REPORT

Amended 2014 Load Impact Evaluation for Pacific Gas and Electric Company's SmartAC™ Program

Amended June 2015

Prepared for
Pacific Gas and
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AMENDMENT TO THE APRIL 1, 2015 FILING:

A paragraph on page 3 was referencing an old ex ante model and has been amended to match the correct ex ante model, and now matches the rest of the report and tables.

Old:

Table 1–3 shows the average ex ante impact estimates for the residential SmartAC population in 2015 over the resource adequacy window from 1 to 6 PM. These estimates include the contribution of dually enrolled customers. For the 1-in-2 PG&E weather year, the highest estimated impact is on the June ~~peak day~~, with an average load reduction of ~~81~~ MW and a peak hourly impact of ~~97~~ MW. For a 1-in-10 weather year, the July peak day shows the highest impacts, with a mean impact during the five-hour event window of ~~101~~ MW and a maximum hourly impact of ~~120~~ MW. Under CAISO 1-in-2 conditions, the peak month changes from July to June, with mean and peak hourly impacts of ~~76~~ and ~~92~~ MW, respectively. Under 1-in-10 CAISO conditions, July is again the peak month with a mean aggregate impact of ~~93~~ MW and a peak of ~~110~~ MW.

New:

Table 1–3 shows the average ex ante impact estimates for the residential SmartAC population in 2015 over the resource adequacy window from 1 to 6 PM. These estimates include the contribution of dually enrolled customers. For the 1-in-2 PG&E weather year, the highest estimated impact is on the June and July peak days, with an average load reduction of 83 MW and a peak hourly impact of 99 MW. For a 1-in-10 weather year, the July peak day shows the highest impacts, with a mean impact during the five-hour event window of 104 MW and a maximum hourly impact of 125 MW. Under CAISO 1-in-2 conditions, the peak month changes from July to June, with mean and peak hourly impacts of 79 and 95 MW, respectively. Under 1-in-10 CAISO conditions, July is again the peak month with a mean aggregate impact of 96 MW and a peak of 114 MW.

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1 Executive Summary

PG&E's SmartAC program had approximately 150,000 residential customers enrolled at the end of 2014. 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 Pacific Gas and Electric's (PG&E) SmartAC™ Program for the year 2014. SmartAC 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 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 customers are also allowed to participate in PG&E's critical peak pricing program, SmartRate™. For those who do, PG&E's cycles participants' air conditioners during the SmartRate peak period from 2 to 7 PM.

SmartAC events can be called under a variety of conditions when peak demand reductions are needed, including testing purposes that 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 are typically called in late afternoons on hot summer days. No localized emergency events were called in 2014. Four test events were called for subsets of the population as discussed in detail throughout this report. Two events coincided with SmartRate events while the remaining two were SmartAC only events.

Residential customer enrollment at the end of summer 2014 consisted of approximately 165,000 control devices belonging to 150,000 customers. Small- and medium-sized business (SMB) customer enrollment was around 7,000 control devices on 5,000 premises. Just over 40,000 customers with nearly 45,000 devices were dually enrolled in SmartAC and SmartRate. Historically, SmartAC and SmartRate events have often overlapped. As such, 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.

1.1 Residential SmartAC Ex Post Load Impact Summary

In 2014, M&E test events were called on June 30, July 30, August 1, and September 11. For the July 30 event, 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 adequacy window. On June 30 and August 1, multi-hour test events were called between 3 and 6 PM. Finally, on September 11, a 3-hour test event was called from 3 to 6 PM.

Table 1–1 shows the estimated load impact from 3 to 6 PM for the four 2014 test events. The table focuses on 3 to 6 PM because those hours were common to all events so that the estimated load impacts are comparable with each other without confounding time-of-day effects with other reasons for impact variability. The overall average impact from 3 to 6 PM was 0.52 kW per customer, or about 21% of the whole house load.

Table 1–1: Ex Post Loads, Impacts, and Temperatures from 3 to 6 PM on 2014 Event Days

Event Date	Event Hours[1]	Average Whole-Building Reference Load (kW)	Average Event Impact (kW)	Percent Impact	Aggregate Impact (MW)	Average Temperature 3 to 6 PM (°F)
6/30	3 to 6 PM	2.73	0.62	22.6%	13.6	98
7/30	3 to 6 PM	2.43	0.50	20.7%	15.1	95
8/1	3 to 6 PM	2.70	0.62	22.8%	18.5	98
9/11	3 to 6 PM	1.94	0.32	16.5%	31.6	95
Average	**3 to 6 PM**	**2.45**	**0.52**	**20.7%**	**19.7**	**97**

Table 1–2 shows the average impact in each hour for the multiple test events held on July 30. 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, 0.06 kW, is only about 1/10th as large as the peak hourly impact of 0.57 kW, which occurred between 5 and 6 PM. The impact of 0.17 kW in the hour just prior to the resource adequacy window is roughly half the average impact of 0.40 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 6% of total building load to a high of 21%. The average percent reduction during the resource adequacy window from 1 to 6 PM was 18%.

[1] With the exception of the September 11 event, treatment devices were called 30 minutes prior to the event start time due to anticipated communication delays.

Table 1–2: Ex Post Loads,[2] Impacts and Temperatures for the July 30, 2014 Event Day (Average Impact per Device for SmartAC-only customers)

Hour Ending	Treatment Group	Average Whole-Building Reference Load (kW)	Average Impact per Customer	Percent Impact	Aggregate Impact (MW)[3]	Average Temperature
11	1	1.01	0.06	6.2%	0.9	81
12	2	1.17	0.12	9.9%	1.8	84
13	3	1.40	0.17	12.2%	2.6	88
14	4	1.65	0.21	12.9%	3.3	90
15	5	1.90	0.31	16.5%	4.7	92
16	6+7	2.19	0.42	19.2%	12.7	95
17	6+7	2.46	0.52	21.1%	15.6	95
18	6+7	2.65	0.57	21.5%	17.1	94
19	8	2.67	0.51	19.0%	7.8	93
20	9	2.52	0.43	17.0%	6.4	89
Average	**N/A**	**1.96**	**0.33**	**16.9%**	**7.3**	**90**

1.2 Residential SmartAC Ex Ante Load Impacts 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). Normal and extreme weather conditions are defined two ways, one based on PG&E peak operating conditions, and one based on the California Independent System Operator (CAISO) statewide peak operating conditions.

Table 1–3 shows the average ex ante impact estimates for the residential SmartAC population in 2015 over the resource adequacy window from 1 to 6 PM. These estimates include the contribution of dually enrolled customers. For the 1-in-2 PG&E weather year, the highest estimated impact is on the June and July peak days, with an average load reduction of 83 MW and a peak hourly impact of 99 MW. For a 1-in-10 weather year, the July peak day shows the highest impacts, with a mean impact during the five-hour event window of 104 MW and a maximum hourly impact of 125 MW. Under CAISO 1-in-2 conditions, the peak month changes from July to June, with mean and peak hourly impacts of 79 and 95 MW, respectively. Under 1-in-10 CAISO conditions, July is again the peak month with a mean aggregate impact of 96 MW and a peak of 114 MW.

2 Reference loads are whole-building loads.

3 The aggregate impacts shown in the table represent only 10-20% of SmartAC customers due to the number of treatment groups that were called in each hour.

Table 1–3: 2015 Residential SmartAC Ex Ante Load Impact Estimates by Weather Year and Day Type (Average Impact Over Event Period from 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 PG&E	Typical Event Day	0.52	0.63	80	96
	May Peak Day	0.34	0.43	52	65
	June Peak Day	0.54	0.65	83	99
	July Peak Day	0.54	0.65	83	99
	August Peak Day	0.52	0.63	80	97
	September Peak Day	0.48	0.58	74	90
	October Peak Day	0.24	0.32	38	49
1-in-10 PG&E	Typical Event Day	0.60	0.71	93	110
	May Peak Day	0.56	0.67	85	102
	June Peak Day	0.60	0.72	92	110
	July Peak Day	0.68	0.81	104	125
	August Peak Day	0.63	0.75	96	115
	September Peak Day	0.51	0.62	79	95
	October Peak Day	0.40	0.50	62	77
1-in-2 CAISO	Typical Event Day	0.44	0.54	67	82
	May Peak Day	0.32	0.41	49	62
	June Peak Day	0.51	0.62	79	95
	July Peak Day	0.50	0.60	77	92
	August Peak Day	0.38	0.48	59	74
	September Peak Day	0.36	0.45	55	69
	October Peak Day	0.24	0.32	37	49
1-in-10 CAISO	Typical Event Day	0.53	0.64	82	98
	May Peak Day	0.41	0.51	63	78
	June Peak Day	0.50	0.60	76	92
	July Peak Day	0.63	0.75	96	114
	August Peak Day	0.57	0.68	88	105
	September Peak Day	0.44	0.54	68	83
	October Peak Day	0.36	0.45	55	69

1.3 SMB SmartAC Ex Ante Load Impacts Summary

The SMB segment of the SmartAC program is currently closed to new customers. No M&E test events have been called for this group since 2011. The ex ante estimates presented in this report are based on the average impacts per device estimated in the 2011 evaluation, adjusted for customer attrition.

Table 1–4 shows the average ex ante load reductions for the SMB population for the resource adequacy window from 1 to 6 PM. For the 1-in-2 PG&E weather year, the highest estimated impact is on the July peak day, with an average impact of 3.2 MW and a peak hourly impact of 3.8 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 3.7 MW and the peak hourly impact is 4.3 MW. Under CAISO conditions, June and July have approximately the same forecasted impacts under 1-in-2 conditions (3.0 MW average, 3.5 MW peak), but the highest load impacts occur in July for the 1-in-10 weather year (3.6 MW mean, 4.2 MW peak).

Table 1–4: 2015 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 PG&E	Typical Event Day	0.67	0.78	3.1	3.7
	May Peak Day	0.43	0.51	2.0	2.4
	June Peak Day	0.68	0.79	3.2	3.7
	July Peak Day	0.68	0.79	3.2	3.7
	August Peak Day	0.66	0.77	3.1	3.6
	September Peak Day	0.56	0.67	2.6	3.1
	October Peak Day	0.28	0.34	1.3	1.6
1-in-10 PG&E	Typical Event Day	0.73	0.85	3.4	4.0
	May Peak Day	0.67	0.79	3.2	3.8
	June Peak Day	0.72	0.85	3.4	4.0
	July Peak Day	0.78	0.91	3.7	4.3
	August Peak Day	0.76	0.88	3.6	4.2
	September Peak Day	0.59	0.70	2.8	3.3
	October Peak Day	0.47	0.56	2.2	2.6
1-in-2 CAISO	Typical Event Day	0.55	0.65	2.6	3.1
	May Peak Day	0.42	0.51	2.0	2.4
	June Peak Day	0.64	0.75	3.0	3.5
	July Peak Day	0.63	0.74	3.0	3.5
	August Peak Day	0.49	0.58	2.3	2.8
	September Peak Day	0.47	0.56	2.2	2.6
	October Peak Day	0.29	0.34	1.3	1.6
1-in-10 CAISO	Typical Event Day	0.68	0.80	3.2	3.8
	May Peak Day	0.52	0.62	2.5	2.9
	June Peak Day	0.61	0.71	2.9	3.4
	July Peak Day	0.76	0.88	3.6	4.2
	August Peak Day	0.72	0.84	3.4	4.0
	September Peak Day	0.53	0.63	2.5	3.0
	October Peak Day	0.45	0.54	2.1	2.5

1.4 Recommendations

The 2014 SmartAC test events were conducted in a way that provided concrete enhancements to both the ex post and ex ante evaluations. The two events called on days when SmartRate was not called and provided an opportunity to directly measure the impacts for dually enrolled customers as opposed to relying on assumptions about the relative magnitude of their impacts compared to SmartAC-only customers. Furthermore, the 2014 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. Understanding demand response impacts during these time periods will become increasingly important as renewable sources of generation make up an increasing share of the generation mix. We recommend that PG&E continue to include M&E events of this nature in the operational plan for SmartAC in 2015.

We also recommend that a review of the ex ante methodology take place prior to the 2015 evaluation to determine if sufficient data is available to make use of a cleaner and more streamlined approach for estimating hourly impacts during the 1 to 6 PM resource adequacy window. Much of the existing ex ante methodology was developed in an environment with severely limited ex post data available, necessitating the use of various ratios and adjustment factors to generate estimates where data was lacking. As more test events have been called, the available data has potentially improved to the point where these adjustments are no longer necessary and impacts could be estimated independently for each hour with a low risk of internally inconsistent results using robust econometric methods. Such an approach would be considerably simpler and more transparent than the current approach, resulting in analysis that is both more sophisticated and less complicated.

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. UtilityPro and ExpressStat PCTs are devices 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 2012–2014 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. There are two basic kinds of cycling: simple and adaptive. Under simple cycling, the CAC compressor's duty cycle is capped at a chosen 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 air conditioner 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	ExpressStat
Residential	50% TrueCycle2	50% TrueCycle2	50% Simple Cycling
SMB	33% TrueCycle2	33% TrueCycle2	33% Simple Cycling

In 2014, no emergency sub-LAP events were called. M&E test events were called on June 30, July 30, August 1, and September 11. 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. The event hours for the other three events were from 3 to 6 PM.

Table 2–2 shows the number of enrolled control devices by customer type, device type, and local capacity area (LCA) at the end of the 2014 program year.

Table 2–2: SmartAC Enrolled Customers and Active Control Devices at End of 2014 Program Year

Customer Class	Local Capacity Area	Enrolled Customers	PCTs	Switches	Total Devices
Residential – SmartAC-only	Greater Bay Area	37,233	4,434	32,799	41,890
	Greater Fresno	13,287	2,684	10,604	14,811
	Kern	5,102	1,088	4,015	5,692
	Northern Coast	6,538	802	5,737	6,896
	Other	24,967	3,521	21,445	26,910
	Sierra	11,876	1,111	10,765	13,562
	Stockton	10,331	1,372	8,959	11,097
	Total	**109,334**	**15,012**	**94,324**	**120,858**
Residential – Dually Enrolled (SmartAC and SmartRate)	Greater Bay Area	15,084	1,655	13,429	16,957
	Greater Fresno	4,037	822	3,215	4,490
	Kern	2,008	714	1,294	2,256
	Northern Coast	2,210	264	1,947	2,326
	Other	8,076	1,068	7,008	8,695
	Sierra	4,771	386	4,385	5,397
	Stockton	4,158	530	3,628	4,474
	Total	**40,344**	**5,439**	**34,906**	**44,595**
SMB	Greater Bay Area	1,719	1,590	129	2,363
	Greater Fresno	527	458	68	784
	Kern	277	258	19	405
	Northern Coast	545	488	56	712
	Other	1,131	1,001	130	1,528
	Sierra	385	331	53	542
	Stockton	425	354	70	599
	Total	**5,009**	**4,480**	**525**	**6,933**
All	**Total**	**154,687**	**24,931**	**129,755**	**172,386**

It is important to distinguish between enrolled customers and enrolled devices since many customers (especially SMB customers) have multiple CAC units and, therefore, multiple control devices. Some accounts may even have both kinds of control devices associated with separate CAC units. Residential customer enrollment at the end of the summer consisted of approximately 150,000 unique residential accounts and 5,000 SMB accounts. Just over 40,000 residential customers with approximately 45,000 devices were dually enrolled in

SmartRate and SmartAC, leaving about 121,000 devices belonging to 109,000 customers in the SmartAC-only population.

The majority of SmartAC devices—96% of all devices, 99% of switches, and 82% of PCTs—are associated with residential households. The majority of devices among residential customers are switches, while SMB customers primarily have PCTs. SMB accounts have roughly 1.4 devices per premise, whereas residential accounts average 1.1 devices per premise.

2.1 SmartAC Analytical Overview

The foundation of the ex post load impact evaluation for SmartAC test events is a randomized control trial.

Detailed discussions of the ex post and ex ante methodologies are contained in Sections 3 and 5, respectively. As in the prior three 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. During a typical test event, some of the groups have their devices activated and the others do not. In this experimental framework, the load impacts are estimated simply 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.[4] Because of the RCT design and a large number of customers in each group, there is virtually no uncertainty in the ex post component of the evaluation. The design eliminates selection and model specification bias and results in a high degree of precision for reference loads, estimated loads during events, and ex post load impacts.

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 used to estimate this relationship is based on ex post load impacts from 2011 to 2014. First, load impacts from 4 to 5 PM are modeled as a function of the average temperature from midnight to 5 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 the four test events that occurred in 2014. Section 4 presents the residential ex post load impact results. Section 5 summarizes the results from a post event survey that was done to determine levels of comfort during events, customer satisfaction, and other questions of interest. Section 6 describes the methods used to estimate ex ante load impacts and Section 7 summarizes the ex ante results for both residential and SMB customers. Section 8 concludes with a summary and

[4] 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

recommendations. Following the main text are several appendices explaining the methodology used to obtain reference loads and snapback estimates for the ex ante analysis and containing the questionnaire used in the post event survey discussed in Section 5.

3 Evaluation Design and Ex Post Methods

This section details the evaluation design and analytical methods used to estimate ex post load impacts for residential customers during the 2014 program year. As mentioned in the prior section, there were four M&E test days in 2014—three of which had an event window from 3 to 6 PM (June 30, August 1, and September 11) and one that had several individual events staggered across the hours from 10 AM to 8 PM (hereafter referred to as a "cascading" event).

3.1 Residential Experimental Design and Operations

Similar to the evaluations conducted for 2011, 2012, and 2013, the ex post estimation was based on an RCT evaluation design. Using the last digit of the serial number for each device, the SmartAC population was randomly assigned to 1 of 10 groups so that each group consisted of approximately 15,000 devices. During an event, the devices in one or more groups were activated (referred to as treatment customers) and the devices in the remaining groups were not (control customers). Within this experimental framework, estimating the load impacts for an event requires simply calculating the difference in loads between the treatment and control groups during the event period as well as in the hours following the event to capture any snapback effect.

The RCT evaluation design combined with large test groups provide extremely precise, completely unbiased ex post load impact estimates for the SmartAC program.

For an RCT to be effective, customers in the treatment and control groups should, on average, be very similar in terms of characteristics that are related to energy consumption so that the only relevant difference between them is that the control group did not experience the treatment. This ensures that any differences in energy consumption that are observed can be attributed to the treatment. Provided the sample sizes are large enough, obtaining groups of similar customers can be accomplished by randomly assigning customers to each group. As a check to see if using the last digit of the serial number to determine a customer's group is indeed random, several comparisons between the groups are presented below. Table 3–1 shows a comparison of the 10 M&E groups along 2 important dimensions: location (LCA) and mean daily usage. Figure 3–1 shows hourly loads for each group on a non-event day (July 11, 2014). In both the table and the figure, differences between the 10 groups are very small, which provides strong evidence of random assignment.

Table 3–1: Average Loads for Randomized Groups on a Non-event Day (July 11, 2014)

Randomized Group	Usage (kW)							
	Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	All LCAs
0	0.69	1.48	1.62	0.66	1.02	1.11	0.97	0.97
1	0.68	1.52	1.66	0.63	1.02	1.11	0.97	0.97
2	0.68	1.47	1.62	0.64	1.00	1.14	0.97	0.96
3	0.70	1.52	1.67	0.62	1.02	1.12	0.99	0.98
4	0.69	1.50	1.67	0.62	1.04	1.08	0.97	0.98
5	0.70	1.50	1.67	0.61	1.04	1.11	0.99	0.98
6	0.67	1.52	1.65	0.65	1.03	1.07	0.96	0.97
7	0.70	1.48	1.62	0.64	1.00	1.12	0.97	0.97
8	0.68	1.48	1.71	0.66	1.01	1.10	0.98	0.97
9	0.70	1.48	1.68	0.62	1.02	1.14	0.97	0.98

Figure 3–1: Comparison of Loads for Randomized Groups on a Non-event Day (July 11, 2014)

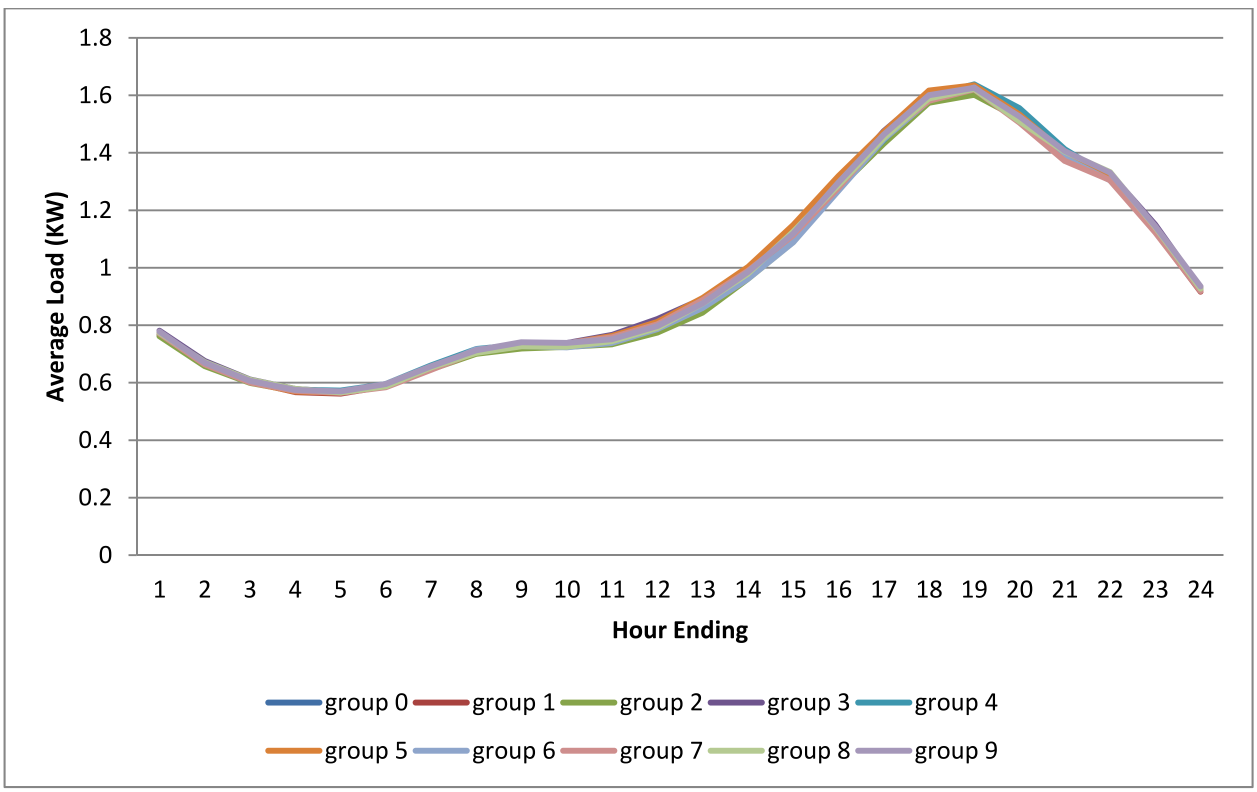
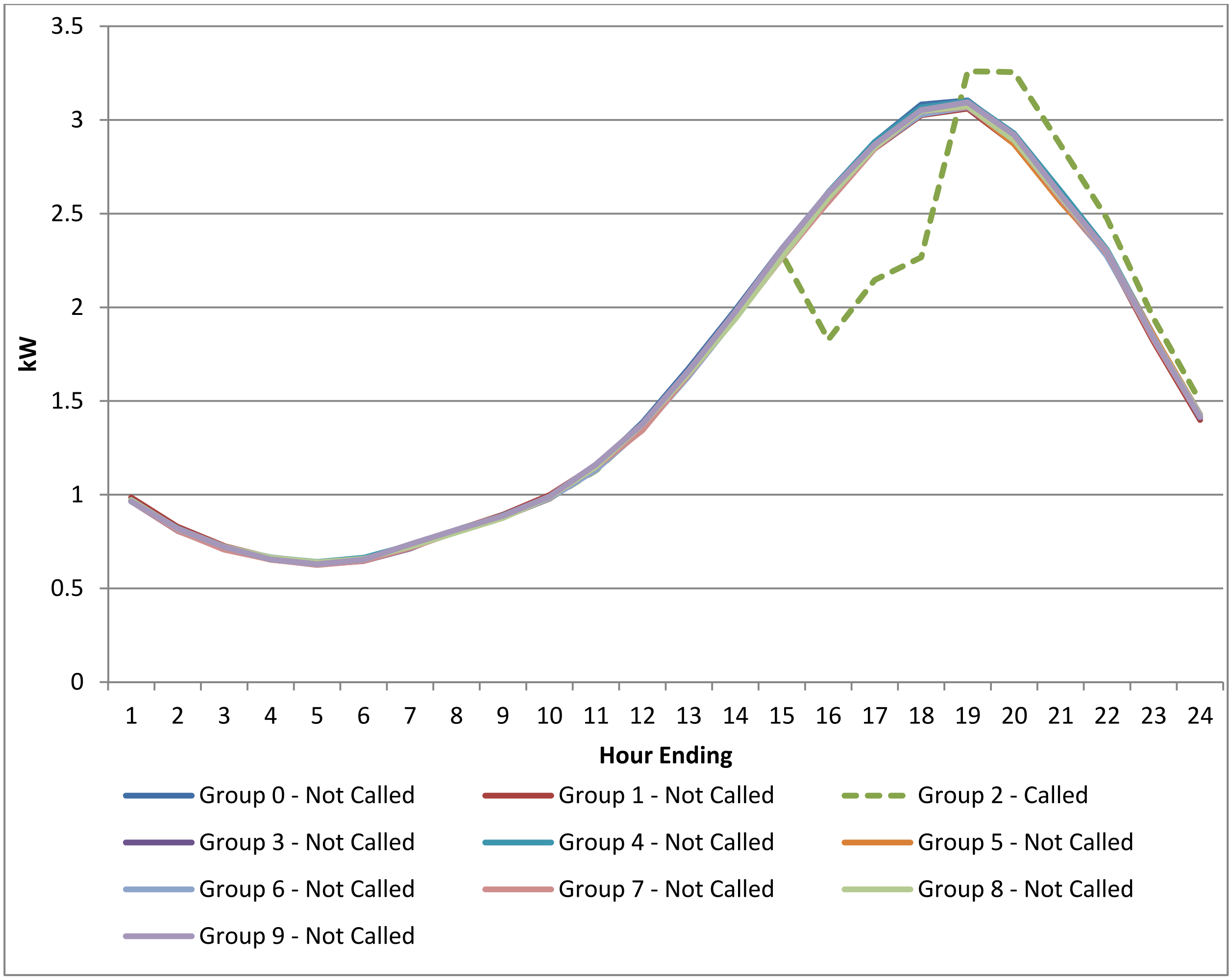


Figure 3–2 illustrates how the load impacts can be estimated by comparing an activated group with the non-activated groups over the course of an event day. Because of the successful randomization, the impact of the event is simply the difference between the load for the group that was called and the average load of the groups that were not called. The graph shows that the event resulted in a clear reduction in loads during the event window from 4 to 6 PM along with a noticeable increase in loads for several hours after the event ended. This post-event "snapback" is a common feature of AC-cycling programs that aim to reduce demand during a pre-scheduled window.

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



On July 30, each test group was called at different hours of the day between 10 AM and 8 PM. Table 3–2 shows the individual event schedules for each of the 10 groups. For each group, devices were activated 30 minutes prior to the hour of interest so that all devices were under control at the start of the hour.[5] To avoid any complications caused by this pre-event

[5] 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.

activity or post-event snapback, Group 0 was used as the control group for all hours since it was not called at all during the course of the day.[6] The impact in each hour was then calculated as the difference between the average load for Group 0 customers and the average load for the customers who were called during that hour. Figure 3–3 shows the load curves for each group during the course of the day. As seen, the difference between treatment and control group loads varies throughout the day, with the largest differences appearing in the hot afternoon hours.

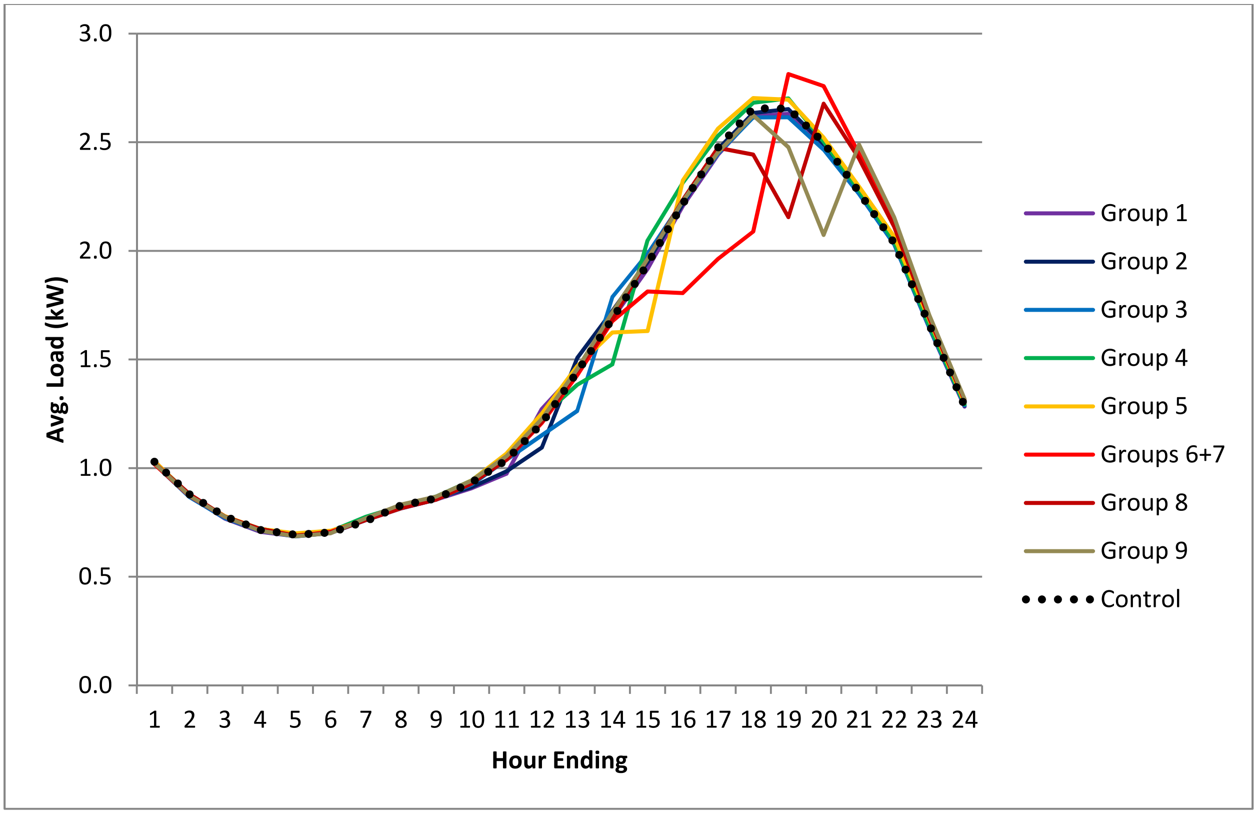
Table 3–2: Individual Event Schedules for July 30, 2014 Event[7]

Randomized Group	Event Start	Event Stop
0	Not Called	Not Called
1	10:00	11:00
2	11:00	12:00
3	12:00	13:00
4	13:00	14:00
5	14:00	15:00
6	15:00	18:00
7	15:00	18:00
8	18:00	19:00
9	19:00	20:00

[6] Including treatment customers as part of the control group during the hours before their event window and several hours after the end of the event window is also a valid approach, but sample sizes are large enough that we chose to simply estimate the impacts in each hour using only Group 0 and the group(s) called during that hour.

[7] Devices were activated 30 minutes prior to the "Event Start" time because activation lags were anticipated from prior years. This ensures that all (or almost all) devices were in fact activated by the "Event Start" time.

Figure 3–3: Comparison of Treatment Loads for Randomized Groups on the July 30, 2014 Event Day



3.2 Dually Enrolled Participants

Out of the roughly 150,000 residential customers enrolled in the SmartAC program in 2014, approximately 40,000 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 dually enrolled customers may differ from that of a SmartAC-only participant. Indeed, as discussed in Section 5, the average reference load for dually enrolled customers is less than the corresponding reference load 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 lower.

In 2014, there were two SmartAC test events on days when SmartRate was not called—July 30 and August 1. These days provided an opportunity to directly compare the impacts for dually enrolled customers with those for SmartAC-only customers. The results of this analysis are presented in Section 4.

3.3 Households with Multiple CAC Units

At the end of the 2014 program year, there were approximately 15,000 SmartAC residential customers (including dually enrolled 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 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 these situations, the whole-house load impact would not necessarily represent the true effect of a SmartAC event on that household, since during a non-test event when all customers were called, both units would be controlled. Secondary analysis of multi-device premises in the 2012 evaluation 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 2013, these multi-device households were 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. This year, multi-device households are excluded from the calculation of per customer impacts, but are included in the calculation of aggregate impacts under the assumption that they provide the same load reductions as single-device customers. An analysis of this assumption is provided in Section 4.5.

3.4 Analyzing Net Metered Customers

Another particular customer group of interest consists of customers that are net metered, indicating that they have a photovoltaic (PV) system installed at their residence. The SmartAC program has approximately 9,000 enrolled customers with PV systems. These customers have a very different load shape than non-net metered customers and it is common for net loads to become negative during the late morning and early afternoon hours when a PV system is producing more electricity than is being consumed by the home. On hot summer days, this can result in a rapid increase in net load from early afternoon to the peak hours in the early evening as solar production declines and usage in the home increases (AC usage, in particular). As the adoption of solar continues to accelerate in PG&E’s service territory, this “duck curve” load shape poses a challenge to system operators due to the fast-ramping generation that is needed to meet the rapidly growing demand. Section 4.6 presents load impact estimates for this growing group of customers and discusses the implications for PG&E.

4 Residential Ex Post Load Impact Estimates

This chapter presents the ex post SmartAC program's load impacts for the 2014 program year. Across the four event days that were called, the average ex post impact per customer for participants that are only enrolled in the SmartAC program equaled 0.52 kW during the period from 3 to 6 PM that was common to all events.

This chapter is divided into six main sections. Section 4.1 summarizes the ex post impact results for the four test events in 2014. Section 4.2 analyzes the distribution of impacts across the population by calculating impact estimates segmented by local capacity area (LCA) and average usage decile. Section 4.3 compares the estimated impacts for dually enrolled customers (SmartAC + SmartRate) with customers who are only enrolled in SmartAC. Section 4.4 compares ex post estimates for 2014 with those from prior evaluations. Section 4.5 analyzes the assumption that multi-device customers provide the same magnitude impact as customers who have only a single installed device and Section 4.6 closes with load impact estimates for net metered customers.

4.1 SmartAC Primary Test Event Results

Characteristics of the four test events in 2014 are shown in Table 4–1. For three of the events, all treatment customers were called simultaneously from 3 to 6 PM, while one event (July 30) was called as a staggered series of shorter events involving only one or two of the treatment groups at a time. Two of the event days were also SmartDays (June 30 and Sept 11) while the remaining two events involved only SmartAC. Calling SmartAC-only events provides the opportunity to analyze load impacts for SmartAC customers who are also enrolled in SmartRate and these results are presented in Section 4.3.

In 2014, a test event was again conducted during 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 to those in the hot afternoon hours.

Table 4–1: 2014 SmartAC Test Event Characteristics

Event Date	Event Hours	Groups Called	SmartRate Event Day
June 30	3 to 6 PM	1&2	Yes
July 30	10 AM to 8 PM	1–9 (staggered)	No
August 1	3 to 6 PM	1&2	No
September 11	3 to 6 PM	2–10	Yes

Table 4–2 shows the average load impact per customer for the four test events that were called in 2014, along with the average temperature over the event period for the residential SmartAC population. The table also shows the standard errors of the estimates which, given the large

sample sizes, are quite small[8] relative to the estimated impact. The average per customer impact for these three events was 0.51 kW, with the September 11 event being roughly half as large as the average of the other three events. More than half of this difference in absolute impacts is attributable to the difference in reference loads. The September 11 reference load is about 25% less than the average reference load on the other three event days, in part due to lower temperatures but also most likely due to changes in behavior following the end of the summer holidays and the return of children to school. But it's also true that the percentage load reduction is lower on September 11 compared with the other days, suggesting that some consumers may have shifted their air conditioners to off by this point in the season. It is worth noting that in the 2012 SmartAC load impact evaluation, September and October event-day impacts also had lower absolute- and percentage-reductions compared with events in July and August, even on days with similar temperatures.

Table 4–2: Ex Post Loads,[9] Impacts, and Temperatures for Event Days (Average Impact per Customer)

Event Day	Hour Ending[10]	Reference (kW)	Per Customer Impact (kW)	Standard Error of Impact (kW)	Percent Impact	Aggregate Impact (MW)[11]	Average Temperature During Event (°F)
June 30	16	2.53	0.56	0.015	22.0%	12.3	99
	17	2.75	0.63	0.014	22.8%	13.9	98
	18	2.91	0.67	0.014	22.8%	14.7	97
July 30	16	2.19	0.42	0.024	19.2%	12.7	95
	17	2.46	0.52	0.025	21.1%	15.6	95
	18	2.65	0.57	0.025	21.5%	17.1	94
August 1	16	2.49	0.53	0.012	21.5%	16.1	98
	17	2.73	0.64	0.012	23.3%	19.1	99
	18	2.88	0.68	0.012	23.5%	20.3	98
Sept. 11	16	1.65	0.26	0.018	16.0%	26.0	95
	17	1.98	0.33	0.019	16.9%	33.1	96
	18	2.20	0.36	0.019	16.4%	35.8	94
Average	**N/A**	**2.45**	**0.52**	**0.017**	**20.7%**	**19.7**	**97**

8 See Table 4-2a, page 18 in the *2012 Load Impact Evaluation for Pacific Gas and Electric Company's SmartAC Program,* by Freeman, Sullivan & Co.

9 Reference loads are whole-building loads.

10 All events technically began half an hour before the stated start time to be sure that the devices received the cycling signals and that the maximum number of devices were functioning properly at the top of the hour.

11 Aggregate loads are not directly comparable since each event had a different number of groups that were called. The August 1 event involved groups 1 and 2 and also included dually enrolled customers. The June 30 event involved the same two groups, but excluded dually enrolled customers because it was also a SmartRate event. There are differences with the other events as well.

Table 4–3 shows similar results for the cascading event on July 30. As discussed in Section 3, this test day involved a series of short tests that called different 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 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 4-3).

Table 4–3: Ex Post Loads,[12] Impacts, and Temperatures for the July 30, 2014 Event Day

Hour Ending	Treatment Group	Reference Load (kW)	Impact (kW)	Standard Error of Impact	Percent Impact	Aggregate Impact (MW)	Average Temperature in the Hour (°F)
11	1	1.01	0.06	0.014	6.2%	0.9	81
12	2	1.17	0.12	0.018	9.9%	1.8	84
13	3	1.40	0.17	0.020	12.2%	2.6	88
14	4	1.65	0.21	0.022	12.9%	3.3	90
15	5	1.90	0.31	0.024	16.5%	4.7	92
16	6+7	2.19	0.42	0.024	19.2%	12.7	95
17	6+7	2.46	0.52	0.025	21.1%	15.6	95
18	6+7	2.65	0.57	0.025	21.5%	17.1	94
19	8	2.67	0.51	0.022	19.0%	7.8	93
20	9	2.52	0.43	0.021	17.0%	6.4	89
Average	**N/A**	**1.96**	**0.33**	**0.021**	**16.9%**	**7.3**	**90**

In general, the results in Table 4–3 show that the 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 per customer impact between 10 and 11 AM (0.06 kW) was only 1/10th as large as the peak hourly impact (0.57 kW), which occurred between 5 and 6 PM. The impact of 0.17 kW in the hour just prior to the resource adequacy window was less than half the average impact of 0.41 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. On a percentage basis, the load reductions range from a low of about 6% of total household load to a high of 22% across the 10 hours tested on this event day. The average percent reduction between 1 and 6 PM is 18%. Most importantly, the aggregate ex post impacts only represent about 10 to 20% of the SmartAC-only population since only one or two test groups were called in each hour. As such, the aggregate impact estimates in the table (ranging from 0.9 MW to 17.1 MW) are not at all representative of the load reduction potential for the SmartAC program as a whole.

[12] Reference loads are whole-building loads.

Load impacts are much greater for customers with switches than for those with PCTs.

The analysis for the July 30 and August 1 events include customers who are also enrolled in SmartRate since they were not SmartDays. For the other two events, dually-enrolled customers are removed and are included in the SmartRate evaluation report. Dually-enrolled customers have smaller absolute impacts on days when only SmartAC is called because they tend to have smaller reference loads than SmartAC-only customers (a more detailed comparison of the impacts for dually enrolled and SmartAC-only customers is provided in Section 4.4).

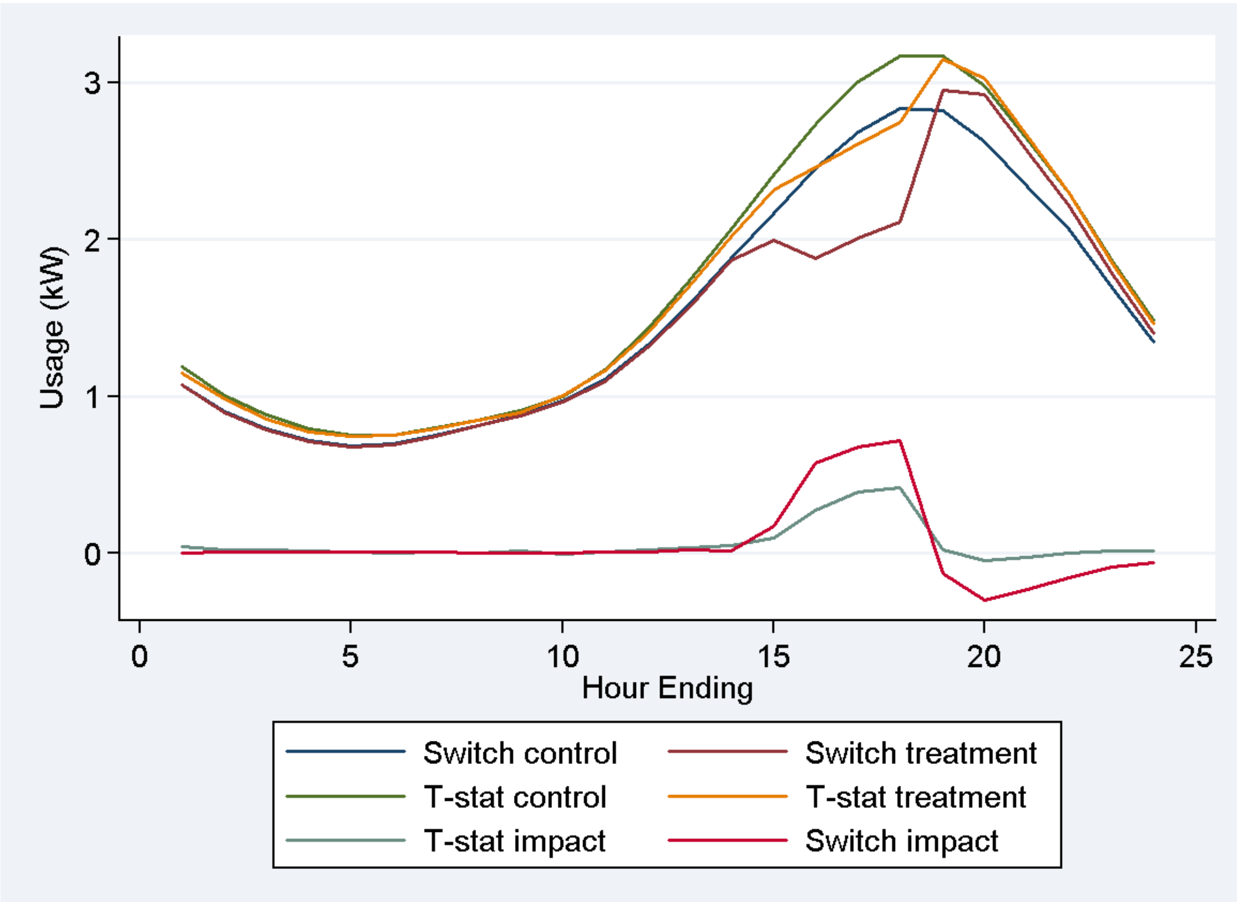
Another way to segment the analysis is by type of control device. There are two types of control devices—thermostats (PCTs) and switches. Table 4–4 shows per customer impacts by device type for residential SmartAC customers. On average, customers with switches provide impacts that are approximately twice as large as the impact for PCT customers.

Table 4–4: Average Residential per Customer Impacts by Device Type (kW)

Event Day	Hour Ending	PCT	Switch
June 30	16	0.28	0.60
	17	0.37	0.67
	18	0.36	0.72
July 30	11	0.03	0.07
	12	0.07	0.12
	13	0.12	0.18
	14	0.19	0.22
	15	0.21	0.33
	16	0.17	0.46
	17	0.26	0.56
	18	0.28	0.61
	19	0.23	0.55
	20	0.30	0.55
August 1	16	0.27	0.58
	17	0.39	0.68
	18	0.42	0.72
September 11	16	0.12	0.28
	17	0.23	0.35
	18	0.20	0.38
Average	**N/A**	**0.24**	**0.45**

Figure 4–1 shows the reference and treatment loads (top part of the figure) and estimated impacts (bottom part of figure) for each type of device on the August 1 event along with the estimated impacts. The top four lines are the average loads for each group based on the raw data, while the impacts are simply the difference between treatment and control. From the graph, we can see lower impacts for PCT customers despite the fact that they have higher reference loads.

Figure 4–1: Reference and Treatment Loads for Customers with PCTs and Switches on August 1 Event



This difference in performance 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 reside in hotter areas and have somewhat higher reference loads than those with switches, showing that the performance gap is even larger than Table 4-4 indicates. While attempting to determine why PCT results were significantly lower than switch results, it was discovered that customers with ExpressStat PCTs produced minimal load reductions. PG&E is looking into the cause of this problem. After adjusting the impact estimates in Table 4–4 for this error, the average UtilityPro PCT impacts are still lower than the average switch impacts (0.34 kW compared to 0.41 kW). This suggests that PCTs, which are located inside the premise, may have higher communication failure rates than switches, which are located outside.

Table 4–5: Comparison of Device Type Distribution by LCA for Residential Customers[13]

Device Type	Usage (kW)							
	Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	All LCAs[14]
Switch	36%	11%	4%	6%	22%	12%	10%	0.96
PCT	30%	17%	9%	5%	22%	7%	9%	1.06

The minimal load reductions of the ExpressStat PCTs lowered the average impact for PCTs as well as all devices. Table 4–6 shows the potential for improvement on 2014 event days if ExpressStats were performing at the level of UtilityPro PCTs. This could also be interpreted as the loss in aggregate impact due to the poor performance of the ExpressStats.

Table 4–6: Expected Performance of PCTs with Properly Functioning ExpressStat PCTs

Event Date	(A) Aggregate Impact for All Thermostats (MW)	(B) Aggregate Impact for All Thermostats if ExpressStat Impact = UtilityPro Impact (MW)	(C) Maximum Possible Increase in Aggregate Impact from Fixing ExpressStat PCTs (MW)	(D) Aggregate Impact for All SmartAC-only Customers (MW)
June 30	4.4	7.2	2.8	68.9
July 30	4.0	6.3	2.3	58.8
Aug 1	6.5	9.1	2.5	72.8
Sept 11	2.4	3.9	1.4	35.2
Average	**4.3**	**6.6**	**2.2**	**58.9**

In Table 4–6, column A shows the actual aggregate impacts for all PCTs (ExpressStat and UtilityPro) on each event day, while column B contains the estimated aggregate impact if the ExpressStat PCTs provided the same load reductions as UtilityPro PCTs. Column C shows the maximum increase in aggregate impact that could be achieved, which is the difference between columns B and A. As a point of reference, column D shows the aggregate ex post impacts scaled up to the entire SmartAC-only population. With ExpressStats performing as well as Utiltipros, the aggregate impact would be expected to be D plus C. On the average 2014 event day, improved ExpressStat performance could result in up to approximately 2.2 MW of additional load reduction.

4.2 Impact Estimates by Geographic Area and Customer Size

This section summarizes an analysis of the distribution of impacts across locations (LCA) and usage decile. Table 4–7 shows the average load impact from 3 to 6 PM for the four event days

13 This table includes multi-device customers and is based on counts from September 11.

14 Calculated on July 12, 2014 (non-event day)

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 4-7 are highly correlated with the average temperature at the same time period. Kern and Greater Fresno are the hottest LCAs and 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, including differences in housing types, lifestyle patterns, and economic conditions.

Table 4–7: Average Event Impacts from 3 to 6 PM by LCA

Local Capacity Area	Impact (kW)	% Impact	Mean 17	Average Temperature during Event Window (°F)
Greater Bay Area	0.42	21.1%	75	91
Greater Fresno	0.56	19.1%	87	103
Kern	0.70	21.9%	88	103
Northern Coast	0.30	20.0%	70	88
Other	0.54	20.5%	82	100
Sierra	0.61	21.9%	81	99
Stockton	0.63	22.3%	83	99
All	0.52	21.2%	79	96

Table 4–8 shows the load impact from 3 to 6 PM averaged across all event days for customers grouped by usage decile. Customers were divided into deciles based on average load for non-event days throughout the summer (June–September). Customers in the lowest decile had an average load of 0.22 kW compared to 2.24 kW for customers in the highest decile of usage. As expected, customers with higher average usage showed greater absolute impacts (eight times larger for the highest decile vs. the lowest), but on a percentage basis, impacts were relatively constant across all deciles. These findings are consistent with a hypothesis that AC size is proportional to home size and total electricity usage.

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

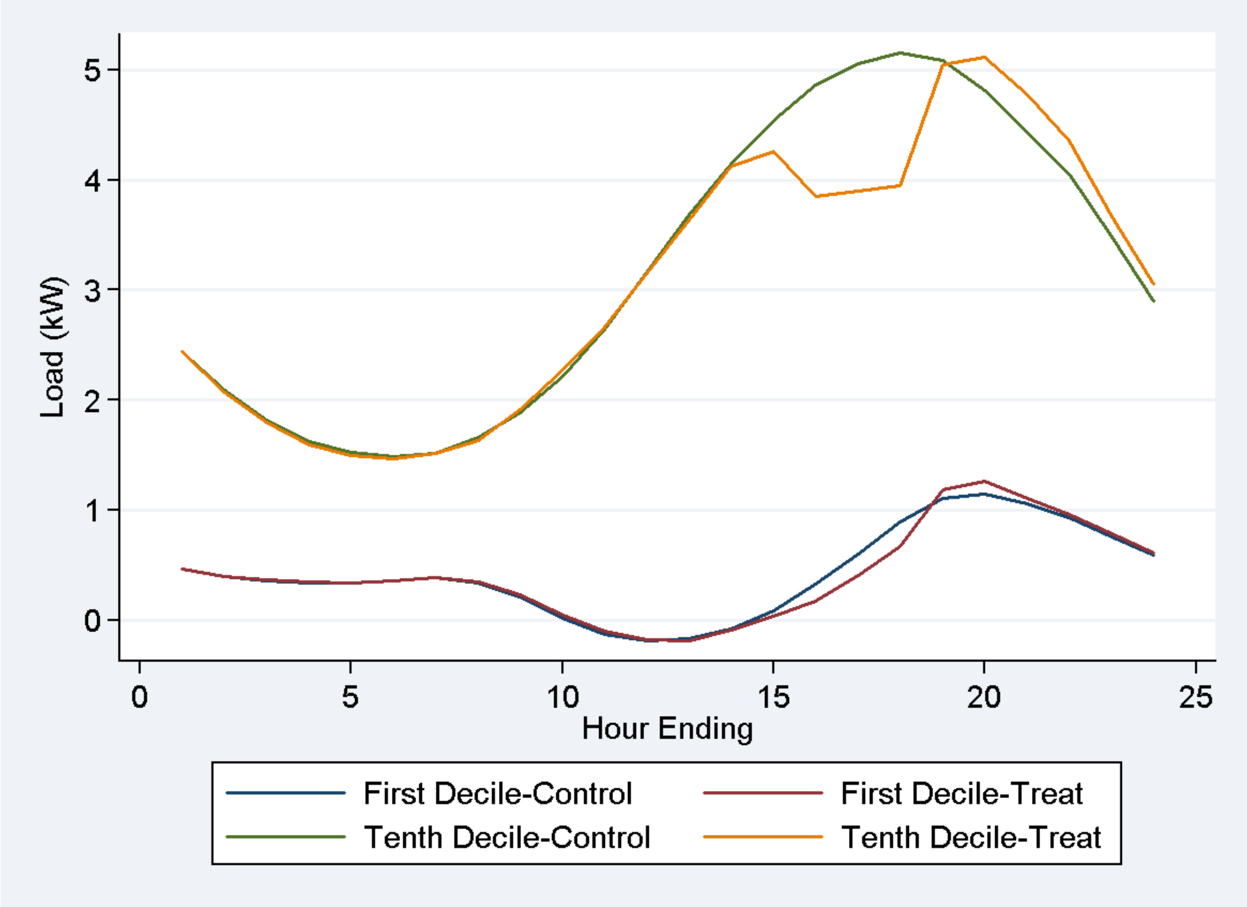
Table 4–8: Average Event Impacts by Usage Decile[15]

Usage Decile	Average Summer Load (kW)	Average Peak Period Load (kW)	Average per Customer Impact from 3 to 6 PM (kW)	Average Percent Impact from 3 to 6 PM
1	0.22	0.71	0.17	24.1%
2	0.46	1.25	0.27	21.6%
3	0.59	1.64	0.32	19.5%
4	0.71	1.97	0.40	20.3%
5	0.84	2.32	0.48	20.7%
6	0.98	2.67	0.56	21.0%
7	1.14	2.99	0.64	21.4%
8	1.33	3.35	0.73	21.8%
9	1.60	3.77	0.80	21.2%
10	2.24	4.74	1.01	21.3%

Figure 4–2 further illustrates the variation in impacts and usage throughout the population. The lines at the top of the graph represent the treatment and control group loads on the August 1 event for customers in the highest decile, while the lines at the bottom of the graph show the treatment and control usages for customers in the first decile. The findings shown in the figure combined with those in Table 4–8 suggest that PG&E could increase program impacts by focusing marketing efforts on customers with higher-than-average monthly usage.

15 The impacts in this table are for only the non-cascading event days

Figure 4–2: Impacts for August 1 Event – Highest and Lowest Summer Usage Deciles



4.3 Comparison of Ex Post Impacts to Previous Years

Compared to previous years, the ex post load impacts for 2014 were slightly lower than the impacts found in prior years after adjusting for differences in weather. There is only one hour that is common to most events in 2011–2014, which is from 4 to 5 PM. Table 4–9 shows the average load reduction per device for each event and the average event for the four years from 2011 to 2014 for the common hour. In addition, the table shows the average temperature for the first 17 hours of the day (*mean17*) for each event. As seen, the load impacts vary significantly across events and are generally correlated with *mean17*. The average impact for 2014 events was in line with averages from past years; however, the average temperature during event days in 2014 was slightly higher. Given the higher temperatures, we would have expected 2014 impacts to be slightly higher than in past years.

Table 4–9: Load Impact per Device from 4 to 5 PM for All Events in 2011–2014

Date	SmartRate Day[16]	*Mean17* (°F)	Load Reduction from 4 to 5 PM (kW)
2011			
15-Jun-11	No	77.1	0.33
21-Jun-11	No	82.2	0.76
22-Jun-11	No	79.9	0.57
24-Aug-11	No	78.6	0.67
6-Sep-11	No	72.9	0.38
7-Sep-11	No	76.6	0.52
8-Sep-11	No	74.3	0.47
Average 2011	**N/A**	**77.4**	**0.53**
2012			
9-Jul-12	No	72.5	0.44
10-Jul-12	No	76.0	0.63
11-Jul-12	No	80.1	0.65
12-Jul-12	Yes	79.9	0.63
2-Aug-12	Yes	76.2	0.60
13-Aug-12	Yes	80.9	0.67
13-Sep-12	No	74.4	0.44
14-Sep-12	No	73.2	0.29
1-Oct-12	No	75.6	0.34
1-Oct-12*[17]	No	75.6	0.49
Average 2012	**N/A**	**76.5**	**0.52**
2013			
1-Jul-13	No	83.3	0.76
2014			
30-Jun-14	No	81.8	0.63
30-Jul-14	Yes	79.3	0.52
1-Aug-14	Yes	81.2	0.64
11-Sep-14	No	76.8	0.33
Average 2014	**N/A**	**79.8**	**0.53**

16 Dually-enrolled customers are excluded from the ex post analysis on SmartRate days.

17 Two test events were called on 10/1/2012. The first occurred from 2 to 5 PM and the second from 4 to 6 PM.

4.4 Comparison of Impacts for Dually Enrolled and SmartAC-only Customers

Historically, the load impacts for customers enrolled in both SmartAC and SmartRate have been challenging to estimate because most SmartAC events have been called on SmartDays.[18] In these situations, it is difficult to separate the impacts of the two programs on dually-enrolled customers since they experience both programs simultaneously. The exception to this was in 2012, when three SmartAC events did not occur on SmartDays (July 12, August 2, and August 13). This allowed impacts to be estimated for dually-enrolled customers on those SmartAC-only days and then compare them with the impacts for SmartAC-only customers to estimate impacts for dually-enrolled customers on the other event days. In 2013, there were no SmartAC-only events and so the results from 2012 were used to factor dually enrolled customers into the per customer and aggregate impacts. For 2014, there were two events called on non-SmartDays (July 30 and August 1), which allowed for an analysis similar to 2012.

Table 4–10 shows the whole-building reference load for SmartAC-only and dually-enrolled customers during event hours (3 to 6 PM) on August 1 by LCA. Across all LCAs, dually-enrolled customers have reference loads that are between 6 and 23% lower than the corresponding reference loads for SmartAC-only customers. The biggest difference is in the Bay Area, which also has the greatest number of customers. One possible explanation for this pattern is that dually-enrolled customers have smaller homes, on average, than their SmartAC-only counterparts. If this is indeed the case and if the size of an AC unit is also proportional to home size, then the absolute impacts for dually-enrolled customers can be expected to be lower than the impacts for SmartAC-only customers because there is less available load to be displaced by cycling.

Table 4–10: Reference Loads for SmartAC-only and Dually Enrolled Customers for August 1 Event (3–6 PM)

Local Capacity Area	SmartAC-only Reference Load (kW)	Dually Enrolled Reference Load (kW)	% Difference	Number of Customers Analyzed	
				SmartAC-only	Dually-enrolled
Greater Bay Area	2.27	1.75	-23%	36,810	15,003
Greater Fresno Area	3.47	3.25	-6%	13,211	4,031
Kern	3.54	3.34	-6%	5,097	2,014
Northern Coast	1.38	1.22	-12%	6,326	2,196
Other	3.04	2.71	-11%	24,315	8,024
Sierra	3.37	3.09	-8%	11,793	4,757
Stockton	3.18	2.80	-12%	10,318	4,144
All	**2.81**	**2.41**	**-14%**	**107,870**	**40,169**

[18] Dually-enrolled customers have their AC units cycled on SmartDays and also experience SmartRate prices. Since usage is metered only at the whole-house level, separately identifying the impacts of the two treatments is not possible.

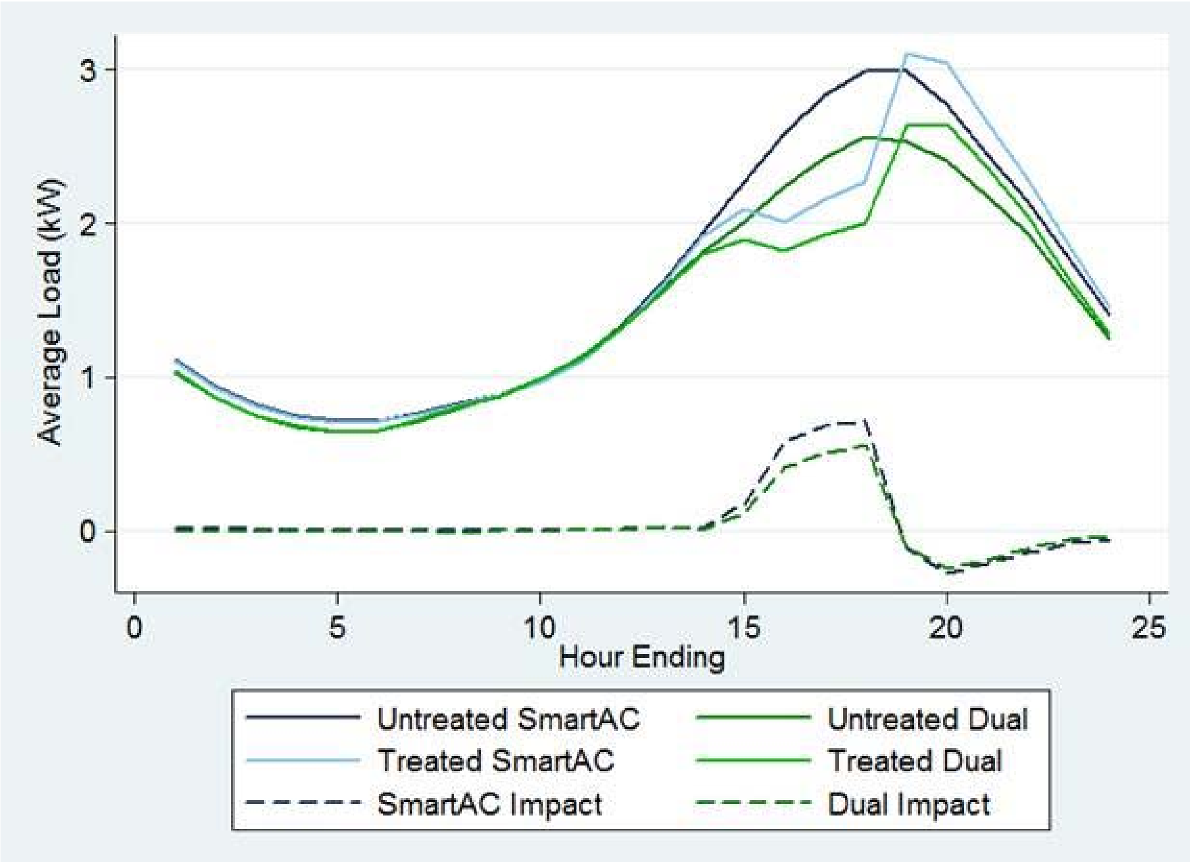
A comparison of the dually-enrolled and SmartAC-only impacts is presented in Table 4–11. As expected, absolute impacts for dually enrolled customers are smaller than for SmartAC-only customers; however, on a percentage basis the impacts are more similar. Absent any SmartAC-only events to work with, the 2013 evaluation assumed that the percentage impacts for both types of customers were equal. Based on the results in Table 4–11, this assumption appears to be more or less correct as the impacts for SmartAC-only customers are generally 0 to 4 percentage points larger than those for dually enrolled customers.

Table 4–11: 2014 Impacts for SmartAC-only and Dually-enrolled Customers

Date	Hour Ending	Impact (kW)		Impact (%)	
		SmartAC-only	Dually-enrolled	SmartAC-only	Dually-enrolled
30-Jul-14	11	0.07	0.04	7%	4%
	12	0.13	0.09	11%	8%
	13	0.19	0.13	13%	10%
	14	0.22	0.18	13%	11%
	15	0.34	0.23	17%	13%
	16	0.45	0.33	20%	17%
	17	0.55	0.41	22%	19%
	18	0.60	0.48	22%	21%
	19	0.52	0.44	19%	19%
	20	0.45	0.36	17%	16%
1-Aug-14	16	0.58	0.41	22%	18%
	17	0.68	0.51	24%	21%
	18	0.72	0.56	24%	22%
Average	**16**	**0.52**	**0.37**	**21%**	**18%**
	17	**0.62**	**0.46**	**23%**	**20%**
	18	**0.66**	**0.52**	**23%**	**22%**

Load curves for the two groups on the August 1 event are shown in Figure 4–3. Although SmartAC-only customers have higher loads (and impacts) during event hours, loads leading up to the event are very similar. Under the hypothesis that SmartAC-only houses are larger than those for dually-enrolled customers and that AC loads are proportional to home size, this would suggest that other loads in the house are comparable between the two groups and that the selection mechanism underlying customer enrollment in SmartRate is significantly influenced by AC usage. Put another way, it suggests that SmartRate households with central air conditioning use their air conditioning much less than SmartAC-only customers. Such a result would also imply that home size is not strongly correlated with non-AC loads for this population of customers. These links are difficult to definitively establish given the current data; however, the pattern is interesting and perhaps worth further investigation outside of this evaluation.

Figure 4–3: Load Curves for SmartAC-only and Dually-enrolled Customers on Event Day (August 1, 2014)



4.5 Impacts for Single and Multiple Device Customers

Another segmentation of interest is how impacts vary with the number of devices installed at a particular premise. Customers with more than one device are unlikely to have both devices fall into the same group; therefore, what happens when one AC unit in a home is cycled but another is not? More specifically, does cycling one AC unit cause another unit to work harder in an attempt to compensate or is each unit independent? Another factor to consider is whether each AC unit in a home with multiple devices is similar in size to the units in single-device homes. If each device in a multiple-device household is smaller than its SmartAC-only counterpart, then cycling one of the units in the multiple-device home could result in smaller impacts even if its usage is independent of the other unit(s).

The answers to these questions can be investigated by comparing the impacts of multiple device customers with customers who only have only one device.[19] Figure 4–4 shows the load curves (treatment and control) for these groups of customers during the August 1 event (top part of graph) along with the impacts for each group (bottom part). Despite the fact that customers with multiple SmartAC devices have larger loads throughout the day, impacts are roughly twice

[19] For the purposes of this analysis, we assume that the number of devices enrolled in SmartAC is equal to the number of AC units in the home.

as large for customers with only one device. The impacts shown in Table 4–12 confirms this as the average per customer impact during the event window for multiple-device customers is slightly less than half of the per customer impact for single-device customers (0.25 kW compared to 0.52 kW).

Figure 4–4: Load Curves for Single and Multiple-Device Customers on Event Day (August 1, 2014)

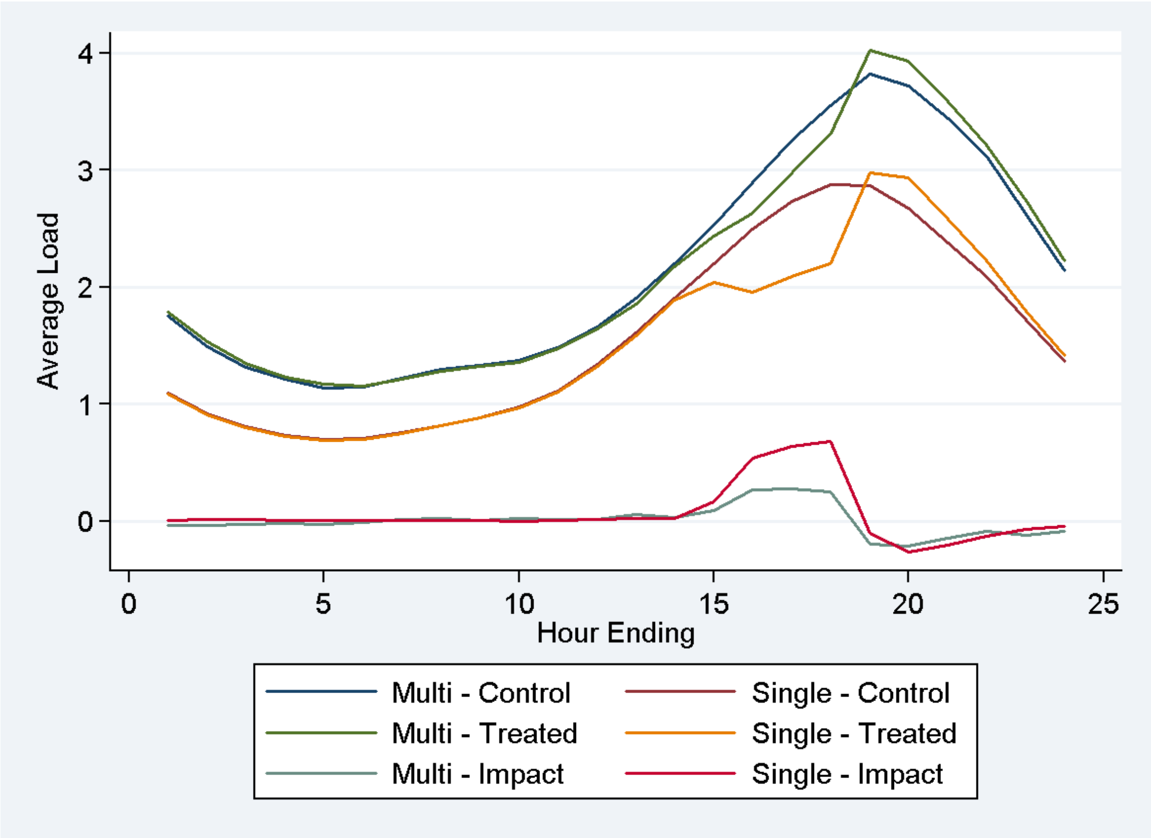


Table 4–12: Load Impacts for Multiple and Single Device SmartAC Customers on Event Days (4–6 PM)

Date	Hour Ending	Impact (kW)		Impact (%)		Enrolled Customers	
		Multiple-Device Customers	Single-Device Customers	Multiple-Device Customers	Single-Device Customers	Multiple-Device Customers	Single-Device Customers
30-Jun-14	16	0.28	0.56	10.2%	22.0%	11,684	99,501
	17	0.34	0.63	10.6%	22.8%	11,684	99,501
	18	0.37	0.67	10.6%	22.8%	11,684	99,501
30-Jul-14	16	0.37	0.42	13.9%	19.2%	15,951	135,538
	17	0.38	0.52	12.7%	21.1%	15,951	135,538
	18	0.39	0.57	12.1%	21.5%	15,951	135,538
1-Aug-14	16	0.26	0.53	9.1%	21.5%	15,863	134,779
	17	0.28	0.64	8.5%	23.3%	15,863	134,779
	18	0.25	0.68	6.9%	23.5%	15,863	134,779
11-Sept-14	16	0.11	0.26	7.2%	16.0%	11,568	98,352
	17	0.19	0.33	9.0%	16.9%	11,568	98,352
	18	0.19	0.36	7.5%	16.4%	11,568	98,352
Average	**N/A**	**0.28**	**0.51**	**9.9%**	**20.6%**	**N/A**	**N/A**

These results provide evidence that either each individual AC unit in a multiple-device home is smaller than the AC units in single-device homes or that uncalled AC unit works harder to maintain the desired set point during an event (or some of both). Without more information about the size of customers' homes or submetered AC usage, it is very difficult to determine which of these explanations is more likely to be true. For the purpose of estimating aggregate impacts in the ex post and ex ante load impact tables in this report, it is assumed that on a *customer* basis, the impacts for customers with multiple devices is equal to the impacts for single-device customers.

4.6 Load Impacts for Net Metered Customers

Impacts were estimated separately for solar customers to allow for comparisons to the general population and to examine how demand response programs perform for this growing class of customers. Table 4–13 and Figure 4–5 show the overall impacts of the SmartAC program during the August 1 event. The duck curve shape is clearly visible for both treatment and control customers, with load reductions ranging from 0.6 kW to 0.8 kW per customer during the event window of 3 to 6 PM. Similar to non-PV customers, there is a snapback period after the event ends when the load for treatment customers increases.[20] In terms of the impact on the shape of

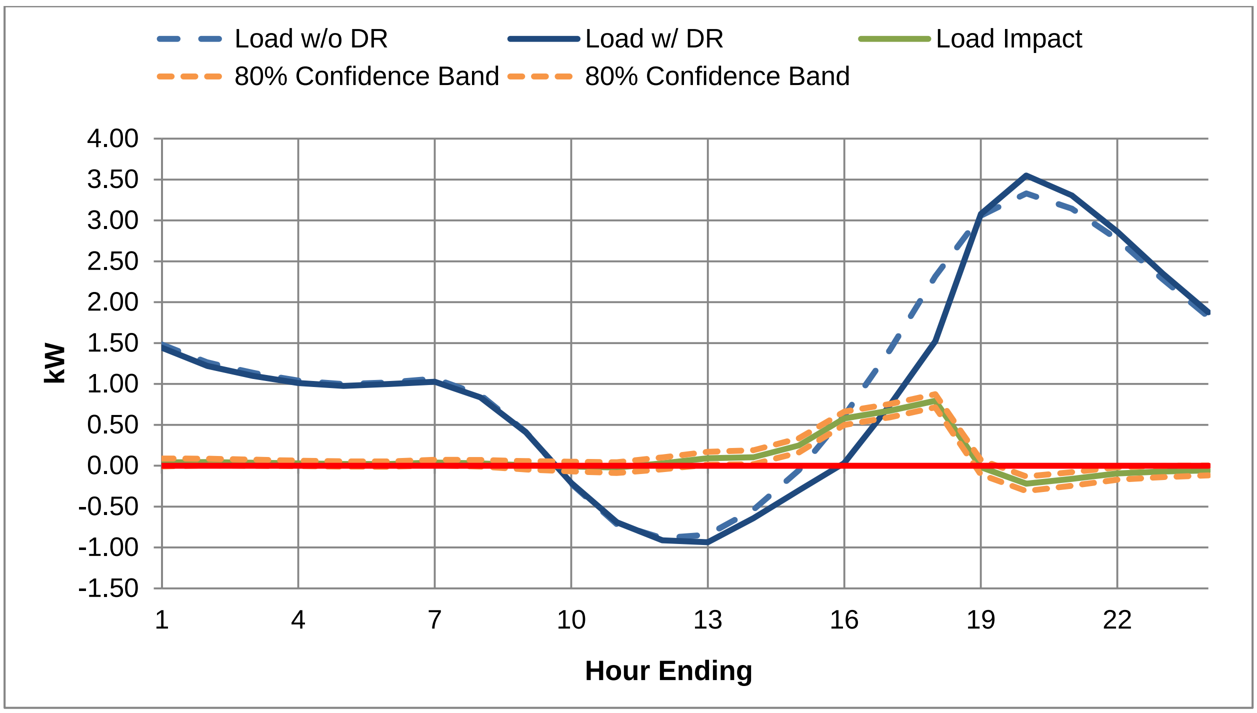
[20] Due to the timing of this particular test event, the snapback actually causes treatment customers to have a higher peak load than control customers on average.

the load curve, a SmartAC event called during the late afternoon/early evening hours creates a gentler ramp in the early afternoon hours but causes the ramp to become steeper toward the end of the event window.

Table 4–13: SmartAC Load Impacts for Solar Customers on Event Day (August 1, 2014)

Hour Ending	Reference Load (kW)	Impact (kW)	Aggregate Impact (MW)	Average Temperature in the Hour (°F)
16	0.61	0.58	1.01	98
17	1.41	0.67	1.17	98
18	2.32	0.79	1.38	97
Average Hour During Event	**1.45**	**0.68**	**1.19**	**98**

Figure 4–5: SmartAC Load Impacts for Solar Customers on Event Day (August 1, 2014)



Though it is tempting to examine solar results within individual LCA regions, limited sample sizes at finer geographic scales make such results noisier than the overall impact estimates. In several individual LCAs, treatment and control loads diverge noticeably during hours leading up to the start of the event, which is unexpected in a randomized control trial setting. This outcome most likely reflects the lack of a large enough sample size in either the treatment or control group (or both) to yield an accurate estimate of the average load. For solar customers, we would expect to need even larger samples to achieve a similar level of accuracy as for non-solar customers due to the increased variability in solar customer loads.[21]

[21] Production from individual PV systems is particularly susceptible to cloud cover and can be very volatile on days having a mix of both clouds and sun.

5 Post Event Survey Analysis for September 11 Event

Following the SmartAC event on September 11, approximately 650 customers were surveyed via telephone. The total number of completed surveys is split roughly into thirds between control, treatment, and dually-enrolled customers.[22] In this context, the control group consists of SmartAC-only customers who did not have their devices cycled on September 11. The analysis below evaluates customer thermal comfort, awareness of events, overall satisfaction with the SmartAC program, demographics, and other questions where responses from treatment and control groups were significantly different. A copy of the survey instrument is contained in Appendix A.

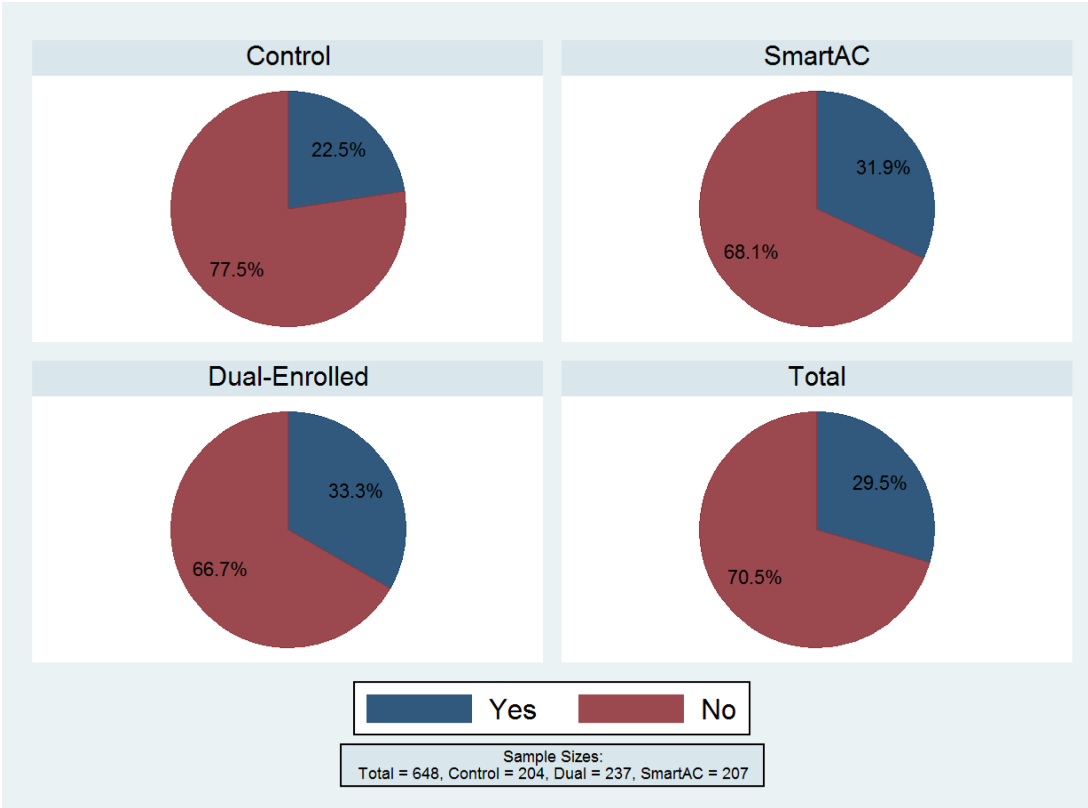
It is important to note that September 11 was a SmartAC + SmartRate day, meaning that all customers in the dually-enrolled group experienced load control. Because the control group does not contain any dually-enrolled customers, making comparisons between the dually-enrolled group and the SmartAC control group is not always advisable and any differences should not be interpreted as being caused by SmartRate. We present the results for the dually-enrolled customers alongside the results for the SmartAC-only survey groups (treatment and control) primarily for completeness, conciseness and to allow for a comparison of response levels for reference purposes.

5.1 Thermal Comfort of Customers During an Event

An important topic in the survey is thermal comfort. Question 4 asks survey participants if the temperature in their house was uncomfortable during the period immediately leading up to and after the event. All survey participants responded to this question and a breakdown of the responses is shown in Figure 5–1. More members of the SmartAC group reported being uncomfortable than in the control group (difference is significant at 95% confidence level), while the responses of dually enrolled and SmartAC-only customers are about the same.

[22] All surveys were fully completed so that there are no missing responses for any of the questions. No surveys were terminated due to customers having a household affiliation with PG&E.

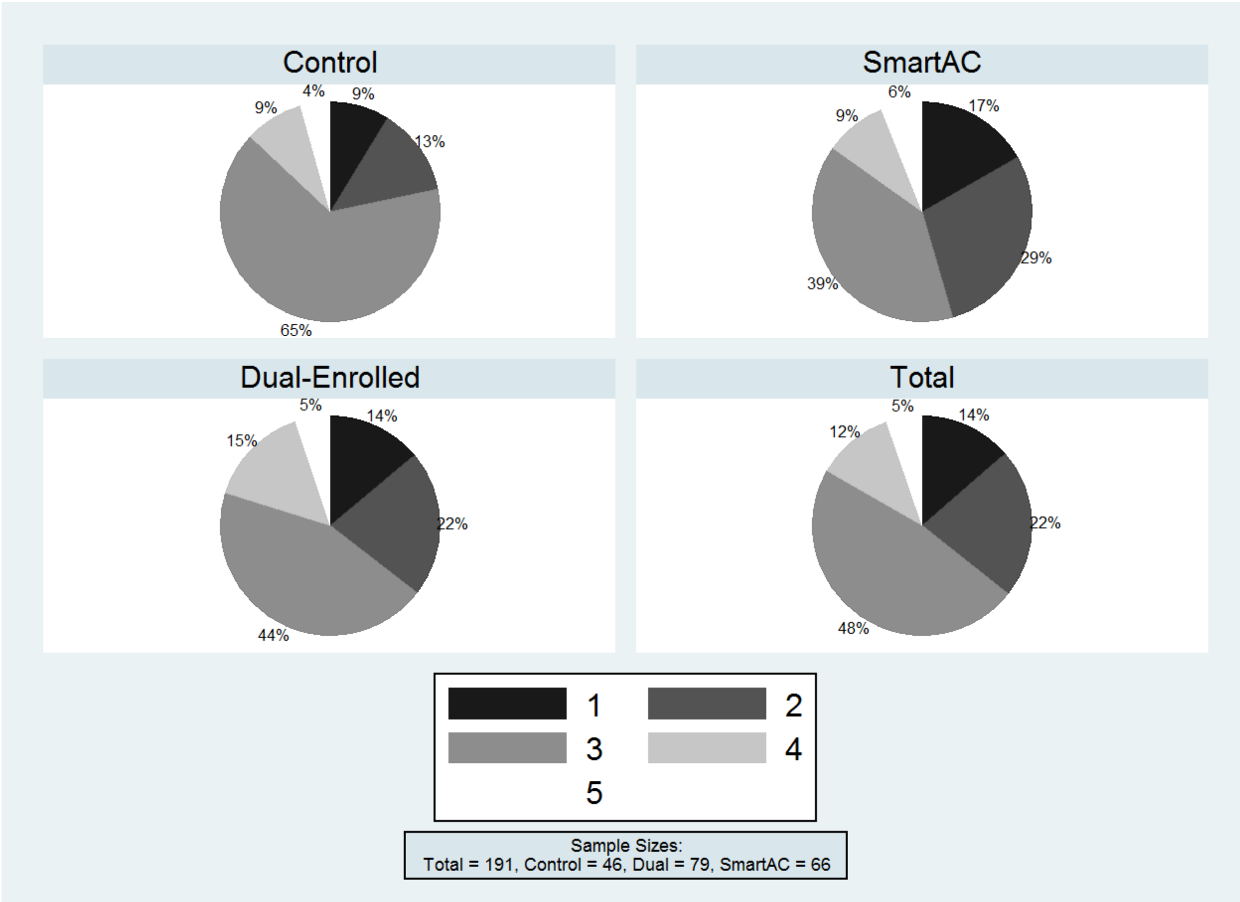
Figure 5–1: Recent Thermal Discomfort



The next question in the survey (4a) asks for a numerical rating of thermal discomfort on a scale of 1–5, where 1 signifies the lowest level of comfort. As shown in Figure 5–2, the SmartAC group contained more customers who reported being uncomfortable and those customers also reported slightly higher levels of discomfort. However, pairwise chi-square ratio tests show that the differences in the distributions of responses between the control group and treatment groups are not statistically significant (again at the 95% confidence level).[23]

[23] The difference in responses between the SmartAC-only group and the control group is significant at a 90% confidence level, but not 95%. The small sample size constrains the statistical power of the test.

Figure 5–2: Ratings of Thermal Discomfort



Question 5 asks survey participants to elaborate by giving start and end times for their thermal discomfort. The control group, SmartAC group, and dually-enrolled group reported average discomfort start times of approximately 2:55 PM, 3:40 PM, and 4 PM, respectively. The average perceived end time of the event by each group was 5:45 PM, 6:30 PM, and 6:05 PM. The actual event occurred from 3 to 6 PM. Histograms of these responses regarding start times and end times are shown in Figure 5–3 and Figure 5–4, respectively.

Figure 5–3: Reported Thermal Discomfort Start Times[24]

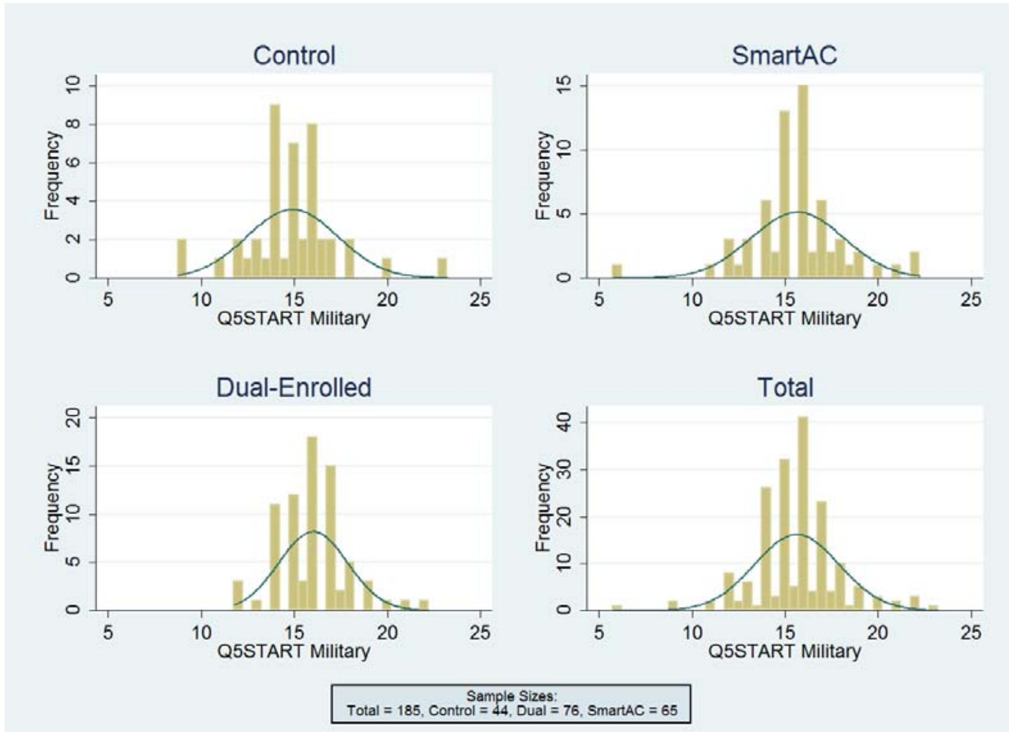
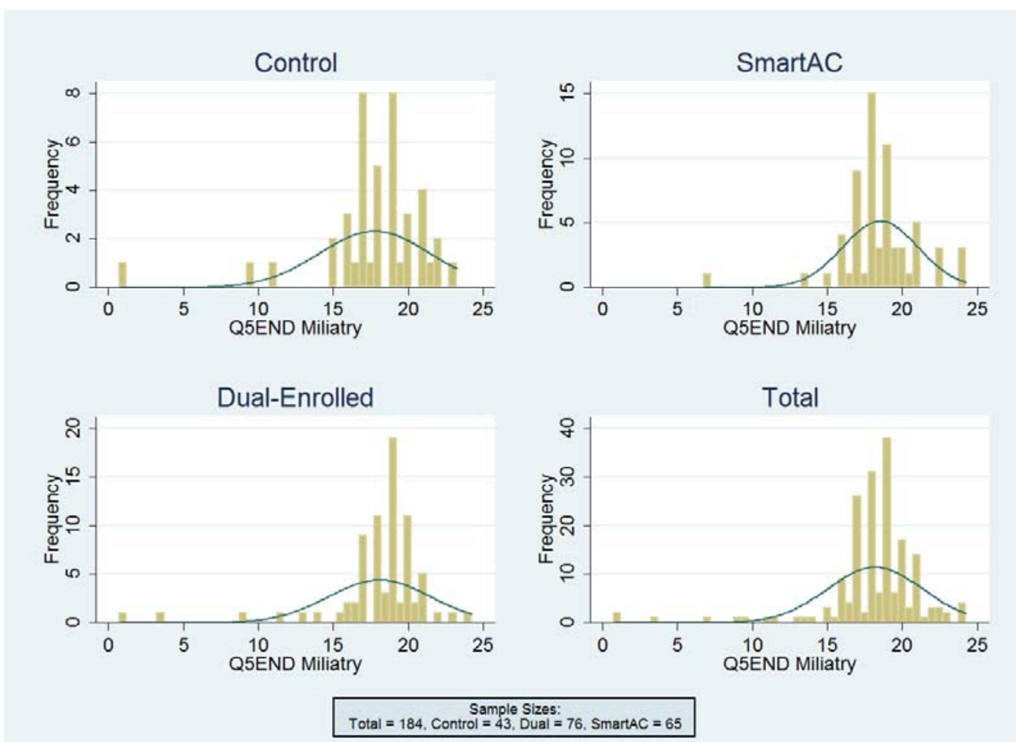


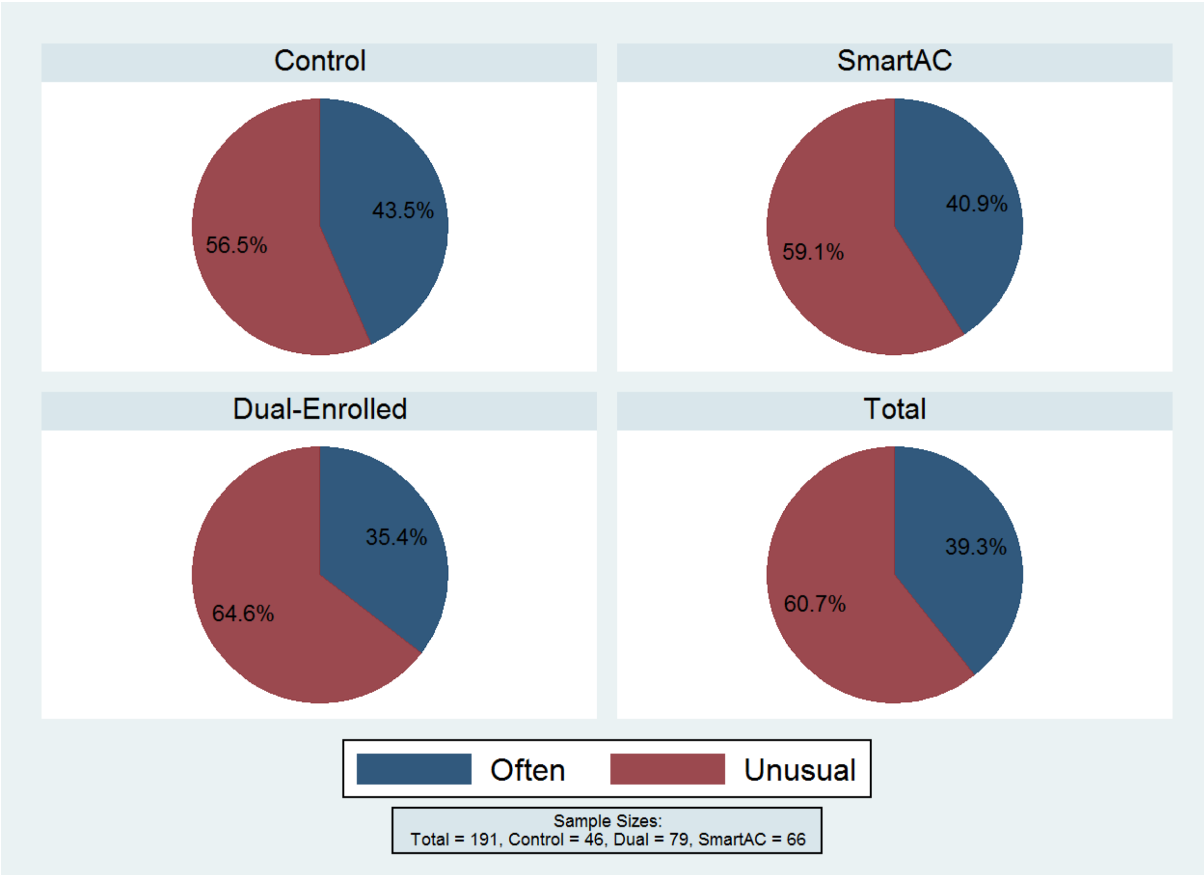
Figure 5–4: Reported Thermal Discomfort End Times



[24] Participants who responded "Unsure" (6 in the start times, 7 in the end times) were dropped

Among those whose homes were uncomfortable in the period around the event, 39% described this discomfort as typical during those hours (Figure 5–5) and there is no statistically significant difference across groups.

Figure 5–5: Is there often thermal discomfort during those hours?

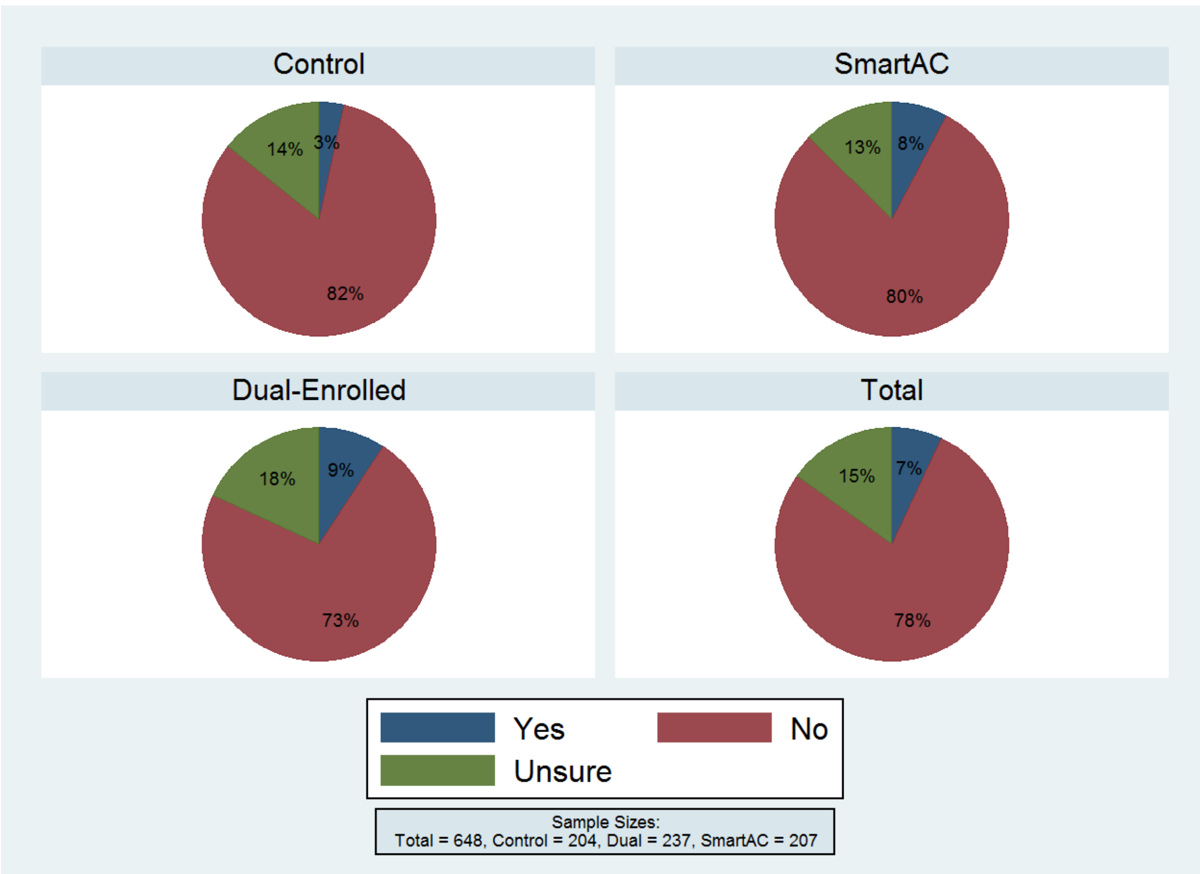


5.2 Customer Awareness of Event

The survey asks several questions pertaining to customer awareness of the event, which does not necessarily correspond directly to their thermal discomfort. Question 7 asks participants who reported recent discomfort in Question 4, “What do you think caused the temperature in your home to be uncomfortable?” Only 16 out of 191 participants attributed the thermal discomfort to PG&E “controlling” the air conditioner, whereas 129 (67.5%) of responses attributed the discomfort to the “very hot day” and 27 (14.1%) reported that their AC unit was either off or not working properly. No significant difference was found between groups.

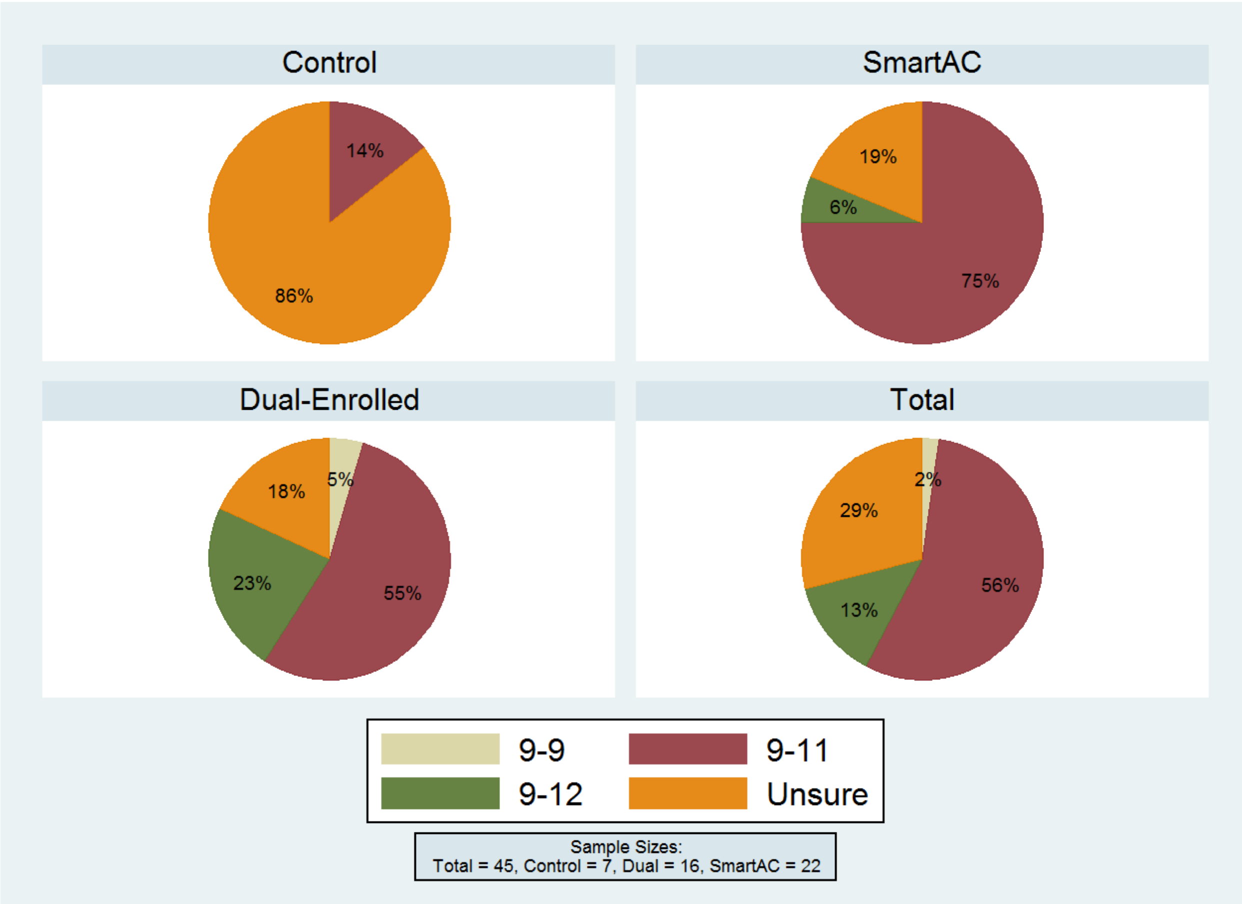
Out of all respondents, 45 customers (7%) believed that their device was activated at some point during the days leading up to the survey (Figure 5-6). Question 13 follows up by asking survey participants how they noticed the event. The most common responses for this question were indoor temperature, not hearing the AC running, and noticing the activation light (24%, 22%, and 13% respectively). Question 14 asked what time participants first noticed the event, with 40% of respondents reporting that they noticed between 3 PM and 4:59 PM. For those who noticed the event, 31% described the time during the event as “somewhat difficult” or “very difficult” (Q18) and only 16 people remember taking “any action” in response to the event (Q15), such as contacting PG&E, changing activities, or relocating. Dually-enrolled customers were the most likely to either notice the activation or to be unsure, which is expected given that they receive notices ahead of SmartRate days. Figure 5–6 shows that the SmartAC group was more likely to believe their device was activated than the control group but the majority of customers in the three groups did not notice their SmartAC device being activated. Differences between the control and treatment groups are not statistically significant but the responses of the control and dually enrolled groups are significantly different at 95% confidence.

Figure 5–6: “Did you notice that your SmartAC device was activated in the last few days?”



Though the sample sizes are small, a breakdown of the days participants thought their device was activated is presented in Figure 5–7. Three-quarters of SmartAC-only customers were able to correctly identify the event day (September 11), while there were a handful of control group participants who mistakenly claimed their device was activated. Importantly, the day following this event day (September12) was also a SmartRate day, which explains why the distribution of responses is significantly different for dually-enrolled customers. Pairwise comparisons between the responses of control vs. treatment customers and control vs. dually-enrolled customers are both significant at the 95% level.

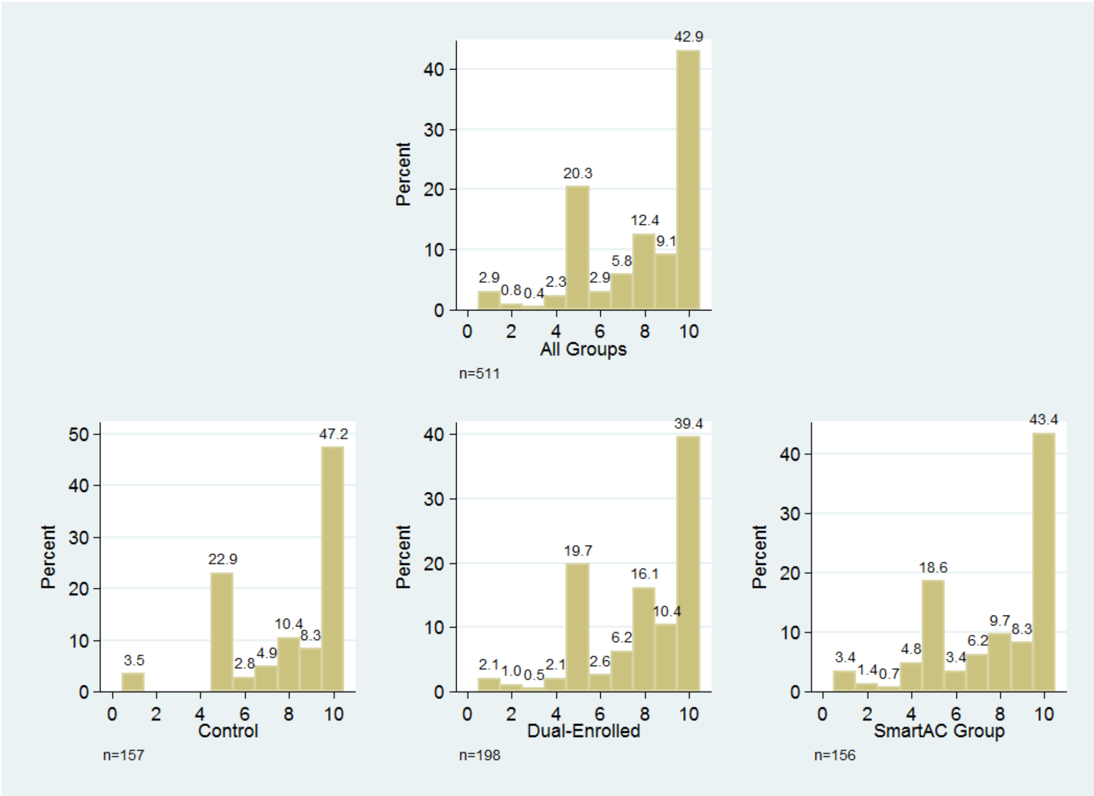
Figure 5–7: "On which day was the device activated?"



5.3 Customer Satisfaction with SmartAC

Survey question 9 asked participants to evaluate their overall satisfaction with the SmartAC program. The responses (Figure 5–8) indicate that customers called for the September 11 event are slightly less likely to have a satisfaction level of "10" compared to the control group. Furthermore, dually-enrolled customers are less likely to report a "10" for satisfaction than SmartAC-only customers. Overall, most customers (~70%) reported their satisfaction with SmartAC as at least a 6 out of 10 and there is no statistically significant difference in satisfaction across the 3 groups.

Figure 5–8: Customer Satisfaction with SmartAC



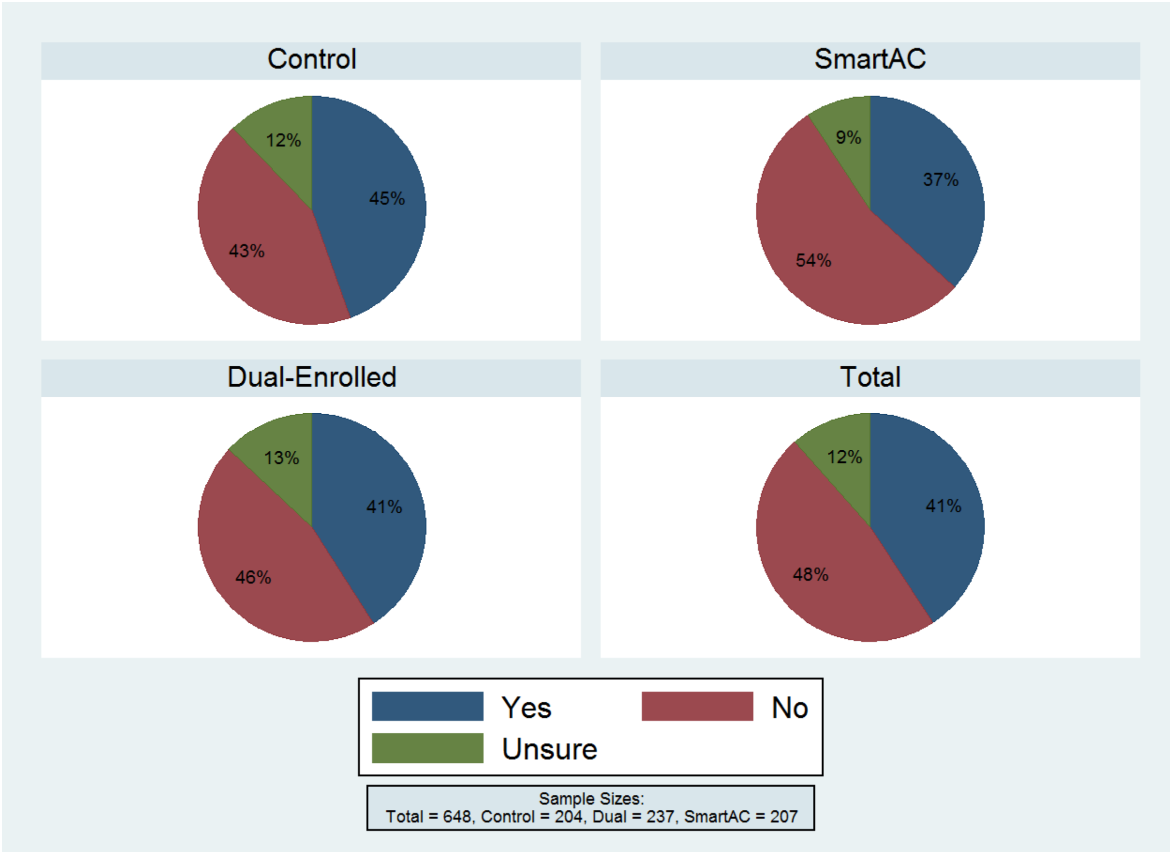
Question 10 asked survey participants for an open-ended explanation of their satisfaction rating. Customers with high satisfaction typically reported something to the effect of the program being unnoticeable. Customers with middling ratings almost always had a similar response, claiming to have “no opinion” or “not even noticing” and giving a rating of 5 despite having no complaints. Popular responses for low ratings included having a higher bill than before, problems with their AC unit being attributed to the program, or having home issues such as a small area or low insulation that make reducing the AC more noticeable.

5.4 Other Differences in Responses

In addition to the topics discussed above, we also examined the rest of the survey in search of any questions where customer responses were significantly different between the control group, SmartAC-only group, and the dually-enrolled group.

One area of apparent difference between treatment and control customers is awareness regarding the ability to opt out of events. Question 19 asked customers about this topic directly and the responses are shown in Figure 5–9. About 54% of SmartAC-only treatment customers reported being unaware of their ability to opt-out of events compared to about 43% of control group customers. This difference is significant at a 90% confidence level.

Figure 5–9: Opt Out Awareness



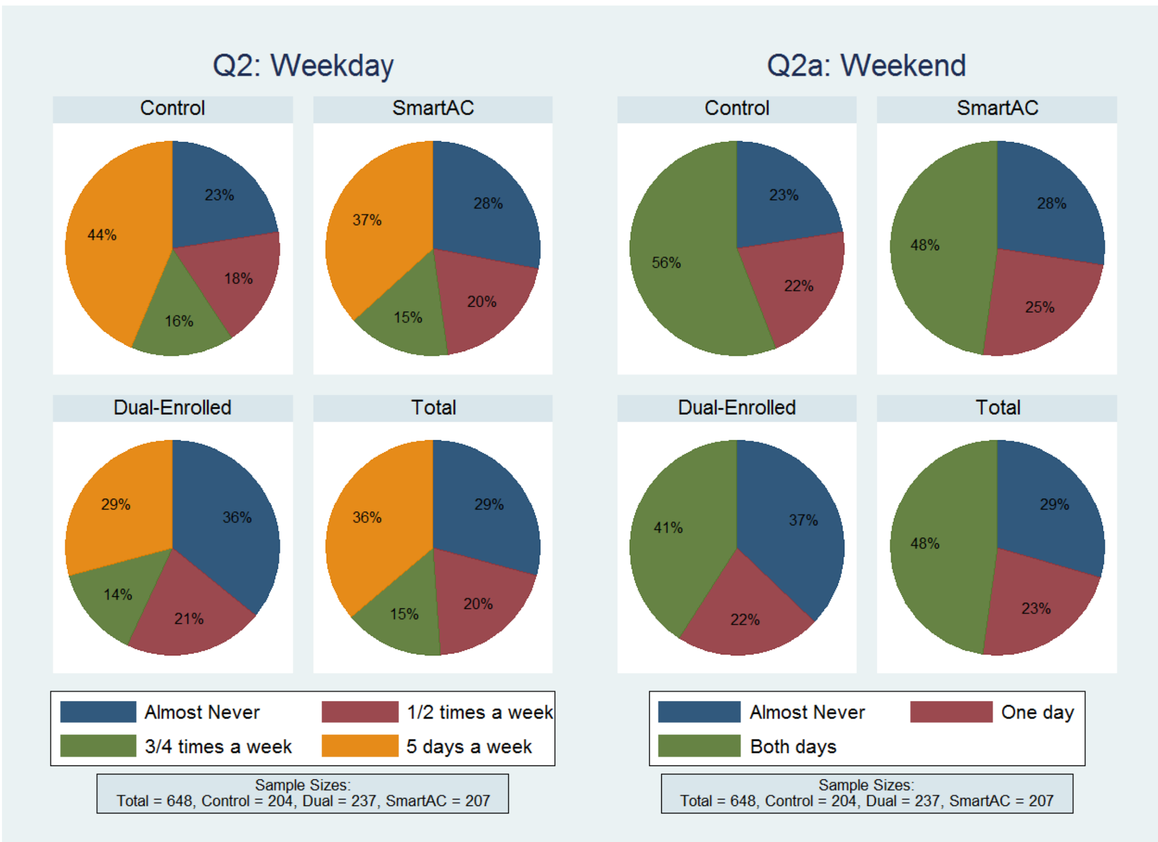
Another apparent difference between the treatment and control groups for this event is the propensity for customers to use AC on weekdays versus weekends. Question 29 asked when customers would be more likely to use their AC. Possible answers include “Weekdays,” “Weekends,” “I always use my AC,” “It varies,” “Equally likely,” and “I never use my AC.” The distributions of these responses are shown in Figure 5-10. SmartAC-only customers were significantly more likely to say “It varies” than control group customers (20% vs. 9%) and less likely to say that they use AC equally on weekdays and weekends (41% vs. 53%). Other than these differences, however, the distribution of responses between the two groups is relatively similar. Regarding usage patterns specifically, the survey contains nine questions in addition to Question 29:

- Question 2/2a (Figure 5–11): “Could you tell me how often you or someone else in your household uses your air conditioning on summer weekday/weekend afternoons between 12 PM and 6 PM?”
- Question 3/3a (Figure 5–12): “Could you tell me how often you or someone else in your household uses your air conditioning on summer weekday/weekend evenings between 6 PM and midnight?”
- Question 24 (Figure 5–13): “Which of the following best describes how you operate your central AC system(s) during the summer?”

- Question 25/25a[25] (Figure 5–14): “How often does your central AC run in your home during summer weekday/weekend afternoons?”
- Question 26/26a (Figure 5–15): “Is someone who might control or adjust your AC temperature typically at home during summer weekday/weekend afternoons between 2 and 7 PM?”

While there is no significant difference in responses between the Control group and SmartAC group in these questions, the dually-enrolled group reported significantly less usage on summer afternoons (Question 2/2a). This appears to contradict the consistency between groups in the other questions and is strongly significant (>99% confidence). However, finding a difference in usage patterns between the SmartAC and dually-enrolled populations is not necessarily unexpected since different types of customers could be selecting into each rate.

Figure 5–10: Summer Afternoon AC Usage Behavior (12 to 6 PM)



25 The sample rate is less than 100% for this set of questions because people who claimed in (Q24) either that they do not use central AC in the summer or that they were unsure of their summer central AC usage were screened out.

Figure 5–11: Summer Evening AC Usage Behavior (6 PM to Midnight)

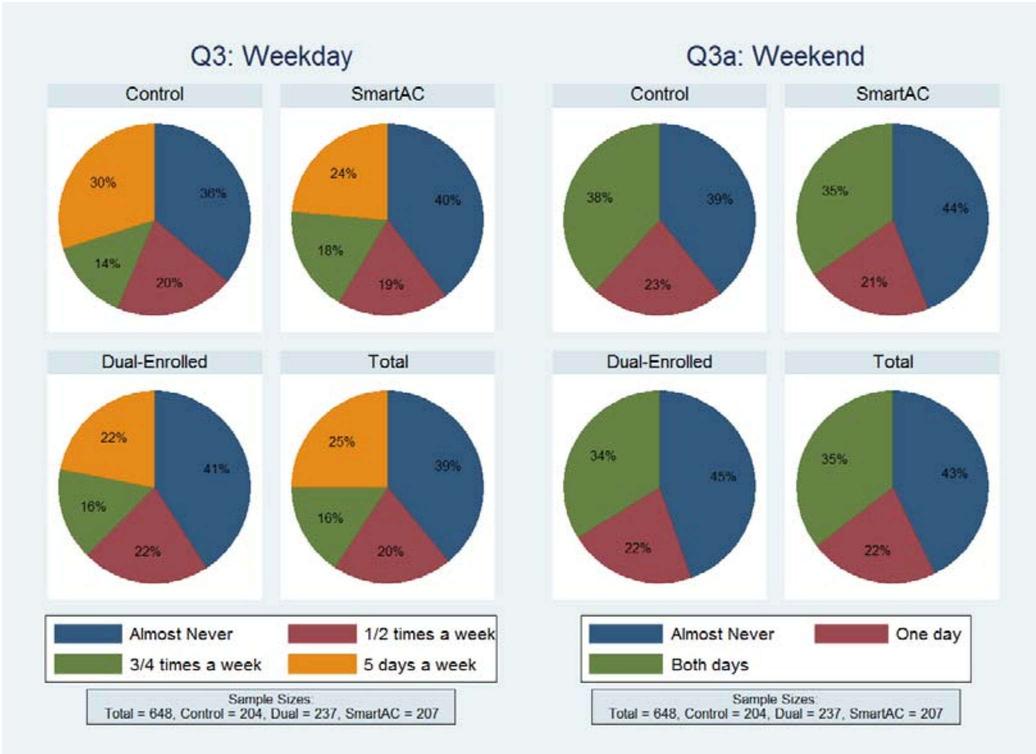
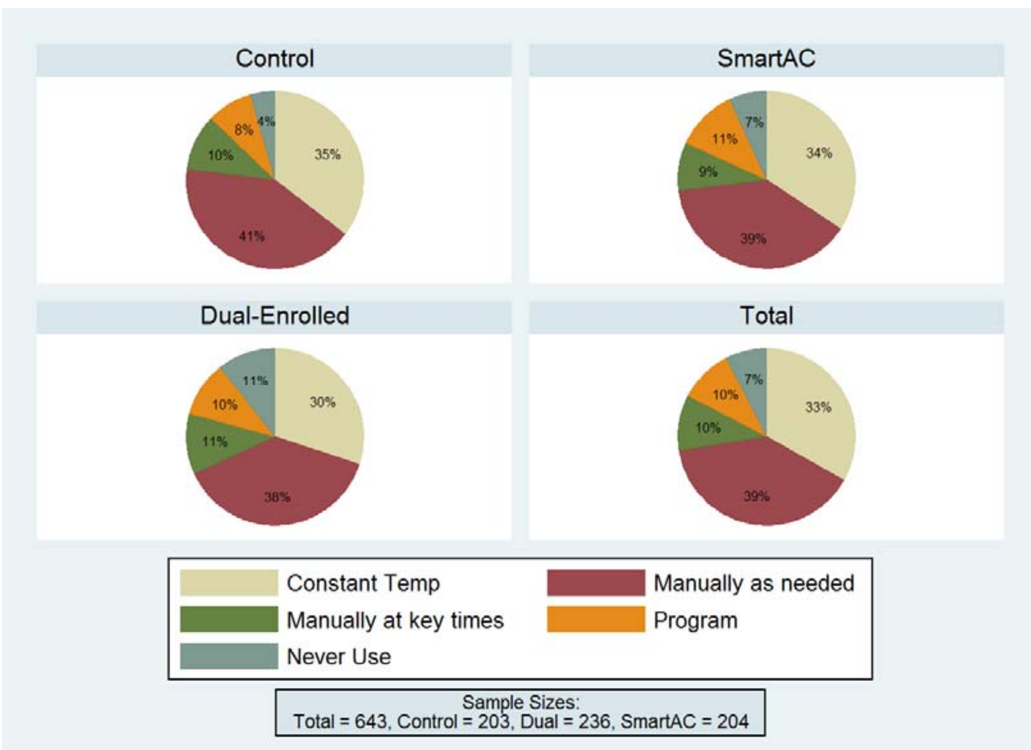


Figure 5–12: Overall Summer Central AC Usage Behavior[26]



26 Doesn't include 5 responses of "Don't know / Not sure"

Figure 5–13: Summer Afternoon Central AC Runtime

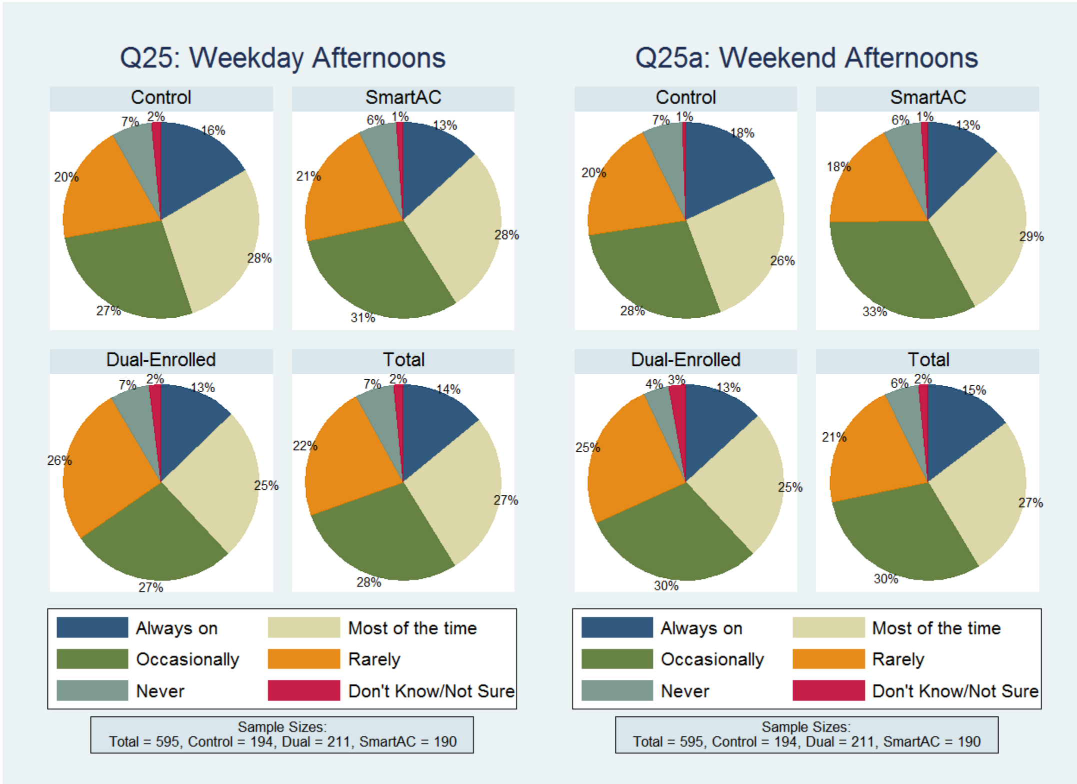
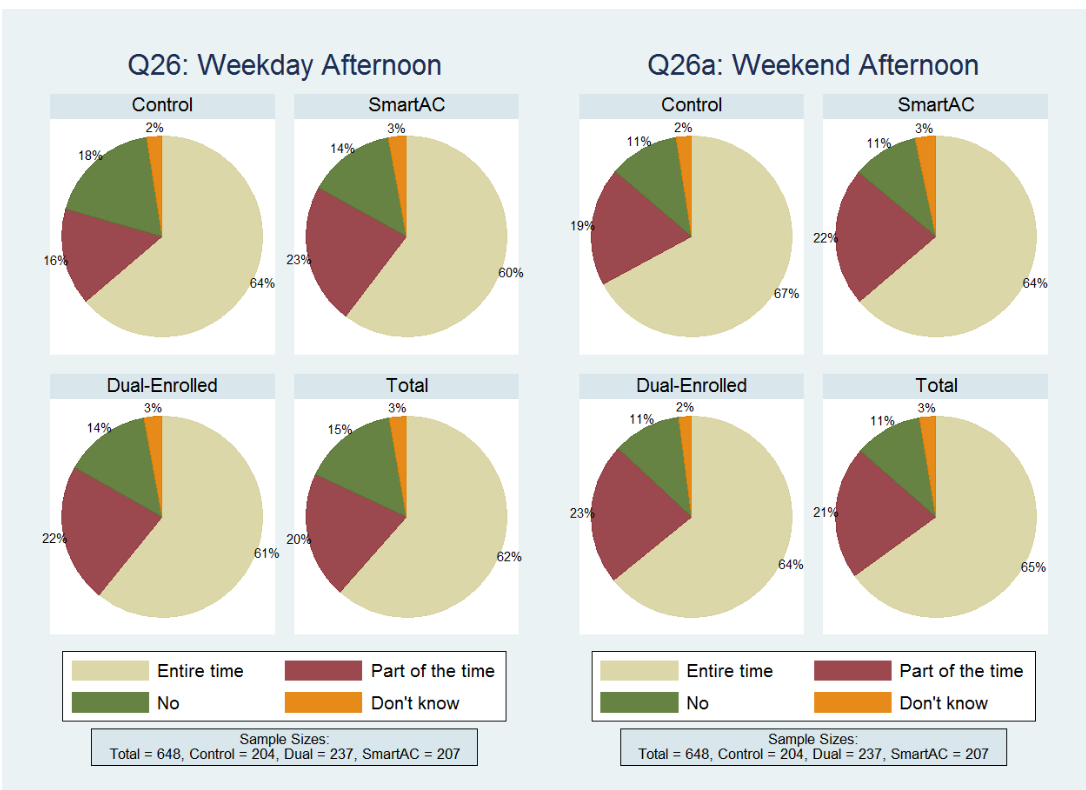
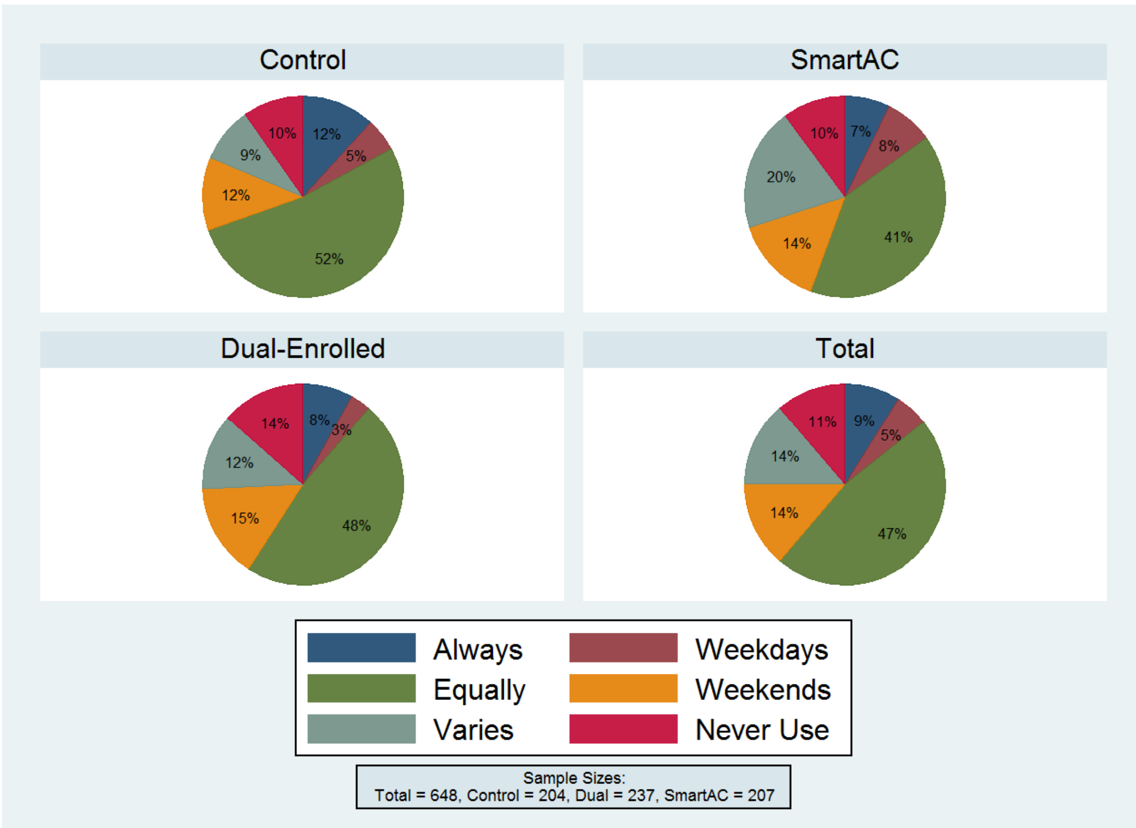


Figure 5–14: Is AC User Home on Summer Afternoons?



Given the few number of questions where responses are significantly different and a lack of sensible hypotheses for what could be causing these differences, we believe it is likely that differences in opt-out awareness and AC usage preferences are due simply to statistical noise and should not be interpreted as meaningful. Question 29 is the only finding of an unexpected difference in usage patterns between the control and SmartAC groups that is significant at a 95% confidence level.

Figure 5–15: Weekend vs. Weekday AC Usage: When are you more likely to use AC?



5.5 Conclusions from Survey

Compared to the control group, SmartAC-only customers were more likely to experience thermal discomfort in the period around the event (32% vs. 23%). For those who experienced discomfort, 42% of customers described it as typical and over 80% attributed the discomfort to the “very hot day” or AC issues.[27] Ratings of discomfort were slightly higher in the SmartAC-only group but this difference was not statistically significant. Only 7% of customers believed that their device was activated at some point during the days leading up to the event and the difference between the control and SmartAC-only groups is not statistically significant. Among those who noticed the event, 31% described it as “somewhat difficult” or “very difficult.”

There is no statistically significant difference in customer satisfaction across the three groups as rated on a 1 to 10 scale by participants who are familiar with the SmartAC program. 94% of the

27 No statistically significant differences were found between the control and SmartAC-only group on these questions.

ratings were a 5 or higher, a cutoff which generally denotes a high level of satisfaction with the program as indicated by corresponding open-ended responses.

Statistically significant differences in opt-out awareness, as well as weekend/weekday usage patterns, were found between the control and SmartAC-only groups but these results seem likely to have been driven by statistical noise from testing so many hypotheses. The SmartAC-only group also reported higher educational attainment and described their type of home differently than the control group. The dually-enrolled group that reported lower summer afternoon AC usage was more likely to report owning a home and was, on average, older than the other two groups. These differences highlight that customers who select into SmartRate are different from SmartAC-only customers in ways that we would expect to affect their energy consumption. It is precisely for this reason that differences between the responses for SmartAC-only customers and dually-enrolled customers are expected.

6 Residential SmartAC Ex Ante Methodology

Ex ante load impacts were estimated based on statistical analysis of ex post load impact estimates from 2011-2014, 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 are based on historical ex post impacts for events[28] that occurred from 2011–2014 and were produced for both PG&E and CAISO system peaking weather conditions.

There are two key methodological issues that must be resolved in order to convert measured ex post impacts into ex ante estimates. First, the weather observed during events in 2011 to 2014 differs from the weather conditions used to represent ex ante conditions. Second, the hours over which each test 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 ex ante modeling process consisted of four general steps:

1. Estimate the relationship between load impacts and weather conditions for the hour between 4 to 5 PM;
2. Convert the estimates of the average impact from 4 to 5 PM to hourly impacts for the other hours in the resource adequacy window (1 to 6 PM);
3. Estimate reference loads under ex ante weather conditions; and
4. Estimate snapback effects during the hours immediately following the resource adequacy window.

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

6.1 Estimating the Relationship between 4 to 5 PM Impacts and Temperature

The anchor point for all ex ante estimates is the predicted impact during the hour from 4 to 5 PM. This hour was chosen for ex ante modeling because it was common to the vast majority of ex post events from 2011 through 2014. Once the impact during this hour is predicted for a given set of ex ante weather conditions, it is then scaled up or down to determine ex ante impacts for the other hours in the resource adequacy window. These adjustments are made using ratios that capture historical relationships between the impacts during 4 to 5 PM and impacts during the other hours.

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

28 Estimates from sub-LAP emergency events are not used as input to ex ante estimation because the populations in the sub-LAPs are not representative of the broader SmartAC population.

conditions and impacts (as is frequently the case), this could lead to internally inconsistent results if the function that determines impacts from 4 to 5 PM is quite different from the function that determines impacts from 5 to 6 PM. Also, it is almost certainly the case that impacts across different hours of an event are not independent but are strongly correlated. In the approach used here, the fundamental relationship between event impact and temperature is allowed to be determined completely by the data; however, we enforce a certain amount of uniformity on the relative load impacts across hours, recognizing that we do not have enough historical events for some of the hours in the resource adequacy window to estimate impacts for those hours separately. As the years go on, and more SmartAC test events are called, this approach should be revisited and alternative estimation strategies should be considered.[29]

While some of the ex post estimates for 2014 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 SmartAC-only impact estimates from 2011 to 2014 were adjusted to reflect the weighted average impacts for SmartAC-only and dually enrolled customers using the results from Section 4.4. Once adjusted to reflect the contribution of dually-enrolled customers, the historical ex post load impacts are used to model ex post load impacts as a function of temperature.

In the 2012 evaluation, 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 the hour from 4 to 5 PM. This cross validation analysis was not repeated for this year's evaluation and the same model specification was used this year as in 2012 and 2013. The model specification is summarized below and a description of each variable in the model is included in Table 6–1.

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

Table 6–1: Definition of Load Impact Regression Model Variables

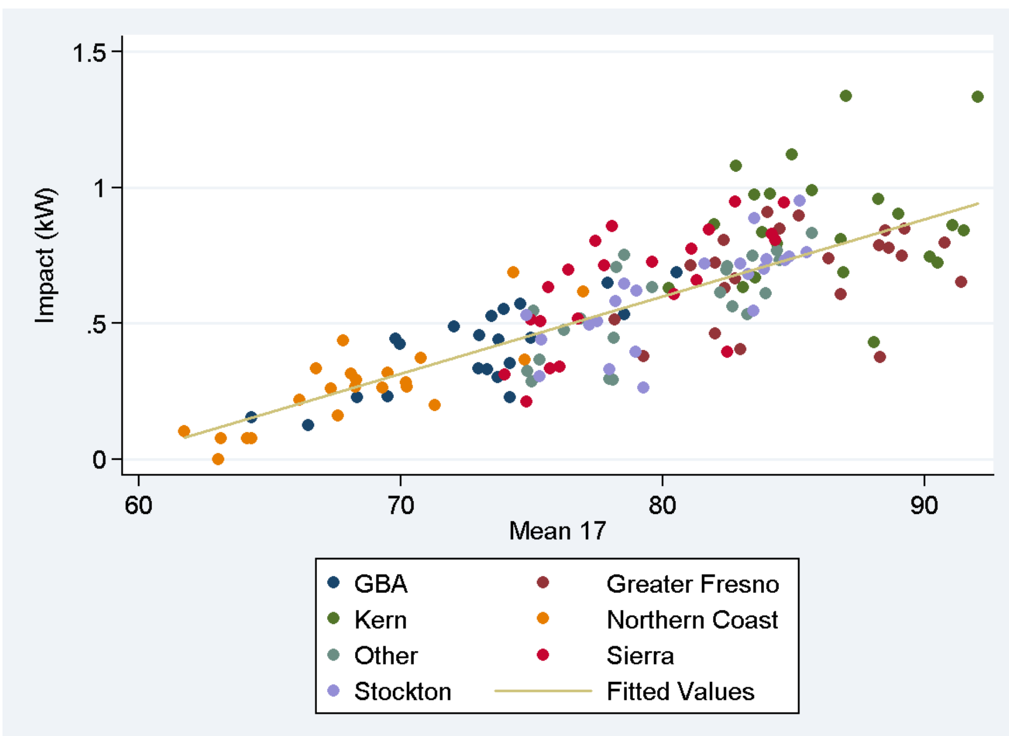
Variable	Description
$Impact_c$	Average per customer ex post load impact for each event day from 4 to 5 PM
a	Estimated constant
b	Estimated parameter coefficient representing relationship between impact and temperature
$mean17_c$	Average temperature over the first 17 hours of an event day
$\boldsymbol{\varepsilon_c}$	The error term, assumed to have a mean of zero and to be uncorrelated with any of the independent variables

29 Given a large enough sample of events for each hour in the resource adequacy window, a promising approach would be to pool all historical event hours into a single dataset and estimate a panel regression model that estimates impacts in each hour and allows for model error to be correlated over time for each event.

The average temperature over the 17 hours from midnight to 5 PM was chosen as the weather variable for modeling load impacts 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 in 2013 and although some performed similarly,[30] 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.

In 2011, modeling was done separately for most LCAs.[31] 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 dataset used to estimate the ex ante model uses data pooled across all LCAs for all events dating back to 2011. 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. Weighted least squares regression was used to estimate the coefficients in the model, with the weights being determined by enrollment in each LCA. Similar to a weighted average, this estimator places more weight on LCAs with larger numbers of enrolled customers. In Figure 6–1, the adjusted impacts from 4 to 5 PM for 2011 through 2014 are graphed against *mean17*.

Figure 6–1: Average Event Impacts from 4 to 5 PM vs. *Mean17* across all LCAs



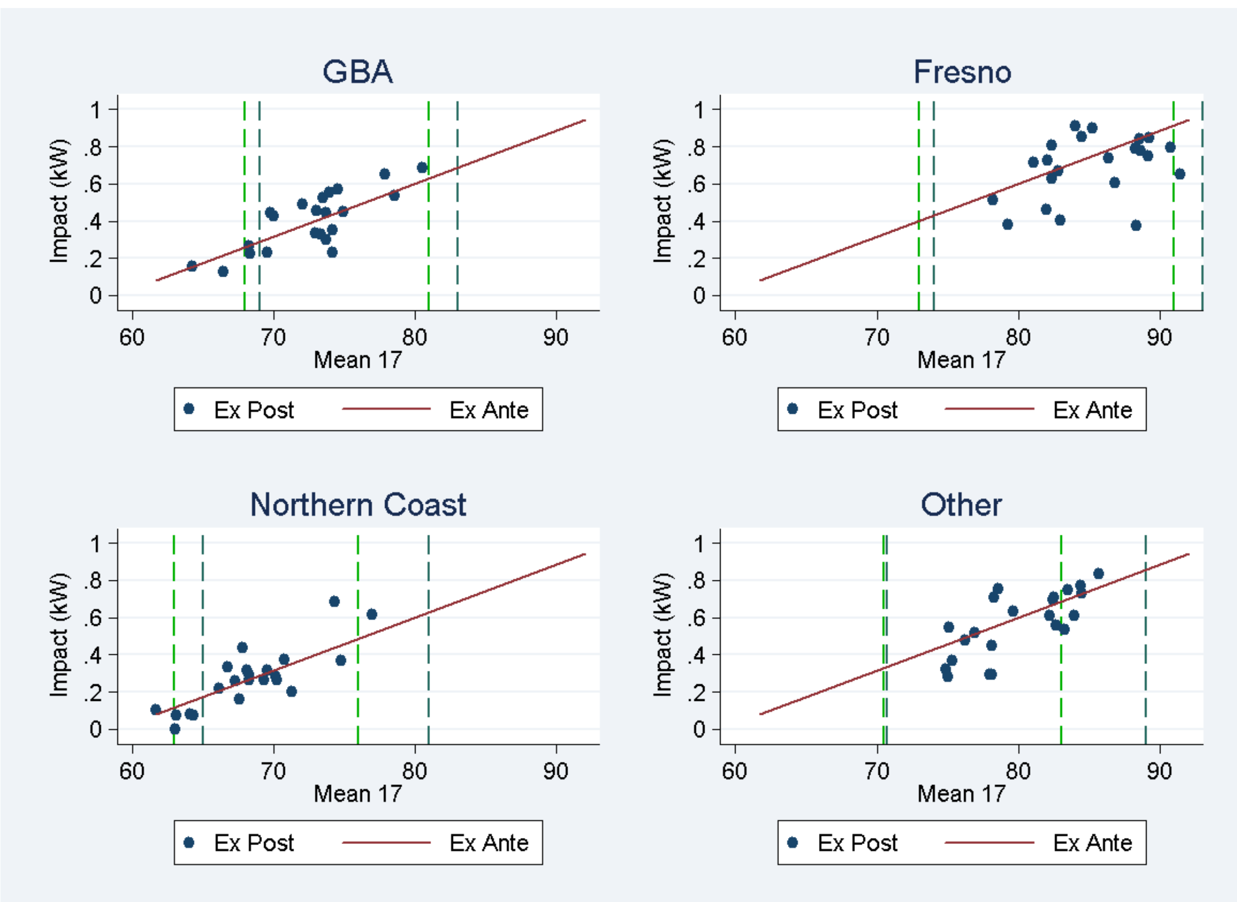
30 Models using temperature as far back as 48 hours prior to the event were tested but were not found to perform better than the model using 17 hours.

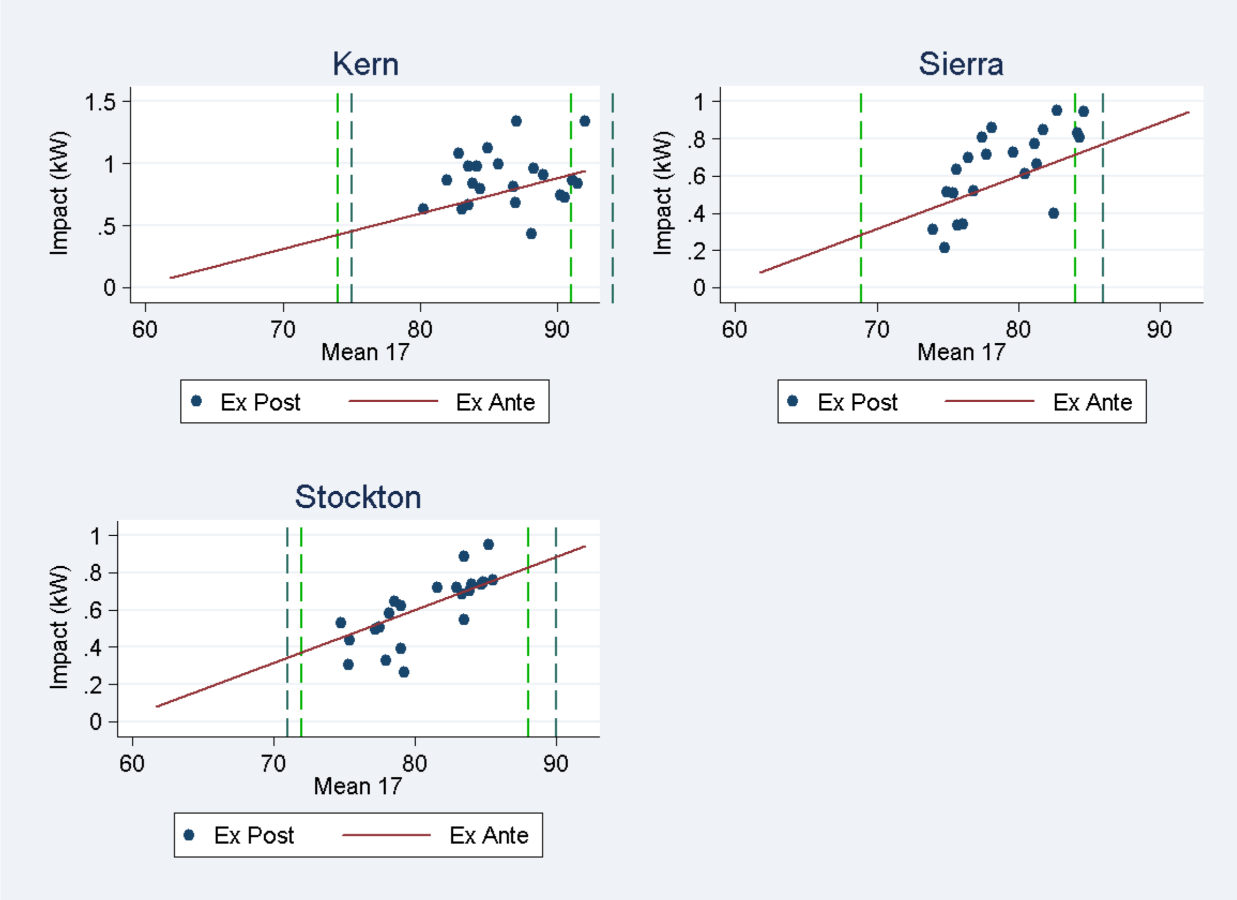
31 Data was pooled across some LCAs in cases where ex ante temperatures exceeded temperatures observed in a particular LCA, as described in the 2011 evaluation report.

Due to relatively lower ex post impacts in 2014 compared to 2011–2013, the estimated regression line for this year is slightly flatter than the line for last year. Because of this, predicted ex ante impacts for high values of *mean17* will be lower this year compared to what they would have been for the same *mean17* value last year (see Section 7.1 for a more detailed comparison of this year's ex ante estimates compared to the estimates from 2013).

Figure 6–2 displays the final ex ante and ex post estimates graphed against *mean17* for each LCA. The solid blue diamonds represent estimated ex post impacts for historical events and the red line represents the regression equation used to obtain the ex ante estimates. Vertical lines on each graph show the range of *mean17* in the ex ante weather conditions for each LCA. The dark green lines represent PG&E peaking weather conditions and the light green lines represent CAISO peaking weather conditions. 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 the difference between PG&E and CAISO ex ante weather conditions and shows that temperatures under both conditions often exceed the ex post conditions within individual LCAs. 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, which carries additional uncertainty relative to interpolation. Avoiding this extrapolation is a key benefit of the pooled approach.

Figure 6–2: Ex Post and Ex Ante Impacts vs. *Mean17* by LCA





6.2 Estimating Ex Ante Impacts for Other Hours in the Resource Adequacy Window

The second step in estimating load impacts was to translate per customer impacts from 4 to 5 PM into hourly impacts over the entire range of time (1 to 6 PM) required for prediction. The conversion entailed using ex post impact estimates from all of the events that included any hours between 1 and 6 PM and calculating the ratio of the per customer impact in each hour to the per customer impact from 4 to 5 PM on the same event day. Then, for each hour, separate regression models were estimated with the impact ratio as the dependent variable and *mean17* as the independent variable. These models made use of the same specification as was used to model impact magnitudes from 4 to 5 PM above:

$$Ratio_h = a + b \cdot mean17_{\mathrm{h}} + \boldsymbol{\varepsilon}_{\boldsymbol{h}}$$

The subscript *h* denotes a specific hour in the resource adequacy window. The results from these models are shown in Figure 6–3 and Figure 6–4. Figure 6–3 shows the data points used to estimate the model 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 from 4 to 5 PM against *mean17*. The graphs include all such ratios calculated for each LCA over all events for 2011 to 2014 (i.e., the ratios for each LCA are pooled). The graphs also show the estimated regression line for each hour, which is used to predict a ratio under each set of ex ante conditions. Figure 6–4 shows all of the estimated regression lines together on one graph.

Figure 6–3: Impact Ratios for Each Hour Compared to Hour 17 (4 to 5 PM) as a Function of *Mean17*

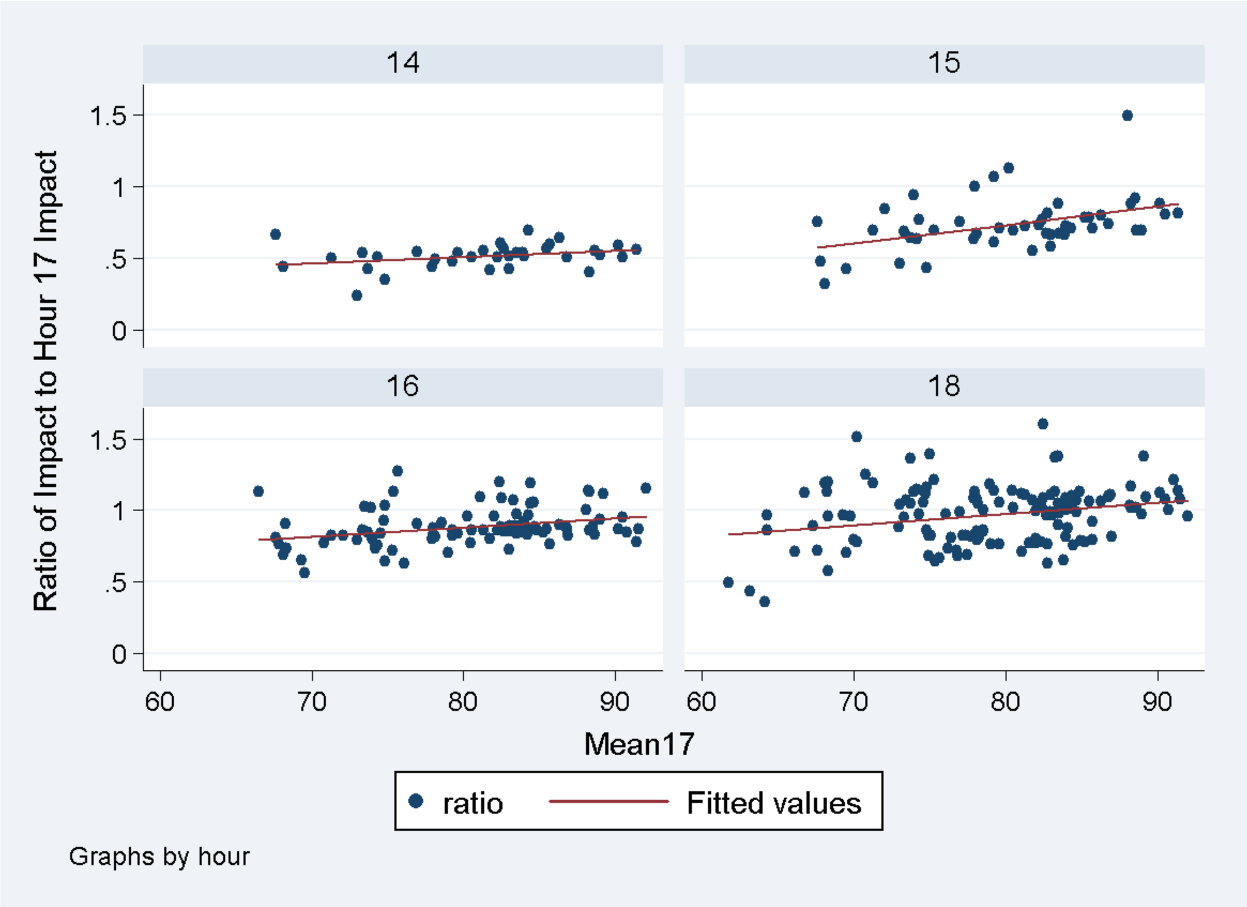
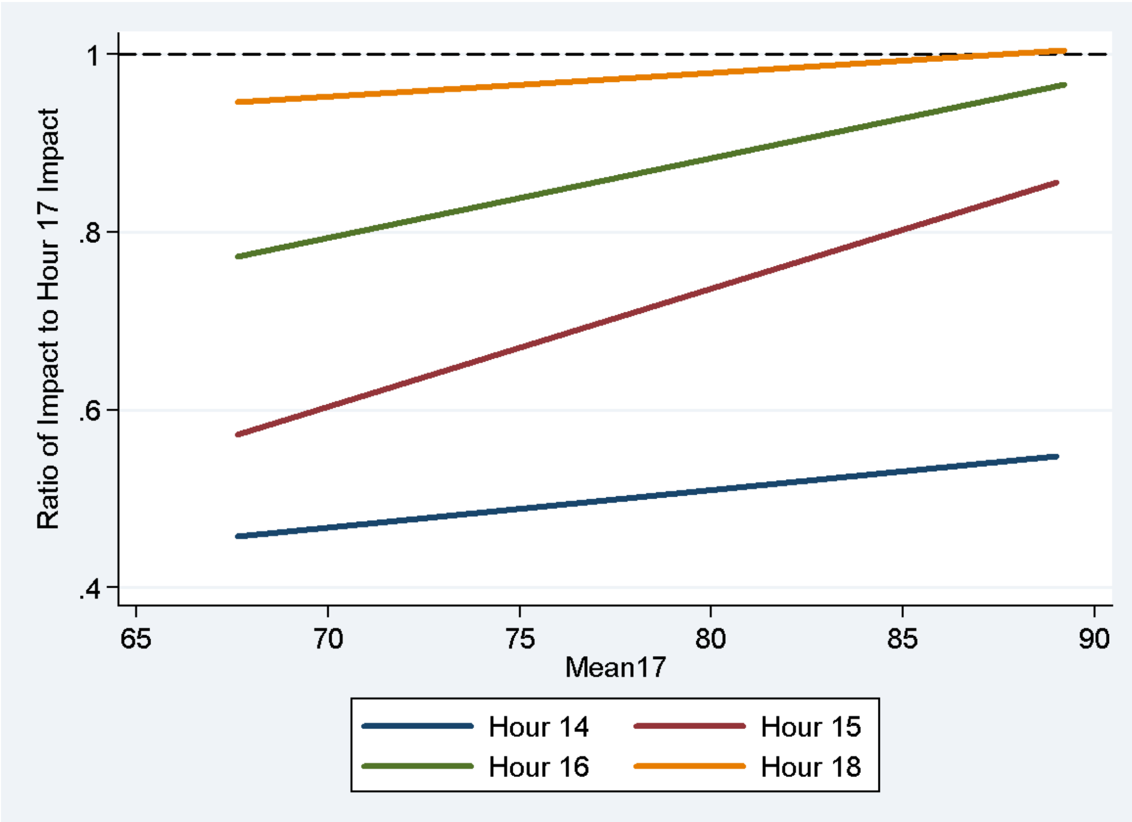


Figure 6–4: Impact Ratios for Each Hour to Hour 17 (4 to 5 PM) as a Function of *Mean17*



To estimate the actual impact (kW) for each hour under a set of ex ante weather conditions in an LCA, the predicted ratio for those conditions was multiplied by the corresponding predicted impact for 4 to 5 PM under those same conditions. As Figure 6–4 shows, the relationships between 4 to 5 PM impacts and impacts in other hours can vary considerably with temperature. Hours ending 14 and 18 have relatively stable ratios across the estimated temperature range but hours ending 15 and 16 show much more variability. For hour ending 15 (2 to 3 PM), the impact is about 60% of the 4 to 5 PM impact at a mean17 of 70 degrees but jumps up to about 80% of the 4 to 5 PM impact at a *mean17* of 85 degrees.

By anchoring all impacts to the impact for 4 to 5 PM, the ratio-based approach acknowledges the fact that the impacts in one hour are closely related to the impacts in other hours. In addition, the ex ante impacts generated using this method are guaranteed to be internally consistent—a desirable trait in a forecasting model.

6.3 Quantifying the Uncertainty Associated with Ex Ante Estimates

A critical piece of any forecast or prediction is the uncertainty associated with a particular estimate. Quantifying this uncertainty usually takes the form of confidence intervals, which are based on standard errors. For SmartAC, standard errors and confidence bands capture some sources of uncertainty, but do not attempt to account for others. The primary source of uncertainty that is addressed in the ex ante evaluation is the uncertainty associated with what load reductions will be for a given set of weather conditions (performance uncertainty). It is important to recognize that we are taking these weather conditions as given and are therefore not accounting for any uncertainty in future weather,[32] nor are we incorporating any uncertainty associated with enrollment or the measurement of the impacts[33] (measurement uncertainty).

In the ex ante model, performance uncertainty is captured in the regression equations used to estimate the relationships between impacts and *mean17*. In these equations, the relevant standard error is the standard error of the regression, which is also referred to as root mean squared error. This value captures the prediction error associated with forecasting the value of the dependent variable (impact) based on a particular value of the independent variable (*mean17*). The confidence bands for each hour in the resource adequacy window and the load impact tables presented in Section 7 were generated using the standard error of regression obtained from regressing the average per customer impact on *mean17* for each hour.[34]

6.4 Estimating Ex Ante Weather Conditions

The CPUC Load Impact Protocols[35] require that ex ante load impacts be estimated assuming weather conditions associated with both normal and extreme utility operating conditions. Normal conditions are those that would be expected to occur once every two years (1-in-2 conditions) and extreme conditions are those that would be expected to occur once every 10 years (1-in-10 conditions). Since 2008, the IOUs have used weather conditions that are associated with 1-in-2 and 1-in-10 year operating conditions specific to each individual utility for estimating ex ante load impacts. However, ex ante weather conditions could alternatively reflect 1-in-2 and 1-in-10 year operating conditions for the California Independent System Operator (CAISO) rather than the operating conditions for each individual IOU. While the protocols are silent on this issue, a letter from the CPUC Energy Division to the IOUs dated October 21, 2014 directed the utilities to provide impact estimates under two sets of operating conditions starting with the April 1, 2015 filings: one reflecting operating conditions for each IOU and one reflecting operating conditions for the CAISO system.

In order to meet this new requirement, California's IOUs contracted with Nexant to develop ex ante weather conditions based on the peaking conditions for each utility and for the CAISO system. The previous ex ante weather conditions for each utility were developed in 2009 and were updated this year along with the development of the new CAISO based conditions. Both sets of estimates used a common methodology, which is documented in a report delivered to the IOUs.[36]

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32 By design, ex ante weather conditions reflect system peaking conditions that are expected to occur approximately once every two years (1-in-2) and once every ten years (1-in-10) based on historical observations.

33 Because of the RCT design and large sample sizes, measurement uncertainty is very low (as evidenced by the small ex post standard errors).

34 The estimated coefficients for the regressions for hours ending 14, 15, 16, and 18 were not used in the analysis and these models were estimated solely to obtain estimates of the standard errors.

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

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

The extent to which utility-specific ex ante weather conditions differ from CAISO ex ante weather conditions largely depends on the correlation between individual utility and CAISO peak loads. Based on CAISO and PG&E system peak loads for the top 25 CAISO system load days each year from 2006 to 2013, the correlation coefficient for PG&E is 0.68, indicating that there are many days on which the CAISO system loads are high while PG&E loads are more modest. This correlation for PG&E tends to be weakest when CAISO loads have been below 45,000 MW. CAISO loads often reach 43,000 MW when Southern California loads are extreme but Northern California loads are moderate (or vice-versa). However, whenever CAISO loads have exceeded 45,000 MW, loads typically have been high across all three IOU's. As will be seen in Section 7, the difference in weather conditions based on PG&E peak conditions and CAISO peak conditions leads to significant differences in ex ante forecasts depending on which set of weather conditions is used.

A summary of the two sets of ex ante weather data is provided in Table 6–2, which shows *mean17* values under both 1-in-2 and 1-in-10 conditions. In general, the PG&E weather conditions are hotter than the CAISO conditions throughout the summer months due to the imperfect correlation between PG&E and CAISO peaking conditions. The hottest months are June and July, followed by August. Under 1-in-2 conditions, June peak days are hotter than those in August, but for 1-in-10 conditions, the reverse is true.

Table 6–2: Enrollment Weighted Ex Ante Weather Values (*Mean17*)

Day Type	PG&E Based Weather		CAISO Based Weather	
	1-in-2	1-in-10	1-in-2	1-in-10
Typical Event Day	81	84	78	81
May Peak Day	74	82	73	77
June Peak Day	82	84	81	80
July Peak Day	82	87	80	85
August Peak Day	81	85	76	83
September Peak Day	79	81	75	78
October Peak Day	70	77	70	75

7 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. As discussed in Section 6.4, for the first time, this year's evaluation predicts impacts for both PG&E and CAISO system peaking weather conditions. 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 155,000 residential and SMB customers enrolled at the end of 2014. It can deliver peak period load reductions of roughly 80 MW under normal weather conditions and more than 100 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 7–1. These estimates were developed by PG&E and reflect modest growth from the enrollment of approximately 150,000 customers that were enrolled in SmartAC at the end of the 2014 program year.

Table 7–1: Projected Residential Enrollment for August of Each Year (Thousands of Customers)

LCA	2015	2016 to 2025
Greater Bay Area	53.5	54.0
Greater Fresno	17.5	17.5
Kern	7.9	8.1
Northern Coast	8.9	9.0
Other	33.9	34.4
Sierra	17.0	16.9
Stockton	14.7	14.7
Total	**153.5**	**154.5**

Ex ante load impact estimates for 2015 are shown for residential customers in Table 7–2, including those who are dually-enrolled in SmartRate. 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. Columns 3 and 4 show the corresponding estimated aggregate load impacts. The top half of the table corresponds to PG&E system peaking conditions, while the bottom half shows results for CAISO system peaking conditions. For the 1-in-2 weather year based on PG&E peaking conditions, the highest estimated impact occurs on the June and July peak days, with an average impact of 83 MW and a peak hourly impact of 99 MW. The mean hourly impact for the typical event day under 1-in-2 year weather conditions is 80 MW. Under 1-in-10 year weather conditions, the highest estimated impacts occur in July, with a peak day impact of 104 MW and a peak hourly impact of 125 MW. The mean hourly impact on the typical event day under 1-in-10 year conditions is 93 MW.

Table 7–2: 2015 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 PG&E	Typical Event Day	0.52	0.63	80	96
	May Peak Day	0.34	0.43	52	65
	June Peak Day	0.54	0.65	83	99
	July Peak Day	0.54	0.65	83	99
	August Peak Day	0.52	0.63	80	97
	September Peak Day	0.48	0.58	74	90
	October Peak Day	0.24	0.32	38	49
1-in-10 PG&E	Typical Event Day	0.60	0.71	93	110
	May Peak Day	0.56	0.67	85	102
	June Peak Day	0.60	0.72	92	110
	July Peak Day	0.68	0.81	104	125
	August Peak Day	0.63	0.75	96	115
	September Peak Day	0.51	0.62	79	95
	October Peak Day	0.40	0.50	62	77
1-in-2 CAISO	Typical Event Day	0.44	0.54	67	82
	May Peak Day	0.32	0.41	49	62
	June Peak Day	0.51	0.62	79	95
	July Peak Day	0.50	0.60	77	92
	August Peak Day	0.38	0.48	59	74
	September Peak Day	0.36	0.45	55	69
	October Peak Day	0.24	0.32	37	49
1-in-10 CAISO	Typical Event Day	0.53	0.64	82	98
	May Peak Day	0.41	0.51	63	78
	June Peak Day	0.50	0.60	76	92
	July Peak Day	0.63	0.75	96	114
	August Peak Day	0.57	0.68	88	105
	September Peak Day	0.44	0.54	68	83
	October Peak Day	0.36	0.45	55	69

Under CAISO system peaking weather conditions, forecasted impacts from SmartAC decline by about 10-15%. This drop results from the fact that demand on the PG&E system is not perfectly correlated with demand for the entire state, which was discussed in Section 6. More specifically, it would suggest that CAISO system peak occurs during times when PG&E system demand is high, but not necessarily peaking.

The SMB segment of the SmartAC program is currently closed to new enrollment. No M&E test events have been called for SMB customers since 2011 so no ex post impacts were estimated for 2014. 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, however new weather data was generated for this year's evaluation (PG&E and CAISO). To incorporate this new data, the ex ante model from 2011 was rerun using the new weather conditions to generate new per customer ex ante estimates. The only other source of change in ex ante load impact estimates for SMB customers stems from a new enrollment forecast that was provided by PG&E. Enrollment projections for SMB customers by local capacity area as of August for the period 2015-2025 are presented in Table 7–3 and show a slow but steady decline in SMB enrollment for each LCA.

Table 7–3: Projected SMB Enrollment for August of Each Year

LCA	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Greater Bay Area	1,631	1,586	1,543	1,501	1,460	1,420	1,381	1,344	1,307	1,272	1,237
Greater Fresno	488	475	462	449	437	425	414	402	391	381	370
Kern	261	254	247	240	233	227	221	215	209	203	198
Northern Coast	517	503	489	476	463	450	438	426	414	403	392
Other	1,055	1,027	999	972	945	919	894	870	847	824	801
Sierra	360	350	341	331	322	314	305	297	289	281	273
Stockton	400	389	378	368	358	348	338	329	320	312	303
Total	**4,711**	**4,583**	**4,458**	**4,337**	**4,219**	**4,103**	**3,992**	**3,883**	**3,777**	**3,674**	**3,574**

Table 7–4 shows the new per-customer and aggregate ex ante impact estimates for the SMB population under both PG&E and CAISO peaking conditions. For the 1-in-2 weather year based on PG&E peaking conditions, the highest average hourly aggregate impact occurs on the June and July peak days, with an impact of 2.9 MW. The maximum hourly impact during a 1-in-2 year for these months equals 3.5 MW. The July peak day shows the highest impacts for the PG&E 1-in-10 weather year. The mean aggregate impact over the five-hour event is 3.5 MW and highest individual hour provides an estimated 4.1 MW of load reduction.

Table 7–4: 2015 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 PG&E	Typical Event Day	0.62	0.72	2.9	3.4
	May Peak Day	0.39	0.46	1.8	2.2
	June Peak Day	0.62	0.73	2.9	3.5
	July Peak Day	0.62	0.73	2.9	3.5
	August Peak Day	0.61	0.72	2.9	3.4
	September Peak Day	0.53	0.63	2.5	3.0
	October Peak Day	0.29	0.34	1.3	1.6
1-in-10 PG&E	Typical Event Day	0.70	0.83	3.3	3.9
	May Peak Day	0.66	0.78	3.1	3.7
	June Peak Day	0.71	0.83	3.4	4.0
	July Peak Day	0.74	0.87	3.5	4.1
	August Peak Day	0.72	0.85	3.4	4.0
	September Peak Day	0.59	0.70	2.8	3.3
	October Peak Day	0.47	0.55	2.2	2.6
1-in-2 CAISO	Typical Event Day	0.49	0.59	2.3	2.8
	May Peak Day	0.38	0.45	1.8	2.2
	June Peak Day	0.58	0.68	2.7	3.2
	July Peak Day	0.57	0.67	2.7	3.2
	August Peak Day	0.45	0.53	2.1	2.5
	September Peak Day	0.43	0.51	2.0	2.4
	October Peak Day	0.29	0.35	1.4	1.6
1-in-10 CAISO	Typical Event Day	0.66	0.77	3.1	3.6
	May Peak Day	0.48	0.57	2.3	2.7
	June Peak Day	0.56	0.66	2.7	3.1
	July Peak Day	0.72	0.85	3.4	4.0
	August Peak Day	0.68	0.79	3.2	3.8
	September Peak Day	0.51	0.60	2.4	2.8
	October Peak Day	0.42	0.51	2.0	2.4

7.1 Comparison of 2013 and 2014 Residential Ex Ante Estimates

The aggregate residential ex ante impacts for 2014 are approximately 10% lower than the ex ante estimates from 2013. There are three possible factors that could explain the difference: changes in the estimated regression coefficients, new weather data for PG&E and CAISO system peaking conditions, and changes in the enrollment forecast provided by PG&E. Table 7–5 shows the incremental contributions of each of these factors to the overall difference in the ex ante estimates.

Table 7–5: Differences in 2013 and 2014 Residential Ex Ante Estimates

	2013 Weather, 2013 Enrollment, 2013 Model	2014 Weather, 2013 Enrollment, 2013 Model	2014 Weather, 2014 Enrollment, 2013 Model	2014 Weather, 2014 Enrollment, 2014 Model
Average per customer impact in Hour 17 (kW)	0.70	0.68	0.68	0.65
Aggregate Hour 17 Impact (MW)	108	105	105	99
Change in Aggregate Impact (MW)	N/A	-3	0	-6
Average Aggregate Impact During Hours 14 to 18 (MW)	92	89	89	83
Change	N/A	-3	0	-6

New PG&E weather conditions account for slightly more than 3% of the overall difference in aggregate impacts during the resource adequacy window and the remainder of the difference can be attributed to differences in the estimated regression coefficients for predicting 4 to 5 PM impacts and hourly ratios (the difference in aggregate impacts due to a change in enrollment forecasts is negligible). The basic structure of the modeling has not changed from last year, but 2014 events have been added to the dataset used to estimate the regressions. Adding these more recent events causes the estimated regression line to rotate so that it is flatter than last year's line and predicts relatively smaller impacts at higher temperatures (as discussed in Section 6.1).

7.2 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, etc. Table 7–6 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

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.

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 uses ex post impacts as inputs.

Table 7–6: 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	76.8 < mean17 < 81.8 (event day) Average event day mean17 = 79.8	Mean17 for the 1-in-2 typical event day (PG&E/CAISO) = 81.0/77.8 Mean17 for the 1-in-10 typical event day (PG&E/CAISO) = 84.0/81.4 CAISO peaking weather conditions significantly different from PG&E peaking weather conditions	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 from event to event with the shortest events lasting only one hour and the longest lasting upwards of 8 hours (cascading events)	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	10-20% of the program is typically dispatched for each event, with the other 80-90% 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 25% in 2014. As discussed in Section 4, the ex post impacts typically can only be estimated for SmartAC-only customers37	Includes dually enrolled customers and assumes their share of total program enrollment does not change from the end of summer 2014	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 four years' worth of ex post impacts	Small impact expected

[37] 2014 is an exception to this, since there were two events called on days that were not SmartDays, which allowed for dually enrolled customers to be included in the analysis.

Table 7–7 and Figure 7–1 show how aggregate load impacts change as a result of differences in the factors underlying ex post and ex ante estimates. Table 7–7 covers the 2014 events and the figure graphs the average values shown at the bottom of the table. For the cascading event on July 30, only the impacts from 3 to 6 PM are shown to allow for an easier comparison.

As seen in column C in Table 7-7, *mean17* varied by roughly 7% across ex post event days, from a low of 76.8 on September 11 to a high of 81.8 on June 30. Given that this was the average temperature across 17 hours, the high end of this range can represent a much hotter day, and thus much higher loads and load impacts, compared with the low end of the range. The percent of the resource dispatched (Column D) was 20% for all events except September 11, when 9 of the 10 groups were called. Column E shows the aggregate impacts for the percent of the program dispatched (excluding dually enrolled customers), whereas Column F represents what the load reduction would have been under the event conditions if all SmartAC-only customers had been dispatched. Column G scales the aggregate impacts up further to include dually-enrolled customers. This represents the maximum impact that could have been achieved under the observed 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, event window, and forecasted enrollment, and also capture 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 over predicts the ex post values by about 12% (85.0 MW vs. 75.2 MW). This over prediction is mainly driven by the very low impact during the September 11, 2014 event. Excluding this event would lead to an over prediction of approximately 2% rather than 12%.

The over prediction that results even when the September 11 event is excluded can be attributed to the fact that the ex post impacts for 2014 are, in general, slightly below the average impacts of events from 2011-2013. Figure 7–2 shows all of the impacts on a kW per customer basis that are used to create the model, with 2014 in red. The red line depicts the ex ante model that was used for this evaluation and the blue line represents what the ex ante predictions would have been if 2014 data was not included. The model is over-predicting for 2014 for the same reason that this year’s regression line has become flatter – namely that the 2014 ex post impacts are lower than what was expected given the observed *mean17*.[38]

[38] Perhaps a better way to interpret this difference is not that the ex ante model’s prediction is too high, but rather given the historical events we have observed, the impacts for the 2014 events were lower than what we would have expected.

Table 7–7: Differences in Ex Post and Ex Ante Impacts Due to Key Factors

(A) Date	2014 Ex Post Aggregate Estimates						Aggregate Estimates Based on Ex Ante Model				
								Standardized Event Window			
	(B) Event Window	(C) *Mean17*	(D) % of Resources Dispatched	(E) Aggregate Reduction of SmartAC-only (MW)	(F) Scaled to Entire SmartAC-only Population	(G) Scaled Up to include Dually Enrolled	(H) Historical Window, Weather & Enrollment	(I) Historical Weather & Enrollment	(J) Historical Weather, Forecast Enrollment	(K) PG&E 1-in-2 Year Weather, Forecast Enrollment	(L) PG&E 1-in-10 Year Weather, Forecast Enrollment
30-Jun-14	3-6 pm	81.8	20%	13.7	68.9	94.1	94.6	87.9	89.5		
30-Jul-14	3-6 pm	79.3	20%	11.8	58.8	75.7	83.0	76.3	77.8		
1-Aug-14	3-6 pm	81.2	20%	14.4	72.8	93.4	91.1	84.5	86.7	80.2	92.7
11-Sep-14	3-6 pm	76.8	90%	31.6	35.2	48.1	71.3	64.7	66.5		
Average	**N/A**	**79.8**	**37.5%**	**17.9**	**55.1**	**75.2**	**85.0**	**78.4**	**80.1**		

Another 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 8% (from 85.0 MW to 78.4 MW). Column J shows the influence of the modest increase in projected enrollment between the end of the summer in 2014 and the projected enrollment in 2015. This factor increases aggregate impacts by about 2%.

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 (PG&E system peaking conditions). Shifting from ex post to ex ante 1-in-2 year weather had a small effect on the impacts, but shifting to 1-in-10 year weather conditions results in impacts that differ from the observed ex post conditions by roughly 15%.

Figure 7–1: Differences in Ex Post and Ex Ante Impacts Due to Key Factors

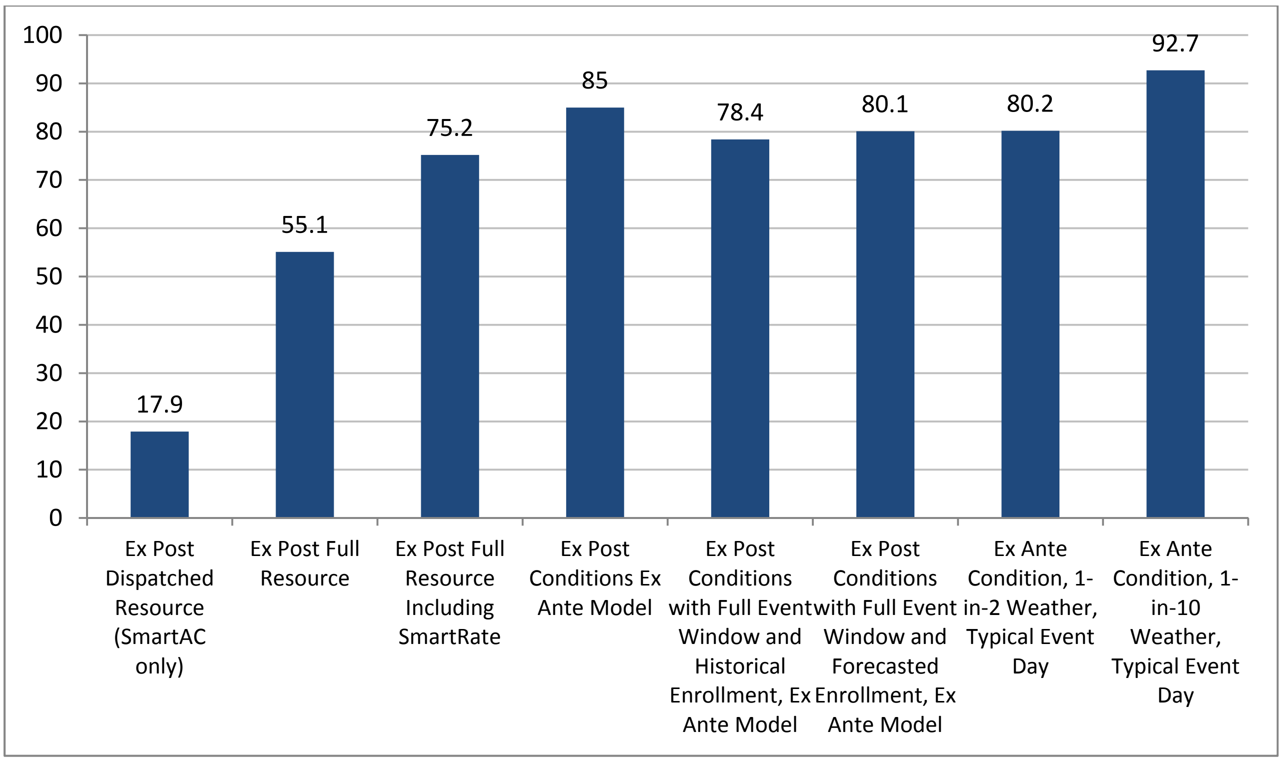
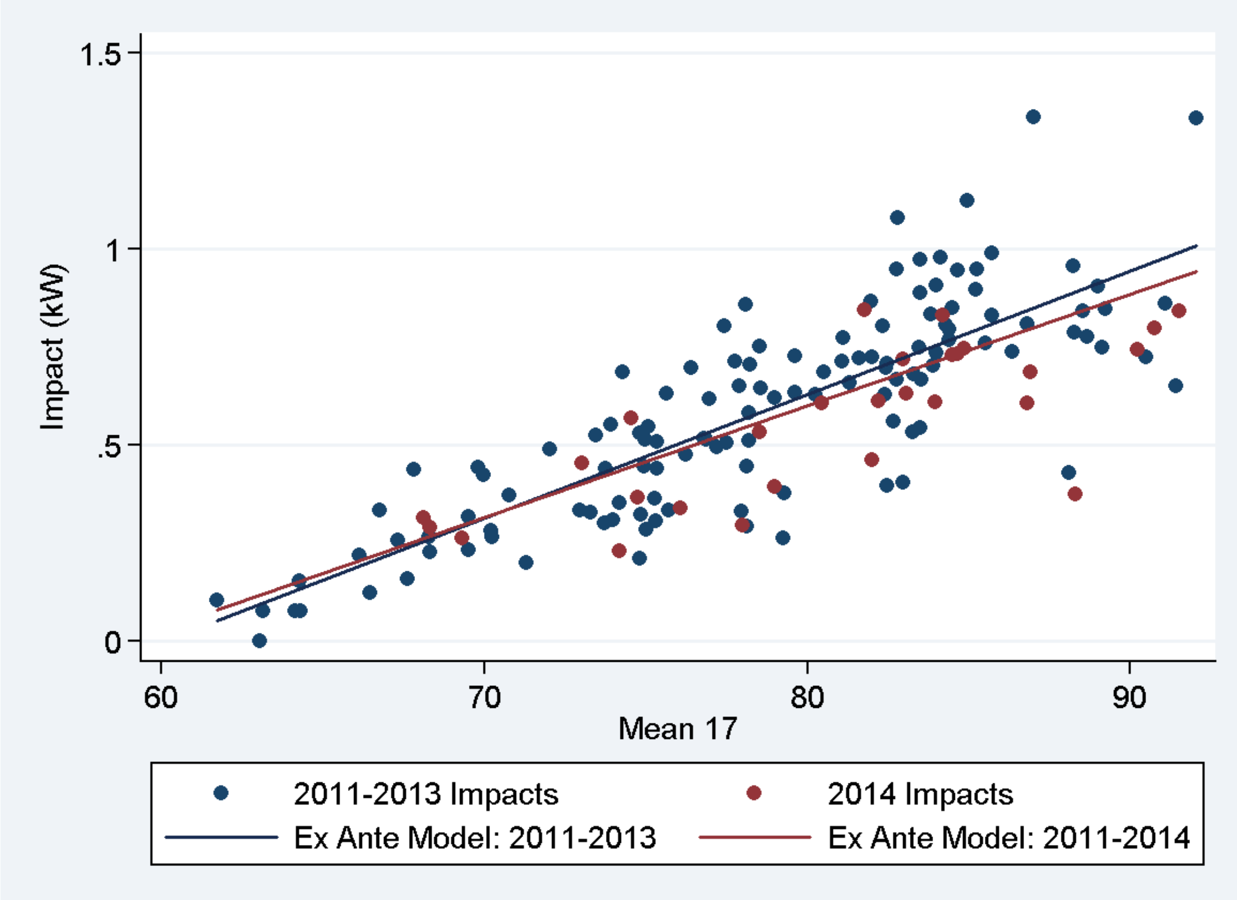


Figure 7–2: Impacts from 4 to 5 PM Used For Ex Ante Model



8 Recommendations

The 2014 SmartAC test events were conducted in a way that provided concrete enhancements to both the ex post and ex ante evaluations. The two events called on days when SmartRate was not called provided an opportunity to directly measure the impacts for dually-enrolled customers as opposed to relying on assumptions about the relative magnitude of their impacts compared to SmartAC-only customers. Furthermore, the 2014 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. Understanding demand response impacts during these time periods will become increasingly important as renewable sources of generation make up an increasing share of the generation mix. We recommend that PG&E continue to include M&E events of this nature in the operational plan for SmartAC in 2015.

We also recommend that a review of the ex ante methodology take place prior to the 2015 evaluation to determine if sufficient data is available to make use of a cleaner and more streamlined approach for estimating hourly impacts during the 1 to 6 PM resource adequacy window. Much of the existing ex ante methodology was developed in an environment with severely limited ex post data available, necessitating the use of various ratios and adjustment factors to generate estimates where data was lacking. As more test events have been called, the available data has potentially improved to the point where these adjustments are no longer necessary and impacts could be estimated independently[39] for each hour with a low risk of internally inconsistent results using robust econometric methods. Such an approach would be considerably simpler and more transparent than the current approach, resulting in analysis that is both more sophisticated and less complicated.

[39] This does not mean that the impacts in each hour are independent in a statistical sense, but rather that a method similar to the regression model used to estimate 4 to 5 PM impacts could also be used for other hours or that all hours could be pooled and estimated with a single equation that allows for correlated impacts over time during each event.

Appendix A 2014 SmartAC Residential Post Event Survey

INTRODUCTION

Hello, my name is (______) and I am calling on behalf of PG&E to ask you a few questions about how your household uses electricity and your satisfaction with our service. This will take only a few minutes and will help us to better understand your service needs and what we can do to improve our service.

For this survey, I need to speak to an adult member of the household. Are you an adult member of the household?

No – ask for adult
Yes – Go to next question

This will just take a few minutes, can we do it now?

No – reschedule
Yes – Proceed with interview

SCREENER

1. Are you or is anyone in your household employed by PG&E?
    1. [Yes] THANK AND TERM
    2. [No] CONTINUE
    3. [Don't Know] THANK AND TERM

QUESTIONS

First, I would like to ask you some questions about your air conditioning system and the way you use it.

2. Could you tell me how often you or someone else in your household uses your air conditioning on <u>summer weekday afternoons</u> between 12 PM and 6 PM?
    1. Almost never
    2. Once or twice a week
    3. Three or four times a week
    4. Five days a week

2a. Could you tell me how often you or someone else in your household uses your air conditioning on <u>summer weekend afternoons</u> between 12 PM and 6 PM?
    1. Almost never
    2. One day
    3. Both days

3. Could you tell me how often you or someone else in your household uses your air conditioning on <u>summer weekday evenings</u> between 6 PM and midnight?
    1. Almost never
    2. Once or twice a week
    3. Three or four times a week
    4. Five days a week

3a. Could you tell me how often you or someone else in your household uses your air conditioning on <u>summer weekend evenings</u> between 6 PM and midnight?
1. Almost never
2. One day
3. Both days

4. Was there any time earlier [today/ yesterday/on Thursday] when the temperature in your home was uncomfortable?
   1. Yes
   2. No – Go to Q8

4a. Can you rate how uncomfortable you were? Please use a discomfort scale of 1 to 5 where 1 means "Very Uncomfortable" and 5 means "Not at all Uncomfortable".

1 Very Uncomfortable
2
3
4
5 Not at all Uncomfortable

5. During what hours were you uncomfortable?
   1. Uncomfortable start _____
   2. Uncomfortable end ____

6. Is the temperature in your home often uncomfortable during those hours or was [today/yesterday/Thursday] an unusual day?
   1. Often uncomfortable during those hours
   2. It was an unusual day

7. What do you think caused the temperature in your home to be uncomfortable?
   1. Air conditioner unit was not on
   2. Air conditioner doesn't work properly
   3. PG&E was controlling air conditioner
   4. It was a very hot day
   5. Other (specify) ____

Now I'd like to ask you some questions regarding PG&E's SmartAC Program.

8. According to our records, your home is enrolled in PG&E's SmartAC™ program. Are you familiar with this program?
   1. [Yes]
   2. [No]
   3. [Don't know/Not sure]

9. **[**IF Q8=a**]** Based on all of your experiences with the SmartAC^{TM} program so far, how satisfied have you been with the program overall? Please use a satisfaction scale of 1 to 10 where 10 means “Very Satisfied,” 5 means neither satisfied nor dissatisfied, and 1 means “Very Dissatisfied.”
    1 Very Dissatisfied
    2
    3
    4
    5 Neither Satisfied nor Dissatisfied
    6
    7
    8
    9
    10 Very Satisfied
    98 [Don’t know/Not sure]

10. [IF Q9<98] Why did you give that rating? OPEN END

11. PG&E recently tested the SmartAC^{TM} system and activated some customers’ SmartAC^{TM} devices. Did you notice if your device was activated in the past few days?
    1. Yes – I did notice the activation
    2. No – I did not notice the activation (skip to 20)
    8. I am unsure

12. [IF Q11=1] On which day was your device activated?
    1. Tuesday, September 9th
    2. Wednesday, September 10th
    3. Thursday, September 11th
    4. Friday, September 12th
    5. Saturday, September 13th
    6. Sunday, September 14th
    7. Monday, September 15th
    8. I am unsure

13. [IF Q11=1] How did you notice this event? *(Check all that apply.)*
    1. [It was a hot day – I knew from the temperature outside]
    2. [It got warmer inside – the inside temperature went up]
    3. [Saw a message on the thermostat]
    4. [Saw a red light on the switch]
    5. [Did not hear the air conditioner running like I knew it should]
    6. [Heard about it on the news]
    7. [Heard about it from someone I know]
    8. [Some other way: ________________________]
    9. [Don’t know/Not sure]

14. [IF Q11=1] About what time did you first notice this event?
    1. Before noon
    2. Noon to 2:59pm
    3. 3:00pm to 4:59pm
    4. 5:00pm to 6:59pm
    5. 7:00pm or later
    6. Next day
    8. [Don't know/Not sure]

15. [IF Q11=1] Did you take any action or do anything differently because of this event?
    1. [Yes]
    2. [No]
    8. [Don't know/Not sure]

16. [IF Q15=1] What action did you take? *(Check all that apply.)*
    1. [Contacted PG&E]
    2. [Left home/work to go somewhere else to keep cool]
    3. [Changed activities, for example, decided to do something less strenuous]
    4. [Turned off lights and other energy using devices]
    5. [Declined to participate in the event (e.g., opted out) for the day]
    6. [Something else: _____________]
    8. [Don't know/Not sure]

17. [IF Q11=1] How did you feel about this activation event?

    ____

    ____

18. [IF Q11=1] Would you say this activation experience was …
    1. [Very easy]
    2. [Somewhat Easy]
    3. [Neither easy nor difficult]
    4. [Somewhat difficult]
    5. [Very difficult]
    8. [Don't know/Not sure]

19. Did you know that you can contact PG&E to decline to participate in a SmartAC event that day, meaning your air conditioner won't be cycled for that day?
    1. [Yes]
    2. [No]
    8. [Don't know/Not sure]

The next few questions are about how you typically use your central air conditioning (AC) on weekdays (Monday through Friday) and weekends (Saturday and Sunday) during the summer.

23. What type of thermostat(s) do you have – manual or programmable? Manual is one that has a dial or lever you move to turn it on and programmable has digital numbers.
    1. [Programmable]
    2. [Manual]
    3. [Both]
    8. [Don't know/Not sure]

24. Which of the following <u>best</u> describes how you operate your central AC system(s) during the summer? Do you … [READ]
    1. [Keep it set at a constant temperature so it runs whenever the temperature goes above this]
    2. [Manually turn the AC on and off when needed]
    3. [Manually adjust the temperature setting at different times such as when you leave your home or go to bed at night]
    4. [IF Q23=1 or 3][Allow the program to automatically change the temperature at different times]
    5. [Never use it]
    8. [Don't know/Not sure]

25. [IF Q24<5] How often does your central AC run in your home during summer <u>weekday</u> afternoons? Would you say it is … [READ]
    1. [Always on]
    2. [On most of time but sometimes cycles on and off]
    3. [On occasionally]
    4. [On rarely]
    5. [Never on]
    8. [Don't know/Not sure]

25a. [IF Q24<5] How often does your central AC run in your home during summer <u>weekend</u> afternoons? Would you say it is … [READ]
    1. [Always on]
    2. [On most of time but sometimes cycles on and off]
    3. [On occasionally]
    4. [On rarely]
    5. [Never on]
    8. [Don't know/Not sure]

26. Is someone who might control or adjust your AC temperature typically at home during summer <u>weekday</u> afternoons between 2 and 7pm?
    1. [Yes – Someone is usually at your home this entire time]
    2. [Yes – Someone is usually at your home for part of this time]
    3. [No]
    8. [Don't know/Not sure]

26a. Is someone who might control or adjust your AC temperature typically at home during summer <u>weekend</u> afternoons between 2 and 7pm?
    1. [Yes – Someone is usually at your home this entire time]
    2. [Yes – Someone is usually at your home for part of this time]
    3. [No]
    8. [Don't know/Not sure]

29. How would you compare your AC use on weekdays (Monday through Friday) vs. weekends (Saturday and Sunday)?
    1. [Use AC all of the time, regardless of time of week]
    2. [Use AC more on weekdays]
    3. [Use AC equally on weekdays and weekends]
    4. [Use AC more on weekends]
    5. [Varies every week]
    6. [Never Use AC]

The remaining questions will help us ensure that we are reaching all customers. Again, your individual identity will remain confidential and all of your answers will be summarized with responses from others.

D1. Do you own or rent your home?
1. [Own]
2. [Rent/lease]
3. [Other]
8. [Don't know/Not sure/Prefer not to answer]

D2. Which of the following best describes the type of home you live in? [READ LIST]
1. [Single family, detached (e.g., freestanding house)]
2. [Single family attached such as town house or row house]
3. [Apartment or condo in multi-unit structure of 2–4 units]
4. [Apartment or condo in multi-unit structure of 5 or more units]
5. [Mobile home]
8. [Don't know/Not sure/Prefer not to answer]

D3. Including yourself, how many people live in your home at least six months of the year?
1. 1
2. 2
3. 3
4. 4
5. 5
6. 6 or more
8. [Prefer not to answer]

D4. What is *your* age?
1. Under 25
2. 25 to 34
3. 35 to 44
4. 45 to 54
5. 55 to 64
6. 65 to 74
7. 75 or older
8. [Prefer not to answer]

D5. Which of the following is the highest level of education you completed?

1. [8th grade]
2. [High school]
3. [Associates degree, vocational or technical school, or some college]
4. [Four year college degree/Undergraduate bachelor's degree]
5. [Graduate or professional degree (Master's, PhD, JD, MD]
8. [Prefer not to answer]

D6. What is your household's total annual income before taxes?

1. [Less than $15,000]
2. [$15,000 to less than $20,000]
3. [$20,000 to less than $30,000]
4. [$30,000 to less than $40,000]
5. [$40,000 to less than $50,000]
6. [$50,000 to less than $75,000]
7. [$75,000 to less than $100,000]
8. [$100,000 to less than $125,000]
9. [$125,000 to less than $175,000]
10. [$175,000 or more]
88. [Don't know/Not sure/Prefer not to answer]

CONCLUSION

Thank you for completing this survey. Your input is very valuable to us, and we appreciate your time and feedback. We use customer input to continually improve our programs.

TERMINATION MESSAGE

Thank you for agreeing to participate. Unfortunately, since a member of your household is employed by PG&E, we cannot include your answers in the results of this study.

Appendix B Survey Responses Related to Customer Demographics

The survey concludes with several questions on customer demographics. Dually-enrolled survey participants are significantly (95% confidence) more likely to report owning a home and less likely to report renting/leasing a home compared with control and SmartAC-only participants (Figure B-1). The SmartAC-only group described their type as home significantly (95% confidence) differently from the control group. Compared to the control group, the SmartAC-only group was more likely to report living in a freestanding house or apartment/condo in a smaller multi-unit structure, and less likely to report living in an attached house, mobile home, or 5+ unit building. However, these results seem likely to be driven by statistical noise from testing so many hypotheses.

Figure B-1: Home Ownership[40]

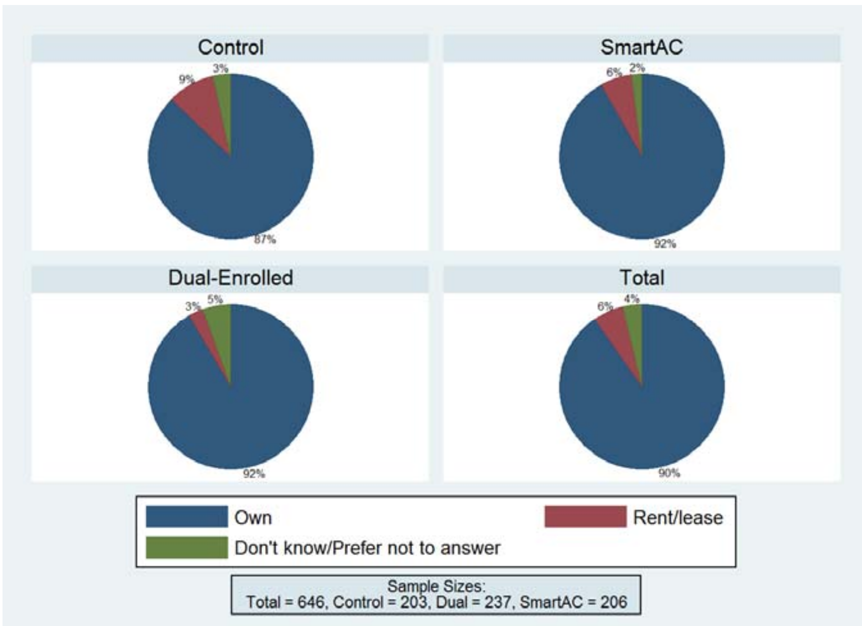


Figure B-2 shows the number of people that live at the survey participant's residence at least six months of the year. There are no significant differences between groups. Ignoring the 4% who preferred not to answer and counting the 6+ category as 6, there average is 2.48.

40 Does not include two participants who responded with "Other."

Figure B-2: How Many Live in Home at Least Six Months of the Year

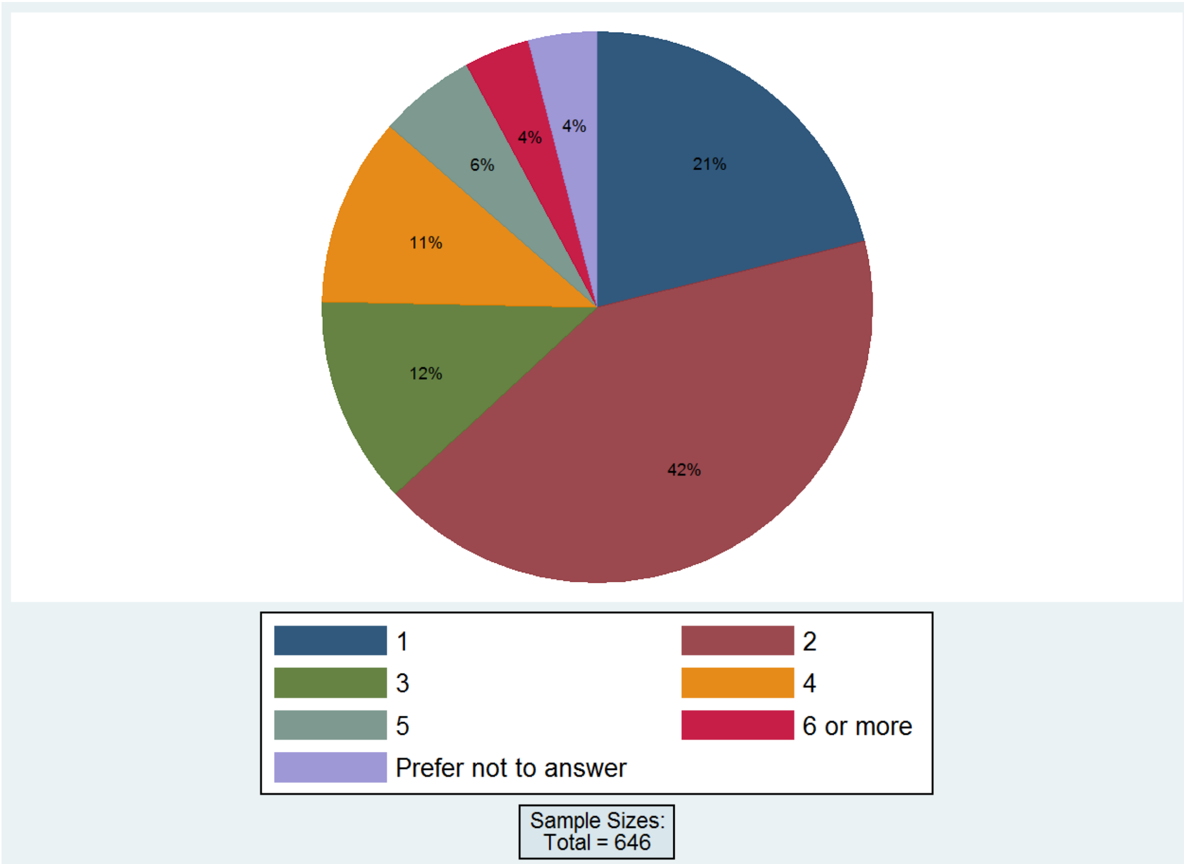


Figure B-3 shows the survey participants' age. There is a strongly significant (99% confidence) difference between the dually enrolled and SmartAC-only groups, which is driven mostly by there being fewer people with ages below 35 and greater than 64 in the dually-enrolled group.

Figure B-3: Survey Participant Ages

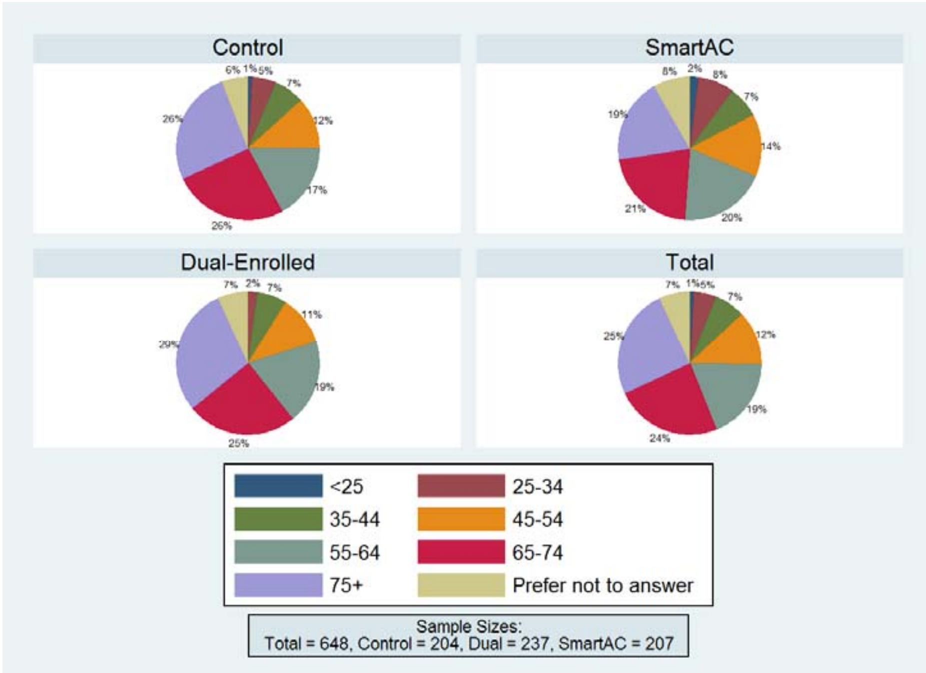
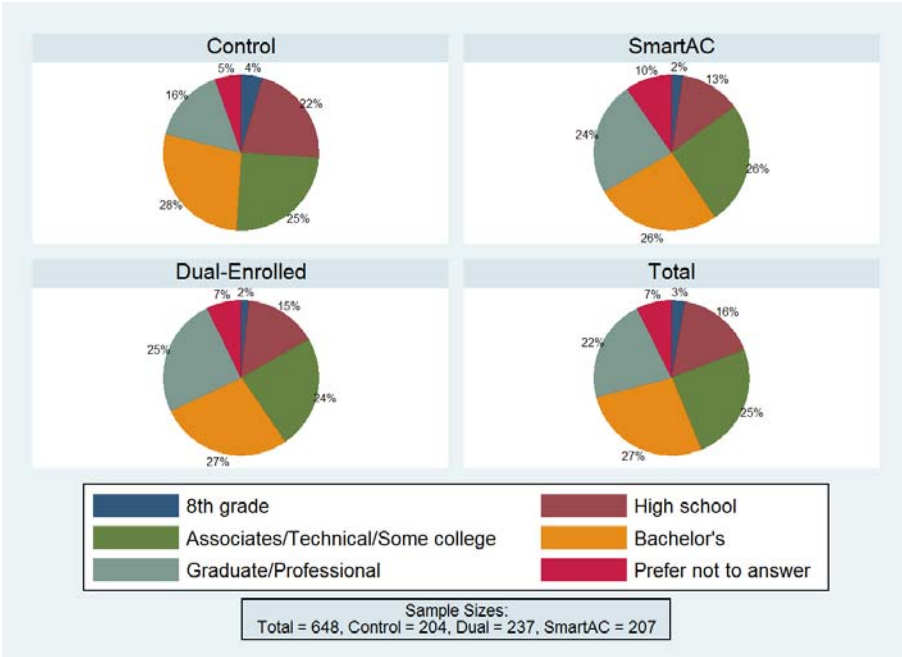


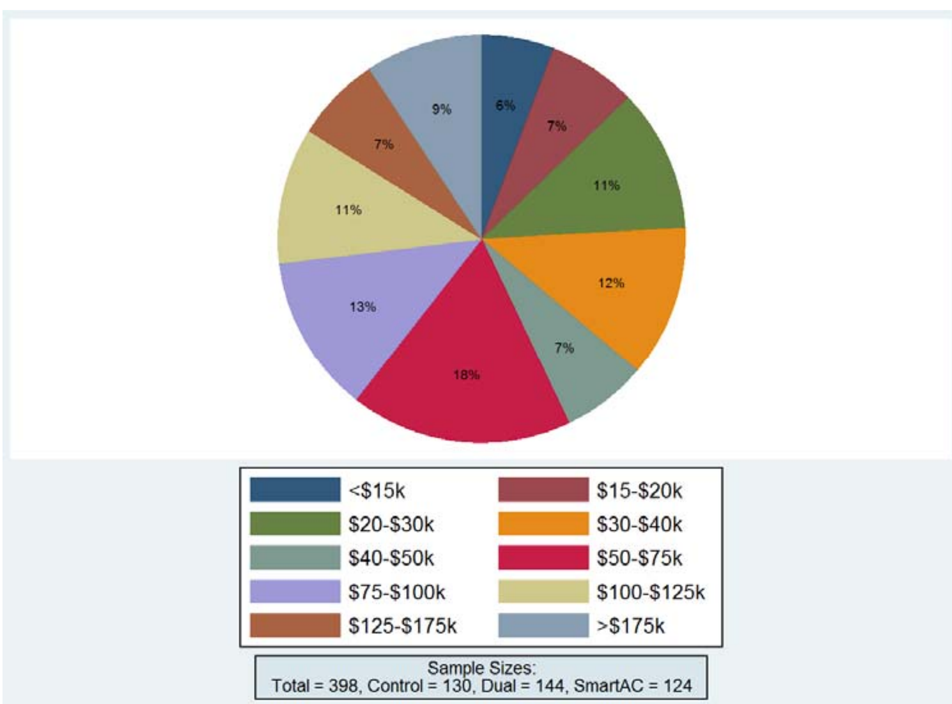
Figure B-4 summarizes the educational level of survey respondents. The SmartAC group differs significantly (>95% confidence) from the Control group. The control group is more likely to respond that their highest level of education is high school, while the SmartAC group is more likely to report completing a graduate degree or preferring not to answer. The control and dually-enrolled customer comparison is similar, except that the differences aren't quite significant at 95% confidence.

Figure B-4: Educational Attainment



Finally, Figure B-5 summarizes the average, pre-tax household income of survey respondents. There were no significant differences between groups. Roughly 40% in each group responded as unsure or preferred not to answer, and were excluded from Figure 5-21.

Figure B-5: Household Pre-tax Income



Appendix C Estimating Whole House Reference Loads for Residential Customers

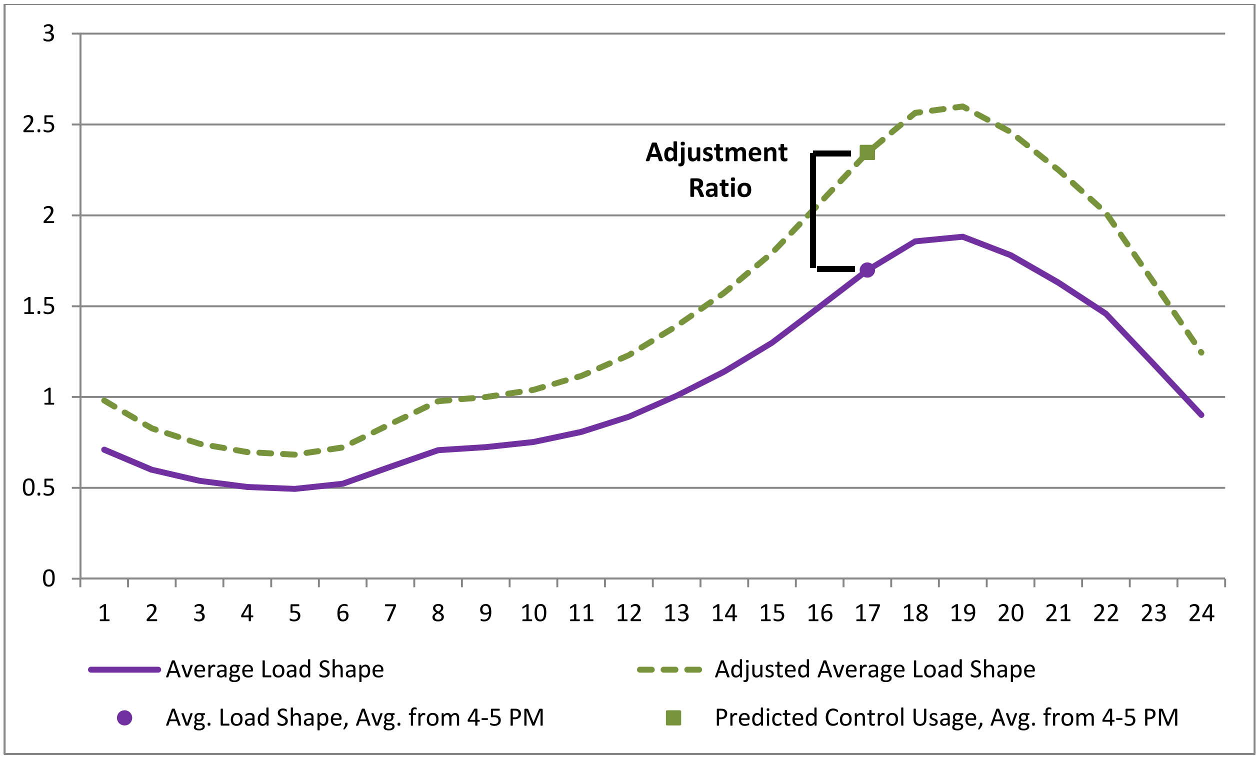
Although estimating impacts is the most important part of the ex ante analysis, whole house reference loads are needed to illustrate the magnitude of impacts and to meet the requirements of the CPUC Load Impact Protocols. This appendix discusses the process used to estimate those reference loads.

Reference load estimation took place in three steps:

1. The average hourly usage for each LCA was calculated based on control group load for all 21 event days from 2011 to 2014. This provides an average hot-day load shape, but does not account for temperature variation;
2. Next, a regression model (similar to the one used to predict load impacts) was 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. Key differences from the impact estimation, however, were that each regression was estimated only at the LCA level—i.e., no pooling was done—and the values for whole house loads were not capped. The estimated coefficients from this model were used to predict average loads without demand response from 4 to 5 PM for each set of ex ante weather conditions; and
3. 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.

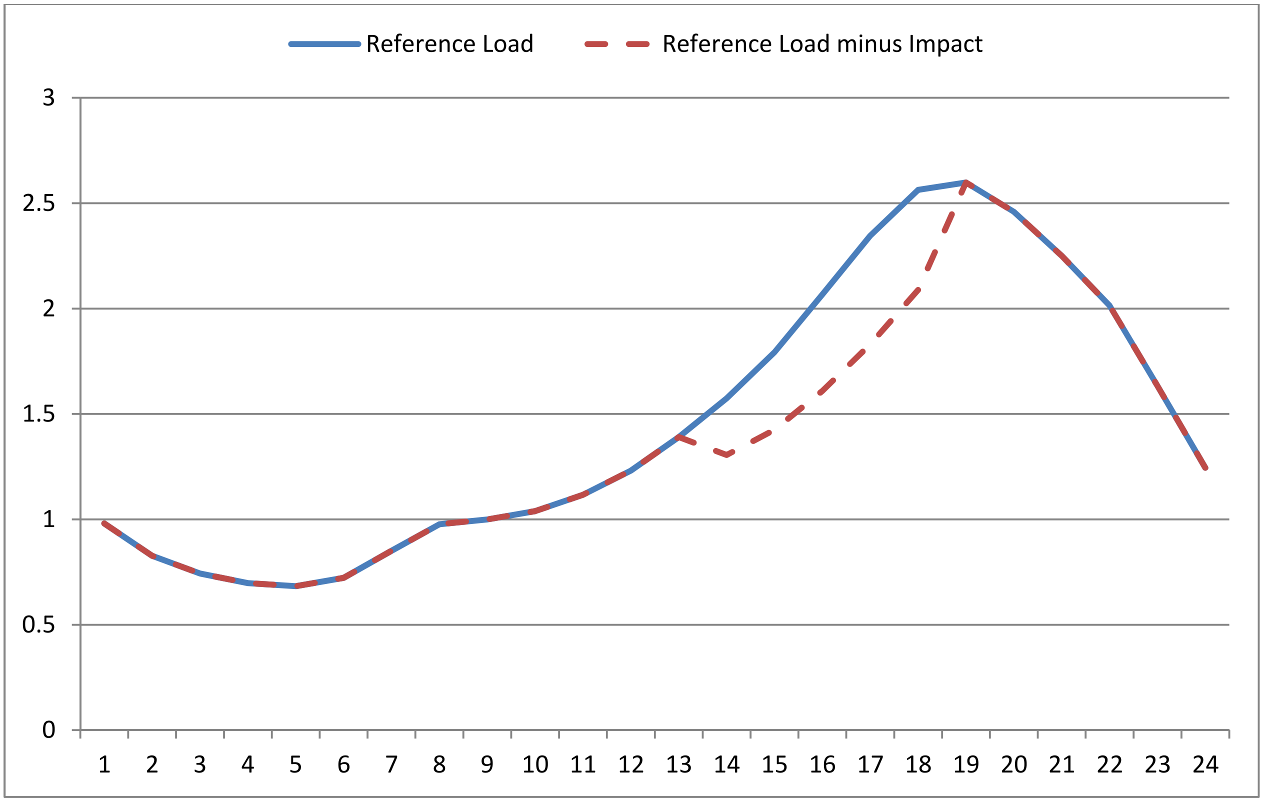
Figure C-1 depicts the process graphically. As an illustrative example, the figure shows the ex ante scenario for the typical event day for the Greater Bay Area during a 1-in-2 weather year. The solid purple line shows the average load shape for all Greater Bay Area control group customers for the 2011–2014 events. The purple circle shows the average usage from 4 to 5 PM over all event days and 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 in the load impact tables.

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



Once reference loads have been estimated, impact estimates can be applied so that the results can be shown graphically. An example of this step is provided in Figure C-2, which 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 load with DR.

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

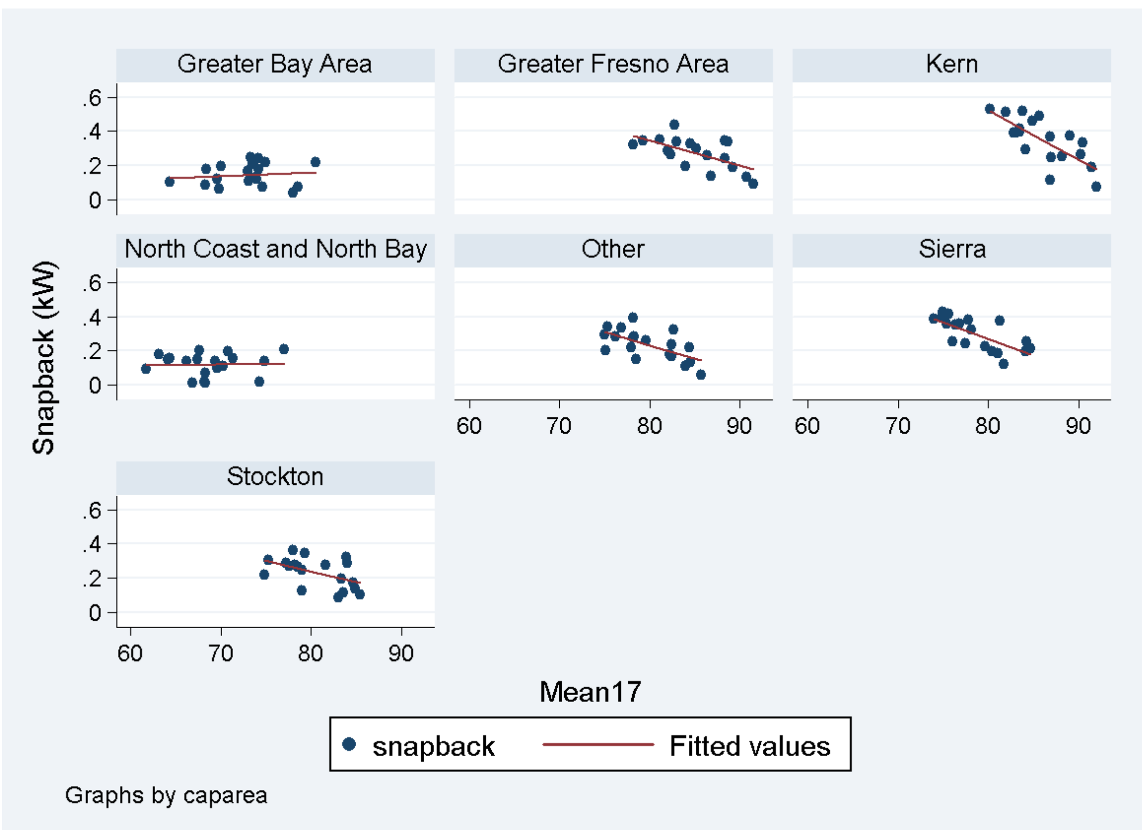


Appendix D Estimating Ex Ante Snapback

The final step in the estimation of ex ante impacts was to predict snapback loads for all hours after the event ends. Like the reference load estimation, the snapback analysis included all historical events from 2011 to 2014. 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 D-1 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 an AC unit is controlled for an event, the building becomes hot enough that the unit 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.[41]

Figure D-1: Scatter Plots of Snapback versus *Mean17* by LCA



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

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, (as in past years) the average snapback across all event days ending at 6 PM for each LCA was used for ex ante prediction.[42] Table D-1 shows the average snapback in the first hour after the event for each LCA.

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

LCA	Average Snapback From 6 to 7 PM (kW)
Greater Bay Area	0.15
Greater Fresno	0.27
Kern	0.35
Northern Coast	0.12
Other	0.23
Sierra	0.30
Stockton	0.23

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 D-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 115% of the snapback from 6 to 7 PM.[43] By multiplying this ratio by the value in Table B-1, the snapback from 7 to 8 PM is 0.173 kW.

Table D-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	1.15	1.20	1.23	0.89	1.13	1.09	1.23
8 to 9 PM	0.68	0.76	0.80	0.53	0.65	0.70	0.84
9 to 10 PM	0.34	0.44	0.51	0.31	0.36	0.38	0.53
10 to 11 PM	0.21	0.24	0.36	0.14	0.20	0.23	0.33
11 PM to 12 AM	0.15	0.19	0.22	0.06	0.13	0.15	0.27

42 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.

43 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 D-2 shows the final ex ante results for the Greater Bay Area typical event day during a 1-in-2 weather year and PG&E's peaking conditions. 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.

Figure D-2: Ex Ante Results Example
Greater Bay Area, 1-in-2 Weather Year (PG&E System Peak), Typical Event Day