2013 Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-based Pricing Programs

Final Report

Pacific Gas and Electric Company

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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 2013. 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 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 to 7 PM in the summer and from 5 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 program. The program underwent significant expansion in early 2013. Approximately 78,000 customers were enrolled on the last event day in 2012 and nearly 119,000 were enrolled at the end of 2013. Additionally, the dually enrolled population, which consists of customers enrolled on both SmartRate and SmartAC—PG&E's central air conditioning (CAC) load control program—has expanded significantly since 2011. At the end of 2013, two thirds of program participants were SmartRate only customers and one-third were dually enrolled.

PG&E's SmartRate program had roughly 119,000 customers enrolled at the end of 2013. The average peak period load reduction delivered by the program over the 8 SmartDays called in 2013 was almost 45 MW. This is a substantial increase in both enrollment and demand response compared with 2012.

Eight SmartDays were called in 2013. Table 1-1 shows load impact estimates for the 2013 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 customer segments. The average load impact across the 8 SmartDays in 2013 equaled 0.26 kW for SmartRate-only participants and 0.62 kW for dually enrolled participants. Aggregate load reduction for the average event was 20.5 MW and 23.7 MW for SmartRate-only customers and dually enrolled customers, respectively, which produced a total average aggregate impact of 44.2 MW.

In 2012, the average load reduction for SmartRate-only customers was 0.20 kW and the average load reduction for dually enrolled customers was 0.42 kW. Both of these values are higher in 2013, which indicates successful targeting of new customers, especially dually enrolled customers where the average

[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.

impacts were 50% higher in 2013 than in 2012. PG&E's refined targeting efforts produced dramatically larger average impacts even within the perceived cooler Bay Area which, in fact, is a climatically diverse region with very cool summer temperatures near the coast and quite hot temperatures in many East Bay cities. By targeting the hotter areas within the Bay Area, the significant increase in enrollment in the region between 2012 and 2013 led to an increase in average load reduction per customer for SmartRate-only participants of roughly 80%, from 0.10 kW in 2012 to 0.18 kW in 2013, and an increase of 75%, from 0.28 kW to 0.49 kW, for dually enrolled customers.

Average impacts per customer in 2013 were significantly higher than in 2012, reflecting PG&E's successful efforts to target high use and SmartAC customers.

Table 1-1: Ex Post Load Impact Estimates for SmartRate-only Customers (Average Impacts from 2 to 7 PM)

Date	Day of week	Avg. Reference Load (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Daily Maximum Temp (°F)
7-Jun-13	F	1.47	0.25	17%	19.2	90
28-Jun-13	F	1.75	0.34	19%	27.1	94
1-Jul-13	M	1.80	0.30	16%	23.5	93
2-Jul-13	T	1.87	0.30	16%	23.9	93
19-Jul-13	F	1.39	0.21	15%	16.7	86
19-Aug-13	M	1.65	0.25	15%	20.4	89
9-Sep-13	M	1.50	0.24	16%	19.7	89
10-Sep-13	T	1.26	0.16	13%	12.7	83
Average Event Day	**N/A**	**1.59**	**0.26**	**16%**	**20.5**	**89**

Table 1-2: SmartRate Ex Post Load Impact Estimates for Dually Enrolled Customers and Aggregate Impacts for All Customers (Average Impacts from 2 to 7 PM)

Date	Enrolled participants	Avg. Reference Load (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Daily Maximum Temp (°F)	Total Aggregate Load Reduction (MW)
7-Jun-13	F	1.92	0.61	32%	23.2	96	42.4
28-Jun-13	F	2.46	0.82	33%	31.3	99	58.4
1-Jul-13	M	2.55	0.75	29%	28.5	99	52.1
2-Jul-13	T	2.63	0.75	29%	28.8	99	52.6
19-Jul-13	F	1.77	0.48	27%	18.3	93	35.0
19-Aug-13	M	2.22	0.63	28%	24.3	95	44.7
9-Sep-13	M	1.99	0.57	29%	22.0	95	41.7
10-Sep-13	T	1.51	0.33	22%	12.8	85	25.5
Average Event Day	**N/A**	**2.13**	**0.62**	**29%**	**23.7**	**95**	**44.2**

In addition to providing estimates of ex post load impacts for the participant population, this report presents results from the analysis of a wide variety of issues that can improve program performance and inform future pricing strategy. These include, but are not limited to, the following:

- For the first time since the program began, PG&E explored whether the enrollment rate would increase if structural winners were told that their bills would likely decrease by going on SmartRate. The assessment also examined whether informing structural winners about bill savings affect the average demand response compared with customers who do not get such information. This analysis found that the enrollment rate increased by a small but statistically significant amount and that demand response for customers that were told that they are structural winners was not statistically significantly different from structural winners that were not informed.
- PG&E also examined whether customers on the Company's Balanced Payment Plan (BPP) responded differently from customers that are not on BPP. Some people fear that BPP masks the price signal that drives demand response and that customers on BPP would have lower load reductions compared with those who are not on this program. This is not the case. In fact, BPP customers actually had higher absolute load reductions (and higher loads) than customers that were not on BPP and the percent load reduction was very similar across BPP and non-BPP customers.
- The average load reduction for SmartRate-only CARE customers in 2013 was about half as large as for non-CARE customers. This large difference is not evident between dually enrolled CARE and non-CARE 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 provided significantly greater demand response than those who are on SmartRate alone. Average impacts for dually enrolled customers were more than twice as large as for SmartRate only customers and the aggregate impact for dually enrolled customers was larger than for SmartRate only customers in spite of the fact that there were twice as many SmartRate only customers in the program.
- The vast majority of customers who sign up for SmartRate stay on the program. Attrition due to de-enrollment is quite low (less than 1.5%).
- Across the summer months of 2013, 99% of SmartRate customers saved money compared with their otherwise applicable tariff (OAT). This is much higher than in 2012, primarily because only 8 events were called in 2013 whereas 10 events were called in 2012.

1.2 SmartRate Ex Ante Evaluation Summary

Ex ante load impact estimates for SmartRate-only and dually enrolled customers for 2013 are shown in Table 1-3. The first and second (numerical) columns show the estimated average ex ante load reduction 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 corresponds to 1-in-2 year weather conditions while the second set covers 1-in-10 year weather conditions. The enrollment forecast underlying the ex ante estimates was provided by PG&E. Program enrollment is predicted to stay nearly flat over the forecast horizon and the mix between SmartRate-only and dually enrolled participants is expected to be constant. Both populations within the program are forecasted to provide their largest impacts on the July monthly peak day under both 1-in-2 and 1-in-10 year weather conditions. Under 1-in-2 year conditions, the aggregate impact in July is forecasted to equal 44 MW, with almost 60% of the total provided by dually enrolled customers. Under 1-in-10 conditions, the predicted peak impact is 52 MW.

The SmartRate program is forecasted to provide up to 38 MW of load reduction on a typical event day under normal weather conditions and as much as 47 MW on a typical event day under 1-in-10 year weather conditions. On the system peak day, the demand response potential for the SmartRate program is estimated to equal 44 MW and 52 MW under normal and extreme weather conditions,

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

Weather Year	Day Type	Mean Hourly Per Customer Impact (SmartRate Only) (kW)	Mean Hourly Per Customer Impact (Dually Enrolled) (kW)	Aggregate Mean Hourly Impact (SmartRate Only) (MW)	Aggregate Mean Hourly Impact (Dually Enrolled) (MW)	Aggregate Mean Hourly Impact (Full Program) (MW)
1-in-2	Typical Event Day	0.21	0.52	17.2	20.4	37.6
	May Monthly Peak	0.14	0.35	11.5	13.6	25.1
	June Monthly Peak	0.20	0.45	15.9	17.6	33.5
	July Monthly Peak	0.24	0.62	19.5	24.4	43.9
	August Monthly Peak	0.21	0.50	17.2	19.8	36.9
	September Monthly Peak	0.20	0.50	16.1	19.8	35.9
	October Monthly Peak	0.16	0.30	12.7	11.8	24.4
1-in-10	Typical Event Day	0.26	0.66	21.0	25.9	46.9
	May Monthly Peak	0.23	0.57	18.5	22.3	40.9
	June Monthly Peak	0.27	0.62	21.5	24.6	46.2
	July Monthly Peak	0.28	0.75	22.4	29.7	52.1
	August Monthly Peak	0.26	0.67	20.5	26.6	47.0
	September Monthly Peak	0.24	0.58	19.5	22.8	42.2
	October Monthly Peak	0.21	0.51	16.8	20.2	37.0

1.3 TOU Ex Post Evaluation Summary

PG&E has two time-of-use (TOU) tariffs—E-6 and E-7—with 31,000 and 66,000 residential customers, respectively. On both tariffs, 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 E-7 rate was closed to new enrollment in 2006 when it was replaced by E-6, but there are still more E-7 customers than E-6 customers on the tariff. Over 80% of the 31,000 E-6 customers and 20% of the E-7 customers are net metered. This evaluation excludes net-metered customers because they likely have solar panels and are already accounted for in the evaluation of solar programs. In total, the evaluation results presented here represent approximately 60,000 non net-metered E-6 and E-7 accounts.

This is the first year that the number of non-net metered customers was large enough to allow for estimation of impacts for E-6 separate from E-7. The methodology used to estimate impacts for E-6 allows for at least some correction for selection bias that that can easily lead to over estimation of load impacts. The data available for E-7 does not allow for use of the same approach and very likely overstates what the true impacts are for this tariff. However, we have attempted to reduce the bias that is likely present based on reasonable assumptions and an estimate of the magnitude of bias that was identified (and controlled for) using the E-6 methodology. Nevertheless, we have less confidence in the estimated impacts for E-7 than for E-6, especially during winter months. These caveats should be kept in mind when reviewing the results from this analysis.

Tables 1-4 and 1-5 show the average load reduction on monthly system peak days for E-6 and E-7 customers during the time period covered by this analysis, from November 1, 2012 through October 31, 2013. TOU load reductions were greater over the summer (May–Oct) than the winter (Nov–Apr) for E-6 customers, when the difference between peak and off-peak prices is the largest and the peak period goes from 1 to 7 PM. During the summer, the average load reduction for E-6 customers was 0.22 kW, or 20%, and the aggregate load reduction was 1.1 MW. This is substantially less than the aggregate impacts for the SmartRate tariff and also less than for the E-7 tariff, as seen in Table 1-5. The average summer impact for E-7 is estimated to equal 0.1 kW and the aggregate impact is roughly 6 MW. Winter values are slightly less.

Table 1-4: E-6 Monthly System Peak Day Load Reductions (1 to 7 PM Summer, 5 to 8 PM Winter) November 2012 to October 2013

Month	Average Reference Load (kW)	Average Load Impact (kW)	Aggregate Load Impact (MW)	Percent Reduction (%)	Average Temp. (°F)
January	1.43	0.02	0.12	2%	48.2
February	1.38	0.01	0.04	1%	43.5
March	1.22	-0.03	-0.14	-2%	51.2
April	1.22	0.20	0.99	16%	74.8
May	0.91	0.13	0.64	14%	85.8
June	1.35	0.31	1.58	23%	89.2
July	1.41	0.24	1.22	17%	85.1
August	1.19	0.24	1.24	21%	81.8
September	1.17	0.32	1.60	27%	83.6
October	0.74	0.09	0.47	13%	70.9
November	1.35	0.02	0.10	1%	58.3
December	1.64	0.05	0.25	3%	44.5
Average	**1.25**	**0.13**	**0.68**	**11%**	**68.1**
Summer	**1.13**	**0.22**	**1.12**	**20%**	**82.7**
Winter	**1.37**	**0.04**	**0.23**	**3%**	**53.4**

Table 1-5: E-7 Monthly System Peak Day Load Reductions (12 to 6 PM) November 2012 to October 2013

Month	Average Reference Load (kW)	Average Load Impact (kW)	Aggregate Load Impact (MW)	Percent Reduction (%)	Average Temp. (°F)
January	1.32	0.08	4.54	6%	54.8
February	1.39	0.10	5.39	7%	45.5
March	1.18	0.07	3.66	6%	55.5
April	1.35	0.11	5.92	9%	82.2
May	1.07	0.08	4.37	8%	85.9
June	1.89	0.12	6.75	7%	91.7
July	2.02	0.11	5.80	5%	90.2
August	1.70	0.12	6.39	7%	86.5
September	1.56	0.15	8.11	10%	87.4
October	0.92	0.09	4.98	10%	72.3
November	1.31	0.10	5.66	8%	59.6
December	1.48	0.08	4.53	6%	49.5
Average	**1.43**	**0.10**	**5.51**	**7%**	**71.8**
Summer	**1.53**	**0.11**	**6.07**	**7%**	**85.7**
Winter	**1.34**	**0.09**	**4.95**	**7%**	**57.9**

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 forecast period, and the only factor affecting the population is attrition. The E-6 tariff allows new enrollment and is predicted to grow significantly over the forecast horizon.

Table 1-6 summarizes the ex ante estimates for TOU rates for the 1-in-2 and 1-in-10 year annual peak days, which occur in June and July, respectively. Enrollment across the two rates is roughly constant as the decline in enrollment for the E-7 tariff is offset by increases in E-6. Aggregate load reductions increase by about 30% over the forecast horizon, although the reference load declines. This is due to the larger average impacts provided by E-6 customers relative to E-7 customers, in spite of the fact that E-6 customers have smaller reference loads.

Table 1-6: Summary of Aggregate Ex Ante Load Impacts for Non-net-metered Residential TOU by Year (Average 1 to 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	2014	61,059	93.1	83.7	9.4	10%	91.3
	2015	60,355	91.1	81.6	9.5	10%	
	2016	59,846	89.4	79.7	9.7	11%	
	2017	59,522	88.0	78.1	10.0	11%	
	2018	59,371	86.9	76.7	10.2	12%	
	2019	59,381	86.1	75.6	10.5	12%	
	2020	59,546	85.4	74.7	10.8	13%	
	2021	59,856	85.0	74.0	11.1	13%	
	2022	60,301	84.9	73.4	11.4	13%	
	2023	60,874	84.9	73.1	11.8	14%	
	2024	61,568	85.1	72.9	12.1	14%	
1-in-10	2014	61,059	101.6	91.2	10.4	10%	94.5
	2015	60,355	99.4	88.8	10.6	11%	
	2016	59,846	97.5	86.8	10.8	11%	
	2017	59,522	96.0	85.0	11.0	11%	
	2018	59,371	94.7	83.4	11.3	12%	
	2019	59,381	93.8	82.2	11.6	12%	
	2020	59,546	93.0	81.1	11.9	13%	
	2021	59,856	92.6	80.3	12.3	13%	
	2022	60,301	92.3	79.7	12.6	14%	
	2023	60,874	92.3	79.3	13.0	14%	
	2024	61,568	92.5	79.0	13.4	15%	

2 Overview of Time-varying Tariffs

PG&E has offered time-varying tariffs on a voluntary basis since the mid-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.

PG&E has offered voluntary time varying rates to residential customers for almost three decades. In 2013, more than 216,000 residential customers were on one of the three time varying rates available to PG&E's customers – SmartRate, E-6 TOU or E-7 TOU.

The E-7 tariff was closed to new enrollment in 2006,[3] 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 plan transition SmartRate customers to PDP on a default basis 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 and by June of 2013 there were about 120,000 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).[4] SmartRate pricing consists of an incremental charge that applies during the peak period on

[3] 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).

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

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 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[5] 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, 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 10% of SmartRate-only customers and 7% 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, which means it is effectively a four-tier rate). 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.

[5] 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[6]

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%	32.0	14.0
4	300%	36.0	14.0
5	>300%	36.0	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.

Customers who enroll in SmartRate may also enroll in PGE&'s SmartAC program. Smart AC is a program in which customers receive a payment from PG&E in return for having their air conditioner controlled 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.[7]

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. CARE customers represent roughly 26% of PG&E's customer population, and about 22% of the SmartRate population. They represent about 24% of the SmartRate-only population but only 18% of the dually enrolled population. Participants are distributed throughout the LCAs roughly in proportion to the PG&E population in each LCA. For example, roughly 45% of program participation and PG&E population are from the Greater Bay Area LCA. Table 2-3 shows the number of enrolled customers in each LCA at the end of 2012 and 2013. Participation grew by roughly 45% over this period.

6 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.

7 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 2-2: Customers in the PG&E Population and SmartRate Program by Local Capacity Area and CARE Status

Local Capacity Area	SmartRate Participants (End of 2013)								PG&E Residential Population			
	SmartRate-Only				Dually Enrolled							
	Non-CARE	%	CARE	%	Non-CARE	%	CARE	%	Non-CARE	%	CARE	%
Greater Bay Area	34,386	54%	4,288	23%	13,388	43%	1,158	17%	1,698,789	50%	391,759	33%
Greater Fresno Area	3,378	5%	2,612	14%	2,414	8%	1,252	19%	190,225	6%	148,737	13%
Humboldt	571	1%	370	2%	147	0%	46	1%	83,003	2%	39,673	3%
Kern	3,538	6%	3,736	20%	976	3%	784	12%	113,909	3%	90,830	8%
North Coast and North	2,763	4%	483	3%	1,924	6%	179	3%	317,180	9%	74,031	6%
Other	11,541	18%	4,075	22%	5,645	18%	1,695	25%	678,748	20%	285,465	24%
Sierra	4,394	7%	1,106	6%	3,925	13%	543	8%	185,674	5%	57,268	5%
Stockton	3,327	5%	2,254	12%	2,713	9%	1,014	15%	151,118	4%	82,614	7%
Total	**63,898**	**100%**	**18,924**	**100%**	**31,132**	**100%**	**6,671**	**100%**	**3,418,646**	**100%**	**1,170,377**	**100%**

Table 2-3: Comparison of 2012 and 2013 Participants by Local Capacity Area

LCA	SmartRate-only				Dually Enrolled				All Customers			
	2012	%	2013	%	2012	%	2013	%	2012	%	2013	%
Greater Bay Area	22,585	43%	38,674	47%	11,156	41%	14,546	38%	33,741	42%	53,220	44%
Greater Fresno Area	5,212	10%	5,990	7%	3,174	12%	3,666	10%	8,386	11%	9,656	8%
Humboldt	-	-	941	1%	-	-	193	1%	-	-	1,134	1%
Kern	5,823	11%	7,274	9%	1,398	5%	1,760	5%	7,221	9%	9,034	7%
Northern Coast	2,540	5%	3,246	4%	1,678	6%	2,103	6%	4,218	5%	5,349	4%
Other	7,998	15%	15,616	19%	4,093	15%	7,340	19%	12,091	15%	22,956	19%
Sierra	4,062	8%	5,500	7%	3,386	12%	4,468	12%	7,448	9%	9,968	8%
Stockton	4,211	8%	5,581	7%	2,443	9%	3,727	10%	6,654	8%	9,308	8%
Total	**52,431**	**100%**	**82,822**	**100%**	**27,328**	**100%**	**37,803**	**100%**	**79,759**	**100%**	**120,625**	**100%**

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 E-7 tariff 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 2-4 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

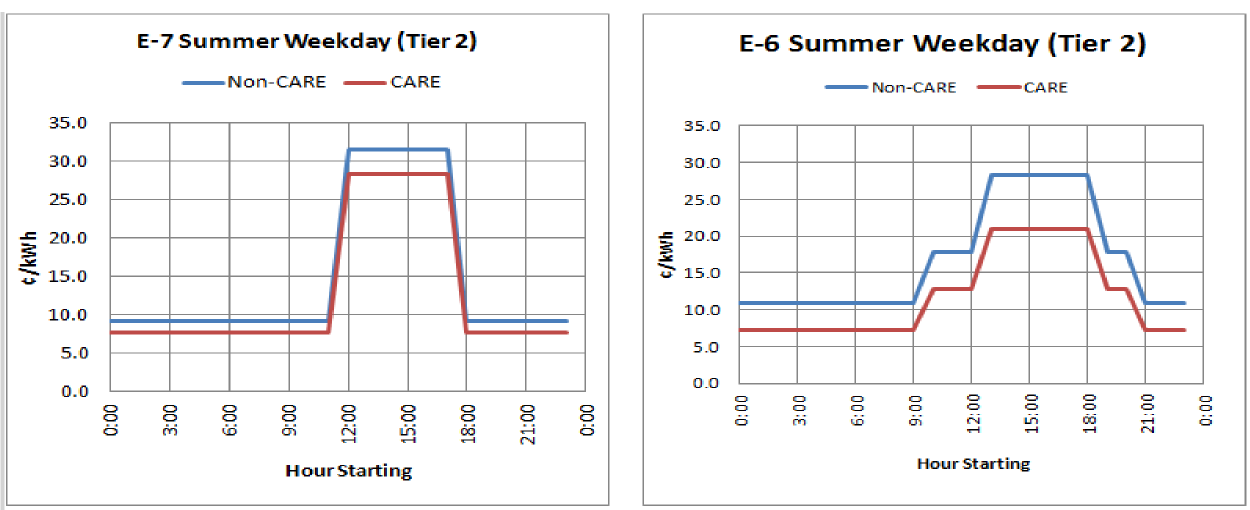


Table 2-4: E-6 and E-7 Prices[8]

Tariff	Rate Description	Season	TOU Period	Energy Charge (¢/kWh)					Average Total Rate (¢/kWh) Rate Sheet
				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+)	
E7	Residential time-of-use (4 periods)	Summer	Peak	32.3	34.1	51.5	55.5	55.5	18.791
			Off-Peak	8.2	10.0	27.4	31.4	31.4	
		Winter	Peak	11.4	13.3	30.6	34.6	34.6	
			Off-Peak	8.5	10.4	27.7	31.7	31.7	
EL-7	Residential time-of-use, CARE (4 periods)	Summer	Peak	26.8	28.4	41.7	41.7	41.7	9.721
			Off-Peak	6.1	7.7	10.7	10.7	10.7	
		Winter	Peak	8.9	10.5	14.9	14.9	14.9	
			Off-Peak	6.4	8.0	11.1	11.1	11.1	
E6	Residential time-of-use (6 periods)	Summer	Peak	28.7	30.5	47.8	51.8	51.8	19.943
			Part-Peak	17.5	19.3	36.6	40.6	40.6	
			Off-Peak	10.1	11.9	29.1	33.1	33.1	
		Winter	Part-Peak	12.1	13.9	31.2	35.2	35.2	
			Off-Peak	10.5	12.3	29.6	33.6	33.6	
EL-6	Residential time-of-use, CARE (6 periods)	Summer	Peak	19.7	21.0	31.0	31.0	31.0	9.733
			Part-Peak	11.5	12.8	18.7	18.7	18.7	
			Off-Peak	6.0	7.3	10.5	10.5	10.5	
		Winter	Part-Peak	7.5	8.8	12.7	12.7	12.7	
			Off-Peak	6.3	7.6	10.9	10.9	10.9	

[8] 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.

In total, there were approximately 97,000 customers being served under the four versions of the TOU tariffs at the end of summer 2013, with about 31,000 on E-6 and approximately 66,000 on E-7. Table 2-6 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 approximately 1% of customers on flat rates are net metered, approximately 78% of E-6 customers and 13% of E-7 customers are net-metered.

Table 2-5: Customer Characteristics by Tariff (E-6 and E-7 Excluding Net Metered Customers)

Characteristic	Rate		
	E-1	E-6	E-7
Accounts	4,431,792	5,822	53,334
Average Annual kWh	6,669	6,377	10,425
% Net Metered	1	0	0
% CARE	25.2	7.5	9.7
% All Electric	14.8	18.8	33.4
% with Smart Meters (July 27, 2012)	92	67	28
% with Smart Meters (December 17, 2013)	98	96	89

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 25% of PG&E's customers on the non-time varying E-1 tariff are CARE customers, only about 8% to 10% 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 33% 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 customers, more than 10,000 kWh, is about 50% higher than the 6,700 kWh average annual consumption of E-1 customers and the 6,400 kWh annual consumption for E-6 customers.

In comparison to customers on flat rates, a smaller share of E-7 customers have had smart meters installed. Over 98% of customers on flat rates had smart meters installed by December 17, 2013. In contrast, 96% of E-6 and 89% of E-7 customers had smart meters installed. In past years, 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. Unlike last year, the evaluation produces separate load impact estimates for E-6 and E-7 customers since the number of E-6 customers that had at least a year's worth of interval data is large enough this year to allow for estimation of E-6 load reductions.

Finally, although the peak period in the rate structures differs between the two groups, we have produced ex ante impacts for 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 PM to 6 PM, regardless of what the actual peak period is for 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. Indeed, as will be seen later, customers on the E-6 tariff do not change their usage behavior much across the winter and summer seasons, even though the peak periods differ significantly across seasons for this tariff.

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 and Section 4 provides ex post results for SmartRate. Section 5 discusses the ex ante methods and results for SmartRate. Section 6 discusses the ex post load impact estimation methods for the E-6 and E-7 rates and Section 7 contains the ex post load impact estimates for these tariffs. Section 8 contains ex ante methods and results for E-6 and E-7. In addition, there are four appendices providing additional detail on technical issues.

3 SmartRate Ex Post Methods and Validation

The fundamental problem for estimating load impacts is developing an estimate of the 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, measuring such an effect is very difficult using the quasi-experimental methods applied here rather than through a controlled experiment.[9]

The evaluation methods used in the 2013 SmartRate evaluation are similar to those used for the 2012 evaluation. The approach relies on selection of a control group using statistical matching, as explained in Section 3.1 below. In 2012, the SmartRate population changed significantly over the course of the summer, which required creating multiple control groups across SmartRate events. This year one matched control group was selected for the entire SmartRate population.

The matched control group method used for this analysis is superior to a within-subjects analysis 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.[10] 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, a within-subjects analysis is used 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 perform high responder analysis 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, is a series of matched control groups. These control groups are assembled from among the non-SmartRate population. The methods

[9] The design necessary to measure such an effect would involve either a randomized control trial or a randomized encouragement design. These designs are more practical within the confines of a pricing pilot than with an actual program like SmartRate. For examples of how these methods have been used within a pricing pilot, see the interim report on Sacramento Municipal Utility District's Smart Pricing Options pilot: https://www.smartgrid.gov/sites/default/files/MASTER_SMUD%20CBS%20Interim%20Evaluation_Final_SUBMITTED%20TO%20TAG%2020131023.pdf .

[10] For a comparison of results using various research methods, including RCT/RED designs, statistical matching and within-subjects regression analysis, see the aforementioned SMUD pilot interim report.

used to assemble the groups are designed to ensure that the control group load on 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. Two different control groups were assembled: one for the SmartRate-only population and one for the group of SmartRate customers also enrolled in SmartAC.

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 a 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 usage quartile and was based on 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 to 7 PM), all calculated over the 6 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). 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.

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 2013. The last two columns of Table 3-1 show t-statistics and p-values for tests of the hypothesis that the mean values 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

[11] See Appendix B for a full list of variables used in the matching process.

[12] The days were July 9, July 24, July 25, July 26, August 16, and August 20.

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 1% and not statistically significant.

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

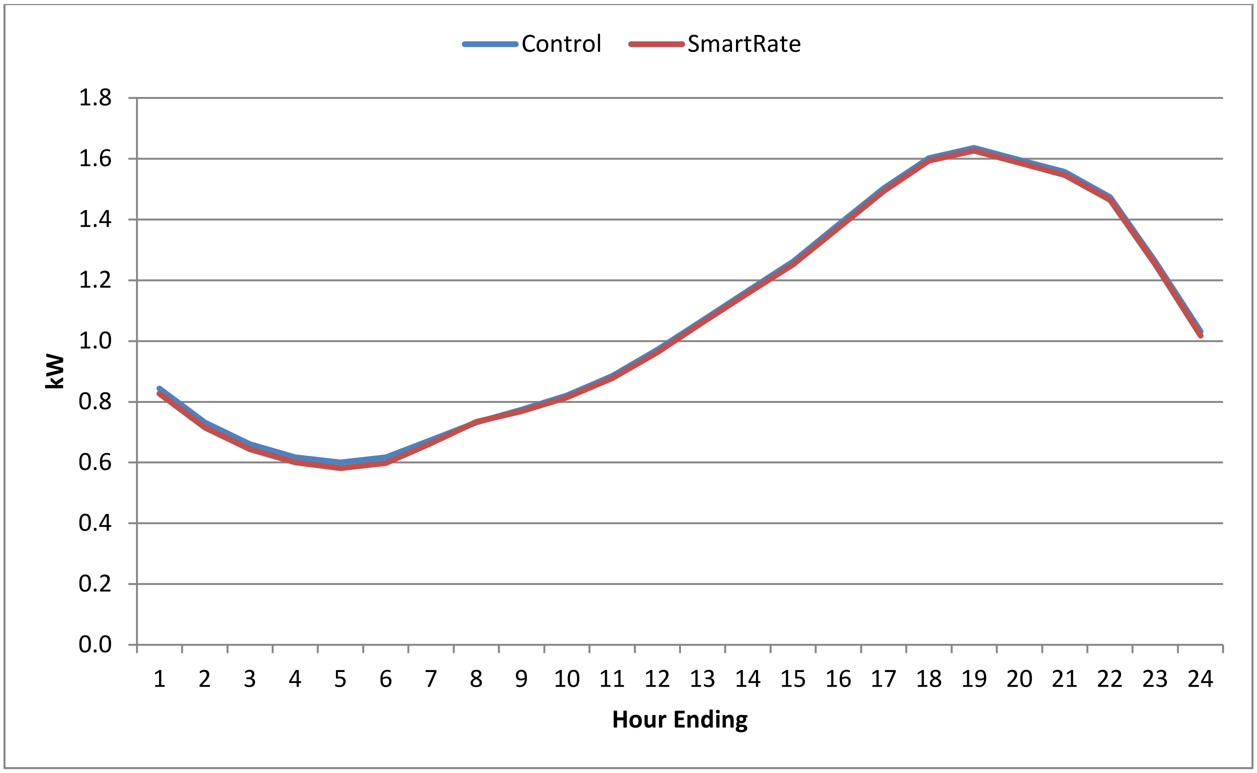
Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	44%	44%	0.0	1.0
Greater Fresno	8%	8%	0.0	1.0
Humboldt	1%	1%	0.0	1.0
Kern	7%	7%	0.0	1.0
Northern Coast	4%	4%	0.0	1.0
Other	19%	19%	0.0	1.0
Sierra	8%	8%	0.0	1.0
Stockton	8%	8%	0.0	1.0
June 2013 kWh	695	699	2.0	0.0
July 2013 kWh	759	793	14.9	0.0
Non-CARE	78%	78%	-2.4	0.0
CARE	22%	22%	-2.4	0.0

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.

Figure 3-1 shows average hourly usage for SmartRate and matched control customers 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.

[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.

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

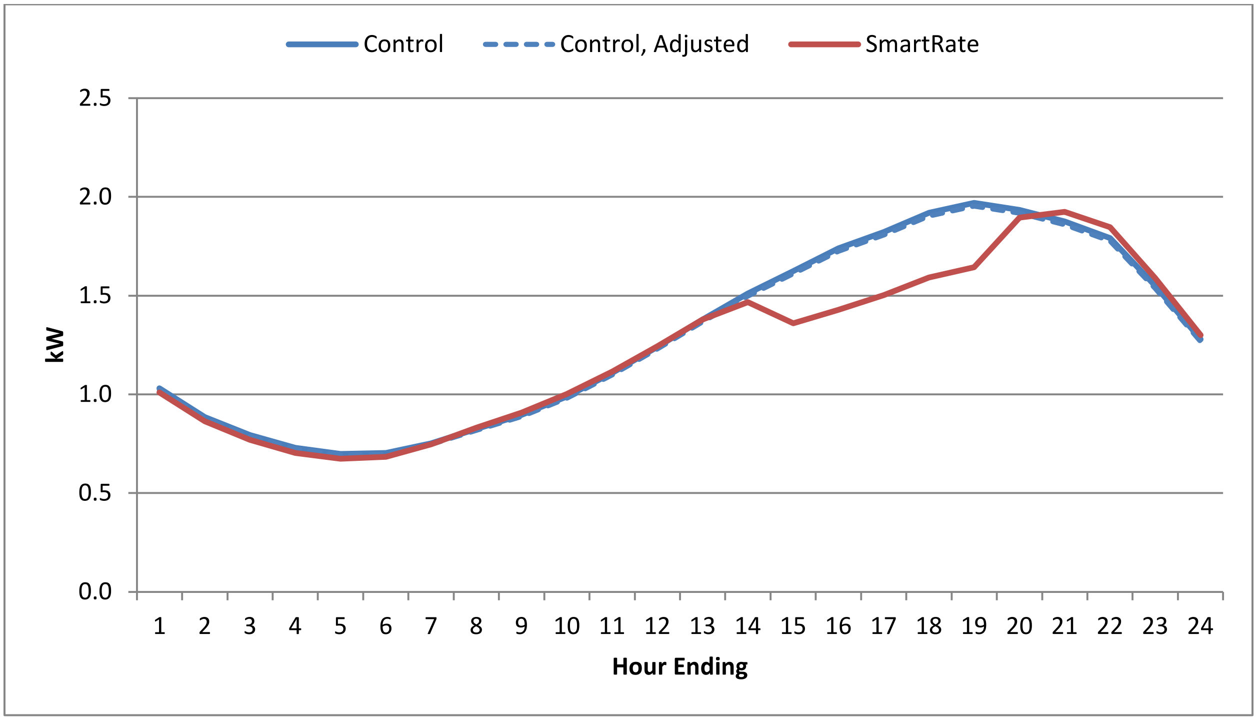


Once the control groups were matched and validated, load impacts were estimated using a difference-in-differences methodology. This methodology calculates the estimated impacts as the difference in average loads between SmartRate and control customers on event days minus the difference between the two 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.

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 1.3%. 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; July 1, 2013, 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 Group Load)

LCA	SMR-Only	Dually Enrolled
Greater Bay Area	0.81%	0.72%
Greater Fresno	1.35%	0.61%
Humboldt	1.11%	0.69%
Kern	0.93%	0.66%
Northern Coast	-0.86%	-0.05%
Other	0.61%	1.01%
Sierra	0.54%	1.07%
Stockton	1.22%	-0.08%

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. 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 20 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 20 out-of-sample days used in this analysis. 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.

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 (%)
14-Jun-13	1.00	1.11	-0.11	-11%
27-Jun-13	1.44	1.40	0.04	3%
8-Jul-13	1.36	1.27	0.09	7%
9-Jul-13	1.51	1.41	0.11	7%
10-Jul-13	1.38	1.43	-0.05	-4%
18-Jul-13	1.25	1.22	0.03	3%
24-Jul-13	1.47	1.43	0.04	3%
25-Jul-13	1.54	1.50	0.04	2%
26-Jul-13	1.40	1.39	0.01	1%
13-Aug-13	1.24	1.26	-0.02	-1%
14-Aug-13	1.29	1.32	-0.03	-2%
15-Aug-13	1.36	1.34	0.01	1%
16-Aug-13	1.43	1.40	0.03	2%
20-Aug-13	1.45	1.45	0.01	0%
27-Aug-13	1.18	1.22	-0.04	-3%
28-Aug-13	1.23	1.26	-0.03	-2%
29-Aug-13	1.25	1.27	-0.02	-1%
30-Aug-13	1.38	1.36	0.03	2%
6-Sep-13	1.14	1.18	-0.04	-4%
19-Sep-13	0.94	1.05	-0.10	-11%
All Days	**1.31**	**1.31**	**0.00**	**0%**

Event day impacts estimated using individual regressions for the SmartRate population that experienced all the events in 2013 were compared to load impacts 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 0.26 kW, 16% of whole-house usage. Using individual customer regressions, the average adjusted impact was 0.19 kW, or 12% 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. The correlation between the absolute impacts from the matched control group and the absolute impacts from the individual customer regressions is 21%.[14]

[14] 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

A correlation of 21% 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.

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 Reduction (kW)	% Load Reduction
7-Jun-13	1.47	0.25	17%	1.35	0.12	9%
28-Jun-13	1.75	0.34	19%	1.64	0.22	13%
1-Jul-13	1.80	0.30	16%	1.69	0.18	10%
2-Jul-13	1.87	0.30	16%	1.80	0.21	12%
19-Jul-13	1.39	0.21	15%	1.32	0.13	10%
19-Aug-13	1.65	0.25	15%	1.63	0.22	13%
9-Sep-13	1.50	0.24	16%	1.45	0.18	13%
10-Sep-13	1.26	0.16	13%	1.32	0.22	16%
Average Event Day	1.59	0.26	16%	1.52	0.19	12%

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 Reference Load (kW)	Average Load Reduction (kW)	% Load Reduction	Average Reference Load (kW)	Average Load Reduction (kW)	% Load Reduction
7-Jun-13	1.92	0.61	32%	1.65	0.34	20%
28-Jun-13	2.46	0.82	33%	2.17	0.52	24%
1-Jul-13	2.55	0.75	29%	2.25	0.44	20%
2-Jul-13	2.63	0.75	29%	2.41	0.53	22%
19-Jul-13	1.77	0.48	27%	1.61	0.31	19%
19-Aug-13	2.22	0.63	28%	2.14	0.54	25%
9-Sep-13	1.99	0.57	29%	1.85	0.42	23%
10-Sep-13	1.51	0.33	22%	1.60	0.42	26%
Average Event Day	2.13	0.62	29%	1.96	0.44	23%

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.

4 SmartRate 2013 Ex Post Load Impacts

This section summarizes the ex post load impact estimates for SmartRate for the 2013 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 a number of factors, including:

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

PG&E's SmartRate program had roughly 119,000 customers enrolled at the end of 2013. The average peak period load reduction delivered by the program over the 8 SmartDays called in 2013 was almost 45 MW. This is a substantial increase in both enrollment and demand response compared with 2012.

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

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

- Whether informing customers during recruitment that they are structural winners and likely to benefit from going on the rate increases the enrollment rate, changes the average load reductions of those who do enroll, or both?
- Whether PG&E's Balanced Payment Plan (BPP) masks the price signal inherent in time-based pricing and, consequently, results in more modest load reductions for customers on BPP.
- The magnitude of program attrition.
- Whether bill protection affects customer load impacts.
- 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 primary impact evaluation relied on the matched control group methodology summarized in Section 3.1.

4.1 Average Event Impacts

Figure 4-1 shows the hourly load impacts for the average SmartRate-only customer across the eight event days in 2013. Fewer events were called in 2013 than were called in prior years because there were fewer hot days that met the trigger requirements for the program. The number of enrolled customers shown in Figure 4-1, roughly 80,000, is the average number of enrolled customers across the 8 event days in 2013.

The average impact for all events across the 5-hour, SmartRate event window was 0.26 kW, or 16%, compared to the 0.20 kW average ex post load impact estimate in the 2012 evaluation. This increase of

30% in average load reductions reflects the success of PG&E's new targeting strategy which focused on marketing to customers that have high peak period loads.

The percentage load reduction was relatively constant across the hours from 3 to 7 PM but lower in the first hour from 2 to 3 PM. Average hourly load impacts vary from a low of 0.21 kW in the first hour to a high of 0.28 kW in the hour between 5 to 6 PM. The reference load increases from a low of 1.38 kW from 2 to 3 PM, when the average temperature is 89°F, to a high of 1.73 kW between 6 to 7 PM. The load is higher between 6 to 7 PM even though the temperature is lower than in mid-afternoon because household loads increase typically when people return home from work. 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 snapback impact 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 eight event days in 2013. The average impact for all events across the 5-hour event window was 0.62 kW, or 29% of the reference load. The absolute reduction is more than twice as large as for SmartRate-only customers. The reference load for dually enrolled customers is about 34% higher than for SmartRate-only customers. Both of these findings reflect the fact that all dually enrolled customers have central air conditioning whereas only a portion of SmartRate only customers have AC. Furthermore, dually enrolled customers have their air conditioners automatically controlled by PG&E, whereas SmartRate only customers with AC must manually control their AC units.

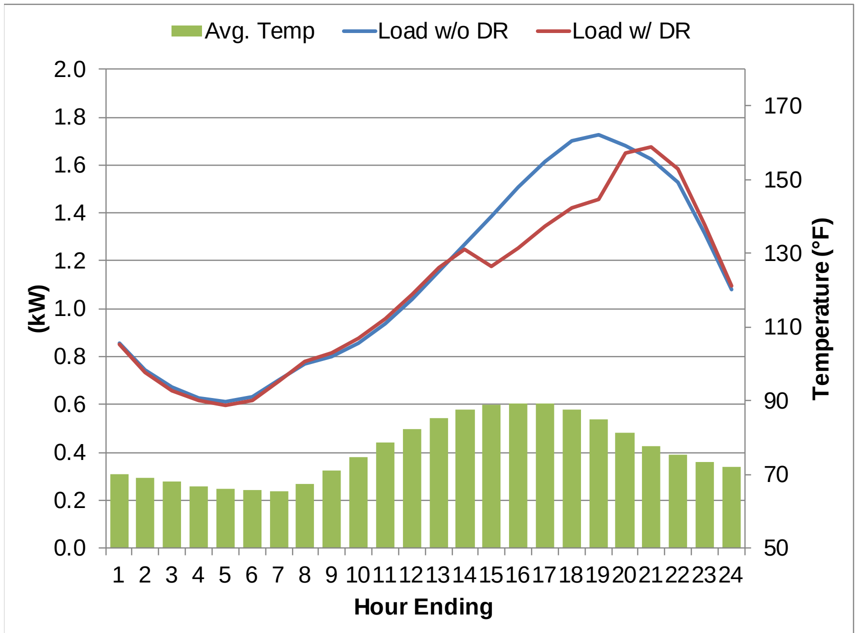
Figure 4-1: Average Load Impact per Hour for All 2013 Event Days (Average SmartRate-only Participant)

TABLE 1: Menu options

Local Capacity Area	All
Date	Average Event Day
Result Type	Average Customer
Group	SmartRate Only
Enrolled Customers	79,842

TABLE 2: Event Day Information

Event Start	2 PM
Event End	7 PM
Average Temp. for Event Window	88
Mean17	76
Load Reduction for Event Window	0.26
% Load Reduction for Event Window	16%



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	0.86	0.85	0.01	1%	70	0.01	0.01	0.01	0.01	0.01
2	0.74	0.73	0.01	1%	69	0.01	0.01	0.01	0.01	0.01
3	0.67	0.66	0.01	2%	68	0.01	0.01	0.01	0.01	0.01
4	0.63	0.61	0.01	2%	67	0.01	0.01	0.01	0.02	0.02
5	0.61	0.60	0.02	3%	66	0.01	0.02	0.02	0.02	0.02
6	0.63	0.62	0.01	2%	66	0.01	0.01	0.01	0.01	0.02
7	0.70	0.70	0.00	0%	66	0.00	0.00	0.00	0.00	0.00
8	0.77	0.78	-0.01	-2%	68	-0.02	-0.01	-0.01	-0.01	-0.01
9	0.80	0.82	-0.02	-2%	71	-0.02	-0.02	-0.02	-0.02	-0.02
10	0.86	0.88	-0.02	-2%	75	-0.02	-0.02	-0.02	-0.02	-0.02
11	0.94	0.96	-0.02	-2%	79	-0.02	-0.02	-0.02	-0.02	-0.02
12	1.04	1.06	-0.02	-2%	82	-0.02	-0.02	-0.02	-0.02	-0.02
13	1.16	1.17	-0.01	-1%	85	-0.02	-0.02	-0.01	-0.01	-0.01
14	1.27	1.25	0.02	2%	87	0.02	0.02	0.02	0.02	0.03
15	1.38	1.18	0.21	15%	89	0.20	0.20	0.21	0.21	0.21
16	1.51	1.25	0.25	17%	89	0.25	0.25	0.25	0.25	0.26
17	1.61	1.34	0.27	17%	89	0.27	0.27	0.27	0.27	0.28
18	1.70	1.42	0.28	16%	88	0.27	0.28	0.28	0.28	0.28
19	1.73	1.45	0.27	16%	85	0.27	0.27	0.27	0.28	0.28
20	1.68	1.65	0.03	2%	81	0.03	0.03	0.03	0.03	0.04
21	1.63	1.67	-0.05	-3%	78	-0.05	-0.05	-0.05	-0.05	-0.04
22	1.53	1.58	-0.05	-3%	75	-0.06	-0.05	-0.05	-0.05	-0.05
23	1.32	1.35	-0.03	-3%	74	-0.04	-0.04	-0.03	-0.03	-0.03
24	1.08	1.09	-0.02	-1%	72	-0.02	-0.02	-0.02	-0.01	-0.01

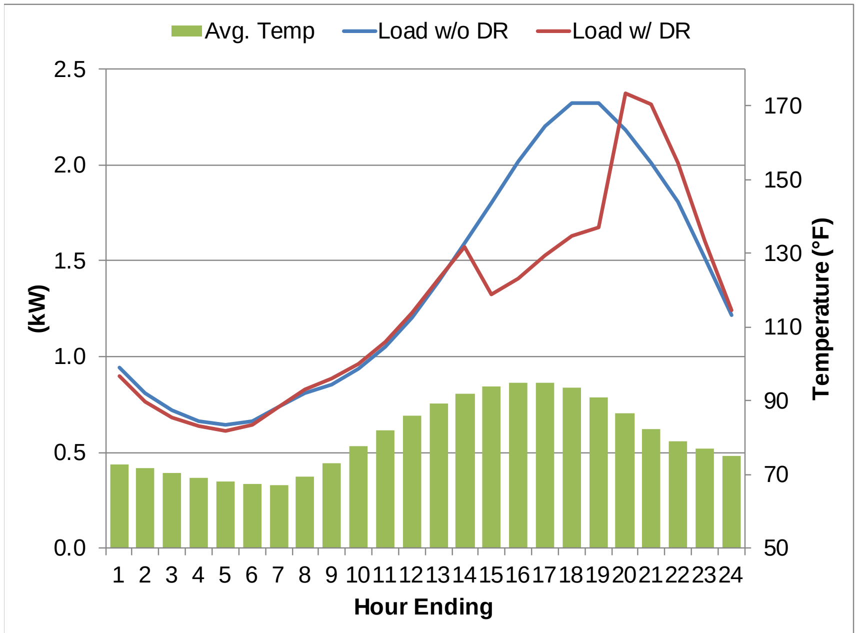
Figure 4-2: Average Load Impact per Hour for All 2013 Event Days (Average Dually Enrolled Participant)

TABLE 1: Menu options

Local Capacity Area	All
Date	Average Event Day
Result Type	Average Customer
Group	Dually Enrolled
Enrolled Customers	38,302

TABLE 2: Event Day Information

Event Start	2 PM
Event End	7 PM
Average Temp. for Event Window	94
Mean17	79
Load Reduction for Event Window	0.62
% Load Reduction for Event Window	29%



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	0.94	0.90	0.05	5%	73	0.04	0.04	0.05	0.05	0.05
2	0.81	0.77	0.04	5%	72	0.04	0.04	0.04	0.04	0.05
3	0.72	0.68	0.04	5%	70	0.03	0.04	0.04	0.04	0.04
4	0.66	0.63	0.03	5%	69	0.03	0.03	0.03	0.03	0.03
5	0.64	0.61	0.03	5%	68	0.03	0.03	0.03	0.03	0.03
6	0.67	0.64	0.02	3%	67	0.02	0.02	0.02	0.02	0.03
7	0.74	0.74	0.00	0%	67	0.00	0.00	0.00	0.00	0.01
8	0.81	0.83	-0.02	-2%	69	-0.02	-0.02	-0.02	-0.02	-0.02
9	0.85	0.89	-0.03	-4%	73	-0.03	-0.03	-0.03	-0.03	-0.03
10	0.93	0.96	-0.03	-3%	78	-0.03	-0.03	-0.03	-0.03	-0.03
11	1.05	1.07	-0.02	-2%	82	-0.03	-0.02	-0.02	-0.02	-0.02
12	1.20	1.23	-0.02	-2%	86	-0.03	-0.02	-0.02	-0.02	-0.02
13	1.39	1.41	-0.02	-1%	89	-0.02	-0.02	-0.02	-0.01	-0.01
14	1.59	1.57	0.02	1%	92	0.01	0.02	0.02	0.02	0.03
15	1.80	1.33	0.47	26%	94	0.47	0.47	0.47	0.48	0.48
16	2.02	1.41	0.61	30%	95	0.61	0.61	0.61	0.61	0.62
17	2.20	1.53	0.68	31%	95	0.67	0.67	0.68	0.68	0.68
18	2.32	1.63	0.69	30%	94	0.69	0.69	0.69	0.69	0.70
19	2.32	1.68	0.65	28%	91	0.64	0.64	0.65	0.65	0.65
20	2.18	2.37	-0.19	-9%	87	-0.20	-0.20	-0.19	-0.19	-0.19
21	2.01	2.32	-0.31	-15%	82	-0.31	-0.31	-0.31	-0.31	-0.30
22	1.81	2.01	-0.20	-11%	79	-0.21	-0.20	-0.20	-0.20	-0.20
23	1.52	1.60	-0.09	-6%	77	-0.09	-0.09	-0.09	-0.09	-0.08
24	1.22	1.24	-0.02	-2%	75	-0.03	-0.02	-0.02	-0.02	-0.02

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 2013. As shown, the average percentage reduction ranged from a low of 13% on September 1, to a high of 19% on July 28. An average reduction of 16% was obtained across the 8 event days. The average load reduction per participant ranged from a low of 0.16 kW to a high of 0.34 kW. Aggregate average reductions in demand on Smart Days ranged from 12.7 MW to 27.1 MW. Aggregate load reductions for the summer averaged 20.5 MW per event.

PG&E's focus on targeting SmartAC customers to also participate in SmartRate has significantly increased average and aggregate load reductions. Aggregate impacts are larger for dually enrolled participants than for SmartRate only customers although there only half as many dually enrolled customers on the program.

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)
7-Jun-13	76,855	1.47	0.25	17%	19.2	90
28-Jun-13	79,625	1.75	0.34	19%	27.1	94
1-Jul-13	79,740	1.80	0.30	16%	23.5	93
2-Jul-13	79,785	1.87	0.30	16%	23.9	93
19-Jul-13	80,495	1.39	0.21	15%	16.7	86
19-Aug-13	80,785	1.65	0.25	15%	20.4	89
9-Sep-13	80,744	1.50	0.24	16%	19.7	89
10-Sep-13	80,710	1.26	0.16	13%	12.7	83
Average Event Day	**79,842**	**1.59**	**0.26**	**16%**	**20.5**	**89**

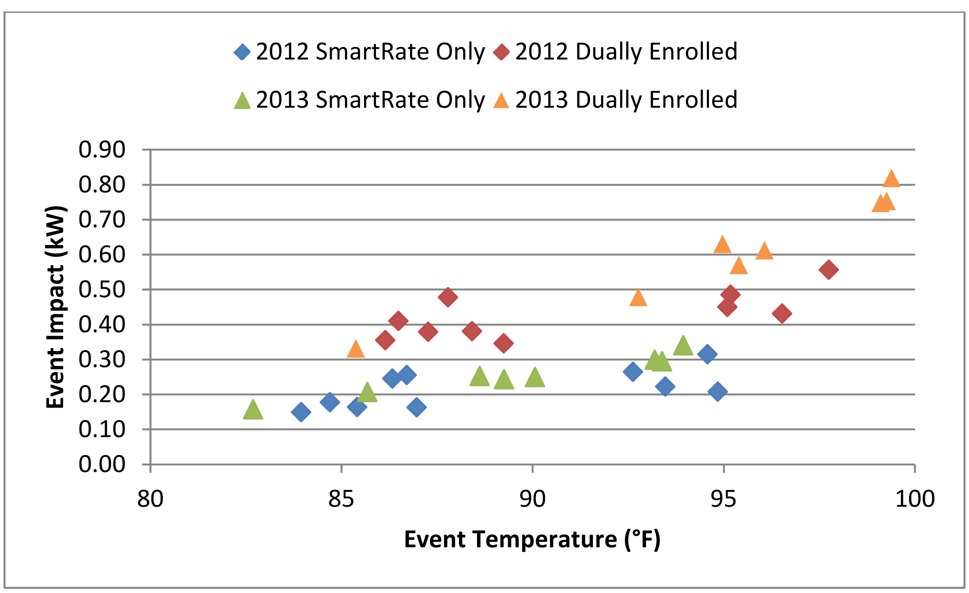
Table 4-2 summarizes the average load reduction across the five-hour event window provided by residential dually enrolled SmartRate customers on each event day during the summer of 2013. For this group, the average percentage reduction ranged from a low of 22% on September 10, to a high of 33% on June 28. An average reduction of 29% was obtained across the 8 event days. The average load reduction per participant ranged from a low of 0.33 kW to a high of 0.82 kW. Aggregate average reductions in demand on Smart Days ranged from 12.8 MW to 31.3 MW. Aggregate load reductions for the summer averaged 23.7 MW per event. The aggregate load reduction for dually enrolled customers is greater than for SmartRate only customers in spite of the fact that SmartRate only customers outnumber dually enrolled customers by roughly 2 to 1.

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)
7-Jun-13	37,909	1.92	0.61	32%	23.2	96
28-Jun-13	38,171	2.46	0.82	33%	31.3	99
1-Jul-13	38,179	2.55	0.75	29%	28.5	99
2-Jul-13	38,192	2.63	0.75	29%	28.8	99
19-Jul-13	38,315	1.77	0.48	27%	18.3	93
19-Aug-13	38,493	2.22	0.63	28%	24.3	95
9-Sep-13	38,576	1.99	0.57	29%	22.0	95
10-Sep-13	38,578	1.51	0.33	22%	12.8	85
Average Event Day	**38,302**	**2.13**	**0.62**	**29%**	**23.7**	**95**

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 2012 and 2013. Two major similarities show up between 2013 and 2012. First, SmartRate-only customers tended to produce smaller average load impacts than dually enrolled customers. Second, dually enrolled customers experienced higher event temperatures in both years.

Figure 4-3: Average Load Impacts for SmartRate-only and Dually Enrolled Participants for 2012 and 2013



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; and
- Central AC saturation and temperature.

The subsection also discusses the results of a marketing test to determine whether structural winners who are provided with bill savings information as part of the marketing offer are more likely to enroll and, once they enroll, whether they respond more or less than customers who are not provided with such information. SmartRate load impacts are also compared between customers that are also enrolled in PG&E's Balanced Payment Program and those that are not. Finally, an analysis that identifies and characterizes high responders is summarized.

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).[15] 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 was seen 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 the eight LCAs in PG&E's service territory for SmartRate-only and dually enrolled customers, respectively. These estimates are based on the same methodology involving statistically matched control groups as was used to develop the program level load impacts. Stockton, Greater Fresno and Sierra provide the highest average load impacts. Although the Bay Area, which has the greatest number of participants by far compared with the other LCAs, has relatively low average load reductions, the average reductions this year are substantially greater than in 2012, once again showing the significant improvements made by PG&E's targeting strategy. The Bay Area has many different micro-climates, from the foggy coastal regions in San Francisco to the hot East Bay areas around Walnut Creek and Concord. It is not uncommon for temperatures to vary by 30 degrees or more across these micro-climates during summer days. By targeting these hotter areas, the significant increase in enrollment in the Bay Area between 2012 and 2013 led to an increase in average load reduction per customer of roughly 80%, from 0.10 kW in 2012 to 0.18 kW in 2013, for SmartRate-only customers and an increase of 75%, from 0.28 kW to 0.49 kW, for dually enrolled customers.

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

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

Local Capacity Area	# of SmartRate Customers	Avg. Reference Load (kW)	Avg. Load Reduction (kW)	% Load Reduction	Aggregate Load Reduction (MW)	Average Temp. During Event (°F)
Greater Bay Area	37,408	1.01	0.18	18%	6.6	81
Greater Fresno Area	5,800	2.69	0.40	15%	2.3	102
Humboldt	933	1.50	0.22	15%	0.2	88
Kern	6,885	2.61	0.32	12%	2.2	101
Northern Coast	3,139	1.06	0.14	14%	0.5	86
Other	15,000	1.71	0.27	16%	4.0	89
Sierra	5,223	2.34	0.56	24%	2.9	96
Stockton	5,455	2.35	0.35	15%	1.9	97
All	**79,842**	**1.59**	**0.26**	**16%**	**20.5**	**88**

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

Local Capacity Area	# of SmartRate Customers	Avg. Reference Load (kW)	Avg. Load Reduction (kW)	% Load Reduction	Aggregate Load Reduction (MW)	Average Temp. During Event (°F)
Greater Bay Area	14,626	1.67	0.49	29%	7.2	88
Greater Fresno Area	3,782	2.86	0.80	28%	3.0	102
Humboldt	195	2.29	0.41	18%	0.1	96
Kern	1,816	2.91	0.82	28%	1.5	100
Northern Coast	2,109	1.38	0.33	24%	0.7	86
Other	7,470	2.29	0.66	29%	4.9	98
Sierra	4,495	2.49	0.82	33%	3.7	96
Stockton	3,809	2.49	0.70	28%	2.6	97
All	**38,302**	**2.13**	**0.62**	**29%**	**23.7**	**94**

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. About 22% of SmartRate customers are CARE customers, while CARE customers constitute about 26% of PG&E's customer population.

Load reductions from SmartRate only CARE customers are significantly less than for SmartRate only non-CARE customers. However, reductions from dually enrolled CARE customers are comparable to those of non-CARE customers.

Table 4-5 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 8 event days in 2013, SmartRate-only CARE customers reduced their peak period load on average by 0.14 kW, or 7%. Non-CARE customers, on the other hand, reduced load on average by 0.28 kW, or 19%.

Table 4-5: Load Reductions for CARE and Non-CARE 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	59,070	1.48	1.20	0.28	19%	86
	CARE	18,297	1.91	1.77	0.14	7%	94
Dually enrolled	Non-CARE	31,382	2.05	1.45	0.60	29%	93
	CARE	7,035	2.50	1.84	0.66	27%	97

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 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 the size of the reduction for non-CARE customers. Across the 8 event days in 2013, dually enrolled CARE customers reduced their peak period load on average by 0.66 kW, or 27%. Non-CARE customers, on the other hand, reduced load on average by 0.60 kW, or 29%. The incremental impact of load control is much greater for CARE customers than for non-CARE customers. This is consistent with a hypothesis that it is more difficult to notify CARE customers about event days due to more limited channels of communication (e.g., less access to the internet, fewer phone options, etc.). If effective notification is less for CARE customers compared with non-CARE customers, load control, which eliminates the need for notification to reduce air conditioning load, will be more impactful for CARE customers than for non-CARE customers.

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 percent of 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 Table 4-6 shows, for the average event, 10% of customers were not successfully notified. Thirty-one percent of customers were successfully notified once per event, 36% were notified twice per event and 23% were notified either three or four times for the average event.

Successful event notification is essential to producing load reductions with event based programs like SmartRate. The magnitude of load reductions is highly correlated with the number of notification options provided by and used to reach a customer.

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

Date	Number of successful notifications				
	None	1	2	3	4
7-Jun-13	9%	29%	37%	16%	8%
28-Jun-13	9%	30%	37%	16%	8%
1-Jul-13	10%	32%	36%	16%	7%
2-Jul-13	11%	33%	35%	15%	6%
19-Jul-13	9%	31%	36%	16%	7%
19-Aug-13	9%	31%	36%	16%	7%
9-Sep-13	9%	31%	36%	16%	7%
10-Sep-13	10%	32%	36%	16%	6%
Average	**10%**	**31%**	**36%**	**16%**	**7%**

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, 7% of customers were not successfully notified. Thirty-three percent of customers were successfully notified once per event, 40% were notified twice per event and 21% were notified either three or four times for the average event.

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

Date	Number of successful notifications				
	None	1	2	3	4
7-Jun-13	6%	30%	41%	16%	7%
28-Jun-13	6%	31%	41%	16%	6%
1-Jul-13	6%	33%	40%	16%	6%
2-Jul-13	8%	35%	38%	14%	5%
19-Jul-13	6%	33%	40%	15%	6%
19-Aug-13	6%	33%	40%	15%	5%
9-Sep-13	7%	33%	40%	15%	5%
10-Sep-13	7%	33%	39%	15%	5%
Average	**7%**	**33%**	**40%**	**15%**	**6%**

Table 4-8 shows the load impacts for successfully notified customers and compares them with the average load impacts for all customers. These load impacts were calculated using matched control groups. As shown in the table, the average load reduction across all 8 events increases from 16% to 18% when comparing impacts for the entire SmartRate-only population to impacts for SmartRate-only customers who were notified. The average load impact rose from 0.26 kW to 0.28 kW and 0.62 to 0.64 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 Customers

Customer Segment	# of Customers	Average Impact (kW)	% Load Reduction
All SmartRate-only	79,842	0.26	16%
Notified SmartRate-only Customers	71,926	0.28	18%
All Dually enrolled Customers	38,302	0.62	29%
Notified Dually enrolled Customers	35,756	0.64	30%

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 nearly 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 0.19 kW. The same values for customers who receive four successful notifications are 31% and 0.51 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 increase, 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 30% and 0.65 kW, and dually enrolled customers successfully notified three times reduced load on average by 35% and 0.78 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	0.07	4%
	One	0.19	12%
	Two	0.27	18%
	Three	0.39	24%
	Four	0.51	31%
Dually enrolled	Zero	0.42	19%
	One	0.54	26%
	Two	0.65	30%
	Three	0.78	35%
	Four	0.82	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 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 (now Nexant) used the 2009 Residential Appliance Saturation Survey (RASS),[16] 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.[17] 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.[18]

The likelihood of owning central air conditioning is positively correlated with load impacts for non-Care, SmartRate only customers. Dually enrolled customers, all of whom have central air conditioning, provide the largest average reduction among the SmartRate participant population.

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. The estimated saturation of AC ownership among CARE customers (71%) is higher than among non-CARE customers (58%) 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 Humboldt and Other LCAs, 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 in the region. 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.

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

17 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.

18 In a recent test of the model based on newly available survey data, the model's results were found to be highly accurate, even in distinguishing the likelihood of AC ownership among a group of customers who all had high likelihoods.

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

CARE Status	Local Capacity Area	Estimated Central AC Saturation	% Dually Enrolled on SmartAC
Non-CARE	Greater Bay Area	41%	30%
	Greater Fresno Area	90%	46%
	Humboldt	50%	21%
	Kern	91%	25%
	North Coast and North Bay	45%	44%
	Other	64%	35%
	Sierra	88%	50%
	Stockton	84%	49%
	Total	**58%**	**35%**
CARE	Greater Bay Area	39%	22%
	Greater Fresno Area	86%	35%
	Humboldt	54%	12%
	Kern	88%	19%
	North Coast and North Bay	38%	28%
	Other	76%	32%
	Sierra	82%	36%
	Stockton	80%	34%
	Total	**71%**	**28%**

Table 4-11 shows the relationship between the likelihood of air conditioning ownership, CARE status, dual-enrollment and demand response. Several trends are noteworthy. First, for non-CARE customers, the absolute load reductions increase substantially with the likelihood of owning central AC although the percent reductions are relatively constant. Absolute impacts are two times higher for high likelihood households than for low likelihood households. For CARE customers, there is not as much of an increase in average load impact across the lowest three categories of AC likelihood, and percent reductions actually decrease significantly as the likelihood of air conditioning ownership increases. However, there is a very significant increase in average load reductions, to 0.60 kW, among dually enrolled customers. This highlights, once again, the value of load control to enable demand response for CARE customers.

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

CARE Status	CAC Likelihood Bin	Impact (kW)	% Impact
Non-CARE	0-25%	0.19	23%
	25-50%	0.17	18%
	50-75%	0.29	19%
	75-100%	0.44	18%
	Dually Enrolled	0.60	29%
CARE	0-25%	0.14	16%
	25-50%	0.14	12%
	50-75%	0.16	10%
	75-100%	0.18	7%
	Dually Enrolled	0.66	27%
All	0-25%	0.18	22%
	25-50%	0.17	16%
	50-75%	0.24	16%
	75-100%	0.36	15%
	Dually Enrolled	0.62	29%

4.2.5 Load Impacts of Structural Winners

Two important issues often arise in the context of policy decisions concerning time-varying rates. One concerns whether structural winners – that is, customers who will see bill reductions when they enroll on a time-varying rate even if they don't change their behavior – will also respond to the new price signals and reduce usage during peak periods when prices are high. The other key issue is whether structural winners will enroll at significantly higher rates than non-winners. This second issue has two important corollary issues. One is that if structural winners enroll at much higher rates than non-winners, there could be significant lost revenue. If, in addition, they are much less responsive to the price signal, the short-term lost revenue will not be offset by the long term benefits of avoided capacity costs that dynamic rates are meant to produce. The second corollary issue is that if consumers who are informed that they are structural winners enroll at a much higher rate than customers who are not informed, and if they produce similar demand reductions as customers who are not informed, then providing personalized bill comparison information to structural winners as part of the marketing offer could significantly increase aggregate demand reductions compared with a marketing campaign that provides more generic information about the potential benefits of the rate. The analysis summarized below provides important empirical evidence concerning these issues for PG&E's SmartRate tariff.

In conjunction with its marketing effort in 2013, PG&E conducted a test in which roughly 64,000 structural winners were sent mailings encouraging them to sign up for the SmartRate program. A randomly selected treatment group of nearly 49,000 customers received marketing materials with a bill comparison, which alerted customers that they were structural winners and would likely save money on

SmartRate. The 15,000 randomly selected control customers were also structural winners, but received marketing materials without a bill comparison (the same mail piece as the one used for the general population campaign).

For the first time, PG&E tested whether informing customers that they are structural winners increased enrollment and/or changed average load reductions. The enrollment rate was higher for informed customers and load reductions were not statistically different from those who were not informed.

Table 4-12 shows the enrollment and 2013 SmartDay load reductions for customers that did and did not receive bill comparison information as part of the marketing solicitation. Bill comparison customers were more likely to sign up for SmartRate, with an enrollment rate of 4.8% relative to 3.9% in the control group. This difference is statistically significant at the 99% confidence level. Customers who were alerted that they can save money on SmartRate (without changing their behavior) provided slightly smaller event impacts (0.28 kW) than those who were not made aware that they were structural winners (0.32 kW), on an absolute and percent basis. However, this difference is not statistically significant. Considering that the enrollment rates are different between the two groups, this slight difference could be the result of differences in the characteristics of enrolled customers rather than differences in the awareness of being a structural winner. In addition, it should be noted that the average ex post demand reduction for all SmartRate customers in 2013 was 0.38, or 21%. While the absolute reduction is larger (because the reference load for the average customer is larger), the percent reduction is nearly identical to that of structural winners, both those who do and don't receive bill comparison information. Based on this evidence, there is little support for the claim by some that structural winners are free riders. From this evidence, it appears that structural winners respond very similarly to the average SmartRate customer and informing customers that they are winners increases enrollment and does not lead to lower average load reductions.

The last column in Table 4-12 estimates the aggregate event load reductions assuming that 100,000 mailings were sent to two groups, one that received bill comparison information and one that did not. Due to the lower enrollment rate for the customers who do not receive bill comparisons, the aggregate load reduction per 100,000 customers is smaller for this group, but not by a large amount. As such, deciding whether or not to provide bill comparison information as part of the marketing offer will depend on the incremental cost of doing so.

Table 4-12: Enrollment and 2013 SmartDay Load Reductions of Treatment and Control Customers

Group	Number of Customers	Enrolled In SmartRate	Avg. Per Customer Impact (kW)	% Impact	Aggregate Impact (MW)	MW per 100,000 Mailings
Control – Did Not Receive Bill Comparison	15,158	3.9%	0.32	22.9%	0.19	1.26
Treatment – Received Bill Comparison	48,852	4.8%	0.28	21.4%	0.66	1.34

Table 4-13 details enrollment rates by bill savings for customers that did and did not receive bill comparison information. Among customers with likely savings of $20 to $70, enrollment rates are generally higher for customers that received bill comparison information. However, for a couple of bill savings categories, one at the lowest end of the spectrum and one near the high end of the spectrum, the opposite is true.

Table 4-13: Control and Treatment Group Enrollment Rates by Bill Savings

Savings	# of Customers		% of Customers	
	Control – Did Not Receive Bill Comparison	Treatment – Received Bill Comparison	Control – Did Not Receive Bill Comparison	Treatment – Received Bill Comparison
$10 - $20	2,251	7,425	3.5%	3.3%
$20 - $30	2,790	8,843	4.4%	4.9%
$30 - $40	2,802	9,204	4.1%	5.7%
$40 - $50	2,201	7,006	3.7%	5.8%
$50 - $60	1,487	5,088	4.5%	5.1%
$60 - $70	1,047	3,296	3.5%	4.6%
$70 - $80	686	2,237	4.2%	4.8%
$80 - $90	464	1,591	3.7%	3.9%
$90 - $100	391	1,039	5.9%	5.0%
$100 - $110	1,039	3,123	2.0%	4.0%

Finally, Table 4-14 shows the distribution of treatment and control customers across PG&E's 10 climate zones. The customers are distributed similarly across both groups, which shows that the treatment and control selection was valid. Considering that this test focused on structural winners, customers in relatively cool climate zones, such as T, were more likely to be included in this test campaign. Therefore, this table is not indicative of the distribution of mailings for the 2013 general population campaign, which focused more on the hotter climate zones in which structural winners make up a small percentage of the population.

Table 4-14: Distribution of Treatment and Control Customers by Climate Zone

Climate Zone	Control – Did Not Receive Bill Comparison	Treatment – Received Bill Comparison
P	3.1%	3.3%
Q	0.1%	0.2%
R	11.1%	11.1%
S	4.0%	4.2%
T	47.6%	48.1%
V	0.5%	0.4%
W	8.9%	9.3%
X	23.9%	22.8%
Y	0.7%	0.7%
Z	0.0%	0.0%

4.2.6 Load Impacts for Balanced Payment Plan Customers

Customers enrolled in PG&E's Balanced Payment Plan (BPP) receive bills averaged over the prior 12 months. The BPP provides the convenience of paying the same amount each month and also helps customers avoid unexpected bill increases that can occur between spring and summer bills as a result of the increasing block tariffs employed by California's utilities or that can occur for SmartRate customers in months when numerous Smart Days are called. While BPP is convenient for consumers, some stakeholders have expressed concerns that BPP masks the price signals associated with time-varying rates and is likely to lead to lower reductions for consumers who are on such plans compared with those who are not. This memo summarizes an analysis of the average load reductions for SmartRate customers that are and are not on PG&E's BPP.

Fears that PG&E's Balanced Payment Plan may mask price signals for SmartRate customers are unfounded. SmartRate customers on the BPP actually provided larger absolute load reductions per customer, and the same percent reductions, as those who are not on the plan.

Table 4-15 shows the distribution of non-BPP and BPP SmartRate customers across the eight local capacity areas (LCAs) in PG&E's territory. BPP customers are slightly more concentrated in hotter areas than non-BPP customers.

Table 4-15: Distribution of Non-BPP and BPP SmartRate Customers Across LCAs

LCA	Non-BPP	BPP
Greater Bay Area	45%	37%
Greater Fresno Area	8%	10%
Humboldt	1%	1%
Kern	7%	9%
Northern Coast	4%	5%
Other	19%	20%
Sierra	8%	9%
Stockton	8%	8%

Table 4-16 shows the percent of non-BPP and BPP customers that are enrolled in both SmartRate and SmartAC. BPP customers are more likely to be dually enrolled than non-BPP customers. This may be tied to the fact that BPP customers are more concentrated in warm areas and are therefore more likely to have central air conditioning.

Table 4-16: Percent of Non-BPP and BPP SmartRate Customers Enrolled in SmartAC

Group	Total Customers	SmartRate Only	Dually Enrolled
Non-BPP	108,192	69%	31%
BPP	12,247	60%	40%

Table 4-17 shows the reference loads and per-customer impacts for the average SmartRate event for non-BPP and BPP customers. As seen, BPP customers provide larger absolute impacts and essentially the same percentage impacts as non-BPP customers. The difference in the absolute impacts is statically significant at the 95% confidence level. The larger absolute impacts result from the fact that BPP customers have higher reference loads compared with non-BPP customers. Importantly, the fact that the percentage impacts are the same between the two groups indicates clearly that BPP does not mask the time-varying price signal associated with SmartRate.

Table 4-17: Per-Customer SmartRate Event Load Reductions

Group	Reference Load (kW)	Impact (kW)	Percent Impact
Non-BPP	1.73	0.36	21%
BPP	2.13	0.48	22%

4.2.7 Characteristics of High Responders

Determining the characteristics of customers that provide above average load reductions is important for improving the cost effectiveness of demand response programs through better targeting. This subsection identifies SmartRate customers who appear to be high responders (i.e., customers who provide large impacts) and examines their characteristics.

High responders are more likely to:

- *Be dually enrolled on SmartRate and SmartAC*
- *Be from hot climate regions*
- *Have high average electricity use*
- *Be non-CARE customers*
- *Have central air conditioning*
- *Have recently enrolled in the program (due to better targeting, not lack of persistence over time).*

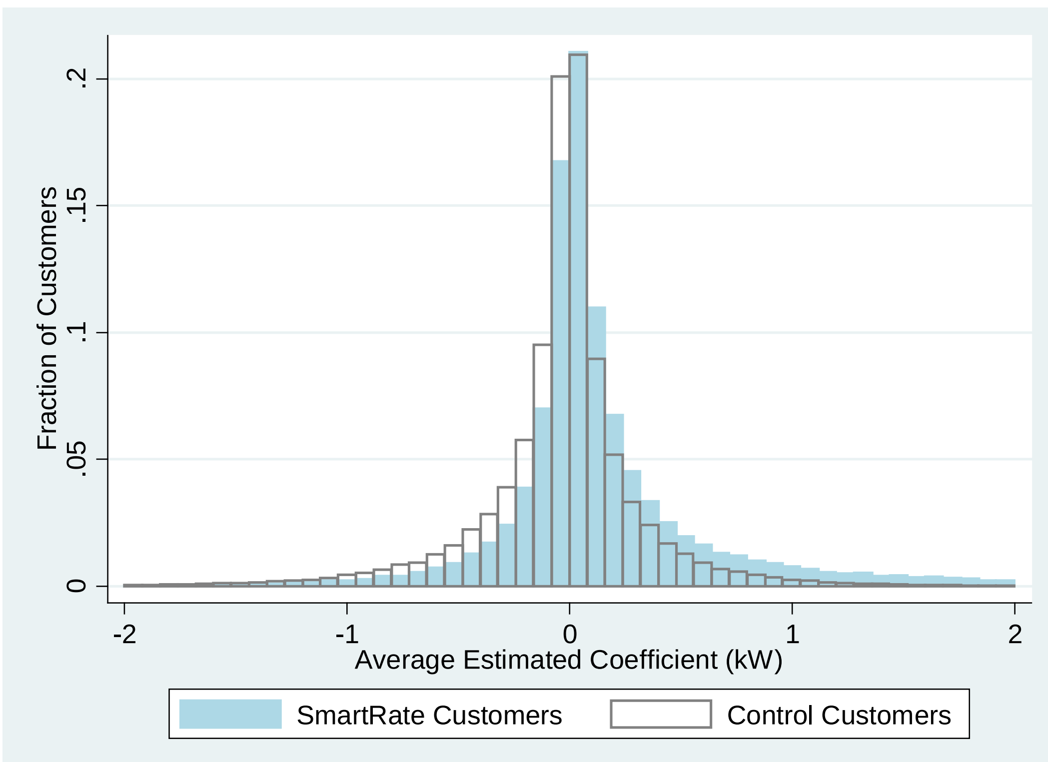
This analysis necessarily involves using impact estimates based on individual customer regressions. However, when examined at the individual customer level, these impact estimates include error or noise. This is an unavoidable aspect of regression methodology. If this was not the case, then it would 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 and statistics literatures 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 from individual customer regressions, these regressions were also run on the matched control group. These customers have very similar usage profiles to the SmartRate customer population but did not experience any events so their estimated impacts should be 0. 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. However, 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 customers in this group are similar to SmartRate customers across all observable characteristics, that the level of noise in this group is similar to the level of noise in the SmartRate group.

The blue columns in Figure 4-4 show the distribution of estimated impacts for the SmartRate population. The median impact estimate for SmartRate customers is about 0.04 kW and the mean (or average) impact for SmartRate customers is 0.18 kW. The transparent columns outlined in black show the distribution of impacts for control customers. The median 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.

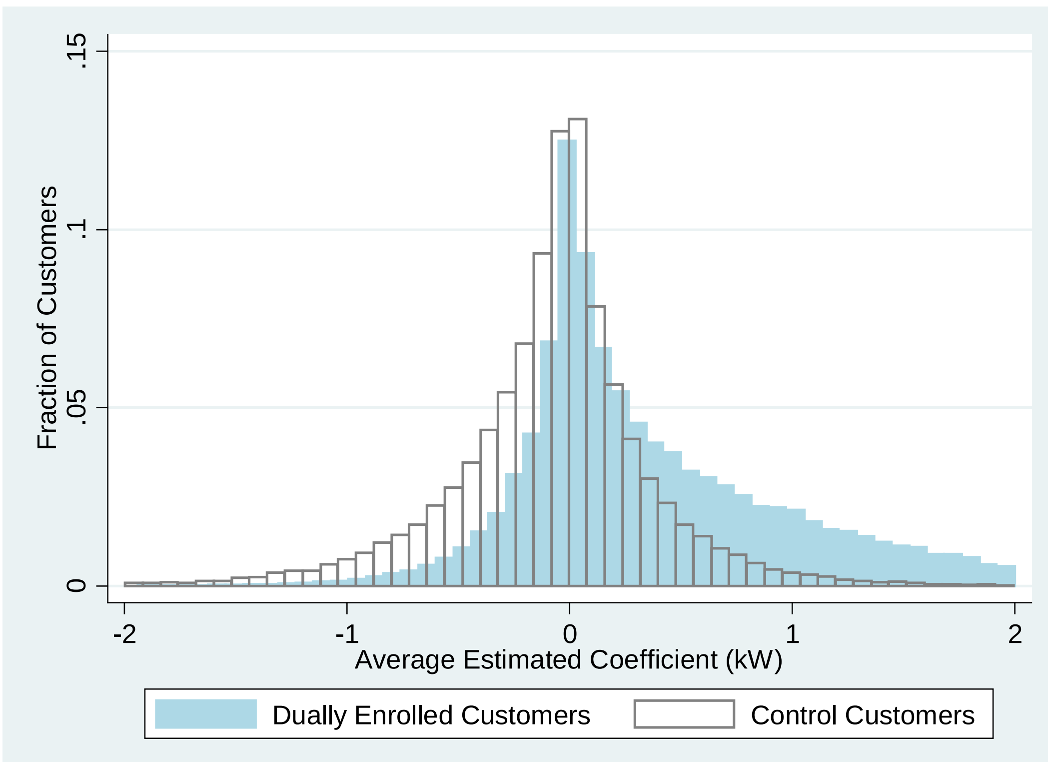
Figure 4-4: Distribution of Average Event Impacts for SmartRate-only Customers



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 the 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 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 hot, non-event days, but was on vacation for several 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 4-5 shows the same two histograms for dually enrolled customers, and the same basic points apply. 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 4-7: Distribution of Average Event Impacts for Dually Enrolled 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 which ones 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 0.69 kW, there is a 95% chance or greater that each customer's true impact is larger than 0.18 kW, which is the overall mean. That is, customers with impact estimates greater than or equal to 0.69 kW have at least a 95% probability of having impacts greater than the mean. Using the same logic, for dually enrolled SmartRate customers with estimated impact values above 1.07 kW, there is a 95% chance or greater that each customer's true impact is larger than 0.44 kW, which is the overall mean.

There are about 9,100 SmartRate only and 6,400 dually enrolled customers for which this is true.[19] This group is labeled high responders. Combined, high responders account for roughly 13% of the SmartRate population. They account for roughly 11% of the SmartRate-only population and 17% of the dually enrolled population. 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. Tables 4-18 through 4-28 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 4-18 and 4-19 show the distribution of high responders for SmartRate-only and dually enrolled customers across PG&E's territory compared to the SmartRate population. High responders in both groups are more likely to be located in hotter LCAs such as Fresno, Kern, Other and Sierra. Although almost half of SmartRate-only customers live in the Greater Bay Area, only 16% 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 4-18: Distribution of SmartRate-only High Responders by LCA

LCA	High Responders	SmartRate Population	Percentage Point Difference
Greater Bay Area	15.9%	47.1%	-31.2
Greater Fresno Area	16.8%	7.2%	9.6
Humboldt	1.2%	1.2%	0.0
Kern	14.0%	8.8%	5.2
North Coast and North	1.5%	3.8%	-2.3
Other	24.0%	18.5%	5.5
Sierra	15.9%	6.5%	9.4
Stockton	10.6%	6.9%	3.8
Total	100.0%	100.0%	-

19 For details of this calculation see Appendix C.

Table 4-19: Distribution of Dually Enrolled High Responders by LCA

LCA	High Responders	SmartRate Population	Percentage Point Difference
Greater Bay Area	12.3%	38.2%	-25.9
Greater Fresno Area	20.4%	9.9%	10.6
Humboldt	0.7%	0.5%	0.1
Kern	9.7%	4.8%	4.9
North Coast and North	1.0%	5.5%	-4.4
Other	25.2%	19.4%	5.8
Sierra	19.4%	11.7%	7.7
Stockton	11.3%	10.0%	1.4
Total	100.0%	100.0%	-

Additionally, high responders are more likely to be non-CARE customers, as shown in Tables 4-20 and 4-21. 76% of SmartRate-only customers are not on the CARE rate but 82% of high responders fall into that category. For dually enrolled customers, the difference is very similar.

Table 4-20: Distribution of SmartRate-only High Responders by CARE Status

CARE Status	High Responders	SmartRate Population	Percentage Point Difference
Non-CARE	82.3%	76.4%	5.9
CARE	17.7%	23.6%	-5.9
Total	100.0%	100.0%	-

Table 4-21: Distribution of Dually Enrolled High Responders by CARE Status

CARE Status	High Responders	SmartRate Population	Percentage Point Difference
Non-CARE	75.6%	81.7%	-6.1
CARE	24.4%	18.3%	6.1
Total	100.0%	100.0%	-

Bill protection does not appear to play a role in the size of impacts, as shown in Table 4-22 and 4-23. This is especially true for dually enrolled customers. Indeed, there is a higher percent of bill protected customers in the high responder group than in the general SmartRate population. It should be noted, however, that this finding may be the result of the recent targeting of high use, high responder customers rather than anything to do with bill protection itself.

Table 4-22: Distribution of SmartRate-only High Responders by Bill Protection Status

Bill Protected	High Responders	SmartRate Population	Percentage Point Difference
No	52.1%	59.1%	-7.0
Yes	47.9%	40.9%	7.0
Total	100.0%	100.0%	-

Table 4-23: Distribution of Dually Enrolled High Responders by Bill Protection Status

Bill Protected	High Responders	SmartRate Population	Percentage Point Difference
No	59.4%	63.7%	-4.4
Yes	40.6%	36.3%	4.4
Total	100.0%	100.0%	-

Monthly usage, however, is highly correlated with higher-than-average impacts, as shown in Tables 4-24 and 4-25. The higher the decile of average monthly usage a customer is in, the more likely he or she is to be a high responder, for both SmartRate-only and dually enrolled customers. This is not a surprising result. Only 9% of SmartRate-only high responders are found in the bottom five deciles of usage. On the other hand, nearly 30% of SmartRate-only high responders come from the 10th decile alone. The situation is similar for dually enrolled customers. Only 12% of dually enrolled high responders fall into the bottom five deciles of usage, while 28% of this group are in the 10th decile.

Table 4-24: Distribution of SmartRate-only High Responders by Monthly Usage Decile

Monthly Usage Decile	High Responders	SmartRate Population	Percentage Point Difference
1	0.2%	10.0%	-9.8
2	0.6%	10.0%	-9.4
3	1.2%	10.0%	-8.8
4	2.3%	10.0%	-7.7
5	4.4%	10.0%	-5.6
6	7.2%	10.0%	-2.8
7	12.2%	10.0%	2.2
8	18.0%	10.0%	8.0
9	24.0%	10.0%	14.0
10	29.7%	10.0%	19.7
Total	100.0%	100.0%	–

Table 4-25: Distribution of Dually Enrolled High Responders by Monthly Usage Decile

Monthly Usage Decile	High Responders	SmartRate Population	Percentage Point Difference
1	0.3%	10.0%	-9.8
2	0.9%	10.0%	-9.2
3	1.6%	10.0%	-8.4
4	3.0%	10.0%	-7.1
5	5.9%	10.0%	-4.1
6	7.8%	10.0%	-2.2
7	12.0%	10.0%	2.0
8	17.2%	10.0%	7.2
9	23.0%	10.0%	13.0
10	28.4%	10.0%	18.4
Total	100.0%	100.0%	–

There is also the question of whether customers provide lower impacts the longer they are on SmartRate. Tables 4-26 and 4-27 show high responders broken down by the number of summers each customer has been enrolled. Newer customers tend to have higher impacts. SmartRate marketing targeted different geographical areas at different times, which means that the values in Table 4-26 and 4-27 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. Very importantly, for the reasons just explained, the fall in average usage by length of tenure in the program should not be interpreted as lack of persistence in rate impacts. Persistence would have to be analyzed by looking at impacts for the same cohort of customers over time, not by examining the average for different cohorts as this analysis does.

Table 4-26: Distribution of SmartRate-only High Responders by Number of Summers on SmartRate

Number of Summers on SmartRate	High Responders	SmartRate Population	Percentage Point Difference
0	47.03%	39.58%	7.5
1	34.09%	42.33%	-8.2
2	1.40%	1.00%	0.4
3	1.55%	1.70%	-0.2
4	10.41%	10.85%	-0.4
5	5.52%	4.55%	1.0
Total	100.00%	100.00%	-

Table 4-27: Distribution of Dually Enrolled High Responders by Number of Summers on SmartRate

Number of Summers on SmartRate	High Responders	SmartRate Population	Percentage Point Difference
0	40.3%	35.9%	4.4
1	47.5%	55.3%	-7.8
2	0.2%	0.2%	0.0
3	0.5%	0.4%	0.1
4	8.1%	6.2%	1.9
5	3.4%	1.9%	1.4
Total	100.0%	100.0%	-

Finally, Table 4-28 shows high responders by their likelihood of having central AC. There are very few high responders with CAC likelihood under 75%. In contrast, 39% 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 4-28: Distribution of High Responders by CAC Likelihood[20]

CAC Likelihood	High Responders	SmartRate Population	Percentage Point Difference
0%-25%	2.2%	23.4%	-21.2
25%-50%	2.1%	8.5%	-6.5
50%-75%	4.5%	6.8%	-2.2
75%-100%	49.4%	28.9%	20.5
Dually enrolled	41.8%	32.4%	9.5
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;
- Be dually enrolled in SmartRate and SmartAC; and
- Customers with central AC likelihoods of 75% or more.

It should be noted, of course, that most of these variables are correlated. For example, higher usage is correlated with air conditioning likelihood which is correlated with LCA.

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 96% of SmartRate customers, the OAT is E-1.[21] Although about 61% of SmartRate customers are bill protected, they are still included in this analysis because bill protection was not found to be related to the magnitude of impacts (see Section 4-4). 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.

[20] 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.

[21] 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.

Table 4-29 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 $73 (14%) compared to bills under the OAT;
- Savings were highest in October because customers experienced no events; and
- Overall savings were slightly higher than in 2012 ($73 compared to $67 in 2012), which is at least partially due to their only being 8 events in 2013 as opposed to 10 in 2012.

Table 4-29: SmartRate Customer Savings by Month

Month	Average SMR Bill	Savings	% Savings	% Winners
June–October	$502	$73	14%	99%
June	$105	$14	13%	98%
July	$136	$13	9%	92%
August	$105	$18	17%	100%
September	$89	$12	13%	97%
October	$67	$16	24%	100%

Table 4-30 shows bill savings estimates by local capacity area (LCA). Average savings are highest for customers in the Kern LCA. They saved an average of $102 from May through October 2013. Greater Bay Area, Greater Fresno, Northern Coast and Other LCAs have similar percent savings although they have lower actual savings.

Table 4-30: SmartRate Customer Percent Winners and Savings by LCA

LCA	# of Customers	Total Summer SMR Bill	Savings	% Savings	% Winners
Greater Bay Area	51,776	$481	$61	13%	82%
Greater Fresno Area	9,482	$748	$100	13%	82%
Humboldt	1,115	$596	$83	14%	80%
Kern	8,778	$716	$102	14%	82%
Northern Coast	5,089	$511	$65	13%	81%
Other	22,043	$587	$75	13%	80%
Sierra	9,642	$697	$84	12%	81%
Stockton	9,227	$584	$70	12%	78%

Table 4-31 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. Both groups save $73 on average. However, on a percentage basis, this comes out to 11% bill savings for non-CARE customers and a 22% savings for CARE customers.

Table 4-31: SmartRate Customer Percent Winners and Savings by CARE Status

CARE Status	# of Customers	Total Summer SMR Bill	Savings	% Savings	% Winners
Non-CARE	90,452	$634	$73	11%	99%
CARE	25,332	$335	$73	22%	99%

4.4 2013 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 a customer enrolls 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 2013, 61% of SmartRate customers were covered under bill protection. This is a reduction compared with 2012 when 75% of customers had bill protection.

Table 4-32: SmartRate Customers with Bill Protection

Bill Protected	# of customers	% of customers
No	45,689	39%
Yes	71,462	61%
Total	117,151	100%

Of the approximately 70,000 customers covered under bill protection in 2013, only 164 (0.2%) received refunds after the summer of 2013.

Table 4-33: SmartRate Customers with Refunds (Bill Protected Customers Only)

Refund	# of Customers	% of Customers
No refund	71,298	99.8%
Refund	164	0.2%
Total	71,462	100%

4.6 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. 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.

Very few SmartRate customers drop out of the program. Only about 1.5% of enrolled customers left the program between late 2012 and October 2013.

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?

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.

4.6.1 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 2012 to October 2013, 1,665 customers de-enrolled from SmartRate. Table 4-34 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 June and July. This is not surprising, considering this is when five of the eight 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 events and dropouts. Only about 1.5% of enrolled customers dropped out between late 2012 and October 2013.

Table 4-34: Customer De-enrollments by Month

Month	# of Drop Outs	% of Customers that Dropped Out
Nov. 2012	42	0.06%
Dec. 2012	33	0.05%
Jan. 2013	17	0.02%
Feb. 2013	8	0.01%
Mar. 2013	7	0.01%
Apr. 2013	57	0.07%
May. 2013	327	0.30%
Jun. 2013	322	0.28%
Jul. 2013	636	0.55%
Aug. 2013	87	0.07%
Sep. 2013	95	0.08%
Oct.2013	34	0.03%
Total	1,665	1.44%

Dropouts can also be analyzed by looking at customer demographics. Table 4-35 shows the number and percentage of customers who dropped out from November 2012 through October 2013 by LCA. The table also includes the percent of customers 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, the Greater Bay Area had a lower number of dropouts than would be expected. 35% of customers who dropped out came from the Greater Bay Area whereas 44% 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—1,665 de-enrolled customers—is small enough that no strong conclusions should be drawn from small differences in rates across LCAs.

Table 4-35: Customer De-enrollments by LCA

LCA	# of De-enrolled Customers	% of De-enrolled Customers	% of SmartRate Customers
Greater Bay Area	576	35%	44%
Greater Fresno	174	10%	8%
Humboldt	21	1%	1%
Kern	111	7%	7%
Northern Coast	79	5%	4%
Other	362	22%	19%
Sierra	192	12%	8%
Stockton	150	9%	8%
All	**1665**	**100%**	**100%**

Customer de-enrollments can also be broken down by CARE status. Table 4-36 shows that non-CARE customers de-enroll at a higher rate than CARE customers. Although 78% of the SmartRate population is non-CARE, 85% of de-enrollments in 2013 were non-CARE customers.

Table 4-36: Customer De-enrollments by CARE Status

CARE Status	# of De-enrolled Customers	% of De-enrolled Customers	% of SmartRate Customers
Non-CARE	1419	85%	78%
CARE	245	15%	22%
All	1665	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 4-37 shows the average OAT and SmartRate monthly bills for active SmartRate customers and those who de-enrolled starting in June 2013.[22] Both groups showed savings over the summer months. Customers who were still active on SmartRate showed slightly higher savings than customers who de-enrolled.

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

Table 4-37: Bill Impacts by Customer De-enrollment Status

	Mean Monthly OAT Bill	Mean Monthly SmartRate Bill	Difference	% Difference
Customers who are still enrolled	$153.86	$132.88	$20.98	14%
Customers who de-enrolled	$106.88	$94.75	$12.13	11%

Finally, customer dropout rates in relation to the length of time customers have been enrolled in the program were examined. Currently enrolled customers have been on SmartRate longer, on average, than customers who dropped out in 2013. Currently enrolled customers have been on SmartRate on average for 17 months. Customers who de-enrolled after June this year had been with the program on average for 11 months. 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 among customers who signed up in the beginning of May but this seems to be due to a large number of enrollments during that time as well. This means that customers who dropped out in 2013 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).

5 SmartRate Ex Ante Methodology and Results

This section explains the steps used to predict ex ante load impacts for the SmartRate tariff. There are a few issues that must be addressed when developing ex ante load impact estimates. First, the weather observed during events in 2013 is different from the ex ante weather conditions. Second, the population that experienced each event was not constant over the estimating sample since the analysis relies on ex post estimates for two years during which the population changed significantly. The ex ante estimates must reflect the current population mix (or future mix which, in this case, is nearly identical to the current population). Finally, even after combining observations from 2012 and 2013, there are only 15[23] 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 at the end of 2013 and who experienced all the 2012 and 2013 SmartRate events. Propensity score matching was used to find these groups;
- Next, ex post estimates were developed for these customers for 2012 and 2013 using matched control groups of non-SmartRate customers for each year;
- Then an ex ante regression model was developed to explain average ex post impacts from 2 to 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 to 7 PM was used as the dependent variable. Last year, this model was estimated at the level of each LCA separately. This year, the data from all LCAs was pooled. Pooling increases the range of temperatures included in the estimating sample, thus reducing the need to extrapolate outside of the historical conditions to estimate impacts for 1-in-10 year weather conditions, which represent temperatures within many LCAs that are not often experienced during the ex post period. 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 from 2 to 7 PM were then converted to hourly impacts from 2 to 7 PM using a scaling factor based on the average ratio between impacts at different hours. 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 2013. These reference loads are needed to comply with the load impact protocols but are not necessary for ex ante load impact estimation, as impacts are estimated directly from ex post impact values. Reference load shapes were estimated by taking the average load for each hour of the day, by LCA;

[23] There were actually 18 events across the 2 years, 10 in 2012 and 8 in 2013. However, as explained more fully later, there was a tradeoff between including all event days and maintaining the size of the estimating sample of customers that are present across all events and consistent with the current population. As such, the first three events from 2012 were excluded from the ex ante estimating sample.

- Ex ante impact estimates were then adjusted to apply to the resource adequacy window of 1 to 6 PM rather than the SmartRate event window from 2013 of 2 to 7 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.

5.1 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 2012 and 2013. The decision to use 2012 and 2013, but not earlier years, was made in order to produce a reasonable number of events for modeling without reducing the number of customers included in the ex post estimation to a point where the sample is too small. There were not enough customers who experienced all of the events in 2012 and 2013, so the first three events in 2012 were excluded. The SmartRate population had grown sufficiently after these first few events to have a large enough sample of customers. In total, 15 ex post events were included in the regression analysis.

The ex ante weather conditions are the same as those used for the 2012 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, a sample of customers that experienced nearly all the 2012 and all the 2013 events was developed that had similar observable characteristics to the SmartRate population as of October 2013. October 2013 is the most up-to-date snapshot available of the SmartRate population and the ex ante load impact estimates are designed to be representative of that population since enrollment is not expected to change much over the forecast horizon. These groups of customers were identified using the same procedure used to identify matched control groups for the 2012 and 2013 evaluations, except that customers were matched based on event-day loads rather than hot-non-event day loads since the match was being done among the SmartRate population, all of whom experienced events. This process is conceptually similar to simply reweighting the segment of SmartRate participants that have been in the program for two years to look like the population that was present at the end of 2013. Details of this match and evidence of its validity are discussed in Appendix D. These customers were used to develop a set of ex post estimates for 2012 and 2013 that represent what the October 2013 SmartRate population would have provided if they had been in the program the whole time. These ex post estimates are also shown in Appendix D. With these estimates in hand, the remaining steps for ex ante estimation were quite similar to what was done in 2012.

In 2012, to determine the best regression to use for ex ante predictions, dozens of models were tested that predict ex post impacts based on a wide variety of variables representing weather conditions on the leading up to and during SmartRate events. 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. 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 analysis this year used the same model specification that was used in 2012. However, this year, the estimating sample pooled the ex post estimates across LCAs rather than estimating separate models for each LCA. The final model specification, which was used for both the SmartRate only and dually enrolled populations, takes as its dependent variable the ex post impact for each event, averaged over the entire event period. For SmartRate-only customers, the independent variables are the average temperature from midnight to 5 PM on the event day, and dummy variables for customers in the Other and Sierra LCAs. These dummy variables were used to account for outliers in the impact and mean17 dataset. These variables were not needed for the dually enrolled customers. The final specification was:

$$Impact = a + b \cdot mean17 \ + c \cdot other + d \cdot sierra \ + \boldsymbol{\varepsilon}$$

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
a	Estimated constant
b	Estimated parameter coefficient
mean17	Average temperature period midnight to 5 PM
other	Equals 1 for customers in Other LCA (only used for SmartRate-only regression)
sierra	Equals 1 for customers in Sierra LCA (only used for SmartRate-only regression)
ε	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. The red circles show 2013 ex post values for the representative population and the gray circles show the same for 2012. The trend lines show the average impacts that were used as a basis for ex ante forecasts. Neither the 2012 nor 2013 impacts are consistently higher than the other, again suggesting that the program performance has been stable. For dually enrolled customers the situation is similar.

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

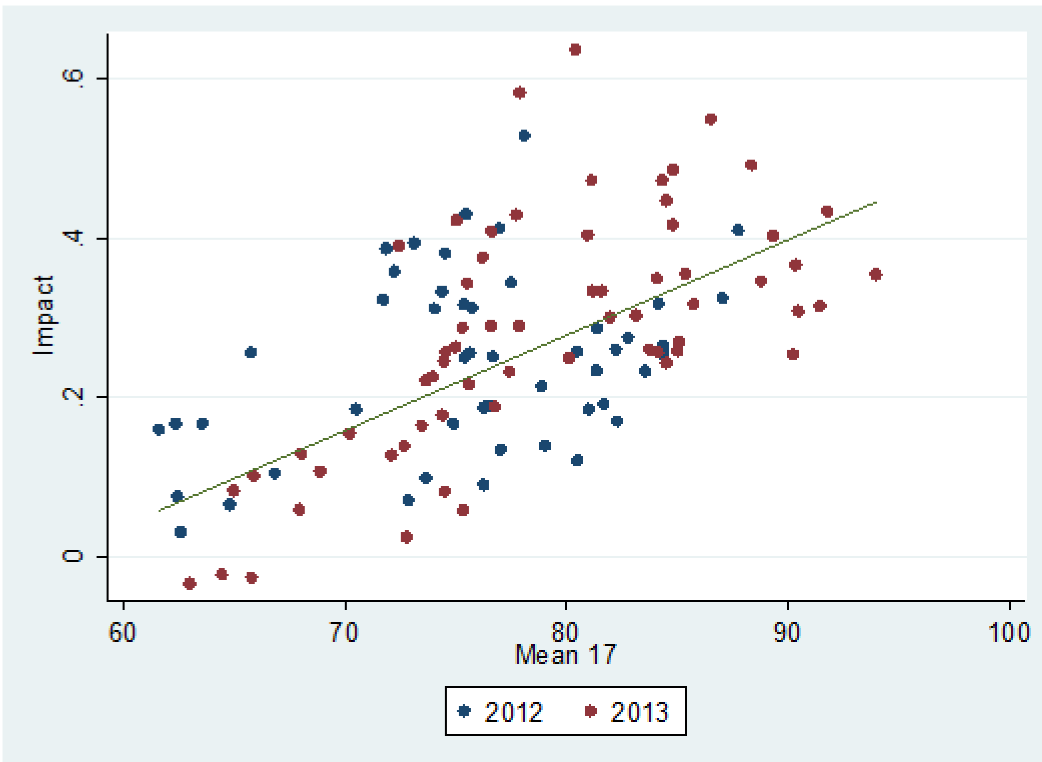
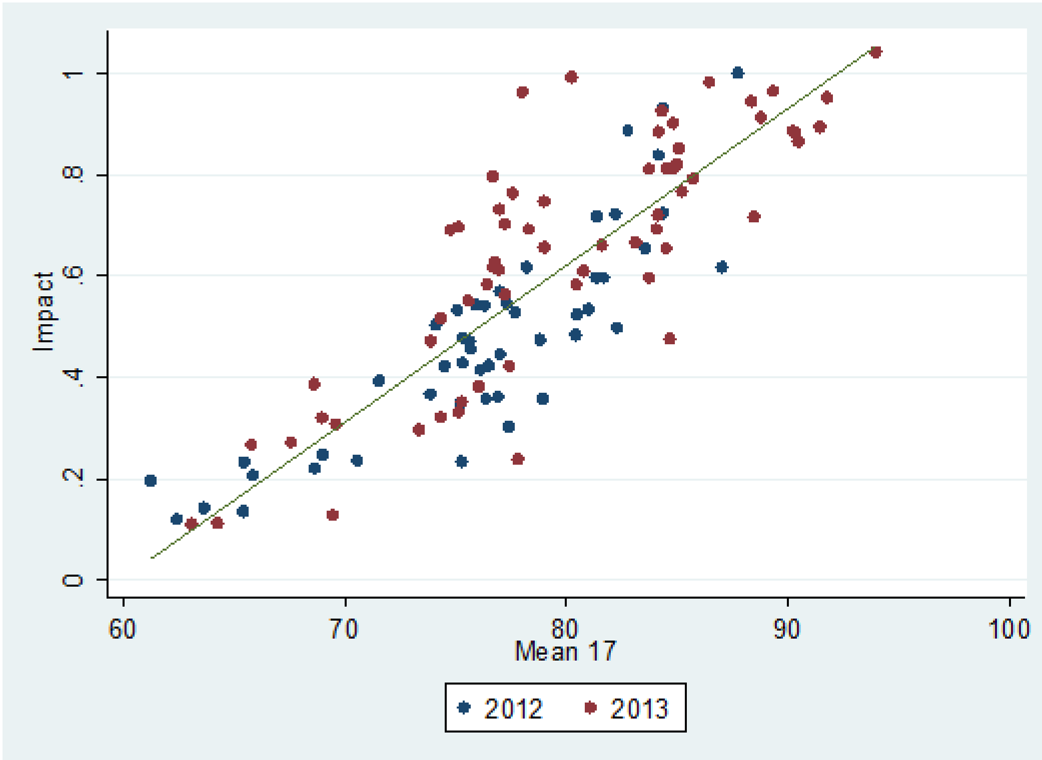


Figure 5-2: Ex Post and Ex Ante Impacts versus *Mean17* for Dually Enrolled Customers



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 in 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 1 to 6 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	0.21	0.74	0.16
	3–4 PM	0.21	0.80	0.17
	4–5 PM	0.21	1.06	0.23
	5–6 PM	0.21	1.18	0.25
	6–7 PM	0.21	1.23	0.26
Dually Enrolled	2–3 PM	0.52	0.68	0.35
	3–4 PM	0.52	0.78	0.40
	4–5 PM	0.52	1.07	0.55
	5–6 PM	0.52	1.21	0.63
	6–7 PM	0.52	1.26	0.65

*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 impacts and average impacts 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.

5.2 Adjusting Event Hours for the Resource Adequacy Event Window

All SmartRate events in 2013 were called from 2 to 7 PM. For 2014 and beyond, events are expected to be called from 1 to 6 PM, to match the resource adequacy window.[24] In order to incorporate these changes into the ex ante results, event impacts had to be adjusted.

Of the five-hour event, four of the hours will stay the same; events in 2013 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

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

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.

5.3 SmartRate Ex Ante Load Impact Results

Section 5.2 summarized the methodology used to develop ex ante impact estimates for the average customer that reflected ex ante weather conditions and event timing. Aggregate ex ante estimates combine these average estimates with projections of program enrollment, developed in a separate effort by PG&E. Enrollment projections by local capacity area as of August of each year from 2014 through 2024 are shown in Table 5-3. 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	
	2014	2015–2024	2014	2015–2024
Greater Bay Area	36.4	36.5	14.7	14.7
Greater Fresno	5.2	5.2	3.9	3.9
Humboldt	0.9	0.9	0.2	0.2
Kern	6.2	6.2	2.1	2.1
Northern Coast	3.0	3.0	2.1	2.1
Other	18.8	18.8	7.9	8.0
Sierra	4.7	4.8	4.6	4.7
Stockton	4.9	4.9	4.0	4.0
Total	**80.2**	**80.4**	**39.5**	**39.6**

Ex ante load impact estimates are shown for 2014 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 for dually enrolled customers. The first set of rows corresponds to 1-in-2 weather conditions while the second set covers 1-in-10 weather conditions.

The SmartRate program is forecasted to provide up to 38 MW of load reduction on a typical event day under normal weather conditions and as much as 47 MW on a typical event day under 1-in-10 year weather conditions. On the system peak day, the demand response potential for the SmartRate program is 44 MW and 52 MW under normal and extreme weather conditions, respectively.

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 20 MW. For the dually enrolled population, the high is on the July peak day with a mean aggregate impact of 24 MW. The largest aggregate mean impact under 1-in-10 conditions for the SmartRate-only population is in July, with an impact of 22 MW. For dually enrolled customers, the greatest aggregate mean impact also occurs on the July peak day with an impact of 30 MW. Aggregate impacts for dually enrolled customers are predicted to exceed those for the SmartRate only population in spite of the fact that SmartRate only customers outnumber dually enrolled customers by a factor of 2. In total, combining SmartRate-only and dually enrolled customers, SmartRate is estimated to provide up to 44 MW of load reduction capability under 1-in-2 year weather conditions and 52 MW under 1-in-10 year conditions.

Table 5-4: 2014 SmartRate Ex Ante Load Impact Estimates by Weather Year and Day Type (Event Period 1 to 6 PM)

Weather Year	Day Type	Mean Hourly Per Customer Impact (SmartRate-only) (kW)	Mean Hourly Per Customer Impact (Dually Enrolled) (kW)	Aggregate Mean Hourly Impact (SmartRate-only) (MW)	Aggregate Mean Hourly Impact (Dually Enrolled) (MW)	Aggregate Mean Hourly Impact (Full Program) (MW)
1-in-2	Typical Event Day	0.21	0.52	17.2	20.4	37.6
	May Monthly Peak	0.14	0.35	11.5	13.6	25.1
	June Monthly Peak	0.20	0.45	15.9	17.6	33.5
	July Monthly Peak	0.24	0.62	19.5	24.4	43.9
	August Monthly Peak	0.21	0.50	17.2	19.8	36.9
	September Monthly Peak	0.20	0.50	16.1	19.8	35.9
	October Monthly Peak	0.16	0.30	12.7	11.8	24.4
1-in-10	Typical Event Day	0.26	0.66	21.0	25.9	46.9
	May Monthly Peak	0.23	0.57	18.5	22.3	40.9
	June Monthly Peak	0.27	0.62	21.5	24.6	46.2
	July Monthly Peak	0.28	0.75	22.4	29.7	52.1
	August Monthly Peak	0.26	0.67	20.5	26.6	47.0
	September Monthly Peak	0.24	0.58	19.5	22.8	42.2
	October Monthly Peak	0.21	0.51	16.8	20.2	37.0

On a per customer basis, the ex ante impact estimates for SmartRate-only customers are very similar to those from the 2012 evaluation. For example, for SmartRate-only customers, the July 1-in-10 per customer value in 2012 was 0.29, while it is 0.28 here. The other monthly ex ante values are also close. On the other hand, dually enrolled per customer impacts are significantly higher than in last year's evaluation. Last year's evaluation estimated a per customer impact of about 0.51 kW for a typical event day for dually enrolled customers,[25] while here it is 0.75 kW. The dually enrolled population has expanded so it is not surprising that the impact estimates differ between the two years. It is clear that PG&E's strategy of targeting high use customers and marketing SmartRate to SmartAC customers in order to increase impacts has been effective.

On an aggregate basis, this program is expected to provide quite a bit more load impact than in the 2012 evaluation. For example, under typical event conditions in a 1-in-10 year, last year's forecast was for 31 MW of demand response. This year that value is 47 MW. This is due to the expansion of the population and higher per-customer impacts from the dually enrolled 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 Microsoft Excel tables that accompany this report, portfolio-adjusted impacts of the dually enrolled customers are intended to represent 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 because the SmartRate program was called on most SmartAC days. Indeed, there were no days in 2013 on which the SmartAC program was called and the SmartRate program wasn't, and there were only three days in 2013 when only SmartAC was called. Furthermore, device addressing issues that were discovered after the 2012 evaluation indicated that the estimates used in 2012 underrepresented the impacts for dually enrolled customers on SmartAC days. Consequently, the method of estimating impacts for dually enrolled customers on SmartAC days was changed. This year, those values were estimated by taking the percent reduction for SmartAC only customers and applying it to the reference load for dually enrolled customers.

5.4 Relationship Between Ex Post and Ex Ante Estimates

The ex post estimates presented in Section 4 and the ex ante estimates presented above differ due to several potential factors, including differences in weather, the event window, enrollment and estimating methodology. This section discusses the impact of each of these factors on the difference between ex post and ex ante impact estimates.

Table 5-5 summarizes the key factors that might lead to differences in ex post and ex ante estimates for the SmartRate program and the expected influence that these factors have on the relationship between ex post and ex ante impact estimates. As seen, there are only small differences between the ex post weather on event days in 2013 and the weather used for ex ante estimation under 1-in-2 year weather conditions, but there are significant differences compared with the 1-in-10 year weather. The switch from a 2 to 7 PM SmartRate event window to the 1 to 6 PM window that will be used in the future will

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

reduce average event period impacts because the reference load for the new hour from 1 to 2 PM is below the average from 2 to 7 PM and the load impact for the lost hour from 6 to 7 PM is above the SmartRate event average. For SmartRate, there are only marginal differences in enrollment between ex post and ex ante forecasts. However, as will be seen, differences in the population used for ex ante modeling and the ex post population are contributing to a downward bias in the ex ante predictions primarily for SmartRate-only customers. Finally, although the estimation methods for ex post and ex ante are quite different, the ex ante model is based on the ex post impact estimates and, as such, should predict well for the average ex post event conditions, although there could be significant differences for any single event due to day-to-day variation that is not captured by a simple model that is based only on variation in weather conditions.

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

Factor	Ex Post	Ex Ante	Expected Impact
Weather	SmartRate-only customers: 71 < event day mean17 < 81 Average event day mean17 = 76 Dually enrolled customers: 74 <event day mean17 <84 Average event day mean17 = 79	SmartRate only mean17 for 1-in-2 typical event day = 76 Dually enrolled mean17 for 1-in-2 typical event day = 78	1-in-2 year peak day impact should be quite similar to ex post impacts given the similarity in weather
		SmartRate only mean17 for 1-in-10 typical event day = 81 Dually enrolled mean17 for 1-in-10 typical event day = 83	1-in-10 year peak day impacts will be significantly higher due to weather
Event window	All events called from 2 to 7 PM	Common ex ante event window is 5 hours, from 1 to 6 PM	Average ex ante impacts will be lower because reference load from 1 to 2 PM is lower than from 2 to 7 PM and the load impact from 6 to 7 PM is above average
Enrollment	The enrollment was largely constant throughout 2013 but much greater and with different characteristics compared with 2012. After selecting a population of customers that were in the program for two years but that were intended to represent the population characteristics in 2013, average impacts for this group were about 9% lower for SmartRate only customers and 2% lower for dually enrolled customers.	Assumed to be similar to 2013	The ex ante estimates will be biased downward by about 9% for SmartRate only customers and about 2% for dually enrolled customers due to imperfections in the matching process used to select customers for ex ante modeling.
Methodology	2013 impacts based on matched control groups and slight adjustment based on differences in pre-event hours.	Regression of ex post impacts against mean17 for all event hours using two years' worth of ex post impacts	Small difference should have only a marginal impact

Table 5-6 and Figure 5-3 show how aggregate load impacts change for the SmartRate only population as a result of differences in the factors underlying ex post and ex ante estimates. The figure graphs the average values at the bottom of the table. Column C replicates the ex post impacts that were shown previously in Table 4-1. Column D shows the ex post impacts for 2013 based on the population for which two years of ex post data exist. Recall from the prior discussion that this population is intended to represent the characteristics of the 2013 population but was chosen using statistical matching techniques from the subpopulation that experienced impacts in both 2012 and 2013. Column E uses the ex ante model to predict impacts based on 2013 weather and the historical event window from 2 to 7 PM and column F uses the same ex post weather but predicts impacts for the ex ante event window from 1 to 6 PM. Finally, columns G and H show the influence of a change from ex post to ex ante weather conditions.

Table 5-6: Differences in Ex Post and Ex Ante Impacts Due to Key Factors for SmartRate Only Customers

<table>
<tr><th rowspan="3">Date</th><th colspan="3">2013 Ex Post Aggregate Estimates</th><th colspan="4">Aggregate Estimates Based on Ex Ante Model</th></tr>
<tr><th rowspan="2">Mean17</th><th rowspan="2">Ex Post Aggregate Reduction (MW)</th><th rowspan="2">Adjusted Population Aggregate Reduction (MW)</th><th rowspan="2">Historical Window & Weather</th><th colspan="3">1 to 6 PM Event Window</th></tr>
<tr><th>Historical Weather</th><th>1-in-2 Year Weather</th><th>1-in-10 Weather</th></tr>
<tr><td>A</td><td>B</td><td>C</td><td>D</td><td>E</td><td>F</td><td>G</td><td>H</td></tr>
<tr><td>Jun 7</td><td>72.0</td><td>19.2</td><td>17.0</td><td>14.7</td><td>14.1</td><td rowspan="9">17.2</td><td rowspan="9">21.0</td></tr>
<tr><td>June 28</td><td>79.6</td><td>27.1</td><td>24.8</td><td>20.6</td><td>19.8</td></tr>
<tr><td>July 1</td><td>79.4</td><td>23.5</td><td>21.7</td><td>20.6</td><td>19.7</td></tr>
<tr><td>July 2</td><td>81.1</td><td>23.9</td><td>22.7</td><td>21.7</td><td>20.8</td></tr>
<tr><td>July 19</td><td>71.4</td><td>16.7</td><td>15.0</td><td>14.9</td><td>14.3</td></tr>
<tr><td>Aug 19</td><td>78.6</td><td>20.4</td><td>18.3</td><td>20.2</td><td>19.4</td></tr>
<tr><td>Sep 9</td><td>75.0</td><td>19.7</td><td>18.6</td><td>17.6</td><td>16.9</td></tr>
<tr><td>Sep 10</td><td>72.6</td><td>12.7</td><td>11.5</td><td>15.8</td><td>15.2</td></tr>
<tr><td>Average</td><td>76.2</td><td>20.5</td><td>18.7</td><td>18.3</td><td>17.5</td></tr>
</table>

The 1-in-2 year ex ante estimates are roughly 16% lower than the average ex post impact and the 1-in-10 year estimates are only about 2% higher than the ex post impacts even though the weather is quite a bit warmer. There are several factors that contribute to these differences. First, more than half of the difference between ex post and ex ante under 1-in-2 year weather conditions is due to imperfections in the matching process between the full ex post population that underlies the ex post estimates and the population that underlies the ex ante modeling. This difference can be seen by comparing the average values in columns C and D. As discussed previously, this factor was an outgrowth of the decision to base the ex ante regressions on two years' worth of event data while trying to preserve the mix of customer characteristics that existed in 2013. This decision, which was designed to increase the precision of the ex ante models, appears to have introduced a downward bias in the average impacts. It might also be possible to reduce this bias with a different approach to matching or simply by re-estimating the ex ante models using just 2013 event data.

Of the remaining factors that explain the difference between ex post and ex ante impacts, the most significant one is the shift in the event window timing, which reduces the average impact by about 5% (comparing columns E and F in Table 5-6). The shift from ex post to ex ante weather had very little impact for the 1-in-2 year estimates (comparing columns F and G) and a larger impact for 1-in-10 year weather (columns F and H).

Figure 5-3: Differences in Ex Post and Ex Ante Impacts Due to Key Factors for SmartRate-only Customers

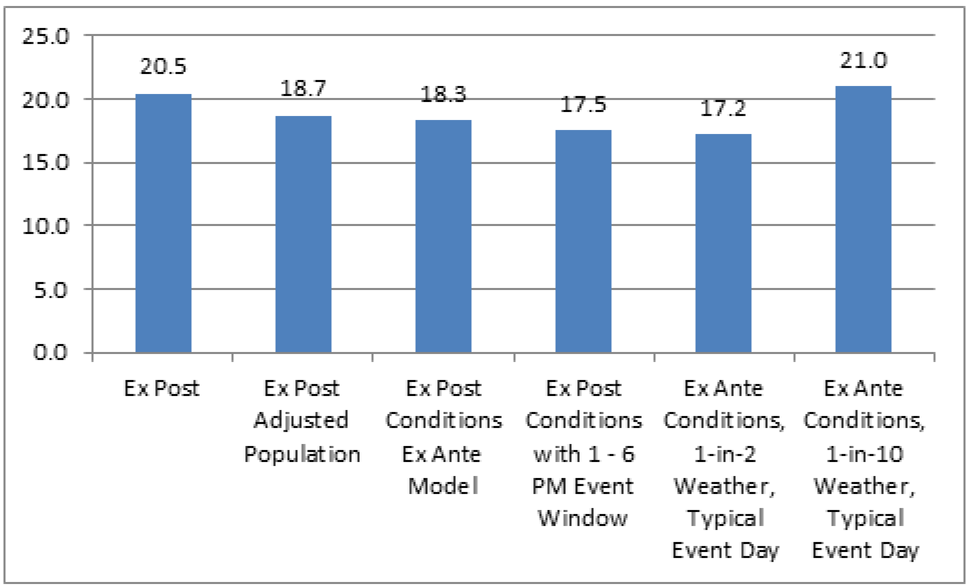
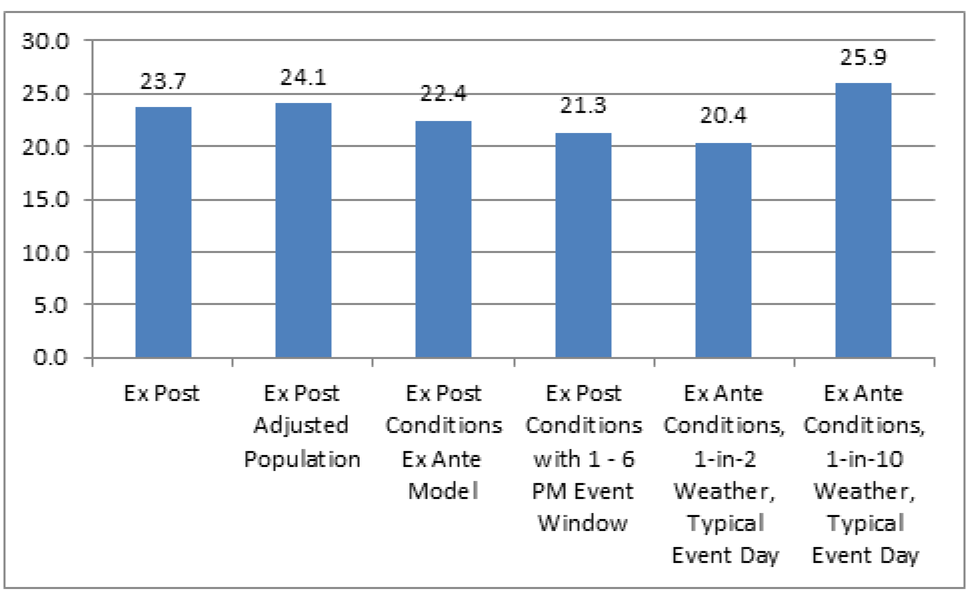


Table 5-7 and Figure 5-4 show the relationship between ex post and ex ante estimates for the dually enrolled customers. Once again we find that the ex post impacts are lower than the 1-in-2 year impacts but the underlying factors differ for this customer segment. Here, the impact of differences in the sample of customers underlying the ex post and ex ante values is not great, as seen by comparing columns C and D in Table 5-7. In this instance, the population adjustment actually increases the ex post impacts by about 2%. Columns D and E reflect a downward bias of about 7% in the ex ante model as a function of weather. This is likely due to the fact that the ex ante model relies on impacts from 2012 and 2013 whereas the ex post values obviously reflect only 2013 events. The 2012 event impacts were somewhat lower than the 2013 impacts and this will bias the model downward. A shift in the event window timing reduces the impact estimates by another 5%, as seen by comparing columns E and F. The final differences are due to differences in weather, as seen by comparing columns F and G and F and H.

Table 5-7: Differences in Ex Post and Ex Ante Impacts Due to Key Factors for Dually Enrolled Customers

Date	2013 Ex Post Aggregate Estimates			Aggregate Estimates Based on Ex Ante Model			
	Mean17	Ex Post Aggregate Reduction (MW)	Adjusted Population Aggregate Reduction (MW)	Historical Window & Weather	1 to 6 PM Event Window: Historical Weather	1 to 6 PM Event Window: 1-in-2 Year Weather	1 to 6 PM Event Window: 1-in-10 Weather
A	B	C	D	E	F	G	H
Jun 7	74.2	23.2	23.5	16.5	15.6		
June 28	82.0	31.3	31.7	26.6	25.3		
July 1	82.3	28.5	29.6	27.0	25.7		
July 2	84.4	28.8	29.5	29.8	28.3		
July 19	73.7	18.3	19.2	15.9	15.1	20.4	25.9
Aug 19	81.4	24.3	24.5	26.1	24.8		
Sep 9	77.6	22.0	22.0	21.2	20.1		
Sep 10	74.0	12.8	12.9	16.4	15.6		
Average	78.7	23.7	24.1	22.4	21.3		

Figure 5-4: Differences in Ex Post and Ex Ante Impacts Due to Key Factors for Dually Enrolled Customers



6 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 2012, the impact evaluation did not contain separate load impact estimates for E-6 and E-7 customers because the number of net-metered, E-6 customers that had smart meters installed for a full year was too small. However, that is no longer true and for the first time, separate evaluations are possible for each tariff.

The approach used to estimate impacts for E-6 and E-7 customers is conceptually similar to the approach used for the SmartRate evaluation in that both evaluations rely on statistical matching on observable variables to develop a control group that can be used as the reference load for customers on each rate. However, with SmartRate, matching was done based on loads on hot, non-event days during the summer period since the price impacts are assumed to not be in effect on those non-event days. For TOU rates such as E-6 and E-7, price effects influence usage by rate period on all days so it is not possible to match on hourly usage during the period after when customers go on a TOU rate. Ideally, matching would be done using hourly loads prior to customers going onto the rate. This approach was used for E-6 customers since this tariff is relatively new and a sufficiently large group of E-6 customers enrolled after their interval meters had been in place for at least a year. Unfortunately, the E-7 tariff has been closed to new enrollment since 2006, when E-6 went into effect, and there is no hourly data available for these customers prior to when they went on the rate. As such, the statistical matching for E-7 customers was based on monthly usage data from the post enrollment period. This is far from ideal and may introduce a significant selection bias as discussed further below.

Selection bias is a concern with evaluation of any voluntary rate program. Customers that use a smaller share of their overall consumption during the peak period compared with the average customer are likely to see their bills go down under any TOU rate that is revenue neutral for the average customer. These structural winners will have load shapes that show lower usage during the peak period compared with the average customer. As long as pretreatment data exists, a suitable control group can be chosen by basing the statistical matching on pretreatment data that reflects this selection effect and, therefore, does not introduce selection bias into the impact estimate. However, if, as is the case with E-7, matching is based on post enrollment, monthly usage data, the load impacts will be biased upward. While it is not possible to test for selection effects for the E-7 population because of the lack of pretreatment data, it is possible to do so for E-6.

To test for selection effects for E-6 customers, the impacts were estimated two ways. One way used the preferred approach that select a control group based on pretreatment, hourly data. This allows for matching on load shape so that control group customers that are structural winners but that did not enroll are matched with the structural winners that did enroll (and, likewise, non-winners are matched with non-winners). This reduces significantly or may completely eliminate any selection bias based on observable data. A second analysis was also done using the only approach available for the E-7 tariff, namely, statistical matching based on monthly usage data, which is inferior to the approach that was used for E6. This approach masks any underlying load shape differences between customers on the tariff and those in the control group. Put another way, if a the enrolled customer enrolled because they already had a preferable load shape and, therefore, would see their bills fall even if they did nothing in response to the rate, but had the same monthly usage as a customer that had much more load during the peak period, that customer would be chosen for inclusion in the control group. The resulting impact estimate, calculated as the difference in peak period usage, would be biased upward. By comparing the impact estimates for E-6 customers using the two different methods, we can observe how much selection bias there is for E-6 customers with the inferior matching methodology.

Table 6-1 shows the ratio of load impacts estimated using the preferred approach alternative. This is a summary measure of the amount of bias introduced by using the inferior methodology. As seen, the bias ratio varies significantly across months, ranging from 0.2 to 2.4. A ratio of 0.2 means that the peak impact based on statistical matching using pretreatment data is 80% less than the impact estimate based on matching on post enrollment, monthly usage. It means that, for this month, the inferior method leads to an estimate that is 80% too high compared to the preferred method. There is a lot of variation in these ratios, but that variation mostly occurs in the winter months when impacts are quite small and largely unimportant from a practical standpoint. Even a small ratio (or large ratio greater than 1) might simply reflect a change in the absolute impact from, say .02 kW to .01 kW. It should also be kept in mind that the ratio in the winter is for the peak period from 5 to 8 PM, not in the afternoon as it is in the summer. In the summer months, when this issue is most important and the peak period is from 1 to 7 PM for E-6, the bias ratio is quite consistent across months and shows an upward bias of 40% to 50% for the inferior methodology for most months for both the average weekday and the monthly peak day.

Table 6-1: Ratio of Load Impact Estimates Using Two Methodologies

Month	Average Weekday	Monthly Peak Day
January	0.9	0.7
February	0.4	0.2
March	0.2	-1.2
April	0.7	0.8
May	0.5	0.5
June	0.5	0.5
July	0.6	0.5
August	0.6	0.5
September	0.8	0.6
October	0.7	0.7
November	0.9	0.7
December	1.4	2.4

The extent of selection bias that would be introduced into the E-6 impact estimates by using the monthly matching approach is not necessarily representative of what might exist for the E-7 population. The E-7 rate is quite different from the E-6 rate, especially in the winter period when the peak period for E-7 is from noon to 6 PM and the peak period for the E-6 rate is from 5 to 8 PM. E-7 customers are also quite different from E-6 customers in that they use much more electricity overall, as was seen in Table 2-5, which showed that the average annual usage for E-6 customers is 6,377 kWh and the average for E-7 customers is 10,425 kWh). Nevertheless, in the absence of a better solution, we have assumed that the degree of selection bias introduced by monthly matching is the same for the two tariffs in the summer months and adjusted both the ex post and ex ante impacts for E-7 by the E-6 bias ratio. This is superior to assuming that there is no selection bias whatsoever, which is what the E-7 methodology implicitly assumes. However, we have not made any adjustment to the winter estimates for E-7, except for the month of April. This is because the peak periods are so different between the two rates that the E-6 ratios in the winter, which reflect the 5 to 8 PM peak period, have little relevance to the E-7 winter peak period from noon to 6 PM. As such, E-7 estimates in the winter may overstate the true impact of the rate, perhaps significantly so, and should be used with caution. We did adjust the E-7 impact estimate in April, which was 50% higher than any other month and about 3 times larger than the estimates in the surrounding months, using the May bias ratio from E-6. This seemed appropriate since an inspection of the load shapes for E-7 customers in April showed a shape that was much more reflective of summer months than winter months.

The remainder of this section provides more details about the matching process that was used for the two tariffs, and describes the regression models that were used to estimate ex post impacts once the control groups were selected.

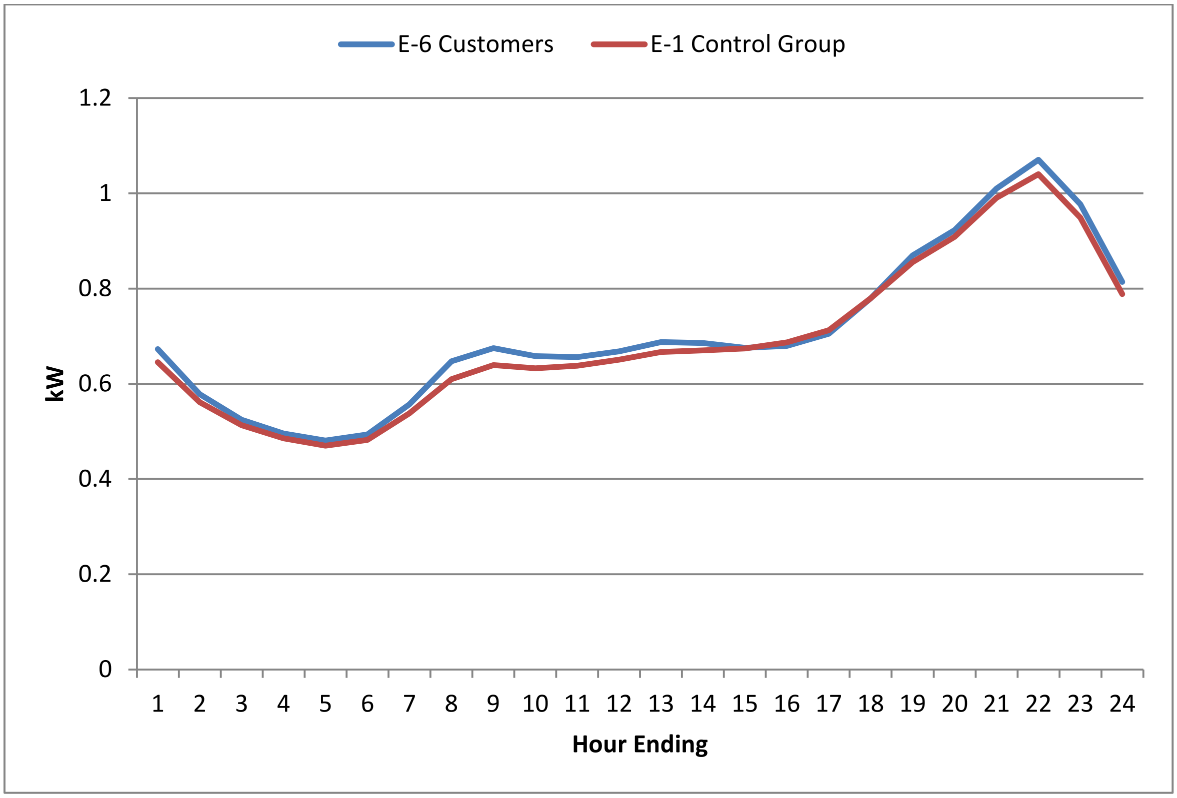
6.1 Control Group Selection

As described above, control group customers for the E-6 tariff were chosen using pretreatment interval data. The process was as follows:

A sample of approximately 3,000 E-6 customers with one year of pretreatment interval data was matched to a group of E-1 customers. This process was different from the propensity score matching used for E-7 customers. First, the average weekday profile was determined for each E-6 customer for a 12-month pretreatment period. Then, the absolute difference between the E-6 load profiles and those of the control pool was calculated. For each E-6 customer, the E-1 customer with the smallest absolute difference was chosen as a control. This matching process was performed separately for each calendar month so one E-6 customer could be matched to up to twelve different control customers. This is because two customers may behave similarly in some months but not in others.

Figure 6-1 presents an average weekday load shape of E-6 customers and their control group for July during the pretreatment period. This particular graph is representative of the Greater Bay Area. This shows the success of the matching process.

Figure 6-1: July Weekday Load Profile of E-6 Treatment and Control Customers (Greater Bay Area)



Control group selection for E-7 customers was done using propensity score matching and post-enrollment, monthly usage data. As discussed in the SmartRate methods section, propensity score matching is a method for finding a control group that is similar to the E-7 group across several observable characteristics. In this case, the dimensions chosen for matching were:

- 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.

The control group was chosen from the E-1 population to match the TOU matched group. Table 6-2 compares the representative sample of E-7 TOU customers with smart meter data to the matched control group. The participant and control groups are comparable across the observable metrics.

Table 6-2: Comparison of E-7 Sample to E-1 Control Group

Characteristic	E7 with SM	E-1 Control Group
Number of Customers	17,093	16,681
Annual usage (kWh)	9,316	9,055
Summer usage (Jun-Sep)	4,398	4,277
Ratio of summer (Jun-July) to shoulder month (Mar-Apr) usage	1.27	1.28
CARE	7%	7%
Percent all electric customers	27%	26%
Climate Zone R (e.g., Fresno)	17%	17%
Climate Zone S (e.g., Stockton/Sacramento)	27%	27%
Climate Zone T (Coastal)	17%	16%
Climate Zone X (e.g., San Jose/Concord)	38%	40%

6.2 Analysis Method

Once the control groups were chosen for each tariff, 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.[26] Standard errors are estimated allowing for correlation of the error term within customers.[27]

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.

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

[27] 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.

The regression models can be expressed as:

Day Type		Regression Model
1	Monthly peak model	$kW_{i,h,m,l} = \alpha_{h,m,l} + \beta_{h,m,l} \cdot TOU_i$
2	Average weekday model	$kW_{i,h,m,l,d} = \alpha_{h,m,l} + \beta_{h,m,l} \cdot TOU_i$

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*.

After initially estimating the impacts for the E-7 tariff using the models summarized above, the impacts summer impacts (and April impact) were adjusted by multiplying them by the bias ratio in each month shown in Table 6-1, for reasons discussed in Section 6.1.

7 TOU 2013 Ex Post Load Impacts

This section summarizes the ex post load impact estimates for TOU customers. Separate estimates are produced for E-6 and E-7 customers for the monthly system peak day and the average weekday for each month from November 2012 through October 2013. The analysis excludes net-metered customers that have solar panels and are accounted for through the evaluation of solar programs.

7.1 2013 System Peak Day Load Impacts

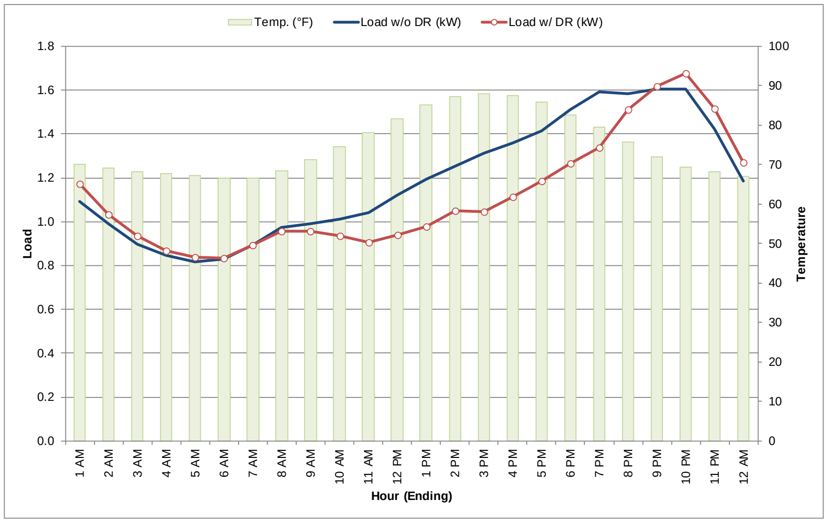
Figure 7-1 shows estimates of hourly load impacts for the average E-6 customer on the annual system peak day, which occurred on July 2, 2013, and Figure 7-2 shows estimates for the average weekday in July. On the system peak day, the average reduction during the peak period from 1 to 7 PM was 0.24 kW, which equaled 17% of whole house load during that period. Load impacts in the first peak period hour equaled 0.20 kW and in the last hour equaled 0.25 kW. The greatest reduction, 0.27 kW, occurred between 2 and 3 PM. During the partial peak hours from 10 AM to 1 PM and 7 to 9 PM, load reductions were much smaller, ranging from a low of -0.01 kW between 8 and 9 PM to a high of 0.22 between noon and 1 PM. Load increased during off-peak hours, showing some load shifting. On the average weekday in July, reference loads and load impacts were significantly lower than on the system peak day. The average peak period reduction was 0.16 kW. Most of this difference was due to differences in the reference load, which was almost 30% lower than on the July peak day.

Figures 7-3 and 7-4 show load shapes for the July peak day and average July weekday for the E-7 tariff. Recall that the E-7 tariff is a two-period rate, with a peak period from noon to 6 PM. The average peak day impact is 0.11 kW or 5% of the reference load, which is much lower than for E-6 customers. On the average July weekday, the average load reduction across the six-hour peak period is 0.10 kW, which is 7% of the reference load and about one-third less than for the E-6 tariff.

Figure 7-1: Average Hourly Load Impact Estimates for E-6 Customers for Annual Peak Day (July 2, 2013)

Result Type	Individual Customer
Customer Type	E6
Day Type	Monthly Peak
Month	July
LCA	All
Population Size	5,075

Peak Period Start	1 PM
Peak Period End	7 PM
Average Temp. for Peak Hours	85
Reference Load for Peak Hours	1.41
Load Reduction for Peak Hours	0.24
% Load Reduction for Peak Hours	17%



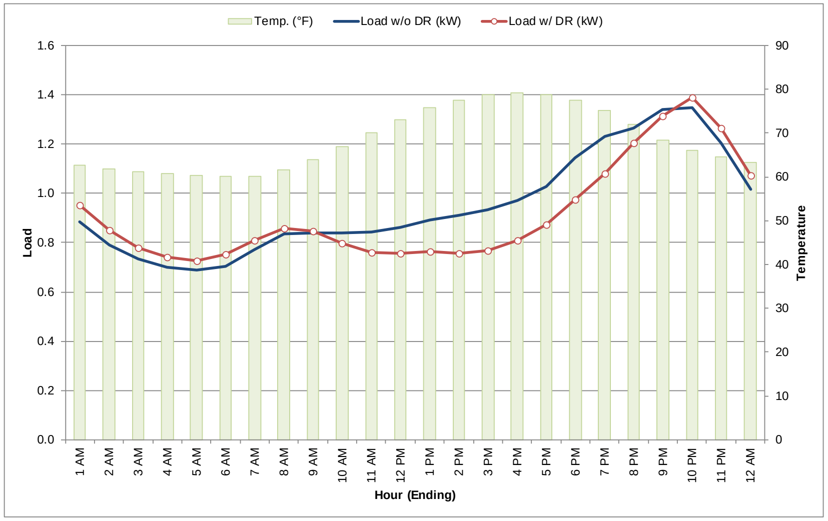
	Hour	Load w/o DR (kW)	Load w/ DR (kW)	Impact (kW)	% Load Impact (%)	Temp. (°F)	Uncertainty Adjusted Impact - Percentiles					
							10th	30th	50th	70th	90th	
1	12 AM - 1 AM	1.09	1.17	-0.08	-7.3%	70.1	-0.15	-0.11	-0.08	-0.05	-0.01	*
2	1 AM - 2 AM	0.99	1.03	-0.04	-4.1%	69.1	-0.11	-0.07	-0.04	-0.01	0.03	*
3	2 AM - 3 AM	0.90	0.93	-0.04	-4.3%	68.3	-0.11	-0.07	-0.04	-0.01	0.03	*
4	3 AM - 4 AM	0.85	0.87	-0.02	-2.5%	67.8	-0.09	-0.05	-0.02	0.01	0.05	*
5	4 AM - 5 AM	0.82	0.84	-0.02	-2.5%	67.2	-0.09	-0.05	-0.02	0.01	0.05	*
6	5 AM - 6 AM	0.83	0.83	0.00	-0.4%	66.7	-0.07	-0.03	0.00	0.02	0.06	*
7	6 AM - 7 AM	0.89	0.89	0.00	-0.1%	66.6	-0.06	-0.03	0.00	0.02	0.06	*
8	7 AM - 8 AM	0.97	0.96	0.02	1.9%	68.5	-0.02	0.00	0.02	0.04	0.06	*
9	8 AM - 9 AM	0.99	0.96	0.03	3.3%	71.3	-0.01	0.02	0.03	0.05	0.07	*
10	9 AM - 10 AM	1.01	0.94	0.08	7.5%	74.6	0.03	0.06	0.08	0.09	0.12	*
11	10 AM - 11 AM	1.04	0.90	0.14	13.1%	78.2	0.09	0.12	0.14	0.15	0.18	*
12	11 AM - 12 PM	1.12	0.94	0.18	16.2%	81.6	0.14	0.16	0.18	0.20	0.23	*
13	12 PM - 1 PM	1.19	0.98	0.22	18.0%	85.1	0.17	0.19	0.22	0.24	0.27	*
14	1 PM - 2 PM	1.25	1.05	0.20	16.3%	87.3	0.15	0.18	0.20	0.23	0.26	*
15	2 PM - 3 PM	1.31	1.05	0.27	20.3%	87.9	0.21	0.24	0.27	0.29	0.32	*
16	3 PM - 4 PM	1.36	1.11	0.24	17.9%	87.4	0.19	0.22	0.24	0.27	0.30	*
17	4 PM - 5 PM	1.42	1.19	0.23	16.3%	85.8	0.17	0.21	0.23	0.25	0.29	*
18	5 PM - 6 PM	1.51	1.27	0.24	16.0%	82.6	0.18	0.22	0.24	0.27	0.30	*
19	6 PM - 7 PM	1.59	1.34	0.25	15.9%	79.5	0.19	0.23	0.25	0.28	0.31	*
20	7 PM - 8 PM	1.58	1.51	0.07	4.4%	75.8	-0.01	0.04	0.07	0.10	0.15	*
21	8 PM - 9 PM	1.61	1.62	-0.01	-0.6%	71.9	-0.09	-0.04	-0.01	0.02	0.07	*
22	9 PM - 10 PM	1.60	1.68	-0.07	-4.5%	69.4	-0.15	-0.10	-0.07	-0.04	0.01	*
23	10 PM - 11 PM	1.42	1.51	-0.09	-6.3%	68.3	-0.17	-0.12	-0.09	-0.06	-0.01	*
24	11 PM - 12 AM	1.18	1.27	-0.09	-7.2%	67.0	-0.16	-0.12	-0.09	-0.06	-0.01	*
	Entire Day	**28.54**	**26.84**	**1.71**	**6.0%**	**74.9**	**-94.31**	**-37.58**	**1.71**	**40.99**	**97.72**	

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

Figure 7-2: Average Hourly Load Impact Estimates for E-6 Customers for Average July Weekday

Result Type	Individual Customer
Customer Type	E6
Day Type	Average Weekday
Month	July
LCA	All
Population Size	5,075

Peak Period Start	1 PM
Peak Period End	7 PM
Average Temp. for Peak Hours	78
Reference Load for Peak Hours	1.04
Load Reduction for Peak Hours	0.16
% Load Reduction for Peak Hours	15%



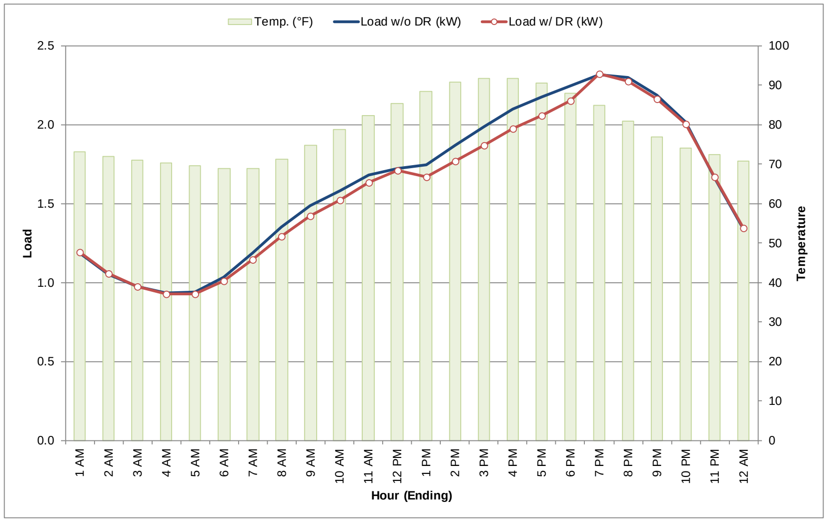
	Hour	Load w/o DR (kW)	Load w/ DR (kW)	Impact (kW)	% Load Impact (%)	Temp. (°F)	Uncertainty Adjusted Impact - Percentiles					
							10th	30th	50th	70th	90th	
1	12 AM - 1 AM	0.89	0.95	-0.07	-7.4%	62.6	-0.13	-0.09	-0.07	-0.04	0.00	*
2	1 AM - 2 AM	0.79	0.85	-0.06	-7.5%	61.9	-0.12	-0.09	-0.06	-0.03	0.00	*
3	2 AM - 3 AM	0.73	0.78	-0.05	-6.2%	61.3	-0.11	-0.07	-0.05	-0.02	0.02	*
4	3 AM - 4 AM	0.70	0.74	-0.04	-5.7%	60.8	-0.10	-0.07	-0.04	-0.01	0.02	*
5	4 AM - 5 AM	0.69	0.73	-0.04	-5.7%	60.4	-0.10	-0.06	-0.04	-0.01	0.02	*
6	5 AM - 6 AM	0.70	0.75	-0.05	-6.9%	60.1	-0.11	-0.07	-0.05	-0.02	0.01	*
7	6 AM - 7 AM	0.77	0.81	-0.04	-4.9%	60.1	-0.09	-0.06	-0.04	-0.02	0.02	*
8	7 AM - 8 AM	0.83	0.86	-0.02	-2.7%	61.6	-0.06	-0.04	-0.02	-0.01	0.01	*
9	8 AM - 9 AM	0.84	0.85	-0.01	-0.9%	63.9	-0.04	-0.02	-0.01	0.01	0.02	*
10	9 AM - 10 AM	0.84	0.80	0.04	5.0%	66.9	0.01	0.03	0.04	0.05	0.07	*
11	10 AM - 11 AM	0.84	0.76	0.08	9.5%	70.0	0.05	0.07	0.08	0.09	0.11	*
12	11 AM - 12 PM	0.86	0.76	0.11	12.2%	73.1	0.07	0.09	0.11	0.12	0.14	*
13	12 PM - 1 PM	0.89	0.77	0.13	14.2%	75.7	0.10	0.11	0.13	0.14	0.16	*
14	1 PM - 2 PM	0.91	0.76	0.15	16.9%	77.5	0.12	0.14	0.15	0.17	0.19	*
15	2 PM - 3 PM	0.93	0.77	0.17	18.0%	78.7	0.14	0.16	0.17	0.18	0.20	*
16	3 PM - 4 PM	0.97	0.81	0.16	16.9%	79.2	0.13	0.15	0.16	0.18	0.20	*
17	4 PM - 5 PM	1.03	0.87	0.15	15.0%	78.8	0.12	0.14	0.15	0.17	0.19	*
18	5 PM - 6 PM	1.14	0.98	0.17	14.5%	77.4	0.13	0.15	0.17	0.18	0.20	*
19	6 PM - 7 PM	1.23	1.08	0.15	12.3%	75.3	0.11	0.14	0.15	0.17	0.19	*
20	7 PM - 8 PM	1.27	1.20	0.06	4.9%	72.0	0.00	0.04	0.06	0.09	0.12	*
21	8 PM - 9 PM	1.34	1.31	0.03	2.0%	68.3	-0.04	0.00	0.03	0.05	0.09	*
22	9 PM - 10 PM	1.35	1.39	-0.04	-3.0%	66.0	-0.11	-0.07	-0.04	-0.01	0.03	*
23	10 PM - 11 PM	1.20	1.26	-0.06	-5.0%	64.6	-0.13	-0.09	-0.06	-0.03	0.00	*
24	11 PM - 12 AM	1.02	1.07	-0.06	-5.6%	63.3	-0.12	-0.08	-0.06	-0.03	0.01	*
	Entire Day	**22.77**	**21.90**	**0.88**	**3.8%**	**68.3**	**-86.68**	**-34.95**	**0.88**	**36.70**	**88.43**	

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

Figure 7-3: Average Hourly Load Impact Estimates for E-7 Customers for Annual Peak Day (July 2, 2013)

Result Type	Individual Customer
Customer Type	E7
Day Type	Monthly Peak
Month	July
LCA	All
Population Size	54,701

Peak Period Start	12 PM
Peak Period End	6 PM
Average Temp. for Peak Hours	90
Reference Load for Peak Hours	2.02
Load Reduction for Peak Hours	0.11
% Load Reduction for Peak Hours	5%



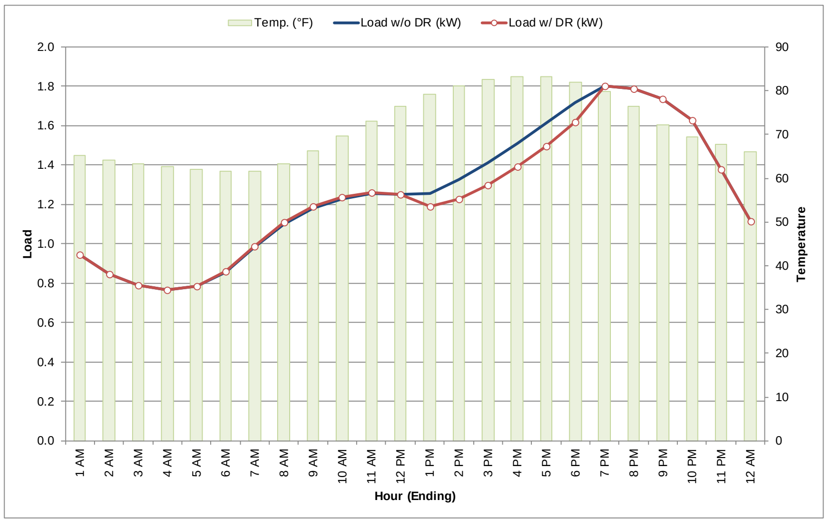
	Hour	Load w/o DR (kW)	Load w/ DR (kW)	Impact (kW)	% Load Impact (%)	Temp. (°F)	Uncertainty Adjusted Impact - Percentiles					
							10th	30th	50th	70th	90th	
1	12 AM - 1 AM	1.19	1.19	-0.01	-0.6%	73.2	-0.03	-0.01	-0.01	0.00	0.01	*
2	1 AM - 2 AM	1.05	1.06	0.00	-0.3%	72.1	-0.02	-0.01	0.00	0.00	0.01	*
3	2 AM - 3 AM	0.98	0.98	0.00	0.0%	71.1	-0.02	-0.01	0.00	0.01	0.02	*
4	3 AM - 4 AM	0.93	0.93	0.00	0.3%	70.3	-0.01	0.00	0.00	0.01	0.02	*
5	4 AM - 5 AM	0.94	0.93	0.01	1.2%	69.7	0.00	0.00	0.01	0.02	0.03	*
6	5 AM - 6 AM	1.03	1.01	0.02	2.4%	69.0	0.01	0.02	0.02	0.03	0.04	*
7	6 AM - 7 AM	1.18	1.14	0.04	3.5%	69.0	0.02	0.03	0.04	0.05	0.06	*
8	7 AM - 8 AM	1.35	1.30	0.06	4.3%	71.2	0.04	0.05	0.06	0.07	0.08	*
9	8 AM - 9 AM	1.49	1.42	0.07	4.5%	74.8	0.05	0.06	0.07	0.08	0.09	*
10	9 AM - 10 AM	1.58	1.52	0.06	3.9%	78.8	0.04	0.05	0.06	0.07	0.08	*
11	10 AM - 11 AM	1.68	1.63	0.05	3.0%	82.4	0.03	0.04	0.05	0.06	0.08	*
12	11 AM - 12 PM	1.73	1.71	0.02	1.0%	85.5	-0.01	0.01	0.02	0.03	0.04	*
13	12 PM - 1 PM	1.75	1.67	0.08	4.6%	88.4	0.05	0.07	0.08	0.09	0.11	*
14	1 PM - 2 PM	1.87	1.77	0.10	5.6%	90.7	0.08	0.09	0.10	0.12	0.13	*
15	2 PM - 3 PM	1.99	1.87	0.12	6.0%	91.7	0.09	0.11	0.12	0.13	0.15	*
16	3 PM - 4 PM	2.10	1.98	0.12	5.7%	91.7	0.09	0.11	0.12	0.13	0.15	*
17	4 PM - 5 PM	2.18	2.06	0.12	5.4%	90.5	0.09	0.10	0.12	0.13	0.15	*
18	5 PM - 6 PM	2.25	2.15	0.10	4.2%	88.0	0.06	0.08	0.10	0.11	0.13	*
19	6 PM - 7 PM	2.32	2.32	0.00	-0.1%	85.0	-0.04	-0.02	0.00	0.01	0.03	*
20	7 PM - 8 PM	2.30	2.28	0.02	0.9%	80.9	-0.01	0.01	0.02	0.03	0.05	*
21	8 PM - 9 PM	2.19	2.16	0.02	1.1%	77.0	0.00	0.01	0.02	0.04	0.05	*
22	9 PM - 10 PM	2.01	2.01	0.01	0.5%	74.0	-0.02	0.00	0.01	0.02	0.04	*
23	10 PM - 11 PM	1.66	1.67	-0.01	-0.3%	72.5	-0.03	-0.02	-0.01	0.00	0.02	*
24	11 PM - 12 AM	1.34	1.35	-0.01	-0.6%	70.7	-0.03	-0.02	-0.01	0.00	0.01	*
	Entire Day	**39.10**	**38.10**	**1.00**	**2.6%**	**78.7**	**-99.84**	**-40.26**	**1.00**	**42.26**	**101.84**	

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

Figure 7-4: Average Hourly Load Impact Estimates for E-7 Customers for Average July 2013 Weekday

Result Type	Individual Customer
Customer Type	E7
Day Type	Average Weekday
Month	July
LCA	All
Population Size	54,701

Peak Period Start	12 PM
Peak Period End	6 PM
Average Temp. for Peak Hours	82
Reference Load for Peak Hours	1.47
Load Reduction for Peak Hours	0.10
% Load Reduction for Peak Hours	7%



	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	0.95	0.95	0.00	0.1%	65.1	-0.01	-0.01	0.00	0.01	0.02	*
2	1 AM - 2 AM	0.85	0.85	0.00	0.0%	64.1	-0.01	-0.01	0.00	0.01	0.01	*
3	2 AM - 3 AM	0.79	0.79	0.00	-0.1%	63.3	-0.01	-0.01	0.00	0.00	0.01	*
4	3 AM - 4 AM	0.77	0.77	0.00	-0.2%	62.6	-0.01	-0.01	0.00	0.00	0.01	*
5	4 AM - 5 AM	0.78	0.79	0.00	-0.3%	62.0	-0.02	-0.01	0.00	0.00	0.01	*
6	5 AM - 6 AM	0.86	0.86	0.00	-0.5%	61.5	-0.02	-0.01	0.00	0.00	0.01	*
7	6 AM - 7 AM	0.98	0.99	-0.01	-0.7%	61.5	-0.02	-0.01	-0.01	0.00	0.01	*
8	7 AM - 8 AM	1.10	1.11	-0.01	-0.8%	63.4	-0.02	-0.01	-0.01	0.00	0.00	*
9	8 AM - 9 AM	1.18	1.19	-0.01	-0.8%	66.3	-0.02	-0.02	-0.01	0.00	0.00	*
10	9 AM - 10 AM	1.23	1.24	-0.01	-0.8%	69.7	-0.02	-0.02	-0.01	0.00	0.01	*
11	10 AM - 11 AM	1.25	1.26	-0.01	-0.5%	73.1	-0.02	-0.01	-0.01	0.00	0.01	*
12	11 AM - 12 PM	1.25	1.25	0.00	-0.2%	76.4	-0.02	-0.01	0.00	0.00	0.01	*
13	12 PM - 1 PM	1.26	1.19	0.07	5.2%	79.2	0.05	0.06	0.07	0.07	0.08	*
14	1 PM - 2 PM	1.32	1.23	0.10	7.3%	81.2	0.08	0.09	0.10	0.10	0.11	*
15	2 PM - 3 PM	1.41	1.30	0.11	8.0%	82.6	0.10	0.11	0.11	0.12	0.13	*
16	3 PM - 4 PM	1.51	1.39	0.12	7.9%	83.2	0.10	0.11	0.12	0.13	0.14	*
17	4 PM - 5 PM	1.61	1.49	0.12	7.4%	83.1	0.10	0.11	0.12	0.13	0.14	*
18	5 PM - 6 PM	1.72	1.62	0.10	5.9%	81.9	0.08	0.09	0.10	0.11	0.12	*
19	6 PM - 7 PM	1.80	1.80	0.00	0.1%	79.8	-0.02	-0.01	0.00	0.01	0.02	*
20	7 PM - 8 PM	1.79	1.79	0.00	-0.1%	76.4	-0.02	-0.01	0.00	0.01	0.02	*
21	8 PM - 9 PM	1.73	1.74	0.00	-0.1%	72.3	-0.02	-0.01	0.00	0.01	0.02	*
22	9 PM - 10 PM	1.63	1.63	0.00	0.0%	69.5	-0.02	-0.01	0.00	0.01	0.02	*
23	10 PM - 11 PM	1.38	1.38	0.00	0.0%	67.7	-0.02	-0.01	0.00	0.01	0.02	*
24	11 PM - 12 AM	1.12	1.11	0.00	0.1%	66.1	-0.01	-0.01	0.00	0.01	0.02	*
	Entire Day	**30.27**	**29.71**	**0.56**	**1.9%**	**71.3**	**-90.86**	**-36.85**	**0.56**	**37.97**	**91.99**	

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

7.2 Monthly System Peak Day Load Impacts

Tables 7-1 and 7-2 show 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, 2012 through October 31, 2013. For both rates, 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 from E-6 customers were greater during summer than winter, both in absolute and percentage terms. During the summer, the average load reduction was 0.22 kW, or 20%. E-7 customers provided average load reductions of 0.11 kW or 7% during the summer. 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, E-6 and E-7 customers had electricity use that was 3% and 7% lower than that of the control group during winter peak period hours, respectively.

Table 7-1: E-6 Monthly System Peak Day Load Reductions (1 to 7 PM Summer, 5 to 8 PM Winter) November 2012–October 2013

Month	Average Reference Load (kW)	Average Load Impact (kW)	Aggregate Load Impact (MW)	Percent Reduction (%)	Average Temp. (°F)
January	1.43	0.02	0.12	2%	48.2
February	1.38	0.01	0.04	1%	43.5
March	1.22	-0.03	-0.14	-2%	51.2
April	1.22	0.20	0.99	16%	74.8
May	0.91	0.13	0.64	14%	85.8
June	1.35	0.31	1.58	23%	89.2
July	1.41	0.24	1.22	17%	85.1
August	1.19	0.24	1.24	21%	81.8
September	1.17	0.32	1.60	27%	83.6
October	0.74	0.09	0.47	13%	70.9
November	1.35	0.02	0.10	1%	58.3
December	1.64	0.05	0.25	3%	44.5
Average	**1.25**	**0.13**	**0.68**	**11%**	**68.1**
Summer	**1.13**	**0.22**	**1.12**	**20%**	**82.7**
Winter	**1.37**	**0.04**	**0.23**	**3%**	**53.4**

Table 7-2: E-7 Monthly System Peak Day Load Reductions (12 PM to 6 PM) November 2012 to October 2013

Month	Average Reference Load (kW)	Average Load Impact (kW)	Aggregate Load Impact (MW)	Percent Reduction (%)	Average Temp. (°F)
January	1.32	0.08	4.54	6%	54.8
February	1.39	0.10	5.39	7%	45.5
March	1.18	0.07	3.66	6%	55.5
April	1.35	0.11	5.92	9%	82.2
May	1.07	0.08	4.37	8%	85.9
June	1.89	0.12	6.75	7%	91.7
July	2.02	0.11	5.80	5%	90.2
August	1.70	0.12	6.39	7%	86.5
September	1.56	0.15	8.11	10%	87.4
October	0.92	0.09	4.98	10%	72.3
November	1.31	0.10	5.66	8%	59.6
December	1.48	0.08	4.53	6%	49.5
Average	**1.43**	**0.10**	**5.51**	**7%**	**71.8**
Summer	**1.53**	**0.11**	**6.07**	**7%**	**85.7**
Winter	**1.34**	**0.09**	**4.95**	**7%**	**57.9**

7.3 Average Weekday Load Impact by Month

Table 7-3 and 7-4 show the change in peak-period energy use for the average weekday for each month for E-6 and E-7 customers, respectively. The average reduction across the year was 0.08 kW for E-6 customers and 0.09 for E-7 customers. 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 for E-6 customers is 0.13 kW or 15%, while the average in winter months is 0.03 kW or 3%. The largest average weekday load reductions for E-7 customers, 0.12 kW, occurred in September. All of the summer results are statistically significant.

Table 7-3: E-6 Average Weekday Peak Period Load Reduction (1 to 7 PM Summer, 5 to 8 PM Winter) November 2012–October 2013

Month	Average Reference Load (kW)	Average Load Impact (kW)	Aggregate Load Impact (MW)	Percent Reduction (%)	Average Temp. (°F)
January	1.42	0.03	0.17	2%	50.4
February	1.25	0.01	0.06	1%	53.5
March	1.03	0.02	0.08	2%	60.0
April	0.96	0.06	0.29	6%	65.7
May	0.81	0.09	0.46	11%	71.3
June	0.87	0.11	0.56	13%	75.0
July	1.04	0.16	0.81	15%	77.8
August	0.92	0.16	0.80	17%	76.7
September	0.86	0.16	0.80	18%	75.7
October	0.75	0.09	0.45	12%	69.4
November	1.26	0.03	0.14	2%	58.5
December	1.53	0.06	0.31	4%	50.8
Average	**1.06**	**0.08**	**0.41**	**8%**	**65.4**
Summer	**0.87**	**0.13**	**0.65**	**15%**	**74.3**
Winter	**1.24**	**0.03**	**0.18**	**3%**	**56.5**

Table 7-4: E-7 Average Weekday Peak Period Load Reduction (12 PM to 6 PM) November 2012–October 2013

Month	Average Reference Load (kW)	Average Load Impact (kW)	Aggregate Load Impact (MW)	Percent Reduction (%)	Average Temp. (°F)
January	1.33	0.09	5.19	7%	55.3
February	1.18	0.09	5.19	8%	58.8
March	1.05	0.10	5.30	9%	64.4
April	1.03	0.05	2.86	5%	70.1
May	0.98	0.06	3.30	6%	73.1
June	1.16	0.08	4.19	7%	77.2
July	1.47	0.10	5.61	7%	81.9
August	1.27	0.11	5.93	9%	80.1
September	1.12	0.12	6.41	10%	77.7
October	0.92	0.08	4.17	8%	70.8
November	1.22	0.09	5.01	7%	63.0
December	1.45	0.08	4.47	6%	53.6
Average	**1.18**	**0.09**	**4.80**	**7%**	**68.8**
Summer	**1.15**	**0.09**	**4.94**	**8%**	**76.8**
Winter	**1.21**	**0.09**	**4.67**	**7%**	**60.9**

7.4 Load Impacts by Geographic Region

Results by LCA are less reliable than the overall results for all customers because sample sizes are smaller. This is particularly true for monthly peak results, which include fewer days for impact estimation than the average weekday results.

Tables 7-5 and 7-6 show the average impacts on the annual system peak day, July 2, by LCA for each rate. E-6 customers with the greatest absolute load reductions, 0.44 kW, were located in the Greater Fresno area. Stockton saw the greatest absolute load reduction among E-7 customers.

Table 7-5: E-6 Peak Period (1 to 7 PM) Load Reductions by Local Capacity Area Annual Peak Day (July 2, 2013)

LCA	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	Percent Reduction (%)	Average Temp. (°F)
Greater Bay Area	0.90	0.80	0.10	11%	69.6
Greater Fresno Area	1.64	1.21	0.44	27%	78.3
Humboldt	1.46	1.44	0.02	1%	62.4
Kern	1.75	1.51	0.24	14%	79.2
North Coast and North Bay	1.13	0.92	0.21	19%	72.3
Other	1.16	1.04	0.12	11%	69.2
Sierra	1.54	1.34	0.20	13%	71.6
Stockton	1.57	1.16	0.41	26%	74.6
All	**1.07**	**0.93**	**0.13**	**13%**	**70.1**

Table 7-6: E-7 Peak Period (12 to 6 PM) Load Reductions by Local Capacity Area Annual Peak Day (July 2, 2013)

LCA	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	Percent Reduction (%)	Average Temp. (°F)
Greater Bay Area	1.27	1.19	0.08	6%	71.0
Greater Fresno Area	2.01	1.72	0.29	14%	78.2
Humboldt	1.16	1.11	0.05	4%	65.4
Kern	1.65	1.51	0.14	8%	79.2
North Coast and North Bay	1.34	1.25	0.09	6%	72.8
Other	1.46	1.33	0.13	9%	71.1
Sierra	1.76	1.59	0.17	10%	71.8
Stockton	1.98	1.61	0.38	19%	74.9
All	**1.43**	**1.32**	**0.11**	**8%**	**71.8**

Tables 7-7 and 7-8 show the impacts for each LCA and rate for the average weekday peak period during the summer and winter months. E-6 customers saw greater load impacts in the summer months.

Table 7-7: E-6 Load Reductions for Peak Period (1 to 7 PM Summer, 5 to 8 PM Winter) 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	0.72	0.63	0.08	12%	72.4
	Greater Fresno Area	1.55	1.19	0.37	24%	88.4
	Humboldt	1.29	1.17	0.12	9%	66.1
	Kern	1.85	1.52	0.34	18%	87.8
	North Coast and North Bay	0.91	0.72	0.19	21%	76.1
	Other	0.98	0.84	0.13	14%	76.0
	Sierra	1.23	0.99	0.24	19%	80.9
	Stockton	1.27	0.94	0.33	26%	82.7
	All	**0.87**	**0.75**	**0.13**	**15%**	**74.3**
Winter (Nov-Apr)	Greater Bay Area	1.07	1.06	0.01	1%	57.1
	Greater Fresno Area	1.33	1.26	0.07	5%	60.9
	Humboldt	2.53	2.34	0.19	8%	50.5
	Kern	1.14	1.03	0.11	9%	61.1
	North Coast and	1.36	1.29	0.07	5%	55.3
	Other	1.30	1.28	0.02	2%	56.5
	Sierra	1.57	1.55	0.02	1%	52.5
	Stockton	1.40	1.21	0.19	14%	57.0
	All	**1.24**	**1.21**	**0.03**	**3%**	**56.5**

Table 7-8: E-7 Load Reductions for Peak Period (12 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	0.97	0.91	0.06	6%	73.6
	Greater Fresno Area	1.87	1.61	0.26	14%	87.7
	Humboldt	0.92	0.91	0.01	1%	69.5
	Kern	1.64	1.51	0.14	8%	87.1
	North Coast and	1.05	1.00	0.05	5%	76.1
	Other	1.18	1.08	0.11	9%	77.6
	Sierra	1.38	1.23	0.15	11%	80.7
	Stockton	1.71	1.25	0.46	27%	82.6
	All	**1.15**	**1.06**	**0.09**	**8%**	**76.8**
Winter (Nov-Apr)	Greater Bay Area	1.09	1.03	0.06	6%	61.2
	Greater Fresno Area	1.21	1.07	0.14	11%	63.8
	Humboldt	1.23	1.17	0.07	5%	55.7
	Kern	0.96	0.90	0.06	6%	64.3
	North Coast and	1.23	1.16	0.07	6%	60.8
	Other	1.26	1.16	0.11	9%	61.6
	Sierra	1.42	1.31	0.11	8%	58.5
	Stockton	1.35	1.21	0.14	10%	60.9
	All	**1.20**	**1.12**	**0.09**	**7%**	**60.9**

7.5 Bill Impacts for TOU

Table 7-9 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 saved 18%. Over the course of the entire year, the average customer in the sample saved about 9%, while 83% of customers experienced bill savings of some kind. 90% of customers experienced bill decreases up to 27% and increases up to 9%. Most customers experienced 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 increase usage during cheaper off-peak periods.

Bills were calculated using hourly interval data for the sample of 20,000 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 7-9 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 2013. Table 2-5 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 7-9 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 7-9: 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	
12-Nov	$151	$125	-18%	-33%	-2%	96%
12-Dec	$201	$168	-16%	-31%	-2%	96%
13-Jan	$192	$160	-17%	-32%	-2%	96%
13-Feb	$151	$124	-18%	-33%	-2%	96%
13-Mar	$143	$116	-19%	-34%	-4%	98%
13-Apr	$129	$104	-19%	-34%	-4%	98%
13-May	$144	$141	-2%	-27%	23%	69%
13-Jun	$171	$166	-3%	-25%	20%	71%
13-Jul	$200	$202	1%	-25%	27%	57%
13-Aug	$173	$173	0%	-26%	26%	60%
13-Sep	$150	$146	-3%	-27%	21%	70%
13-Oct	$140	$137	-2%	-29%	25%	69%
Summer	**$976**	**$965**	**-1%**	**-25%**	**23%**	**66%**
Winter	**$900**	**$741**	**-18%**	**-32%**	**-3%**	**97%**
Annual	**$1,857**	**$1,691**	**-9%**	**-27%**	**9%**	**83%**

8 TOU Ex Ante Load Impacts

This section summarizes the ex ante evaluation methodology and results for the E-6 and E-7 tariffs. The estimates presented here exclude the approximately 30,000 net-metered customers that have solar panels because they are already accounted for through the evaluation of solar programs.

8.1 Methodology

The ex ante methodology used here is conceptually similar to the methodology used to estimate ex ante SmartRate impacts that was described in Section 5. There is a difference in how the E-6 and E-7 impacts are estimated. For the E-6 tariff, the approach uses the ex post estimates described in Section 7 as the dependent variable in a regression model relating load impacts to weather conditions. The estimates were developed through the following 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 year weather conditions.
4. Predict the reference loads and the impacts.
5. Combine the two.

For the E-7 tariff, the above steps were followed but instead of using the impacts after making the adjustment for self selection as described in Section 6, Table 6-1, the regression was estimated using the pre-adjusted impacts and then the adjustment was made to the ex ante estimates that arise from the regression model using ex ante weather. Only 2013 data was used to estimate the ex ante impacts this year because this is the only year that has sufficient data to estimate separate models for the E-6 and E-7 rates. Figures 8-1 and 8-2 show scatter plots of absolute (kW) and relative (percentage) E-6 and E-7 TOU impacts by temperature during the summer peak period for each day for a single LCA. 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 these two figures show, 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. Like in the ex post analysis, load impacts were estimated separately for E-6 and E-7 in the ex ante analysis.

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 nine hours preceding each hour.

Figure 8-1: E-6 Peak Period Impacts by Temperature

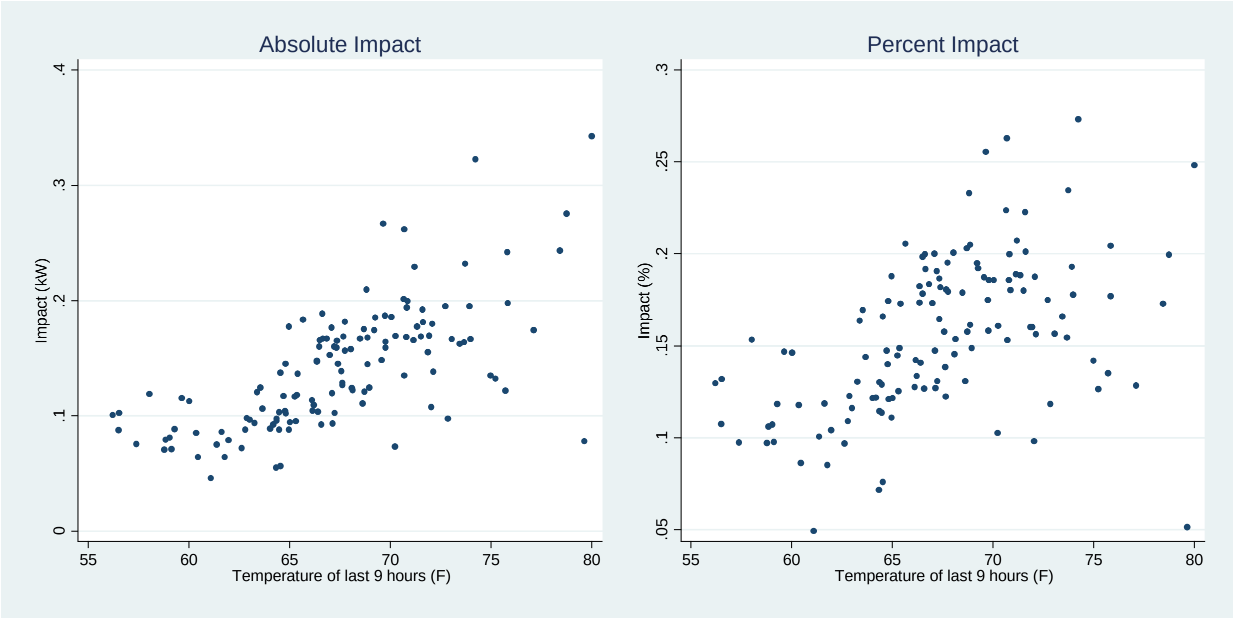
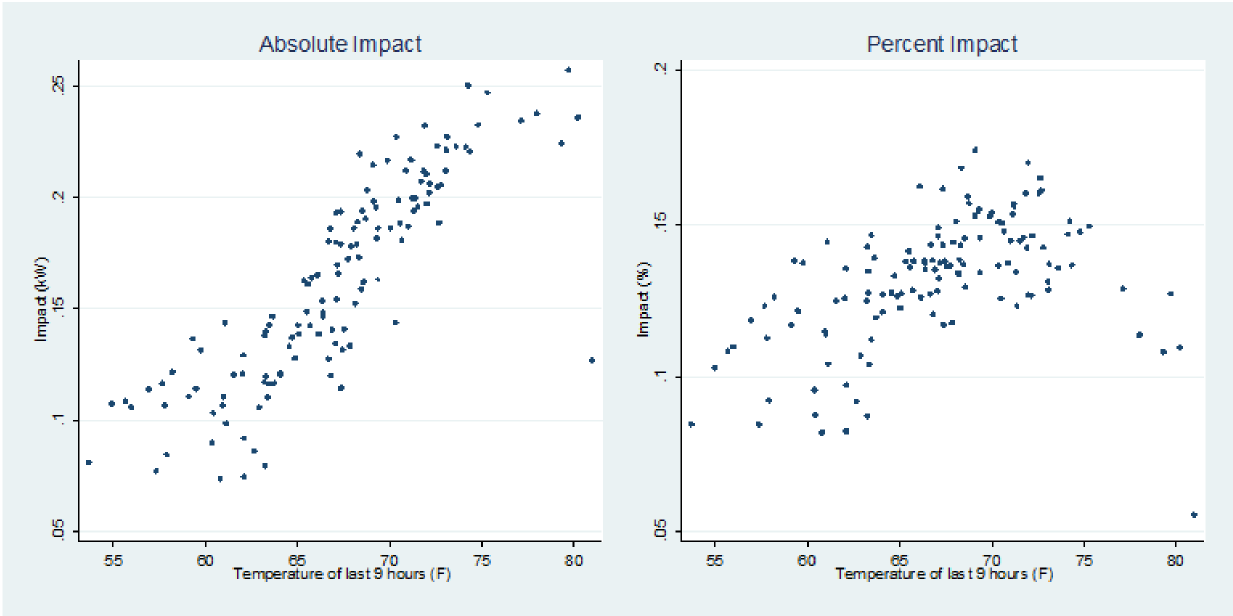


Figure 8-2: E-7 Peak Period Impacts by Temperature



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	$\Delta kW_{t,LCA,season} = a + b * \text{last\_nine\_temp}_{t,LCA,season} + \epsilon$
Variation in Reference loads	$kW_{t,LCA,season} = a + b * \text{last\_nine\_temp}_{t,LCA,season} + \epsilon$

Table 8-1: Impact Regression Parameters and Description

Variable	Description
Δkw	The difference between the control group and TOU groups for each hour and date in 2013. The treatment and control groups are the same as those used for the ex post evaluation.
$a - e$	Estimated parameters (coefficients).
$t, LCA, season$	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).
ϵ	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);
- 8 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., 2014 through 2024); 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.

8.2 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 enrollment for the E-7 rate is attrition as customers drop out or close their accounts over time. On the other hand, the E-6 population is forecasted to increase significantly. Table 8-2 shows the population forecasts used in this report, which were developed by PG&E. While the number of customers on the two rates combined is nearly constant, the mix of customers changes significantly over the forecast horizon. Since, as seen in Section 7, E-6 customers have higher load impacts than E-7 customers, this change in the mix drives up the average and aggregate load impacts over time. As another reminder, these forecasts represent non-net metered customers only.

Table 8-2: Residential TOU Population Forecast, 2014 though 2024

Year	E6 Non-net Metered	E7 Non Net Metered	Total
2014	6,872	54,121	60,993
2015	9,344	50,961	60,305
2016	11,826	47,986	59,812
2017	14,318	45,185	59,503
2018	16,818	42,547	59,365
2019	19,326	40,063	59,389
2020	21,842	37,725	59,567
2021	24,365	35,522	59,887
2022	26,895	33,449	60,344
2023	29,431	31,496	60,927
2024	31,974	29,657	61,631

8.3 Aggregate Load Impacts by Year

Tables 8-3 and 8-4 summarize the projected program load reduction for E-6 and E-7 customers 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. On the annual system peak day in 2014, E-6 customers are expected to provide load impacts of 1.6 MW, or 20%. E-7 customers are expected to provide 7.8 MW on the same day, which is a 9% load reduction. 1-in-10 weather conditions are expected to cause slightly greater load reductions. By 2024, given the significant shift in enrollment, E-6 customers are predicted to deliver more demand reduction, 7.9 MW under 1-in-2 year conditions, than E-7 customers, 4.3 MW.

Table 8-3: Summary of Aggregate Ex Ante Load Impacts for Residential TOU Tariffs by Year, E-6 Non-net Metered Customers (Average 1 to 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	2014	6,644	7.8	6.2	1.6	20%	90.6
	2015	9,117	10.8	8.6	2.2		
	2016	11,599	13.8	11.0	2.8		
	2017	14,091	16.9	13.4	3.4		
	2018	16,592	19.9	15.8	4.1		
	2019	19,100	23.0	18.3	4.7		
	2020	21,616	26.0	20.7	5.3		
	2021	24,140	29.1	23.1	6.0		
	2022	26,670	32.2	25.6	6.6		
	2023	29,207	35.2	28.0	7.2		
	2024	31,749	38.3	30.5	7.9		
1-in-10	2014	6,644	8.4	6.7	1.7	21%	93.8
	2015	9,117	11.7	9.2	2.4		
	2016	11,599	14.9	11.8	3.1		
	2017	14,091	18.2	14.4	3.8		
	2018	16,592	21.5	17.0	4.5		
	2019	19,100	24.8	19.6	5.2		
	2020	21,616	28.1	22.2	5.9		
	2021	24,140	31.4	24.8	6.6		
	2022	26,670	34.7	27.4	7.3		
	2023	29,207	38.1	30.1	8.0		
	2024	31,749	41.4	32.7	8.7		

Table 8-4: Summary of Aggregate Ex Ante Load Impacts for Residential TOU Tariffs by Year, E-7 Non-net Metered Customers (Average 1 to 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	2014	54,415	85.3	77.5	7.8	9%	92.0
	2015	51,238	80.3	72.9	7.3		
	2016	48,247	75.6	68.7	6.9		
	2017	45,431	71.2	64.7	6.5		
	2018	42,779	67.0	60.9	6.1		
	2019	40,281	63.1	57.3	5.8		
	2020	37,930	59.4	54.0	5.4		
	2021	35,716	56.0	50.8	5.1		
	2022	33,631	52.7	47.9	4.8		
	2023	31,667	49.6	45.1	4.5		
	2024	29,819	46.7	42.5	4.3		
1-in-10	2014	54,415	93.2	84.5	8.6	9%	95.2
	2015	51,238	87.7	79.6	8.1		
	2016	48,247	82.6	75.0	7.6		
	2017	45,431	77.8	70.6	7.2		
	2018	42,779	73.2	66.5	6.8		
	2019	40,281	69.0	62.6	6.4		
	2020	37,930	64.9	58.9	6.0		
	2021	35,716	61.1	55.5	5.7		
	2022	33,631	57.6	52.2	5.3		
	2023	31,667	54.2	49.2	5.0		
	2024	29,819	51.0	46.3	4.7		

Table 8-5 summarizes the projected load reduction for the two rates combined for each forecast year under 1-in-2 and 1-in-10 year weather conditions. Based on 1-in-2 year weather conditions, aggregate average peak period load reductions equal 9.4 MW for the roughly 61,000 customers enrolled in 2014, and grow steadily until 2024, as the E-6 population grows. Percent reductions also grow as the customer mix changes.

Table 8-5: Summary of Aggregate Ex Ante Load Impacts for Residential TOU Tariffs by Year, E-6 and E-7 Non-net Metered Customers (Average 1 to 6 PM Peak Period Reduction on the Annual System Peak Day)

Weather Conditions	Year	Accounts	Reference Load (MW)	Load Impact (MW)	% Load Reduction
1-in-2	2014	61,059	93.1	9.4	10%
	2015	60,355	91.1	9.5	10%
	2016	59,846	89.4	9.7	11%
	2017	59,522	88.0	10.0	11%
	2018	59,371	86.9	10.2	12%
	2019	59,381	86.1	10.5	12%
	2020	59,546	85.4	10.8	13%
	2021	59,856	85.0	11.1	13%
	2022	60,301	84.9	11.4	13%
	2023	60,874	84.9	11.8	14%
	2024	61,568	85.1	12.1	14%
1-in-10	2014	61,059	101.6	10.4	10%
	2015	60,355	99.4	10.6	11%
	2016	59,846	97.5	10.8	11%
	2017	59,522	96.0	11.0	11%
	2018	59,371	94.7	11.3	12%
	2019	59,381	93.8	11.6	12%
	2020	59,546	93.0	11.9	13%
	2021	59,856	92.6	12.3	13%
	2022	60,301	92.3	12.6	14%
	2023	60,874	92.3	13.0	14%
	2024	61,568	92.5	13.4	15%

The ex ante values produced in this year's evaluation are smaller, by a small amount, than those produced in last year's evaluation. For example, the 2012 evaluation forecasted 14 MW of demand reduction for the 2020 annual system peaks under 1-in-2 weather conditions. This year, we project 10.8 MW for the same year. The main reason for this is the change in the ex post methodology which accounts for structural winners. Because of data limitations, the 2012 evaluation was not able to reflect the impact of the changing customer mix in the ex ante estimates.

8.4 1-in-2 Annual Peak Impacts per Customer

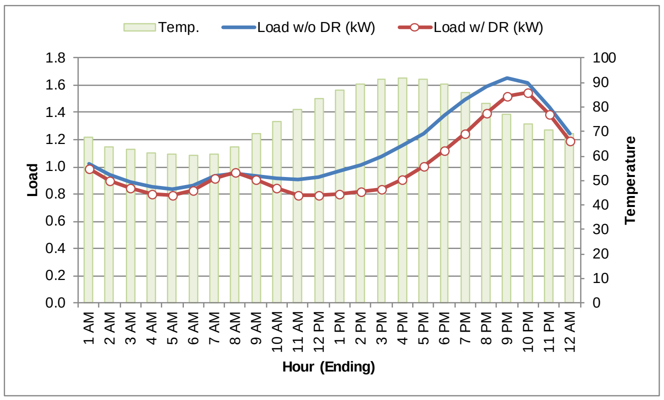
Figures 8-3 and Figure 8-4 show estimates of hourly load impacts for the forecast year 2014 for the average E-6 and E-7 customer, respectively, based on 1-in-2 annual peak conditions. For E-6, the impacts per customer equal 0.25 kW for the 4 to 5 PM period, which is when the system peak typically occurs. This same period, the impacts per E-7 customer equal 0.16 kW. The average reduction during the peak period is 20% for E-6 customers and 9% 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 smaller than those found in last year's evaluation; the difference can be explained by differences in control group selection methodology. 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 8-3: Average E-6 Non-net Metered Customer Hourly Load Impact Estimates Based on 2013 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	2014
Rate	E6

Table 2: Population Statistics	
Population (2013)	5,075
Population (2014)	6,644

Table 3: Event Information	
Peak Period Start	1 PM
Peak Period Stop	7 PM
Peak Period Reference Load (kW)	1.23
Peak Period Reduction (kW)	0.24
Peak Period Reduction (%)	20%



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	1.02	0.99	0.03	3.5%	67.6	-0.06	-0.01	0.03	0.08	0.13	*
1 AM - 2 AM	0.94	0.90	0.04	4.3%	63.7	-0.05	0.00	0.04	0.08	0.13	*
2 AM - 3 AM	0.89	0.84	0.04	5.3%	62.5	-0.04	0.01	0.04	0.08	0.13	*
3 AM - 4 AM	0.85	0.80	0.05	6.2%	61.5	-0.03	0.02	0.05	0.08	0.13	*
4 AM - 5 AM	0.84	0.79	0.05	6.2%	60.9	-0.04	0.01	0.05	0.08	0.13	*
5 AM - 6 AM	0.86	0.83	0.04	4.4%	60.3	-0.05	0.00	0.04	0.07	0.12	*
6 AM - 7 AM	0.94	0.91	0.02	2.6%	60.5	-0.07	-0.01	0.02	0.06	0.12	*
7 AM - 8 AM	0.95	0.96	-0.01	-1.0%	63.7	-0.10	-0.05	-0.01	0.03	0.08	*
8 AM - 9 AM	0.93	0.90	0.03	3.5%	68.9	-0.07	-0.01	0.03	0.07	0.13	*
9 AM - 10 AM	0.92	0.84	0.08	9.1%	74.1	-0.02	0.04	0.08	0.12	0.17	*
10 AM - 11 AM	0.91	0.80	0.12	14.5%	79.0	0.02	0.08	0.12	0.15	0.21	*
11 AM - 12 PM	0.93	0.79	0.14	17.3%	83.4	0.04	0.10	0.14	0.17	0.23	*
12 PM - 1 PM	0.97	0.80	0.16	20.2%	86.8	0.07	0.12	0.16	0.20	0.26	
1 PM - 2 PM	1.01	0.82	0.19	23.8%	89.4	0.10	0.16	0.19	0.23	0.29	
2 PM - 3 PM	1.07	0.84	0.23	27.7%	91.2	0.13	0.19	0.23	0.27	0.33	
3 PM - 4 PM	1.15	0.91	0.25	27.3%	91.9	0.15	0.21	0.25	0.29	0.35	
4 PM - 5 PM	1.25	1.00	0.25	24.7%	91.2	0.13	0.20	0.25	0.29	0.36	
5 PM - 6 PM	1.38	1.12	0.26	23.7%	89.1	0.14	0.21	0.26	0.32	0.39	
6 PM - 7 PM	1.49	1.24	0.25	20.0%	85.9	0.12	0.19	0.25	0.30	0.38	
7 PM - 8 PM	1.59	1.40	0.19	13.6%	81.6	0.07	0.14	0.19	0.24	0.32	*
8 PM - 9 PM	1.66	1.52	0.14	9.2%	76.8	0.02	0.09	0.14	0.19	0.26	*
9 PM - 10 PM	1.61	1.54	0.07	4.5%	73.3	-0.05	0.02	0.07	0.12	0.19	*
10 PM - 11 PM	1.44	1.39	0.05	3.5%	70.8	-0.06	0.00	0.05	0.09	0.16	*
11 PM - 12 AM	1.24	1.19	0.05	4.1%	69.2	-0.05	0.01	0.05	0.09	0.15	*
Daily	**26.84**	**24.12**	**2.72**	**11.3%**	**75.1**	**2.62**	**2.68**	**2.72**	**2.76**	**2.82**	

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

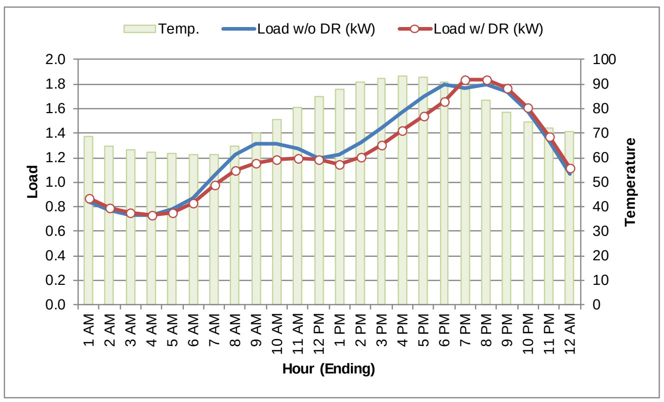
Note: Program Specific and Portfolio Adjusted impacts are the same for Residential TOU

Figure 8-4: Average E-7 Non-net Metered Customer Hourly Load Impact Estimates Based on 2013 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	2014
Rate	E7

Table 2: Population Statistics	
Population (2013)	54,701
Population (2014)	54,415

Table 3: Event Information	
Peak Period Start	12 PM
Peak Period Stop	6 PM
Peak Period Reference Load (kW)	1.51
Peak Period Reduction (kW)	0.13
Peak Period Reduction (%)	9%



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	0.84	0.87	-0.03	-3.7%	68.9	-0.06	-0.04	-0.03	-0.02	-0.01	*
1 AM - 2 AM	0.77	0.79	-0.02	-2.1%	64.8	-0.04	-0.03	-0.02	-0.01	0.01	*
2 AM - 3 AM	0.73	0.75	-0.01	-1.9%	63.5	-0.03	-0.02	-0.01	-0.01	0.01	*
3 AM - 4 AM	0.73	0.73	0.00	-0.5%	62.3	-0.02	-0.01	0.00	0.00	0.01	*
4 AM - 5 AM	0.78	0.76	0.02	2.8%	61.7	0.00	0.01	0.02	0.03	0.04	*
5 AM - 6 AM	0.87	0.83	0.04	4.5%	61.1	0.02	0.03	0.04	0.05	0.06	
6 AM - 7 AM	1.05	0.98	0.08	7.8%	61.2	0.05	0.06	0.08	0.09	0.11	
7 AM - 8 AM	1.22	1.10	0.12	11.2%	64.6	0.09	0.11	0.12	0.14	0.16	
8 AM - 9 AM	1.31	1.16	0.16	13.4%	70.0	0.12	0.14	0.16	0.17	0.19	
9 AM - 10 AM	1.32	1.19	0.13	11.0%	75.4	0.10	0.12	0.13	0.14	0.17	
10 AM - 11 AM	1.27	1.20	0.08	6.4%	80.4	0.04	0.06	0.08	0.09	0.11	
11 AM - 12 PM	1.19	1.19	0.00	0.4%	84.7	-0.03	-0.01	0.00	0.02	0.04	*
12 PM - 1 PM	1.23	1.15	0.08	7.0%	88.1	0.04	0.06	0.08	0.10	0.12	
1 PM - 2 PM	1.32	1.21	0.12	9.7%	90.6	0.07	0.10	0.12	0.13	0.16	
2 PM - 3 PM	1.44	1.30	0.14	10.6%	92.5	0.09	0.12	0.14	0.16	0.18	
3 PM - 4 PM	1.57	1.42	0.16	11.0%	93.3	0.11	0.14	0.16	0.18	0.20	
4 PM - 5 PM	1.70	1.54	0.16	10.6%	92.7	0.11	0.14	0.16	0.18	0.22	
5 PM - 6 PM	1.80	1.65	0.14	8.6%	90.9	0.09	0.12	0.14	0.16	0.20	
6 PM - 7 PM	1.77	1.83	-0.06	-3.4%	87.9	-0.11	-0.08	-0.06	-0.04	-0.01	*
7 PM - 8 PM	1.80	1.83	-0.04	-2.0%	83.4	-0.09	-0.06	-0.04	-0.01	0.02	*
8 PM - 9 PM	1.74	1.77	-0.03	-1.6%	78.5	-0.08	-0.05	-0.03	-0.01	0.02	*
9 PM - 10 PM	1.58	1.61	-0.03	-2.1%	74.7	-0.08	-0.05	-0.03	-0.02	0.01	*
10 PM - 11 PM	1.33	1.37	-0.03	-2.5%	72.2	-0.07	-0.05	-0.03	-0.02	0.00	*
11 PM - 12 AM	1.07	1.11	-0.04	-4.0%	70.4	-0.08	-0.06	-0.04	-0.03	-0.01	*
Daily	**30.44**	**29.33**	**1.12**	**3.8%**	**76.4**	**1.08**	**1.10**	**1.12**	**1.13**	**1.15**	

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

Note: Program Specific and Portfolio Adjusted impacts are the same for Residential TOU

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

Table 8-6 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 8-6: 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 to 6 PM Summer, 4 to 9 PM Winter)

Weather Conditions	Year	Accounts	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-2	2013	61,059	2.3	2.4	2.9	3.2	9.1	10.2	10.4	10.3	10.5	9.7	3.4	1.8
	2014	60,355	2.5	2.5	3.0	3.4	9.2	10.2	10.6	10.4	10.5	9.7	3.5	2.0
	2015	59,846	2.6	2.7	3.2	3.6	9.2	10.4	10.8	10.5	10.6	9.7	3.6	2.2
	2016	59,522	2.8	2.8	3.3	3.8	9.3	10.5	11.1	10.7	10.7	9.8	3.8	2.4
	2017	59,371	3.0	3.0	3.5	4.0	9.4	10.7	11.4	10.9	10.9	9.8	3.9	2.6
	2018	59,381	3.1	3.2	3.7	4.2	9.5	10.9	11.7	11.1	11.1	10.0	4.1	2.8
	2019	59,546	3.3	3.4	3.8	4.4	9.7	11.1	12.0	11.3	11.3	10.1	4.2	3.0
	2020	59,856	3.5	3.6	4.0	4.6	9.9	11.3	12.4	11.6	11.5	10.2	4.4	3.2
	2021	60,301	3.7	3.8	4.2	4.8	10.1	11.6	12.8	11.9	11.8	10.4	4.6	3.5
	2022	60,874	3.9	4.0	4.4	5.0	10.3	11.9	13.2	12.2	12.1	10.6	4.8	3.7
	2023	61,568	4.1	4.2	4.6	5.3	10.5	12.2	13.6	12.5	12.4	10.8	5.0	3.9
1-in-10	2013	61,059	2.0	2.1	2.3	3.4	11.2	11.9	11.0	11.7	11.2	11.5	2.1	1.6
	2014	60,355	2.1	2.3	2.5	3.6	11.3	12.0	11.2	11.8	11.3	11.5	2.2	1.8
	2015	59,846	2.3	2.5	2.6	3.8	11.4	12.2	11.4	11.9	11.4	11.6	2.4	2.0
	2016	59,522	2.5	2.7	2.8	4.0	11.5	12.3	11.7	12.1	11.5	11.7	2.6	2.3
	2017	59,371	2.7	2.8	3.0	4.1	11.7	12.5	12.0	12.3	11.7	11.8	2.8	2.5
	2018	59,381	2.9	3.0	3.1	4.3	11.9	12.8	12.3	12.6	11.9	12.0	3.0	2.7
	2019	59,546	3.1	3.2	3.3	4.5	12.1	13.1	12.6	12.9	12.2	12.1	3.2	2.9
	2020	59,856	3.3	3.4	3.5	4.8	12.3	13.3	13.0	13.2	12.4	12.3	3.4	3.1
	2021	60,301	3.5	3.7	3.7	5.0	12.6	13.7	13.4	13.5	12.7	12.6	3.6	3.4
	2022	60,874	3.7	3.9	3.9	5.2	12.9	14.0	13.8	13.9	13.0	12.8	3.8	3.6
	2023	61,568	3.9	4.1	4.1	5.4	13.2	14.4	14.2	14.2	13.4	13.1	4.0	3.8

8.6 Relationship Between Ex Post and Ex Ante Estimates

Table 8-7 summarizes the key factors that might lead to differences in ex post and ex ante estimates for the TOU program. As seen, timing of the peak period is expected to explain very little if any of the observed differences between ex post and ex ante impacts. Differences in weather and enrollment are the primary drivers of any observed differences.

Table 8-7: Summary of Factors Underlying Differences Between Ex Post and Ex Ante Impacts for the TOU Program

Factor	Ex Post	Ex Ante	Expected Impact
Weather	The average weekday peak period temperature across the 6 summer months = 74.3 for E-6 76.8 for E-7	Average weekday peak period temperature across the 6 summer months for 1-in- 2 year weather: 75.8 for E-6 77.0 for E-7 For 1-in-10 year weather: 79.0 for E-6 80.3 for E-7	Ex ante impacts will be higher than ex post under both 1-in-2 and 1-in-10 year weather
Peak Period	1 to 7 PM for E-6, 12 to 6 PM for E-7	Ex ante impacts are estimated for every hour of the day	No major difference in impacts from 1 to 6 PM
Enrollment	TOU population was approximately 10% E-6 and 90% E-7 customers	E-6 population is expected to grow and E-7 population is getting smaller	Higher per customer impacts

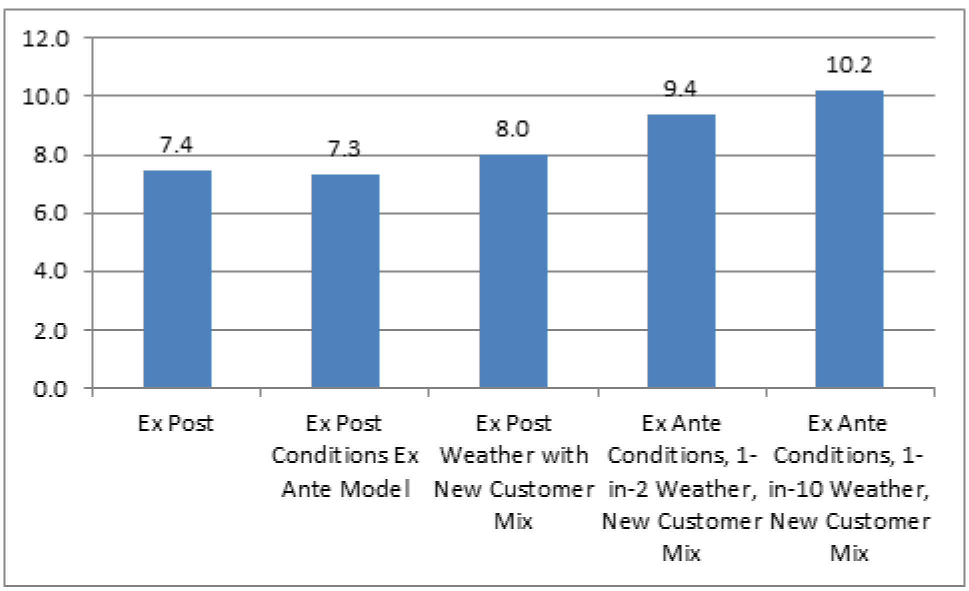
Table 8-8 and Figure 8-5 show how aggregate load impacts change as a result of differences in the factors underlying ex post and ex ante estimates for E-6 and E-7 rates combined for each of the six summer months. The figure graphs the average across the six summer months for each impact estimate. Column C shows the ex post estimates, which equal the sum of the aggregate values from Tables 7-1 and 7-2. Column D uses the ex ante model to estimate impacts based on ex post weather and the ex post distribution of participants across the two tariffs. Column E shows the effect of the shift in the participant population between E-6 and E-7 across the years from 2013 through 2024. In 2013, only about 10% of the total E-6/E-7 population was on the E-6 rate whereas in 2024, more than half of the total participation population was on E-6. Finally, columns F and G show the impact of ex ante weather conditions on the aggregate impact estimate.

Focusing on Figure 8-5, a comparison of the first two bar graphs shows that the ex ante model does a very good job of predicting average ex post impacts given ex post weather and the population mix. Indeed, there is only about a 1% difference in the two values. Changing the participant mix to reflect the forecasted participant mix in 2024 shows an increase of about 10% in the average value, reflecting the higher average load reduction for E-6 participants relative to E-7 participants. The last two columns reflect the effect of ex ante weather on aggregate load response. The increase of about 17%, from 8.0 to 9.4 MW going from ex post to 1-in-2 year ex ante weather is higher than one would expect. There was not sufficient time to try and determine what might be causing what, on the surface, appears to be higher than expected sensitivity to differences in weather. This should be an area of focus in subsequent evaluations.

Table 8-8: Differences in Ex Post and Ex Ante Impacts Due to Key Factors

Month	2013 Ex Post Aggregate Estimates		Aggregate Estimates Based on Ex Ante Model			
	Last Nine Temp	Aggregate Reduction	Historical Enrollment and Weather	Forecasted Enrollment: Historical Weather	Forecasted Enrollment: 1-in-2 Year Weather	Forecasted Enrollment: 1-in-10 Weather
A	B	C	D	E	F	G
May	61.9	5.0	5.1	4.4	6.9	7.5
Jun	65.1	4.8	9.0	6.6	9.1	9.6
Jul	68.3	7.2	7.0	8.2	10.9	11.7
Aug	71.1	9.2	7.7	9.9	10.9	11.9
Sep	69.8	10.2	9.4	10.0	10.7	11.5
Oct	68.8	8.1	5.5	8.8	7.7	8.9

Figure 8-5: Differences in Ex Post and Ex Ante Impacts Due to Key Factors



Appendix A Estimation of Whole House Reference Loads and Snapback for Ex Ante Estimation

This appendix contains relevant technical details on the steps used to predict whole-house loads and snap-back for the SmartRate ex ante impact analysis. 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 summers of 2012 and 2013.

A regression model similar to the model used to explain average ex post impacts from 2 to 7 PM as a function of temperatures was used to predict whole-house reference loads from 2 to 7 PM. This model was not estimated separately for each hour; rather, a single average value from 2 to 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 reference loads from 2 to 7 PM for the set of ex ante weather conditions.

The model was estimated across all LCAs and by SmartRate-only and dually enrolled customers separately. The final model specification takes as its dependent variable the whole-house reference load for each the last 7 events in 2012 and each event in 2013, 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:

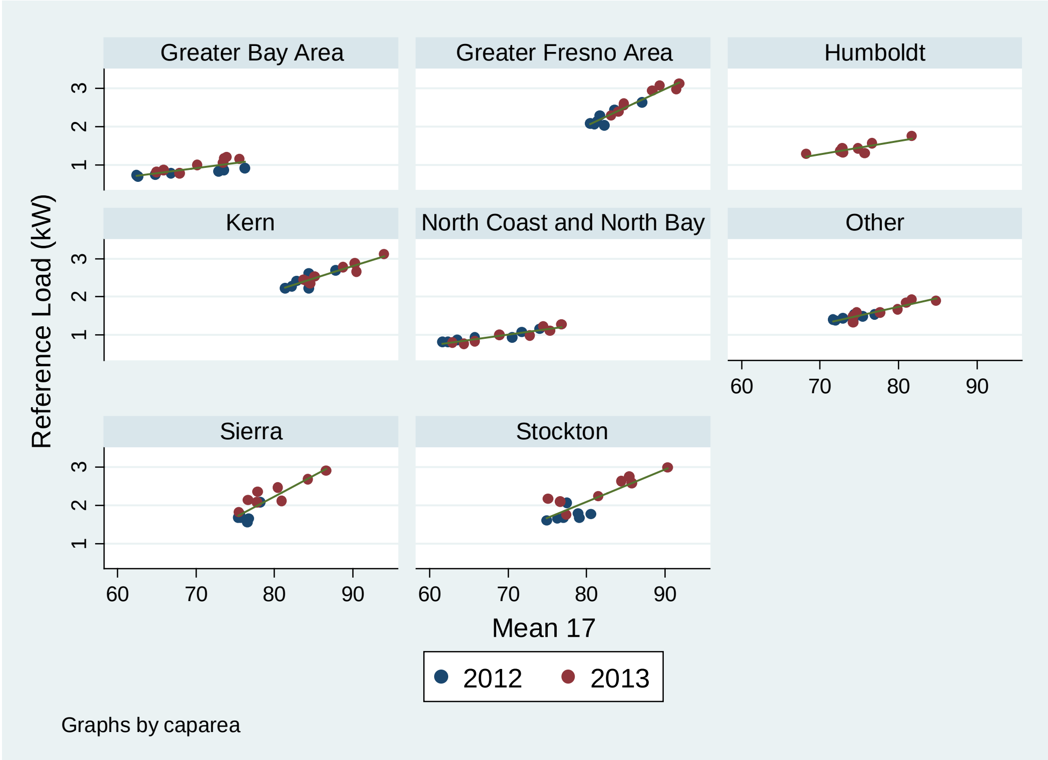
$$Reference\ Load = a + b \cdot mean17\ + \boldsymbol{\varepsilon}$$

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

Variable	Description
Reference Load (kW)	Per customer reference load for each event day, averaged over the event period
a	Estimated constant
b	Estimated parameter coefficient
$mean17$	Average temperature period midnight to 5 PM
$\boldsymbol{\varepsilon}$	The error term, assumed to be a mean zero and uncorrelated with any of the independent variables

Figures A-1 and A-2 show the results of the regressions for SmartRate-only and dually enrolled customers by LCA. The red circles show 2013 ex post reference loads for the representative population and the blue-gray circles show the same for 2012. The trendlines show the average whole-house reference loads we use as a basis for ex ante forecasts. Each LCA shows a different level of temperature sensitivity.

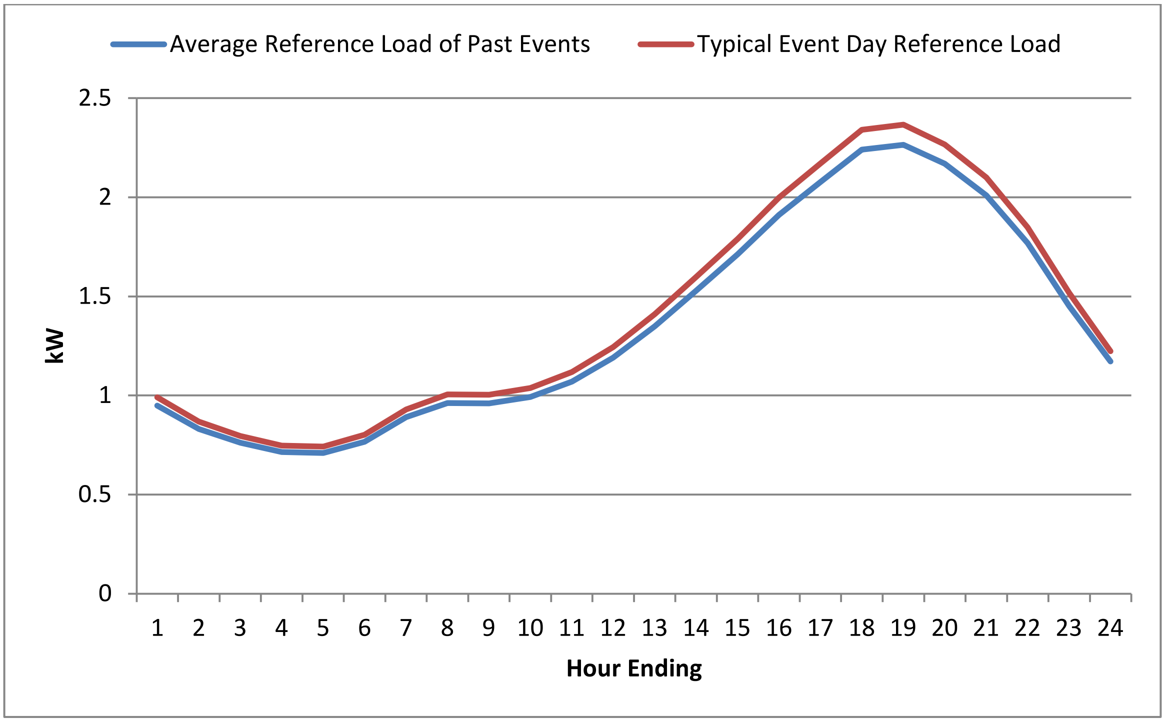
Figure A-1: 2012 and 2013 Reference Loads versus Mean17 by LCA for SmartRate-only Customers



The next step in estimating whole-house reference loads was to translate event-level reference load estimates to reference loads for each hour in the event window. The shape of the reference load was determined by the average of the control loads across each LCA for each of the events used in the ex ante analysis. Once the event-level reference loads were estimated using the regression model, these average hourly control usage estimates were adjusted up or down depending on ex ante weather conditions. The adjustment was based on the percentage difference between the predicted event-level reference loads and the average reference loads from 2012 and 2013. For example, if the predicted control group usage from 2 to 7 PM was 1% higher than the average control group usage from 2 to 7 PM across the 2012 and 2013 events, the hourly reference load was increased by 1%.

Figure A-2 illustrates this adjustment for the typical event day for Sierra in a 1-in-2 weather year. In the Sierra LCA, the average reference load from 2 to 7 PM in 2012 and 2013 was 2.04 kW. The predicted reference load from 2 to 7 PM on the typical event day was 2.13 kW. This is a difference of approximately 4%, so each hour in the average reference load was multiplied by 1.04 to achieve a full day's load shape for the event.

Figure A-2: Typical Event Day Reference Load Adjustment in Sierra (1-in-2 Weather Year)



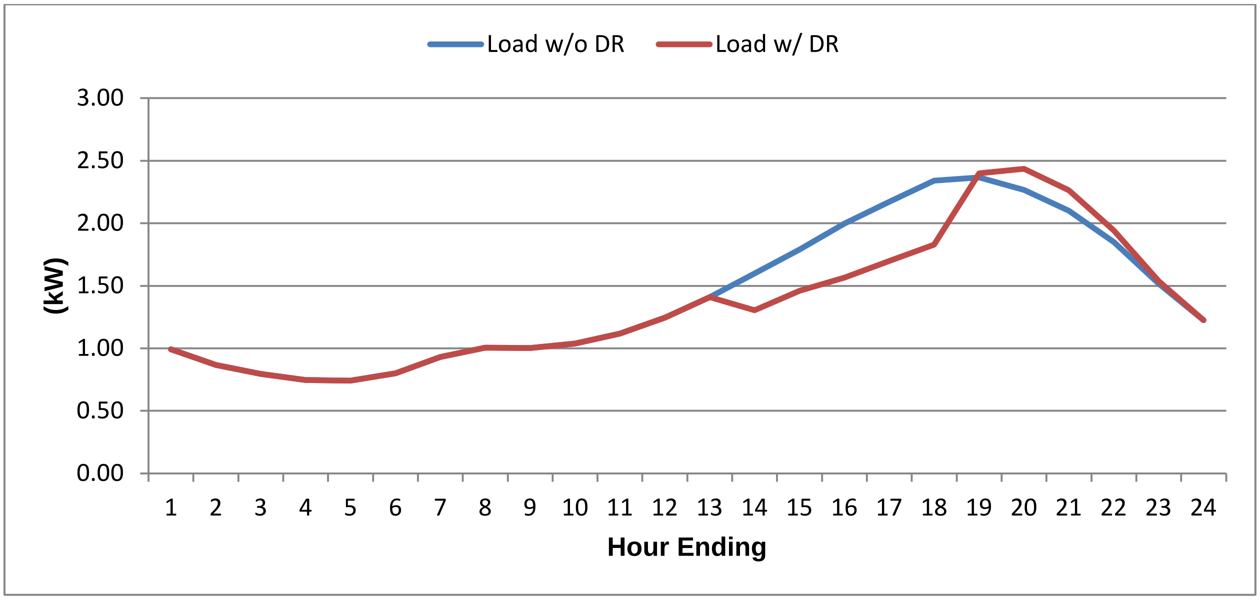
The next step was to calculate snapback for the ex ante weather conditions. First, the average snapback from 7 to 8 PM during the 2012 and 2013 events was calculated for each LCA. Snapback for the following hours was calculated as a percent of the snapback from 7 to 8 PM. Table A-2 presents the results of this calculation for the Sierra LCA for SmartRate-only customers. This illustrates that snapback is largest during the second hour after an event for this LCA. This is true for all LCAs.

Table A-2: Hourly Snapback as a Percentage of Snapback from 7 to 8 PM

Hour	Snapback as % of Snapback from 7 to 8 PM	Estimated Snapback (kW)
7–8 PM	100%	0.03
8–9 PM	489%	0.17
9–10 PM	476%	0.16
10–11 PM	273%	0.09
11 PM–12 AM	64%	0.02

To estimate SmartRate event load shapes, the hourly impact and snapback estimates were applied to the estimated whole-house reference load. The result of these calculations is presented in Figure A-3. This shows the estimated reference and SmartRate-only load shapes for the typical event day in Sierra with a 1-in-2 weather conditions. The impacts and snapback have been shifted to an event from 1 to 6 PM. This process is described in section 5.2.

Figure A-3: SmartRate Ex Ante Load Shape Estimate (Sierra, 1-in-2 Weather Year)



Appendix B Details on the Propensity Score Match for 2013 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 1.9 million PG&E residential customers who are not on SmartRate and for whom FSC (now Nexant) had interval data covering summer 2013. A propensity score matching procedure was then used to select from this pool a group 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.

Tables B-1 and B-2 compare the final matched control groups to the SmartRate sample based on LCA, CARE status and average monthly usage in June and July 2013. 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 B-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 B-1: Distributions of LCA, Usage and CARE Status for SmartRate-only Customers and Control Customers

Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	47%	47%	0.0	1.0
Greater Fresno	7%	7%	0.0	1.0
Humboldt	1%	1%	0.0	1.0
Kern	9%	9%	0.0	1.0
Northern Coast	4%	4%	0.0	1.0
Other	19%	19%	0.0	1.0
Sierra	7%	7%	0.0	1.0
Stockton	7%	7%	0.0	1.0
June 2012 kWh	682	678	-1.7	0.1
July 2012 kWh	738	761	7.9	0.0
Non-CARE	76%	78%	-9.5	0.0
CARE	24%	22%	-9.5	0.0

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

Characteristic	SmartRate Population	Matched Control Group	t	p
Greater Bay Area	38%	38%	0.0	1.0
Greater Fresno	10%	10%	0.0	1.0
Humboldt	1%	1%	0.0	1.0
Kern	5%	5%	0.0	1.0
Northern Coast	5%	5%	0.0	1.0
Other	19%	19%	0.0	1.0
Sierra	12%	12%	0.0	1.0
Stockton	10%	10%	0.0	1.0
June 2012 kWh	723	745	6.5	0.0
July 2012 kWh	804	862	15.4	0.0
Non-CARE	82%	79%	10.3	0.0
CARE	18%	21%	10.3	0.0

Figures B-1 and B-2 show histograms of average hourly usage during the 2 to 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 B-1: Histogram of Average Hourly Usage for SmartRate-only Customers and Control Group

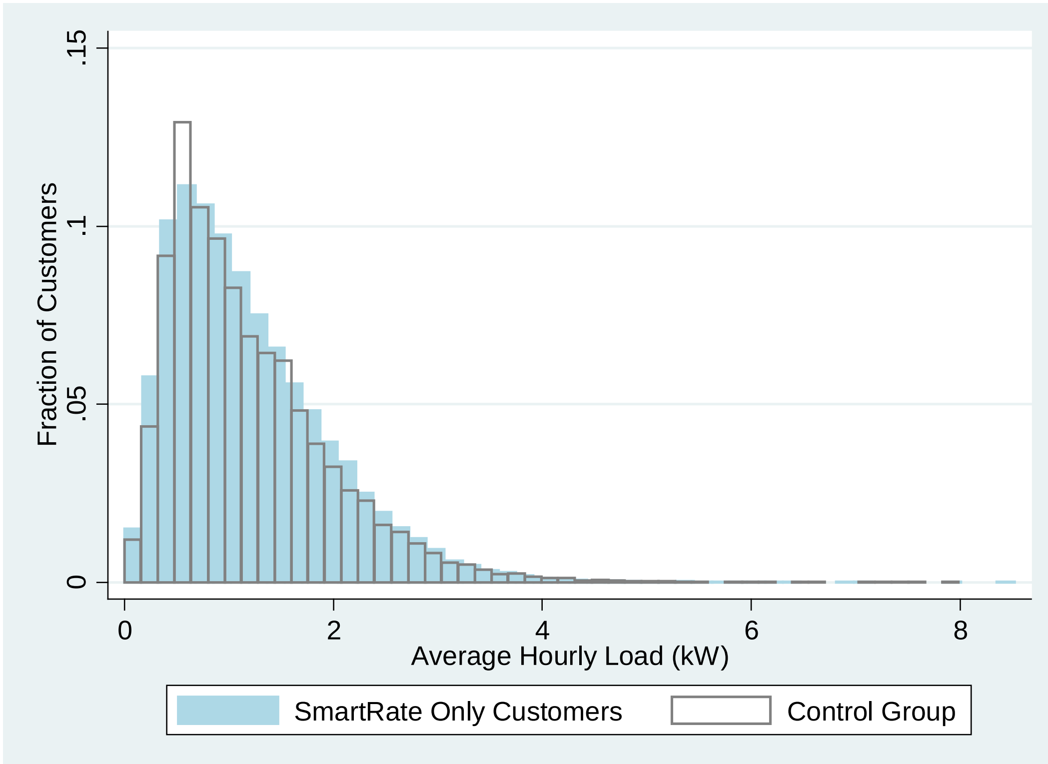
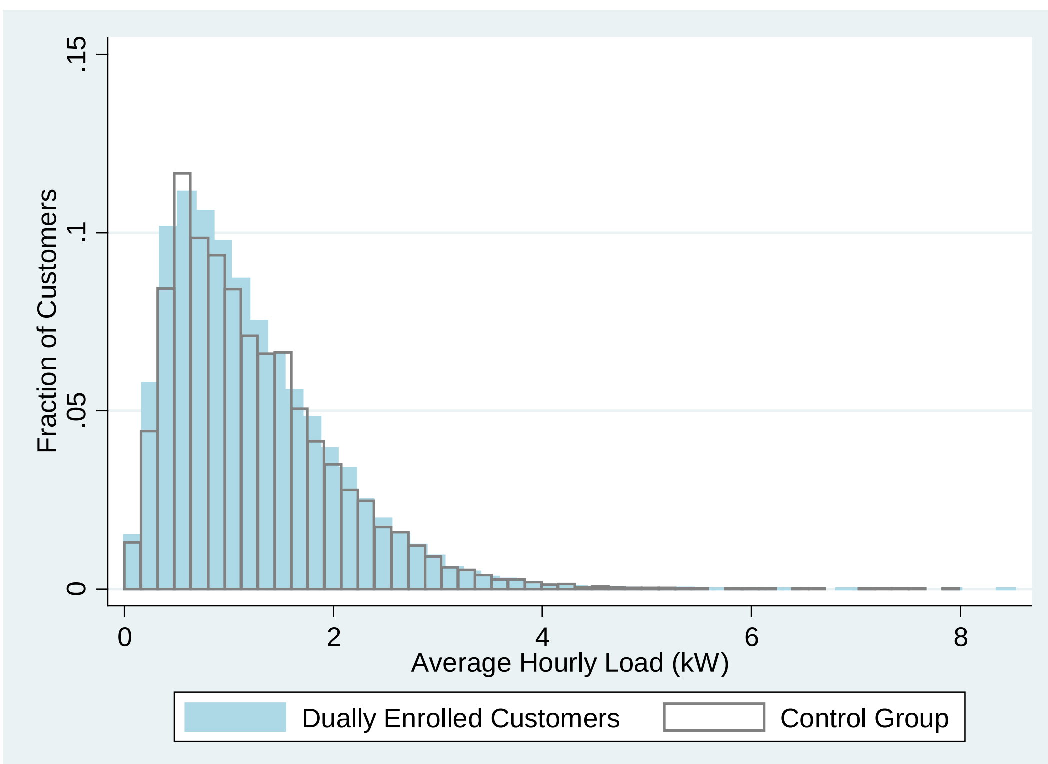


Figure B-2: Histogram of Average Hourly Usage for Dually Enrolled Customers and Control Group



Figures B-3 and B-4 show that the loads of 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.

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

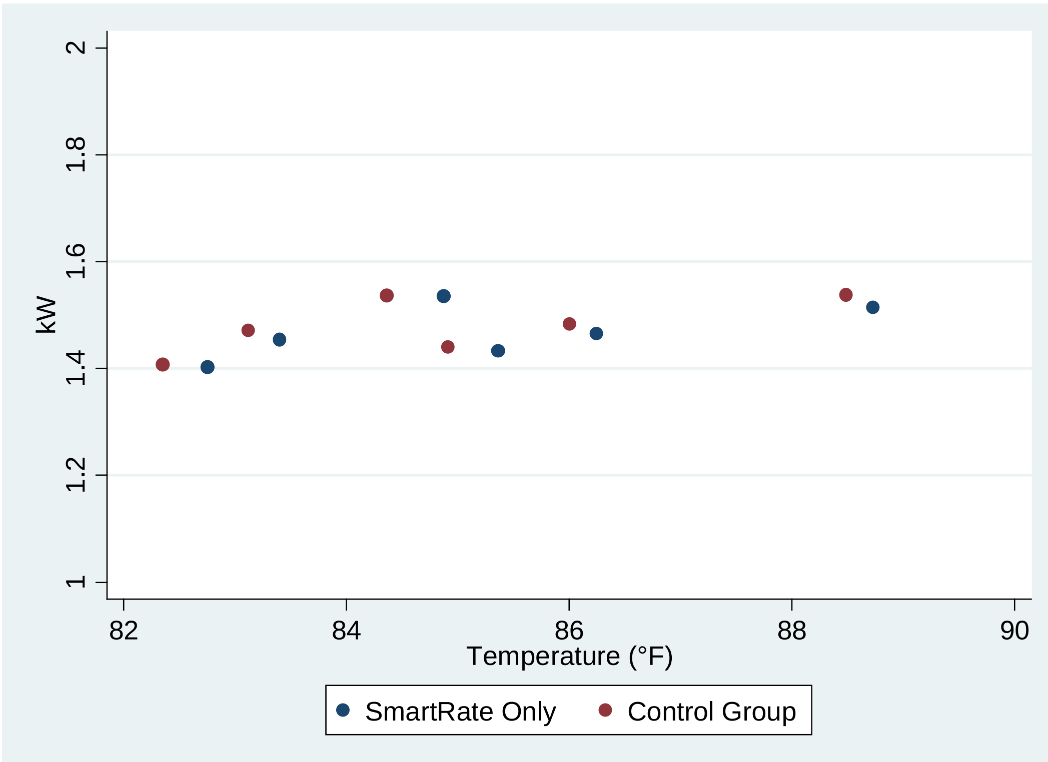


Figure B-4: Average Loads and Temperatures from 2 to 7 PM on Hot, Non-event Days

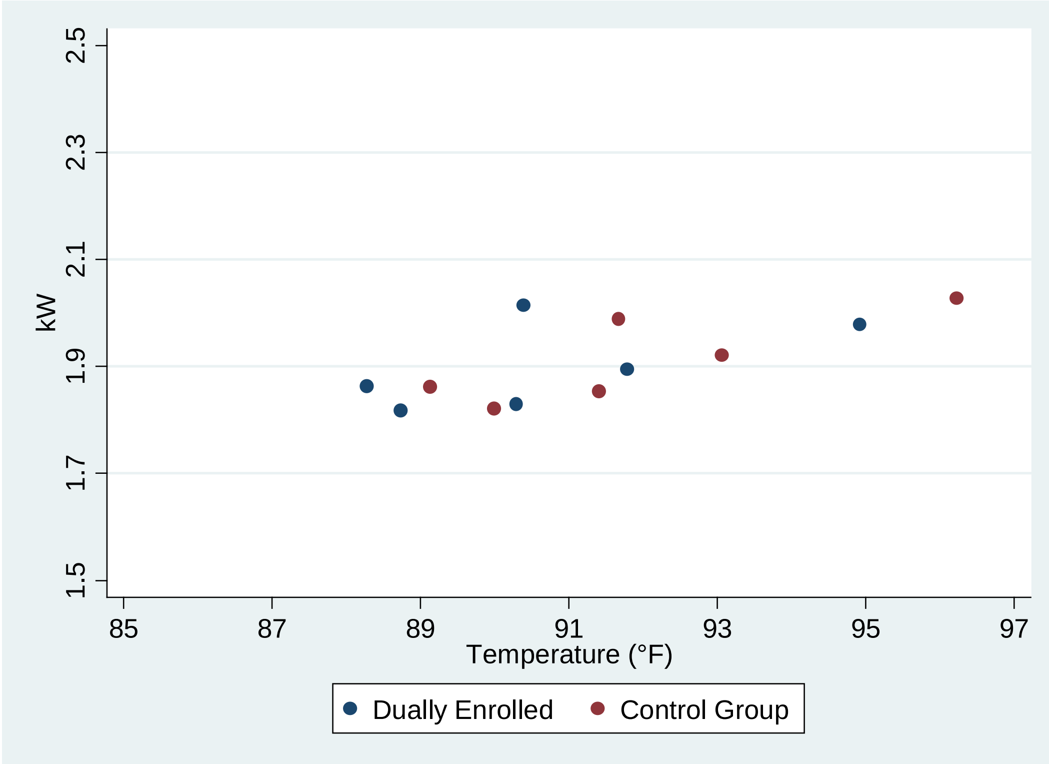
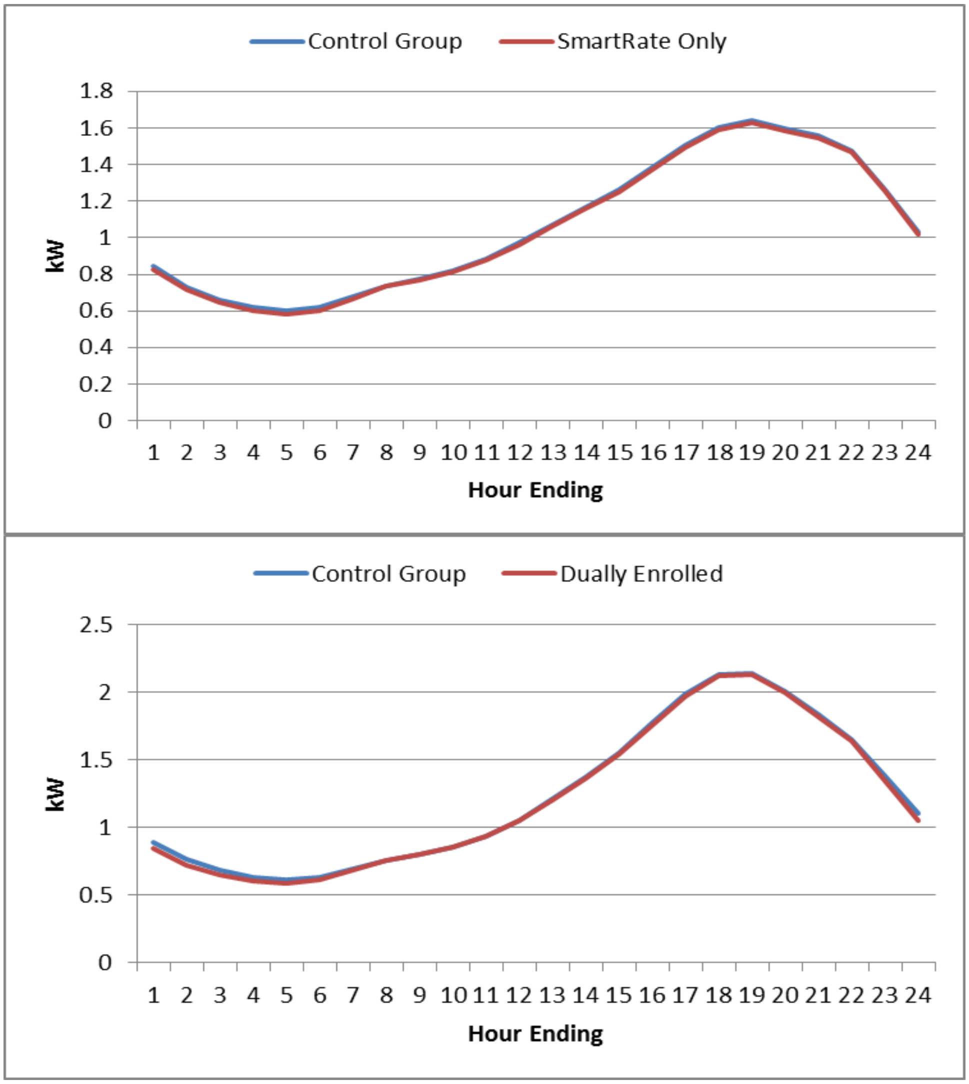


Figure B-5 shows average hourly usage for each hour of the 10 hot, non-event days used in the match. When averaged over the 10 days, the match is close to perfect. The match is less perfect on a day-by-day basis and Nexant will provide that data by request.

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

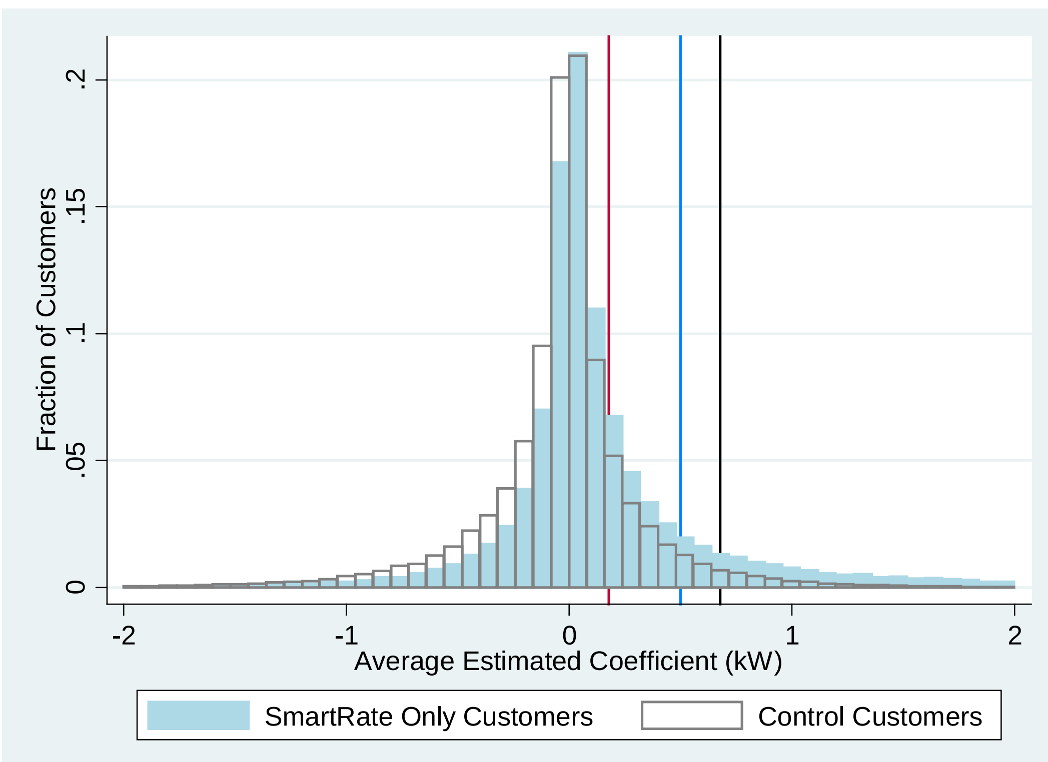


Appendix C Details of Determining High Responders

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 0.18 kW, we note that only 5% of customers in the control group have a noise estimate greater than 0.50 kW. Given that the mean SmartRate impact is 0.18 kW (per the individual customer regressions), any customer with a load impact estimate greater than 0.68 kW has a 95% or greater of having a true impact greater than 0.18 kW.[28] This is a fairly weak statement, since only a relatively small fraction of customers have impact estimates above 0.68 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 0.18 kW, the blue line is at 0.50 kW and the black line is at 0.68 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



28 This calculation is explained in detail in the next paragraph.

To calculate the value 0.68 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 (0.18 kWh) given that the estimated impact equals threshold t (Equation 1). It is a given that the estimated impact ($\hat{\imath}$) is equal to the true impact (i) plus noise, ε (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, ε, 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 0.50 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 0.68 kWh.

$$P(i > 0.18 \mid \hat{\imath} = t) = 95\% \text{ (Equation 1)}$$

$$\hat{\imath} = i + \varepsilon \text{ (Equation 2)}$$

$$i = \hat{\imath} - \varepsilon \text{ (Equation 3)}$$

$$P(\hat{\imath} - \varepsilon > 0.18 \mid \hat{\imath} = t) = 95\% \text{ (Equation 4)}$$

$$P(t - \varepsilon > 0.18) = 95\% \text{ (Equation 5)}$$

$$P(\varepsilon < t - 0.18) = 95\% \text{ (Equation 6)}$$

$$P(\varepsilon < 0.50) = 95\% \text{ (Equation 7)}$$

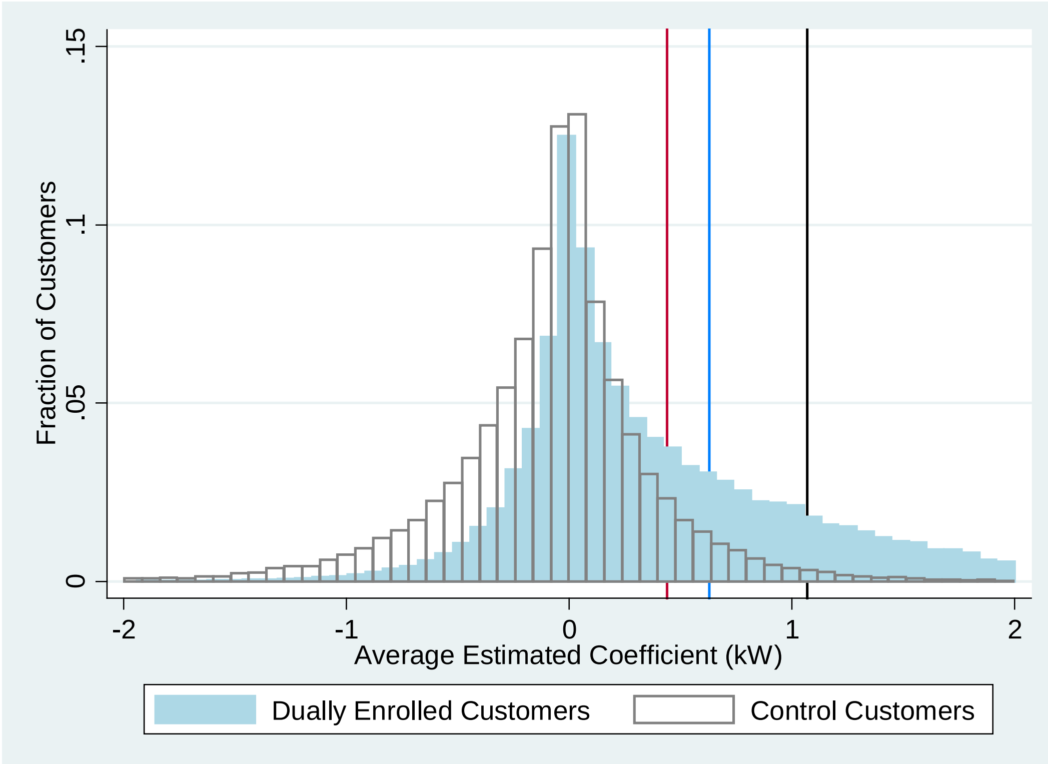
$$0.50 = t - 0.18 \text{ (Equation 8)}$$

$$t = 0.68 \text{ (Equation 9)}$$

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 0.63 kW. Given that the mean SmartRate impact is 0.44 kW for dually enrolled customers, any customer with a load impact estimate greater than 1.07 kW has a 95% or greater of having a true impact greater than 0.44 kW.[29] Figure C-2 shows the distribution of estimated coefficients for both the dually enrolled population and control group. The red line marks 0.44 kW, the blue line is at 0.63 kW and the black line is at 1.07 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.

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

Figure C-2: Distribution of Average Estimated Coefficients for Dually Enrolled and Control Group Customers



Appendix D 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 2012 and 2013.

Prior to regression modeling, Nexant developed a sample of customers that experienced most of the 2012 events and all the 2013 events and that had similar observable characteristics to the SmartRate population as of October 2013. October 2013 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 2012 and 2013 evaluations. Customers were matched on CARE status, event day hourly usage from 7 AM to 7 PM, and an average hourly usage throughout the event days. The match was performed within each LCA.

Next, the same matched control customers from the ex post analyses from 2012 and 2013 were used as the control group for the ex ante analysis. Table D-1 shows evidence of the validity of this match. The four groups are distributed similarly over the eight LCAs. The groups have comparable event period usage from the hours from 2 to 7 PM and approximately the same percentage of customers in each group are CARE customers.

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

Characteristic	SmartRate Population as of 10-30-2013	Customers on SmartRate for Two Years	Control Group for 2012 Event Days	Control Group for 2013 Event Days
Greater Bay Area	47.55%	47.55%	52.22%	47.61%
Greater Fresno	7.03%	7.03%	7.46%	7.03%
Humboldt	1.16%	1.16%	0.00%	1.17%
Kern	8.69%	8.69%	8.65%	8.59%
Northern Coast	3.78%	3.78%	4.10%	3.79%
Other	18.69%	18.69%	15.41%	18.71%
Sierra	6.40%	6.40%	6.64%	6.40%
Stockton	6.69%	6.69%	5.52%	6.69%
Care	23.64%	23.70%	28.79%	22.36%
kW from 2-7 PM	1.33	1.33	1.28	1.33

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

Characteristic	SmartRate Population as of 10-30-2013	Customers on SmartRate for Two Years	Control Group for 2012 Event Days	Control Group for 2013 Event Days
Greater Bay Area	38.30%	38.30%	42.45%	38.14%
Greater Fresno	9.89%	9.89%	10.68%	9.93%
Humboldt	0.47%	0.47%	0.00%	0.48%
Kern	4.84%	4.84%	4.84%	4.85%
Northern Coast	5.28%	5.28%	5.90%	5.21%
Other	19.46%	19.46%	14.78%	19.55%
Sierra	11.76%	11.76%	12.71%	11.82%
Stockton	9.99%	9.99%	8.64%	10.02%
Care	18.04%	17.98%	27.56%	20.77%
kW from 2-7 PM	1.52	1.52	1.47	1.52

Figures D-1 and D-2 show average hourly usage for both groups and their control groups on event days. Over the event period (2 to 7 PM), usage is very similar between the two groups.

Figure D-1: Average Usage on Event Days for the Current SmartRate-only Population, Two-year SmartRate-only Population, and the 2012 and 2013 Control Groups

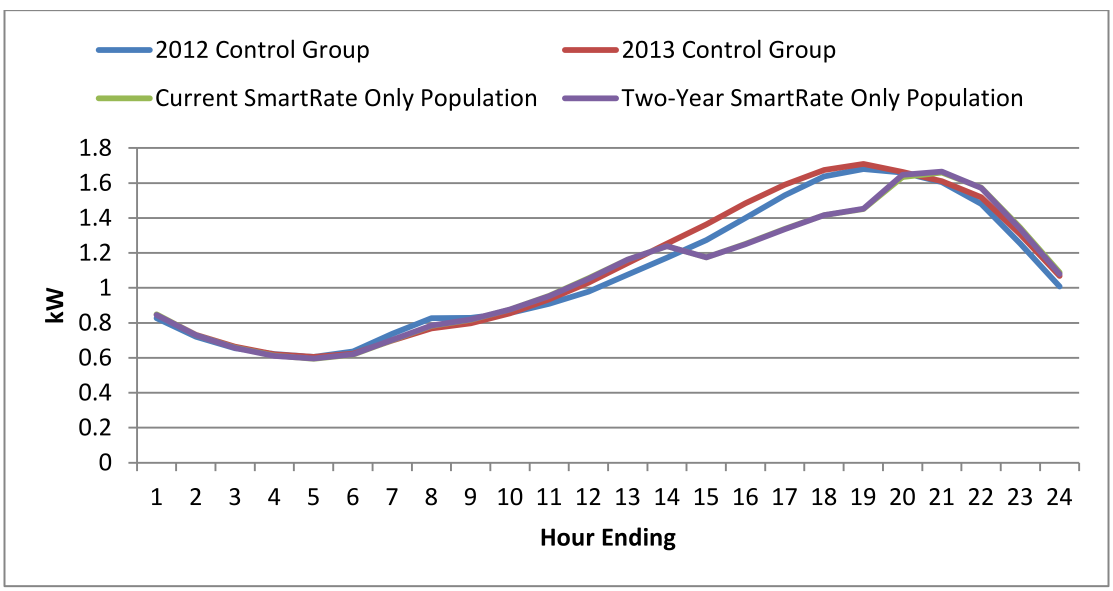
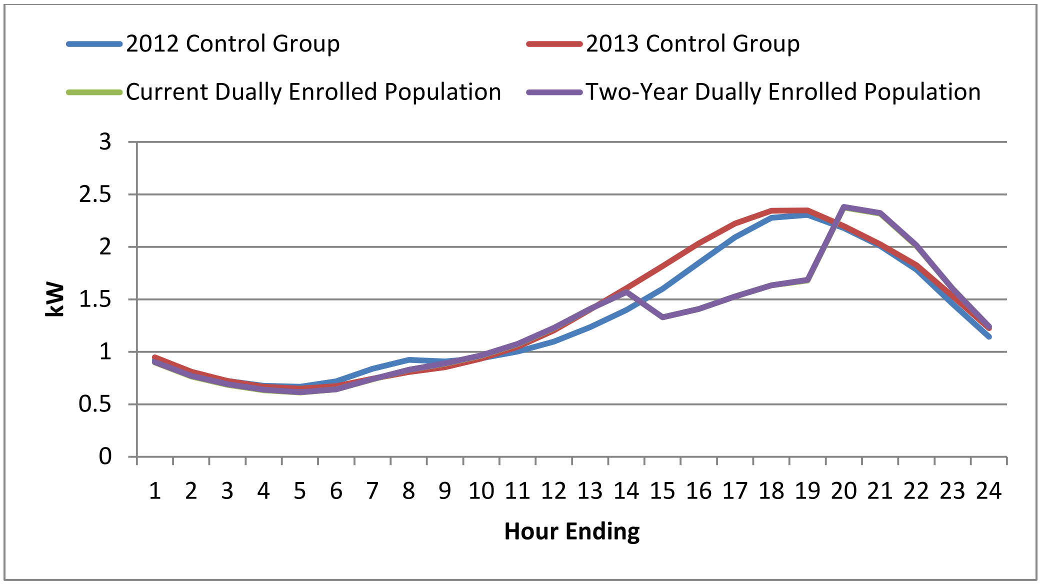


Figure D-2: Average Usage on Event Days for the Current SmartRate-only Population, Two-year Dually Enrolled Population, and the 2012 and 2013 Control Groups



These matched sample and control groups were used to estimate a set of ex post estimates for 2012 and 2013 that represent what the October 2013 SmartRate population would have provided if they had been in the program the whole time. These ex post estimates are shown in Table D-3 and Table D-4. The impact estimates are similar to those in the Ex-Post analysis.

Table D-3: 2012 and 2013 Event Impacts for SmartRate-only Sample

Date	Load without DR (kW)	Impact (kW)	Percent Impact	Temperature (ºF)
23-Jul-12	1.37	0.24	17%	83
4-Sep-12	1.20	0.18	15%	82
13-Sep-12	1.22	0.16	13%	83
14-Sep-12	1.23	0.15	12%	81
1-Oct-12	1.27	0.21	16%	93
2-Oct-12	1.31	0.18	14%	94
3-Oct-12	1.22	0.15	12%	84
7-Jun-13	1.45	0.22	15%	89
28-Jun-13	1.73	0.31	18%	94
1-Jul-13	1.77	0.27	15%	93
2-Jul-13	1.85	0.28	15%	92
19-Jul-13	1.37	0.19	14%	85
19-Aug-13	1.62	0.23	14%	88
9-Sep-13	1.48	0.23	16%	89
10-Sep-13	1.25	0.14	11%	81

Table D-4: 2012 and 2013 Event Impacts for Dually Enrolled Sample

Date	Load without DR (kW)	Impact (kW)	Percent Impact	Temperature (ºF)
23-Jul-12	1.74	0.44	25%	86
4-Sep-12	1.44	0.37	26%	87
13-Sep-12	1.50	0.38	25%	88
14-Sep-12	1.47	0.35	24%	86
1-Oct-12	1.61	0.44	28%	95
2-Oct-12	1.67	0.42	25%	96
3-Oct-12	1.52	0.34	23%	88
7-Jun-13	1.93	0.62	32%	95
28-Jun-13	2.49	0.83	33%	98
1-Jul-13	2.58	0.78	30%	98
2-Jul-13	2.66	0.77	29%	97
19-Jul-13	1.79	0.50	28%	91
19-Aug-13	2.24	0.64	28%	93
9-Sep-13	2.01	0.57	28%	94
10-Sep-13	1.52	0.33	22%	83