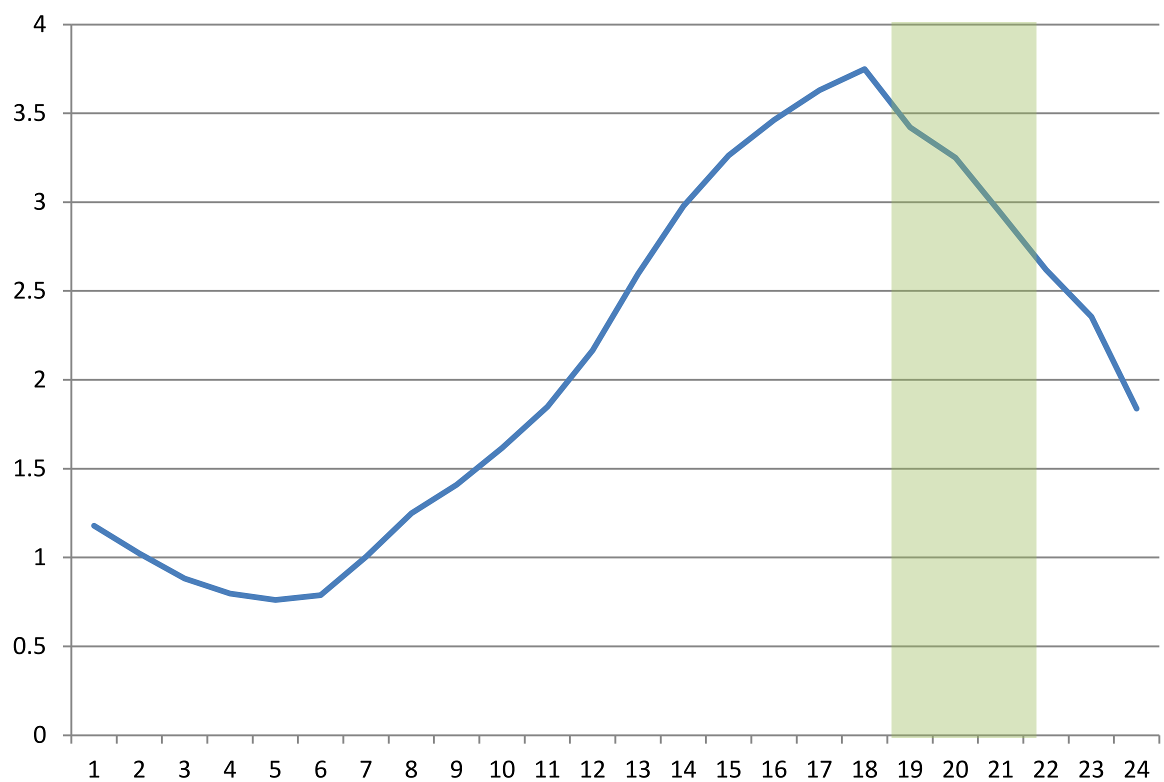


Figure A-3: Load of Treatment Customers Who Did Not Experience a Power Outage in the Northern Coast LCA



Sierra also experienced an outage due to a fire on the July 1, 2013 test event day. Though originally masked when looking at the entire SmartAC population, there was an obvious dip in the reference load that was not expected for the Sierra local capacity area between 4 and 5 PM. Figure A-4 shows this dip in the control group.

Figure A-4: Reference Load in the Sierra LCA During the July 1st, 2013 Event

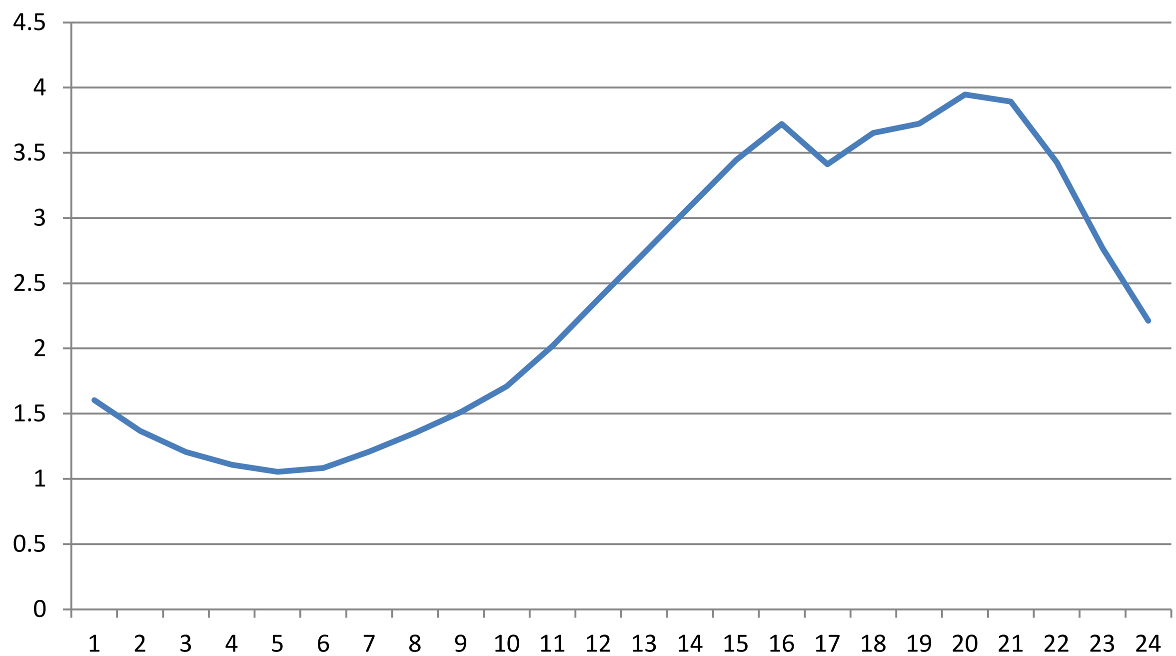


Figure A-5 shows the same reference load on July 1, 2013 for the approximately 600 devices that experienced the power outage when the devices were not experiencing any load control. Since every group was called during a different hour of the day, the hours of load control and snapback needed to be taken into account when creating the reference load, as discussed in Table 3-2.. Instead of a smooth curve, like in Figure 3-3, there is an even more pronounced dip than in Figure A-4. When these customers are removed from the analysis, leaving around 700 devices in Sierra, the dip in the reference load disappears, as seen in Figure A-6. The results presented earlier in the report thus reflect the impacts without these 600 Sierra devices.

Figure A-5: Reference Load of Sierra Customers Who Experienced a Power Outage on July 1, 2013

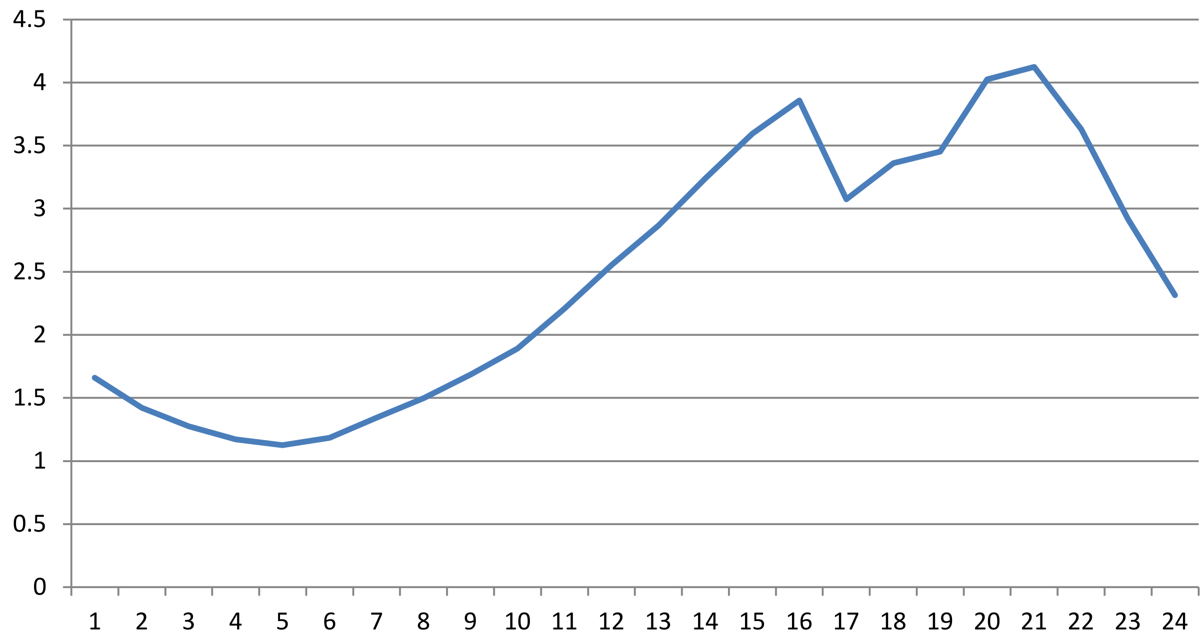
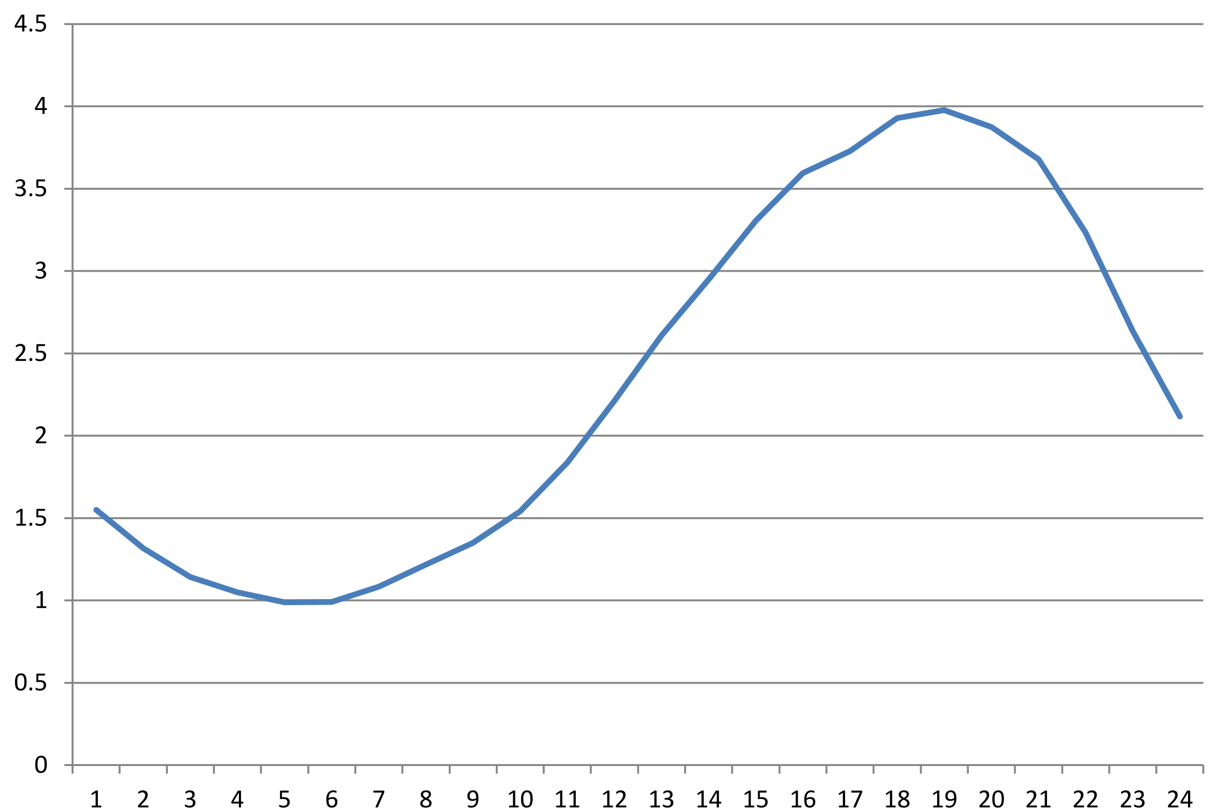


Figure A-6: Reference Load of Sierra Customers with no Power Outage on July 1, 2013



Appendix B Residential Ex Ante Load Impact Tables Methodology

Although estimating impacts is the most important part of the ex ante analysis, whole-building reference loads are needed to illustrate the magnitude of impacts. This appendix discusses the process approach to estimating those reference loads.

B.1 Estimating Ex Ante Load Without DR

This estimation took place in three steps:

- The average hourly usage for each LCA was calculated based on control group load for all 17 event days from 2011 to 2013. This provides an average hot-day load shape, but does not account for temperature variation;
- Next, a regression model, which was similar to the one used to predict load impacts, was also used to model average whole-building loads from 4 to 5 PM. The regression had the same form and the same independent variable as the load impact regression. Only the dependent variable was different. Also, each regression was estimated only at the LCA level — no pooled estimates were used — and the values for whole-building load were not capped. This model was used to predict average loads without demand response from 4 to 5 PM for each set of ex ante weather conditions; and
- Finally, each LCA's control load during each hour for each set of ex ante conditions was adjusted up or down by the ratio of the load predictions from step 2 by the average building load from 4 to 5 PM in step 1.

Figure B-1 depicts the process used to calculate the load shapes for ex ante results. As an illustrative example, the figure shows the ex ante scenario for the typical event day for the Greater Bay Area during a 1-in-2 weather year. The solid purple line shows the average load shape for all Greater Bay Area control group customers over the 17 events during the summers of 2011, 2012 and 2013. The purple circle shows the average usage from 4 to 5 PM over all 2011, 2012 and 2013 event days while the green square shows the predicted average usage from 4 to 5 PM for the typical event day in a 1-in-2 weather year for the Greater Bay Area. Finally, the dotted green line shows the average control usage adjusted upwards using the ratio between the green square and the purple circle (represented by the black bracket). The values represented by the dotted green line are the load without demand response.

Figure B-1: Graphic Depiction of Control Load Calculations
Greater Bay Area, 1-in-2 Weather Year, Typical Event Day

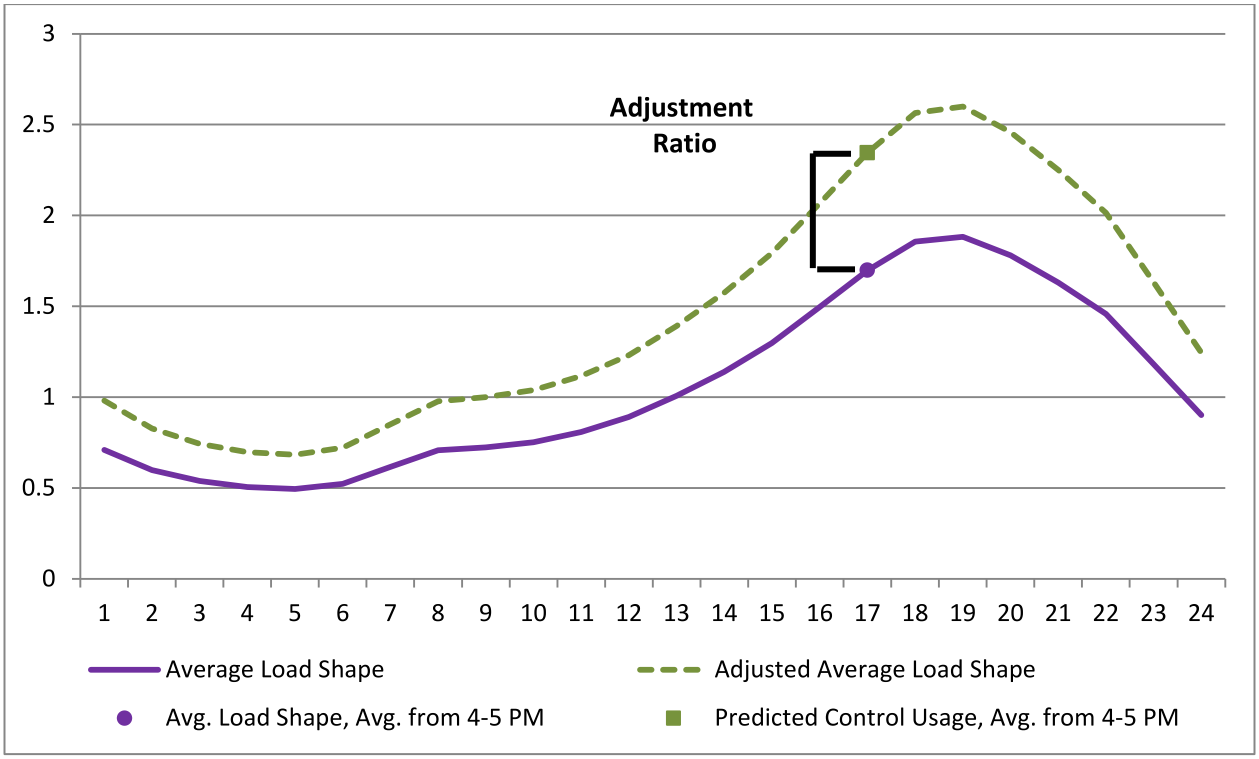
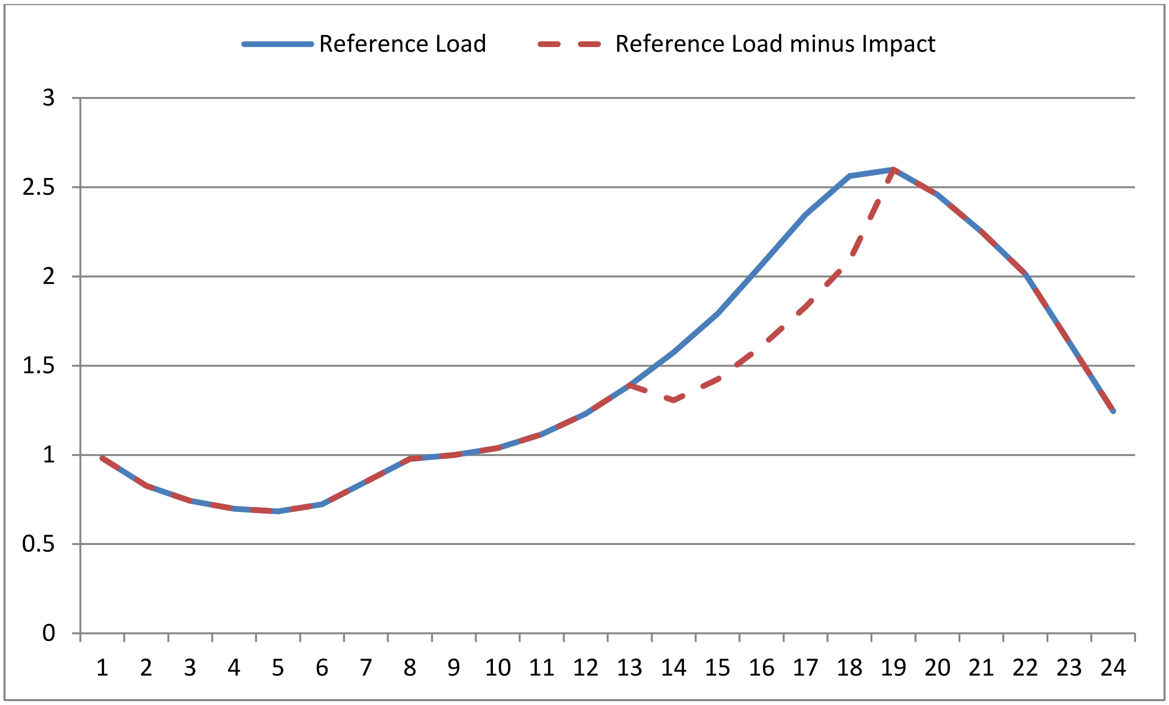


Figure B-2 shows the next step in creating the ex ante tables. As an example, it shows the Greater Bay Area under 1-in-2 weather conditions for the typical event day. The figure shows the loads as exactly the same for all hours except during the event, where the magnitude of the impact has been subtracted from the reference load to create the event load.

**Figure B-2: Graphic Depiction of Ex Ante Impact Calculations
Greater Bay Area, 1-in-2 Weather Year, Typical Event Day**



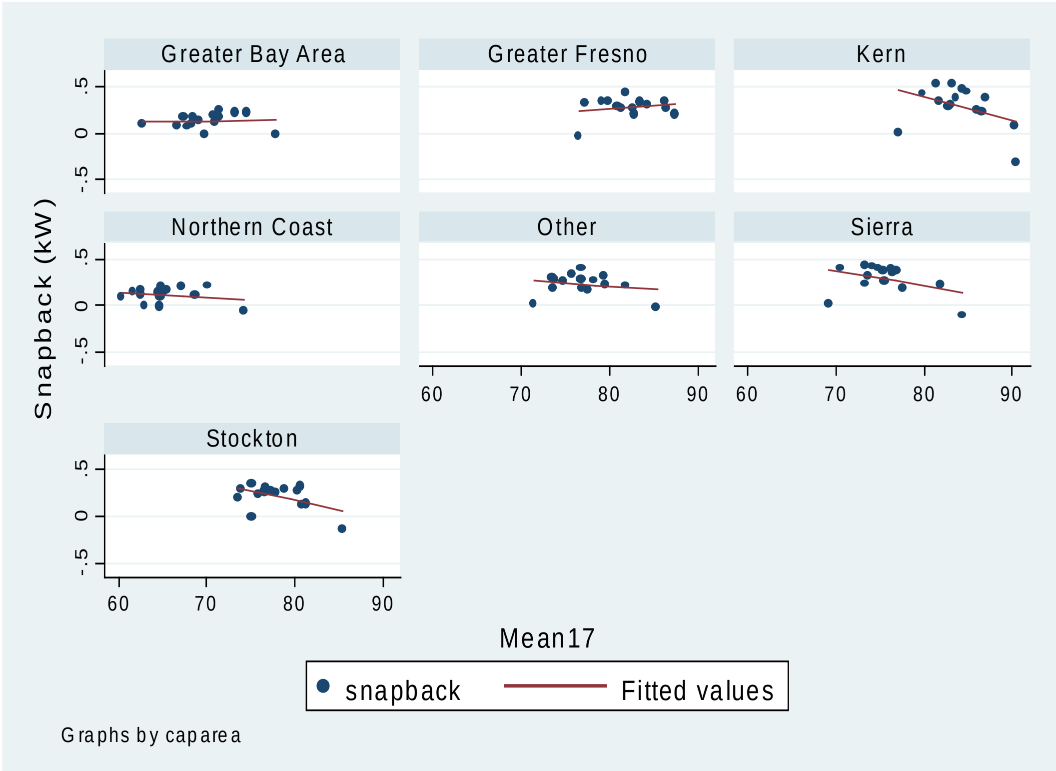
B.2 Estimating Ex Ante Snapback

As the final step in the ex ante analysis, snapback loads are predicted for all hours after the event ends. In addition to the 6 events in 2011 and the 5 events ending at 6 PM in 2012, the one group called from 5 to 6 PM on July 2, 2013 was included in the analysis of snapback. The reasoning behind this is that all ex ante events end at 6 PM, running from 1 to 6 PM. Snapback was not found to be a consistent function of temperature.

Figure B-3 shows the scatter plot of snapback — measured as the average difference between reference load and event-day load during the first post-event hour — versus *mean17* for each LCA. The figure shows that the relationship varies across LCAs. For example, in the cooler LCAs (Greater Bay Area and Northern Coast) higher temperatures over the 17 hours before the event are associated with larger snapback. For the other five LCAs, where temperatures were warmer, snapback is fairly consistent across temperatures or even tends to be lower at higher temperatures. It is likely that when a CAC is controlled for an event, the building becomes hot enough that the CAC turns on full blast during the hour after the event is over. Regardless of whether it is 95°F or 105°F, the CAC will work at its maximum capacity for the hour after the event.[20]

[20] This statement is a hypothesis based on the data currently available. In future evaluations, more data will be available to better test this idea.

Figure B-3: Scatter Plots of Snapback Versus *Mean17* by LCA



Perhaps with more data in future years, a regression would be able to more accurately model snapback over the full spectrum of temperatures for each LCA. However, for this year's analysis, the average snapback across all event days ending at 6 PM for each LCA was used for ex ante prediction.[21] Table B-1 shows the average snapback in the first hour after the event for each LCA.

Table B-1: Average Snapback from 6 to 7 PM by LCA

LCA	Average Snapback From 6 to 7 PM (kW)
Greater Bay Area	0.13
Greater Fresno	0.25
Kern	0.28
Northern Coast	0.11
Other	0.22
Sierra	0.28
Stockton	0.21

21 Although the length of the events varies from 2 to 5 hours, a side-by-side test was conducted in the 2011 evaluation on June 21, 2011 that showed the snapback for five-hour and two-hour events was nearly identical. Thus, we believe it safe to assume the same applies for two and three hour events.

Just as with event load impacts, the average snapback for 6 to 7 PM was translated to hourly snapback using the ratio of average snapback in each hour to average snapback from 6 to 7 PM. Table B-2 shows these ratios for each LCA. For the Greater Bay Area, for example, the table shows that the snapback from 7 to 8 PM is 106% of the snapback from 6 to 7 PM.[22] Multiplying this ratio by the value in Table B-1, the snapback from 7 to 8 PM is 0.138 kW.

Table B-2: Hourly Snapback Compared to Average Snapback from 6 to 7 PM

Hour	Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton
6 to 7 PM	1.00	1.00	1.00	1.00	1.00	1.00	1.00
7 to 8 PM	1.06	1.09	1.12	0.90	1.03	0.96	1.05
8 to 9 PM	0.58	0.69	0.71	0.57	0.57	0.59	0.67
9 to 10 PM	0.27	0.40	0.47	0.31	0.32	0.30	0.42
10 to 11 PM	0.19	0.21	0.33	0.20	0.18	0.20	0.25
11 PM to 12 AM	0.14	0.17	0.23	0.13	0.11	0.10	0.20

Figure B-4 shows the final ex ante results for the Greater Bay Area typical event day during a 1-in-2 weather year. All hours leading up to the event have exactly the same load with and without demand response. For the event hours, impacts are subtracted from the reference load as described above. For hours after the event, the snapback is added to the reference load based on the calculations also described above. This produces the estimates of load with DR for the post-event hours.

[22] Second hour snap-backs are generally larger than first hour snap-backs because events actually end sometime between 0 and 30 minutes after the official event end time, with the actual time determined randomly for each customer. This is similar to how events begin randomly as discussed in section 6.

Figure B-4: Ex Ante Results Example
Greater Bay Area, 1-in-2 Weather Year, Typical Event Day