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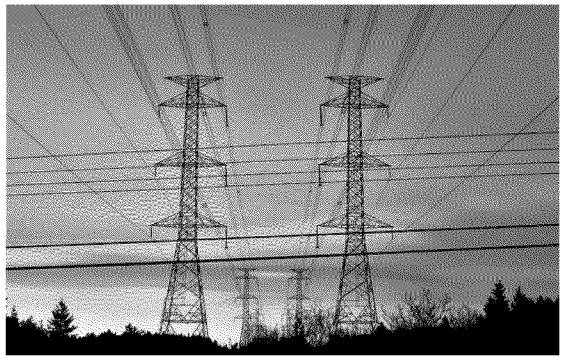
A MEMBER OF THE FSC GROUP

2012 Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-based Pricing Programs



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1 Executive Summary

This report contains ex post and ex ante load impact estimates for PG&E's residential time-based pricing tariffs for 2012. PG&E has three time-based tariffs in effect, although only two are open to new enrollment:

- SmartRate™ [1]is an overlay on other available tariffs including CARE[2] versions of these tariffs. The program has a high price during the peak period on event days, referred to as SmartDays, and slightly lower prices at all other times during the summer. Prices vary by time of day only on SmartDays;
- Rate E-7 is a two-period, static time-of-use (TOU) rate with a peak period from 12 PM to 6 PM. This rate is closed to new enrollment; and
- Rate E-6 is a three-period TOU rate with a peak period from 1 PM to 7 PM in the summer and from 5 PM to 8 PM in the winter (when partial peak prices are in effect).

1.1 SmartRate Ex Post Evaluation Summary

SmartRate is PG&E's residential critical peak pricing. The program underwent significant expansion in 2012. Approximately 21,000 customers were enrolled at the end of 2011; approximately 37,000 were enrolled for the first event on July 9, 2012; and approximately 78,000 were enrolled for the last event on October 3, 2012. This expansion has important implications for interpreting ex post and ex ante results—the main one being that the ex post results for each 2012 event reflects the response of a different population of customers. This also means that ex ante estimation requires steps that are not required when the program population remains stable over the summer. Additionally, the dually-enrolled population, which consists of customers enrolled on both SmartRate and SmartAC—PG&E's AC load control program—expanded significantly in 2012 over 2011. For that reason, all results are reported separately for SmartRate-only and dually-enrolled customers.

Table 1-1 shows load impact estimates for the 2012 events for SmartRate-only customers and Table 1-2 shows estimates for dually-enrolled customers. Table 1-2 also has a final column showing the total aggregate impacts over both segments of customers. The average impacts are 0.20 kW and 0.42 kW, respectively. Aggregate load reduction for the average event was 7.9 MW and 9.2 MW for SmartRate-only customers and dually-enrolled customers, respectively; which gives a total average aggregate impact of 17.1 MW. Aggregate impacts tended to grown through the summer as the program population expanded. One important point that the tables show is that these populations each experienced different weather during the events because they are distributed differently across the territory. Dually-enrolled customers are located in hotter areas, on average.

Because of the shifting population, the aggregate impact for the average event is less informative than when the population is stable. One way to consider the performance of the program is to focus on the last three events, when the program population was stable at about 78,000 customers. For these three events, the average aggregate impact was 10.0 MW and 11.1 MW for SmartRate-only and dually-enrolled customers respectively. The total average aggregate impact over these three events is 21.1

[1] Any use of the term SmartMeter, SmartRate or SmartAC in this document is intended to refer to the trademarked term, whether or not ™ is included. SmartMeter™ is a trademark of SmartSynch, Inc. and is used by permission.

[2] CARE stands for California Alternate Rates for Energy and is a program through which low-income consumers receive lower rates than non-CARE customers.

MW, when the average daily maximum temperature for the population over those events was 94°F. This also leads to an average per customer impact for the whole program during the last three events of 0.27 kW, which is slightly higher than the program average of 0.24 kW for the 2011 season, when the average high temperature of SmartDays was 93°F. Overall, this suggests that the program's per customer average impact has not changed much since 2011.

This overall stability masks a shift in the underlying responses of SmartRate-only and dually-enrolled customers, though. As described later, SmartRate-only customers appeared to provide higher load impacts in 2012 than in 2011, while dually-enrolled customers appeared to provide lower average impacts compared to 2011.

In addition to ex post load impacts, this report contains several other analyses on the characteristics associated with high and low load impacts and the bill impacts for SmartRate customers. These findings virtually all confirm previous findings for the SmartRate program. They include:

- Load impacts vary significantly across Local Capacity Areas (LCAs),[3] with the Greater Bay Area providing the lowest impacts for both populations of customers, the Sierra LCA providing the highest impacts for SmartRate-only customers and Kern providing the largest impacts for dually-enrolled customers;
- The average load reduction for SmartRate-only CARE customers in 2012 was about half as large as for non-CARE customers. Dually-enrolled CARE customers provided about 64% of the per customer load impacts of non-CARE dually-enrolled customers;
- Event notification is highly correlated with load reductions, even among customers notified more than once;
- Air conditioning ownership is a strong driver of demand response;
- Customers enrolled in both SmartRate and SmartAC provide significantly greater demand response than those who are on SmartRate alone;
- The vast majority of customers who sign up for SmartRate stay on the program. Attrition due to de-enrollment is quite low (less than 1%); and
- Between June and September 2012, 94% of SmartRate customers saved money compared with their otherwise applicable tariff (OAT). This is much higher than in 2011, primarily because only 10 events were called in 2012.

Table 1-1: SmartRate Ex Post Load Impact Estimates for SmartRate-only Customers

Date	Day of Week	Avg. Reference Load (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Daily Maximum Temp (°F)
9-Jul-12	M	1.58	0.26	16	5.9	88
10-Jul-12	T	1.71	0.27	16	6.3	94
11-Jul-12	W	1.87	0.32	17	7.8	96
23-Jul-12	M	1.58	0.25	16	7.5	88
4-Sep-12	T	1.32	0.18	13	7.3	86

[3] A local capacity area is a transmission constrained load pocket designated by the California Independent System Operator (CAISO).

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13-Sep-12	Th	1.34	0.16	12	7.4	87
14-Sep-12	F	1.36	0.15	11	6.8	86
1-Oct-12	M	1.36	0.22	16	11.2	95
2-Oct-12	T	1.40	0.21	15	10.5	96
3-Oct-12	W	1.30	0.16	12	8.3	89
Average Event Day	N/A	1.44	0.20	14	7.9	90

Table 1-2: SmartRate Ex Post Load Impact Estimates for Dually-enrolled Customers and Aggregate Impacts for All Customers

Date	Day of Week	Avg. Reference Load (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Daily Maximum Temp (°F)	Aggregate Load Reduction All Customers (MW)
9-Jul-12	T	1.65	0.48	29	6.6	89	12.5
10-Jul-12	Th	1.90	0.49	26	7.1	96	13.4
11-Jul-12	F	2.19	0.56	25	8.5	99	16.3
23-Jul-12	W	1.76	0.41	23	7.6	88	15.1
4-Sep-12	M	1.47	0.38	26	9.6	89	16.9
13-Sep-12	M	1.53	0.38	25	10.0	90	17.4
14-Sep-12	T	1.50	0.35	24	9.4	88	16.2
1-Oct-12	M	1.63	0.45	28	12.2	97	23.4
2-Oct-12	T	1.71	0.43	25	11.7	98	22.2
3-Oct-12	W	1.53	0.35	23	9.4	92	17.7
Average Event Day	N/A	1.65	0.42	25	9.2	92	17.1

1.2 SmartRate Ex Ante Evaluation Summary

Ex ante load impact estimates for SmartRate-only and dually-enrolled customers are shown for 2012 in Table 1-3. The first and second (numerical) columns show the average hourly per customer ex ante load impact estimate over the event period from 1 to 6 PM for SmartRate-only customers and dually-enrolled customers, respectively. The third column shows the aggregate mean hourly impact for the SmartRate only population while the fourth column shows the same measure for dually-enrolled customers. The first set of rows correspond to 1-in-2 weather conditions while the second set covers 1-in-10 weather conditions. In interpreting the results in this table, it is important to keep in mind that, just like the ex post results, these reflect the effect of a growing population during the period. PG&E provided FSC with the enrollment forecast for the program for the next 11 years. From May-October 2013, the total program is expected to grow from about 90,000 to 100,000 customers, with the SmartRate-only population expected to increase from about 54,000 to about 57,000 customers

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and the dually-enrolled population is expected to increase from about 32,000 to about 39,000 customers. With that in mind, both populations within the program are expected to provide their largest impacts in July under both 1-in-2 and 1-in-10 conditions.

Table 1-3: 2013 SmartRate Ex Ante Load Impact Estimates by Weather Year and Day Type (Event Period 1 PM-6 PM)

Weather Year	Day Type	Mean Hourly Per Customer Impact (SmartRate Only)	Mean Hourly Per Customer Impact (Dually Enrolled)	Aggregate Mean Hourly Impact (SmartRate Only)	Aggregate Mean Hourly Impact (Dually Enrolled)	Aggregate Mean Hourly Impact (Full Program)
		(kW)	(kW)	(MW)	(MW)	(MW)
1-in-2	Typical Event Day	0.18	0.40	11	13	23
	May Monthly Peak	0.09	0.29	5	9	14
	June Monthly Peak	0.15	0.37	9	11	20
	July Monthly Peak	0.23	0.47	13	15	28
	August Monthly Peak	0.18	0.40	11	13	23
	September Monthly Peak	0.16	0.38	10	13	22
	October Monthly Peak	0.07	0.27	5	9	14
1-in-10	Typical Event Day	0.25	0.51	15	16	31
	May Monthly Peak	0.21	0.45	12	13	26
	June Monthly Peak	0.24	0.49	14	15	29
	July Monthly Peak	0.29	0.57	17	18	35
	August Monthly Peak	0.27	0.52	16	17	33
	September Monthly Peak	0.22	0.45	13	15	28
	October Monthly Peak	0.17	0.40	11	13	24

1.3 TOU Ex Post Evaluation Summary

PG&E has two time-of-use (TOU) tariffs—E-7 and E-6—with 70,500 and 20,700 residential customers, respectively. Prices during peak periods are substantially higher than during off-peak periods, particularly during summer months (May-October), encouraging customers to shift electricity use away from peak hours. The time-varying rates are in effect every weekday.

The evaluation excludes net-metered customers because they likely have solar panels (and are already accounted for in the evaluation of solar programs). In addition, the evaluation does not produce separate load impact estimates for E-6 customers. Nearly 90% of the 20,700 E-6 customers are net metered and relatively few of the non-net-metered E-6 customers (11%) had smart meters installed for a full year. In total, the evaluation results are representative for approximately 60,000 non net-metered E-6 and E-7 accounts.

Table 1-4 shows the average load reduction on monthly system peak days for E-6 and E-7 customers during the time period included in the analysis, from November 1, 2011 through October 31, 2012.

Table 1-4: TOU Monthly System Peak Day Load Reductions (12 PM to 6 PM) November 2011 to October 2012

Month	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	Percent Reduction (%)	Average Temp. (°F)
January	1.34	1.21	0.12	9	45
February	1.16	1.06	0.10	8	49
March	0.99	0.87	0.12	12	52
April	1.00	0.90	0.10	10	72
May	1.31	1.12	0.19	15	74
June	1.53	1.32	0.21	14	76
July	1.78	1.68	0.10	5	78
August	1.99	1.81	0.19	9	79
September	1.37	1.15	0.22	16	71
October	1.58	1.29	0.29	19	77
November	1.10	1.07	0.03	2	52
December	1.16	1.12	0.04	3	46
Average	**1.36**	**1.22**	**0.14**	**10**	**64**
Summer	**1.59**	**1.39**	**0.20**	**13**	**76**
Winter	**1.12**	**1.04**	**0.08**	**7**	**53**

TOU load reductions were greater over the summer (May-Oct) than the winter (Nov-Apr), when the difference between peak and off-peak prices is the largest. The reductions were larger both in absolute and percentage terms. During the summer, the average load reduction was 0.20 kW, or 12.6%. Average load impacts for TOU are consistent with the ex post estimates from 2012, although the available evaluation methods do not allow for highly precise comparisons.

One other key finding is that given their price response, about 76% of customers enrolled on TOU rate saved in comparison to what their electricity bill would have been with flat rates.

1.4 TOU Ex Ante Evaluation Summary

As with the ex post evaluation, the ex ante evaluation only includes non-net metered E-6 and E-7 customers. Because E-7 is a closed rate, no new customers will join during the ex ante forecast period, and the only factor affecting the population is attrition. E-6 enrollment allows new enrollment and is expected to grow modestly. Based on 2011 and 2012 enrollment data, for E-6 and E-7 combined, the growth rate is forecasted to be 2.2% per year and the attrition rate is expected to be 0.13% per year. And we have assumed the fraction of non-net-metered E-6 customers out of all E-6 customers will remain constant in the future.

Table 1-5 shows a summary of the ex ante estimates for TOU. It shows the load impacts for the 1-in-2 and 1-in-10 annual peak days, which occur in June and July, respectively. Impacts remain somewhat constant because enrollment isn't expected to change drastically over the next ten years.

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Table 1-5: Summary of Aggregate Ex Ante Load Impacts for Non-net-metered Residential TOU by Year (Average 1 PM – 6 PM Peak Period Reduction on the Annual System Peak Day)

Weather Conditions	Year	Accounts	Reference Load (MW)	Load with DR (MW)	Load Impact (MW)	% Load Reduction	Avg. Temp (°F)
1-in-2	2013	55,796	117.2	100.9	16.3	13.9%	92
	2014	55,810	117.2	100.9	16.3		
	2015	55,826	117.3	101.0	16.3		
	2016	55,843	117.3	101.0	16.3		
	2017	55,863	117.3	101.0	16.3		
	2018	55,884	117.4	101.1	16.3		
	2019	55,908	117.4	101.1	16.3		
	2020	55,934	117.5	101.2	16.3		
	2021	55,962	117.6	101.2	16.3		
	2022	55,992	117.6	101.3	16.3		
	2023	56,024	117.7	101.3	16.3		
1-in-10	2013	55,796	128.7	110.4	18.3	14.2%	95
	2014	55,810	128.7	110.4	18.3		
	2015	55,826	128.7	110.4	18.3		
	2016	55,843	128.8	110.5	18.3		
	2017	55,863	128.8	110.5	18.3		
	2018	55,884	128.9	110.6	18.3		
	2019	55,908	128.9	110.6	18.3		
	2020	55,934	129.0	110.6	18.3		
	2021	55,962	129.0	110.7	18.3		
	2022	55,992	129.1	110.8	18.3		
	2023	56,024	129.2	110.8	18.4		

2 Overview of Time-varying Tariffs

PG&E has offered time-varying tariffs on a voluntary basis since the early 1980s. The E-7 tariff was first offered in 1986. E-7 was targeted at large users with air conditioning (and therefore was not revenue neutral for the average PG&E customer) and succeeded in signing up a relatively large fraction of the target audience. Enrollment peaked at 130,000 customers in 1995. New enrollment essentially stopped in 1996 when the California Public Utilities Commission (CPUC) changed the payment policy for the time-of-use meters that were needed to be on the E-7 tariff. Prior to 1996, the incremental meter charges were collected in the form of a modest monthly meter charge. In 1996, the Commission changed the policy to require an upfront installation charge of roughly $200 to obtain a TOU meter. New enrollment essentially stopped after that point and program enrollment began a slow, steady decline due primarily to customer churn.

The E-7 tariff was closed to new enrollment in 2006,[4] when it was replaced with the new E-6 tariff. E-6 was designed to be a revenue neutral tariff. As discussed below, enrollment in E-6 has been modest and is comprised largely of customers with rooftop solar installations.

PG&E's SmartRate tariff was initially offered to customers with SmartMeters starting in May 2008. Roughly 10,000 customers enrolled in the Kern County region in summer 2008, which was the only area that had a sufficiently large number of SmartMeters at the time. SmartRate was marketed much more broadly in 2009 since SmartMeter deployment was more widespread. Enrollment peaked at around 25,000 customers in 2009, after which PG&E ceased marketing the rate in response to the CPUC proposed decision leading to D.10-02-032 indicating that SmartRate would be closed in early 2011 and replaced with an alternative Peak Day Pricing (PDP) rate. Enrollment in SmartRate declined moderately in 2010 and 2011, due largely to customer churn. In November 2011, the Commission agreed to allow SmartRate to continue as an option and to eliminate the transition to PDP until a decision was obtained in Phase 2 of its 2014 General Rate Case. Starting in early 2012, SmartRate was marketed heavily, and enrollment more than tripled between the beginning and end of 2012. As of the end of October 2012, there were about 78,000 SmartRate customers.

2.1 SmartRate Overview

SmartRate is a critical peak pricing (CPP) tariff that is an overlay on a customer's otherwise applicable tariff (OAT).[5] SmartRate pricing consists of an incremental charge that applies during the peak period on SmartDays and a per kilowatt-hour credit that applies for all other hours from June through September. For residential customers, the additional peak-period charge on SmartDays is 60¢/kWh. The SmartRate credit has two components, both of which apply only during the months of June

[4] E-7 was re-opened briefly E-7 on January 1, 2007 for customers with rooftop solar installations, and again between January 1, 2008 through June 30, 2009 to solar customers with interconnections in progress who had filed interconnection agreements prior to December 31, 2007 (see Advice 3285-E, dated June 26, 2008).

[5] Except for 5 E-7 customers and 20 E-6 customers, all other SmartRate customers have E-1 as their underlying tariff.

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through September. The first SmartRate credit, 3¢/kWh, applies to all usage other than peak-period usage on SmartDays. An additional credit of 1¢/kWh applies to Tier 3 and higher usage for residential customers regardless of time period.

Under SmartRate, there can be up to 15 SmartDays (also referred to as event days) during the summer season, which runs from May 1 through October 31. SmartDays are called based on a trigger temperature that is equal to 98°F at the beginning of the summer and is adjusted up or down throughout the summer. When the average temperature[6] is expected to be above the trigger temperature based on a day-ahead forecast, customers are notified that the next day will be a SmartDay. Every two weeks, the trigger may be adjusted upward if there were more events than expected in the previous two weeks or downward if there were fewer. The goal is for there to be an average of 12 event days each summer, with no fewer than 9 and no more than 15 during any particular summer.

Unless a customer's underlying rate is also a time-of-use (TOU) rate, which is rare (300 customers in 2012), prices vary by time of day on SmartDays only . The peak period on SmartDays is from 2 PM to 7 PM and customers are notified by 3 PM on the business day prior to the SmartDay. Customers have several options for receiving event notification (e.g., email, phone, etc.), including not being notified at all. Roughly 12% of SmartRate-only customers and 6% of dually-enrolled customers either chose not to be notified or provided notification information that was initially incorrect or has become outdated.

Customers who enroll on SmartRate receive bill protection for the first full season. Bill protection is designed to address the risk aversion that pilot programs and market research have shown to be a significant barrier to enrolling customers onto dynamic rates. Bill protection offers a risk-free trial and ensures that, during the first full season on SmartRate, customer's bills will not increase under the new rate option relative to what they would have been over the same period under the prior tariff.

PG&E's standard residential tariff, E-1, is a five-tier, increasing block rate, with the price per kWh increasing nearly threefold between Tier 1 and Tiers 4 & 5 (which have the same marginal price). The usage levels where prices change are multiples of a baseline usage amount that varies by climate zone. Table 2-1 shows the prices for each tier for the E-1 tariff for both CARE and non-CARE customers who do not have all-electric homes. As shown in Table 2-1, the CARE discount is quite significant, especially for low income households that have usage in Tier 3 and above.

[6] The average is calculated over forecasts for Sacramento, Concord, San Jose, Red Bluff and Fresno.

Table 2-1: E-1 CARE and Non-CARE per kWh Prices for PG&E[7]

Usage Tier	% of Baseline Usage	E-1 Price for Tier (¢/kWh)	CARE Price for Tier (¢/kWh)
1	100%	13.2	8.3
2	130%	15.0	9.6
3	200%	30.0	14.0
4	300%	34.0	14.0
5	>300%	34.0	14.0

With the tiered pricing used in PG&E's service territory, the price ratio between peak-period prices on SmartDays and the average price on normal days on the SmartRate tariff (which is roughly 3¢/kWh lower than the averages in Table 2-1 because of the SmartRate credit during those hours), varies significantly with usage and also varies between CARE and non-CARE customers. For example, for a Tier 1 customer on the E-1 tariff, the peak-period price on SmartDays is about seven times higher than on non-SmartDays. On the other hand, for a Tier 4 or 5 customer, the peak period price would equal roughly 94¢/kWh and the price ratio would be less than 3 to 1. For CARE customers in Tier 1, the SmartDay peak-period price is approximately 68¢/kWh and the price ratio between SmartDay peak-period prices and non-SmartDay prices is roughly 13 to 1.

Table 2-2 shows the proportion of customers in the PG&E residential population, the SmartRate-only population, and the dually-enrolled population by LCA and CARE status. Customers enrolled on SmartRate are more likely to be located in hotter regions than the general population. In the past, SmartRate customers had tended to be located in hotter areas than the general population, but with the increased enrollment in 2012, this is much less true. There is still some tendency in that direction, particularly among CARE customers, but it is only moderate.

Another important aspect of Table 2-2 is that Kern and Greater Fresno—the two hottest LCAs—have a very large fraction of CARE customers who tend to provide lower load impacts. This is important to keep in mind in reviewing the ex post load impacts.

[7] These are the prices that were in effect for the majority of the summer (starting June 20, 2011). Current E-1 prices are slightly different. Both current and historical rates can be found here: http://www.pge.com/nots/rates/tariffs/electric.shtml#RESELEC.

Table 2-2: Customers in Population and SmartRate Program by Local Capacity Area and CARE Status

Local Capacity Area	SmartRate Participants (End of 2012)								PG&E Residential Population			
	SmartRate-Only				Dually Enrolled							
	Non-CARE	%	CARE	%	Non-CARE	%	CARE	%	Non-CARE	%	CARE	%
Greater Bay Area	18,492	54%	4,093	23%	11,008	43%	148	8%	1,650,223	49%	424,221	35%
Greater Fresno	2,404	7%	2,808	15%	2,725	11%	449	24%	263,079	8%	209,967	17%
Kern	2,425	7%	3,398	19%	892	4%	506	27%	103,743	3%	75,505	6%
Northern Coast	1,820	5%	720	4%	1,657	7%	21	1%	362,070	11%	104,229	8%
Other	4,300	13%	3,698	20%	3,768	15%	325	17%	616,615	18%	271,925	22%
Sierra	2,737	8%	1,325	7%	3,261	13%	125	7%	197,714	6%	69,388	6%
Stockton	2,093	6%	2,118	12%	2,112	8%	331	17%	141,699	4%	72,436	6%
Total	**34,271**	100%	**18,160**	100%	**25,423**	100%	**1,905**	100%	**3,335,143**	100%	**1,227,671**	100%

Of the roughly 58,000 customers who were newly enrolled in SmartRate in 2012, approximately 23,000 were also enrolled in PG&E's SmartAC program. SmartAC is a program in which customers receive a payment from PG&E in return for allowing PG&E to remotely turn down their air conditioner (AC) at times of high system load. PG&E accomplishes this control through the use of switches that are installed directly on the customer's AC or through the use of programmable communicating thermostats that can receive a radio signal. Customers who enroll in both programs are given the option of having their AC controlled during the peak period on SmartDays. Choosing this option provides these customers an automatic boost to their savings due to reduced AC usage on SmartDays.[8]

One important aspect of the increased enrollment in 2012 is that it tended to take place in cooler parts of the service territory. Table 2-3 shows the 2011 and 2012 enrollment by LCA for SmartRate-only and dually-enrolled customers. The Greater Bay Area LCA has been split into two regions—cool and warm—based on the overall average summer temperatures by zip code. Both the cooler parts of the Greater Bay Area and the Northern Coast LCA significantly increased their relative size from 2011 to 2012, while Kern and Greater Fresno—two of the hottest LCAs—saw significant reductions in relative population size. Both parts of the Greater Bay Area saw particularly large relative gains among the dually-enrolled population. Even the warmer parts of the Greater Bay Area are not as hot as Kern or Greater Fresno. This is important because we will see that the per customer impacts for dually-enrolled customers decreased from 2011 to 2012, and this is a likely reason.

[8] For more information about the SmartAC program see "2012 Load Impact Evaluation for Pacific Gas and Electric Company's Smart AC Program" which is available on the CPUC website.

Table 2-3: Comparison of 2011 and 2012 Participants by Local Capacity Area

LCA	SmartRate-only				Dually-enrolled				All Customers			
	2011	%	2012	%	2011	%	2012	%	2011	%	2012	%
Greater Bay Area - Cool	4,640	28%	21,096	40%	267	6%	6,118	22%	4,907	24%	27,214	34%
Greater Bay Area - Warm	659	4%	1,489	3%	162	4%	5,038	18%	821	4%	6,527	8%
Greater Fresno	2,322	14%	5,212	10%	874	19%	3,174	12%	3,196	15%	8,386	11%
Kern	4,697	29%	5,823	11%	1,003	22%	1,398	5%	5,700	27%	7,221	9%
Northern Coast	75	0%	2,540	5%	9	0%	1,678	6%	84	0%	4,218	5%
Other	2,057	13%	7,998	15%	845	19%	4,093	15%	2,902	14%	12,091	15%
Sierra	780	5%	4,062	8%	474	11%	3,386	12%	1,254	6%	7,448	9%
Stockton	1,091	7%	4,211	8%	856	19%	2,443	9%	1,947	9%	6,654	8%
Total	**16,321**	**100%**	**52,431**	**100%**	**4,490**	**100%**	**27,328**	**100%**	**20,811**	**100%**	**79,759**	**100%**

As an additional illustration of this trend, FSC divided the entire service territory into cool and hot regions based on average summer temperatures by zip code. In this tabulation, all of the Greater Bay Area falls into the cool region even though parts are quite a bit hotter than others. Table 2-4 shows the proportion of customers in cool and hot zip codes for the SmartRate-only and dually-enrolled populations. As the SmartRate program grew over the summer of 2012, the population became more concentrated in cooler areas. At the end of 2011, 36% of SmartRate-only customers resided in cool zip codes. By the end of 2012, 54% of these customers lived in cooler areas. The difference is more pronounced in the dually-enrolled population where the population in cooler regions grew from 15% to 55% from 2011 to 2012.

Table 2-4: Comparison of 2011 and 2012 Participants by Weather

Weather	SMR Only		Dually Enrolled		All	
	2011	2012	2011	2012	2011	2012
Cool	36%	54%	15%	55%	31%	55%
Hot	64%	46%	85%	45%	69%	45%

2.2 TOU Overview

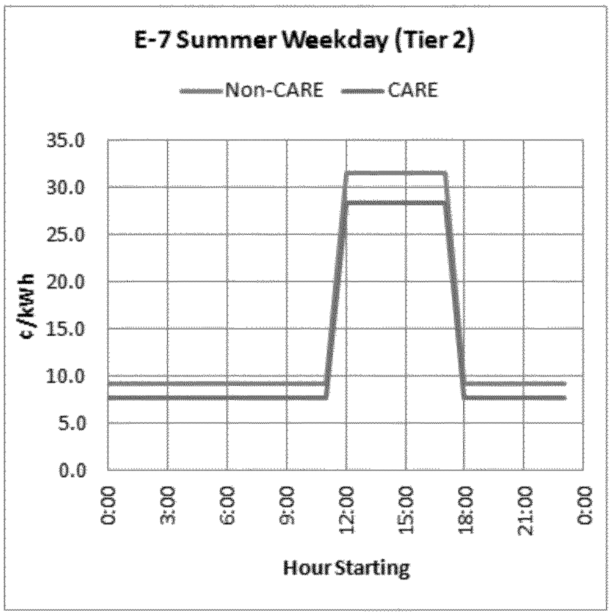
The E-7 tariff is a two-period rate, with a peak period from 12 to 6 PM on weekdays and off-peak prices in effect at all other times. The peak period is the same the entire year, although rates change seasonally. Summer rates are in effect from May 1 through October 31. The rate has been closed to new customers since 2007 and the number of customers on the rate has been steadily decreasing as existing customers close their accounts or change rates.

The E-7 tariff was replaced by the E-6 tariff, which is a three-period TOU rate with rate periods that vary by season. During summer weekdays, the peak period is from 1 PM to 7 PM, and the partial peak period is from 10 AM to 1 PM and 7 PM to 9 PM; there is another partial peak from 5 PM to 8 PM on Saturdays and Sundays. All other hours are priced at the off-peak rate. In the winter, peak period prices do not apply, and partial peak prices occur from 5 PM to 8 PM on weekdays only. All other hours are at off-peak prices.

There are two versions of both E-7 and E-6: one for CARE customers and one for non-CARE customers. In addition, as with all California utilities, residential customers are charged more for electricity use above a certain baseline level each month to encourage conservation. Different prices apply as customers exceed the baseline level by 100%, 130%, 200% and 300%. Each of these percentage breaks is known as a tier. The baseline level varies by climate region and takes into account whether customers live in homes that receive both electric and gas service or receive all electric service.

Figure 2-1 illustrates the variation in prices across hours of the day for both rates. For simplicity, the figure only plots the hourly prices for summer weekdays, assuming Tier 2 usage levels (usage between 100% and 130% of the baseline level). During peak hours, the E-7 price signal is stronger than the E-6 signal. However, E-6 also includes a semi-peak period and encourages customers to shift loads for more hours. For both E-6 and E-7, CARE customers experience lower prices across all rate periods. Table 2-3 provides additional detail and shows the electricity price by rate period, tier and CARE status for E-6 and E-7 customers.

Figure 2-1: Illustrative E-7 and E-6 Summer Weekday Hourly Prices



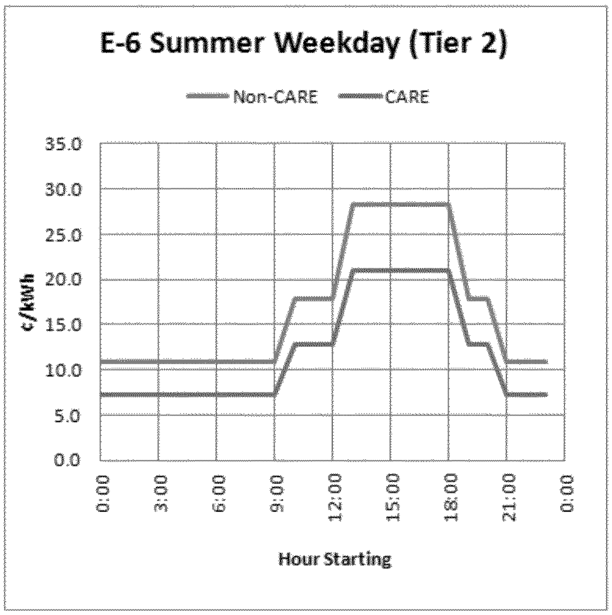


Table 2-3: E-6 and E-7 Prices[9]

Rate	Rate Description	Season	TOU Period	Energy Charge (¢/kWh) Tier 1 (baseline)	Tier 2 (101-130% of baseline)	Tier 3 (131-200% of baseline)	Tier 4 (201-300% of baseline)	Tier 5 (300% of baseline+)	Average Total Rate (¢/kWh) Rate Sheet
E7	Residential time-of-use (4 periods)	Summer	Peak	31.3	33.1	48.1	52.1	52.1	16.3
			Off-Peak	7.9	9.7	24.7	28.7	28.7	
		Winter	Peak	11.1	12.9	27.9	31.9	31.9	
			Off-Peak	8.3	10.1	25.0	29.0	29.0	
EL-7	Residential time-of-use, CARE (4 periods)	Summer	Peak	26.8	28.4	40.2	40.2	40.2	9.2
			Off-Peak	6.1	7.7	9.2	9.2	9.2	
		Winter	Peak	8.9	10.5	13.4	13.4	13.4	
			Off-Peak	6.4	8.0	9.6	9.6	9.6	
E6	Residential time-of-use (6 periods)	Summer	Peak	27.9	29.6	44.7	48.7	48.7	18.6
			Part-Peak	17.0	18.8	33.8	37.8	37.8	
			Off-Peak	9.8	11.5	26.6	30.6	30.6	
		Winter	Part-Peak	11.8	13.5	28.5	32.5	32.5	
			Off-Peak	10.2	11.9	27.0	31.0	31.0	
EL-6	Residential time-of-use, CARE (6 periods)	Summer	Peak	19.7	21.0	29.5	29.5	29.5	9.6
			Part-Peak	11.5	12.8	17.2	17.2	17.2	
			Off-Peak	6.0	7.3	9.0	9.0	9.0	
		Winter	Part-Peak	7.5	8.8	11.2	11.2	11.2	

[9] The rates shown here were those in effect as of December 2012. Rates changed four times during the study period. Current and historical rates can be found online at http://www.pge.com/nots/rates/tariffs/electric.shtml#RESELEC_TOU.

			Off-Peak	6.3	7.6	9.4	9.4	9.4	

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In total, there were approximately 91,000 customers being served under the four versions of the TOU tariffs at the end of summer 2012, with about 21,000 on E-6 and approximately 70,000 on E-7. Table 2-4 compares E-6 and E-7 non-net metered customers to customers on the standard (non-time varying) E-1 rate. We have excluded net metered customers from our analysis, but in general E-6 and E-7 customers are much more likely to be net metered than a typical customer. Net metered customers tend to have very different load patterns compared with standard metered customers; they often have solar power or some other form of distributed generation. While less than 1% of customers on flat rates are net metered, approximately 89% of E-6 customers and 18% of E-7 customers are net-metered.

Table 2-4: Customer Characteristics by Tariff (E-6 and E-7 Exclude Net Metered Customers)

Characteristic	Rate		
	E-1	E-6	E-7
Accounts	4,396,326	3,025	57,074
Average Annual kWh	6,679	14,175	11,531
% Net Metered	1	0	0
% CARE	27	12	11
% All Electric	15	21	34
% with Smart Meters (Sept 30, 2011)	93	4	23
% with Smart Meters (July 27, 2012)	92	67	28

E-6 and E-7 customers differ in several ways from the E-1 population. For example, customers on E-6 and E-7 are less likely to be on the low income rate, CARE. While approximately 27% of PG&E's customers on the non-time varying E-1 tariff are CARE customers, only about 12% of E-6 and E-7 customers, are on the CARE tariff. E-7 customers are also more likely to be all electric households and thus consume more electricity. Approximately 34% of E-7 customers receive all electric service, which is more than twice the percentage of such customers on the E-1 tariff. The annual electricity consumption of E-7 and E-6 customers, more than 10,000 kWh, is about 50% higher than the 6,700 kWh average annual consumption of E-1 customers.

In comparison to customers on flat rates, a much smaller share of E-6 and E-7 customers have had smart meters installed. Over 90% of customers on flat rates had smart meters installed by September 30, 2011. In contrast, 4% of E-6 and 23% of E-7 customers had smart meters installed. The limited availability of smart meters among TOU customers has important implications for the load impact evaluation since at least one year of interval data is needed to estimate load impacts.

The load impact estimates presented in this report exclude net-metered customers because most of these customers have solar installations and differences in their loads are mostly or exclusively attributable to that fact rather than to the TOU rate. In addition, the evaluation does not produce separate load impact estimates for E-6 customers, because there are only 1,500 non-net-metered customers, few of which have smart meters. As a result, there are not enough E-6 customers from which to draw a representative sample.

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Finally, although the peak period in the rate structures differs between the two groups, we have analyzed E-6 and E-7 customers together for two reasons. First, the required output of this analysis is estimated ex ante load impacts from 1-6 PM, regardless of what the actual peak period is in the rates. Second, customer response to a TOU rate is unlikely to be precisely bracketed around the peak period anyway. The types of changes in lifestyle that people make to adjust to the rate will not precisely match the peak period.

2.3 Report Organization

The remainder of this report is organized as follows. Section 3 provides an overview of the ex post methodology used to evaluate SmartRate. Section 4 provides ex post results for SmartRate. Section 5 discusses the ex ante methods and results for SmartRate. Section 7 discusses the ex post load impact estimation methods for the E-6 and E-7 rates and contains the ex post load impact estimates for these tariffs. Section 8 contains ex ante methods and results for E-6 and E-7.

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3 SmartRate Ex Post Methods and Validation

The fundamental problem for estimating load impacts is developing an estimate of reference load. The reference load is an estimate of what load would have been in the absence of the price incentives that are in effect for participants. For this evaluation, the focus is on what load would have been on SmartDays in particular. It may be true that customer load is different on non-SmartDays due to the SmartRate bill credit or due to habit formation in energy conservation (these effects work in opposite directions); however an experiment to precisely measure such a subtle effect would be difficult to design and implement.[10]

The methods used in the 2012 SmartRate evaluation are similar to those used for the 2011 evaluation, but adjusted to account for the changing enrollment over the summer. This year a series of matched control groups were selected for the entire SmartRate population and SmartMeter data was used to directly estimate impacts without the need for regression. Different control groups were used for different sets of SmartRate events because the population changed between events, which meant that the control group that matched well to the SmartRate population early in the summer did not match well later in the summer.

In this situation, where the program is available to the entire population, precluding a controlled experiment, the main alternative method to using a matched control group is to use a within-subjects analysis. The matched control group method is superior to a within-subjects analysis in this case because there is a large population of non-SmartRate customers to use as a pool for matching and because it eliminates the problem of model misspecification. Any reference load model based on loads observed at non-event times requires the modeler to make assumptions about the relationships between load, time and temperature. If this assumed function does not reflect the true relationships between load, time and temperature, then the model can produce incorrect results. In contrast, the matched control group automatically deals with this problem by assuming that the customers who behave similarly to SmartRate customers during non-event periods would also behave similarly during event periods. This eliminates the need to specify load as a function of weather.

As discussed below, we do use a within-subjects analysis for certain parts of this evaluation; however, in those cases the emphasis is on relative load impacts across different types of customers. It is a weaker assumption to believe that the biases this method produces are relatively stable across customer segments than to believe that we can completely eliminate them. Therefore, we use the matched control group method wherever possible, particularly for the primary impact estimates to be reported. We use the within-subjects analysis only to compare load impacts across segments of customers where developing control groups within each segment would be infeasible.

3.1 Matched Control Group Methodology

The primary source of reference loads, and hence impact estimates, was a series of matched control groups. These control groups are assembled from among the non-SmartRate population. The methods used to assemble the groups are designed to ensure that the control group load on

[10] The design necessary to measure such an effect would be a large-scale randomized controlled trial with tens of thousands of customers such as those used to measure the impact of Opower-type interventions, only with the further complication that customers have to opt-in to the program. This complication can be dealt with using a recruit and deny methodology, which is logistically demanding and could negatively impact customer satisfaction.

event days is an accurate estimate of what load would have been among SmartRate customers on event days.

The fundamental idea behind the matching process is to find customers who were not subject to SmartRate events that have similar characteristics to those who were subject to SmartRate events. To account for the changes the SmartRate population experienced over the summer of 2012, six different control groups were assembled: three for the SmartRate-Only population and three for the group of SmartRate customers also enrolled in SmartAC. This is because the group of SmartRate customers who participated in the first three events was different than the set of customers who experienced the fourth event and those who experienced the last six events. The difference in the population across the first three events only was trivial because they were on consecutive days. A similar point applies to the last six events, although they were not all across consecutive days. Each control group was used to match the SmartRate population for these specific sets of events.

The control groups were selected using a propensity score match to find customers who had load shapes most similar to SmartRate customers. In this procedure, a probit model is used to estimate a score for each customer based on a set of observable variables that are assumed to affect the decision to join SmartRate. A probit model is a regression model designed to estimate probabilities—in this case, the probability that a customer would choose SmartRate. The score can be interpreted two different ways. First, the propensity score can be thought of as a summary variable that includes all the relevant information in the observable variables about whether a customer would choose to be on SmartRate. Each customer in the SmartRate population is matched with a customer in the non-SmartRate population that has the closest propensity score. The second way to think of the propensity score is as the probability that that customer will join SmartRate based on the included independent variables. Thinking of it this way, each customer in the control group is matched to a SmartRate customer with a similar probability of joining SmartRate given the observed variables.

The match was performed within each LCA and was based on an extensive list of customer characteristics including a set of variables that characterize load shape and the magnitude of electricity use on hot, non-event days.[11]

The set of usage variables in the propensity score model were average hourly usage for the whole day and the average hourly usage for each of the hours in the morning and each of the hours that SmartRate events are called (2-7 PM), all calculated over the 10 hottest, non-event, non-holiday weekdays.[12] These days were chosen because they were the only days with temperatures that best reflected those on event days. Matches were tested based on other sets of hours and the final model was chosen because it resulted in the closet match between SmartRate and control customer average usage during event hours on hot, non-event days (discussed below). The final probit model results from the second match are shown in Appendix A.

A match was found for each SmartRate customer, but the same control customer could be matched to multiple SmartRate customers, meaning that a control customer would be represented more than once in the control group.

[11] See Appendix A for a full list of variables used in match.

[12] The days were June 1, June 12, June 17, June 20, July 22, July 31, August 1, August 8, August 9 and September 30.

Table 3-1 compares the final matched control group to the SmartRate sample based on LCA, CARE status and average monthly usage in June and July 2011. The last two columns of Table 3-1 show t-statistics and p-values for tests of the hypothesis that the mean value do not differ between the groups. The two groups match closely across LCAs. For average usage during summer months and CARE status, fairly small but statistically significant differences exist between the groups. This shows that the groups are fairly well, but not perfectly balanced. It is uncertain what bias this imbalance would lead to in the results, but it is not likely to be large. For example, the difference in average June usage between the SmartRate group and the matched control group is only about 2% and not statistically significant.

Table 3-1: Distributions of LCA, Usage and CARE Status for SmartRate Customers, Control Customers and the Residential Population[13]

Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	37%	37%	0.00	1.00
Greater Fresno	12%	12%	0.00	1.00
Kern	21%	21%	0.00	1.00
Northern Coast	2%	2%	-0.03	0.98
Other	14%	14%	0.00	1.00
Sierra	6%	6%	0.00	1.00
Stockton	7%	7%	0.00	1.00
June 2012 kWh	672	686	3.16	0.00
July 2012 kWh	750	762	2.24	0.03
Non-CARE	60%	67%	-14.68	0.00
CARE	40%	33%	-14.68	0.00

A potential source of bias in this methodology is that SmartRate customers may behave differently on non-event days than they would if they were not on SmartRate, either because they face slightly different rates than non-SmartRate customers due to SmartRate credits or due to energy saving habit formation. This means that there is a potential bias introduced by matching SmartRate customers to customers who have similar loads on hot, non-event days because those loads may not be an accurate representation of what SmartRate customers would have used if they were not on the program. As mentioned above, our maintained hypothesis is that this effect is very small. For the current analysis, we assume that the difference in usage between SmartRate and control customers due to price differences is negligible.

After the matched control groups were identified, they were validated by comparing SmartRate customer characteristics to control group characteristics. The most important of these characteristics

[13]These statistics are for the matched control group for the first set of event days for SmartRate-only Customers. Analogous tables for later summer control groups and for dually-enrolled control groups are in Appendix A.

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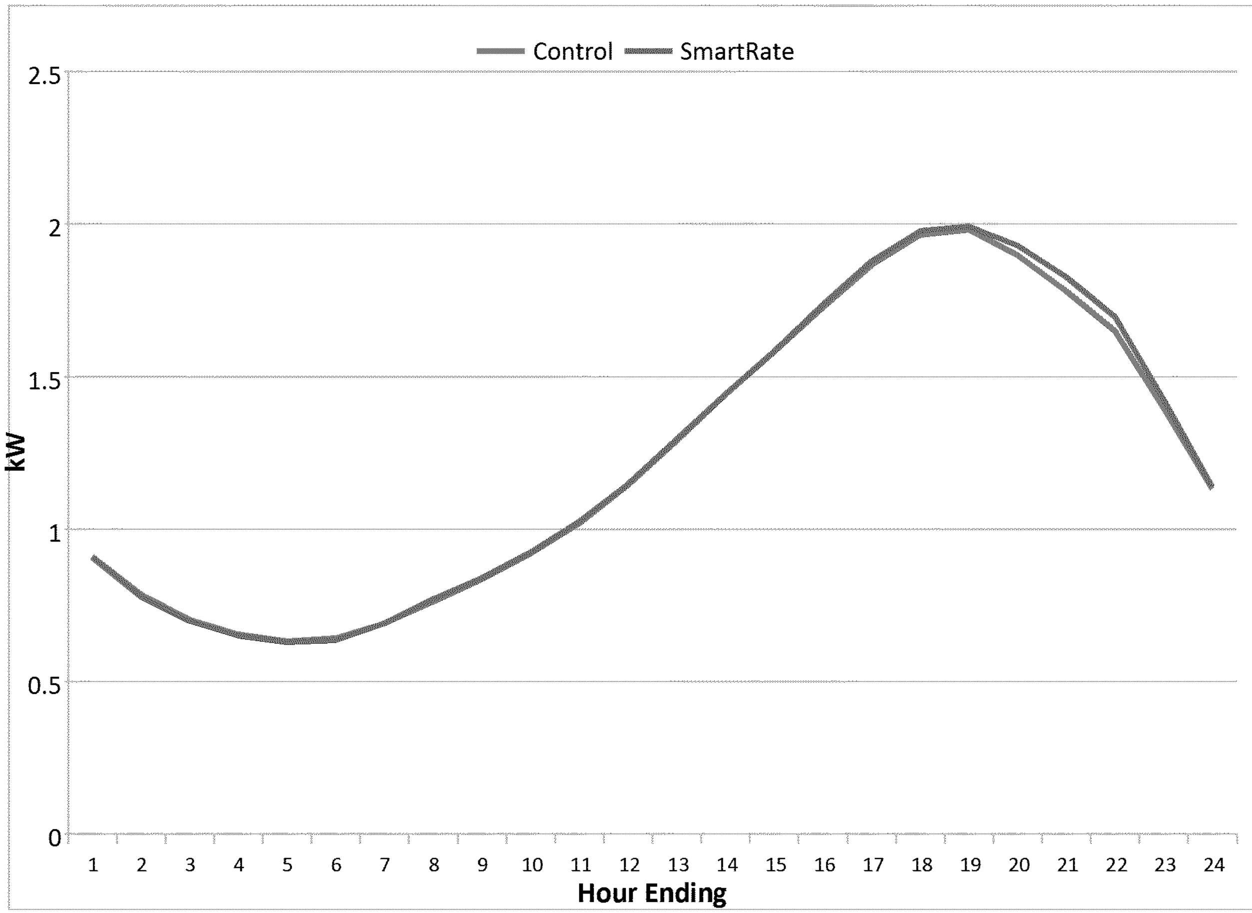
was usage on hot, non-event days. If the two groups have similar usage on hot non-event days, then it is likely that the control group's usage is an accurate estimate of event day reference load. Figure 3-1 shows average hourly usage for both groups on hot, non-event days during event hours. Over the event period (2 to 7 PM), usage is very similar between the two groups, with a difference of about 1%, on average. Appendix A includes more detail on the data underlying Figure 3-1, including the data for each day separately.

Figure 3-1: Average Usage on Hot, Non-event Days for SmartRate Customers and Control Group[14]



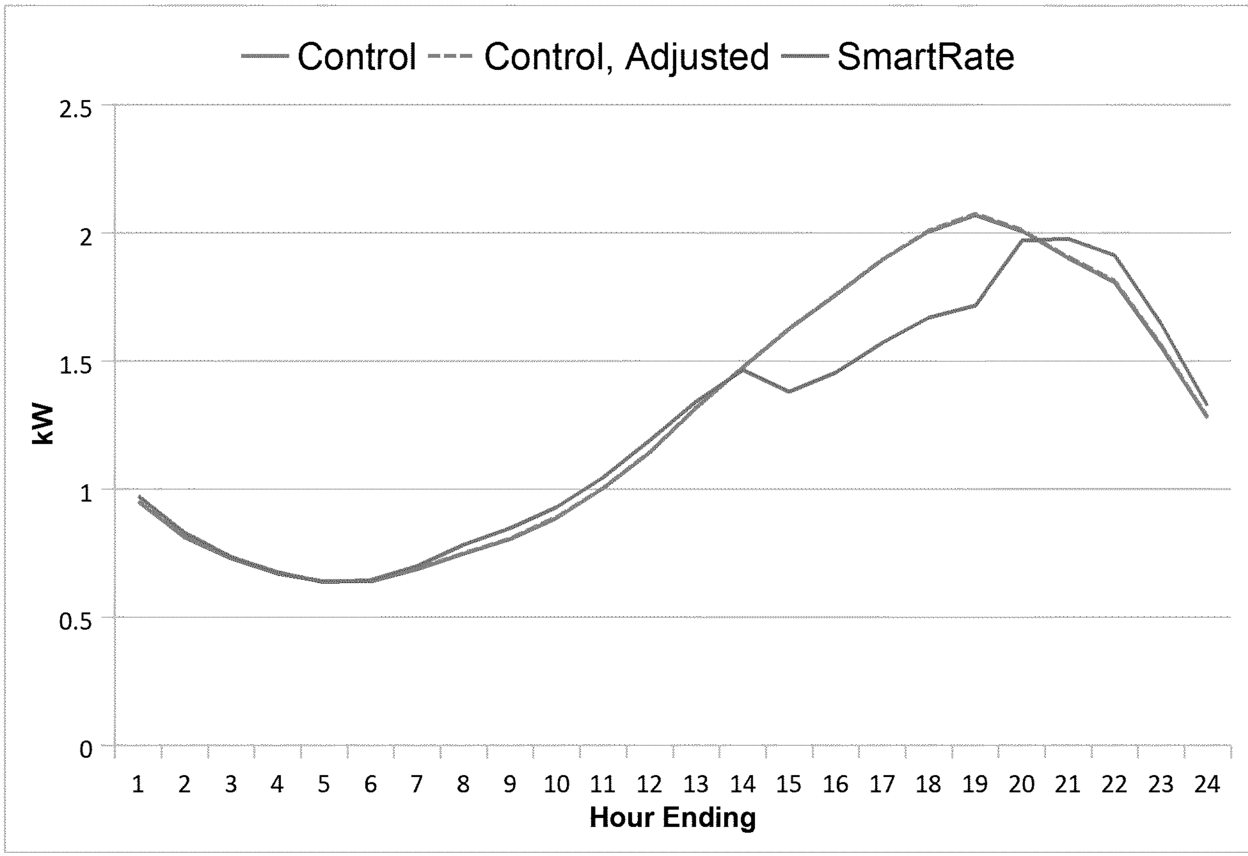
Once the control groups were matched and validated, load impacts were estimated using a difference-in-differences methodology. This methodology calculates the estimated impacts as the difference in average loads between SmartRate and control customers on event days minus the difference between the two groups on hot, non-event days. This calculation controls for residual differences in load between the groups that are not eliminated through the matching process, thus reducing bias. In the following discussion, this process is framed as an adjustment to control group usage. This preserves the reference load framework, while still making use of the difference-in-differences methodology.

[14] These statistics are for the matched control group for the first set of event days for SmartRate-Only Customers. Analogous graphs for later summer control groups and for dually-enrolled control groups are in Appendix A.

In this process, control group usage was adjusted based on the percentage difference between SmartRate and control usage on the same hot, non-event days used in the matching process. For example, if control group usage was 1% higher than SmartRate group usage from 2 to 7 PM across the hot, non-event days, the control group usage was decreased by 1% on all event days. These adjustments were all quite small among the LCAs, the largest being 5.7%. Although usage was already very close between the treatment and control groups due to matching, this adjustment was made in order to further minimize any differences between the groups that exist at relevant times.

Figure 3-2 illustrates the adjustment process. The solid blue line shows the unadjusted control group usage and the solid red line shows the unadjusted SmartRate usage. As the figure shows, the adjustment is quite modest, which should be expected since matching was done based on hot, non-event day load.

Figure 3-2: Example of Control Group Usage Adjustment; June 11, 2012, SmartRate-only



After the adjustment, impact estimates are calculated by subtracting average hourly usage on each event day for SmartRate customers from adjusted average hourly usage on each event day for the matched control group.

The same methods were used to calculate impacts by CARE status and LCA. Sample sizes were sufficiently large that average usage in the treatment and control groups matched closely even when the population was broken down into smaller categories. Hourly adjustments based on average control usage on event days were calculated separately for each CARE status and LCA. Table 3-2 shows the range of adjustments for each category of customers for each matched control group.

Table 3-2: Range of Adjustments on Control Usage By LCA and CARE Status (% of Control Load)

LCA	First 3 Events		Fourth Event		Last 6 Events	
	SMR-Only	Dually Enrolled	SMR-Only	Dually Enrolled	SMR-Only	Dually Enrolled
Greater Bay Area	2.2%	-0.7%	1.0%	-0.6%	0.8%	-0.8%
Greater Fresno	-1.4%	-2.2%	-0.1%	-2.4%	-1.1%	-4.8%
Kern	-1.0%	-1.4%	-1.2%	-4.7%	-1.1%	-2.1%
Northern Coast	3.0%	-0.1%	0.0%	-0.8%	1.6%	-5.7%
Other	0.6%	-3.1%	-2.6%	-4.8%	-1.9%	-2.6%
Sierra	2.7%	1.2%	1.0%	0.5%	-0.1%	1.2%
Stockton	0.2%	-0.7%	1.7%	0.0%	0.7%	-1.9%
Non-CARE	-2.9%	-4.5%	-5.3%	-5.2%	-4.5%	-4.4%
CARE	2.8%	19.3%	6.3%	21.0%	3.8%	20.5%

3.2 Individual Customer Regression Methodology

Having used the matched control group to estimate overall event impacts, the individual regressions were used to create impact estimates on a per-customer basis, which allows for relatively simple analyses of different segments of customers without repeatedly matching new control groups for each segment. A sample of SmartRate customers who have been part of the program since May 1, 2012 was used. This sample was used because these customers experienced all of the events in 2012. This means that this sample is not fully representative of the SmartRate population. This is acceptable because the results from this analysis are only used for comparing relative event impacts across different customer segments, rather than for producing impact estimates for the whole program.

After testing a number of regressions on this sample of SmartRate customers, the final model was chosen. This model was selected because it gave the best predictions in a cross-validation test (also called an out-of-sample test) of all specifications tested. Event effects were modeled as the difference between predicted reference load and actual load for each customer for each hour of each event day. The equation is as follows:

Equation 3-1: Model Specification for Individual Customer Regressions

$$kW_t = a + \sum_{y=2}^{24} b_y \cdot hour_y + \sum_{y=2}^{24} c_y \cdot hour_y \cdot mean17 + \sum_{y=2}^{24} d_y \cdot hour_y \cdot (mean17)^2$$
$$+ \sum_{z=1}^{15} e_z \cdot eventday_z + \cdot\varepsilon_t$$

Table 3-3: Description of Energy Use Regression Variables

Variable	Description
a	a is an estimated constant
b-e	b-e are estimated parameters
mean17	The mean temperature from midnight until 5 PM
eventday	Dummy variables for the event period of each event day
ε	The error term

The model was validated using cross-validation testing on the sample of SmartRate customers. Cross-validation refers to holding back data on event-like days from the model-fitting process in order to test model accuracy. The process involves running the regressions without allowing the model to use one day out of the 10 hottest non-event days. The regression model is used to predict electricity use on these event-like days that were withheld, and then the model's predictions are compared directly to actual electricity use observed on those days. This process provides an indication of the overall level of accuracy of the model under relevant conditions.

Table 3-4 shows predicted and actual usage during event hours on the 10 out-of-sample days. Because the individual regressions are only being used to predict impacts (as opposed to full event day load shapes), these are the only hours important to the analysis. On average, predicted values are no different than actual usage on the out-of-sample days. This difference on individual days is small and helps to validate the results of the regression model for the entire population.

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Table 3-4: Predicted Versus Actual Usage During Event Hours on Hot Non-event Days, SmartRate-only Customers

Date	Observed Load (kW)	Predicted Load (kW)	Error (kW)	Percent Error (%)
1-Jun-12	1.68	1.80	-0.12	-7%
12-Jun-12	1.60	1.72	-0.12	-8%
17-Jun-12	2.13	2.11	0.02	1%
20-Jun-12	1.59	1.64	-0.05	-3%
22-Jul-12	2.08	1.95	0.14	7%
31-Jul-12	1.87	1.86	0.01	0%
1-Aug-12	1.85	1.85	0.01	0%
8-Aug-12	1.78	1.75	0.03	2%
9-Aug-12	2.00	1.92	0.08	4%
30-Sep-12	1.57	1.55	0.02	1%
All Days	**1.82**	**1.82**	**0.00**	**0%**

Event day impacts estimated using individual regressions for the SmartRate population that experienced all the events in 2012 were compared to load impact estimated using the matched control group method. Table 3-5 shows the average impacts on each event day of the summer under both estimation methods. The matched control method found an average impact of 0.20 kW, 14% of whole-house usage. Using individual customer regressions, the average adjusted impact was 0.22 kW, or 11% of whole-house usage. On individual event days, impacts calculated by the two methods differ more so than on average, which is to be expected. Even apart from the different models used, we expect these estimates to differ because the matched control group estimates represent the full population at any given time, while the individual customer regression estimates represent only the sample that was enrolled as of May 2012. The correlation between the absolute impacts from the matched control group and the absolute impacts from the individual customer regressions is 74%.[15] A correlation of 74% indicates that the two values tend to both be high on the same days and low on the same days, but the relationship is not perfect.

[15] The correlation coefficient calculated here is Pearson's correlation. It is a measurement of how strongly two sets of measurements are related. Its value can range from -1 to 1. A positive correlation indicates that when one measurement is above its average that the other is likely to be above its average as well. The closer the correlation is to 1, the more the values vary together in this way.

Table 3-5: Ex Post Impact Comparison for Control Group Method and Individual Customer Regression Method, SmartRate-only Customers

Date	Matched Control Group			Individual Customer Regressions		
	Average Reference Load (kW)	Average Load Reduction (kW)	% Load Reduction	Average Reference Load (kW)	Average Load Reductio n (kW)	% Load Reduction
9-Jul-12	1.58	0.26	16%	1.64	0.16	10%
10-Jul-12	1.71	0.27	15%	1.78	0.18	10%
11-Jul-12	1.87	0.32	17%	1.98	0.24	12%
23-Jul-12	1.58	0.25	15%	1.84	0.25	13%
4-Sep-12	1.32	0.18	13%	1.66	0.25	15%
13-Sep-12	1.34	0.16	12%	1.65	0.21	13%
14-Sep-12	1.36	0.15	11%	1.66	0.15	9%
1-Oct-12	1.36	0.22	16%	1.60	0.23	14%
2-Oct-12	1.40	0.21	15%	1.65	0.22	13%
3-Oct-12	1.30	0.16	12%	1.69	0.30	18%
Average Event Day	1.44	0.20	14%	1.71	0.22	13%

Table 3-6: Ex Post Impact Comparison for Control Group Method and Individual Customer Regression Method, Dually-enrolled Customers

Date	Matched Control Group			Individual Customer Regressions		
	Average Referenc e Load (kW)	Average Load Reductio n (kW)	% Load Reductio n	Average Referenc e Load (kW)	Average Load Reductio n (kW)	% Load Reductio n
9-Jul-12	1.65	0.48	29%	1.96	0.40	21%
10-Jul-12	1.90	0.49	25%	2.19	0.47	22%
11-Jul-12	2.19	0.56	25%	2.57	0.63	25%
23-Jul-12	1.76	0.41	23%	2.25	0.52	23%
4-Sep-12	1.47	0.38	25%	1.99	0.55	27%
13-Sep-12	1.53	0.38	25%	2.01	0.50	25%
14-Sep-12	1.50	0.35	23%	1.98	0.45	22%
1-Oct-12	1.63	0.45	28%	1.94	0.54	28%
2-Oct-12	1.71	0.43	25%	2.02	0.56	28%

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3-Oct-12	1.53	0.35	23%	2.05	0.61	30%
Average Event Day	1.65	0.42	25%	2.10	0.52	25%

4 SmartRate 2012 Ex Post Load Impacts

This section summarizes the ex post load impact estimates for SmartRate for the 2012 program year. In keeping with the requirements for ex post load impact evaluations, results are presented for each hour of each event day for the average customer and for all customers enrolled at the time of the event. In addition to meeting the basic load impact protocol requirements, detailed analysis has been conducted to understand how load impacts vary across several factors, including:

- Local capacity area;
- CARE status;
- Number of successful notifications; and
- Central AC saturation and temperature.

The characteristics of customers who give greater-than-average load impacts are also discussed.

The analysis presented here also addresses several important policy questions, including:

- Attrition rates and the pattern of attrition for SmartRate participants;
- Whether bill protection affects customer load impacts; and
- The extent to which automated load response via thermostats or direct load control switches produces incremental impacts over and above what customers with central AC provide on their own.

Different methods and models are used to analyze different issues. The assessments of overall impacts and impacts by local capacity area and CARE status are based on results from the matched control groups. These analyses reflect impact estimates that are accurate for the population enrolled as of each event. All of the other issues are investigated using individual customer regressions for the group of customers who experienced all 2012 event days.

4.1 Average Event Impacts

Figure 4-1 shows the hourly load impacts for the average SmartRate-only customer across the 10 event days in 2012. The average impact for all events across the 5-hour event window was 0.20 kW, or 14%, compared to the 0.25 kW average ex post load impact estimate in the 2011 evaluation, while as discussed in Section 2, the population grew in 2012 and the geographic distribution shifted. Finally, in 2011, the dually-enrolled population was small enough that it wasn't specifically broken out for ex post estimation, so the 0.25 kW value includes the effect of dually-enrolled customers who made up about 20% of the program in 2011. With all these differences, we shouldn't expect impact estimates to be the same for 2012 as 2011.

The percentage load reduction is highest from 4 to 7 PM, and lowest in the first hour, from 2 to 3 PM. Average hourly load impacts vary from a low of 0.15 kW in the first hour to a high of 0.24 kW in the hour between 5 and 6 PM. The reference load increases from a low of 1.21 kW from 2 to 3 PM, when the average temperature is 88°F, to a high of 1.59 kW between 6 and 7 PM, when the temperature is about 87°F and people generally return home from work.

The number of enrolled customers shown in Figure 4-1 is the average number of enrolled customers across the 10 event days in 2012.

For the average customer, there is an increase in electricity consumption relative to the reference load in the evening hours following the end of the event. This probably occurs because many customers voluntarily reduce their AC use during events and the AC unit must run more to cool the house after the event period ends than it would have in the absence of an event.

Figure 4-2 shows the hourly load impacts for the average dually-enrolled customer across the 10 event days in 2012. The average impact for all events across the 5-hour event window was 0.42 kW, or 25% of reference load.

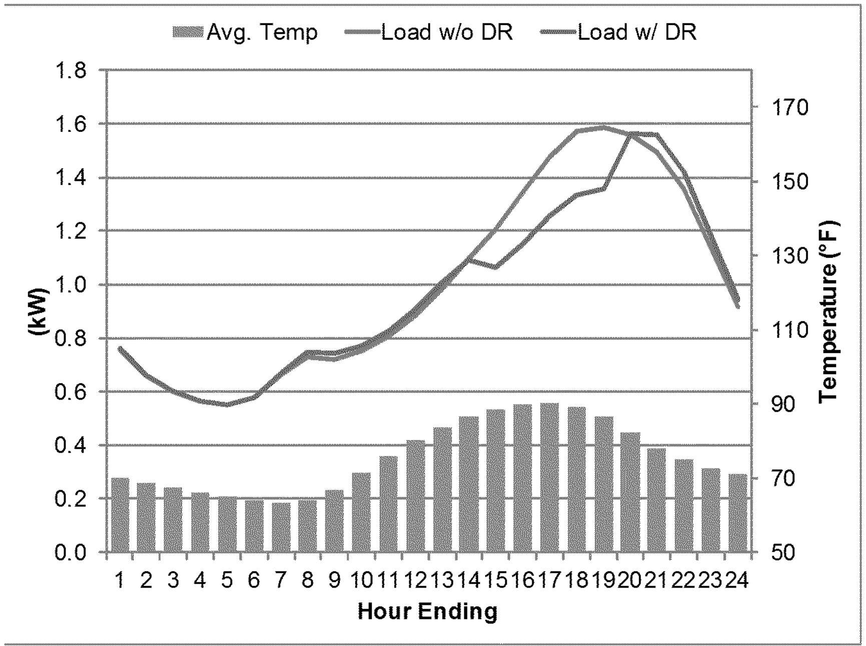
Figure 4-1: Average Load Impact per Hour for All 2012 Event Days
(Average SmartRate-only Participant)

TABLE 1: Menu options

Local Capacity Area	All
Date	Average Event Day
Result Type	Average Customer
Enrolled Customers	38,667

TABLE 2: Event Day Information

Event Start	2 PM
Event End	7 PM
Average Temp. for Event Window	89
Load Reduction for Event Window	0.20
% Load Reduction for Event Window	14%



Hour Ending	Load w/o DR (kW)	Load w/ DR (kW)	Impact (kW)	Impact (%)	Avg. Temp (°F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1	0.76	0.76	0.00	-1%	70	-0.14	-0.06	0.00	0.05	0.13
2	0.66	0.66	0.00	0%	69	-0.13	-0.05	0.00	0.05	0.12
3	0.60	0.60	0.00	0%	67	-0.12	-0.05	0.00	0.05	0.11
4	0.56	0.56	0.00	0%	66	-0.11	-0.04	0.00	0.05	0.11
5	0.55	0.55	0.00	0%	65	-0.10	-0.04	0.00	0.04	0.10
6	0.58	0.58	0.00	0%	64	-0.11	-0.04	0.00	0.05	0.11
7	0.67	0.67	0.00	0%	64	-0.13	-0.05	0.00	0.05	0.12
8	0.73	0.75	-0.02	-3%	64	-0.15	-0.07	-0.02	0.04	0.12
9	0.72	0.74	-0.02	-3%	67	-0.16	-0.08	-0.02	0.04	0.12
10	0.75	0.77	-0.02	-3%	72	-0.17	-0.08	-0.02	0.04	0.13
11	0.81	0.83	-0.02	-3%	76	-0.18	-0.09	-0.02	0.05	0.14
12	0.88	0.91	-0.02	-3%	80	-0.20	-0.10	-0.02	0.05	0.15
13	0.99	1.01	-0.02	-2%	84	-0.22	-0.10	-0.02	0.06	0.17
14	1.09	1.09	0.00	0%	87	-0.21	-0.08	0.00	0.09	0.21
15	1.21	1.06	0.15	12%	88	-0.07	0.06	0.15	0.23	0.36
16	1.34	1.15	0.19	14%	90	-0.04	0.10	0.19	0.29	0.42
17	1.47	1.26	0.22	15%	90	-0.03	0.12	0.22	0.32	0.46
18	1.57	1.33	0.24	15%	89	-0.01	0.14	0.24	0.34	0.49
19	1.59	1.36	0.23	15%	87	-0.01	0.13	0.23	0.33	0.47
20	1.56	1.56	0.00	0%	82	-0.25	-0.10	0.00	0.10	0.24
21	1.49	1.56	-0.07	-4%	78	-0.30	-0.16	-0.07	0.03	0.17
22	1.36	1.42	-0.07	-5%	75	-0.28	-0.16	-0.07	0.02	0.15
23	1.14	1.18	-0.05	-4%	73	-0.24	-0.12	-0.05	0.03	0.15
24	0.92	0.94	-0.02	-3%	71	-0.19	-0.09	-0.02	0.04	0.14

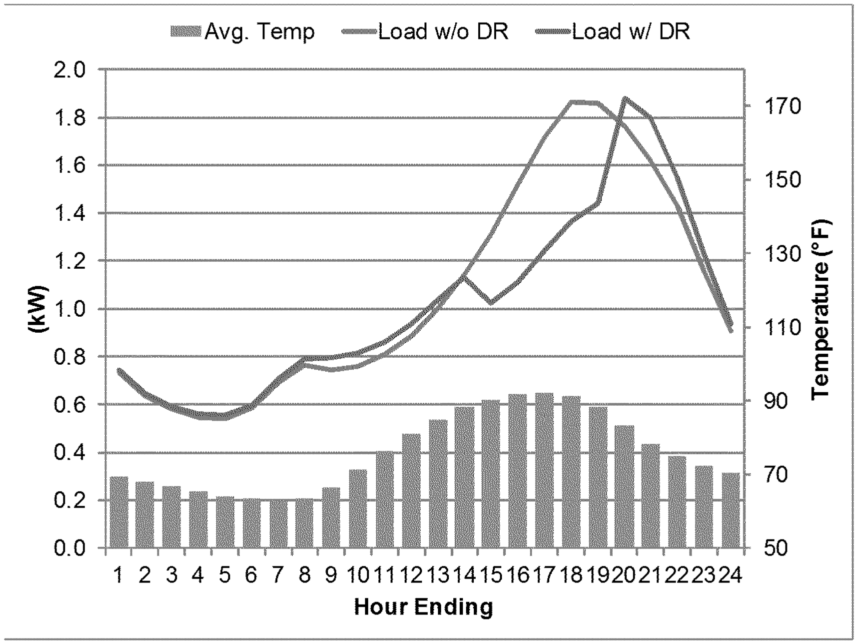
Figure 4-2: Average Load Impact per Hour for All 2012 Event Days
(Average Dually-enrolled Participant)

TABLE 1: Menu options

Local Capacity Area	All
Date	Average Event Day
Result Type	Average Customer
Enrolled Customers	22,132

TABLE 2: Event Day Information

Event Start	2 PM
Event End	7 PM
Average Temp. for Event Window	91
Load Reduction for Event Window	0.42
% Load Reduction for Event Window	25%



Hour Ending	Load w/o DR	Load w/ DR	Impact	Impact	Avg. Temp	Uncertainty Adjusted Impact - Percentiles				
	(kW)	(kW)	(kW)	(%)	(°F)	10th	30th	50th	70th	90th
1	0.74	0.74	-0.01	-1%	69	-0.17	-0.07	-0.01	0.06	0.15
2	0.64	0.64	-0.01	-1%	68	-0.14	-0.06	-0.01	0.05	0.13
3	0.58	0.59	-0.01	-2%	67	-0.14	-0.06	-0.01	0.04	0.11
4	0.55	0.56	-0.01	-2%	65	-0.13	-0.06	-0.01	0.03	0.10
5	0.54	0.56	-0.01	-2%	64	-0.13	-0.06	-0.01	0.03	0.10
6	0.58	0.60	-0.01	-2%	63	-0.13	-0.06	-0.01	0.04	0.11
7	0.69	0.71	-0.02	-2%	63	-0.16	-0.08	-0.02	0.04	0.12
8	0.76	0.79	-0.03	-3%	63	-0.18	-0.09	-0.03	0.04	0.13
9	0.74	0.79	-0.05	-7%	66	-0.21	-0.12	-0.05	0.01	0.11
10	0.76	0.81	-0.05	-7%	71	-0.23	-0.12	-0.05	0.02	0.12
11	0.81	0.86	-0.05	-7%	76	-0.24	-0.13	-0.05	0.03	0.14
12	0.89	0.94	-0.05	-6%	81	-0.26	-0.14	-0.05	0.04	0.16
13	1.00	1.04	-0.03	-3%	85	-0.27	-0.13	-0.03	0.06	0.20
14	1.14	1.13	0.01	1%	88	-0.25	-0.09	0.01	0.12	0.28
15	1.31	1.02	0.29	22%	90	0.02	0.18	0.29	0.39	0.55
16	1.52	1.11	0.40	27%	92	0.11	0.29	0.40	0.52	0.69
17	1.71	1.24	0.47	28%	92	0.16	0.35	0.47	0.60	0.78
18	1.86	1.37	0.50	27%	91	0.18	0.37	0.50	0.63	0.81
19	1.86	1.44	0.42	23%	88	0.11	0.29	0.42	0.55	0.73
20	1.76	1.88	-0.12	-7%	83	-0.45	-0.25	-0.12	0.02	0.21
21	1.62	1.80	-0.18	-11%	78	-0.49	-0.30	-0.18	-0.05	0.13
22	1.43	1.55	-0.12	-8%	75	-0.39	-0.23	-0.12	-0.01	0.15
23	1.16	1.23	-0.07	-6%	72	-0.30	-0.16	-0.07	0.03	0.17
24	0.91	0.94	-0.03	-4%	70	-0.22	-0.11	-0.03	0.05	0.16

Table 4-1 summarizes the average load reduction across the five-hour event window provided by residential SmartRate-only customers on each event day during the summer of 2012. As shown, the average percentage reduction ranged from a low of 11% on September 14, to a high of 17% on July 11. An average reduction of 14% was obtained across the 10 event days. The average load reduction per participant ranged from a low of 0.15 kW to a high of 0.32 kW. Aggregate average reductions in demand on Smart Days ranged from 5.9 MW to 11.2 MW. Aggregate load reductions for the summer averaged 7.9 MW per event.

Table 4-2 summarizes the average load reduction across the five-hour event window provided by residential dually-enrolled SmartRate customers on each event day during the summer of 2012. For this group, the average percentage reduction ranged from a low of 23% on July 23 and October 3, to a high of 29% on July 9. An average reduction of 25% was obtained across the 10 event days. The average load reduction per participant ranged from a low of 0.35 kW to a high of 0.56 kW. Aggregate average reductions in demand on Smart Days ranged from 6.6 MW to 12.2 MW. Aggregate load reductions for the summer averaged 9.2 MW per event.

Table 4-1: SmartRate-only Ex Post Load Impact Estimates

Date	Enrolled participants	Avg. Reference Load (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Daily Maximum Temp (°F)
9-Jul-12	23,194	1.58	0.26	16%	5.9	88
10-Jul-12	23,902	1.71	0.27	16%	6.3	94
11-Jul-12	24,819	1.87	0.32	17%	7.8	96
4-Sep-12	41,273	1.32	0.18	13%	7.3	86
13-Sep-12	45,057	1.34	0.16	12%	7.4	87
14-Sep-12	45,508	1.36	0.15	11%	6.8	86
23-Jul-12	30,792	1.58	0.25	16%	7.5	88
1-Oct-12	50,464	1.36	0.22	16%	11.2	95
2-Oct-12	50,715	1.40	0.21	15%	10.5	96
3-Oct-12	50,941	1.30	0.16	12%	8.3	89
Total	**38,667**	**1.44**	**0.20**	**14%**	**7.9**	**90**

Table 4-2: Dually-enrolled Ex Post Load Impact Estimates

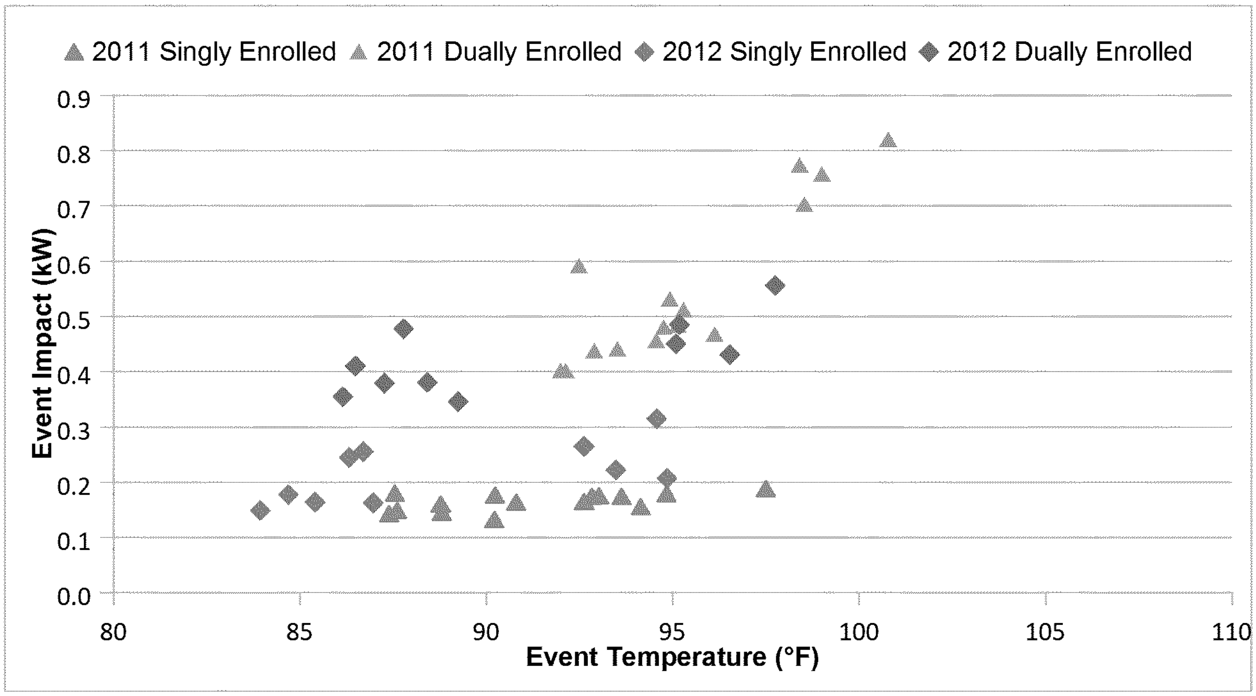
Date	Enrolled participants	Avg. Reference Load (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Daily Maximum Temp (°F)
9-Jul-12	13,914	1.65	0.48	29%	6.6	89
10-Jul-12	14,526	1.90	0.49	26%	7.1	96
11-Jul-12	15,263	2.19	0.56	25%	8.5	99
4-Sep-12	25,267	1.47	0.38	26%	9.6	89
13-Sep-12	26,345	1.53	0.38	25%	10.0	90
14-Sep-12	26,427	1.50	0.35	24%	9.4	88
23-Jul-12	18,461	1.76	0.41	23%	7.6	88
1-Oct-12	27,016	1.63	0.45	28%	12.2	97
2-Oct-12	27,045	1.71	0.43	25%	11.7	98
3-Oct-12	27,058	1.53	0.35	23%	9.4	92
Total	**22,132**	**1.65**	**0.42**	**25%**	**9.2**	**92**

In order to better understand any changes in program performance over the past two years, Figure 4-3 shows a scatter plot of average event impacts against average event temperatures for SmartRate-only and dually-enrolled customers for all events in 2011 and 2012.[16] Two major differences show up between 2011 and 2012. First, SmartRate-only customers tended to produce larger average load impacts in 2012 for similar weather conditions. Examination of reference loads and percentage (as opposed to absolute) reductions did not provide any further insight into this issue. That is, percentage reductions for SmartRate-only customers also tended to be higher in 2012. Given how much the population increased, it is not too surprising that different types of customers would sign up. Additionally, it is our understanding that PG&E used a sophisticated targeting method to try to solicit customers likely to provide higher load reductions. This may be evidence that speaks to the efficacy of the method.

Second, both SmartRate-only and dually-enrolled customers had noticeably cooler weather in 2012 than 2011, on average. Given, that, dually-enrolled customers produced load impacts broadly in line with 2011 impacts.

Figure 4-3: SmartRate-only and Dually-enrolled Ex Post Load Impact for 2011 and 2012

[16] Although separate ex post estimates for dually-enrolled customers were not reported in 2011, they were calculated for ex ante analysis.



4.2 Load Impacts for Specific Customer Segments

This subsection examines how load impacts vary across a number of customer segments, including:

- Local capacity area;
- CARE status;
- Number of successful notifications;
- Central AC saturation and temperature; and
- The characteristics of customers who provide greater-than-average load impacts.

4.2.1 Load Impacts by Local Capacity Area

PG&E's service territory is climatically diverse and the variation in temperature and AC use is significant, especially on summer days when the coastal fog is thick but the inland valleys are very hot. PG&E is comprised of eight resource planning zones known as local capacity areas (LCAs).[17] These areas are defined by the California Independent System Operator (CAISO) based on transmission lines and the location of generation. LCAs differ significantly in terms of climate and population characteristics. Kern and Fresno are the hottest LCAs which, all other things equal, would produce larger load impacts compared with milder climate regions. However, as shown in Table 2-2, enrollment in some of these warmer LCAs is dominated by low income customers on the CARE rate discount program. These customers reduce electricity use during events significantly less than customers who are not enrolled in the CARE program. As such, the average load reduction across LCAs is influenced by at least two countervailing factors.

Tables 4-3 and 4-4 show the average hourly load reduction for seven of the eight LCAs in PG&E's

[17] There are very few or no SmartRate customers in the Humboldt LCA.

SB_GT&S_0888599

service territory for SmartRate-only and dually-enrolled customers, respectively. The impact estimates in this table are based on SmartMeter data from SmartRate and matched control customers. Kern, Greater Fresno and Sierra provide the highest average load impacts. Kern and Greater Fresno are also the hottest LCAs. Sierra stands out as providing quite high load impacts while not having particularly high average temperatures.

Table 4-3: SmartRate Average Hourly Load Reduction for Event Period (2 to 7 PM) by Local Capacity Area (SmartRate-only Participants)

Local Capacity Area	# of SmartRate Customers	Avg. Referenc e Load (kW)	Avg. Load Reduction (kW)	% Load Reduction	Aggregat e Load Reduction (MW)	Average Temp. During Event (°F)
Greater Bay Area	15,922	0.77	0.10	13%	1.6	79
Greater Fresno	4,036	2.21	0.31	14%	1.3	100
Kern	5,360	2.43	0.27	11%	1.4	99
Northern Coast	1,582	0.95	0.17	18%	0.3	88
Other	5,648	1.62	0.26	16%	1.5	93
Sierra	2,761	1.94	0.50	26%	1.4	94
Stockton	2,984	1.89	0.29	15%	0.9	94
Total	**38,667**	**1.44**	**0.20**	**14%**	**7.9**	**89**

Table 4-4: SmartRate Average Hourly Load Reduction for Event Period (2 to 7 PM) by Local Capacity Area (Dually-enrolled Participants)

Local Capacity Area	# of SmartRate Customers	Avg. Referenc e Load (kW)	Avg. Load Reduction (kW)	% Load Reduction	Aggregat e Load Reduction (MW)	Average Temp. During Event (°F)
Greater Bay Area	8,817	1.21	0.28	23%	2.5	85
Greater Fresno	2,542	2.39	0.56	24%	1.4	99
Kern	1,288	2.70	0.69	26%	0.9	99
Northern Coast	1,353	1.16	0.29	25%	0.4	86
Other	3,355	1.74	0.47	27%	1.6	95
Sierra	2,698	2.07	0.61	30%	1.7	94
Stockton	2,030	1.95	0.49	25%	1.0	94
Total	**22,132**	**1.65**	**0.42**	**25%**	**9.2**	**91**

4.2.2 Load Impacts for Low Income Tariff Customers (CARE)

Low income consumers in California are eligible for lower rates through the California Alternate Rates for Energy program, known as CARE. Qualification for CARE is based on self-reported, household income and varies with the number of persons per household. The proportion of customers enrolled in CARE has increased steadily in PG&E's territory since 2008.

About 35% of SmartRate customers are CARE customers, which is smaller than the proportion in 2011. In contrast, only 27% of the PG&E population was on the CARE rate at the end of 2012.

Table 4-5[18] shows the average load reduction and percent load reduction for CARE and non-CARE SmartRate customers. The average load reduction for SmartRate-only CARE customers is about one-half the size of the reduction for non-CARE customers. This is particularly interesting because non-CARE customers tend to be located in cooler areas than CARE customers. Across the 10 event days in 2012, SmartRate-only CARE customers reduced their peak period load on average by 0.16 kW, or 9%. Non-CARE customers, on the other hand, reduced load on average by 0.27 kW, or 19%. Table 4-5 also shows the average load reduction and percent load reduction for CARE and non-CARE dually-enrolled customers. The proportion of CARE customers in the dually-enrolled population is much smaller than the proportion of CARE customers in the SmartRate-only population. For this group, the average load reduction for CARE customers is slightly more than one-half the size of the reduction for non-CARE customers. Across the 10 event days in 2012, dually-enrolled CARE customers reduced their peak period load on average by 0.35 kW, or 16%. Non-CARE customers, on the other hand, reduced load on average by 0.41 kW, or 25%. The impact estimates in the table are based on a comparison between the SmartRate group and the matched control group.

Table 4-5: Load Reductions for CARE and Non-CARE SmartRate-only Participants

CARE Status		# of Accounts	Average Reference Load (kW)	Average Estimated Load with DR (kW)	Average Load Reduction (kW)	% Load Reduction	Average Temperature During Event (°F)
SMR-Only	Non-CARE	24,529	1.40	1.13	0.27	19%	87
	CARE	13,762	1.75	1.59	0.16	9%	94
Dually-Enrolled	Non-CARE	20,298	1.62	1.21	0.41	25%	91
	CARE	1,786	2.13	1.78	0.35	16%	96

4.2.3 Load Impacts and Event Notification

At the time they sign up for SmartRate, customers are asked to indicate whether or not they want to be notified about events and, if so, to provide up to four different notification options (e.g., one or more email addresses, one or more telephone numbers). Table 4-6 shows the percentage of

[18] Values in Table 4-5 will differ somewhat from the primary ex post impact estimates because different control groups had to be developed for CARE and non-CARE customers than were developed at the LCA level for the primary ex post estimates.

SmartRate-only customers who were successfully notified through one or more options for each event. The column labeled "none" in the table includes both customers who did not provide notification information as well as those who provided information that subsequently became invalid. As the table shows, for the average event, 12% of customers were not successfully notified. Thirty-three percent of customers were successfully notified once per event, 35% were notified twice per event and 21% were notified either three or four times for the average event.

Table 4-7 shows the percentage of dually-enrolled customers who were successfully notified through one or more options for each event. For this group, for the average event, 6% of customers were not successfully notified. Twenty-nine percent of customers were successfully notified once per event, 41% were notified twice per event and 24% were notified either three or four times for the average event.

Table 4-6: Percent of SmartRate-only Customers Notified for Each Event

Date	Number of successful notifications				
	None	1	2	3	4
9-Jul-12	13%	33%	34%	15%	6%
10-Jul-12	13%	32%	34%	15%	6%
11-Jul-12	13%	32%	34%	15%	6%
23-Jul-12	11%	31%	36%	16%	7%
4-Sep-12	11%	32%	36%	15%	6%
13-Sep-12	11%	32%	36%	15%	6%
14-Sep-12	11%	33%	35%	15%	6%
1-Oct-12	14%	36%	33%	13%	4%
2-Oct-12	13%	34%	34%	14%	5%
3-Oct-12	notification data not available				
Average	**12%**	**33%**	**35%**	**15%**	**6%**

Table 4-7: Percent of Dually-enrolled Customers Notified for Each Event

Date	Number of successful notifications				
	None	1	2	3	4
9-Jul-12	5%	25%	42%	19%	9%
10-Jul-12	5%	26%	41%	19%	9%
11-Jul-12	5%	25%	41%	19%	8%
23-Jul-12	5%	25%	42%	19%	9%
4-Sep-12	6%	29%	41%	18%	6%
13-Sep-12	6%	29%	42%	17%	6%
14-Sep-12	6%	30%	41%	17%	6%
1-Oct-12	9%	33%	39%	15%	4%

2-Oct-12	8%	32%	39%	16%	5%
3-Oct-12	no notification data available				
Average	6%	29%	41%	17%	7%

Table 4-8 shows the load impacts for successfully notified customers and compares them with the average load impacts for customers who were not notified. These estimates are based on individual customer regressions and differ from the primary ex post estimates (for more discussion of this issue see Section 3). The number of customers shown in the table is number included in this estimation exercise—the number that experienced all 10 SmartRate events. As shown in the table, the average load reduction across all 10 events increases from 13% to 15% when comparing impacts for the entire SmartRate-only population to impacts for SmartRate-only customers who were notified. The average load impact rose from 0.22 kW to 0.25 kW and 0.52 to 0.55 kW for SmartRate-only and dually-enrolled customers, respectively. The differences are small because the non-notified group is a small fraction of the population.

Table 4-8: Comparison of Load Impacts Between Notified and All SmartRate-only Customers

	# of Customers	Average Impact (kW)	% Load Reduction
All SmartRate-only	38,667	0.22	13%
Notified SmartRate-only Customers	32,108	0.25	15%
All Dually-enrolled Customers	22,132	0.52	25%
Notified Dually-enrolled Customers	20,102	0.55	26%

Table 4-9 shows the average impact and percent load reduction by number of successful notifications averaged over all events. The basic pattern is quite similar on each event day separately. Not surprisingly, average load impacts are very low for SmartRate-only customers who are not notified. What is more surprising is the fact that load impacts increase significantly as the number of notifications increase, even for customers who are successfully notified more than once. Both the average and percentage load reduction triple between SmartRate-only customers who are successfully notified through one option and those that receive four successful notifications. The percent and average load reduction for SmartRate-only customers who receive only a single notification, respectively, are 12% and 0.15 kW. The same values for customers who receive four successful notifications are 24% and 0.49 kW.

Dually-enrolled customers who receive no notification still provide quite large load impacts due to the automatic control of their AC. However, they also provide increasing impacts as the number of notifications increases, which indicates that dually-enrolled customers probably take significant steps to save energy aside from the AC load control. The percent and average reduction for dually-enrolled customers receiving two notifications equal 22% and 0.57 kW, and dually-enrolled customers successfully notified three times reduced load on average by 35% and 0.76 kW. There is virtually no difference in impact between three and four notifications for dually-enrolled customers.

It is difficult to determine from the existing data whether the significant increase in load reduction with the number of successful notifications is due to self selection, greater event awareness or both. While it seems reasonable to assume that customers who are notified through multiple channels are more likely to be made aware of an upcoming event than are customers who are only notified through a single channel, it may also be true that those who provide multiple notification options are more interested in avoiding the high-priced periods on Smart Days.

Table 4-9: Average SmartRate Load Impacts and Percent Load Reductions by Number of Successful Notifications per Event

# of Successful Contacts		Average Load Impact (kW)	% Impact
SmartRate-only	**Zero**	0.03	2%
	One	0.15	9%
	Two	0.29	17%
	Three	0.41	24%
	Four	0.49	30%
Dually-enrolled	**Zero**	0.32	15%
	One	0.44	21%
	Two	0.57	27%
	Three	0.76	36%
	Four	0.76	37%

4.2.4 Load Impacts and Central AC Ownership

Load impact estimates for SmartRate participants are highly positively correlated with central AC ownership and temperature. PG&E does not have direct knowledge of AC ownership among the SmartRate population except for the customers that are also enrolled in PG&E's SmartAC program. However, it has estimates of the likelihood of AC ownership for nearly every residential customer in its territory. In 2010, FSC used the 2009 Residential Appliance Saturation Survey (RASS),[19] which includes information on air conditioning ownership, to develop econometric models of the likelihood of AC ownership that could be applied to PG&E's 4.5 million residential customers. This model was an update of a model developed in the 2009 evaluation of PG&E's SmartRate, TOU and SmartAC programs.[20] The model estimated AC ownership as a function of monthly usage data, weather sensitivity, location and enrollment on the low income CARE tariff and various other factors.[21]

[19] See "2009 California Residential Appliance Saturation Survey," prepared for the California Energy Commission by KEMA, Inc.

[20] For model documentation see "2009 Load Impact Evaluation for Pacific Gas and Electric Company's Residential SmartRate™—Peak Day Pricing and TOU Tariffs and SmartAC Program, Volume 2: Ex Ante Load Impacts," prepared for PG&E by FSC.

[21] In a recent test of the model based on newly available survey data, the model's results were found to be highly accurate,

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Table 4-10 summarizes the AC saturation and percent of customers dually-enrolled on SmartAC (meaning they definitely have CAC) for each LCA and CARE status. As expected, the saturation of AC ownership among SmartRate participants is lower in the more temperate zones such as the Bay Area and higher in hotter, inland zones such as Greater Fresno and Kern County. Saturation of AC ownership among CARE customers (69%) is higher than among non-CARE customers (60%) due to their geographic location. Most CARE customers are located in the hottest areas—Kern and Fresno—and, as a result, are likely to own central AC units. Except for the Greater Bay Area, within each LCA, low income CARE customers have lower AC saturation levels than non-CARE customers, although AC ownership is generally comparable. The higher AC saturation among low income Bay Area customers is again a function of the unique micro climates of the area. The proportion of low income customers is higher in outlying, hotter areas of the Bay Area than in the more temperate areas close to the economic hubs of San Francisco, San Jose and the Silicon Valley.

Table 4-10: Central Air Conditioning Saturation for SmartRate Customers by Geographic Area and Low Income Tariff Enrollment

even in distinguishing the likelihood of AC ownership among a group of customers who all had high likelihoods.

CARE Status	Local Capacity Area	Estimated Central AC Saturation	% Dually Enrolled on SmartAC
Non-CARE	Greater Bay Area	41%	37%
	Greater Fresno	88%	53%
	Kern	92%	27%
	Northern Coast	43%	48%
	Other	75%	47%
	Sierra	87%	54%
	Stockton	84%	50%
	Total	**60%**	**43%**
CARE	Greater Bay Area	31%	3%
	Greater Fresno	84%	14%
	Kern	88%	13%
	Northern Coast	42%	3%
	Other	75%	8%
	Sierra	78%	9%
	Stockton	79%	14%
	Total	**69%**	**9%**

Table 4-11 shows the relationship between the likelihood of air conditioning ownership, temperature, CARE status, dual-enrollment and demand response. Several trends are noteworthy. First, for non-CARE customers, the percentage and absolute load reductions increase substantially with the likelihood of owning central AC. Absolute impacts are nearly five times higher for high likelihood households than for low likelihood households. For CARE customers, there is virtually no increase in average load impact across the lowest three categories of AC likelihood. Then there is a significant jump from 0.04 kW in the 50-75% range to 0.14 kW in the 75-100% range. Then there is a much larger jump to 0.46 kW among dually-enrolled customers.

Table 4-11: SmartRate Load Impacts by Central Air Conditioning Ownership Likelihood, Daily Maximum Temperature and CARE Status

CARE Status	CAC Likelihood Bin	Impact (kW)	% Impact
Non-CARE	0-25%	0.09	13%
	25-50%	0.09	12%
	50-75%	0.22	19%
	75-100%	0.48	20%
	Dually Enrolled	0.56	28%
CARE	0-25%	0.03	5%

	25-50%	0.03	4%
	50-75%	0.04	3%
	75-100%	0.14	7%
	Dually Enrolled	0.46	20%
All	0-25%	0.07	11%
	25-50%	0.07	8%
	50-75%	0.13	10%
	75-100%	0.31	13%
	Dually Enrolled	0.52	25%

4.2.5 Characteristics of High Responders

As a complement to the previous section where average load impacts were examined across different customer segments, this section specifically identifies customers who appear to be high responders (i.e., customers who provide large impacts) and examines their characteristics. This necessarily involves examining impact estimates for individual customers from individual customer regressions. However, when examined at the individual customer level, these impact estimates include error or noise. This is an unavoidable aspect of regression methodology. If this was not the case, then it would not be necessary to use such large sets of customers for analysis. The fundamental assumption underlying all the analyses in this report is that these errors tend to cancel each other out when averaged over thousands of customers. There is a substantial body of evidence built up in both the program evaluation literature and the statistics literature over many years that this assumption holds up well. If this were not true, estimated program results would deviate unpredictably from year to year and there would be no value to these evaluations. Instead, results tend to vary mildly and usually due to identifiable causes. However, this is true on an aggregate basis. Without further investigation, it is not clear how large the errors are on an individual customer basis.

In order to assess how much noise there is around estimated customer-level impacts, the individual customer regressions were also run on the matched control group. As discussed above, these customers have very similar usage profiles to the SmartRate customer population and did not experience any events. Therefore, regression results for this group are a measure of the noise in the individual customer regression process for the SmartRate group.

Figure 4-4 shows two histograms. For the SmartRate-only group it shows the distribution of average event impact estimates across customers. For the matched control group it shows the distribution of average estimated coefficients for indicator variables that only equal one on SmartDays and over the SmartRate event hours. These are the same variables used to estimate the coefficients that yield estimated event impacts for SmartRate customers, but for the matched control group, nothing happened at these times, which means that for every customer, the true effect is zero. Therefore, whenever the individual customer regression model produces a non-zero estimate for the matched control group, it is actually just a measure of the noise in the process. The histogram for the matched control group is a histogram of the noise in regression estimates for this group. It is assumed that because the customers in this group are similar to SmartRate customers across all observable

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characteristics, that the level of noise in this group is similar to the level of noise in the SmartRate group.

The blue columns show the distribution of estimated impacts for the SmartRate population. The median impact estimate for SmartRate customers is about 0.08 kW and the mean (or average) impact for SmartRate customers is 0.23 kW, the same as was reported above when using individual customer regressions. The transparent columns outlined in black show the distribution of impacts for control customers. The median impact and mean impact estimates for these customers are very close to zero. These results makes sense, and show that, on average, SmartRate customers respond to events and control customers do not. What is more useful from this figure, however, is the distribution of impact estimates. Even though control customers have not reacted to events, a substantial fraction of them have estimated impacts that are far from zero. Averaged over the whole control group, the predictions are spot-on—control customers have estimated impacts of zero. But on a per-customer basis, impact estimates vary greatly.

This noise arises because customer usage does not follow a precise function of temperature. Customers have daily routines that vary for many reasons other than temperature. The regression coefficient estimate of SmartRate impact is an average of the usage observed on SmartDays subtracted from an average of the usage observed on non-event days with similar conditions. The regression specification determines the exact form that each average takes, but it remains a weighted average of these sets of data. If a customer happens to have low use on the hot, non-event days, perhaps because he or she was on vacation for several of them, then the regression will produce a small, or even negative, estimated effect of SmartRate for that customer, even if the customer responded to the event. Conversely, if the customer had high usage on the hot, non-event days, but was on vacation for several of the SmartDays, then the regression will produce a large estimated effect, even though the customer may have done nothing to respond to SmartRate. Without an unfeasibly detailed knowledge of customer behavior, this situation is unavoidable.

Figure 4-4: Distribution of Average Estimated Coefficients For SmartRate-only and Control Group Customers

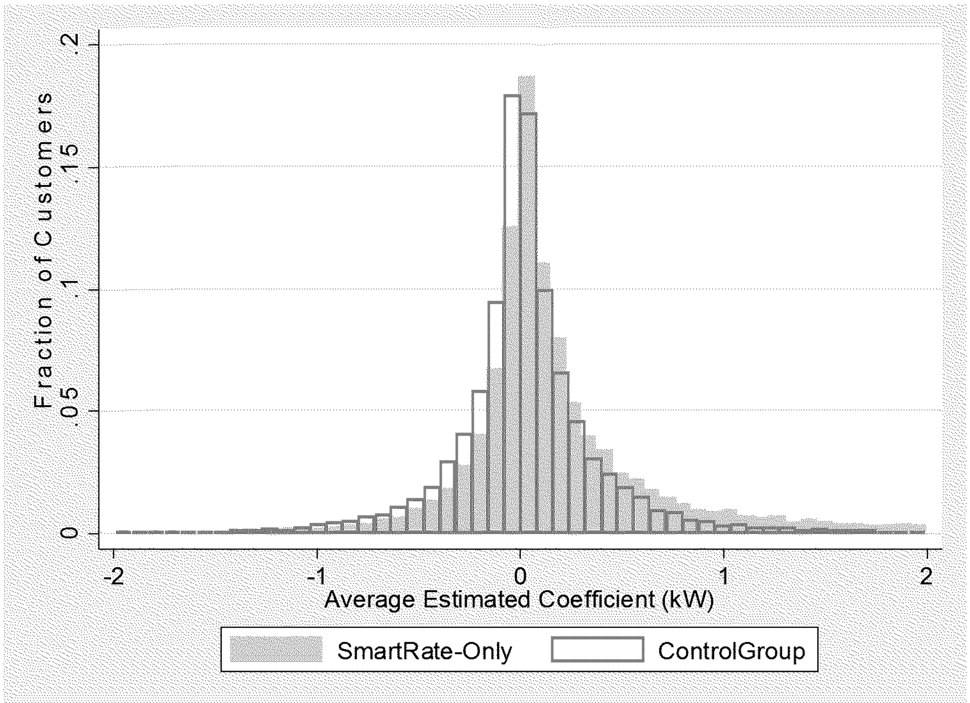
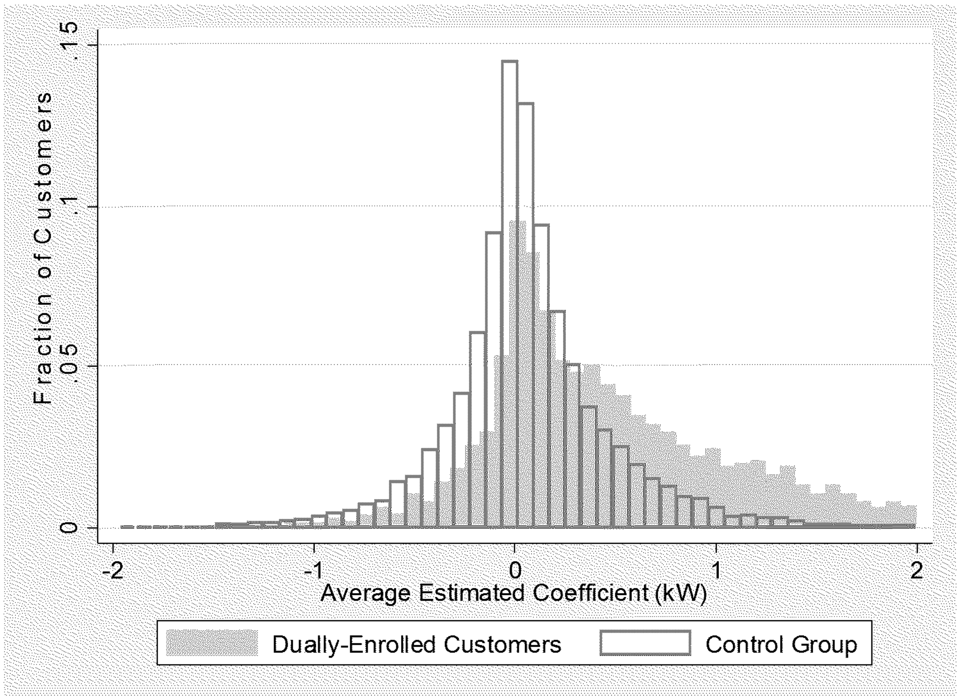


Figure 4-5 shows the same two histograms for dually-enrolled customers, and the same basic points apply. Although in this case, the distribution of estimates for dually-enrolled customers is more different from the distribution for matched control customers than in the SmartRate-only case, and the difference suggests stronger event response among dually-enrolled customers. This makes sense given that we have already established that dually-enrolled customers provide much larger average impacts. There is still a large amount of noise in the estimates however and the point that we cannot take individual estimates at face value remains true.

Figure 4-5: Distribution of Average Estimated Coefficients For Dually-enrolled Customers and Control Group Customers



Within each figure, comparing the two distributions to one another provides insight into which SmartRate customers' impact estimates appear to provide strong evidence of response to SmartDays and those that are more likely to be dominated by noise. The distribution of control group impact estimates serves as an estimate of the distribution of noise in the SmartRate group estimates. Assuming that the distribution of true impacts and the distribution of noise are independent (which is a strong assumption, but necessary to make useful inferences about high responders), probability assessments can be made about the true impact for SmartRate customers, given their estimated impact. For example, among SmartRate-only customers with estimated impact values above 0.86 kW, there is a 95% chance or greater that each customer's true impact is larger than 0.23 kW, which is the overall mean. That is, customers with impact estimates greater than or equal to 0.86 kW have at least a 95% probability of having impacts greater than the mean. There are about 2,550 customers (12.44% of the SmartRate population) for which this is true.[22] This group is labeled high responders. In order to understand some of the drivers of load impacts, the rest of this section will explore the demographics of this group of high responders.

Using the same logic, for dually-Enrolled SmartRate customers with estimated impact values above 1.33 kW, there is a 95% chance or greater that each customer's true impact is larger than 0.53 kW, which is the overall mean.

Tables 4-12 through 4-22 show the distribution of high responding customers across a variety of categories compared to the whole SmartRate population. The final column of each table shows the percentage point difference between high responders and the full SmartRate population for that category. Tables 4-12 and 4-13 show the distribution of high responders for SmartRate-only and dually-enrolled customers across PG&E's territory compared to the SmartRate population. High

[22] For details of this calculation see Appendix C.

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responders in both groups are more likely to be located in Kern and Sierra. Although almost a third of SmartRate-only customers live in the Greater Bay Area, only 9% of SmartRate-only high responders are located in that LCA. These results match up well with the earlier analysis of average impacts across LCAs.

Table 4-12: Distribution of SmartRate-only High Responders by LCA

LCA	High Responders	Full Summer SmartRate Population	Percentage Point Difference
Greater Bay Area	9.0%	32.2%	-23.3
Greater Fresno	16.8%	14.3%	2.5
Kern	40.1%	28.3%	11.8
Northern Coast	0.2%	0.6%	-0.4
Other	13.9%	12.6%	1.3
Sierra	11.1%	4.8%	6.3
Stockton	8.9%	7.1%	1.8
Total	100.0%	100.0%	-

Table 4-13: Distribution of Dually-enrolled High Responders by LCA

LCA	High Responders	Full Summer SmartRate Population	Percentage Point Difference
Greater Bay Area	6.7%	10.2%	-3.4
Greater Fresno	19.8%	19.0%	0.8
Kern	32.3%	22.0%	10.3
Northern Coast	0.0%	0.3%	-0.3
Other	10.1%	19.1%	-9.0
Sierra	15.1%	10.9%	4.3
Stockton	15.9%	18.7%	-2.8
Total	100.0%	100.0%	-

Additionally, high responders are much more likely to be non-CARE customers, as shown in Tables 4-14 and 4-15. 55% of SmartRate-Only customers are not on the CARE rate but almost 75% of high responders fall into that category. For dually-enrolled customers, the difference is much smaller.

Table 4-14: Distribution of SmartRate-only High Responders by CARE Status

CARE Status	High Responders	Full Summer SmartRate Population	Percentage Point Difference
Non-CARE	74.3%	54.8%	19.51
CARE	25.7%	45.2%	-19.51
Total	100.0%	100.0%	-

Table 4-15: Distribution of Dually-enrolled High Responders by CARE Status

CARE Status	High Responders	Full Summer SmartRate Population	Percentage Point Difference
Non-CARE	66.5%	61.2%	5.31
CARE	33.5%	38.8%	-5.31
Total	100.0%	100.0%	-

Bill protection does not appear to play a role in the size of impacts, as shown in Table 4-16 and 4-17. For high responders and the whole SmartRate population, the percentage of customers with bill protection is 12%. The same point holds true for dually-enrolled customers.

Table 4-16: Distribution of SmartRate-only High Responders by Bill Protection Status[23]

Bill Protected	High Responders	Full Summer SmartRate Population	Percentage Point Difference
No	89.1%	91.9%	-2.8
Yes	10.9%	8.1%	2.8
Total	100.0%	100.0%	-

Table 4-17: Distribution of Dually-enrolled High Responders by Bill Protection Status

Bill Protected	High Responders	Full Summer SmartRate Population	Percentage Point Difference
No	95.1%	97.0%	-1.9

[23] Average values of bill protection status is much lower for this population than for the population used to estimate bill savings. This is because this population (which only includes customers on the program for the whole summer of 2012) has, on average, been on the program much longer.

Yes	4.9%	3.0%	1.9
Total	100.0%	100.0%	-

Monthly usage, however, is highly correlated with higher-than-average impacts, as shown in Tables 4-18 and 4-19. The higher the decile of average monthly usage a customer is in, the more likely he is to be a high responder, for both SmartRate-only and dually-enrolled customers. This is not a surprising result. Only 11% of SmartRate-only high responders are found in the bottom five deciles of usage. On the other hand, more than 25% of SmartRate-Only high responders come from the 10th decile alone. The situation is similar for dually-enrolled customers. Only 22% of dually-enrolled high responders fall into the bottom five deciles of usage, while 35% of this group are in the 10th decile.

Table 4-18: Distribution of SmartRate-only High Responders by Monthly Usage Decile

Monthly Usage Decile	High Responders	Full Summer SmartRate Population	Percentage Point Difference
1	0.1%	10.0%	-9.9
2	0.6%	10.0%	-9.4
3	1.2%	10.0%	-8.8
4	3.9%	10.0%	-6.1
5	5.2%	10.0%	-4.8
6	9.9%	10.0%	-0.1
7	14.7%	10.0%	4.7
8	18.1%	10.0%	8.1
9	20.7%	10.0%	10.7
10	25.3%	10.0%	15.3
Total	100.0%	100.0%	-

Table 4-19: Distribution of Dually-enrolled High Responders by Monthly Usage Decile

Monthly Usage Decile	High Responders	Full Summer SmartRate Population	Percentage Point Difference
1	0.5%	10.0%	-9.5
2	2.6%	10.0%	-7.4
3	5.6%	10.0%	-4.4
4	4.4%	10.0%	-5.6
5	9.2%	10.0%	-0.8

6	16.9%	10.0%	6.9
7	18.2%	10.0%	8.2
8	20.3%	10.0%	10.3
9	23.6%	10.0%	13.6
10	35.1%	10.0%	25.1
Total	100.0%	100.0%	-

There is also the question of whether customers provide lower impacts the longer they are on SmartRate. Tables 4-20 and 4-21 show high responders broken down by the number of summers each customer has experienced. There are slightly fewer high responders that have been on SmartRate for three or four summers than if the distribution was the same as the whole SmartRate population. However, the difference is small enough that it is hard to conclusively say that being on SmartRate for longer periods of time leads to lower impacts. SmartRate marketing targeted different geographical areas at different times, which means that the values in Table 4-13 and 4-14 are also related to geography. This is especially true for dually-enrolled customers. As shown above, customers in certain regions provide higher impacts. Given self-selection effects associated with signing up at different times, it would take an experiment to separate these effects.

Table 4-20: Distribution of SmartRate-only High Responders by Number of Summers on SmartRate

Number of Summers on SmartRate	High Responders	Full Summer SmartRate Population	Percentage Point Difference
0	0.0%	0.0%	0.0
1	8.5%	6.7%	1.7
2	9.8%	9.5%	0.3
3	40.3%	50.2%	-9.9
4	41.4%	33.6%	7.9
Total	100.0%	100.0%	-

Table 4-21: Distribution of Dually-enrolled High Responders by Number of Summers on SmartRate

Number of Summers on SmartRate	High Responders	Full Summer SmartRate Population	Percentage Point Difference
0	3.9%	0.0%	3.9

1	4.5%	2.4%	2.1
2	54.4%	3.9%	50.5
3	37.2%	57.7%	-20.5
4	0.4%	36.0%	-35.6
Total	100.0%	100.0%	-

Finally, Table 4-22 shows high responders by their likelihood of having central AC. There are very few high responders with CAC likelihood under 75%. In contrast, 32% of the general SmartRate population falls into those categories. This finding suggests it would be highly useful for PG&E to target SmartRate marketing to customers with high central AC likelihood and, particularly, customers on SmartAC.

Table 4-22: Distribution of High Responders by CAC Likelihood[24]

CAC Likelihood	High Responders	Full Summer SmartRate Population	Percentage Point Difference
0%-25%	1.8%	17.2%	-15.4
25%-50%	1.4%	6.2%	-4.8
50%-75%	4.4%	8.5%	-4.1
75%-100%	68.0%	48.9%	19.1
Dually-Enrolled	24.4%	19.2%	5.2
Total	100.0%	100.0%	-

In exploring the characteristics of high responding customers, there are a few important takeaways. Customers with the following attributes are much more likely to be high responders:

- Non-CARE customers;
- Customers in hotter LCAs, such as Kern and Sierra;
- Customers with higher-than-average usage; and
- Customers with central AC likelihoods of 75% or more.

4.3 SmartRate Bill Impacts

Individual customer bills were estimated for SmartRate customers under SmartRate and the otherwise applicable tariff (OAT) using monthly usage data in order to quantify how much each customer saves or loses by being on SmartRate. For approximately 75% of SmartRate customers, the OAT is E-1.[25] Although about 75% of SmartRate customers are bill protected, they are still included in this analysis

[24] The percentage of dually-enrolled customers is that for customers who experienced all of the 2012 events and does match the fraction in the descriptive population tables of the beginning of summer.

[25] A very small number of SmartRate customers (25) are on TOU rates. An additional 300 customers are on E-8. These customers are excluded from the billing analysis because monthly usage data cannot be used to estimate their OAT bills.

because bill protection was not found to be related to the magnitude of impacts (see Section 4.2.5). Because SmartRate is an overlay onto each customer's already existing rate, savings and losses were estimated using SmartMeter data to calculate SmartRate credits and losses for each month and over the whole summer. The SmartRate bills are based on actual PG&E bills, which are available on a monthly basis according to when meters are read. In this analysis, for reporting purposes, bills are assigned to each month based on the date of the billing cycle.

Table 4-23 shows the distribution of customer savings on SmartRate compared to what they would have spent on the OAT. Three points are noteworthy:

- Between June and October, SmartRate customers saved an average of $67 (12%) compared to bills under the OAT;
- Savings were highest in June and August because customers receive rate credits those months and experienced no events; and
- Overall savings were quite a bit higher than in 2011 ($67 compared to $27 in 2011), which is at least partially due to their only being 10 events in 2012 as opposed to 15 in 2011.

Table 4-23: SmartRate Customer Savings by Month

Month	Average SMR Bill	Saving s	% Saving s	% Winners
June thru October	$493	$74	13%	94%
June	$80	$22	22%	100%
July	$123	$8	6%	82%
August	$116	$27	19%	100%
September	$95	$10	10%	94%
October	$79	$6	8%	83%

Table 4-24 shows bill savings estimates by local capacity area (LCA). Average savings are highest for customers in the Kern LCA. They saved an average of $99 from May through October 2012. Greater Bay Area, Greater Fresno, Northern Coast, and Other LCAs have similar percent savings although they have lower actual savings. The Northern Coast LCA has the lowest absolute impact and the Sierra and Stockton LCAs have the lowest percent impacts, but customers still saved money on SmartRate compared to the OAT.

Table 4-24: SmartRate Customer Percent Winners and Savings by LCA

LCA	# of Customers	Total Summer SMR Bill	Saving s	% Savings	% Winner s
Greater Bay Area	32,713	$376	$57	13%	97%
Greater Fresno	8,180	$617	$90	13%	85%
Kern	7,173	$654	$99	13%	84%

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Northern Coast	4,044	$416	$64	13%	96%
Other	11,701	$463	$69	13%	88%
Sierra	7,270	$643	$87	12%	90%
Stockton	6,449	$491	$70	12%	85%

Table 4-25 shows average customer savings by CARE status. The size of the bill impacts for CARE and non-CARE customers is very similar in absolute terms. Non-CARE customers save an average of $75 on SmartRate over the summer while the average CARE customer saves $71. However, on a percentage basis, this comes out to 12% bill savings for non-CARE customers and a 19% savings for CARE customers.

Table 4-25: SmartRate Customer Percent Winners and Savings by CARE Status

CARE Status	# of Customers	Total Summer SMR Bill	Savings	% Savings	% Winners
Non-CARE	58,244	$575	$75	12%	93%
CARE	19,388	$305	$71	19%	85%

4.4 2012 Bill Protection and Reimbursements

In order to encourage enrollment, prospective SmartRate participants are offered bill protection to try the new rate with no risk. Bill protection is offered from the time they start on SmartRate through the end of the first full summer they are on the rate (May 1 through October 31). With bill protection, customers will not pay more under SmartRate than they would have paid on the OAT for the first full summer and any partial summer that preceded it. If a bill protection eligible customer experiences higher bills under SmartRate than under the OAT, PG&E will pay the difference after the end of the event season. Customers still experience and must pay their monthly bills from May to October under the SmartRate tariff. During the summer of 2012, 75% of SmartRate customers were covered under bill protection. This is a large change from 2011 when only 13% of customers had bill protection but not much different from 2010 when over 60% of customers had bill protection.

Table 4-26: SmartRate Customers with Bill Protection

Bill Protected	# of customers	% of customers
No	19,424	25%
Yes	58,208	75%
Total	77,632	100%

Of the approximately 58,208 customers covered under bill protection in 2012, 2543 (4%) received refunds after the summer of 2012.

Table 4-27: SmartRate Customers with Refunds (Bill Protected Customers Only)

Refund	# of Customers	% of Customers
No refund	55,665	96%
Refund	2543	4%
Total	58,208	100%

4.5 SmartRate Retention Patterns

Retention rates are important components of program performance. They affect the overall load reduction level, costs and the cost-effectiveness of DR programs. There are two main types of attrition from SmartRate. The first is normal turnover due to accounts opening and closing as customers relocate. This is mainly a function of customer characteristics and is only incidentally related to participation in SmartRate. For example, a program with a high share of renters typically has higher participant turnover simply because renters relocate more frequently than homeowners.

The second type of attrition is active customer de-enrollment. These are instances when a participant actively requests to leave the program. There are several important questions associated with customer attrition, including:

- Do customers de-enroll at higher rates when SmartRate events are concentrated in particular months?
- Do CARE customers de-enroll at higher or lower rates?
- Do actual bill increases and decreases relative to the OAT have any relationship to attrition rates?
- Do attrition rates vary across geographic regions?

4.5.1 SmartRate Attrition Due to Accounts Closing

The majority of customers who leave SmartRate do so because their service accounts close. The main reason for this is that the customer changes addresses. These customers were not necessarily unhappy with the program, so this type of attrition should generally not be counted against the program. We have excluded this type of attrition from the analysis.

4.5.2 SmartRate Attrition Due to De-enrollment

This second type of attrition is more important; customers who de-enroll from the program may do so because of dissatisfaction with the program. Over the period from November 2011 to October 2012, only 826 customers de-enrolled from SmartRate. Table 4-28 shows the number of customers who de-enrolled during each month of the period. Nearly half of the customers who dropped out during that period did so in July and September. This is not surprising as this is when most events were called. As a percentage of all SmartRate customers, less than 1% dropped out even in July, the month with the highest number of dropouts.[26]

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Table 4-28: Customer De-enrollments by Month

Month	# of Drop Outs	% of Customers that Dropped Out
Nov. 2011	5	0.02%
Oct. 2011	6	0.03%
Jan. 2012	5	0.02%
Feb. 2012	10	0.05%
Mar. 2012	7	0.03%
Apr. 2012	8	0.04%
May. 2012	151	0.72%
Jun. 2012	23	0.07%
Jul. 2012	254	0.47%
Aug. 2012	60	0.09%
Sep. 2012	171	0.22%
Oct.2012	126	0.16%
Total	826	1.03%

Dropouts can also be analyzed by looking at customer demographics. Table 4-29 shows the number and percentage of customers who dropped out from November 2011 through October 2012 by LCA. The table also includes the percent of customer in the SmartRate program by LCA. The Greater Bay Area had the largest number of dropouts, but that LCA also has the greatest number of SmartRate customers. In fact, Greater Bay Area had a lower number of dropouts than would be expected. 31% of customers who dropped out came from the Greater Bay Area whereas 42% of all SmartRate customers are located in the Greater Bay Area. Overall, drop-outs were fairly uniform across the territory, accounting for SmartRate population size. The sample size underlying this analysis—781 de-enrolled customers—is small enough that no strong conclusions should be drawn from small differences in rates across LCAs.

Table 4-29: Customer De-enrollments by LCA

LCA	# of De-enrolled Customers	% of De-enrolled Customers	% of SmartRate Customers
Greater Bay Area	241	29%	42%
Greater Fresno	129	16%	11%
Humboldt	1	0%	0%
Kern	108	13%	9%

[26] The precise value of these percentages depends on the correct denominator, properly accounting for customers whose accounts close due to churn. However, regardless of how those customers are treated, the percentages are the same for any practical purposes.

Northern Coast	40	5%	5%
Other	133	16%	15%
Sierra	102	12%	9%
Stockton	72	9%	8%
All	826	100%	100%

Customer de-enrollments can also be broken down by CARE status. Table 4-30 shows that non-CARE customers de-enroll at a higher rate than CARE customers. Although 75% of the SmartRate population is non-CARE, 83% of de-enrollments in 2012 were non-CARE customers.

Table 4-30: Customer De-enrollments by CARE Status

CARE Status	# of De-enrolled Customers	% of De-enrolled Customers	% of SmartRate Customers
Non-CARE	683	83%	75%
CARE	143	17%	25%
All	826	100%	100%

There is also the question of how bill impacts affect customer dropout rates, however in a summer with almost no losers, this effect may be trivial. Table 4-31 shows the average OAT and SmartRate monthly bills for active SmartRate customers and those who de-enrolled starting in June 2012.[27] Both groups showed savings over the summer months. Customers who are still active on SmartRate showed slightly lower savings than customers who de-enrolled, but the difference is not significant. This finding implies that customers are not dropping out due to bill losses.

Table 4-31: Bill Impacts by Customer De-enrollment Status

	Mean Monthly OAT Bill	Mean Monthly SmartRate Bill	Differenc e	% Differenc e
Customers who are still enrolled	$110.03	$96.61	$13.42	12%
Customers who de-enrolled	$156.89	$135.32	$21.57	14%

Finally, we examined customer dropout rates in relation to the length of time customers stayed in SmartRate. Currently enrolled customers have been on SmartRate longer, on average, than customers who dropped out in 2012. Currently enrolled customers have been on SmartRate on average for 12 months, with 50% of customers enrolled for more than 4 months. Customers who de-enrolled after June this year had been with the program on average for 9 months. However, 50% of

[27] Customers who dropped out earlier were excluded because they would not have experienced any SmartRate savings or losses in those months.

those drop outs were amongst customers who had been with the program for a month or less. This difference is not very large, and part of the difference is due to the drop-out itself. In addition, the overall distribution of time on SmartRate is similar across the groups, with the de-enrolled group having slightly lower values everywhere on the distribution, as expected. There were more drop outs amongst the customers who signed up in the beginning of July but this seems to be due to large number of enrollments during that time as well. This means that customers who dropped out in 2012 are not clustered in a specific group based on sign-up timing (i.e., customers who joined SmartRate early on or customers who recently joined SmartRate).

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SmartRate Ex Ante Methods

This section explains the steps used to predict ex ante load impacts. There are a few issues that must be dealt with in this modeling. First, the weather observed during events in 2012 is different than the ex ante weather conditions of interest. Second, the population that experienced each event was not constant throughout the summer, and was not representative of the population for whom load impacts need to be forecasted.

Finally, even if we combine load impact observations across 2011 and 2012, there are only 25 test events for each LCA to use for modeling. The modeling procedure outlined here makes the most of the data that exists.

At a high level, the modeling steps consist of the following (each step was performed separately for SmartRate-only and dually-enrolled customers:

- First, groups of SmartRate customers were identified who were representative of the population as of the end of 2012 and who experienced all the 2011 and 2012 SmartRate events. Propensity score matching was used to find these groups;
- Next, ex post estimates were developed for these customers for 2011 and 2012 using matched control groups of non-SmartRate customers for each year. These control groups differ from those used to produce ex post estimates for reporting;
- Then an ex ante regression model was developed to explain average ex post impacts from 2-7 PM as a function of temperatures that day. This model was not estimated separately for each hour; rather, a single average value from 2-7 PM was used as the dependent variable. This model was estimated at the level of each LCA separately. The model was used to predict average impacts from 2 to 7 PM for the set of ex ante weather conditions;
- The ex ante impact estimates of average impact from 2 to 7 PM were then converted to hourly impacts from 2 to 7 PM using a scaling factor based the average ratio between impacts at different hours. This step is necessary in order to adapt overall average event impact estimates from the first step to the need for hourly estimates. The scaling factor was calculated by comparing average impacts from the entire event period to average impacts for each event hour based on ex post results;
- Next, whole-house reference loads from 2 to 7 PM were predicted for each set of ex ante weather conditions based on the loads observed over the summer of 2012. Load shapes were estimated by taking the average load for each hour of the day, by LCA;
- Ex ante impact estimates were then adjusted to apply to the resource adequacy window of 1-6 PM rather than the SmartRate event window from 2011 of 2 to7 PM. This calculation relied on the reference load estimates from the previous step; and
- Finally, a similar regression model was used to model snapback.

The steps for estimating load impacts are described in detail below. The steps used to predict whole-house loads and snap-back are described in Appendix A.

4.6 Estimating Ex Ante Load Impacts for SmartRate

Ex ante impact estimates were calculated by making predictions for ex ante weather conditions using a regression model of ex post impacts from 2011 and 2012. The decision to use 2011 and 2012, but not earlier years was made in order to produce a reasonable number of events for modeling, but to also limit the number of hours spent finding representative populations of SmartRate populations and matched control groups.

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The ex ante weather conditions are the same that were used for the 2011 SmartRate evaluation and have been chosen to be representative of 1-in-2 and 1-in-10 monthly peak days and 1-in-2 and 1-in-10 typical event days.

Prior to regression modeling, FSC developed two samples of customers--one that experienced all the 2011 events and one that experienced all the 2012 events--that had similar observable characteristics to the SmartRate population as of October 2012. October 2012 is the most up-to-date snapshot we have of the SmartRate population and our ex ante load impact estimates are designed to be representative of that population. These groups of customers were identified using the same procedure used to identify matched control groups for the 2011 and 2012 evaluations. Customers were matched primarily on usage observed on hot, non-event days. Details of this match and evidence of its validity are shown in Appendix C.

Matched control groups were then developed for these groups of SmartRate customers, again using the same propensity score matching process. Details of this match and evidence of its validity are also shown in Appendix C. These matched control groups were used to estimate a set of ex post estimates for 2011 and 2012 that represent what the October 2012 SmartRate population would have provided if they had been in the program the whole time. These ex post estimates are also shown in Appendix C. With these estimates in hand, the remaining steps for ex ante estimation were quite similar to what was done in 2011.

An ex ante regression model of ex post impacts as a function of temperature was developed. To determine the best regression to use for ex ante predictions, FSC tested dozens of models predicting ex post impacts based on different measures of recent temperature. The testing regime consisted of cross-validation (which we also sometimes refer to as out-of-sample testing). In this technique, the impact of each test event in each LCA is withheld from the regression model sequentially, one at a time, and the model is fit to the remaining test events each time and used to predict the load impact for the withheld event. This leads to a dataset of estimated load impacts for each test event, which can be compared to the actual ex post load impact for that event. Each model's performance is summarized using the mean absolute percent error across all test events. The same procedure was used for the 2011 evaluation. An important point is that the predictive abilities of several different models were virtually identical, and more sophisticated models (including polynomials in temperature or cooling degree hours, or more complicated weighted averages of temperature) did not perform better than simpler averages of temperature. The final model was chosen because it has predictive ability approximately as good as any other, and it uses the maximum amount of pre-event temperature information available in the specified ex ante weather conditions, without requiring assumptions about temperatures on the day prior to the event.

The model was estimated separately for each LCA and by SmartRate-only and dually-enrolled customers separately. The final model specification takes as its dependent variable the ex post impact for each event, averaged over the entire event period. Its only independent variable is the average temperature from midnight to 5 PM on the event day. The final specification was:

Table 5-1:
Description of SmartRate Ex Ante Load Regression Variables

Variable	Description
Impact (kW)	Per customer ex post load impact for each event day, averaged over the event period
	Estimated constant
	Estimated parameter coefficient
	Average temperature period midnight to 5 PM
	The error term, assumed to be a mean zero and uncorrelated with any of the independent variables

It is quite likely that event impacts depend on variables other than this average of recent temperatures, but with limited event impact estimates for modeling and with virtually no other time-varying characteristics to use for modeling, it is not possible to identify these effects sufficiently accurately to be of use in prediction.

Figures 5-1 and 5-2 show the results of the regressions for SmarRate-only and dually-enrolled customers by LCA. The red circles show 2012 ex post values for the representative population and the blue-gray circles show the same for 2011. The trendlines show the average impacts we use as a basis for ex ante forecasts. For SmartRate-only customers, each LCA shows a different level of temperature sensitivity. Also neither 2011 nor 2012 impacts are consistently higher than the other, again suggesting that the program performance has been stable. For dually-enrolled customers the situation is similar.

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Figure 5-1:
Ex Post and Ex Ante Impacts versus *Mean17* by LCA for SmartRate-Only Customers

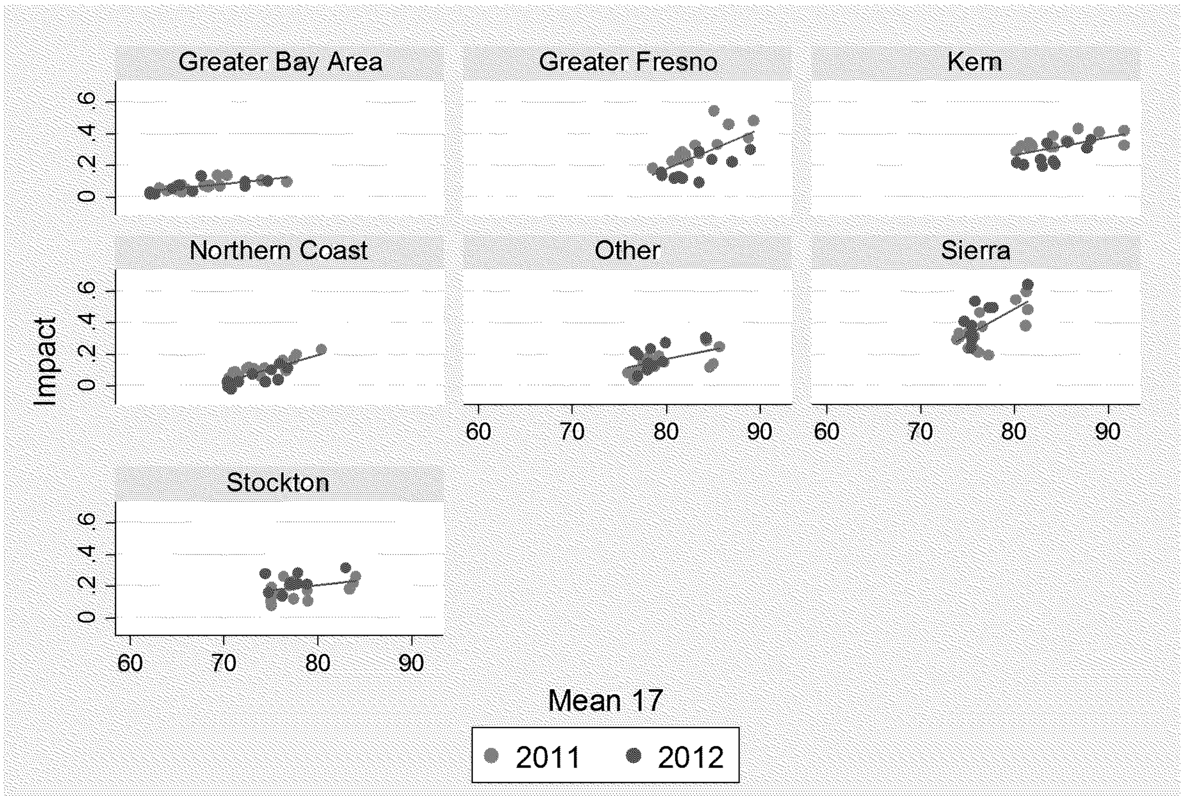

Figure 5-2:
Ex Post and Ex Ante Impacts versus *Mean17* by LCA for Dually-Enrolled Customers

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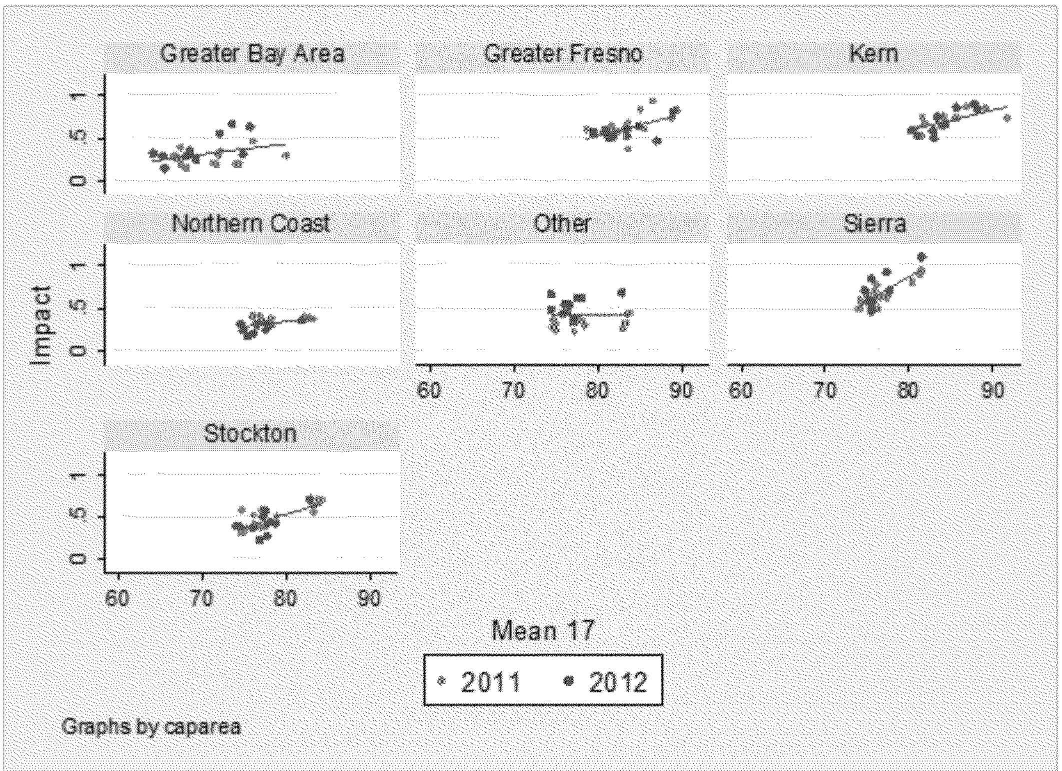

The next step in estimating load impacts was to translate event-level impact estimates to impacts for each hour in the event window. First, a ratio of each hour's impacts to the average impact across the entire event window was calculated. This ratio was calculated using the average ex post impact results for each category of customers. For example, the ratio for the hour from 3 to 4 PM was calculated by taking the average hourly ex post impact from 3 to 4 PM and dividing it by the average ex post impact for the entire event window. Table 5-2 gives an example of this process. The second column of Table 5-2 shows the predicted average event impact across all event hours (i.e. the output from the ex ante regression) using the entire territory on a typical event day on a 1-in-2 weather year as an example. To illustrate, the third column shows the ratio of hourly impact to average whole-event impacts. To calculate the average hourly impact, the average predicted impact was simply multiplied by the category-specific ratio.

Table 5-2:
Example of Converting Average Impact to Hourly Impact from 2–7 PM
Territory Wide, 1-in-2 Typical Event Day

Group	Hour	Predicted Average Impact (kW)*	Ratio (based on ex post impacts)	Predicted Hourly Impact (kW)
SMR-Only	2-3 PM	0.19	0.69	0.13
	3-4 PM	0.19	0.95	0.19
	4-5 PM	0.19	1.11	0.22
	5-6 PM	0.19	1.17	0.23

	6-7 PM	0.19	1.08	0.21
Dually Enrolled	2-3 PM	0.46	0.64	0.29
	3-4 PM	0.46	0.89	0.41
	4-5 PM	0.46	1.10	0.50
	5-6 PM	0.46	1.23	0.56
	6-7 PM	0.46	1.12	0.51

*output from ex ante model; model predicts one average value for all hours

The implication of this strategy is that the ratio between any two hours of predicted event impacts is constant across all ex ante conditions. While this is an assumption forced on the data, it is roughly accurate. Moreover, the available data do not allow for accurately modeling the nuanced relative differences in the event impacts for different hours that may occur under different conditions. The emphasis is on accurately predicting average event impact and average impact for each hour, without additionally trying to estimate whether, for example, impacts at 2 PM tend to be relatively greater than impacts at 3 PM on hot days compared to cooler days.

Impacts for the overall population were calculated by taking a weighted average of the results from each LCA.

4.7 Adjusting Event Hours

All SmartRate events in 2012 were called from 2 to 7 PM. For 2014 and beyond, events are expected be called from 1 to 6 PM, to match the resource adequacy window.[28] In order to incorporate these changes into the ex ante results, event impacts had to be adjusted. For 2013, impacts are estimated for 1-6 PM as well, for the sake of consistency.

Of the five-hour event, four of the hours will stay the same; events in 2011 and in future years cover the hours from 2 to 6 PM. For those hours, the event impact estimates were not changed. However, from 1 to 2 PM, the model described so far provides no event impact estimates. In order to fill that gap, the percentage impact estimated for the hour from 2 to 3 PM was applied to the reference load from 1 to 2 PM. This means the percentage impact for hours 1 to 2 PM is always the same as the percent impact for hours 2 to 3 PM in the ex ante results. The level of inaccuracy for the overall average predicted impact due to this assumption is likely to be quite small.

4.8 SmartRate Ex Ante Load Impact Results

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

[28] *Decision Adopting Local Procurement Obligations for 2012 and Further Refining the Resource Adequacy*, D.11-06-022, p. 60, (June 23, 2011).

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Enrollment projections by local capacity area as of August of each year are presented in Table 5-3. The source for these projections is PG&E's enrollment projections for 2013-2023. Enrollment is projected to increase slightly over the next two years, and then remain constant. The current fraction of dually-enrolled customers is not expected to change significantly, nor is the distribution of customers across LCAs.

Table 5-3:
Projected Enrollment for August of Each Year (in Thousands)

LCA	SmartRate-only		Dually-Enrolled	
	2013	2014-2023	2013	2014-2023
Greater Bay Area	26.1	28.1	13.1	14.3
Greater Fresno	6.0	6.4	3.7	4.0
Humboldt	0.1	0.1	0.0	0.0
Kern	6.6	7.1	1.6	1.8
Northern Coast	2.9	3.1	1.9	2.1
Other	9.2	9.9	5.0	5.4
Sierra	4.7	5.0	3.8	4.2
Stockton	4.8	5.2	2.9	3.1
Total	60.4	65.0	32.1	35.0

Ex ante load impact estimates are shown for 2013 in Table 5-4. The first and second columns show the average hourly per customer ex ante load impact estimate over the event period from 1 to 6 PM for SmartRate only customers and dually enrolled customers, respectively. The third column shows the aggregate mean hourly impact for the SmartRate only population while the fourth column shows the same measure but for the dually enrolled population. The first set of rows corresponds to 1-in-2 weather conditions while the second set covers 1-in-10 weather conditions. Looking at the SmartRate only population, for the 1-in-2 weather year, the highest estimated impact is on the July peak day, with an aggregate impact of 13 MW. For the dually-enrolled population, the high is on the July peak day with a mean aggregate impact of 15 MW. The largest aggregate mean impact under 1-in-10 conditions for the SmartRate-only population is in July, with an impact of 17 MW. For dually-enrolled customers, the greatest aggregate mean impact also occurs on the July peak day with an impact of 18 MW.

Table 5-4:
2013 SmartRate Ex Ante Load Impact Estimates
by Weather Year and Day Type
(Event Period 1-6 PM)

Weather Year	Day Type	Mean Hourly Per Customer Impact (SmartRate	Mean Hourly Per Customer Impact (Dually	Aggregate Mean Hourly Impact (SmartRate	Aggregate Mean Hourly Impact (Dually Enrolled)	Aggregate Mean Hourly Impact (Full Program)

		Only)				
		(kW)	(kW)	(MW)	(MW)	(MW)
1-in-2	**Typical Event Day**	0.18	0.40	11	13	23
	May Monthly Peak	0.09	0.29	5	9	14
	June Monthly Peak	0.15	0.37	9	11	20
	July Monthly Peak	0.23	0.47	13	15	28
	August Monthly Peak	0.18	0.40	11	13	23
	September Monthly Peak	0.16	0.38	10	13	22
	October Monthly Peak	0.07	0.27	5	9	14
1-in-10	**Typical Event Day**	0.25	0.51	15	16	31
	May Monthly Peak	0.21	0.45	12	13	26
	June Monthly Peak	0.24	0.49	14	15	29
	July Monthly Peak	0.29	0.57	17	18	35
	August Monthly Peak	0.27	0.52	16	17	33
	September Monthly Peak	0.22	0.45	13	15	28
	October Monthly Peak	0.17	0.40	11	13	24

On a per customer basis, the ex ante impact estimates for SmartRate-only customers are similar to those from the 2011 evaluation. For example, for SmartRate-only customers, the July 1-in-10 per customer value in 2011 was 0.27, while it is 0.29 here. The other monthly ex ante values are also close. On the other hand, dually-enrolled per customer impacts are lower than in last year's evaluation. Although not directly reported, last year's evaluation implied a per customer impact of about 0.78 kW for a typical event day for dually-enrolled customers, while here it is 0.51 kW. The dually-enrolled population has expanded by a factor of about 4-5 in that time so it is not surprising that the impact estimates differ between the two years. In this year's SmartAC evaluation[29], we find evidence that the dually-enrolled population tends to have lower usage than the typical SmartAC customer. If the newly dually-enrolled population tends to be low users, then this would explain the per customer load impact reductions for this group.

On an aggregate basis, this program is expected to provide quite a bit more load impact than in the 2011 evaluation. For example, under typical event conditions in a 1-in-10 year, last year's forecast was for 12 MW of demand response. This year that value is 31 MW. This is due to the expansion of the population.

The values in Table 5-4 are program specific. They are a forecast of what would happen if SmartRate was called alone. If a SmartAC event happens concurrently, then for the sake of reporting portfolio-adjusted impacts, we must decide how to allocate impacts between SmartAC and SmartRate for dually-enrolled customers. We do not report portfolio-adjusted impacts here, but in the excel tables that

[29] See "2012 Load Impact Evaluation for Pacific Gas and Electric Company's SmartAC Program" prepared for PG&E by the FSC Group.

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accompany this report, portfolio-adjusted impacts of the dually-enrolled customers are the impacts of the dually-enrolled customers in excess of their impacts under SmartAC. That is, we attribute to SmartAC the full value of program-specific ex ante impacts for dually-enrolled customers and then attribute the remainder to SmartRate. Little event data was available for determining program-specific SmartAC impact estimates for dually-enrolled customers,[30] with the consequence that under some event conditions program-specific SmartRate impacts for these customers are lower than their program specific SmartAC impacts. It is highly implausible that this would actually occur (dually-enrolled customers automatically have their ACs controlled during a SmartRate event so for this to occur they would have to respond to the SmartRate event by increasing other loads) so in this case, the portfolio-adjusted impacts for SmartRate for dually-enrolled customers have been set to zero.

[30] The method for estimation is discussed in the 2012 SmartAC evaluation (referenced previously). The main issue is that there were only three SmartAC event days that were not SmartRate days, providing few observations of that population's load impacts when SmartAC is called in absence of SmartRate.

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5 TOU Ex Post Evaluation Methodology

This section describes the control group selection and analysis methods used to estimate E-6 and E-7 load impacts. As noted earlier, the analysis excludes net-metered customers because they likely have solar panels (and are already accounted for in the evaluation of solar programs). In addition, the evaluation does not produce separate load impact estimates for E-6 customers. A large fraction of E-6 customers are net metered and few E-6 customers without net metering had smart meters installed for a full year. As a result, there were not enough E-6 customers to develop a representative sample.

The evaluation of TOU rates is different than for event based programs and rates. With event based programs, it is possible to repeatedly observe the behavior of participants with and without the intervention in effect. This repeated treatment enables an assessment of whether the outcome of interest—electricity consumption—changes with the presence of the treatment. In contrast, once a customer is enrolled on a TOU rate, it is not possible to observe their behavior absent TOU prices. Ideally, an evaluation of TOU prices would use pre-treatment data, a control group, or preferably, both. Pre-treatment data is useful because it introduces information about electricity use patterns under flat prices, which can then be compared to electricity use patterns for the same customers when they are on the TOU rate. However, pre-enrollment data is not available for E-6 and E-7 customers because most participants enrolled prior to the installation of smart meters. As a result, this evaluation relies solely on a control group.

A control group can provide information about how TOU participants would have used electricity had they not been exposed to the time-varying price signals. However, the use of a control group does not guarantee accurate results; to eliminate alternative explanations for differences in electricity use, it is critical that the only systematic difference between the two groups is the fact that one group was exposed to TOU prices while the other group was not. Because TOU participants self-selected onto the rates, they are different from customers on flat rates, and it becomes necessary to account for these differences.

In order to address this problem, the same technique used to select the SmartRate control group—propensity score matching—was used to select a TOU control group. However, there is one key difference: for the TOU evaluation, it was not possible to match on non-event day load shapes, since TOU rates are in effect at all times. In the absence of pre-enrollment data or a randomly assigned control group, propensity score matching is the best approach available.

The key limitation of propensity score matching without good pre-treatment data is that it cannot eliminate the possibility that a factor not included in the selection model accounts for differences in the TOU and control group load shapes.

The remainder of this section details the control group development and the weights applied to produce local capacity area estimates.

5.1 Control Group Selection

As discussed in the SmartRate methods section, propensity score matching is a method for finding a control group that is similar to the TOU group across several observable characteristics. In this case, the dimensions chosen for matching were:[31]

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- Annual usage;
- Summer usage;
- CARE status;
- Climate region;
- CAC likelihood;
- Annual usage interacted with CARE status;
- Annual usage interacted with CAC likelihood;
- CARE status interacted with all electric status;
- CARE status interacted with CAC likelihood; and
- Ratio of usage in July and August compared to usage in March and April.

Because of the limited number of E-6 and E-7 customers with a full year of smart meter data (4% of E-6 and 23% of E-7), a two-stage matching process was required. First, TOU customers with smart meters were matched to the full TOU population so that those with smart meter data were representative of the overall participant population. This produced a representative sample of about 3,000 TOU customers with smart meter data. Then a control group was chosen from the E-1 population to match the TOU matched group. Table 6-1 compares the representative sample of TOU customers with smart meter data to the matched control group. The participant and control groups are comparable across the observable metrics, although the average annual usage and summer usage of the control group is notably larger, which suggests the possibility of an upward bias in the impact estimates.

Table 6-1: Comparison of TOU Sample to TOU Population

Characteristic	E6 & E7 with SM	E-1 Control Group
Number of Customers	3,019	1,978
Annual usage (kWh)	7884	8338
Summer usage (Jun-Sep)	2250	2418
Ratio of summer (Jun-July) to shoulder month (Mar-Apr) usage	0.78	0.77
CARE	11%	10%
Percent all electric customers	27%	25%
Climate Zone R (e.g., Fresno)	17%	17%
Climate Zone S (e.g., Stockton/Sacramento)	21%	23%

[31] It is plausible that the price response to TOU could affect annual consumption, summer consumption and weather sensitivity, primarily because of reductions in air conditioner use that cannot be fully shifted to off-peak hours. If so, including these variables in the matching process would lead to reference loads that are too low, leading to lower demand reduction estimates. As a result, the evaluation produces a potentially conservative estimate of the reductions. However, given the substantial differences in annual electricity consumption by E-7 customers compared to E-1 customers, it was necessary to account for it.

Climate Zone T (Coastal)	17%	16%
Climate Zone X (e.g., San Jose/Concord)	45%	44%

5.2 Analysis Method

A simple comparison of means, implemented with regression, was used to estimate demand reductions. For monthly system peak days, the model calculates the difference in loads between customers on E-6 and E-7 versus the control group for each month and hour. These results are identical to implementing a comparison of means using a t-test, a standard statistical technique used when control groups are available.[32]

Standard errors are estimated allowing for correlation of the error term within customers.[33]

Separate regressions were calculated for:

- Each hour of the day (24);
- Two day types – monthly system peaks and average weekdays;
- Each month in the evaluation period (12); and
- Seven local capacity areas.

The regression models can be expressed as:

Day Type		Regression Model
1	Monthly peak model	▪
2	Average weekday model	▪

In the regressions, *i, h, m* and *l* are indicators for each customer, hour, month and local capacity area, respectively. The only difference between the monthly peak and average weekday model is that the latter includes multiple days, as noted by the indicator, *d*.

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[32] Using regression allows this process to be quickly and easily automated.

[33] The propensity score model is treated as producing the correct control group without error. There is assumed to be no additional uncertainty due to the matching process itself.

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6 TOU 2012 Ex Post Load Impacts

This section summarizes the ex post load impact estimates for TOU customers. The impact estimates are based on the comparison of means described above. The analysis excludes approximately 30,000 net-metered customers that have solar panels and are accounted for through the evaluation of solar programs. This evaluation does not produce separate load impact estimates for E-6 and E-7 customers for reasons discussed previously.

6.1 2012 System Peak Day Load Impacts

Figure 7-1 shows estimates of hourly load impacts for the average customer on the annual system peak day, which occurred on August 12, 2012. During the peak price period, from 12 PM (noon) to 6 PM, customers used an average of 9% less electricity compared to the reference load.[34] Hourly reductions across the peak period range from 0.09 kW to 0.24 kW and from 6% to 12%. The differences during peak hours are all statistically significant, with 95% confidence, except for the hour from 12 PM to 1 PM and 5 PM to 6 PM, which are statistically significant with 90% confidence. Except for the period from 5 AM to 11 AM, when customers show an increase in electricity use, the differences for almost all remaining hours in the day are not statistically significant. Note that the confidence intervals for all hours are relatively wide, in part because results are less precise for individual days because only a relatively small amount of data is available.

Figure 7-2 shows the average weekday load shapes for the month of July, which is typically the hottest month in PG&E's territory. The results for the average weekday are more stable and precise than results for the monthly peak day because more days are used to calculate the estimate. In this month, TOU customers decreased electricity use in tandem with the peak period prices. Customers increased electricity use from 5 PM to 11 PM, when prices were lower, indicating that they are shifting load to these hours. When the peak period prices went into effect, from 12 PM to 6 PM, TOU customers consistently reduced electricity consumption by 0.09 kW to 0.16 kW, depending on the hour. On average, they reduced electricity use by 10% across the event period. The reductions for all peak hours are statistically significant. As soon as the peak period prices end, at 6 PM, TOU customers no longer reduce electricity use. Their electricity use in the evening and late night hours (6 PM to 12 AM) was similar to that of the control group. The small differences in the load shapes during these hours were not statistically significant.

[34] E-7 customers have a peak period of 1-7 PM. E-6 customers have a peak period of 12-6 PM. Because our sample is highly dominated by the more numerous E-6 customers, we have focused our ex post effort on that period, with the recognition that the inclusion of a relatively small number of E-7 customers in the estimation probably introduces some inaccuracy into the impact estimates during the hours 12-1 PM and 6-7 PM. This inaccuracy is likely to be quite small given the small number of E-6 customers and the overall imprecision of the evaluation method.

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Figure 7-1: Average Hourly Load Impact Estimates for Residential TOU Customers
Annual Peak Day (August 12, 2012)

Result Type	Individual Customer
Day Type	Monthly Peak
Month	August
LCA	All
Population Size	60,099

Peak Period Start	12 PM
Peak Period End	6 PM
Average Temp. for Peak Hours	79
Load Reduction for Peak Hours	0.19
% Load Reduction for Peak Hours	9%

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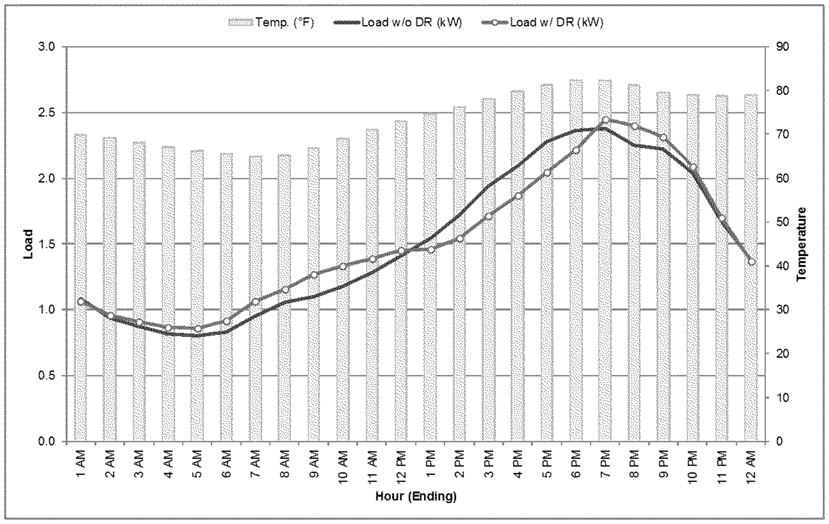

	Hour	Load w/o DR (kW)	Load w/ DR (kW)	Impact (kW)	% Load Impact (%)	Temp. (°F)	Uncertainty Adjusted Impact - Percentiles					
							10th	30th	50th	70th	90th	
1	12 AM - 1 AM	1.09	1.06	0.02	2.3%	69.9	-0.03	0.00	0.02	0.05	0.08	*
2	1 AM - 2 AM	0.94	0.96	-0.02	-2.4%	69.2	-0.07	-0.04	-0.02	0.00	0.02	*
3	2 AM - 3 AM	0.87	0.91	-0.04	-4.4%	68.2	-0.08	-0.06	-0.04	-0.02	0.01	*
4	3 AM - 4 AM	0.81	0.87	-0.05	-6.6%	67.2	-0.10	-0.07	-0.05	-0.04	-0.01	*
5	4 AM - 5 AM	0.80	0.86	-0.06	-7.8%	66.2	-0.10	-0.08	-0.06	-0.05	-0.02	*
6	5 AM - 6 AM	0.83	0.92	-0.09	-10.8%	65.5	-0.13	-0.11	-0.09	-0.07	-0.05	
7	6 AM - 7 AM	0.95	1.06	-0.11	-11.8%	65.0	-0.16	-0.13	-0.11	-0.09	-0.07	
8	7 AM - 8 AM	1.06	1.16	-0.10	-9.2%	65.2	-0.15	-0.12	-0.10	-0.07	-0.04	
9	8 AM - 9 AM	1.10	1.27	-0.17	-15.5%	67.0	-0.22	-0.19	-0.17	-0.15	-0.12	
10	9 AM - 10 AM	1.18	1.33	-0.16	-13.2%	69.0	-0.21	-0.18	-0.16	-0.13	-0.10	
11	10 AM - 11 AM	1.28	1.39	-0.11	-8.5%	71.1	-0.17	-0.13	-0.11	-0.09	-0.05	
12	11 AM - 12 PM	1.41	1.45	-0.04	-3.2%	73.1	-0.11	-0.07	-0.04	-0.02	0.02	*
13	12 PM - 1 PM	1.55	1.46	0.09	5.8%	74.8	0.02	0.06	0.09	0.12	0.16	*
14	1 PM - 2 PM	1.72	1.54	0.17	10.2%	76.2	0.10	0.15	0.17	0.20	0.25	
15	2 PM - 3 PM	1.94	1.71	0.23	11.7%	78.2	0.13	0.19	0.23	0.27	0.33	
16	3 PM - 4 PM	2.10	1.87	0.23	11.0%	79.8	0.13	0.19	0.23	0.27	0.33	
17	4 PM - 5 PM	2.28	2.04	0.24	10.4%	81.4	0.13	0.19	0.24	0.28	0.35	
18	5 PM - 6 PM	2.37	2.21	0.15	6.5%	82.5	0.05	0.11	0.15	0.20	0.26	*
19	6 PM - 7 PM	2.38	2.45	-0.07	-2.9%	82.3	-0.17	-0.11	-0.07	-0.03	0.03	*
20	7 PM - 8 PM	2.25	2.40	-0.15	-6.5%	81.4	-0.24	-0.18	-0.15	-0.11	-0.05	
21	8 PM - 9 PM	2.23	2.31	-0.09	-4.0%	79.7	-0.18	-0.12	-0.09	-0.05	0.00	*
22	9 PM - 10 PM	2.04	2.09	-0.05	-2.5%	79.0	-0.13	-0.08	-0.05	-0.02	0.03	*
23	10 PM - 11 PM	1.67	1.70	-0.03	-1.5%	78.8	-0.10	-0.05	-0.03	0.00	0.04	*
24	11 PM - 12 AM	1.38	1.37	0.01	0.4%	78.9	-0.06	-0.02	0.01	0.03	0.07	*
	Entire Day	**36.21**	**36.40**	**-0.19**	**-0.5%**	**73.7**	**-0.26**	**-0.22**	**-0.19**	**-0.16**	**-0.12**	

** The impact percentiles indicate that it is uncertain whether the impact is positive or negative in this hour*

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Figure 7-2: Average Hourly Load Impact Estimates for Residential TOU Customers
Average July 2012 Weekday

Result Type	Individual Customer
Day Type	Average Weekday
Month	July
LCA	All
Population Size	60,099

Peak Period Start	12 PM
Peak Period End	6 PM
Average Temp. for Peak Hours	72
Load Reduction for Peak Hours	0.13
% Load Reduction for Peak Hours	10%

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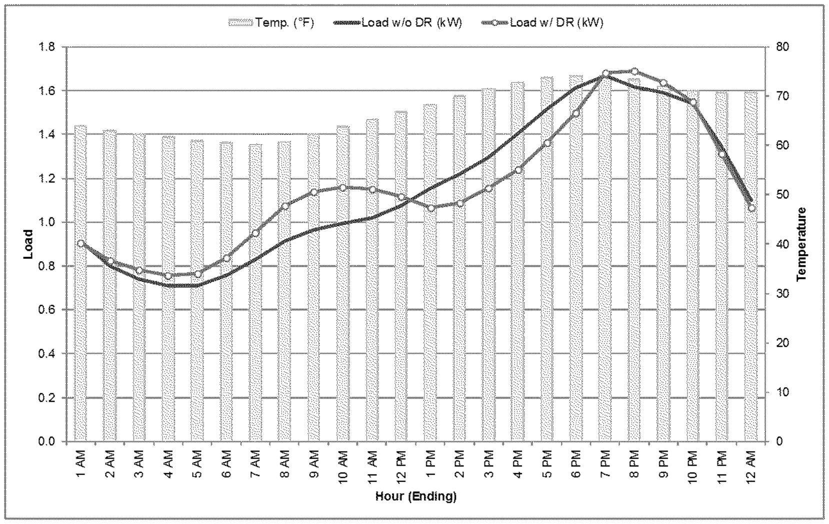

	Hour	Load w/o DR (kW)	Load w/ DR (kW)	Impact (kW)	% Load Impact (%)	Temp. (°F)	Uncertainty Adjusted Impact - Percentiles					
							10th	30th	50th	70th	90th	
1	12 AM - 1 AM	0.92	0.90	0.01	1.3%	64.0	-0.03	0.00	0.01	0.03	0.05	*
2	1 AM - 2 AM	0.80	0.82	-0.02	-2.9%	63.1	-0.06	-0.04	-0.02	-0.01	0.02	*
3	2 AM - 3 AM	0.74	0.78	-0.04	-5.6%	62.3	-0.08	-0.06	-0.04	-0.03	0.00	*
4	3 AM - 4 AM	0.71	0.76	-0.05	-6.4%	61.7	-0.08	-0.06	-0.05	-0.03	-0.01	*
5	4 AM - 5 AM	0.71	0.76	-0.05	-7.5%	61.0	-0.09	-0.07	-0.05	-0.04	-0.02	*
6	5 AM - 6 AM	0.76	0.84	-0.08	-10.5%	60.5	-0.12	-0.10	-0.08	-0.06	-0.04	
7	6 AM - 7 AM	0.83	0.95	-0.12	-15.0%	60.2	-0.17	-0.14	-0.12	-0.11	-0.08	
8	7 AM - 8 AM	0.92	1.07	-0.16	-17.4%	60.8	-0.20	-0.18	-0.16	-0.14	-0.12	
9	8 AM - 9 AM	0.96	1.14	-0.18	-18.2%	62.2	-0.22	-0.19	-0.18	-0.16	-0.14	
10	9 AM - 10 AM	1.00	1.16	-0.17	-16.7%	63.8	-0.21	-0.18	-0.17	-0.15	-0.13	
11	10 AM - 11 AM	1.02	1.15	-0.13	-13.0%	65.4	-0.17	-0.15	-0.13	-0.12	-0.10	
12	11 AM - 12 PM	1.07	1.12	-0.04	-4.0%	66.9	-0.08	-0.06	-0.04	-0.03	-0.01	*
13	12 PM - 1 PM	1.16	1.07	0.09	7.8%	68.4	0.05	0.07	0.09	0.10	0.13	
14	1 PM - 2 PM	1.22	1.09	0.13	11.0%	70.0	0.09	0.12	0.13	0.15	0.17	
15	2 PM - 3 PM	1.30	1.15	0.14	11.0%	71.5	0.10	0.13	0.14	0.16	0.18	
16	3 PM - 4 PM	1.40	1.24	0.16	11.6%	72.8	0.12	0.14	0.16	0.18	0.21	
17	4 PM - 5 PM	1.51	1.36	0.15	10.1%	73.7	0.10	0.13	0.15	0.17	0.20	
18	5 PM - 6 PM	1.61	1.50	0.11	7.0%	74.2	0.06	0.09	0.11	0.13	0.17	
19	6 PM - 7 PM	1.67	1.68	-0.02	-1.0%	74.1	-0.07	-0.04	-0.02	0.01	0.04	*
20	7 PM - 8 PM	1.62	1.69	-0.07	-4.5%	73.4	-0.12	-0.09	-0.07	-0.05	-0.02	*
21	8 PM - 9 PM	1.59	1.64	-0.04	-2.8%	72.1	-0.10	-0.07	-0.04	-0.02	0.01	*
22	9 PM - 10 PM	1.54	1.55	-0.01	-0.6%	71.2	-0.06	-0.03	-0.01	0.01	0.04	*
23	10 PM - 11 PM	1.34	1.31	0.03	2.4%	70.8	-0.02	0.01	0.03	0.05	0.08	*
24	11 PM - 12 AM	1.10	1.07	0.03	3.2%	70.7	-0.01	0.02	0.03	0.05	0.08	*
	Entire Day	**27.51**	**27.82**	**-0.31**	**-1.1%**	**67.3**	**-0.36**	**-0.33**	**-0.31**	**-0.30**	**-0.27**	

** The impact percentiles indicate that it is uncertain whether the impact is positive or negative in this hour*

6.2 Monthly System Peak Day Load Impacts

Table 7-1 shows the average load reduction on monthly system peak days for E-6 and E-7 customers during the time period included in the analysis, from November 1, 2011 through October 31, 2012. Peak-period prices are higher in the summer rate period, which runs from May 1 through October 30. As shown in Table 7-1, load reductions were greater during summer than winter, both in absolute and percentage terms. During the summer, the average load reduction was 0.20 kW, or 13%. All summer results are statistically significantly different from zero. Customers provided smaller, statistically insignificant, demand reductions during winter months, when prices are lower. On average, TOU customers had electricity use that was 0.08 kW, or 7%, lower than that of the control group during winter peak period hours.

Table 7-1: TOU Monthly System Peak Day Load Reductions (12 PM to 6 PM) November 2011 to October 2012

Month	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	Percent Reduction (%)	Average Temp. (°F)
January	1.34	1.21	0.12	9	44.6
February	1.16	1.06	0.10	8	49.1
March	0.99	0.87	0.12	12	51.6
April	1.00	0.90	0.10	10	71.9
May	1.31	1.12	0.19	15	73.8
June	1.53	1.32	0.21	14	76.1
July	1.78	1.68	0.10	5	78.5
August	1.99	1.81	0.19	9	78.8
September	1.37	1.15	0.22	16	71.4
October	1.58	1.29	0.29	19	77.4
November	1.10	1.07	0.03	2	52.3
December	1.16	1.12	0.04	3	46.1
Average	**1.36**	**1.22**	**0.14**	**10**	**64.3**
Summer	**1.59**	**1.39**	**0.20**	**13**	**76.0**
Winter	**1.12**	**1.04**	**0.08**	**7**	**52.6**

6.3 Average Weekday Load Impact by Month

Table 7-2 shows the change in peak-period energy use for the average weekday for each month. The average reduction across the year was 0.11 kW, or 10%. It also shows the seasonal pattern of larger demand reductions during summer months, when peak prices are higher. The average peak period reduction in the summer months is 0.15 kW or 12%, while the average for winter months is 0.08 kW or 7%. The largest average weekday load reductions, 0.18 kW, occurred in August and September. All of the results are statistically significant.

Table 7-2: TOU Average Weekday Peak Period Load Reduction (12 PM to 6 PM)

November 2011 to October 2012

Month	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	Percent Reduction (%)	Average Temp. (°F)
January	1.14	1.05	0.09	8	50
February	1.03	0.94	0.09	9	53
March	1.03	0.92	0.11	11	54
April	0.98	0.87	0.10	10	58
May	1.03	0.90	0.12	12	65
June	1.21	1.06	0.15	12	69
July	1.37	1.24	0.13	10	72
August	1.54	1.36	0.18	12	74
September	1.24	1.06	0.18	14	70
October	1.05	0.92	0.13	12	66
November	1.07	1.04	0.03	3	53
December	1.20	1.16	0.04	3	48
Average	**1.16**	**1.04**	**0.11**	**10**	**61**
Summer	**1.24**	**1.09**	**0.15**	**12**	**69**
Winter	**1.07**	**1.00**	**0.08**	**7**	**53**

6.4 Load Impacts by Geographic Region

Results by Local Capacity Area (LCA) are less reliable than the overall results presented in the section above because sample sizes are smaller. This is particularly true for monthly peak results, which include fewer days to estimate an impact than the average weekday results.

Table 7-3 shows the average impacts on the annual system peak day, August 12, 2012 by LCA. These results are informative, but should be used with caution. Table 7-4 shows the impacts for each LCA for the average weekday peak period during the summer and winter months. The additional data leads to results that are statistically significant for local capacity areas Greater Bay Area, Sierra, Kern and Greater Fresno. These areas reduce peak period electricity use by 8% to 18% during summer peak periods. For the coastal areas such as the Northern Coast, the demand reductions are too small to be statistically significant.

Table 7-3: TOU Peak Period (12 PM to 6 PM) Load Reductions by Local Capacity Area Annual Peak Day (August 12, 2012)

LCA	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	Percent Reduction (%)	Average Temp. (°F)
Greater Bay Area	1.48	1.28	0.21	14	73
Greater Fresno	3.26	3.07	0.19	6	92
Kern	4.20	3.40	0.80	19	94
Northern Coast	1.50	1.39	0.11	7	77
Other	1.93	1.66	0.27	14	77
Sierra	2.82	2.84	0	0	88
Stockton	2.57	2.51	0.06	2	88
All Customers	**1.99**	**1.81**	**0.19**	**9**	**79**

Table 7-4: TOU Load Reductions for Peak Period (12 PM to 6 PM) by Season and Local Capacity Area

Season	LCA	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	Percent Reduction (%)	Average Temp. (°F)
Summer (May-Oct)	Greater Bay Area	0.93	0.86	0.08	8	67
	Greater Fresno	1.89	1.64	0.25	13	79
	Kern	2.36	1.92	0.44	19	79
	Northern Coast	1.09	0.98	0.12	11	67
	Other	1.20	1.07	0.13	11	68
	Sierra	1.61	1.33	0.27	17	72
	Stockton	1.63	1.33	0.30	18	74
	All	**1.24**	**1.09**	**0.15**	**12**	**69**
Winter (Nov-Apr)	Greater Bay Area	0.87	0.82	0.05	6	55
	Greater Fresno	1.09	0.98	0.11	10	56
	Kern	1.07	0.95	0.12	11	56
	Northern Coast	1.15	1.03	0.12	10	51
	Other	1.06	0.96	0.10	9	53
	Sierra	1.32	1.15	0.17	13	51
	Stockton	1.31	1.11	0.20	16	53
	All	**1.04**	**0.95**	**0.10**	**9**	**54**

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6.5 Bill Impacts for TOU

Table 7-5 shows the average monthly, seasonal and annual bills under rates E-1, E-6 and E-7 for the sample of currently enrolled E-6 and E-7 customers. In addition, the table shows the percent change in bills these customers experienced by being on E-6 or E-7; it also shows the percentage of customers that experienced lower bills. The average customer experienced bill decreases in all months. Bill decreases were greatest during the winter, when, on average, customers savings of 17%. Over the course of the entire year, the average customer in the sample saved about 8%, while 76% of customers experienced bill savings of some kind. 90% of customers experienced bill decreases up to 22% and increases up to 17%. Most customers experience bill savings because they have responded to the price signals inherent in the E-6 and E-7 tariffs: they consume less electricity during expensive peak periods than they do during cheaper off-peak periods.

Bills were calculated using hourly interval data for the sample of 3,019 currently enrolled E-6 and E-7 customers. This interval data was used to calculate both the E-1, E-6 and E-7 bills because the model used to determine the E-6 and E-7 impacts does not predict what customers' usage would have been if they had been E-1 customers. Thus, both bills in Table 7-5 are calculated using the E-6 and E-7 sample's actual load profiles.

The rate schedules used to calculate bills were those in effect in the summer of 2012. Table 2-3 shows the rates used to calculate the E-6 and E-7 bills. The 315 CARE customers in the sample are billed under the CARE rate. Thus, the bills shown in Table 7-5 average both CARE and non-CARE bills. In addition, customers are allotted a baseline allowance based on their end usage (basic service versus all-electric service) and climate zone, as is the case when PG&E calculates actual customer bills.

Table 7-5: TOU Treatment Group Customer Bill Impacts by Month

Month	Average Bill		Percent Change	90% of Customers Experience Change Between…		Percentage of Customers Experiencing Lower Bills
	E-1	E-6 and E-7		Lower Bound	Upper Bound	
Jan-12	$175	$145	-17	-33	-1	96
Feb-12	$147	$121	-18	-33	-2	96
Mar-12	$151	$124	-18	-33	-4	98
Apr-12	$133	$108	-19	-33	-4	98
May-12	$137	$136	-1	-19	33	65
Jun-12	$153	$153	0	-17	34	61
Jul-12	$180	$181	1	-17	33	58
Aug-12	$193	$200	4	-17	40	47
Sep-12	$152	$149	-2	-21	29	66
Oct-12	$138	$139	1	-18	39	58
Nov-11	$153	$127	-17	-33	-1	96
Dec-11	$184	$154	-16	-33	0	95
Summer	**$155**	**$152**	**-2**	**-17**	**34**	**59**
Winter	**$162**	**$134**	**-17**	**-33**	**-2**	**97**
Annual	**$158**	**$145**	**-8**	**-22**	**17**	**76**

7 TOU Ex Ante Load Impacts

Ex post impacts do not necessarily reflect the full load reduction capability of demand response programs. Demand response load impacts can vary as a function of weather, participant characteristics, changes in the number of program participants and other factors such as the use of enabling technology. For many programs, event impacts are tied to conditions—e.g., weather—and the number of customers participating in an event. Moreover, in any given year, the extreme weather conditions that drive the system peak and need for additional resources may or may not occur.

Ex ante impacts are based on performance and load reduction patterns during historical event days but are standardized for normal and extreme weather year conditions that align with system planning. The most likely system peaking conditions are reflected in the 1-in-2 weather year, while the 1-in-10 weather year reflects extreme conditions that drive extreme system peaks and the need for more resources.

The ex ante impacts are based solely on E-6 and E-7 customers. They exclude the approximately 30,000 net-metered customers that have solar panels because they are already accounted for through the evaluation of solar programs.

The remainder of this section details the ex ante methodology and enrollment forecast; it also presents the ex ante load impacts on an aggregate and per customer basis.

7.1 Methodology

Whenever possible, ex ante load impacts are grounded on an analysis of historical load impact performance. The protocols governing DR evaluations do not require that ex ante impact estimates be based on the same regression models used to estimate the ex post, because the best ex post evaluation method is not necessarily the best one for producing ex ante impacts. In this instance, the ex post evaluation method relied on taking the difference in usage between a treatment and a control group. It did not attempt to explain how electricity use or TOU impacts varied with weather conditions. The ex ante impacts were developed in five steps:

1. Assess how TOU impacts vary, by LCA, as a function of weather conditions using regression.
2. Assess how overall energy load shapes vary, by LCA, as a function of weather conditions.
3. Replicate the explanatory variables using 1-in-2 and 1-in-10 weather conditions.
4. Predict the reference loads and the impacts.
5. Combine the two.

Only 2012 data was used to estimate the ex ante impacts this year. Figure 8-1 shows a scatter plot of absolute (kW) and relative (percentage) E-6 and E-7 TOU impacts by temperature during the summer peak period. The impacts for each day and hour were calculated as the difference between the treatment and control groups, just as in the ex post analysis. As Figure 8-1 shows, there is a very strong relationship between temperature and TOU demand reductions. It also shows the amount of variation across different days with similar weather conditions. This variation was factored into the uncertainty bands of the ex ante load impacts.

Figure 8-1: Peak Period Impacts by Temperature

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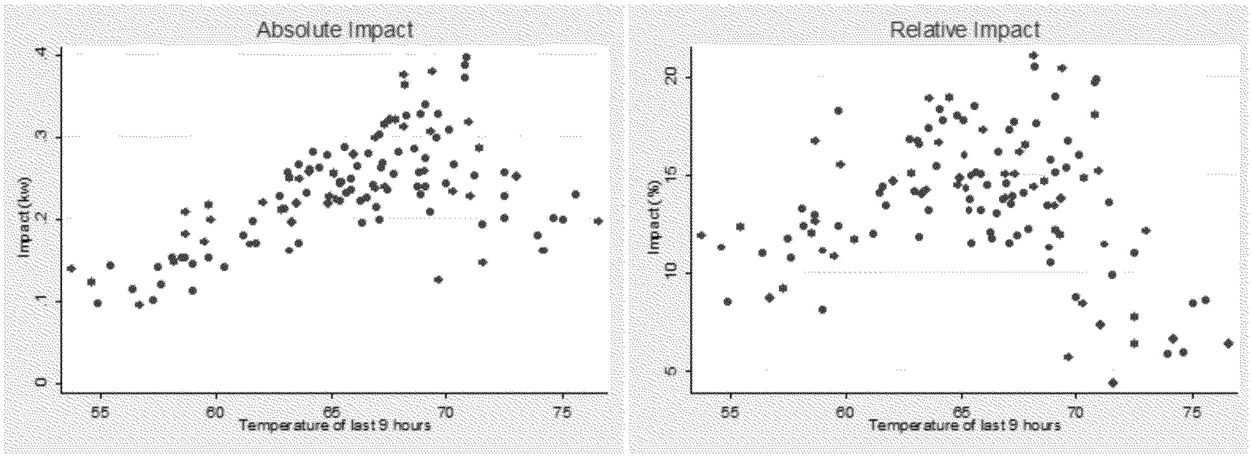

We analyzed the extent to which TOU impacts and reference loads varied with weather conditions separately for each hour, season (summer/winter), and local capacity area. The regression models used to explain variation in TOU impacts and reference loads used the same explanatory variables. The main difference was in the dependent variable. One set of models explained the variation in reference loads; the second set explained the variation in TOU price response. The explanatory variables were simple. For all days, the model uses just the average temperature for the last nine hours.

Mathematically, the models used for the ex ante estimation can be expressed by the following two equations. Table 8-1 defines the variables and terms in the regression.

Variation in TOU Impacts

Variation in Reference loads

Table 8-1: Impact Regression Parameters and Description

Variable	Description
	The difference between the control group and TOU groups for each hour and date in 2011 and 2012. The treatment and control groups are the same as those used for the ex post evaluation.
	Estimated parameters (coefficients).
	Indicators for the unit of analysis. The model is estimated for each LCA at each hour of the day for each season (winter or summer).
Last_nine_temp	Average temperature over the last nine hours for the specific hour (°F).
	The error term.

In keeping with the requirements of the CPUC Load Impact Protocols, ex ante impact estimates were developed for the following customer segments and event conditions:

- 24 day types in each year (i.e., the monthly system peak day and average weekday);
- 7 local capacity area (LCA) regions plus the service territory as a whole;
- 2 weather years (i.e., with 1-in-10 and 1-in-2 conditions);
- 11 forecast years (i.e., 2012 through 2022); and
- 2 customer groupings (i.e., average and aggregate).

Hourly estimates for the roughly 7,400 distinct combinations of the above factors are provided electronically with this report.

7.2 Enrollment Forecast

E-7 is a closed rate. Customers not currently served under the rate schedule are not allowed to obtain E-7 service. Because of this, the only factor impacting E-7's population change is attrition as customers close their accounts over time. On the other hand, the E-6 population experienced an increase in population. Table 8-2 shows the population forecasts used in this report. The population forecast was developed by PG&E. Based on 2011 and 2012 enrollment data, the residential TOU on a whole is forecasted to experience 2.2% new enrollment per year and 0.13% attrition per year. We have also assumed that as the population changes that the fraction of net metered customers stays constant within each LCA within each of the two rates. This means that as some LCAs gain population relative to others, the overall fraction of net metered may change. Our load impact tables only reflect the contribution of non net metered customers.

Table 8-2: Residential TOU Population Forecast, 2013-2023

Year	E6	E7	E6 Non Net Metered	E7 Non Net Metered

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2013	26,561	64,152	3,674	52,123
2014	27,151	64,068	3,756	52,055
2015	27,755	63,985	3,839	51,988
2016	28,372	63,902	3,925	51,920
2017	29,002	63,819	4,012	51,853
2018	29,647	63,736	4,101	51,785
2019	30,305	63,653	4,192	51,718
2020	30,979	63,570	4,285	51,651
2021	31,667	63,488	4,380	51,584
2022	32,371	63,405	4,478	51,517
2023	33,090	63,323	4,577	51,450

7.3 Aggregate Load Impacts by Year

Table 8-3 summarizes the projected program load reduction for each forecast year under 1-in-2 and 1-in-10 year weather conditions. The values reflect the average load reduction capability across the 1 to 6 PM peak period time frame. Hours 12 PM and 7 PM are not included in this table as only the hours 1 to 6 PM are peak hours for both E-6 and E-7. Load reductions vary from hour to hour and are higher for system peak hours. Based on 1-in-2 year weather conditions, aggregate average peak period load reductions equal 16.3 MW for the roughly 56,000 customers enrolled in 2013; and remain that way until 2023, as enrollment stays steady. Percent reductions remain constant because the customer mix is not forecasted to change.

Table 8-3: Summary of Aggregate Ex Ante Load Impacts for Residential TOU Tariffs by Year, E-6 and E-7 Non-Net Metered Customers (Average 1 PM – 6 PM Peak Period Reduction on the Annual System Peak Day)

Weather Conditions	Year	Accounts	Reference Load (MW)	Load with DR (MW)	Load Impact (MW)	% Load Reduction	Avg. Temp (°F)
1-in-2	2013	55,796	117.2	100.9	16.3	13.9%	92
	2014	55,810	117.2	100.9	16.3		
	2015	55,826	117.3	101.0	16.3		
	2016	55,843	117.3	101.0	16.3		
	2017	55,863	117.3	101.0	16.3		
	2018	55,884	117.4	101.1	16.3		
	2019	55,908	117.4	101.1	16.3		
	2020	55,934	117.5	101.2	16.3		
	2021	55,962	117.6	101.2	16.3		
	2022	55,992	117.6	101.3	16.3		
	2023	56,024	117.7	101.3	16.3		
1-in-10	2013	55,796	128.7	110.4	18.3	14.2%	95
	2014	55,810	128.7	110.4	18.3		

	2015	55,826	128.7	110.4	18.3		
	2016	55,843	128.8	110.5	18.3		
	2017	55,863	128.8	110.5	18.3		
	2018	55,884	128.9	110.6	18.3		
	2019	55,908	128.9	110.6	18.3		
	2020	55,934	129.0	110.6	18.3		
	2021	55,962	129.0	110.7	18.3		
	2022	55,992	129.1	110.8	18.3		
	2023	56,024	129.2	110.8	18.4		

Ex ante load impacts closely mirror the ex post results. For example, the 13.9% reduction in a 1-in-2 system peak day compares well with the 10% reduction measured during peak hours on August 12, 2012, the yearly system peak day in 2012. However, the ex ante values produced in this year's evaluation are higher, by a small amount, than those produced in last year's evaluation. For example, the 2011 evaluation forecast 15 MW and 11 MW of demand reduction for the 2013 and 2020 annual system peaks under 1-in-2 weather conditions. This year, we project 14 MW in both cases for the same years. There are two main reasons for the difference: the attrition rate was updated (affecting enrollment) and we adjusted the modeling approach to better account for how weather variation affects TOU impacts. Last year's ex ante estimates factored in a 3.8% attrition rate; this year's estimates use a 2.9% attrition rate. The attrition rate was updated to reflect the most current information. The changes in the modeling approach led to more weather sensitivity in both the reference loads and the TOU impacts. On per customer basis, the reference load and percent impacts for the 1-in-2 annual peak (August) went up from 1.58 kW to 1.66 kW and from a reduction of 14% to a reduction of 16%. These differences are minor and simply reflect improvements compared to last year's analytical approach.

7.4 1-in-2 Annual Peak Impacts per Customer

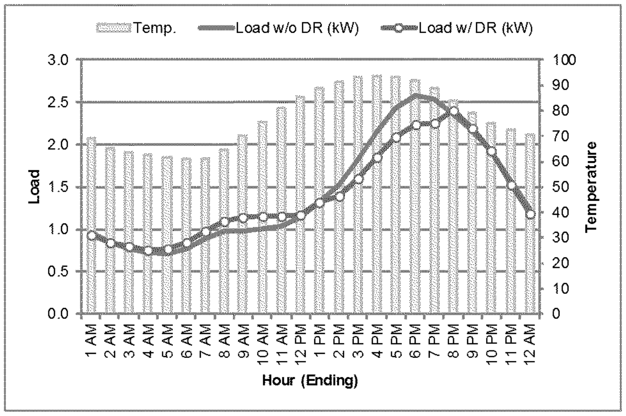
Figures 8-2 and Figure 8-3 show estimates of hourly load impacts for the forecast year 2013 for the average E-6 and E-7 customer, respectively, based on 1-in-2 annual peak conditions. The impacts per customer equal 0.33 kW for the 4 to 5 PM period, which is when the system peak typically occurs. The average reduction during the peak period is 14% for E-6 customers and 16% for E-7 customers. The load patterns indicate that customers are responsive to TOU price signals: during the peak period, they consume less electricity, while during the off-peak period, they consume more electricity. Load reductions are concentrated during the peak period and are statistically significant. Again, these impacts are slightly higher than those found in last year's evaluation; the difference can be explained by differences in the model used. Similar tables are available in electronic format, with drop down menus for local capacity areas, 1-in-2 and 1-in-10 weather years, month of year, and monthly system peak days versus average weekdays.

Figure 8-2: Average E-6 Non-net Metered Customer Hourly Load Impact Estimates Based on 2012 Enrollment (1-in-2 Annual Peak Conditions)

Table 1: Scenario Options	
Result Type	Average Customer
Day Type	Annual System Peak Day
Month	July
Weather Year	1-in-2
Capacity Area	All
Year	2013
Rate	E6

Table 2: Population Statistics	
Population (2012)	2,595
Population (2013)	3,667

Table 3: Event Information	
Event Start	1 PM
Event Stop	7 PM
Event Load (kW)	1.91
Event Reduction (kW)	0.27



Hour	Load w/o DR (kW)	Load w/ DR (kW)	Reduction (kW)	% Reduction	Temp.	Uncertainty Adjusted Impact Percentiles					
						10%	30%	50%	70%	90%	
12 AM - 1 AM	0.96	0.94	0.02	2.4%	69.1	-0.04	0.00	0.02	0.05	0.09	*
1 AM - 2 AM	0.84	0.85	0.00	-0.5%	65.0	-0.06	-0.03	0.00	0.02	0.05	*
2 AM - 3 AM	0.77	0.80	-0.03	-3.4%	63.7	-0.08	-0.05	-0.03	-0.01	0.02	*
3 AM - 4 AM	0.73	0.76	-0.03	-4.5%	62.5	-0.08	-0.05	-0.03	-0.02	0.01	*
4 AM - 5 AM	0.72	0.77	-0.05	-6.3%	61.9	-0.09	-0.07	-0.05	-0.03	-0.01	*
5 AM - 6 AM	0.77	0.84	-0.07	-8.4%	61.3	-0.12	-0.09	-0.07	-0.05	-0.02	*
6 AM - 7 AM	0.88	0.99	-0.10	-10.3%	61.5	-0.17	-0.13	-0.10	-0.07	-0.04	
7 AM - 8 AM	0.98	1.10	-0.13	-11.5%	64.8	-0.20	-0.16	-0.13	-0.10	-0.06	
8 AM - 9 AM	0.97	1.14	-0.17	-14.6%	70.3	-0.25	-0.20	-0.17	-0.13	-0.08	
9 AM - 10 AM	1.00	1.16	-0.15	-13.2%	75.7	-0.24	-0.19	-0.15	-0.12	-0.07	
10 AM - 11 AM	1.05	1.16	-0.11	-9.7%	80.8	-0.20	-0.15	-0.11	-0.08	-0.02	*
11 AM - 12 PM	1.14	1.17	-0.03	-2.7%	85.2	-0.12	-0.07	-0.03	0.01	0.06	*
12 PM - 1 PM	1.32	1.32	0.00	0.0%	88.6	-0.10	-0.04	0.00	0.04	0.10	*
1 PM - 2 PM	1.53	1.39	0.14	10.1%	91.3	0.04	0.10	0.14	0.18	0.24	*
2 PM - 3 PM	1.82	1.60	0.22	14.0%	93.2	0.10	0.17	0.22	0.27	0.34	
3 PM - 4 PM	2.15	1.86	0.29	15.6%	94.0	0.16	0.24	0.29	0.34	0.42	
4 PM - 5 PM	2.43	2.10	0.33	15.8%	93.5	0.20	0.28	0.33	0.39	0.46	
5 PM - 6 PM	2.57	2.24	0.33	14.8%	91.7	0.19	0.28	0.33	0.39	0.47	
6 PM - 7 PM	2.54	2.26	0.28	12.5%	88.6	0.15	0.23	0.28	0.34	0.42	
7 PM - 8 PM	2.35	2.41	-0.05	-2.2%	84.1	-0.19	-0.11	-0.05	0.01	0.09	*
8 PM - 9 PM	2.16	2.19	-0.03	-1.6%	79.0	-0.16	-0.09	-0.03	0.02	0.09	*
9 PM - 10 PM	1.92	1.92	0.00	0.2%	75.1	-0.10	-0.04	0.00	0.05	0.11	*
10 PM - 11 PM	1.58	1.53	0.04	2.9%	72.5	-0.05	0.01	0.04	0.08	0.13	*
11 PM - 12 AM	1.24	1.19	0.05	4.0%	70.7	-0.03	0.02	0.05	0.08	0.13	*
Daily	**34.42**	**33.67**	**0.75**	**2.2%**	**76.8**	**0.66**	**0.71**	**0.75**	**0.79**	**0.84**	

** The impacts in this hour are not statistically significant at the 95% level.*

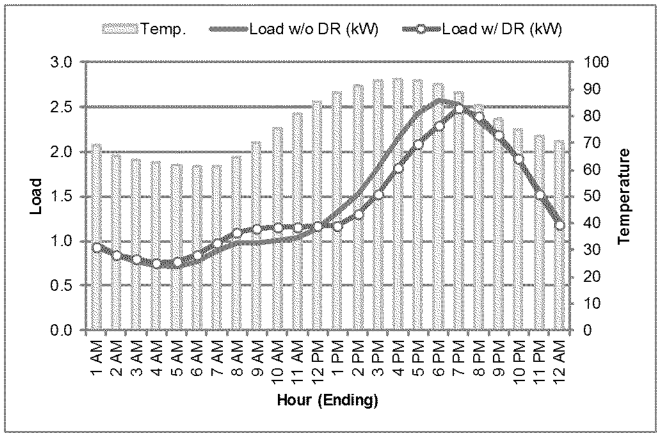
Figure 8-3: Average E-7 Non-net Metered Customer Hourly Load Impact Estimates

Based on 2012 Enrollment (1-in-2 Annual Peak Conditions)

Table 1: Scenario Options	
Result Type	Average Customer
Day Type	Annual System Peak Day
Month	July
Weather Year	1-in-2
Capacity Area	All
Year	2013
Rate	E7

Table 2: Population Statistics	
Population (2012)	58,001
Population (2013)	52,129

Table 3: Event Information	
Event Start	12 PM
Event Stop	6 PM
Event Load (kW)	1.70
Event Reduction (kW)	0.27



Hour	Load w/o DR (kW)	Load w/ DR (kW)	Reduction (kW)	% Reduction	Temp.	Uncertainty Adjusted Impact Percentiles				
						10%	30%	50%	70%	90%
12 AM - 1 AM	0.96	0.94	0.02	2.4%	69.1	-0.04	0.00	0.02	0.05	0.09
1 AM - 2 AM	0.84	0.85	0.00	-0.5%	65.0	-0.06	-0.03	0.00	0.02	0.05
2 AM - 3 AM	0.77	0.80	-0.03	-3.4%	63.7	-0.08	-0.05	-0.03	-0.01	0.02
3 AM - 4 AM	0.73	0.76	-0.03	-4.5%	62.5	-0.08	-0.05	-0.03	-0.02	0.01
4 AM - 5 AM	0.72	0.77	-0.05	-6.3%	61.9	-0.09	-0.07	-0.05	-0.03	-0.01
5 AM - 6 AM	0.77	0.84	-0.07	-8.4%	61.3	-0.12	-0.09	-0.07	-0.05	-0.02
6 AM - 7 AM	0.88	0.99	-0.10	-10.3%	61.5	-0.17	-0.13	-0.10	-0.07	-0.04
7 AM - 8 AM	0.98	1.10	-0.13	-11.5%	64.8	-0.20	-0.16	-0.13	-0.10	-0.06
8 AM - 9 AM	0.97	1.14	-0.17	-14.6%	70.3	-0.25	-0.20	-0.17	-0.13	-0.08
9 AM - 10 AM	1.00	1.16	-0.15	-13.2%	75.7	-0.24	-0.19	-0.15	-0.12	-0.07
10 AM - 11 AM	1.05	1.16	-0.11	-9.7%	80.8	-0.20	-0.15	-0.11	-0.08	-0.02
11 AM - 12 PM	1.14	1.17	-0.03	-2.7%	85.2	-0.12	-0.07	-0.03	0.01	0.06
12 PM - 1 PM	1.32	1.18	0.14	11.9%	88.6	0.04	0.10	0.14	0.18	0.24
1 PM - 2 PM	1.53	1.31	0.22	17.1%	91.3	0.12	0.18	0.22	0.27	0.33
2 PM - 3 PM	1.82	1.53	0.29	18.9%	93.2	0.17	0.24	0.29	0.34	0.41
3 PM - 4 PM	2.15	1.82	0.33	18.3%	94.0	0.20	0.28	0.33	0.39	0.46
4 PM - 5 PM	2.43	2.10	0.33	15.8%	93.5	0.20	0.28	0.33	0.39	0.46
5 PM - 6 PM	2.57	2.29	0.28	12.3%	91.7	0.14	0.22	0.28	0.34	0.42
6 PM - 7 PM	2.54	2.49	0.05	2.0%	88.6	-0.08	0.00	0.05	0.11	0.19
7 PM - 8 PM	2.35	2.41	-0.05	-2.2%	84.1	-0.19	-0.11	-0.05	0.01	0.09
8 PM - 9 PM	2.16	2.19	-0.03	-1.6%	79.0	-0.16	-0.09	-0.03	0.02	0.09
9 PM - 10 PM	1.92	1.92	0.00	0.2%	75.1	-0.10	-0.04	0.00	0.05	0.11
10 PM - 11 PM	1.58	1.53	0.04	2.9%	72.5	-0.05	0.01	0.04	0.08	0.13
11 PM - 12 AM	1.24	1.19	0.05	4.0%	70.7	-0.03	0.02	0.05	0.08	0.13
Daily	**34.42**	**33.62**	**0.80**	**2.4%**	**76.8**	**0.71**	**0.77**	**0.80**	**0.84**	**0.89**

** The impacts in this hour are not statistically significant at the 95% level.*

7.5 Projected 1-in-2 and 1-in-10 Aggregate Peak Period Impacts by Forecast Year and Month

Table 8-4 summarizes the estimated aggregate load reduction capabilities for each forecast year and month under 1-in-2 and 1-in-10 system peak conditions. The load impacts are largest during the summer months, when the difference between peak and off-peak prices is highest. During the winter months the impacts are much smaller and are not significantly different than zero. These results are comparable to last year's.

Table 8-4: Aggregate Ex Ante Load Impacts (MW) for Non-net Metered E-6 & E-7 Customers for Monthly System Peak Days by Year and Weather Conditions (Average Load Impact from 1 PM to 6 PM)

Weather Conditions	Year	Accounts	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-2	2013	55,796	5.6	5.6	5.9	6.4	12.1	15.9	18.0	16.2	15.0	13.1	5.8	5.6
	2014	55,810	5.6	5.6	5.9	6.4	12.1	15.9	18.0	16.2	15.0	13.1	5.8	5.6
	2015	55,826	5.6	5.6	5.9	6.4	12.1	15.9	18.0	16.2	15.0	13.1	5.8	5.6
	2016	55,843	5.6	5.6	5.9	6.4	12.1	15.9	18.1	16.2	15.0	13.1	5.8	5.7
	2017	55,863	5.6	5.6	5.9	6.4	12.1	15.9	18.1	16.2	15.0	13.2	5.8	5.7
	2018	55,884	5.6	5.6	5.9	6.4	12.1	16.0	18.1	16.2	15.0	13.2	5.8	5.7
	2019	55,908	5.6	5.7	5.9	6.4	12.1	16.0	18.1	16.2	15.0	13.2	5.8	5.7
	2020	55,934	5.6	5.7	5.9	6.5	12.2	16.0	18.1	16.2	15.0	13.2	5.8	5.7
	2021	55,962	5.6	5.7	5.9	6.5	12.2	16.0	18.1	16.2	15.0	13.2	5.8	5.7
	2022	55,992	5.6	5.7	5.9	6.5	12.2	16.0	18.1	16.3	15.0	13.2	5.8	5.7
	2023	56,024	5.6	5.7	5.9	6.5	12.2	16.0	18.1	16.3	15.0	13.2	5.8	5.7
1-in-10	2013	55,796	5.6	5.7	5.6	6.6	16.8	19.0	19.1	17.7	17.3	15.6	5.6	5.5
	2014	55,810	5.6	5.7	5.6	6.6	16.8	19.0	19.1	17.7	17.3	15.6	5.6	5.5
	2015	55,826	5.6	5.7	5.6	6.6	16.8	19.0	19.1	17.8	17.3	15.6	5.6	5.5
	2016	55,843	5.6	5.7	5.6	6.6	16.8	19.1	19.1	17.8	17.3	15.6	5.6	5.5
	2017	55,863	5.6	5.7	5.6	6.6	16.8	19.1	19.1	17.8	17.3	15.6	5.6	5.5
	2018	55,884	5.6	5.7	5.6	6.6	16.8	19.1	19.1	17.8	17.3	15.6	5.6	5.5
	2019	55,908	5.6	5.7	5.6	6.6	16.8	19.1	19.1	17.8	17.3	15.6	5.7	5.5
	2020	55,934	5.6	5.7	5.6	6.6	16.9	19.1	19.1	17.8	17.3	15.6	5.7	5.5

	2021	55,962	5.6	5.7	5.6	6.6	16.9	19.1	19.1	17.8	17.3	15.6	5.7	5.5
	2022	55,992	5.6	5.7	5.7	6.6	16.9	19.1	19.1	17.8	17.3	15.6	5.7	5.5
	2023	56,024	5.6	5.7	5.7	6.6	16.9	19.1	19.2	17.8	17.3	15.6	5.7	5.5

Table 8-5 summarizes the average weekday load shifting for the average TOU customer; it reflects the rates' conservation effects (positive values) and any potential increases in consumption (negative values) due to lower prices. Customers tend to decrease electricity use during peak periods, particularly during the summer. The decrease in peak usage is statistically significant in all months. The increase in usage in the hours leading up to the event is also significant. These results follow the same pattern found in last year's evaluation.

Table 8-5: Average E-6 & E-7 Non-net Metered Customer Ex Ante Load Reductions (kW) for the Average Week Day by Hour and Month for 1-in-2 Year Weather Conditions

Hour	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg
1:00 AM	0.05	0.05	0.04	0.03	0.01	0.02	0.02	0.02	0.02	0.02	0.04	0.05	**0.03**
2:00 AM	0.03	0.03	0.02	0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.02	0.02	0.04	**0.00**
3:00 AM	0.02	0.01	0.01	-0.01	-0.04	-0.03	-0.03	-0.03	-0.03	-0.04	0.01	0.02	**-0.01**
4:00 AM	0.01	0.01	0.00	-0.01	-0.05	-0.04	-0.04	-0.04	-0.04	-0.05	0.00	0.01	**-0.02**
5:00 AM	-0.01	-0.01	-0.01	-0.02	-0.04	-0.04	-0.05	-0.05	-0.04	-0.04	-0.01	0.00	**-0.03**
6:00 AM	-0.04	-0.04	-0.04	-0.04	-0.06	-0.07	-0.07	-0.07	-0.07	-0.06	-0.04	-0.04	**-0.05**
7:00 AM	-0.08	-0.08	-0.08	-0.08	-0.09	-0.10	-0.10	-0.10	-0.10	-0.09	-0.08	-0.08	**-0.09**
8:00 AM	-0.11	-0.11	-0.11	-0.11	-0.12	-0.12	-0.13	-0.13	-0.12	-0.12	-0.11	-0.11	**-0.12**
9:00 AM	-0.17	-0.17	-0.17	-0.15	-0.16	-0.17	-0.17	-0.17	-0.17	-0.16	-0.17	-0.18	**-0.17**
10:00 AM	-0.14	-0.14	-0.14	-0.13	-0.16	-0.16	-0.15	-0.15	-0.16	-0.16	-0.14	-0.14	**-0.15**
11:00 AM	-0.08	-0.08	-0.08	-0.08	-0.10	-0.11	-0.11	-0.11	-0.11	-0.10	-0.08	-0.07	**-0.09**
12:00 PM	-0.01	-0.01	-0.01	-0.01	-0.02	-0.03	-0.03	-0.03	-0.03	-0.02	-0.01	-0.01	**-0.02**
1:00 PM	0.07	0.07	0.07	0.06	0.07	0.10	0.11	0.11	0.10	0.07	0.06	0.07	**0.08**
2:00 PM	0.11	0.11	0.10	0.10	0.13	0.17	0.19	0.19	0.17	0.13	0.10	0.11	**0.13**
3:00 PM	0.11	0.10	0.10	0.10	0.16	0.21	0.24	0.23	0.21	0.16	0.10	0.11	**0.15**
4:00 PM	0.11	0.11	0.11	0.11	0.19	0.24	0.26	0.26	0.24	0.19	0.11	0.11	**0.17**
5:00 PM	0.11	0.11	0.12	0.13	0.20	0.24	0.26	0.26	0.25	0.20	0.12	0.11	**0.18**
6:00 PM	0.08	0.09	0.10	0.12	0.17	0.20	0.22	0.22	0.21	0.17	0.11	0.08	**0.15**
7:00 PM	0.01	0.02	0.04	0.06	0.05	0.05	0.04	0.05	0.05	0.06	0.04	0.01	**0.04**
8:00 PM	0.02	0.02	0.03	0.03	-	-	-	-0.04	-	0.00	0.03	0.02	**0.00**

					0.01								
9:00 PM	0.07	0.07	0.06	0.06	0.02	-0.01	-0.03	-0.02	0.00	0.04	0.06	0.07	**0.03**
10:00 PM	0.06	0.06	0.06	0.06	0.03	0.01	0.00	0.01	0.02	0.05	0.06	0.06	**0.04**
11:00 PM	0.07	0.06	0.05	0.04	0.04	0.04	0.03	0.04	0.04	0.05	0.05	0.07	**0.05**
12:00 PM	0.08	0.08	0.06	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.09	**0.06**
Avg	**0.02**	**0.02**	**0.01**	**0.01**	**0.01**	**0.02**	**0.02**	**0.02**	**0.02**	**0.01**	**0.01**	**0.02**	**0.02**

7.6 Comparison of Ex Ante and Ex Post Results

Table 8-6 shows a comparison between the ex ante and 2012 ex post results for the on-peak period common to E-6 and E-7 (1 PM to 6 PM) for the average weekday and the monthly system peak day for the average customer. The ex ante result is based on the 1-in-2 scenario. The conditions in this scenario are generally comparable to weather conditions observed across PG&E's territory in 2012, and thus allow for a good comparison with the ex post results; although this is less so in the summer months. The table shows that ex ante and ex post impacts are generally very similar to one another as a fraction of reference load. Additionally, aside from the summer months, absolute reductions are also quite similar. During the summer, ex ante impacts tend to be higher than ex post impacts due to the ex ante conditions being hotter.

The fact that the ex post and ex ante results are so comparable to one another indicates that the ex ante model does a good job of predicting impacts, and helps validate the ex ante approach.

Table 8-6: Comparison of Ex Ante and Ex Post Results for Non-Net Metered E-6 & E-7 Customers, Average Weekday and Monthly System Peak

Month	Average Weekday				Monthly System Peak			
	% Reduction		kW Reduction		% Reduction		kW Reduction	
	Ex Ante	Ex Post	Ex Ante	Ex Post	Ex Ante	Ex Post	Ex Ante	Ex Post
January	9.7	8.4	0.10	0.10	9.3	8.8	0.10	0.12
February	10.1	8.9	0.11	0.09	9.4	9.6	0.10	0.11
March	10.6	11.1	0.11	0.11	10.0	12.7	0.11	0.13
April	11.3	11.1	0.11	0.11	12.0	10.5	0.12	0.11
May	12.8	13.0	0.17	0.14	12.8	15.3	0.22	0.21
June	13.2	12.8	0.21	0.16	14.1	13.9	0.29	0.22
July	13.1	10.0	0.23	0.14	14.0	5.6	0.32	0.10
August	13.3	12.3	0.23	0.20	13.9	9.8	0.29	0.20
September	13.4	15.2	0.22	0.19	13.5	16.2	0.27	0.23
October	13.3	12.9	0.17	0.14	13.8	19.0	0.24	0.32
November	10.7	2.9	0.11	0.03	9.9	2.3	0.10	0.03
December	9.7	3.1	0.10	0.04	9.3	3.2	0.10	0.04

Appendix A Details on the Propensity Score Match for 2012 SmartRate Ex Post Estimation

This appendix contains relevant technical details on the propensity score matching process used to develop a control group for SmartRate customers.

We began with a pool of approximately 120,000 PG&E residential customers who are not on SmartRate and for whom FSC had interval data covering summer 2012. A propensity score matching procedure was then used to select from this pool three groups of customers who were similar to the SmartRate population in terms of LCA, average summer monthly usage, CARE status and hourly usage on hot non-event days. The matching process was actually done separately within each LCA so that LCA-level estimates could be easily developed. Three groups were chosen because the shifting population during the summer meant that the control group early in the summer did not provide an accurate counterfactual later in the summer.

Tables A-1 through A-6 compare the final matched control groups to the SmartRate sample based on LCA, CARE status and average monthly usage in June and July 2012. These tables are meant to demonstrate the degree to which the treatment group and control group are comparable across several variables that we would expect to be correlated with event day usage. The last two columns of Table 3-1 show t-statistics and p-values for tests of the hypothesis that the mean value do not differ between the groups. In each case, the two groups match closely across LCAs. For average usage during summer months and CARE status, fairly small but statistically significant differences usually exist between the groups.

Table A-1: Distributions of LCA, Usage and CARE Status for SmartRate-Only Customers, Control Customers and the Residential Population for First Three Events

Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	37%	37%	0.00	1.00
Greater Fresno	12%	12%	0.00	1.00
Kern	21%	21%	0.00	1.00
Northern Coast	2%	2%	-0.03	0.98
Other	14%	14%	0.00	1.00
Sierra	6%	6%	0.00	1.00
Stockton	7%	7%	0.00	1.00
June 2012 kWh	672	686	3.16	0.00
July 2012 kWh	750	762	2.24	0.03
Non-CARE	60%	67%	-14.68	0.00
CARE	40%	33%	-14.68	0.00

Table A-2: Distributions of LCA, Usage and CARE Status for SmartRate-Only Customers, Control Customers and the Residential Population for Fourth Event

Characteristic	SmartRate Population	Matched Control Group	t	p

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Greater Bay Area	40%	40%	0.00	1.00
Greater Fresno	11%	11%	0.00	1.00
Kern	17%	17%	0.00	1.00
Northern Coast	3%	3%	0.00	1.00
Other	14%	14%	-0.01	0.99
Sierra	7%	7%	0.00	1.00
Stockton	8%	8%	0.00	1.00
June 2012 kWh	663	671	2.02	0.04
July 2012 kWh	722	738	3.61	0.00
Non-CARE	63%	68%	-13.34	0.00
CARE	37%	32%	-13.34	0.00

Table A-3: Distributions of LCA, Usage and CARE Status for SmartRate-Only Customers, Control Customers and the Residential Population for Last Six Events

Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	42%	42%	0.00	1.00
Greater Fresno	10%	10%	0.00	1.00
Kern	13%	13%	0.00	1.00
Northern Coast	4%	4%	-0.02	0.99
Other	15%	15%	1.00	0.00
Sierra	7%	7%	0.00	1.00
Stockton	8%	8%	0.00	1.00
June 2012 kWh	657	654	-1.00	0.32
July 2012 kWh	710	715	1.29	0.20
Non-CARE	65%	69%	-12.69	0.00
CARE	35%	31%	-12.69	0.00

Table A-4: Distributions of LCA, Usage and CARE Status for Dually-Enrolled Customers, Control Customers and the Residential Population for First Three Events

Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	37%	37%	0.00	1.00
Greater Fresno	11%	11%	0.00	1.00
Kern	8%	8%	0.00	1.00
Northern Coast	6%	6%	0.00	1.00
Other	15%	15%	0.00	1.00
Sierra	12%	12%	0.00	1.00
Stockton	10%	10%	0.00	1.00
June 2012 kWh	666	704	7.56	0.00
July 2012 kWh	739	773	5.87	0.00
Non-CARE	88%	71%	35.36	0.00

CARE	12%	29%	35.36	0.00

Table A-5: Distributions of LCA, Usage and CARE Status for Dually-Enrolled Customers, Control Customers and the Residential Population for Fourth Event

Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	39%	39%	0.00	1.00
Greater Fresno	12%	12%	0.00	1.00
Kern	6%	6%	0.00	1.00
Northern Coast	6%	6%	0.00	1.00
Other	15%	15%	0.00	1.00
Sierra	12%	12%	0.00	1.00
Stockton	10%	10%	0.00	1.00
June 2012 kWh	673	702	6.61	0.00
July 2012 kWh	735	769	7.06	0.00
Non-CARE	91%	72%	47.22	0.00
CARE	9%	28%	47.22	0.00

Table A-6: Distributions of LCA, Usage and CARE Status for Dually-Enrolled Customers, Control Customers and the Residential Population for Last Six Events

Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	40%	40%	0.00	1.00
Greater Fresno	12%	12%	0.00	1.00
Kern	5%	5%	0.00	1.00
Northern Coast	6%	6%	0.00	1.00
Other	15%	15%	0.00	1.00
Sierra	12%	12%	0.00	1.00
Stockton	9%	9%	0.00	1.00
June 2012 kWh	672	702	7.36	0.00
July 2012 kWh	736	767	7.20	0.00
Non-CARE	93%	73%	61.25	0.00
CARE	7%	27%	61.25	0.00

Figures A-1 and A-2 show histograms of average hourly usage during the 2-7 PM on hot non-event days for the SmartRate groups and control groups. The blue columns show the histogram of SmartRate usage and the transparent columns show control group usage. In all cases, the distributions are fairly similar. A red flag that a graph like this could show would be a region where there was a high density of SmartRate customers but a very low density of control group customers. Even in the cases where the distributions are noticeably different, there are no such regions, which is a good sign.

Figure A-1: Histograms of Average Hourly Usage for SmartRate-Only Customers and Control Group

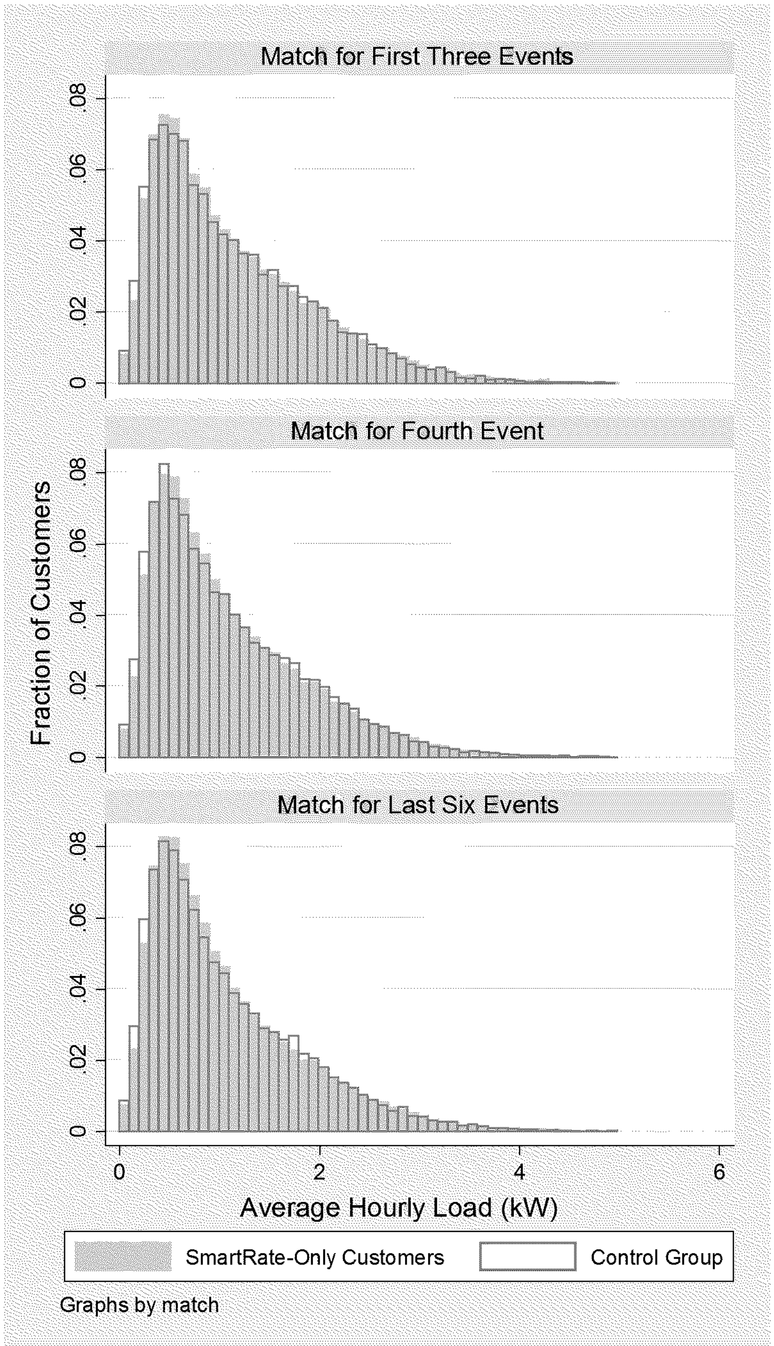


Figure A-2: Histograms of Average Hourly Usage for Dually-Enrolled Customers and Control Group

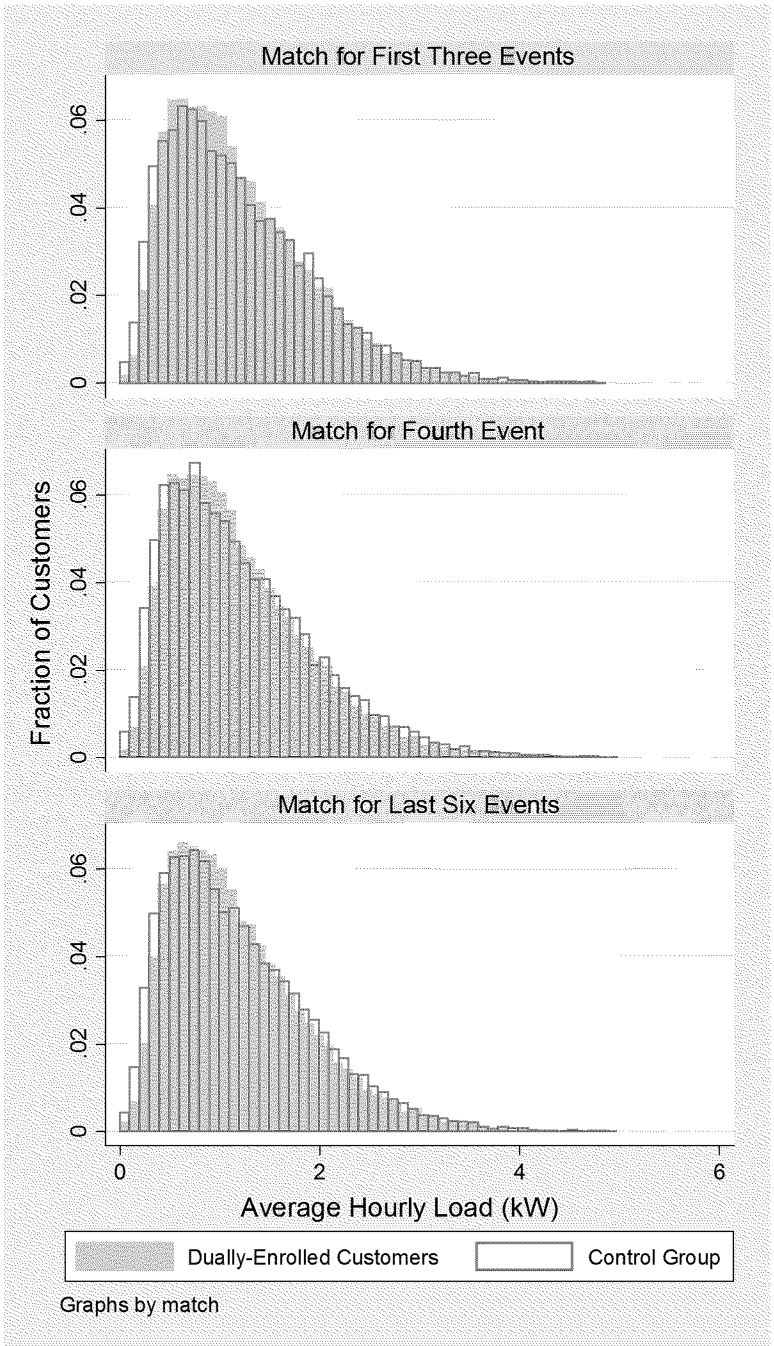
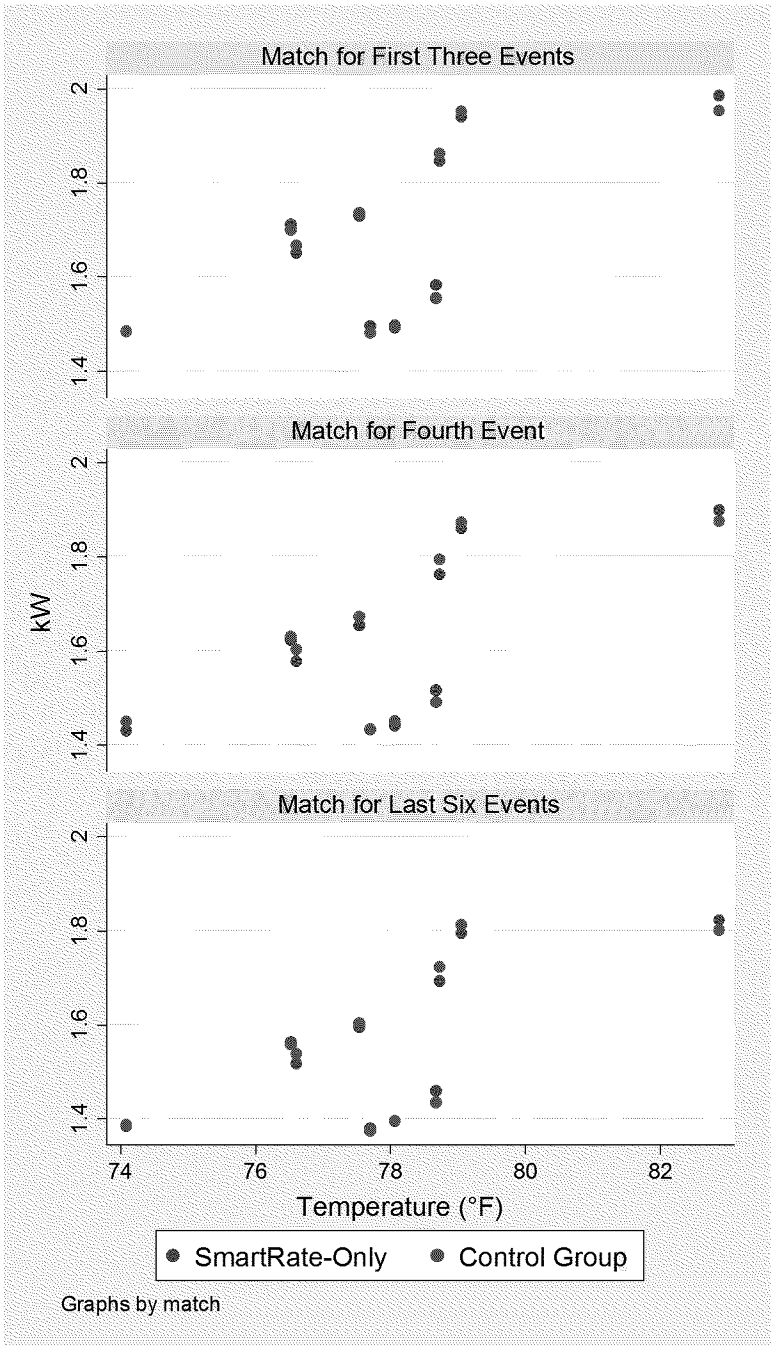


Figure A-3 shows that treatment and control groups are quite similar on the hot, non-event days used in the matching process. It shows a scatter plot of average load during the hours 2 to 7 PM as a function of average temperatures on hot, non-event days. Each point represents the average load on one of the days for either the SmartRate group or control group. Note that the scale of the x-axis only runs from 74°F to 85°F.

Figure A-3: Average Loads and Temperatures from 2-7 PM on Hot, Non-event Days



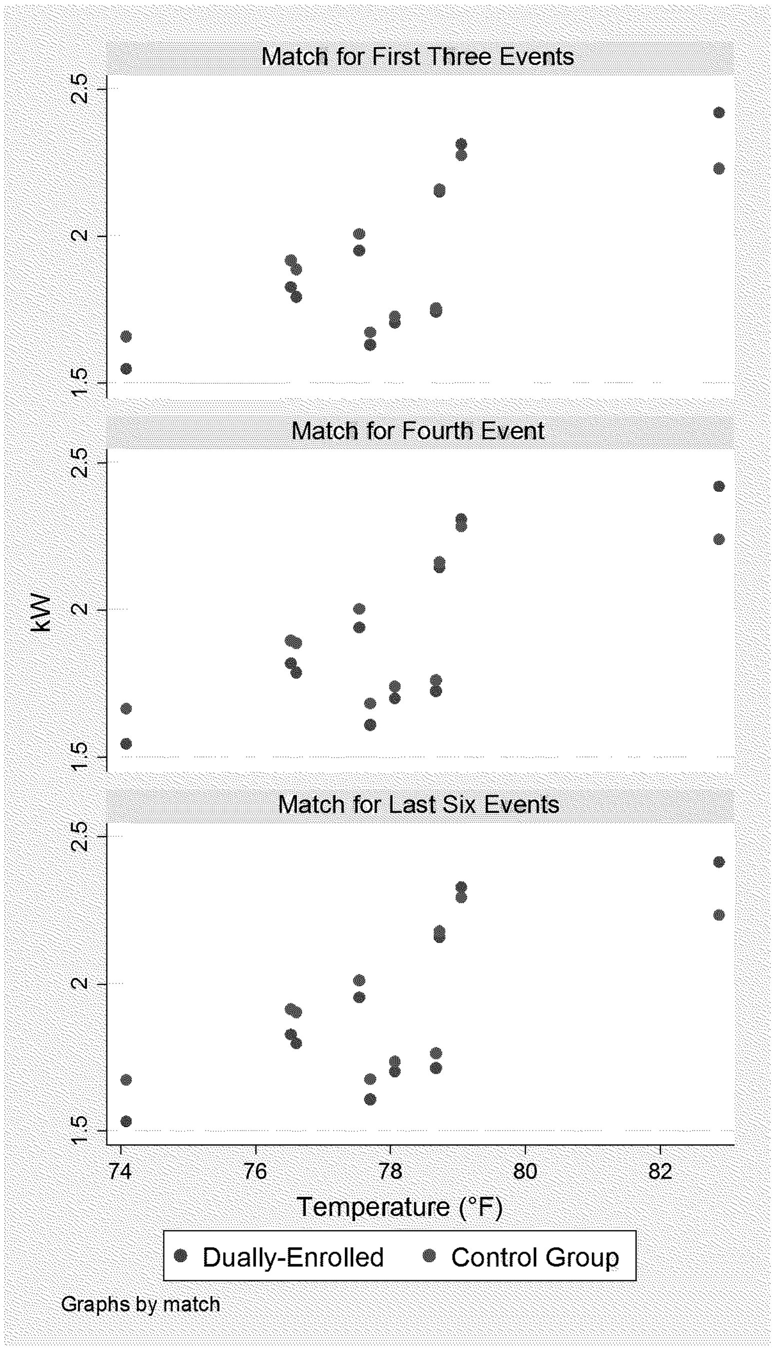
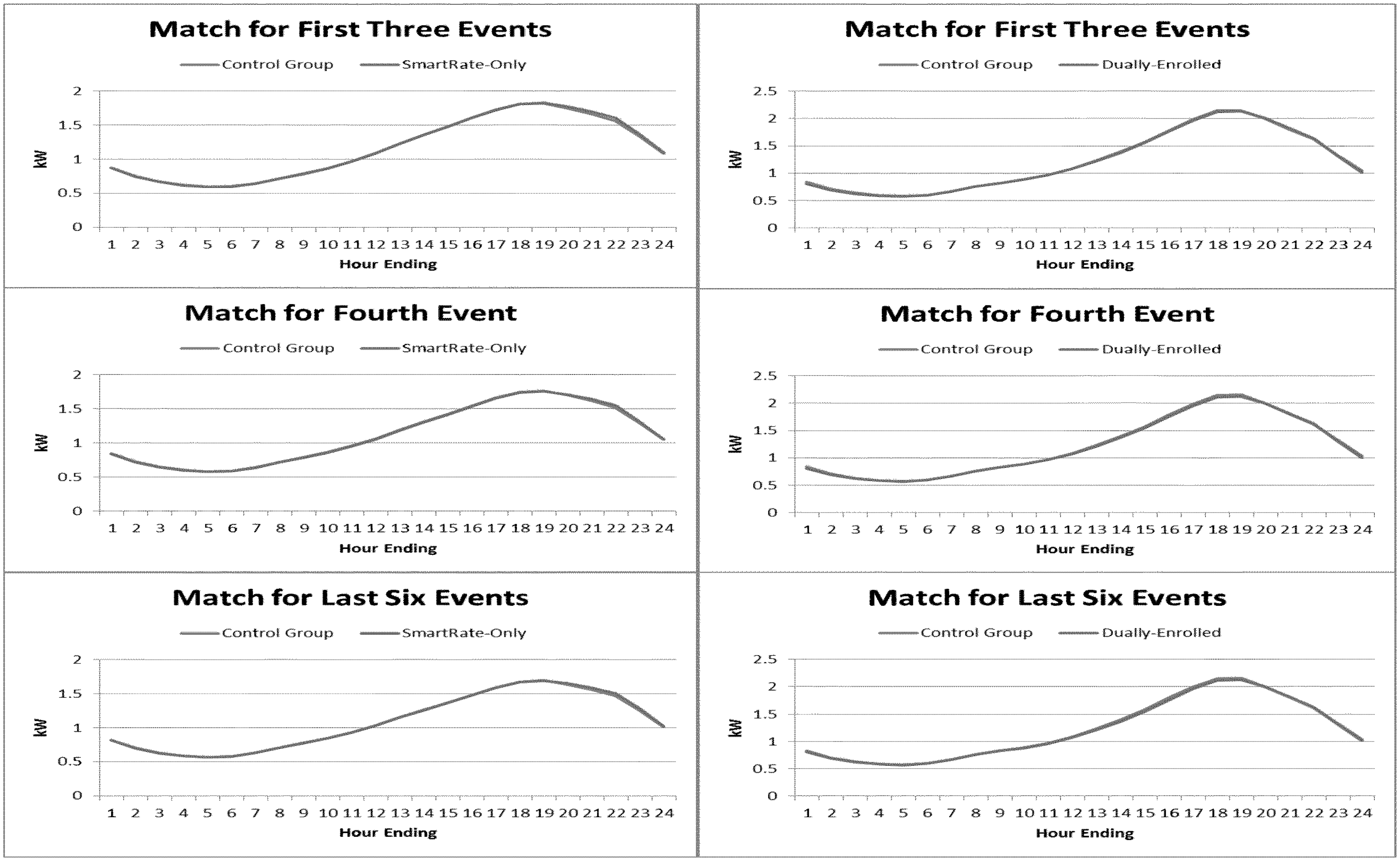


Figure A-4 shows average hourly usage for each hour of the ten hot, non-event days used in the match. When averaged over the 10 days, the match is close to perfect. The match is less perfect on a day-by-day basis and FSC will provide that data by request.

Figure A-5: Average Hourly Usage for SmartRate Population and Control Group
Hot, Non-event Days

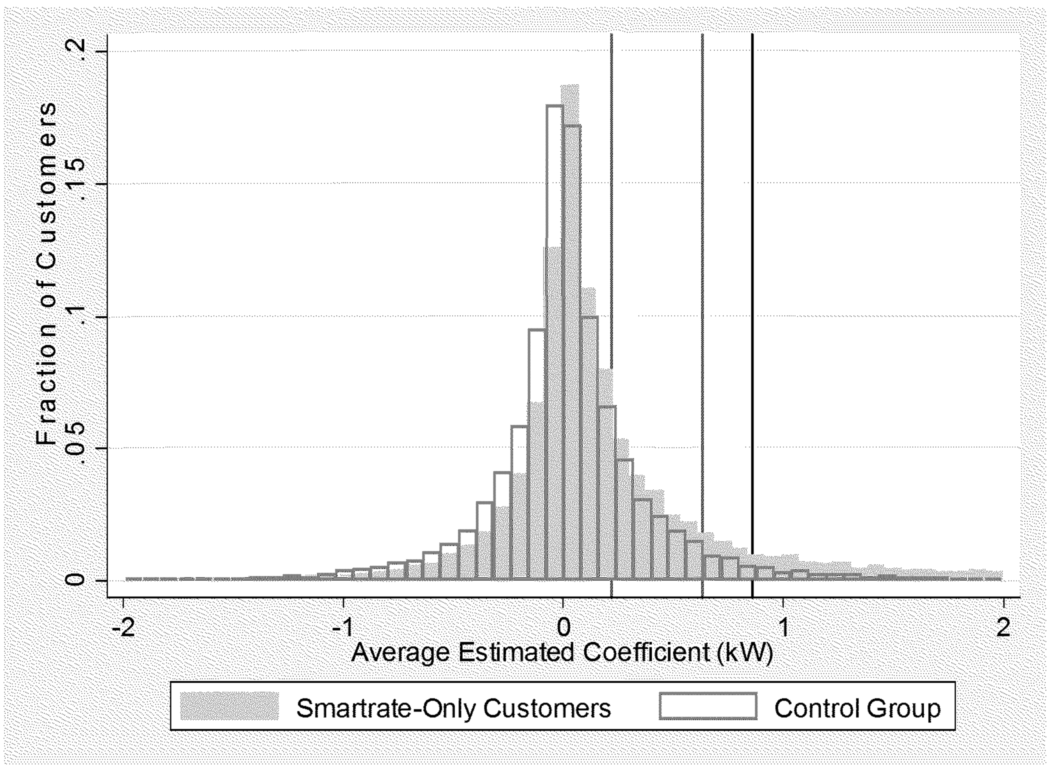


Appendix B **Details of Determining High Responders**

All results in this section are outputs of our within-subjects analysis, not our matched control group analysis. To identify customers who are likely to provide true SmartRate impacts greater than the average impact of 0.23 kW, we note that only 5% of customers in the control group have a noise estimate greater than 0.63 kW. Given that the mean SmartRate impact is 0.23 kW (per the individual customer regressions), any customer with a load impact estimate greater than 0.86 kW has a 95% or greater of having a true impact greater than 0.23 kW.[35] This is a fairly weak statement, since only a relatively small fraction of customers have impact estimates above 0.86 kW. This is due to the inherently large amount of noise in the within-subjects calculation at the individual customer level, as demonstrated by the histogram of false impact estimates in the control group.

This calculation assumes the distribution of the noise is independent of the true impact distribution. Abandoning this assumption would weaken our ability to make inferences about high responders, not strengthen it. Figure C-1 shows the distribution of estimated coefficients for both the SmartRate population and control group. The three reference lines show the relevant values mentioned above. The red line marks 0.23 kW, the blue line is at 0.63 kW and the black line is at 0.86 kW. All customers in the SmartRate group (the light blue distribution) to the right of the black reference line are considered high responders.

Figure C-1: Distribution of Average Estimated Coefficients for SmartRate-Only and Control Group Customers



[35] This calculation is explained in detail in the next paragraph.

To calculate the value 0.86 kW as the relevant threshold, the following steps and equations are used. The first equation shown below is a statement of what the analysis is solving for. The analysis is solving for the impact threshold, *t*, for which there is a 95% probability that the true impact is above the average impact (0.23 kWh) given that the estimated impact equals threshold *t* (Equation 1). It is

a given that the estimated impact (*is equal to the true impact (i*) plus noise, (Equation 2). Rearranging

Equation 2 results in Equation 3, which shows that the true impact is equal to the estimated impact minus the noise term.

Substituting Equation 3 for *i* in Equation 1 produces Equation 4. To get to Equation 5, threshold *t* is

substituted in for the estimated impact based on the given statement that the estimated impact is equal to threshold *t*. Next, Equation 5 is rearranged so that the noise term is the only variable on the

left side of the inequality. The distribution of the noise term, , is known and is shown in the clear

histogram. Based on this known distribution, there is a 95% probability that a customer will have a noise term that is less than 0.63 kWh (Equation 7). Equations 6 and 7 are both statements about the distribution of the noise term. Both are statements describing the 95th percentile of the noise distribution, therefore both expressions of the value of the 95th percentile can be set equal to each other to get Equation 8. Solving Equation 8 for *t*, leaves Equation 9 which shows that threshold *t* equals 0.86 kWh.

(Equation 1)

(Equation 2)

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(Equation 3)

(Equation 4)

(Equation 5)

(Equation 6)

(Equation 7)

(Equation 8)

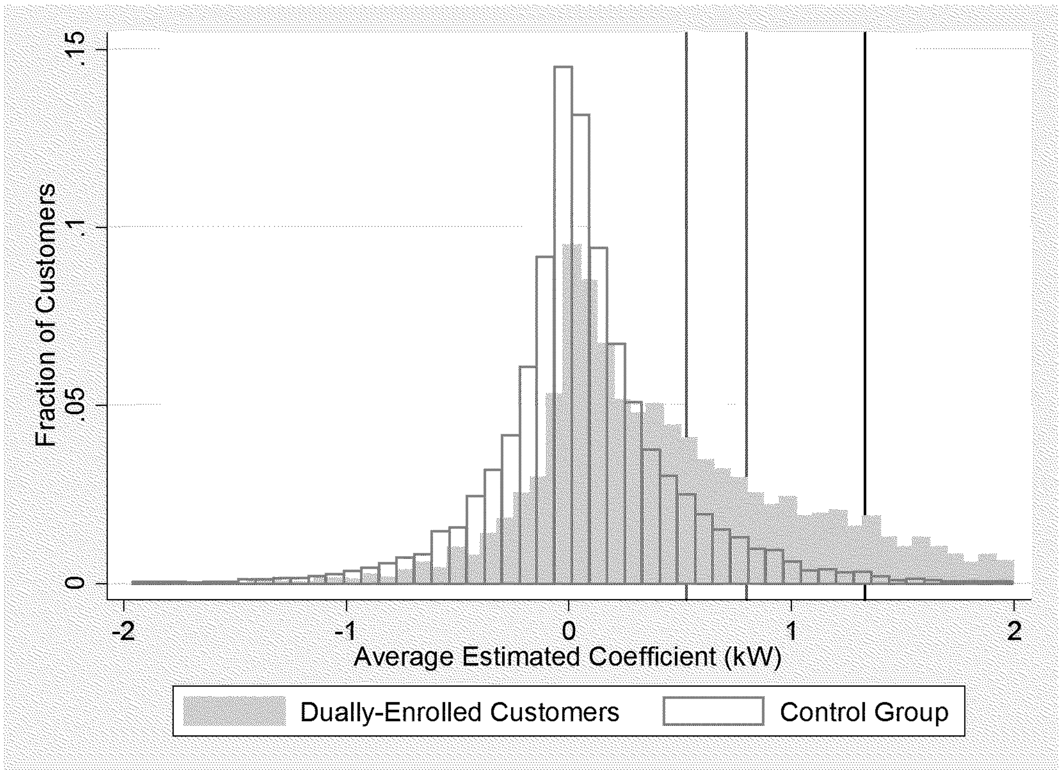
(Equation 9)

Similarly, to identify dually-enrolled customers who are high responders, we note that only 5% of customers in the control group have a noise estimate greater than 0.80 kW. Given that the mean SmartRate impact is 0.53 kW for dually-enrolled customers, any customer with a load impact estimate greater than 1.33 kW has a 95% or greater of having a true impact greater than 0.53 kW.[36] Figure C-1 shows the distribution of estimated coefficients for both the dually-enrolled population and control

[36] This calculation is explained in detail in the next paragraph.

group. The red line marks 0.53 kW, the blue line is at 0.80 kW and the black line is at 1.33 kW. All customers in the dually-enrolled SmartRate group (the light blue distribution) to the right of the black reference line are considered high responders.

Figure C-1: Distribution of Average Estimated Coefficients for SmartRate-Only and Control Group



Customers

Appendix C Propensity Score Matching to Support SmartRate Ex Ante Estimation

Ex ante impact estimates were calculated by making predictions for ex ante weather conditions using a regression model of ex post impacts from 2011 and 2012.

Prior to regression modeling, FSC developed a sample of customers that experienced all the 2011 events and all the 2012 events and that had similar observable characteristics to the SmartRate population as of October 2012. October 2012 is the most up-to-date snapshot we have of the SmartRate population and our ex ante load impact estimates are designed to be representative of that population. These groups of customers were identified using the same procedure used to identify matched control groups for the 2011 and 2012 evaluations. Customers were matched on CARE status, hourly usage from 7 AM to 7 PM, and an average hourly usage throughout the day on hot, non-event days. The match was performed within each LCA.

Next, matched control groups were developed for these groups of SmartRate customers, again using the same propensity score matching process. A control group was created for the 2011 event days and a separate control group was developed for the event days in 2012. Different control groups were not necessary from an analytical point of view because the SmartRate group in 2011 was by design representative of the SmartRate group in 2012. However, FSC had on hand interval data for 2011 for a different pool of non-SmartRate customers than for 2012. This entire process was performed twice, once for SmartRate-Only customers and once for dually-enrolled customers. Table C-1 shows evidence of the validity of this match. The four groups are distributed similarly over the seven LCAs. The groups have comparable usage from the hours from 2 to 7 PM and approximately the same percentage of customers in each group are CARE customers.

Table C-1: Distributions of LCA, Usage and CARE Status for SmartRate-Only Customers, Two-Year Customers, and Control Customers

Characteristic	SmartRate Population as of 10-23-2012	Customers on SmartRate for two years	Control Group for 2011 Event Days	Control Group for 2012 Event Days
Greater Bay Area	43.2%	43.2%	43.4%	43.1%
Greater Fresno	9.9%	9.9%	10.2%	9.9%
Kern	11.1%	11.1%	11.3%	11.1%
Northern Coast	4.9%	4.9%	4.8%	4.9%
Other	15.2%	15.2%	15.4%	15.3%
Sierra	7.7%	7.7%	7.3%	7.7%
Stockton	8.0%	8.0%	7.5%	8.0%
Care	34.6%	34.4%	33.5%	35.7%
kW from 2-7 PM	1.54	1.56	1.47	1.55

Table C-2: Distributions of LCA, Usage and CARE Status for Dually-Enrolled Customers, Two-Year Customers, and Control Customers

Characteristic	Dually Enrolled Population as of 10-23-2012	Customers on SmartRate for two years	Control Group for 2011 Event Days	Control Group for 2012 Event Days
Greater Bay Area	40.9%	40.9%	40.7%	40.9%
Greater Fresno	11.5%	11.5%	11.6%	11.5%
Kern	5.1%	5.1%	5.1%	5.1%
Northern Coast	6.2%	6.2%	6.2%	6.2%
Other	15.0%	15.0%	15.0%	15.0%
Sierra	12.4%	12.4%	12.4%	12.4%
Stockton	8.9%	8.9%	9.0%	8.9%
Care	7.0%	7.0%	6.9%	6.9%
kW from 2-7 PM	1.90	1.88	1.79	1.93

Figures C-1 and C-2 show average hourly usage for both groups on hot, non-event days. Over the event period (2 to 7 PM), usage is very similar between the two groups. Because all four groups have similar usage on hot non-event days, it is likely that the control group's usage is an accurate estimate of event day reference load.

Figure C-1: Average Usage on Hot, Non-event Days for the Current SmartRate-Only Population, Two-Year SmartRate-Only Population, and the 2011 and 2012 Control Groups

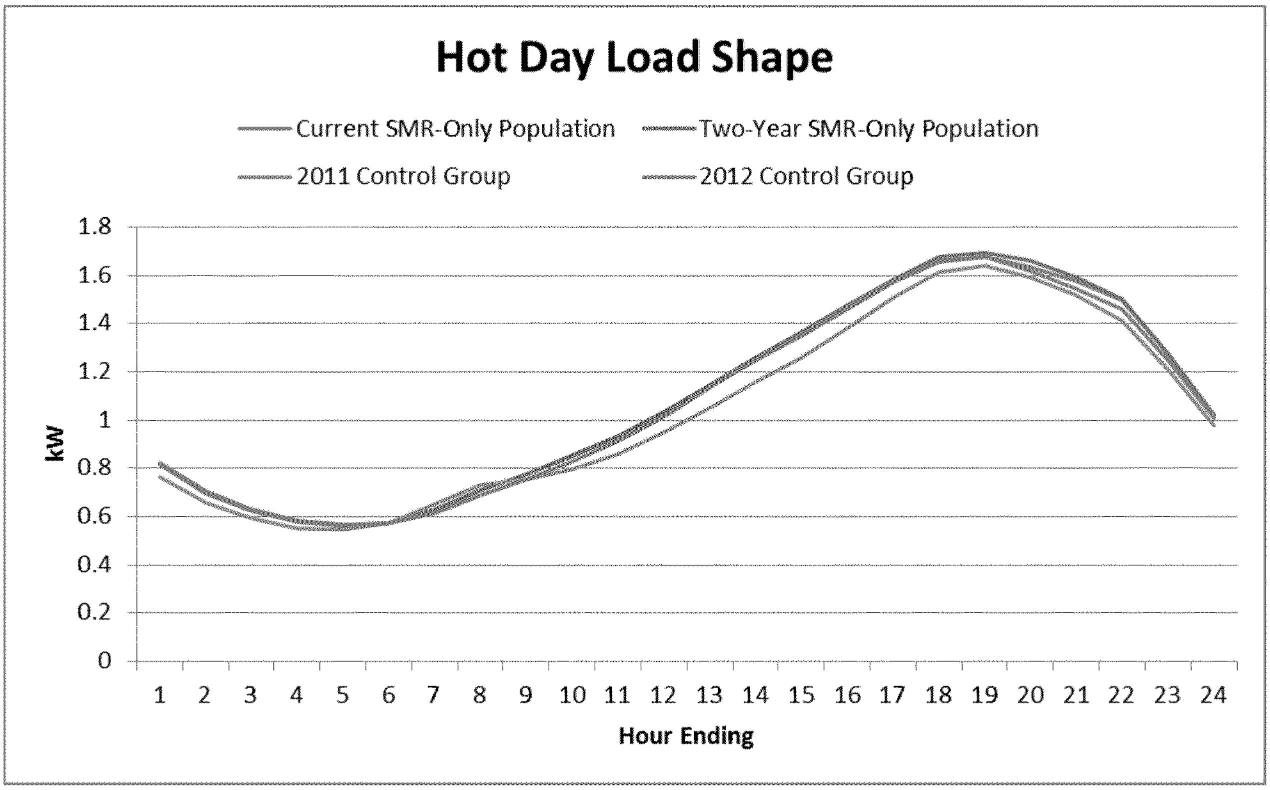
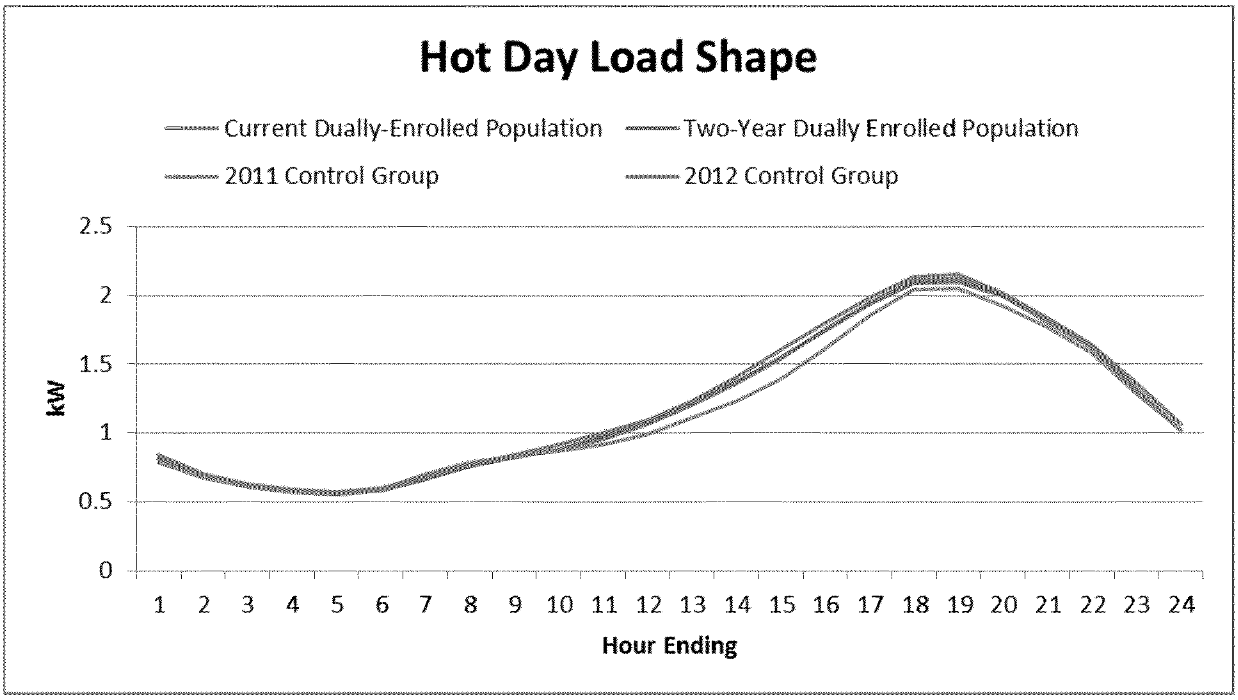


Figure C-2: Average Usage on Hot, Non-event Days for the Current SmartRate-Only Population, Two-Year Dually-Enrolled Population, and the 2011 and 2012 Control Groups



These matched sample and control groups were used to estimate a set of ex post estimates for 2011 and 2012 that represent what the October 2012 SmartRate population would have provided if they had been in the program the whole time. These ex post estimates are shown in Table C-3 and Table C-4. The impact estimates are similar to those in the Ex-Post analysis. In the Ex-Post analysis, the average impact for SmartRate-Only customers was 14% of their reference load. The average impact for dually-enrolled customers was 25% of their reference load. In this analysis SmartRate-Only and dually-enrolled customers provided 12% and 25% event impacts, respectively. With these estimates in hand, the remaining steps for ex ante estimation were quite similar to what was done in 2011.

Table C-3: 2011 and 2012 Event Impacts for SmartRate-Only Sample

Date	Load without DR (kW)	Impact (kW)	Percent Impact	Temperature (°F)
21-Jun-11	1.75	0.26	14.9%	96
22-Jun-11	1.72	0.21	12.5%	88
5-Jul-11	1.80	0.28	15.3%	92
6-Jul-11	1.77	0.21	12.1%	91
28-Jul-11	1.50	0.19	12.5%	87
29-Jul-11	1.49	0.18	11.9%	85
17-Aug-11	1.33	0.13	10.1%	84
18-Aug-11	1.35	0.12	8.8%	84
23-Aug-11	1.42	0.16	11.5%	91

29-Aug-11	1.50	0.17	11.3%	85
2-Sep-11	1.41	0.16	11.2%	88
6-Sep-11	1.35	0.13	9.3%	88
7-Sep-11	1.46	0.16	11.1%	92
8-Sep-11	1.36	0.14	10.4%	84
20-Sep-11	1.43	0.17	11.7%	92
9-Jul-12	1.43	0.18	12.7%	85
10-Jul-12	1.57	0.21	13.5%	91
11-Jul-12	1.76	0.27	15.2%	93
23-Jul-12	1.51	0.16	10.8%	85
4-Sep-12	1.29	0.11	8.4%	85
13-Sep-12	1.35	0.14	10.1%	86
14-Sep-12	1.34	0.10	7.2%	84
1-Oct-12	1.36	0.17	12.8%	93
2-Oct-12	1.42	0.18	12.4%	95
3-Oct-12	1.32	0.13	9.7%	88
Avg.	**1.48**	**0.17**	**12%**	**88**

Table C-4: 2011 and 2012 Event Impacts for Dually-Enrolled Sample

Date	Load without DR (kW)	Impact (kW)	Percent Impact	Temperature (°F)
21-Jun-11	2.18	0.53	24.4%	98
22-Jun-11	2.06	0.48	23.1%	91
5-Jul-11	2.20	0.48	22.0%	95
6-Jul-11	2.18	0.43	19.9%	94
28-Jul-11	1.80	0.44	24.4%	90
29-Jul-11	1.75	0.40	23.0%	87
17-Aug-11	1.57	0.34	21.9%	87
18-Aug-11	1.56	0.33	20.8%	87
23-Aug-11	1.71	0.44	25.9%	94
29-Aug-11	1.78	0.49	27.3%	87
2-Sep-11	1.68	0.38	22.5%	92
6-Sep-11	1.61	0.39	24.3%	91
7-Sep-11	1.77	0.41	23.5%	94
8-Sep-11	1.60	0.37	23.0%	88
20-Sep-11	1.77	0.47	26.2%	94
9-Jul-12	1.71	0.50	28.9%	88
10-Jul-12	1.93	0.54	27.8%	95
11-Jul-12	2.27	0.69	30.2%	98

23-Jul-12	1.80	0.41	22.6%	87
4-Sep-12	1.51	0.38	25.0%	88
13-Sep-12	1.59	0.38	24.2%	89
14-Sep-12	1.55	0.35	22.5%	87
1-Oct-12	1.74	0.60	34.3%	95
2-Oct-12	1.79	0.57	32.0%	96
3-Oct-12	1.58	0.38	24.0%	90
Avg.	**1.79**	**0.45**	**25%**	**91**

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