2015 Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-Based Pricing Programs: *Ex-Post* and *Ex-Ante* Report

Public Version

CALMAC Study ID PGE0371

Steven D. Braithwait
Daniel G. Hansen
David A. Armstrong

April 1, 2016

Christensen Associates Energy Consulting, LLC
800 University Bay Drive, Suite 400
Madison, WI 53705-2299

Voice 608.231.2266 Fax 608.231.2108

Table of Contents

List of Tables

List of Figures

Executive Summary

This report documents *ex-post* and *ex-ante* load impact evaluations for Pacific Gas and Electric Company's ("PG&E") residential time-varying pricing programs for program year 2015. Programs covered include SmartRate™ [1] and several time-of-use (TOU) rates. The report addresses the two primary objectives of providing: 1) estimates of *ex-post* load impacts for residential SmartRate and TOU customers in 2015, and 2) *ex-ante* forecasts of load impacts for 2016 through 2026 that are based on PG&E's enrollment forecasts and the *ex-post* load impact estimates produced in this study.

ES.1 Resources Covered

PG&E's SmartRate is a version of critical peak pricing (CPP) that is implemented as an overlay on customers' otherwise applicable tariff. For most participants, this is the E-1 tariff, which is a multi-tier inclining block rate, with an initial block representing a baseline level of usage that varies by climate zone. SmartRate customers experience a surcharge of $0.60 on consumption during peak hours on event days, and receive discounts on consumption in all other hours of June through September. Low-income customers who qualify for CARE (California Alternative Rates for Energy), receive substantial discounts on each E-1 tier price, including a tail-block price that is less than half the standard price.

SmartRate customers are also eligible to enroll in PG&E's SmartAC program, an air conditioner cycling program. Customers enrolled in both programs have their air conditioner controlled during the event window on SmartRate event days. The current study evaluates load impacts on SmartRate event days for both SmartRate-only and dually enrolled customers. A comprehensive evaluation of the SmartAC program is being conducted in a separate project.

PG&E currently has two voluntary residential TOU rates, E-6 and E-7, although a number of rate changes are currently taking place, or soon will take place. Both current rates are seasonal, with generally higher prices in summer (May through October) than in winter. The E-7 tariff has two pricing periods, a six-hour (12 to 6 p.m.) weekday peak period, and an off-peak period in all other hours. The E-6 tariff has three pricing periods in summer and two in winter. The summer peak period covers the six hours from 1 to 7 p.m. on weekdays, a split partial-peak is from 10 a.m. to 1 p.m. and 7 to 9 p.m. on weekdays, and 5 p.m. to 8 p.m. on weekends. All other hours are off peak. In winter, there is no peak period, and the partial-peak period applies to hours 5 to 8 p.m. on weekdays. All other hours are off peak.

PG&E is on schedule to offer two new optional TOU rates, E-TOU-A and E-TOU-B beginning in 2016. Customers currently on E-6 will be allowed to remain on the rate.

[1] References to the terms SmartRate and/or SmartAC in this report are intended to refer to the trademarked term, whether or not the ™ indication is present.

Customers on E-7 will be defaulted to the new E-TOU-A rate, but will be given the option of moving to E-6 or E-TOU-B. As described below, *ex-ante* forecasts for the two new rates, as well as for E-6, are provided as part of this study.

ES.2 Evaluation Methodologies

The SmartRate and residential TOU evaluations involved conceptually similar methodologies. These included selecting quasi-experimental matched control groups and conducting difference-in-differences analyses using regression analysis. Differences in the evaluations involved the nature and time periods of the customer usage data. For SmartRate, an event-based program, the analysis used hourly load data on event days and comparable non-event days for both SmartRate and matched control group customers. For the non-event-based TOU rates, the analysis involved estimating differences between TOU and control group customer loads for the average and peak weekday in each month from October 2014 to September 2015. For evaluating recently enrolled E-6 customers, data for the prior twelve months were used as the basis for selecting matched control group customers and in the difference-in-differences regression analysis.

ES.3 Ex-Post Load Impacts

SmartRate

Table ES.1 summarizes reference load and load impact results for SmartRate-only customers in 2015. Fifteen events were called from June through September. Program enrollment generally increased over the summer period, averaging just over 92,000 customers. Aggregate load impacts averaged 19.5 MW, which compares to 18.3 MW in the 2014 study. The largest load impact occurring on September 10, on the second of three consecutive events, and the smallest occurring on August 18, which had the mildest temperature (91 degrees) of all the events. The percentage load impacts were consistent across events, averaging 13 percent, which compares to 14 percent in 2014.

Table ES.1: Average Event-Hour Load Impacts, by Event – *SmartRate-only*

Events	Enrolled	Aggregate		Per-Customer		% Load Impact	Ave. Event Temp.
		Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)		
12-Jun-15	89,045	131.3	17.9	1.47	0.20	14%	92
25-Jun-15	88,435	139.0	19.8	1.57	0.22	14%	95
26-Jun-15	88,413	141.5	17.8	1.60	0.20	13%	93
30-Jun-15	88,248	152.4	21.2	1.73	0.24	14%	98
1-Jul-15	88,178	132.8	17.5	1.51	0.20	13%	91
28-Jul-15	89,444	137.8	20.6	1.54	0.23	15%	96
29-Jul-15	89,634	153.6	21.7	1.71	0.24	14%	97
30-Jul-15	89,799	135.4	17.7	1.51	0.20	13%	92
17-Aug-15	93,496	164.6	21.2	1.76	0.23	13%	97
18-Aug-15	93,850	137.5	16.1	1.46	0.17	12%	91
27-Aug-15	96,355	149.5	19.5	1.55	0.20	13%	95
28-Aug-15	96,590	159.3	18.1	1.65	0.19	11%	95
9-Sep-15	97,521	156.1	21.8	1.60	0.22	14%	98
10-Sep-15	97,613	163.5	21.9	1.68	0.22	13%	97
11-Sep-15	97,704	151.6	19.3	1.55	0.20	13%	94
Average Event Day	**92,288**	**147.1**	**19.5**	**1.59**	**0.21**	**13%**	**95**

Table ES.2 shows comparable information for customers that were dually enrolled in SmartRate and SmartAC. Aggregate load reductions for the average event were 20.0 MW, which compares to 20.4 MW in 2014 when enrollment was somewhat higher (approximately 40,300 for the average event compared to 36,600 in 2015). Per-customer load impacts (0.55 kW) for the average event were substantially larger than those for SmartRate-only customers. The percentage load reduction of 25 percent for the average event was the same as in 2014.

Table ES.2: Average Event-Hour Load Impacts, by Event – *Dually-enrolled*

		Aggregate		Per-Customer			
Events	Enrolled	Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)	% Load Impact	Ave. Event Temp.
12-Jun-15	37,607	75.7	20.3	2.01	0.54	27%	96
25-Jun-15	37,215	80.6	22.7	2.16	0.61	28%	98
26-Jun-15	37,146	82.4	21.8	2.22	0.59	26%	97
30-Jun-15	36,989	89.7	25.2	2.42	0.68	28%	101
1-Jul-15	36,938	76.4	18.9	2.07	0.51	25%	95
28-Jul-15	36,611	76.0	21.3	2.08	0.58	28%	98
29-Jul-15	36,573	88.1	25.3	2.41	0.69	29%	100
30-Jul-15	36,545	76.1	19.1	2.08	0.52	25%	95
17-Aug-15	36,364	86.6	21.2	2.38	0.58	24%	100
18-Aug-15	36,336	67.2	13.7	1.85	0.38	20%	93
27-Aug-15	36,262	73.5	17.4	2.03	0.48	24%	97
28-Aug-15	36,254	78.8	17.7	2.17	0.49	22%	97
9-Sep-15	36,069	75.4	19.0	2.09	0.53	25%	100
10-Sep-15	36,044	80.5	20.1	2.23	0.56	25%	100
11-Sep-15	36,016	73.4	17.1	2.04	0.47	23%	96
Average Event Day	**36,598**	**78.7**	**20.0**	**2.15**	**0.55**	**25%**	**98**

In addition to the detailed results reported above, load impact results were also produced for various subsets of customers, and several analyses of SmartRate customers were conducted. These results may be summarized as follows:

- The largest aggregate load reductions for both SmartRate-only and dually enrolled customers occurred in the two LCAs with the largest enrollment – Greater Bay Area and Other (not in any other LCA). The largest per-customer load reductions were generally in the warmer LCAs such as Greater Fresno, Kern, and Sierra.
- CARE customers accounted for 25 to 30 percent of SmartRate-only and dually enrolled customers.[2] For the former group, non-CARE customers provided more than proportionately higher aggregate load reductions, due to per-customer reductions that were twice as large as those for CARE customers. For the latter group, non-CARE customers again produced the largest aggregate reduction, but the per-customer load impacts were more similar.
- Analysis of the load reductions of individual customers found that approximately 67 percent of SmartRate-only customers and 76 percent of dually-enrolled customers had negatively signed load impact coefficients (statistically significant

[2] CARE customers make up 27 percent of the PG&E residential population.

or not), indicating that they reduced usage on average during event hours. Focusing only on estimates that were statistically significant at a strict 95 percent confidence level, 17 percent of SmartRate-only customers and 32 percent of dually enrolled customers provided statistically significant load reductions. At a more relaxed 90 percent level, the numbers were 22 and 38 percent respectively.

- Analysis of bill protection status and refunds found that 36 percent of SmartRate-only customers, and 14 percent of dually-enrolled customers were eligible for bill protection in 2015. Among those refund-eligible customers, 34 percent of SmartRate-only, and 45 percent of dually-enrolled customers experienced bill increases and received refunds. Somewhat smaller percentages of customers who were not eligible for bill protection experienced bill increases: 26 percent of SmartRate-only, and 37 percent of dually-enrolled customers. Overall, 29 percent of SmartRate-only customers and 38 percent of dually-enrolled customers experienced bill increases, while the remainder experienced bill reductions.
- Approximately 25,000 customers dropped out of SmartRate over the period of analysis (October 2014 through September 2015), but 30,000 new customers enrolled, resulting in about 5,000 net new customers.

Residential TOU

Table ES.3 summarizes the average reference loads and load impacts for the E-6 incremental customers (those who enrolled in E-6 during the October 2014 to September 2015 analysis period) for the relevant peak period (*i.e.*, 1 to 7 p.m. for May through October, and 5 to 8 p.m. for November through April), for the average weekday in each month, on an aggregate and per-customer basis.[3] The months are shown starting with the first month included in the analysis (October 2014), and the shaded areas indicate summer months. Enrollment rose throughout the period to nearly 6,500 in September 2015. Aside from May, which had relatively mild temperatures, the summer peak period load reductions averaged 8 to 9 percent. Percentage load reductions in the winter months were somewhat smaller, at 5 to 6 percent. The table also shows the number of E-6 embedded customers in each month, which consists of customers enrolled in E-6 prior to October 1, 2014.

[3] We refer to the 5 to 8 p.m. period as the "peak" period in the winter months since that is the only time period that has a higher differentiated price. However, the tariff refers to the price in that period as a *partial* peak price.

Table ES.3: Average Weekday Peak Load Reductions by Month – *E-6 Incremental*

Month	Incremental Enrollment	Embedded Enrollment	Aggregate		Per-Customer		% Peak Load Impact	Ave. Peak Temp.
			Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)		
10/2014	422	8,962	0.29	0.02	0.68	0.05	8%	71
11/2014	734	8,822	0.74	0.04	1.01	0.05	5%	59
12/2014	1,140	8,739	1.35	0.10	1.19	0.09	7%	55
1/2015	1,547	8,625	1.70	0.11	1.10	0.07	6%	55
2/2015	1,861	8,531	1.83	0.11	0.98	0.06	6%	59
3/2015	2,261	8,431	1.88	0.12	0.83	0.05	6%	65
4/2015	2,842	8,322	2.16	0.11	0.76	0.04	5%	65
5/2015	3,496	8,209	2.03	0.06	0.58	0.02	3%	66
6/2015	4,250	8,055	3.27	0.29	0.77	0.07	9%	81
7/2015	5,476	7,901	4.53	0.39	0.83	0.07	9%	82
8/2015	6,469	7,762	5.34	0.51	0.83	0.08	9%	83
9/2015	6,469	7,762	4.96	0.42	0.77	0.06	8%	81

Table ES.4 shows estimated average peak period (12 p.m. to 6 p.m.) reference loads and load impacts by month for the non-NEM E-7 embedded customers, beginning with the first month of analysis, October 2014. Customers taking service under E-7 have been enrolled for some time, which ruled out the possibility of selecting control group customers on the basis of *pre-treatment* load profiles. As a result, differences between the load profiles of the E-7 customers and the control group customers selected on the basis of matched monthly billing data are likely to reflect a combination of two factors – 1) pre-existing loads that are characterized by relatively low peak period usage (self-selection), and 2) load responses to the TOU rate. The lightly shaded summer months show generally larger reference load values than in winter, and load reductions of 11 or 12 percent, reaching 0.17 kW in the core summer months. The peak load reductions and percentage reductions are slightly smaller in the non-summer months.

Table ES.4: Average Weekday Peak Load Reductions by Month – *E-7 Embedded*

		Aggregate		Per-Customer			
Month	Enrolled	Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)	% Peak Load Impact	Ave. Peak Temp.
October 2014	51,026	53.4	6.3	1.05	0.12	12%	76
November 2014	50,690	55.3	4.9	1.09	0.10	9%	64
December 2014	50,492	65.1	5.0	1.29	0.10	8%	57
January 2015	50,136	56.7	5.5	1.13	0.11	10%	59
February 2015	49,810	50.1	5.2	1.01	0.10	10%	64
March 2015	49,550	47.1	5.2	0.95	0.11	11%	69
April 2015	49,248	47.4	5.3	0.96	0.11	11%	69
May 2015	48,942	47.4	5.5	0.97	0.11	12%	69
June 2015	48,629	68.5	8.2	1.41	0.17	12%	85
July 2015	48,355	72.5	8.2	1.50	0.17	11%	86
August 2015	47,777	67.7	8.0	1.42	0.17	12%	86
September 2015	47,777	59.8	6.7	1.25	0.14	11%	84

ES.4 Ex-Ante Load Impacts

SmartRate

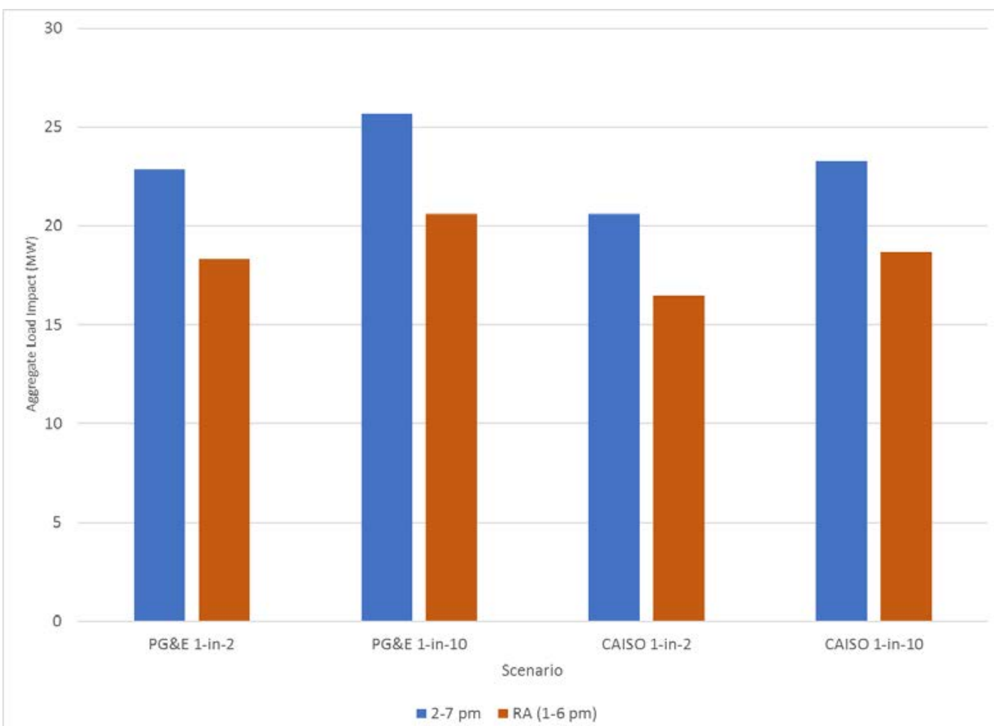
Ex-ante forecasts of SmartRate load impacts were developed based on a weather-sensitivity analysis of the 2015 per-customer *ex-post* load impacts, and PG&E enrollment forecasts. PG&E anticipates enrollment in SmartRate-only and dually-enrolled to remain stable at 110,200 and 34,800, respectively from 2017 onward. Table ES.5 shows average hourly *ex-ante* load impacts in 2017, by month on a per-customer and aggregate basis, for the RA window of 1 to 6 p.m., for the PG&E 1-in-2 weather scenario. Results are shown by enrollment type and in total, and summer months are set off by horizontal lines. The largest load impacts (34.3 MW for the total program) occur on the August peak day.

The use of the RA window rather than the SmartRate event window of 2 to 7 p.m. has the effect of reducing average event-hour load impacts by approximately one-fifth. This effect, along with the weather sensitivity of the load impacts, is illustrated in Figure ES.1, which shows aggregate load impacts for SmartRate-only, for the August peak day in 2017 under the four weather scenarios and the two alternative assumptions regarding the event window –program hours and RA hours. Load impacts are greatest under the PG&E 1-in-10 scenario, and the discounted values for the RA window are apparent.

Table ES.5: *Ex-Ante* Load Impacts by Day Type – *PG&E 1-in-2 Weather*

Day Type	Per-Customer (kW) SmartRate-only	Per-Customer (kW) Dually-enrolled	Aggregate (MW) SmartRate-only	Aggregate (MW) Dually-enrolled	Aggregate (MW) Total Program
January Peak	0.085	0.115	9.4	4.0	13.4
February Peak	0.085	0.115	9.4	4.0	13.4
March Peak	0.085	0.115	9.4	4.0	13.4
April Peak	0.084	0.115	9.3	4.0	13.3
May Peak	0.102	0.238	11.2	8.3	19.5
June Peak	0.161	0.458	17.8	15.9	33.7
July Peak	0.162	0.466	17.9	16.2	34.1
August Peak	0.166	0.459	18.3	16.0	34.3
September Peak	0.140	0.371	15.5	12.9	28.4
October Peak	0.103	0.191	11.3	6.6	18.0
November Peak	0.085	0.115	9.4	4.0	13.4
December Peak	0.085	0.115	9.4	4.0	13.4
Typical Event Day	**0.164**	**0.457**	**18.1**	**15.9**	**34.0**

Figure ES.1: *Ex-Ante* Aggregate Load Impacts by Weather Scenario, and Event and RA Windows – *SmartRate-only*



Residential TOU

Ex-ante load impacts are developed for four groups of customers:

- E-6 incremental customers;
- E-6 embedded customers;
- E-TOU-A customers; and
- E-TOU-B customers.

The enrollment forecast for August by year for each is shown in Figure ES.2.

Figure ES.2: Forecast August TOU Enrollments by Group and Year

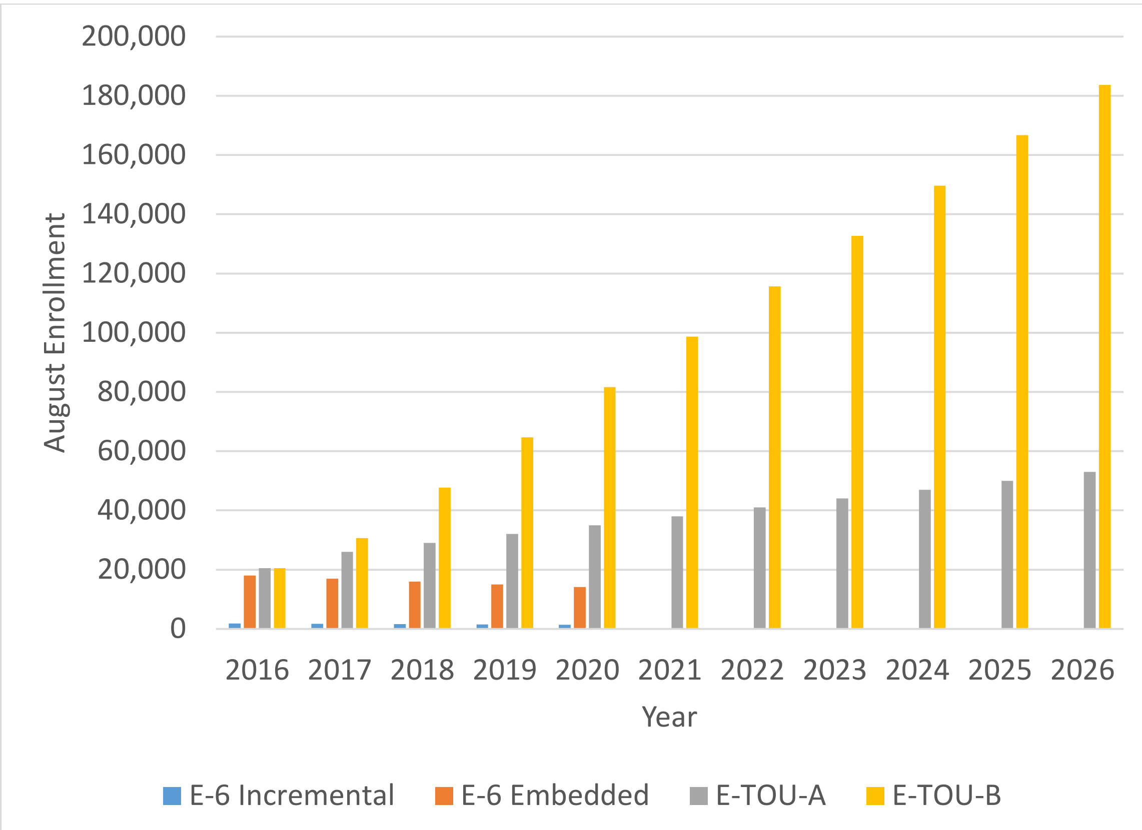


Table ES.6 shows monthly aggregate load impacts for 2017 for all four groups, for the PG&E 1-in-2 weather scenario. Load impact values are averaged over the RA window (1:00 to 6:00 p.m. from April to October and 4:00 to 9:00 p.m. from November through March). Load impacts are largest in the summer months.

Table ES.6: Residential TOU Aggregate *Ex-Ante* Load Impacts by Month (2017) – *PG&E 1-in-2 Weather (MWh/hr)*

Month	E-6 Embedded	E-6 Incremental	E-TOU-A	E-TOU-B
January	0.76	0.08	0.03	0.07
February	0.77	0.08	0.03	0.07
March	0.78	0.08	0.03	0.07
April	1.18	0.12	0.01	0.01
May	1.25	0.13	0.02	0.01
June	2.12	0.21	0.18	0.14
July	2.17	0.22	0.18	0.15
August	2.21	0.22	0.18	0.15
September	2.16	0.22	0.17	0.15
October	1.18	0.12	0.02	0.02
November	0.79	0.08	0.03	0.10
December	0.74	0.07	0.03	0.07

1. Introduction and Purpose of the Study

This report documents *ex-post* and *ex-ante* load impact evaluations for Pacific Gas and Electric Company's ("PG&E") residential time-varying pricing programs for program year 2015. Programs covered include time-of-use rates (E-6, E-7, E-TOU-A, and E-TOU-B) and SmartRate™.[4]

SmartRate is a version of critical peak pricing (CPP) that is implemented as an overlay on customers' otherwise applicable tariff. On event days, a peak-price adder of $0.60 per-kWh is applied during the hours of 2:00 p.m. to 7:00 p.m. In return, SmartRate customers receive credits on non-peak usage from June through September.

Rate E-6 has three pricing periods (peak, partial-peak, and off-peak) during summer months, and two pricing periods (partial-peak and off-peak) in winter months. TOU rate E-7 is characterized by year-round peak and off-peak prices, and is closed to new enrollments. E-TOU-A and E-TOU-B are new TOU offerings in 2016. Both rates have two pricing periods (peak and off-peak) during each of two seasons (summer and winter).

The evaluation involves estimation of *ex-post* load impacts for SmartRate, E-6, and E-7 for program year 2015, and development of *ex-ante* load impacts of SmartRate, E-6, E-TOU-A, and E-TOU-B for eleven years beyond the relevant program year, with the evaluations conforming to the Load Impact Protocols adopted by the CPUC in D-08-04-050.

The report is organized as follows. Section 2 contains descriptions of SmartRate and the TOU rates; Section 3 describes the methods used in the SmartRate portion of the study; Section 4 contains the detailed SmartRate *ex-post* load impact results; Section 5 describes the methods used in the residential TOU portion of the study, while Section 6 contains the detailed TOU *ex-post* load impact results. Section 7 describes the methods used to develop the SmartRate *ex-ante* load impacts and the associated results. Section 8 describes the methods and results of the residential TOU *ex-ante* forecast. Section 9 provides a series of comparisons of *ex-post* and *ex-ante* results, for the current and previous evaluations. Section 10 provides recommendations.

2. Description of Time-varying Rates

This section provides details on the SmartRate and residential TOU rates (E-6, E-7, E-TOU-A, and E-TOU-B). A brief history of these rates may be found in the evaluation report for 2014.[5] In 2015, the California Public Utilities Commission (CPUC) approved the establishment of E-TOU-A and E-TOU-B, which have simpler tier structures and peak

[4] References to the terms SmartRate and/or SmartAC in this report are intended to refer to the trademarked term, whether or not the ™ indication is present.

[5] "2014 Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-Based Pricing Programs," prepared by Nexant, Inc., CALMAC ID PGE0352, April 1, 2015.

periods that are more closely aligned with high marginal generation cost periods.[6] The CPUC also approved the transition toward a default residential TOU rate starting in 2019. In advance of this, PG&E must file a residential rate design window application proposing a default TOU rate structure by January 1, 2018. Because the rate structure has yet to be defined, this future rate is not within scope of this evaluation.

2.1 SmartRate Description

As noted in the introduction, PG&E's SmartRate is a version of critical peak pricing (CPP) that is implemented as an overlay on customers' otherwise applicable tariff. For most participants, this is the E-1 tariff, which is a multi-tier inclining block rate, with an initial block size that represents a baseline level of usage that varies by climate zone, and a price of $0.37 per kWh for the highest tier. Low-income customers who qualify for CARE (California Alternative Rates for Energy), receive substantial discounts on each tier price.

On SmartRate event days, a peak-price adder of $0.60 per-kWh is applied during the hours of 2:00 p.m. to 7:00 p.m. In return, SmartRate customers receive credits on non-peak usage from June through September. A credit of $0.024 per-kWh applies to all usage other than peak-period usage on SmartRate event days. For all SmartRate customers not on E-TOU-B, an additional credit of $0.0075 per-kWh applies to usage above 100% of customers' baseline allocation, regardless of time period. For E-TOU-B customers, an additional credit of $0.005 per-kWh applies to all usage, regardless of time period.

SmartRate has a target of 12 event days during the summer, with a maximum of 15. Events are called on the basis of a trigger temperature that may be adjusted upward or downward during the summer depending upon the number of events that have been called. Participants are notified of events by 3 p.m. on the business day prior to the event, and several notification options are available, including email, phone, and text, unless they have declined notification.

For the first full season following their enrollment, participants are eligible for *bill protection*, which guarantees that their bill will be no larger than what it would have been under their otherwise applicable tariff.

SmartRate customers are also eligible to enroll in PG&E's SmartAC program, an air conditioner cycling program. Customers enrolled in both programs have their air conditioner controlled during the event window on SmartRate event days. The current study evaluates load impacts on SmartRate event days for both SmartRate-only and dually enrolled customers. A comprehensive evaluation of the SmartAC program is being conducted in a separate project.

[6] CPUC D.15-07-001.

Table 2.1 shows the number and percentage of customers enrolled in SmartRate-only and dually enrolled in both SmartRate and SmartAC, by local capacity area (LCA)[7] and CARE status. The total number of SmartRate-only customers has increased from approximately 83,000 and 89,000 in 2013 and 2014, to over 92,000 for the average event in 2015. The number of dually-enrolled customers has fallen somewhat, from approximately 38,300 in 2013 and 40,300 in 2014, to about 36,600 in 2015.

The greatest number of Non-CARE customers in both SmartRate categories reside in the Greater Bay Area, followed by the Other category. The CARE customers are distributed somewhat differently, with relatively larger percentages of customers in the Greater Fresno, Kern and Stockton areas. These LCAs generally have the warmest weather in the PG&E service area, which affects customers' level of usage on hot event days, and their potential load reduction capability, which is reported in Section 4.

Table 2.1: SmartRate-Only and Dually-Enrolled Customers, by LCA and CARE status

	SmartRate-Only				Dually-enrolled			
LCA	**Non-CARE**	**%**	**CARE**	**%**	**Non-CARE**	**%**	**CARE**	**%**
Greater Bay Area	39,287	59%	7,331	28%	12,036	44%	1,707	19%
Greater Fresno Area	2,875	4%	3,554	14%	1,899	7%	1,705	19%
Humboldt	808	1%	529	2%	132	0%	58	1%
Kern	2,568	4%	4,176	16%	838	3%	1,107	12%
North Coast and North Bay	1,349	2%	428	2%	799	3%	161	2%
Other	12,664	19%	5,449	21%	5,916	22%	2,189	24%
Sierra	3,972	6%	1,500	6%	3,361	12%	788	9%
Stockton	2,942	4%	2,858	11%	2,408	9%	1,494	16%
All	**66,465**	**100%**	**25,824**	**100%**	**27,389**	**100%**	**9,209**	**100%**

2.2 TOU Rates Description

PG&E currently has two voluntary residential TOU rates: E-6 and E-7. The latter is closed to new enrollment and its customers will be transitioned to other rates in May 2016. Both rates are seasonal, with generally higher prices in summer (May through October) than in winter. The E-7 tariff has two periods, a six-hour (12 to 6 p.m.) weekday peak period, and an off-peak period in all other hours. The E-6 tariff has three pricing periods in summer and two in winter. The summer peak period covers the six hours from 1 to 7 p.m. on weekdays, a split partial-peak is from 10 a.m. to 1 p.m. and 7 to 9 p.m. on weekdays, and 5 p.m. to 8 p.m. on weekends. All other hours are off peak. In winter, there is no peak period, and the partial-peak period applies to hours 5 to 8 p.m. on weekdays. All other hours are off peak.

[7] Local Capacity Area (or LCA) refers to a CAISO-designated load pocket or transmission constrained geographic area for which a utility is required to meet a Local Resource Adequacy capacity requirement. There are currently seven LCAs within PG&E's service area. In addition, PG&E has many accounts that are not located within any specific LCA.

Both TOU rates are integrated with the E-1 inclining-block rate, effectively resulting in a matrix of prices that vary by both time period and usage level. For billing purposes, the metered usage during peak, partial-peak, and off-peak periods is allocated to price tiers on a pro-rated basis, based on the *share* of usage in each TOU period. Thus, as stated in the tariffs, "if twenty percent of a customer's usage is in the on-peak period, then twenty percent of the total usage in each tier will be treated (and billed) as on-peak usage." Like the case of the standard E-1 tariff, customers qualifying for CARE receive a substantial discount on the tiered TOU prices.

In recent years, many customers who install solar photovoltaic systems have also signed up for a TOU rate and net metering. As a result, approximately three-quarters of E-6 and a quarter of E-7 customers are classified as net energy metered (NEM) customers. As was the case in the previous evaluation, our primary analysis *excludes* those customers. However, we did conduct a high-level examination of E-6 NEM customer usage, as described in Section 5.

For purposes of this study, PG&E's current residential TOU customers are classified into three categories:

1. Non-NEM E-6 *incremental* (newly enrolled customers who signed up for E-6 between October 2014 and September 2015, and whose load impacts are therefore new, or incremental in 2015);
2. Non-NEM E-6 and E-7 *embedded* (those customers who enrolled in E-6 or E-7 prior to October 2014, and whose load impacts are therefore already embedded in their 2015 loads); and
3. E-6 and E-7 NEM (customers who have signed up for either of the TOU rates and for net energy metering).

PG&E has recently received approval to offer two new optional TOU rates, E-TOU-A and E-TOU-B beginning in 2016. Customers currently on E-6 will be allowed to remain on that rate. Customers on E-7 will be defaulted to the new E-TOU-A rate, but will be given the option of instead moving to any other eligible rate, based in part on customer-specific information provided by PG&E about which rate may be most beneficial. As described in Section 8, *ex-ante* forecasts for the two new rates, as well as for E-6, are provided as part of this study.

Table 2.2 summarizes the number of customers enrolled in the current TOU rates in August 2015, by LCA and CARE status.

Table 2.2: E-6 and E-7 Non-NEM Customers, by LCA and CARE Status

Group	E-6 Embedded	E-6 Incremental	E-7 Embedded
Greater Bay Area	4,633	4,231	17,136
Greater Fresno Area	195	218	2,875
Humboldt	274	187	3,199
Kern	77	101	1,058
North Coast	795	330	6,086
Other	1,219	968	11,077
Sierra	381	279	4,160
Stockton	188	155	2,186
Total	**7,762**	**6,469**	**47,777**
Non-CARE	6,923	5,822	42,762
CARE	839	647	5,015

3. *Ex-Post* Evaluation Methodology – SmartRate

This section describes the methodology used to estimate *ex-post* load impacts for SmartRate customer accounts in 2015. Estimating the SmartRate load impacts, as in all evaluations, requires an appropriate method for estimating what customers' usage would have been in the absence of the program; that is, what their usage pattern would have been had they not experienced the incremental charges on SmartRate event days. Load impacts are then calculated as differences between these counter-factual *reference loads* and the *observed loads* of the enrolled customers. For SmartRate, these differences are calculated for each event day.

Since SmartRate has been in place for several years, an appropriate evaluation approach involves the selection of *quasi-experimental* matched control groups, where the matching techniques have the goal of finding customers in the general (E-1) population that are as similar as possible to the enrolled customers. Selection into the control group is made on the basis of available *customer characteristics* (*e.g.*, SmartRate-only and dually-enrolled, CARE status, LCA, and climate zone) and *usage patterns* on non-event days that are similar to event days. Usage pattern statistics include hourly values of averages across the selected non-event days in 2015.

Upon inspection of the non-event-day loads, it became apparent that the average weekday loads for both treatment and potential control group customers seemed to differ during the morning hours of two particular time periods making up the overall summer period. The periods were approximately mid-June through mid-August (which generally include summer non-school days) from days prior to and following that period. In particular, loads in the latter in-school period rose noticeably from approximately 6 to 8 a.m. before dropping slightly and then rising through mid-day. This morning "bump" and "dip" was not present on days during the mid-summer non-school period. Given these different load profiles, we constructed two sets of average non-event-day loads to represent those two periods, and matched customers on the basis of both loads.

Once the matched control group customers have been selected, the hourly load impacts for each SmartRate event day may be calculated as the difference between the average control group customer and treatment customer loads on those days. A difference-in-differences approach is applied, in which the event-day load differences are adjusted by the average difference on the selected non-event days (typically, with good matches, these adjustments are quite small). The difference-in-differences approach is implemented through fixed-effects regression analysis, which has the advantage of producing standard errors around the estimated load impacts and thus allows calculation of confidence intervals.

These activities are described in more detail in the following sub-sections.

3.1 Control group selection

3.1.1 Approach

All customers enrolled in SmartRate, as summarized in Table 2.1, were included in the analysis. For each cell defined by SmartRate-only and dually enrolled, CARE status, LCA, and climate zone, a sample of five times the number of enrolled customers in the cell was selected from a file of E-1 customers.[8] Load data for all of these potential control group customers, as well as the enrolled customers, were requested for the 15 SmartRate event days and 8 hot event-like non-event days.[9] The 48 hourly load statistics (24-hour profiles for two types of days) described above were calculated for each enrolled and potential control group customer.

The matched control group customers were then selected through a "Euclidean distance" minimization approach. This approach minimizes the difference between a standardized usage metric of the treatment and potential control group customers.[10]

---

[8] For matching customers who are dually enrolled in SmartAC, we limit the eligible control-group customers to those with above a 70 percent estimated probability of having central air conditioning (CAC). The CAC probability variable values were provided by PG&E. Its use in our matching process helps ensure that SmartAC customers are matched to customers who have CAC.

[9] The five dates in the "non-school-year" profile are 6/29/2015, 7/16/2015, 7/17/2015, 7/20/2015, and 7/27/2015. The three dates in the "school-year" profile are 6/8/2015, 8/26/2015, and 9/21/2015.

[10] Control group matching in a number of previous load impact evaluations in California has been conducted using a process known as *propensity score matching* (PSM). PSM involves estimation of discrete choice models, such as the logit or probit, where the dependent variable in the model is an indicator variable for SmartRate enrollment (*i.e.*, one for participants and zero for potential control group customers). Independent variables are various possible usage profile or customer characteristics, where the best set of variables is determined from testing the performance of a range of potential models. Recent academic research (Gary King (Harvard) and Richard Nielson (MIT), "Why Propensity Scores Should Not be Used for Matching," August 17, 2015) has recommended matching based directly on factors of interest (*e.g.*, pre-enrollment load profiles) over PSM in applications of intervention analysis such as

The standardized metric combines the 48 hourly load difference statistics for the two load profiles into a single value equal to the square root of the sum of squared differences between the load statistics. That is, each enrolled customer is compared to each potential control group customer, using the distance measure. When the minimum distance statistic is found, the potential control group customer associated with that value is selected as the match for that SmartRate customer. Potential control group customers were allowed to be matched to multiple enrolled customers.

3.1.2 Matching results

Figures 3.1 and 3.2 show the average per-customer loads for SmartRate and matched control-group customer loads across the 8 non-event days. While our matching process was conducted at a much more disaggregated level (by enrollment type, LCA, and CARE status), Figure 3.1 shows the customers who are enrolled in only SmartRate while Figure 3.2 shows the customers who are dually enrolled in SmartRate and SmartAC. During event hours (hours-ending 15 to 19, the control group average usage is 0.5 percent lower than that of the SmartRate-only customers and 0.3 percent lower than that of the dually enrolled customers.

impact evaluations. The previous evaluation of PG&E's SmartRate and residential TOU used PSM in some parts and matching based on direct load comparisons in others.

Figure 3.1: SmartRate-Only and Matched Control Group Loads on Non-event Days

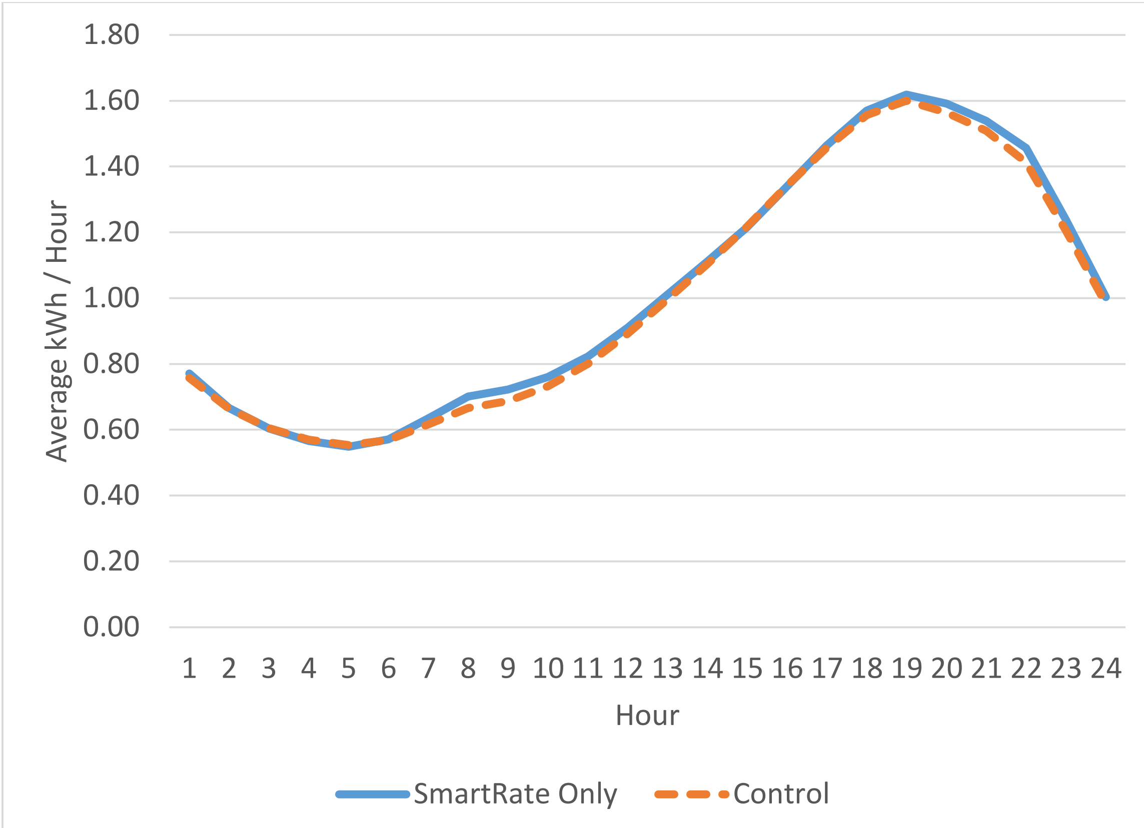
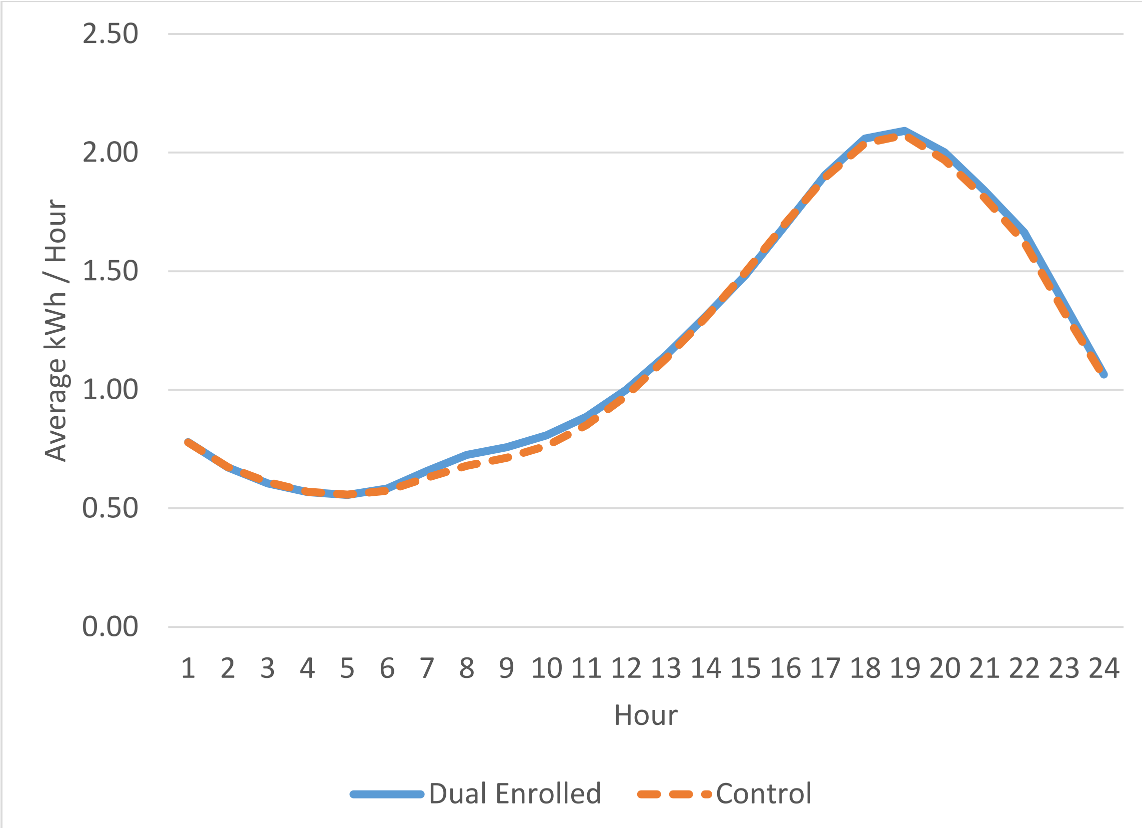


Figure 3.2: Dually-enrolled and Control Group Loads on Non-event Days



3.2 Load impact estimation

The load impact estimation model accounts for customer-specific and date-specific fixed effects (which include weather and day-type factors) and estimates the SmartRate load impact as the difference between SmartRate and control-group customer loads on event days, controlling for the aforementioned fixed effects. This can be described as a difference-in-differences estimate (the difference between treatment and control group usage on event and non-event days). The primary customer-level fixed-effects regression model used in the analysis is shown below, where the equation is estimated separately for each of the 24 hours, and separate models are estimated for the SmartRate-only and dually-enrolled groups. This model produces load impact estimates for each hour of every event:

$$kW_{c,d} = \beta_0 + \Sigma_{\mathrm{Evts(i)}} (\beta_{1,i} \times SR_{c,d} \times Evt_{i,d}) + \Sigma_{\mathrm{Cust}} (\beta_{2,\mathrm{Cust}} \times C_c) + \Sigma_{\mathrm{day}} (\beta_{3,\mathrm{day}} \times D_{day,d}) + \varepsilon_{c,d}$$

The variables and coefficients in the equation are described in the following table:

Symbol	Description
$kW_{c,d}$	Load in a particular hour for customer *c* on day *d*
$SR_{c,d}$	Variable indicating whether customer *c* is a SmartRate (1) or Control (0) customer
$Evt_{i,d}$	Variable indicating that day *d* is the i^{th} event day (1=i^{th} event, 0 if not)
β_0	Estimated constant coefficient
$\beta_{1,d}$	Estimated load impact for event *d*
$\beta_{2,Cust}$ and $\beta_{3,day}$	Customer and day fixed-effects
C_c	Variable indicating that the observation is for customer *c*
$D_{day,d}$	Date indicator variable (1 = date *d* equals date *day*)
$\varepsilon_{c,d}$	Error term

A modified version of the model, designed to estimate load impacts for the *average event*, is estimated separately for SmartRate-only and dually-enrolled, also distinguished by LCA and CARE status.[11] In this version, rather than separate event variables for each event in the second term, there is only one variable, indicating that a day is an event day.

Some detailed questions (*e.g.*, how customer response to the SmartRate prices on event days varies across customer types) requires estimation of customer-specific event-period load impacts. To address these issues, we applied a simplified regression model to data for each SmartRate customer separately to estimate a load impact coefficient and its standard error. To maintain consistency with previous evaluations, we applied the same form of model as in the 2014 evaluation. This model is specified as follows:

$$AvekW_{c,d} = \beta_{0,c} + \beta_{1,c} \times Evt_d + \beta_{2,c} \times Mean17_d + \varepsilon_{c,d}$$

Rather than using load data for all hours of the day, this model uses daily data on the average hourly load within the event window of 2 p.m. to 7 p.m. for the event days and event-like non-event days described above. The variables and coefficients in the equation are described in the following table:

Symbol	Description
$AvekW_{c,d}$	Average hourly load for hours-ending 15 - 19 for customer *c* on day *d*
Evt_d	Variable indicating that day *d* is an event day (1= event, 0 if not)
$\beta_{0,c}$	Estimated constant coefficient
$\beta_{1,c}$ and $\beta_{2,c}$	Estimated load impact and weather effect for customer *c,* respectively
$Mean17_d$	Variable representing the average temperature from midnight to 5 p.m. on day *d*
ε_{cd}	Error term

[11] Load impacts by event are required only at the level of SmartRate-only and dually-enrolled customers. Reporting by LCA and CARE status is required only for the average event.

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. In the case of *ex-post* load impacts, the parameters that constitute the load impact estimates (the coefficients on the *SR* x *Evt* interaction variables in the above equation) are not estimated with certainty. We base the uncertainty-adjusted load impacts on the variances associated with these coefficients. Specifically, the uncertainty-adjusted scenarios were simulated under the assumption that each hour's load impact is normally distributed with the mean equal to the estimated load impact and the standard deviation equal to the standard error associated with the load impact estimate. Results for the 10^{th}, 30^{th}, 70^{th}, and 90^{th} percentile scenarios are generated from these distributions. Hourly uncertainty-adjusted load impacts are produced using standard errors from the hourly models, while the average for the event hours are produced using standard errors from a model using one variable to estimate an average event-hour load impact.

4. SmartRate *Ex-Post* Load Impact Study Findings

This section documents the findings from the various SmartRate *ex-post* load impact evaluation analyses conducted in the project. The primary high-level load impact results include average estimated event-hour load impacts (*i.e.*, the average of the hourly load impacts estimated for the five-hour event window from 2 p.m. to 7 p.m.), in aggregate and per-customer, over the five-hour event window, for each event day and for the average event day. These results are shown separately for SmartRate-only and customers dually enrolled in SmartAC.

Results for all hours for the average event day are also illustrated in figures. Detailed results for each event in electronic form may be found in Protocol table generators provided along with this report. In addition to these high-level results, we also summarize how average event-hour load impacts for the average event are distributed by LCA and CARE status. As described in Section 3, all of the above results were produced by fixed-effects regression analysis using hourly data for all treatment and matched control group customers in the two program-level groups, and in various cells defined by LCA and CARE status.

We also report on additional detailed results that are not required by the Protocols, but enhance understanding of various aspects of the SmartRate program. Some of these results were developed using the customer-level regression approach described in Section 3, and include an assessment of how the characteristics of those high-responding customers who were found to reduce load by a statistically significant amount differed from those who did not. Finally, using billing data provided by PG&E, we summarize findings on customer bill impacts.

4.1 Load impacts by event and the average event

This section summarizes average event-hour reference loads[12] and load impacts, at an aggregate and per-customer basis, for each event and the average event. Results for all hours of the average event day are also illustrated in figures.

4.1.1 SmartRate-only

Table 4.1 summarizes reference load and load impact results for SmartRate-only customers. The first two columns show dates and numbers of customers enrolled in SmartRate for each event. The next two columns show aggregate estimated reference loads and load impacts in MW. The next two columns show the same variables for the average customer, in units of kW. The last two columns show the load impacts as a percentage of the reference loads, and the average temperature during the event window.

Table 4.1: Average Event-Hour Load Impacts, by Event – *SmartRate-only*

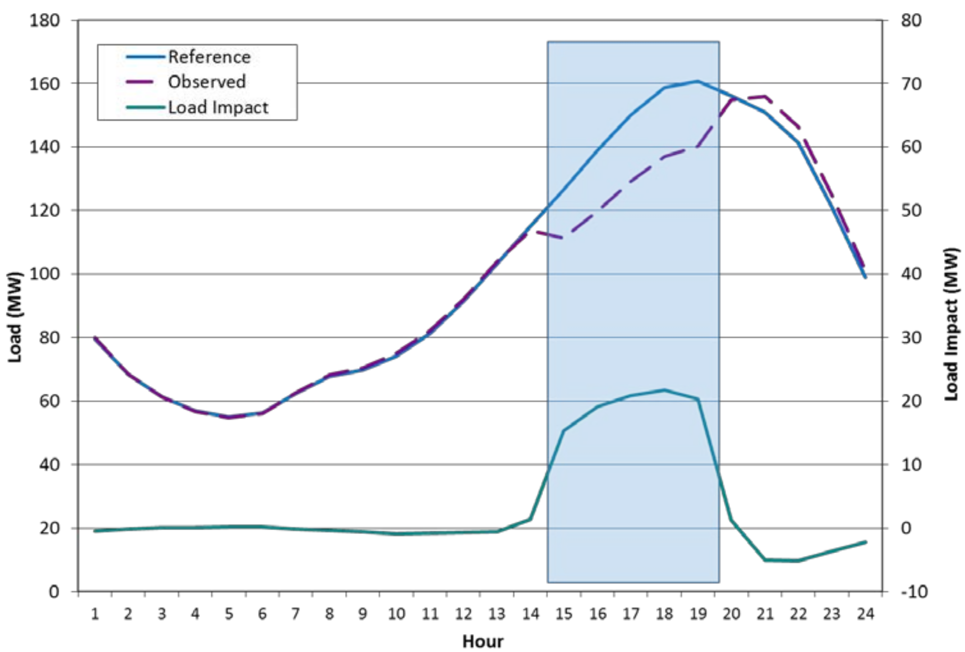
		Aggregate		Per-Customer			
Events	Enrolled	Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)	% Load Impact	Ave. Event Temp.
12-Jun-15	89,045	131.3	17.9	1.47	0.20	14%	92
25-Jun-15	88,435	139.0	19.8	1.57	0.22	14%	95
26-Jun-15	88,413	141.5	17.8	1.60	0.20	13%	93
30-Jun-15	88,248	152.4	21.2	1.73	0.24	14%	98
1-Jul-15	88,178	132.8	17.5	1.51	0.20	13%	91
28-Jul-15	89,444	137.8	20.6	1.54	0.23	15%	96
29-Jul-15	89,634	153.6	21.7	1.71	0.24	14%	97
30-Jul-15	89,799	135.4	17.7	1.51	0.20	13%	92
17-Aug-15	93,496	164.6	21.2	1.76	0.23	13%	97
18-Aug-15	93,850	137.5	16.1	1.46	0.17	12%	91
27-Aug-15	96,355	149.5	19.5	1.55	0.20	13%	95
28-Aug-15	96,590	159.3	18.1	1.65	0.19	11%	95
9-Sep-15	97,521	156.1	21.8	1.60	0.22	14%	98
10-Sep-15	97,613	163.5	21.9	1.68	0.22	13%	97
11-Sep-15	97,704	151.6	19.3	1.55	0.20	13%	94
Average Event Day	**92,288**	**147.1**	**19.5**	**1.59**	**0.21**	**13%**	**95**

[12] Reference loads represent estimates of the counter-factual loads that would have prevailed on an event day if the event had not been called. Mechanically, the *reference* loads are constructed by adding the estimated load impacts (developed in the difference-in-differences analysis) to the *observed* load of the treatment customers on the relevant event day.

Program enrollment generally increased over the summer period, averaging just over 92,000 customers. Aggregate load impacts ranged from 16.1 MW to 21.9 MW across the events, averaging 19.5 MW. The largest load impact occurred on September 10, on the second of three consecutive events, while the smallest occurred on August 18, which had the mildest temperature (91 degrees) of all the events. The value for the average event (19.5 MW) compares to 18.3 MW in 2014. Per-customer load impacts ranged from 0.17 kW to 0.24 kW, averaging 0.21 kW, which is 13 percent of the estimated reference load. Average event-window temperatures ranged from 91 to 98 degrees, and the 95-degree temperature for the average event was substantially higher than the 88 degrees observed in 2014.

Figure 4.1 shows aggregate hourly loads and load impacts for the average event for SmartRate-only customers. The largest hourly load impact was 21.7 MW in hour-ending 18 (5 to 6 p.m.).

Figure 4.1: Hourly Loads and Load Impacts for Average Event – *SmartRate-Only*



4.1.2 Dually-enrolled

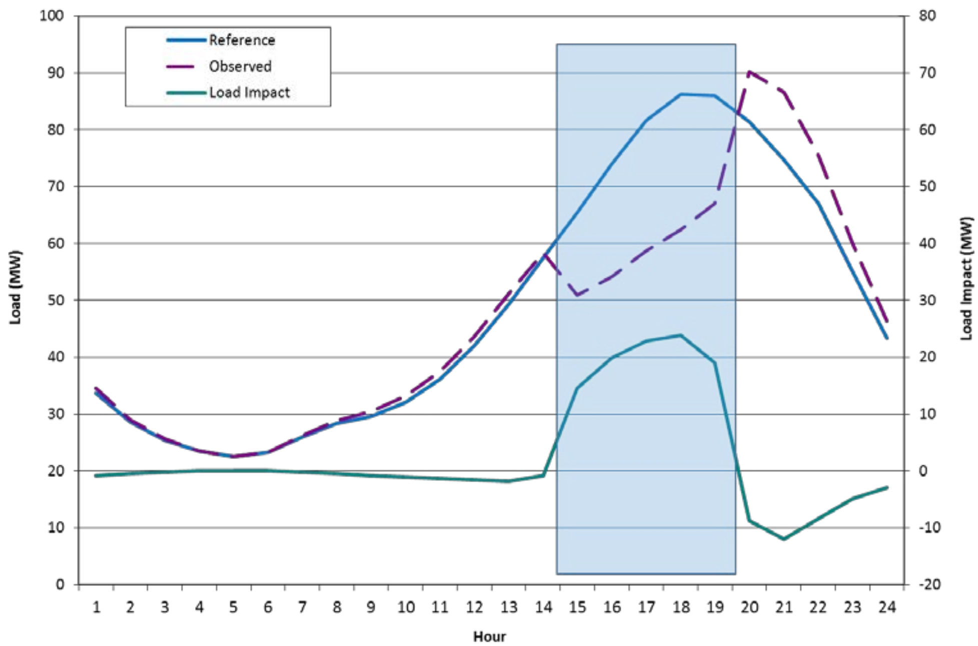
Table 4.2 shows estimated reference loads and load impacts for each event for customers that were dually enrolled in SmartRate and SmartAC. Aggregate load impacts for the average event were 20 MW. Per-customer reference loads and load impacts were substantially larger than those for SmartRate-only customers. Load impacts for the average event were 0.55 kW, which represents 25 percent of the reference load. The larger loads and load impacts relative to SmartRate-only are likely due to a number of key factors, including the presence of central air conditioning, relatively more customers in hotter regions (*e.g.*, fewer in the Greater Bay Area), and the control of customers' air conditioners on SmartRate event days.

Table 4.2: Average Event-Hour Load Impacts, by Event – *Dually-enrolled*

		Aggregate		Per-Customer			
Events	Enrolled	Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)	% Load Impact	Ave. Event Temp.
12-Jun-15	37,607	75.7	20.3	2.01	0.54	27%	96
25-Jun-15	37,215	80.6	22.7	2.16	0.61	28%	98
26-Jun-15	37,146	82.4	21.8	2.22	0.59	26%	97
30-Jun-15	36,989	89.7	25.2	2.42	0.68	28%	101
1-Jul-15	36,938	76.4	18.9	2.07	0.51	25%	95
28-Jul-15	36,611	76.0	21.3	2.08	0.58	28%	98
29-Jul-15	36,573	88.1	25.3	2.41	0.69	29%	100
30-Jul-15	36,545	76.1	19.1	2.08	0.52	25%	95
17-Aug-15	36,364	86.6	21.2	2.38	0.58	24%	100
18-Aug-15	36,336	67.2	13.7	1.85	0.38	20%	93
27-Aug-15	36,262	73.5	17.4	2.03	0.48	24%	97
28-Aug-15	36,254	78.8	17.7	2.17	0.49	22%	97
9-Sep-15	36,069	75.4	19.0	2.09	0.53	25%	100
10-Sep-15	36,044	80.5	20.1	2.23	0.56	25%	100
11-Sep-15	36,016	73.4	17.1	2.04	0.47	23%	96
Average Event Day	**36,598**	**78.7**	**20.0**	**2.15**	**0.55**	**25%**	**98**

Figure 4.2 shows hourly loads and load impacts for the dually-enrolled customers. The largest hourly load impact was 23.8 MW in hour-ending 18 (5 to 6 p.m.).

Figure 4.2: Hourly Loads and Load Impacts for Average Event – *Dually-enrolled*



4.2 Load impacts by customer type and location

This sub-section summarizes the distribution of estimated load impacts across CARE and non-CARE customers, and by the CAISO-defined local capacity areas (LCA).

4.2.1 Load impacts by LCA

Table 4.3 summarizes average event-hour reference loads and load impacts for the average event by LCA for the SmartRate-only customers. On a per-customer basis, customers in the warmer than average LCAs generally produced the largest load impacts. The largest load impacts occurred in Sierra[13], followed by Greater Fresno, Stockton, Other (*i.e.*, outside of the other LCAs) and Kern. The largest aggregate load impacts occurred in the Greater Bay Area and Other, which had the highest absolute enrollment numbers.

Figure 4.3 shows a plot of the average per-customer load impact by LCA. The figure represents the SmartRate-only customers and the load impact and cooling degree days are averaged across all event days. Notice that Sierra (in red) has a significantly higher load impact per customer than other LCAs, even controlling for the temperature.

[13] The Sierra LCA had the largest load impacts in the 2014 study as well.

Table 4.3: Average Event-Hour Load Impacts, by LCA – *SmartRate-only*

LCA	Enrolled	Aggregate		Per-Customer		% Load Impact	Ave. Event Temp.
		Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)		
Greater Bay Area	46,618	49.6	6.9	1.06	0.15	14%	88
Greater Fresno	6,428	17.2	2.0	2.68	0.31	12%	103
Humboldt	1,337	1.8	0.2	1.34	0.18	14%	90
Kern	6,744	17.2	1.6	2.55	0.24	9%	101
Northern Coast	1,777	2.0	0.2	1.10	0.11	10%	91
Other	18,113	31.7	4.5	1.75	0.25	14%	95
Sierra	5,472	13.5	2.5	2.47	0.45	18%	98
Stockton	5,800	14.1	1.6	2.43	0.27	11%	98
All	**92,288**	**147.1**	**19.5**	**1.59**	**0.21**	**13%**	**95**

Figure 4.3: Average SmartRate-Only Load Impacts by LCA

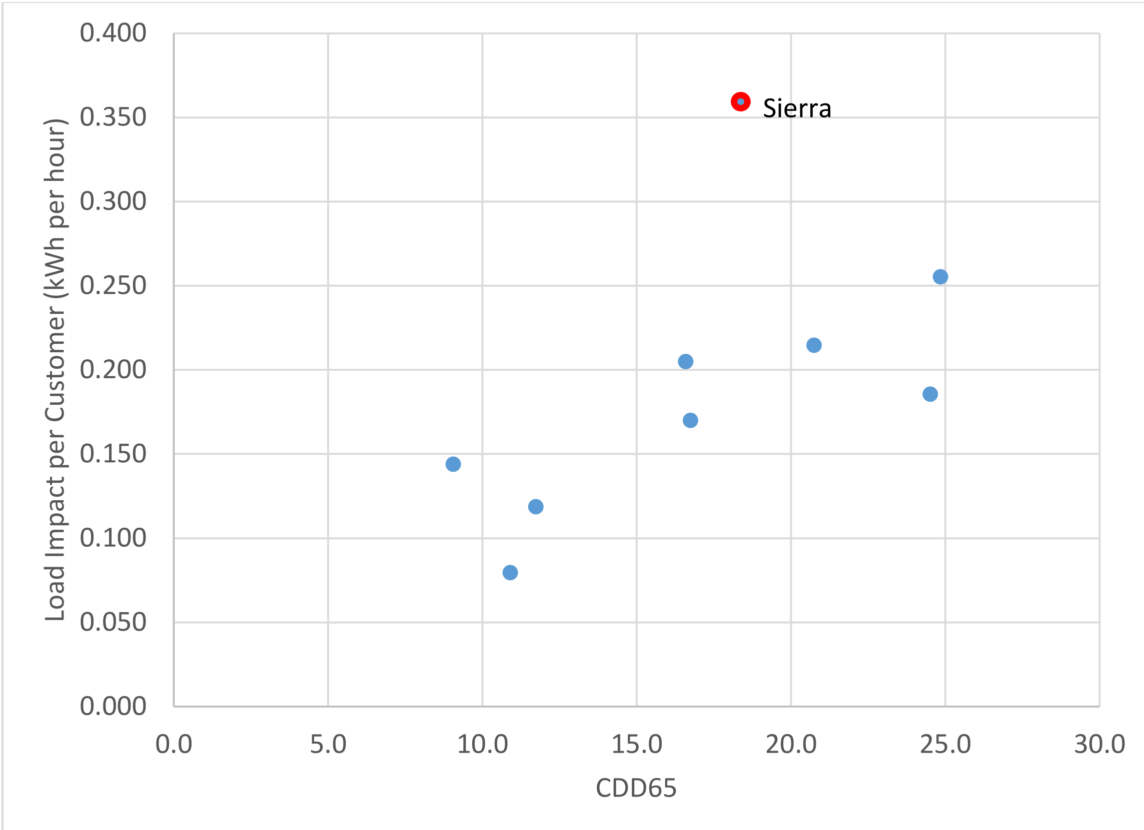


Table 4.4 provides similar information for the dually-enrolled customers. Similar to the SmartRate-only group, the largest aggregate load impacts were produced in the Greater Bay Area and Other areas, which contained more than half of the total enrolled customers. On a per-customer basis, with the exception of the relatively mild Greater Bay Area, Humboldt, and Northern Coast LCAs, estimated load impacts in the other LCAs were larger than the overall average of 0.55 kW.

Table 4.4: Average Event-Hour Load Impacts, by LCA – *Dually-enrolled*

LCA	Enrolled	Aggregate		Per-Customer		% Load Impact	Ave. Event Temp.
		Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)		
Greater Bay Area	13,742	23.9	6.5	1.74	0.48	27%	92
Greater Fresno	3,605	9.8	2.1	2.71	0.59	22%	103
Humboldt	190	0.4	0.1	2.17	0.50	23%	99
Kern	1,945	5.4	1.3	2.79	0.66	24%	101
Northern Coast	960	1.4	0.3	1.45	0.33	23%	92
Other	8,105	18.3	4.6	2.26	0.57	25%	100
Sierra	4,150	10.2	2.9	2.46	0.70	28%	98
Stockton	3,902	9.3	2.2	2.38	0.56	24%	98
All	**36,598**	**78.7**	**20.0**	**2.15**	**0.55**	**25%**	**98**

4.2.2 Load impacts by CARE status

Table 4.5 summarizes estimated reference loads and load impacts, in aggregate and per-customer, by CARE status. For SmartRate-only customers, the non-CARE customers provided more than proportionately higher aggregate load impacts than the CARE customers, due to per-customer load impacts that were twice as large, even with a lower reference load. For the dually-enrolled customers, the non-CARE customers again produced the largest aggregate load impacts, and also had the largest per-customer load impacts.

Table 4.5: Average Event-Hour Load Impacts, by CARE status

Program	CARE Status	Enrolled	Aggregate		Per-Customer		% Load Impact	Ave. Event Temp.
			Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)		
SR-only	Non-CARE	66,465	97.8	16.4	1.47	0.25	17%	93
	CARE	25,824	49.3	3.1	1.91	0.12	6%	98
Dually enrolled	Non-CARE	27,389	56.3	15.6	2.06	0.57	28%	97
	CARE	9,209	22.4	4.4	2.43	0.48	20%	99

4.3 Customers Exhibiting Statistically Significant Response

Previous evaluation studies have found that the customers enrolled in event-based demand response programs like SmartRate tend to exhibit a considerable range of responsiveness to event notification and the financial incentive to reduce load. It is instructive to examine that range of responsiveness among SmartRate customers. To examine this range of response, which underlies the higher-level load impacts reported in the previous section, we estimated separate regression models for each enrolled customer, as described in Section 3.2. We then analyzed the features of the estimated load impact coefficients and the associated standard errors.

Residential customer loads during the late afternoon peak hours of summer weekdays can vary substantially across days due to a variety of factors. We included only two available factors in our simple model – average temperatures, and an indicator that the observed day is a SmartRate event day. As a result of the limited number of explanatory variables, accurate estimation of the coefficient on the event indicator variable requires strong and consistent load reductions to be measurable among the underlying load variability. We tested the statistical significance of the estimated load impact coefficients, and explored patterns in the coefficients.

Table 4.6 summarizes the percentages of SmartRate-only and dually-enrolled customers whose estimated load reductions were found to be statistically significant at the confidence levels shown in the table header. The two rows in the table indicate that at a 95 percent confidence level, 17 percent of SmartRate-only customers and 32 percent of dually-enrolled customers reduced load by statistically significant amounts on average across the 15 SmartRate events. If the confidence level is reduced to 90 percent, 22 percent of SmartRate-only customers and 38 percent of dually-enrolled customers reduced usage by statistically significant amounts. Overall, 67 percent of SmartRate-only customers and 76 percent of dually-enrolled customers had negatively signed load impact coefficients (statistically significant or not), indicating that they reduced usage on average during event hours. However, as shown in the table, generally less than half of those were statistically significant at high degrees of confidence.

One indicator of the variability of these customers' loads is the finding that some customers appear to *increase* usage by statistically significant amounts during SmartRate event hours. The percentages of such customers are shown in the second of the two pairs of columns in the table. They are small relative to the percentage with *negative* and significant load changes. For example, at a 95 percent confidence level, less than two percent of customers were found to have *positive* and statistically significant load changes.

Table 4.6: Percentages of Customers with Statistically Significant Load Reductions

Group	95% Confidence		90% Confidence	
	% Neg. & Sig.	% Pos. & Sig.	% Neg. & Sig.	% Pos. & Sig.
SmartRate-only	16.6%	1.9%	22.1%	3.5%
Dually enrolled	31.8%	1.3%	38.4%	2.3%

In a further effort to assess the validity of the estimated load impacts of the SmartRate customers, we applied the same regression model to the control group customers, including the variable indicating event days, even though those customers were not notified of events and had no incentive to reduce usage. Conducting similar tabulations of statistically significant negative and positive load impact coefficients, we find that 3.3 percent of the control group customers for SmartRate-only customers and 3.2 percent of the control group customers for the dually-enrolled customers had *negative* and statistically significant (at the 95% level) coefficients, while 3.4 percent of SmartRate-only and 4.2 percent of dually-enrolled control group customers had *positive* and statistically significant coefficients. In both cases, the distribution of coefficients for the control group customers was nearly centered around zero, with 51 percent of the SmartRate-only control customers and 50 percent of dually enrolled control customers having negative estimated coefficients. These are the types of coefficient distributions of random effects that would be expected for a variable that presumably had no effect on the control group customer loads.

Table 4.7 breaks down the percentages of statistically significant (at the 90% confidence level) responders (*i.e.*, those customers with negative and statistically significant load impact coefficients) by CARE status. For SmartRate-only customers, the percentages differ substantially by CARE status, with non-CARE customers 10 percentage points more likely to be significant responders. For dually-enrolled customers, however, the percentages are nearly the same, likely due to the control of air conditioners by PG&E during SmartRate events.

Table 4.7: Percentages of Statistically Significant Responders, by CARE Status

CARE Status	SmartRate only	Dually Enrolled
Non-CARE	25%	39%
CARE	15%	37%

Table 4.8 provides the same type of breakdown by percentiles of usage (measured by average summer weekday usage), along with additional indicators of the distribution of usage and estimated load impacts. Three columns are shown for both SmartRate-only and dually-enrolled customers. The first column shows the percentage of statistically significant responders in each usage category. The second column shows the distribution of total usage across the usage percentiles, while the third column shows the distribution of total estimated load impacts (including those that were not

statistically significant and those showing load *increases* rather than reductions).[14] The second two columns sum to 100 percent, but the first column does not.

Table 4.8: Distributions of Statistically Significant Responders, by Usage Percentile

	SmartRate-only			Dually-enrolled		
Usage Percentile	% Signif. Responders	% of Overall Ave. kWh	% of Total Load Impacts	% Signif. Responders	% of Overall Ave. kWh	% of Total Load Impacts
Smallest 10%	17%	3%	2%	19%	1%	1%
10 - 25%	22%	8%	5%	26%	4%	4%
25 - 50%	25%	19%	15%	33%	16%	14%
50 - 75%	29%	24%	25%	42%	28%	29%
75 - 90%	33%	22%	27%	50%	28%	29%
Largest 10%	33%	24%	26%	54%	23%	23%

For SmartRate-only, the percentages of statistically significant responders rise with the level of usage, although the responder share levels out as the usage increases, topping out at 33 percent statistically significant responders (at the 90 percent confidence level) for the top two size categories. In contrast, the percentages of dually-enrolled customers rise uniformly across the percentiles, reaching 54 percent of the largest 10 percent of customers.

Turning to the second and third columns in the groups of three, for SmartRate-only, the 50 percent of smallest customers account for proportionately smaller percentages of total load impacts than of overall usage, while the larger customers in the bottom three rows account for relatively more of the total load impacts. For dually-enrolled customers the relative portions of load impacts and overall usage are nearly the same for each usage percentile.

4.4 Bill Protection and Refunds, and Bill Impacts

PG&E provided a database of SmartRate charges (associated with usage during event hours on event days) and credits (associated with usage on summer non-event-days, and Tier 3 and higher usage) for each enrolled customer, along with indications of eligibility for bill protection and amounts of refunds, if applicable. This subsection summarizes the information in the database.

4.4.1 Bill Protection and Refunds

To encourage residential customers to enroll in SmartRate, participants are provided with bill protection for their first summer season. This ensures that they will not experience a bill increase relative to what they would have paid under their otherwise

[14] We note that the sums across all of the customer-level estimated load impacts are quite similar in magnitude to the aggregate values estimated in the fixed-effects regressions using all treatment and control customers.

applicable tariff (OAT) during that period. Any necessary bill refunds are made at the end of the summer season.

Table 4.9 shows the numbers and percentages of SmartRate-only and dually-enrolled customers, by eligibility for bill protection in 2015, and whether they experienced reduced or increased (before refund) bills under SmartRate. The last column, which is discussed further below, shows the average bill change for each customer group. As indicated in the fifth column of the table, 36 percent of SmartRate-only customers, and 14 percent of dually-enrolled customers were eligible for bill protection in 2015. Among those subsets of customers, 34 percent of SmartRate-only, and 45 percent of dually-enrolled customers experienced bill increases prior to any refunds received (see column six).

Overall, as shown in the bold area of the next to last column, 71 percent of SmartRate-only customers and 62 percent of dually-enrolled customers experienced bill reductions, while 29 percent and 38 percent respectively experienced bill increases. Somewhat smaller percentages of customers who were not eligible for bill protection experienced bill increases: 26 percent of SmartRate-only, and 37 percent of dually-enrolled customers.

Table 4.9: Summary of Bill Protection and Bill Changes

Program	Bill Protected	Neg./ Pos. Bill Change	Cust. count	% Bill Prot.	% Neg/ Pos	Ave. Bill Chg.
SmartRate only	No	All	65,849	64%		-$10
		Neg.	48,596		74%	-$25
		Pos.	17,253		26%	$32
	Yes	All	36,885	36%		-$6
		Neg.	24,250		66%	-$22
		Pos.	12,635		34%	$25
	Total	All	**102,734**	**100%**		**-$9**
		Neg.	**72,846**		**71%**	**-$24**
		Pos.	**29,888**		**29%**	**$29**
Dually-enrolled	No	All	32,555	86%		-$7
		Neg.	20,429		63%	-$28
		Pos.	12,126		37%	$28
	Yes	All	5,195	14%		-$2
		Neg.	2,859		55%	-$32
		Pos.	2,336		45%	$34
	Total	All	**37,750**	**100%**		**-$6**
		Neg.	**23,288**		**62%**	**-$29**
		Pos.	**14,462**		**38%**	**$29**

Table 4.10 shows the numbers and percentages of those customers eligible for bill protection in 2015 who received refunds after the summer. Approximately 30 percent of eligible SmartRate-only customers, and 40 percent of dually-enrolled customers received refunds.[15] This is substantially larger than the overall 5 percent of such eligible customers who received refunds in 2014.

Table 4.10: SmartRate Customers with Bill Protection who Received Refunds

Program	Received Refund?	Customers	% of Bill-Protected Customers	Ave. Refund
SmartRate only	No	25,757	70%	
	Yes	11,128	30%	$7.54
	Total	36,885	100%	
Dually-enrolled	No	3,148	61%	
	Yes	2,047	39%	$13.45
	Total	5,195	100%	

4.4.2 Bill Impacts

The last column in Table 4.9 shows average bill changes for the various customer segments. These bill changes reflect the event-period surcharges and non-event day bill credits received by SmartRate participants. The net bill changes are relative to the customers' OAT, to which the surcharges and credits are linked.[16] Negative values represent bill reductions.

In this section, we refined the bill impact analysis by limiting the sample to customers who were enrolled for the entire program year (June 1 to September 30). This helps ensure consistency across summaries that may otherwise have included customers enrolled in SmartRate for different portions of the summer. Overall, the average customer's bill was reduced by $10.47 for SmartRate-only, and $5.95 for dually-enrolled customers. Table 4.11 shows the range of bill impacts expressed as a percentage of their total bill.[17] Notice that the median percentage bill impact is -4.5 percent for SmartRate-only customers and -2.2 percent for dually enrolled customers. This is somewhat surprising given our expectation that more responsive customers would experience larger savings from the program. The top 1 percentile bill impacts are around -13

[15] The small differences between the numbers of eligible customers who experienced bill increases and those who received a refund (*e.g.*, 34 percent versus 30 percent for SmartRate-only) are presumably due to the fact that a number of bill increases were very small (*e.g.*, less than a dollar).

[16] Note that these bill changes are calculated at customers' observed usage in 2015, including any load changes that they made in response to being enrolled in SmartRate.

[17] Because meter read dates do not perfectly align with the June 1 to September 30 SmartRate season, we used the closest available approximation and then normalized the bill to be expressed on a dollars-per-120-days basis. We added the SmartRate bill change back into the customer's normalized bill to arrive at the denominator in our percentage bill change calculations.

percent for both groups, while the 99th percentile is a 23 and 26 percent bill increase for the two groups.

Table 4.11: Distributions of Percentage Bill Impacts

Percentile of Bill Impacts	SmartRate Only	Dually Enrolled
1%	-13.1%	-13.2%
5%	-9.9%	-9.6%
10%	-8.7%	-8.2%
25%	-6.8%	-5.8%
50%	-4.5%	-2.2%
75%	0.5%	3.5%
90%	7.2%	10.0%
95%	11.9%	14.7%
99%	23.2%	26.0%

Table 4.12 shows the average SmartRate bill impact (in level and percentage terms) and the percentage of customers saving money by LCA and enrollment type. Among SmartRate-only customers, the customers in the Greater Bay Area, Humboldt, and Northern Coast had the largest savings. For the dually enrolled customers, customers in Kern fared best.

Table 4.12: SmartRate Bill Impacts by LCA

Enrollment Status	LCA	Average Bill Change	% of Customers with Bill Decrease	Average % Bill Reduction
SmartRate Only	Greater Bay Area	-$13.64	84.9%	-3.9%
	Greater Fresno	-$5.81	51.5%	0.2%
	Humboldt	-$23.02	82.7%	-4.1%
	Kern	-$10.82	56.7%	-0.6%
	Northern Coast	-$14.43	80.1%	-3.5%
	Other	-$10.50	69.2%	-1.6%
	Sierra	-$3.29	55.5%	0.2%
	Stockton	$9.00	44.3%	2.9%
Dually Enrolled	Greater Bay Area	-$6.16	66.8%	-1.1%
	Greater Fresno	-$11.59	58.6%	-0.7%
	Humboldt	-$0.88	55.7%	0.7%
	Kern	-$26.36	70.3%	-2.7%
	Northern Coast	-$4.40	67.2%	-0.7%
	Other	-$1.29	54.0%	0.8%
	Sierra	-$5.34	57.3%	-0.1%
	Stockton	$0.28	52.8%	1.5%

These overall average bill savings and percentages of customers who achieved bill savings under SmartRate are smaller than those reported for 2014. In that case, overall average bill savings were reported as $9 per month, and the percentage of customers experiencing bill savings averaged approximately 95 percent. One factor likely driving the difference in results is the larger number of events in 2015 (15) compared to 2014 (12). The resulting larger amount of event-period usage that is exposed to the SmartRate surcharge produces larger bills, and thus smaller bill savings.

4.5 SmartRate retention rates

Table 4.13 shows monthly counts of customers who dropped out, or de-enrolled from SmartRate, and those that newly enrolled. Somewhat more customers dropped out than joined in the months immediately following the 2014 summer season. Beginning in the spring of 2015, more customers were added than dropped out. There was a net addition of approximately 5,000 customers.

Table 4.13: SmartRate Drop Outs and Additions

Month	Drop Outs	Additions
October 2014	1,368	1,406
November 2014	1,374	650
December 2014	3,813	306
January 2015	1,219	160
February 2015	1,400	173
March 2015	1,621	3,443
April 2015	1,733	3,134
May 2015	3,003	3,117
June 2015	3,457	2,014
July 2015	2,185	3,455
August 2015	2,055	8,441
September 2015	1,917	3,650
Total	**25,145**	**29,949**

5. *Ex-Post* Evaluation Methodology – TOU Rates

Estimating the extent to which customers respond to TOU rates is generally more challenging than for event-based pricing plans such as SmartRate. Since TOU prices do not change on a day-to-day basis over a season, generally the methods available to measure usage changes are to 1) employ data for treatment customers for a time period prior to their enrollment in the TOU rate (before/after), 2) select a contemporaneous control group of comparable non-TOU customers and compare their load patterns over the same time period (treatment/control), or 3) combine the two methods in a difference-in-differences analysis.

The first approach is typically not available for customers who signed up for a TOU rate several years previously. The second approach is possible in principle in the case of PG&E due to the universal availability of hourly Smart Meter data, even for customers not enrolled in a TOU rate. However, selecting an appropriate control group can be challenging. The third approach is available in some cases, such as the E-6 customers who have only recently signed up for the rate (referred to as "E-6 incremental" customers in the report), as described below.

We estimated *ex-post* load impacts for two groups of TOU customers: the non-NEM E-6 incremental customers;[18] and the E-7 customers who have been on TOU rates for some

[18] The NEM customers who are observed switching to E-6 are especially difficult to analyze because the change to E-6 happens at the same time they become a NEM customer. That prevents us from developing a differences-in-differences approach that isolates the effect of the TOU rate on the customer's usage profile. However, we did conduct a comparison of E-1 NEM and E-6 NEM load profiles. The E-6 NEM load profiles tended to be higher at the beginning and end of the day (when rooftop solar is not producing energy) and more negative in the middle of the day (when rooftop solar is producing energy), relative to E-1 NEM load profiles.

time (E-7 is closed to new enrollment), referred to as "E-7 embedded" customers in this report.[19] The evaluation methodology differs for the two groups because we can observe E-6 incremental customer loads prior to adoption the TOU rate, but cannot do so for the E-7 embedded customers.

The evaluation methodology for the E-6 incremental customers is somewhat analogous to the SmartRate evaluation. Since *pre-enrollment* load data are available for these customers, the approach involves matching potential E-1 control group customers to E-6 treatment customers on the basis of pre-enrollment usage profiles. Once the matched control group customers are selected, we compare treatment and control group loads in the post-enrollment period, while controlling for differences in the pre-enrollment period (*i.e.*, difference-in-differences).

For the E-7 embedded customers, we do not have pre-treatment load data for the TOU customers. Therefore, we match the E-7 customers to E-1 customers using monthly billing data from the treatment period.[20] We then compare E-7 and matched E-1 customer load profiles during a 12-month period to obtain our load impact estimates. This methodology allows us to select comparable customers in terms of observable characteristics (*e.g.*, location, CARE status, overall usage level), but does not allow us to distinguish between two potential sources of differences in load profiles – self-selection and demand response. That is, we may observe differences between E-7 and matched E-1 load profiles due to some combination of changes in behavior in response to TOU price signals or self-selection into the TOU rate based on the customer's pre-existing load profile. Our methodology cannot distinguish between these two causes of differences between E-7 and matched E-1 load profiles.

5.1 Control group selection

5.1.1 Approach

As noted above, control group selection for the E-6 incremental group was analogous to the process for SmartRate. A sample of potential control group customers was selected from the E-1 population, where the sample was five times the size of the number of E-6 participants, and was proportional to the share of customers in each LCA. Hourly load data for two twelve-month periods (pre-enrollment and post-enrollment) were requested for all E-6 incremental customers and the sample of E-1 customers. We then applied the Euclidean distance minimization approach to the pre-enrollment load data to select matched control group customers for each E-6 participant from the pool of potential E-1 control group members. We matched each E-6 customer twice, once for the summer months (using a 24-hour load profile averaged across the "core" summer

[19] We also estimated *ex-post* load impacts for E-6 embedded customers. However, given the analytical limitations, we present only the E-6 incremental estimates (which can and do employ a much more reliable method of estimating load impacts).

[20] Matching on hourly load profiles would not be appropriate because E-6 customer loads presumably reflect load response to the TOU prices.

months of June through September) and once for winter months (using a 24-hour load profile averaged across the "core" winter months of December through February). In addition to the seasonal matches, the matching process was conducted by LCA and CARE status, ensuring matches by those two characteristics.

For the E-7 embedded customers, we matched customers using 23 months of billing data, which were normalized to represent kWh per day and limited so that E-7 customers were only matched to E-1 customers whose meter read dates were within +/- 2 days of those of the E-7 customers. As with the E-6 incremental customers, the matching process was conducted by LCA and CARE status. However, we did not separately match by season for these customers.[21]

5.1.2 Matching results

Figures 5.1 through 5.3 illustrate the quality of our matches. Figures 5.1 and 5.2 show the E-6 incremental and matched control-group customer load profiles for the summer and winter months, respectively. In the summer months, the mean percentage error (MPE) of the control-group profile compared to the E-6 incremental profile is -1.0 percent. The mean absolute percentage error (MAPE) is 1.3 percent. In the winter months, the MPE is -0.9 percent and the MAPE is 1.1 percent.

[21] We expected seasonal matching to be less valuable because of the comparatively limited information provided by billing data versus interval data.

Figure 5.1: E-6 Incremental and Control Group Pre-treatment Load Profiles – *Summer*

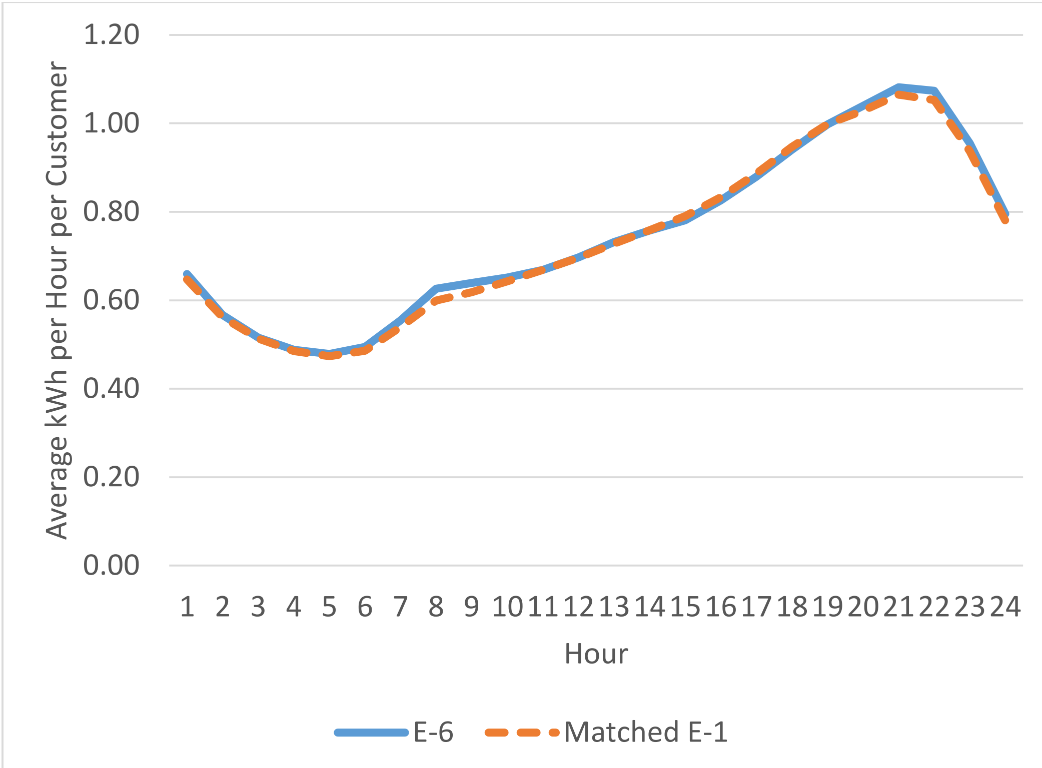


Figure 5.2: E-6 Incremental and Control Group Pre-treatment Load Profiles – *Winter*

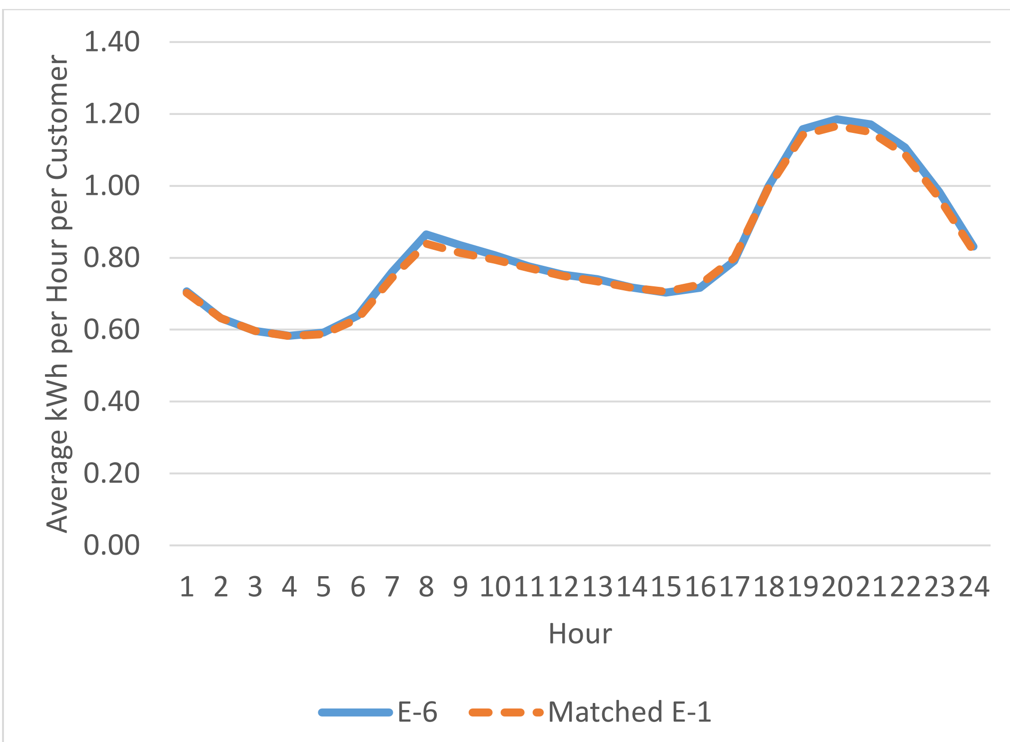
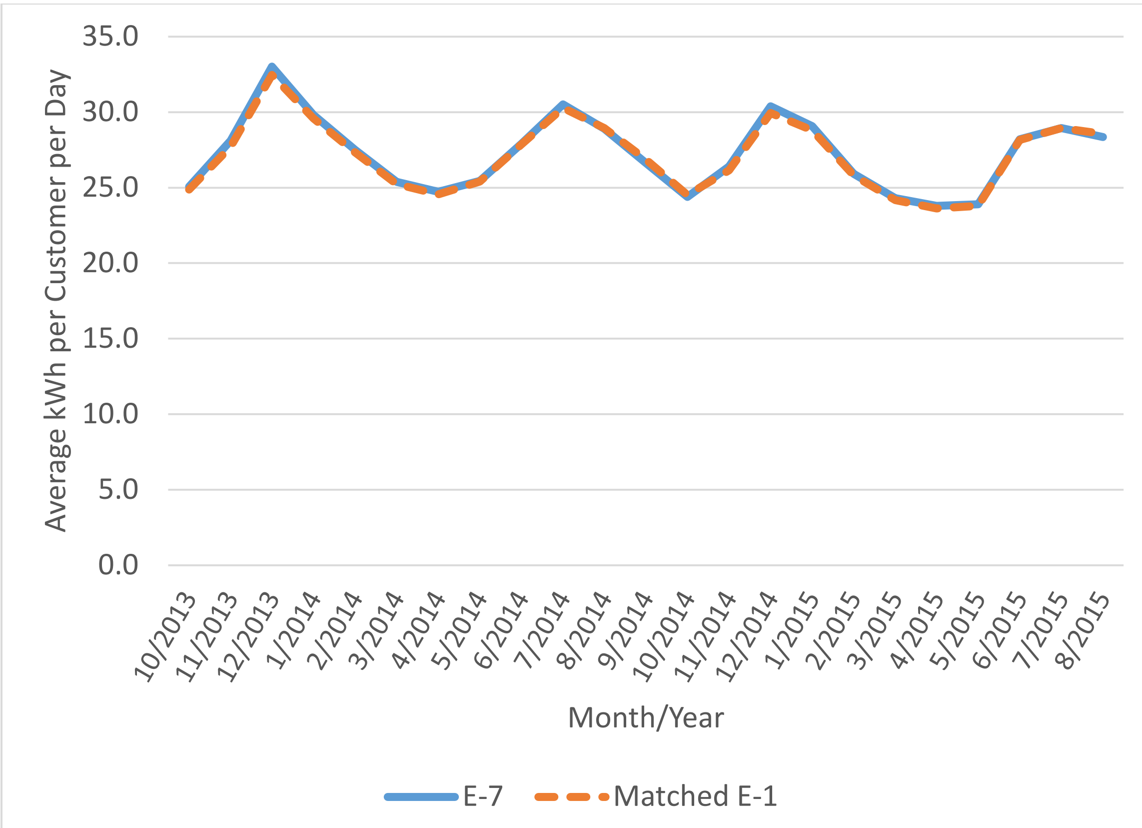


Figure 5.3 compares the monthly billing data (in kWh per customer per day) for the E-7 embedded customers and their matched control-group customers. The billing data cover the October 2013 to August 2015 time period. The MPE for the control-group customers compared to the E-6 customers across the 23 monthly averages is -0.5 percent. The corresponding MAPE is 0.7 percent. The errors tend to be lower in the summer months (*e.g.*, 0.0 percent in July 2015) than in the winter months (e.g., -1.5 percent in December 2014).

Figure 5.3: E-7 Embedded and Control Group Billing Data



5.2 Load impact estimation

The presence of matched control group customers means that the estimation equations for the E-6 incremental *ex-post* evaluation, as for SmartRate, may be quite simple, essentially a formal regression analysis to compare the loads of treatment and control group customers on the day types that are required for load impact evaluations of non-event-based programs like TOU rates. These day types include average weekdays by month, and monthly system peak days. Since the pre-enrollment data that were used in the control group matching process are available, we include data for each non-holiday weekday in a given month for the pre-enrollment period (for the average weekday analysis) in a difference-in-differences model. Separate models are estimated by hour, month, CARE status, and LCA, where the customer-level fixed-effects models are of the following form:[22]

$$kW_{c,d} = \beta_0 + \beta_1 \text{ x } (TOU_c \text{ x } Post_d) + \Sigma_{Cust} (\beta_{2,Cust} \text{ x } C_c) + \Sigma_{days} (\beta_{3,day} \text{ x } D_{day}) + \varepsilon_{c,d}$$

The variables and coefficients in the equation are described in the following table:

Symbol	Description
$kW_{c,d}$	Load in a particular hour for customer *c* on day *d*
TOU_c	Variable indicating whether customer *c* is a TOU (1) or Control (0) customer
$Post_d$	Variable indicating that day *d* is in the post-enrollment period
β_0	Estimated constant coefficient
β_1	Estimate of TOU load impact
$\beta_{2,Cust}$	Estimated customer fixed effects
$\beta_{3,day}$	Day fixed-effects
C_c	Variable indicating that the observation is associated with customer *c*
D_{day}	Variable indicating that the observation is for day *d*
$\varepsilon_{c,d}$	Error term

The *ex-post* estimation model for the E-7 embedded customers needed to be simplified to reflect the fact that we cannot implement a difference-in-differences approach for these customers. Instead, we estimate models that simply compare E-7 embedded customer usage to matched control-group customer usage on the day- and hour-type in question. The regression database includes only dates in the treatment period (there is no pre-treatment data for the E-7 customers), so the model reduces to the following:

$$kW_{c,d} = \beta_0 + \beta_1 \text{ x } TOU_c + \Sigma_{days} (\beta_{2,day} \text{ x } D_{day}) + \varepsilon_{c,d}$$

The model is estimated for each hour by LCA and CARE status.

6. TOU *Ex-Post* Load Impact Study Findings

6.1 E-6 incremental customers

Table 6.1 summarizes the average reference loads and load impacts for the relevant E-6 peak period (*i.e.*, 1 to 7 p.m. for May through October, and 5 to 8 p.m. for November through April), for the average weekday in each month, on an aggregate and per-customer basis.[23] The months are shown starting with the first month included in the

[22] Note that the customer and day fixed effects prevent the need for us to include stand-alone TOU_c and $Post_d$ variables. The former is perfectly collinear with the customer's fixed effect and the latter is perfectly collinear with a combination of day fixed effects.

[23] We refer to the 5 to 8 p.m. period as the "peak" period in the winter months since that is the only time period that has a higher differentiated price. However, the tariff refers to the price in that period as a *partial* peak price.

analysis (October 2014). Since enrollment continued throughout the period, the numbers of enrolled customers rise from only 112 in October 2014 to nearly 6,500 in September 2015.[24] Aside from May, which had relatively mild temperatures, the peak period load reductions in the summer averaged 8 to 9 percent. Peak load reductions in the winter months were somewhat smaller, at 5 to 6 percent. As described in Section 9.2.1, the per-customer reference loads and load impacts are lower than they were in the PY2014 study. We discuss potential explanations in that section.

Table 6.1: E-6 Incremental Peak Load Reductions – *Average Weekday by Month*

		Aggregate		Per-Customer			
Month	Enrollment	Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)	% Peak Load Impact	Ave. Peak Temp.
10/2014	422	0.29	0.02	0.68	0.05	8%	71
11/2014	734	0.74	0.04	1.01	0.05	5%	59
12/2014	1,140	1.35	0.10	1.19	0.09	7%	55
1/2015	1,547	1.70	0.11	1.10	0.07	6%	55
2/2015	1,861	1.83	0.11	0.98	0.06	6%	59
3/2015	2,261	1.88	0.12	0.83	0.05	6%	65
4/2015	2,842	2.16	0.11	0.76	0.04	5%	65
5/2015	3,496	2.03	0.06	0.58	0.02	3%	66
6/2015	4,250	3.27	0.29	0.77	0.07	9%	81
7/2015	5,476	4.53	0.39	0.83	0.07	9%	82
8/2015	6,469	5.34	0.51	0.83	0.08	9%	83
9/2015	6,469	4.96	0.42	0.77	0.06	8%	81

Figure 6.1 shows aggregate hourly observed and estimated reference loads, along with hourly estimated load impacts for the E-6 incremental customers for the average weekday in August. Figure 6.2 shows the same information for the average weekday in February.

[24] We examined only customers who joined E-6 between October 2014 and September 2015, which is why enrollments are low in the earlier portion of this time period. The number of customers that we could examine (because they had all of the required load data before and after joining E-6 is less than the total number of incremental E-6 customers. We therefore scale the results up to account for the correct total.

Figure 6.1: Aggregate Hourly Loads and Load Impacts (MW) – E-6 Incremental (*Average Weekday, August 2015*)

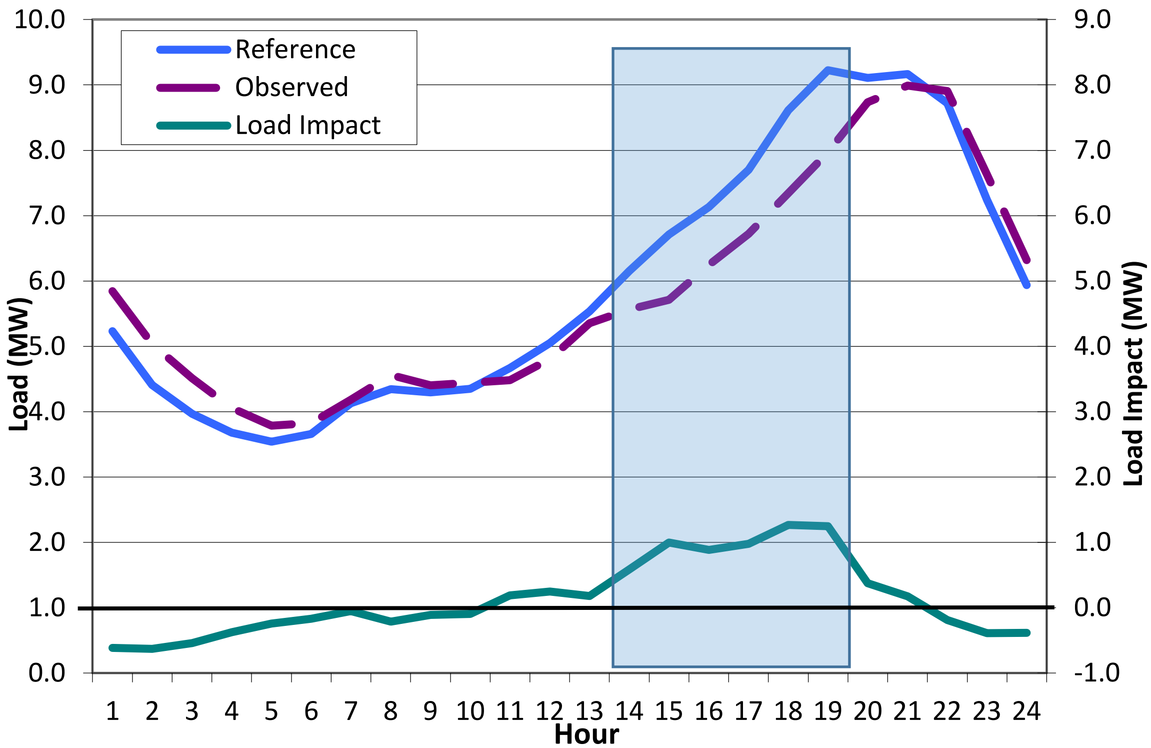


Figure 6.2: Aggregate Hourly Loads and Load Impacts (MW) – E-6 Incremental (*Average Weekday, February 2015*)

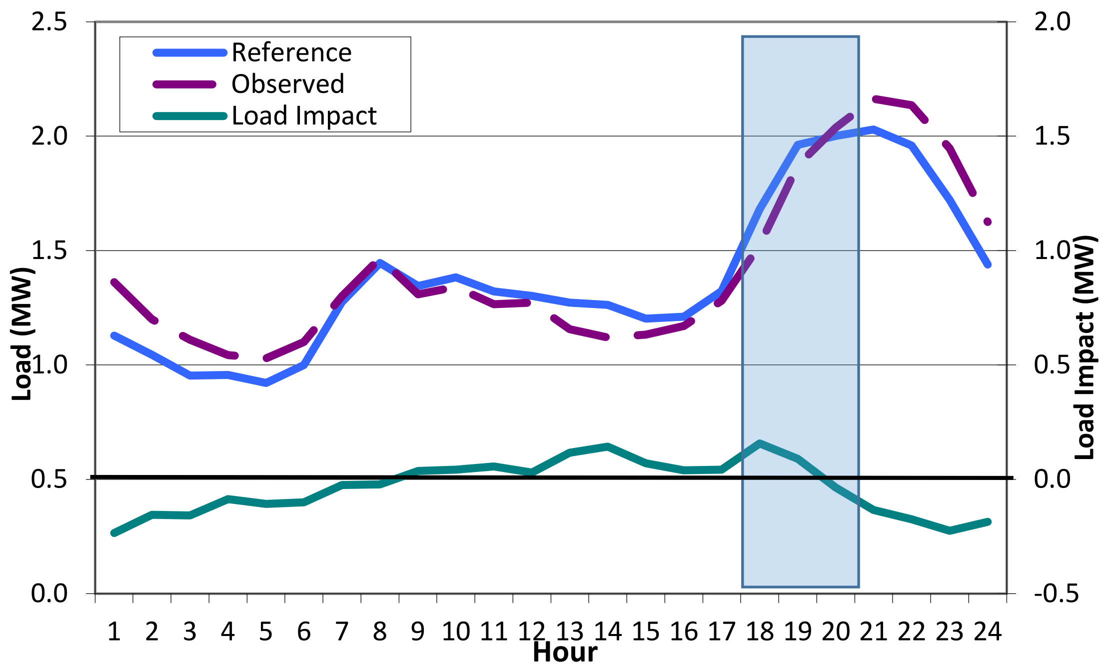


Table 6.2 summarizes loads and load reductions by LCA for the average summer (May through September 2015) weekday. The vast majority of customers reside in the Greater Bay Area, so aggregate load reductions are greatest there. However, per-customer load reductions are lowest in that LCA. Similar results hold for the winter months (Table 6.3), with the lower enrollment numbers producing smaller load reductions.

Table 6.2: E-6 Incremental Peak Load Reductions by LCA – Average *Summer* Weekday

		Aggregate		Per-Customer			
LCA	Enrolled	Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)	% Peak Load Impact	Ave. Peak Temp.
Greater Bay Area	2,858	1.73	0.11	0.61	0.04	6%	75
Greater Fresno	146	0.27	0.02	1.83	0.12	7%	90
Humboldt	138	0.11	0.01	0.83	0.09	11%	66
Kern	[redacted]						
Northern Coast	249	0.22	0.03	0.89	0.11	12%	78
Other	667	0.63	0.06	0.95	0.10	10%	79
Sierra	201	0.28	0.04	1.37	0.18	13%	83
Stockton	[redacted]						
All	**4,430**	**3.40**	**0.28**	**0.77**	**0.06**	**8%**	**77**

Table 6.3: E-6 Incremental Peak Load Reductions by LCA – Average *Winter* Weekday

		Aggregate		Per-Customer			
LCA	Enrolled	Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)	% Peak Load Impact	Ave. Peak Temp.
Greater Bay Area	1,079	0.89	0.04	0.82	0.04	5%	60
Greater Fresno	[redacted]						
Humboldt							
Kern							
Northern Coast	123	0.16	0.02	1.33	0.20	15%	59
Other	263	0.29	0.02	1.11	0.08	7%	59
Sierra	[redacted]						
Stockton							
All	**1,731**	**1.61**	**0.10**	**0.93**	**0.06**	**6%**	**60**

Table 6.4 shows average seasonal peak load reductions by CARE status of the enrolled customers. The CARE customers average a higher peak load in both summer and winter months than non-CARE customers, where the differences are likely due to the CARE

customers residing in LCAs that have greater seasonal variation in weather conditions.[25] The non-CARE customers reduced summer peak load by a greater relative amount (9 percent) than did CARE customers (6 percent). The reverse was the case in winter, although the number of CARE customers enrolled during that time is relatively small.

Table 6.4: E-6 Incremental Peak Load Reductions by CARE Status

Season	CARE Status	Enrolled	Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)	% Peak Load Impact	Ave. Peak Temp.
Summer	Non-CARE	3,969	2.83	0.25	0.71	0.06	9%	77
	CARE	462	0.49	0.03	1.06	0.06	6%	79
Winter	Non-CARE	1,553	1.40	0.07	0.90	0.05	5%	60
	CARE	178	0.20	0.02	1.13	0.11	10%	59

6.2 E-7 embedded customers

This section summarizes estimated *ex-post* load impacts for the non-NEM E-7 embedded customers. As noted in Section 5, customers taking service under E-7 have been enrolled for some time, which ruled out the possibility of selecting control group customers on the basis of *pre-treatment* load profiles. As a result, differences between the load profiles of the E-7 customers and the control group customers selected on the basis of matched monthly billing data are likely to reflect a combination of two factors – 1) pre-existing loads that are characterized by relatively low peak period usage (self-selection), and 2) load responses to the TOU rate. Furthermore, the data are not sufficient to allow us to distinguish these two factors.

Table 6.5 shows estimated average peak period (12 p.m. to 6 p.m.) reference loads and load impacts by month, beginning with the first month of analysis, October 2014. The lightly shaded summer months show generally larger reference load values than in winter, and load reductions of 11 or 12 percent, reaching 0.17 kW in the core summer months. The peak load reductions and percentage reductions are slightly smaller in the non-summer months.

[25] As shown in Table 2.2, CARE customers represented 40 percent or more of E-6 customers in the central valley LCAs (Fresno, Kern and Stockton), while only 11 percent in the Greater Bay Area.

Table 6.5: E-7 Embedded Peak Load Reductions – *Average Weekday by Month*

Month	Enrolled	Aggregate		Per-Customer		% Peak Load Impact	Ave. Peak Temp.
		Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)		
October 2014	51,026	53.4	6.3	1.05	0.12	12%	76
November 2014	50,690	55.3	4.9	1.09	0.10	9%	64
December 2014	50,492	65.1	5.0	1.29	0.10	8%	57
January 2015	50,136	56.7	5.5	1.13	0.11	10%	59
February 2015	49,810	50.1	5.2	1.01	0.10	10%	64
March 2015	49,550	47.1	5.2	0.95	0.11	11%	69
April 2015	49,248	47.4	5.3	0.96	0.11	11%	69
May 2015	48,942	47.4	5.5	0.97	0.11	12%	69
June 2015	48,629	68.5	8.2	1.41	0.17	12%	85
July 2015	48,355	72.5	8.2	1.50	0.17	11%	86
August 2015	47,777	67.7	8.0	1.42	0.17	12%	86
September 2015	47,777	59.8	6.7	1.25	0.14	11%	84

Figure 6.3 shows aggregate hourly observed and estimated reference loads, along with hourly estimated load impacts for the E-7 embedded customers for the average weekday in August. Figure 6.4 shows the same information for the average weekday in February.

Figure 6.3: Aggregate Hourly Loads and Load Impacts (MW) – E-7 Embedded (*Average Weekday, August 2015*)

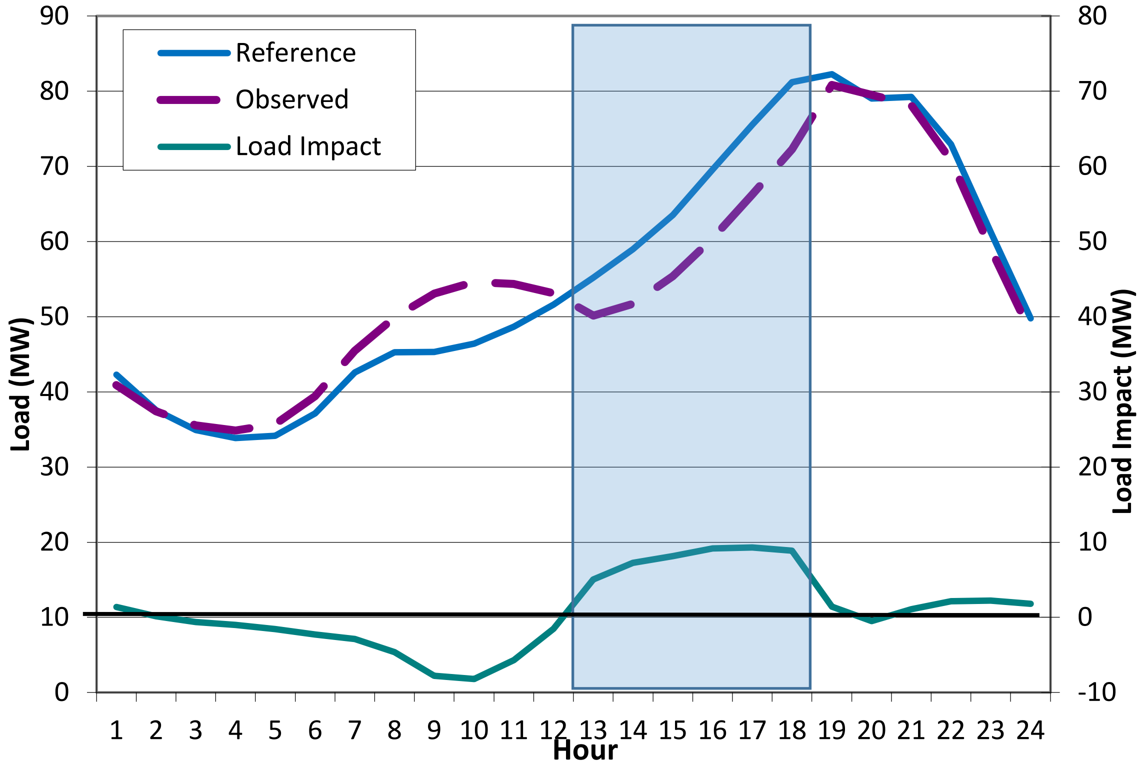


Figure 6.4: Aggregate Hourly Loads and Load Impacts (MW) – E-7 Embedded (*Average Weekday, February 2015*)

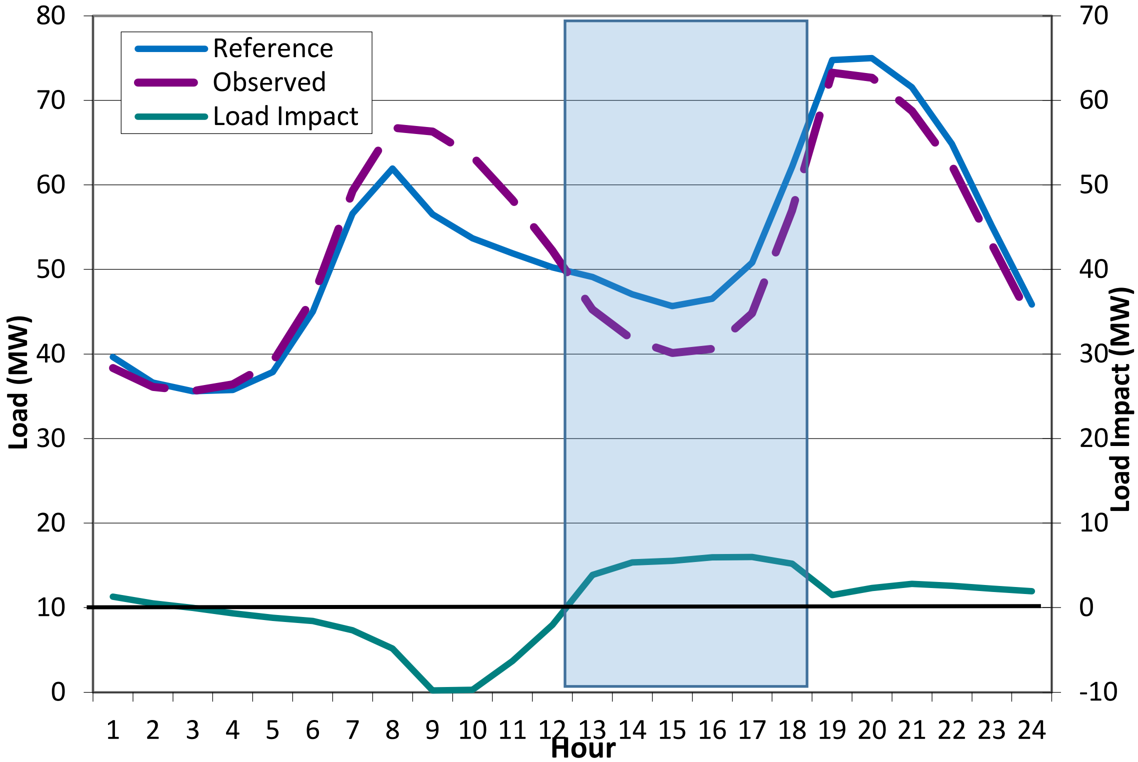


Table 6.6 shows peak load reductions by LCA for the average *summer* weekday. The largest numbers of enrolled customers and aggregate peak load reductions are in the Greater Bay Area and Other LCAs. The largest per-customer peak loads and load reductions are in the relatively warm areas of Greater Fresno, Kern, and Sierra.

Table 6.6: E-7 Embedded Peak Load Reductions by LCA – Average *Summer* Weekday

		Aggregate		Per-Customer			
LCA	Enrolled	Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)	% Peak Load Impact	Ave. Peak Temp.
Greater Bay Area	17,416	18.6	1.5	1.07	0.09	8%	77
Greater Fresno	2,950	5.6	0.8	1.90	0.28	15%	90
Humboldt	3,292	3.5	0.6	1.05	0.17	16%	72
Kern	1,084	2.1	0.3	1.96	0.26	13%	89
Northern Coast	6,187	6.8	0.7	1.09	0.11	10%	78
Other	11,336	15.2	1.9	1.34	0.17	12%	82
Sierra	4,254	6.3	1.0	1.48	0.23	16%	83
Stockton	2,232	3.3	0.4	1.50	0.18	12%	85
All	**48,751**	**61.6**	**7.1**	**1.26**	**0.15**	**12%**	**81**

Table 6.7 shows comparable information for the average *winter* weekday. Peak load reductions are somewhat smaller and vary less than do the summer values.

Table 6.7: E-7 Embedded Peak Load Reductions by LCA – Average *Winter* Weekday

LCA	Enrolled	Aggregate		Per-Customer		% Peak Load Impact	Ave. Peak Temp.
		Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)		
Greater Bay Area	17,790	17.3	1.4	0.97	0.08	8%	64
Greater Fresno	3,051	3.3	0.5	1.10	0.17	15%	66
Humboldt	3,376	3.8	0.5	1.14	0.16	14%	59
Kern	1,121	1.0	0.0	0.93	0.04	4%	67
Northern Coast	6,313	6.9	0.6	1.10	0.10	9%	64
Other	11,670	13.2	1.2	1.13	0.10	9%	64
Sierra	4,373	5.5	0.7	1.26	0.16	13%	61
Stockton	2,294	2.6	0.2	1.15	0.09	8%	63
All	**49,988**	**53.6**	**5.2**	**1.07**	**0.10**	**10%**	**64**

Table 6.8 shows seasonal peak load reductions by CARE status. The per-customer peak loads and load reductions in both seasons differ little by CARE status.

Table 6.8: E-7 Embedded Peak Load Reductions by CARE Status

Season	CARE Status	Enrolled	Peak Ref. Load (MW)	Peak Load Impact (MW)	Peak Ref. Load (kW)	Peak Load Impact (kW)	% Peak Load Impact	Ave. Peak Temp.
Summer	Non-CARE	43,685	54.9	6.4	1.26	0.15	12%	81
	CARE	5,066	6.6	0.7	1.30	0.14	11%	82
Winter	Non-CARE	44,771	47.8	4.7	1.07	0.10	10%	64
	CARE	5,217	5.8	0.5	1.11	0.10	9%	63

7. *Ex-Ante* Load Impacts – SmartRate

This section describes the development of *ex-ante* load impact forecasts for the SmartRate program. We first describe the methodology used, and then present the resulting forecasts. *Ex-Ante* load impacts represent forecasts of load impacts that are expected to occur when program events are called in future years, under standardized weather conditions. The forecasts are based on analysis of per-customer load impact findings from *ex-post* evaluations, development of weather-sensitive reference loads, and incorporation of utility forecasts of program enrollments.

7.1 Methodology

Ex-ante load impacts for SmartRate were developed in a series of steps, as follows:

1. Weather-sensitive per-customer load impacts were developed separately for SmartRate-only and dually-enrolled customers through a regression analysis relating average customer load impacts, by LCA, for *each hour of each event,* to weather conditions on the event day (*e.g.*, CDD65).
2. Weather-sensitive reference loads for the average customer in the same cells (defined by enrollment type and LCA) were also developed through a regression analysis. This step was complicated by the need to develop reference loads for each month of the year, while the *ex-post* analysis was only conducted for the summer months. To reduce the amount of hourly interval data required, representative samples of SmartRate-only and dually-enrolled customers were selected, and their hourly load data for a full twelve months (excluding event days) was used to develop weather-sensitive reference loads.
3. The reference load equations were then used to simulate reference loads for the four required weather scenarios: 1-in-2 and 1-in-10 weather years, for both utility system peak and the utility's load at the time of CAISO's peak operating conditions. (We refer to the former as "utility-specific" scenarios and the latter as "CAISO-coincident" scenarios.) Reference loads were developed separately for SmartRate-only and dually-enrolled customers, and by LCA.
4. The per-customer load impact equations were also used to simulate load impacts for the same cells, under the same four weather scenarios.
5. Per-customer load impacts and reference loads were then applied to PG&E enrollment forecasts to produce aggregate load impacts.

7.1.1 Per-customer load impacts

Weather-sensitive load impacts were developed from a regression model applied separately to the per-customer *ex-post* load impact data for each hour of each event day, for both enrollment types (SmartRate-only and dually-enrolled), and each LCA. The regression equation is the following:

$$LI_{\mathrm{d}} = \beta_0 + \beta_1 * CDD65_d + \varepsilon_{\mathrm{d}}.$$

The left-hand side variable is the average estimated load impact in a particular hour, for a given enrollment type and LCA, and the subscript *d* represents an event-day.

Figures 7.1 and 7.2 illustrate the relationship between estimated *ex-post* load impacts and event-day weather conditions, expressed by CDD65, for SmartRate-only and dually-enrolled customers. The particular values shown in the figures are for hour 18 in the Greater Bay Area. The weather sensitivity of the estimated load impacts is clearly visible for both groups of customers.

Figure 7.1: Relationship between *Ex-Post* Load Impacts and Weather: Hour 18 in Greater Bay Area – *SmartRate-only*

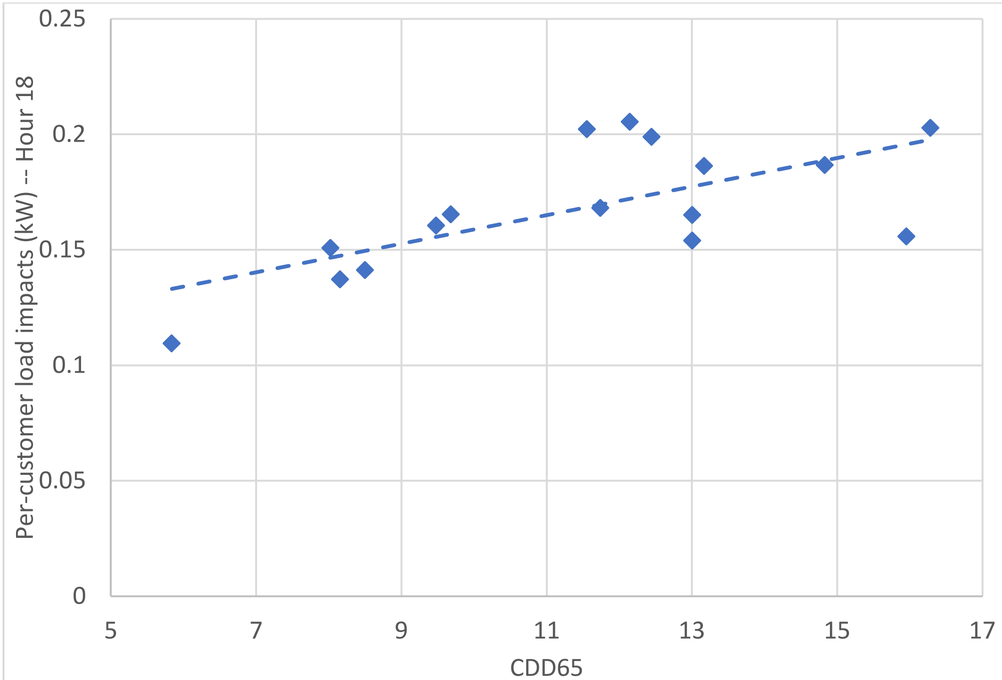
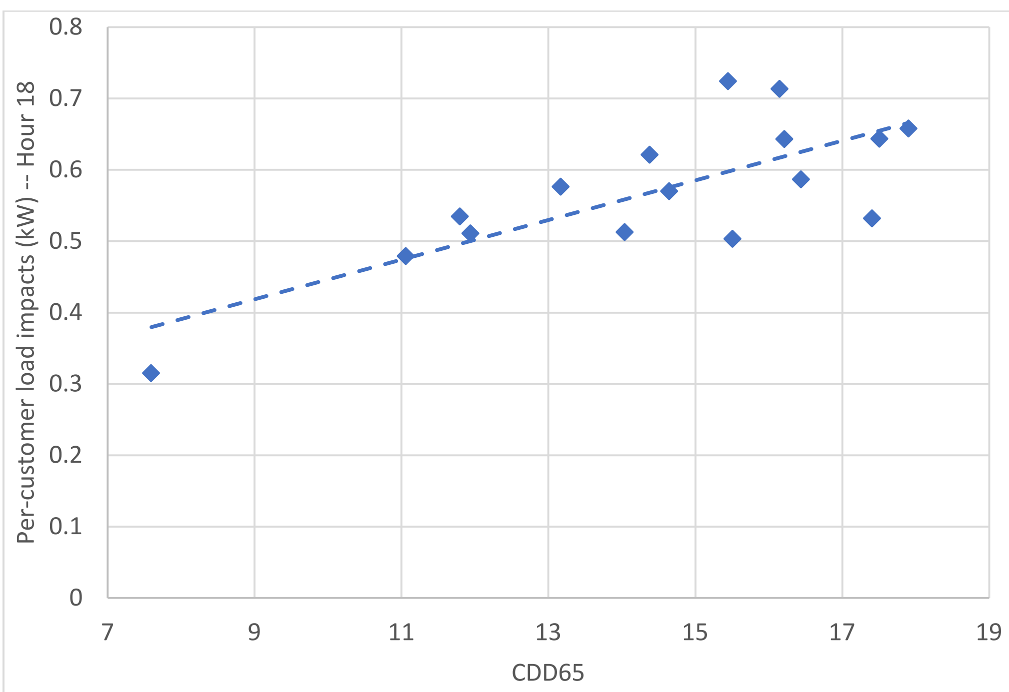


Figure 7.2: Relationship between *Ex-Post* Load Impacts and Weather: Hour 18 in Greater Bay Area – *Dually-enrolled*



Per-customer load impacts by cell for each of the four *ex-ante* weather scenarios were then developed by applying the estimated regression models to the implied CDD65 values for each month in each scenario. No SmartRate events have been called in non-summer months, however *ex-ante* forecasts for non-summer months are required. To produce per-customer load impacts for months with zero CDD65, we interpreted the constant term in the load impact models as a measure of non-cooling load impacts, and used it as the load impact in those cases.[26]

An additional issue in producing the *ex-ante* load impact forecasts is that the Protocols call for estimating load impacts for the RA hours of 1 p.m. to 6 p.m., while by the SmartRate tariff, events are only called during the hours of 2 p.m. to 7 p.m. We simulate the load impacts using the event hours that are required by the tariff, but summarize the load impacts across the RA window as required (there are no event load impacts from 1 to 2 p.m.). Therefore, average *ex-ante* load impacts for the RA window are approximately 20 percent lower than the *ex-post* load impacts estimated for 2015 (*i.e.*, four-fifths of the average event-hour load impacts). In the *ex-ante* load impact summaries below, we show average load impacts for both the SmartRate event period and the RA window.

Finally, the dually enrolled customers have different load impacts in the program and portfolio scenarios. That is, SmartAC takes precedence over SmartRate, so much of the dually enrolled customer load impact goes away in the portfolio scenarios. However, we assume that the dually enrolled customers provide higher load impacts on dual event days than SmartAC-only event days (due to price-based response to the SmartRate event price). PY2015 did not contain event days on which to base such a difference, but PY2014 did. Specifically, from July 29 through August 1, 2014 there were four event days, two of which were SmartAC only. The days were sufficiently similar that a comparison of load impacts across the days provides an indication of the additional load impacts provided by dually enrolled customers on SmartRate event days. We determined that the portfolio load impact of dually enrolled customers is equal to 21 percent of the program-specific load impact during summer months. During winter months, the program and portfolio load impacts are the same because SmartAC is not active.

7.1.2 Per-customer reference loads

As summarized above, weather-sensitive reference loads for the average customer in cells defined by enrollment type and LCA were developed through a regression analysis of hourly load data for weekday non-event days for the period of October 2014 through September 2015 based on representative samples of SmartRate-only and dually-enrolled customers. Regression models were estimated separately for each hour of the day, using a form similar to that of the load impact models, except that a variable for HDD65 was added to account for heating as well as cooling effects, and monthly

[26] The constant terms produce reasonable non-weather load impacts for the SmartRate-only customers, but not for the dually enrolled customers. Therefore, when simulating load impacts for the winter months, we use the SmartRate-only customer load impacts for the dually enrolled customers as well.

indicator variables were added to account for monthly differences in usage patterns. The estimated reference load equations were then used to simulate *ex-ante* reference loads for the four required weather scenarios.

7.2 SmartRate Ex-Ante Forecasts

As described in Section 7.1, *ex-ante* load impact forecasts for SmartRate are constructed based on enrollment forecasts provided by PG&E, and per-customer load impacts developed by analyzing the relationship between *ex-post* load impacts for each event in 2015 and the weather conditions that existed for each of the events.

Table 7.1 shows PG&E's enrollment forecast for SmartRate, in total and by enrollment type, for August of 2016 and for the period 2017 to 2026. PG&E anticipates that going forward new enrollments will largely offset drop-outs, resulting in level enrollments.

Table 7.1: SmartRate Enrollments (*August values*)

	SmartRate-only		Dually Enrolled		Total SmartRate	
LCA	**Aug. 2016**	**2017-2026**	**Aug. 2016**	**2017-2026**	**Aug. 2016**	**2017-2026**
Greater Bay Area	57,748	57,701	13,405	13,480	71,153	71,181
Greater Fresno	8,443	8,436	3,438	3,457	11,881	11,893
Humboldt	1,456	1,455	192	193	1,648	1,648
Kern	7,289	7,283	1,831	1,841	9,120	9,124
Northern Coast	2,288	2,286	925	930	3,213	3,216
Other	19,896	19,880	6,950	6,989	26,846	26,869
Sierra	6,117	6,112	4,084	4,107	10,202	10,220
Stockton	7,052	7,046	3,780	3,801	10,832	10,848
Total	**110,289**	**110,200**	**34,605**	**34,800**	**144,894**	**145,000**

Table 7.2 shows average hourly *ex-ante* program-specific load impacts for 2017 by month on a per-customer and aggregate basis, for the RA window (1 to 6 p.m. from April through October, 4 to 9 p.m. from November through March) for the PG&E 1-in-2 weather scenario.[27] Results are shown by enrollment type and in total, and summer months are set off by horizontal lines. The largest load impacts (34.3 MW for the total program) occur on the August peak day.

[27] Results for the other weather scenarios are available in the table generator spreadsheets provided along with this report.

Table 7.2: ***Ex-Ante*** **Load Impacts by Day Type –** ***PG&E 1-in-2 Weather***

Day Type	Per-Customer (kW)		Aggregate (MW)		
	SmartRate-only	Dually-enrolled	SmartRate-only	Dually-enrolled	Total Program
January Peak	0.085	0.115	9.4	4.0	13.4
February Peak	0.085	0.115	9.4	4.0	13.4
March Peak	0.085	0.115	9.4	4.0	13.4
April Peak	0.084	0.115	9.3	4.0	13.3
May Peak	0.102	0.238	11.2	8.3	19.5
June Peak	0.161	0.458	17.8	15.9	33.7
July Peak	0.162	0.466	17.9	16.2	34.1
August Peak	0.166	0.459	18.3	16.0	34.3
September Peak	0.140	0.371	15.5	12.9	28.4
October Peak	0.103	0.191	11.3	6.6	18.0
November Peak	0.085	0.115	9.4	4.0	13.4
December Peak	0.085	0.115	9.4	4.0	13.4
Typical Event Day	**0.164**	**0.457**	**18.1**	**15.9**	**34.0**

Figure 7.3 illustrates the variation in aggregate load impacts for SmartRate-only, for the August peak day in 2017 under the four weather scenarios and alternative assumptions regarding the event window – the program event hours of 2 to 7 p.m. and the RA hours of 1 to 6 p.m. Load impacts are greatest under the PG&E 1-in-10 scenario, and the discounted values for the RA window are apparent. Figure 7.4 shows similar results for dually-enrolled customers, with the same patterns holding.

Figure 7.3: *Ex-Ante* Load Impacts by Weather Scenario, and Event and RA Window – *SmartRate-only, August Peak Day*

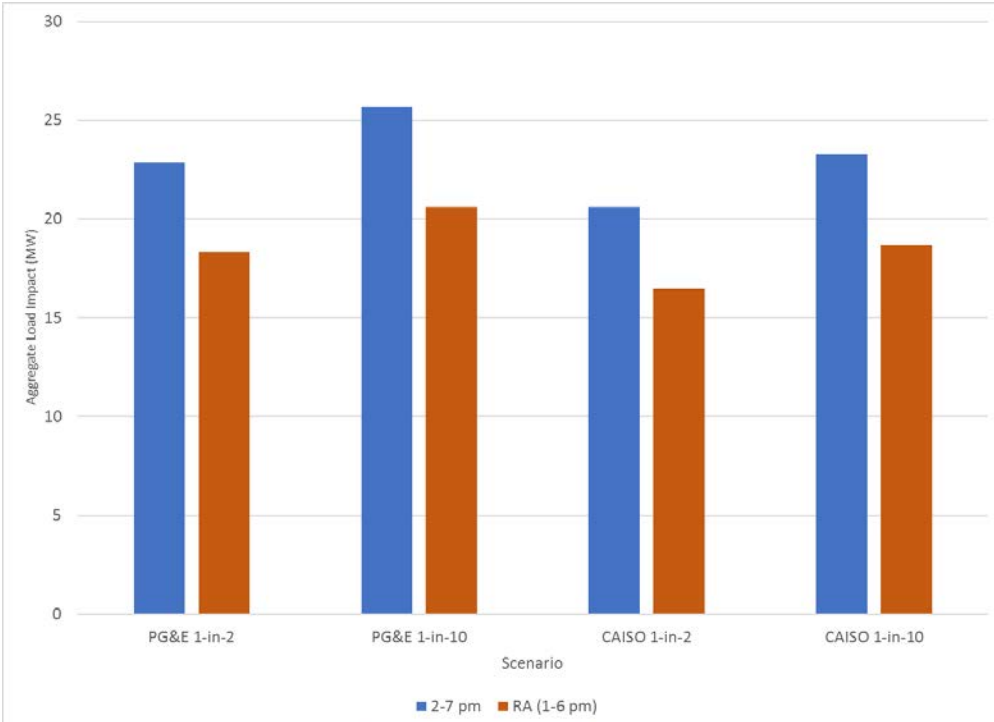
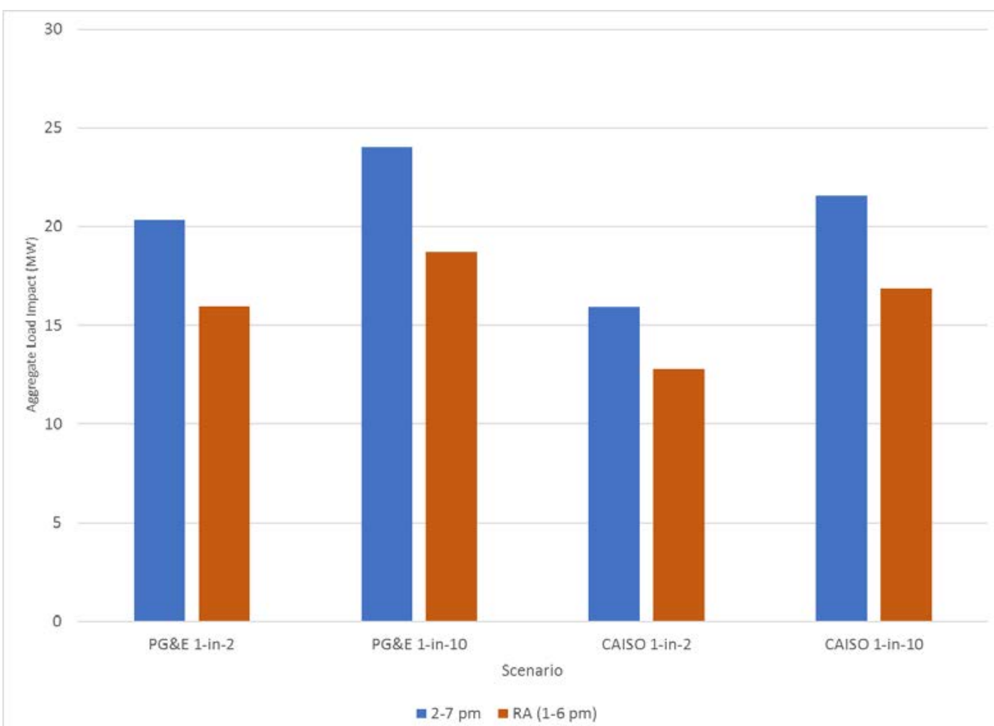


Figure 7.4: *Ex-Ante* Load Impacts by Weather Scenario, and Event and RA Window – *Dually-enrolled, August Peak Day*



8. *Ex-Ante* Load Impacts – *Residential TOU*

8.1 Methodology

For the TOU rates, *ex-ante* load impacts were developed separately for three TOU rates:

- *E-6 non-NEM customers*. This group consists of customers who are enrolled in E-6 as of the initial year of the forecast, and those who migrate from E-7 or sign up in future years.
- *E-TOU-A customers*. These are customers who are assumed to enroll in PG&E's new E-TOU-A rate, either by being transferred from E-7 or signing up in the future.
- *E-TOU-B customers*. These are customers who are assumed to enroll in PG&E's new E-TOU-B rate.

For the first set of customers, *ex-post* load impacts for E-6 incremental customers serve as the basis for the per-customer load impacts by LCA. PG&E provided separate enrollment forecasts for the embedded and incremental E-6 customers. Because we are only able to develop valid *ex-pos*t load impacts for the incremental customers, those load impacts serve as the basis of the *ex-ante* load impacts for both groups. For the two new TOU rates, we use a simulation approach, similar to the approach used in our recent study of Statewide TOU rates.[28]

As with all *ex-ante* studies, we develop four sets of results associated with distinct weather scenarios, which are distinguished by:

- 1-in-2 weather conditions versus 1-in-10 weather conditions; and
- Whether the peak conditions are determined using the utility's peak or the utility's load at the time of CAISO's peak.

The weather conditions for each scenario were provided by PG&E.

8.1.1 E-6 *ex-ante* methods

We develop weather-sensitive per-customer reference loads and load impacts separately, using regression analysis applied to data for the E-6 incremental customers. We then simulate both values for the four weather scenarios and apply them to enrollment forecasts. Reference loads were simulated for E-6 customers using the same methods described in Section 7.1.2, though in this case we need simulations for both monthly peak days and monthly average weekdays.

Additional regression models were developed to estimate the weather sensitivity of the E-6 incremental TOU load impacts. Separate models were estimated by season (summer and winter), LCA, and hour. The model is specified in the same manner as the *ex-post*

[28] "Statewide Time-of-Use Scenario Modeling for 2015 California Energy Commission Integrated Energy Policy Report", Christensen Associates Energy Consulting, November 15, 2015.

regression model shown in Section 5.2, but adds CDD65 and HDD60 variables, both as stand-alone variables and interacted with the load impact variable (TOU_c x $Post_d$). This structure allows us to estimate how seasonal load impacts change with weather conditions on an hourly basis, by LCA.

We then simulate the *ex-ante* load impacts using the three load impact coefficients (the stand-alone load impact, the interaction with CDD65, and the interaction with HDD60).[29] The per-customer reference loads and load impacts are combined for each cell (LCA) and weather scenario and scaled using enrollment forecasts provided by PG&E.

8.1.2 E-TOU-A and E-TOU-B *ex-ante* methods

Because E-TOU-A and E-TOU-B will not have customers until March 2016, we had to derive a basis for the per-customer reference loads and load impacts. Before explaining those methods, it would help to explain the assumptions underlying the forecast.

First, E-7 is being closed, with its customers moving to other rates in May 2016. The default rate for these customers is E-TOU-A, though they can select another option if they choose. Per PG&E's instructions, we assume that E-7 customers will migrate to E-TOU-A and E-TOU-B in equal numbers (and with the same per-customer load profile by LCA). Second, the E-TOU-A peak period will change in January 2020, shifting one hour later (to match the E-TOU-B peak period). This requires a second simulation of E-TOU-A load impacts applied to the dates during which the new peak period will be in effect. Third, per PG&E's instructions, we assume that E-TOU-A and E-TOU-B customers who join in months other than May 2016 (when the E-7 customers are transitioned) will resemble E-6 incremental customers. Because E-TOU-A retains a tier structure while E-TOU-B does not, we assume that larger customers will join E-TOU-B.[30]

Some of the required reference loads are taken directly from the E-6 incremental *ex-ante* forecast. These apply to E-TOU-A and E-TOU-B customers joining in any month other than May 2016. As described above, the customers going to E-TOU-B are scaled up somewhat to reflect the expected higher usage level of those customers (due to the fact that E-TOU-B is not linked to an underlying tiered rate, which should favor higher-use customers). The remaining reference loads, which apply to customers joining E-TOU-A and E-TOU-B in May 2016, are taken from our E-7 embedded analysis. Specifically, we use the matched control group (E-1) customer loads (which are intended

[29] The uncertainty-adjusted load impacts are developed using the variance-covariance matrix for the relevant estimates. That is, the variance of the simulated load impact depends upon the standard errors of the three load impact coefficients, the covariances between each pair, and the CDD65 and HDD60 levels used to simulate the specific load impact.

[30] We base the size difference on a comparison of the E-7 load profiles that were messaged by PG&E to adopt E-TOU-A vs. E-TOU-B. We found a single all-hours multiplier that ranged from 1.2 to 1.85, depending on the LCA and month. This multiplier is applied to the E-6 loads that are placed on E-TOU-B. The E-6 loads placed on E-TOU-A are left unchanged.

to represent what the E-7 customer loads would be if they were not on a TOU rate) as the basis for our reference loads. We develop reference load simulation models that match the methods used for the SmartRate and E-6 incremental analyses.

As described above, the load impacts for the E-TOU-A and E-TOU-B customers are simulated using a constant elasticity of substitution model applied to the reference loads, assuming elasticity values consistent with those used in the aforementioned statewide TOU study. In that study, we separately analyzed CARE and non-CARE customers and CARE customers were assumed to be half as demand responsive as non-CARE customers. In this analysis, we combine the two customer groups (*i.e.*, there is one set of reference loads that represents all customers in an LCA) and apply an elasticity value that is an approximate customer-weighted average across the CARE and non-CARE customers. (The shares come from the existing E-6 and E-7 customers, as appropriate.) In practice, this results in an elasticity of substitution of approximately 0.064.

The table below shows the E-TOU-A and E-TOU-B rates by pricing period and CARE status. We calculate the weighted average of the CARE and non-CARE rates in the same manner applied to the elasticity of substitution described above. The peak period is from 4:00 to 9:00 p.m., except for the E-TOU-A option prior to January 2020, when it is from 3:00 to 8:00 p.m. The summer season is from June through September. Both TOU rates are simulated in comparison to a flat rate. The level of the flat rate (and the existence of the baseline credit in E-TOU-A) are not relevant to the analysis because we set the overall (daily) elasticity to zero (so customers don't respond to changes in the overall price level by increasing or decreasing their overall usage level).

Table 8.1: E-TOU-A and E-TOU-B Rates

CARE Rate?	Pricing Period	E-TOU-A	E-TOU-B
No	Summer peak price	$0.40246	$0.35611
No	Summer off-peak price	$0.32689	$0.25305
No	Winter peak price	$0.28449	$0.21864
No	Winter off-peak price	$0.27020	$0.19985
Yes	Summer peak price	$0.23304	$0.21808
Yes	Summer off-peak price	$0.18543	$0.15315
Yes	Winter peak price	$0.15872	$0.13147
Yes	Winter off-peak price	$0.14972	$0.11963

For the E-TOU-A and E-TOU-B customers, the weather sensitivity of the load impacts is entirely due to weather-induced changes in the simulated reference loads. That is, our load impact simulations produce percentage load impacts by season and pricing period (based on a constant elasticity of substitution model) that are applied to the reference loads in the corresponding hours.[31]

8.2 Ex-Ante Load Impact Results

Ex-ante load impacts are developed for four groups of customers:

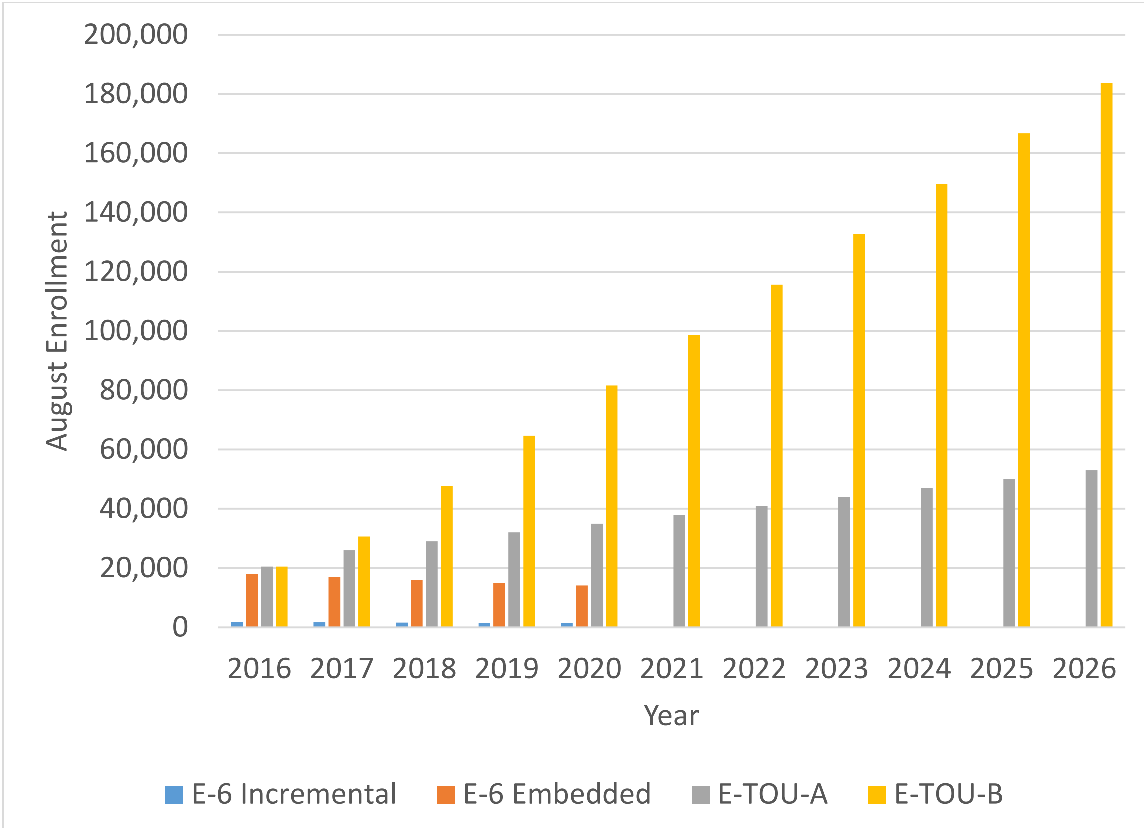
- E-6 incremental customers;
- E-6 embedded customers;
- E-TOU-A customers; and
- E-TOU-B customers.

The enrollment forecast for August by year for each of these groups is shown in Figure 8.1. Notice that the E-6 incremental and embedded customer enrollments are zero beginning in January 2021. In the CPUC's Decision 15-11-013, the Commission outlined a glide path for those actively enrolled in E-6 upon its closure to new enrollments in 2016. The rate is to remain open in its current form through 2020, after which the rate's TOU periods will progressively move into alignment with E-TOU-A and E-TOU-B's 4 to 9 p.m. peak period in 2021 and 2022. Because it is difficult to estimate how these customers will respond to the changing TOU periods, PG&E is including them in the E-TOU-A and E-TOU-B groups for forecasting and load impact modeling purposes.

E-TOU-A and E-TOU-B enrollments increase over time following their introduction in March 2016. By the end of the forecast period (December 2026), E-TOU-A is assumed to have 54,000 enrolled customers and E-TOU-B is assumed to have 189,333 enrolled customers.

[31] The uncertainty-adjusted load impacts for E-TOU-A and E-TOU-B are based on an assumed level of uncertainty about the elasticity of substitution. Specifically, we assume that the standard error of the elasticity of substitution is equal to half its mean. We then derive the 10th, 30th, 50th, 70th, and 90th percentiles of load impacts under the assumption that the elasticity is normally distributed.

Figure 8.1: Forecast August Enrollments by Group and Year



8.2.1 E-6 *ex-ante* load impacts

Two sets of E-6 *ex-ante* load impacts are presented in this section: the embedded forecast, which reflects the load impacts of customers enrolled in E-6 prior to 2016; and the incremental forecast, which reflects the load impacts of newly enrolled E-6 customers.

Table 8.2 shows the E-6 embedded load impacts, averaged during the Resource Adequacy window (1:00 to 6:00 p.m. from April to October and 4:00 to 9:00 p.m. from November through March). The table shows monthly load impacts in 2017 associated with each of the four weather scenarios. As one might expect, summer load impacts are higher than winter load impacts, and load impacts in hotter scenarios are larger than in milder scenarios (*e.g.*, PG&E 1-in-10 versus PG&E 1-in-2 for June).

Table 8.2: E6 Embedded *Ex-Ante* Load Impacts, 2017 Monthly Peak Day during RA Window (MWh / hour)

Month	CAISO 1-in-10	CAISO 1-in-2	PG&E 1-in-10	PG&E 1-in-2
January	0.73	0.75	0.71	0.76
February	0.77	0.76	0.72	0.77
March	0.88	0.79	0.79	0.78
April	2.12	1.11	2.34	1.18
May	1.75	1.07	2.58	1.25
June	2.16	2.15	2.94	2.12
July	2.65	1.93	2.90	2.17
August	2.33	1.81	2.72	2.21
September	1.99	1.69	2.49	2.16
October	1.61	1.29	2.15	1.18
November	0.84	0.84	0.82	0.79
December	0.70	0.76	0.68	0.74

Figure 8.2 shows the hourly load impacts associated with one of the cells in Table 8.2: the August PG&E 1-in-2 scenario. The load reduction during the TOU peak hours averages 13.1 percent.

Figure 8.2: E6 Embedded *Ex-Ante* Load Impacts, 2017 August PG&E 1-in-2 Peak Day

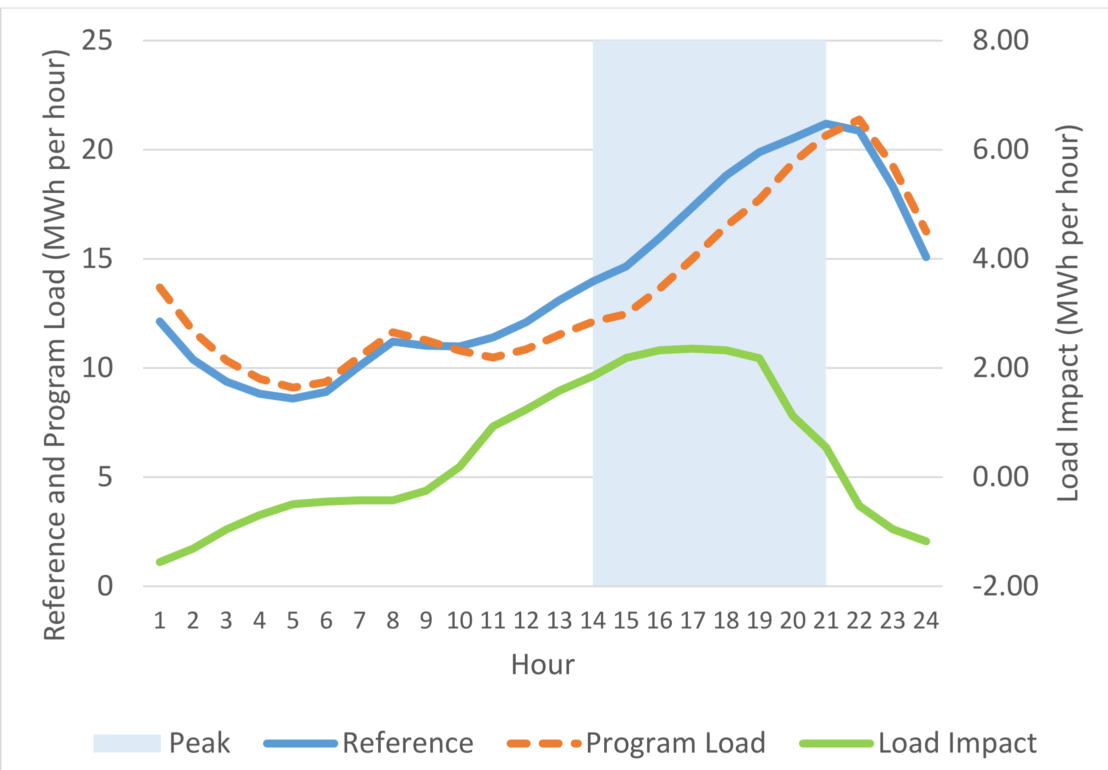


Table 8.3 shows the E-6 incremental load impacts. The results have the same relative patterns as the E-6 incremental results (recall that they are both based on the E-6 incremental *ex-post* load impacts due to the methodological superiority of those load impacts versus the E-6 embedded *ex-post* impacts). However, these load impacts are substantially lower overall because of the lower enrollment forecast (*i.e.*, there are fewer incremental customers than embedded).

Table 8.3: E6 Incremental *Ex-Ante* Load Impacts, 2017 Peak Day during RA Window (MWh / hour)

Month	CAISO 1-in-10	CAISO 1-in-2	PG&E 1-in-10	PG&E 1-in-2
January	0.07	0.08	0.07	0.08
February	0.08	0.08	0.07	0.08
March	0.09	0.08	0.08	0.08
April	0.21	0.11	0.24	0.12
May	0.18	0.11	0.26	0.13
June	0.22	0.22	0.30	0.21
July	0.27	0.20	0.29	0.22
August	0.24	0.18	0.27	0.22
September	0.20	0.17	0.25	0.22
October	0.16	0.13	0.22	0.12
November	0.09	0.09	0.08	0.08
December	0.07	0.08	0.07	0.07

Figure 8.3 shows the hourly load impacts associated with one of the cells in Table 8.3 -- the August PG&E 1-in-2 scenario. The peak-hour load reduction averages 13.1 percent.

Figure 8.3: E6 Incremental *Ex-Ante* Load Impacts, 2017 August PG&E 1-in-2 Peak Day

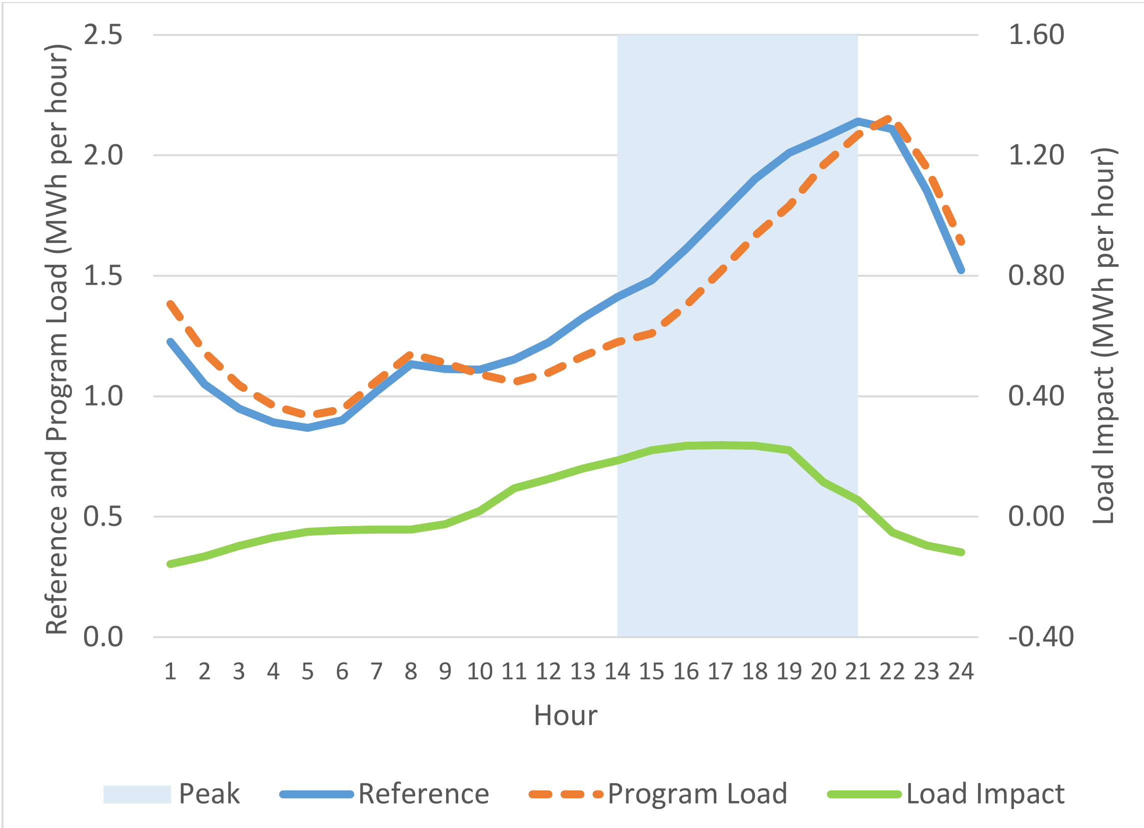
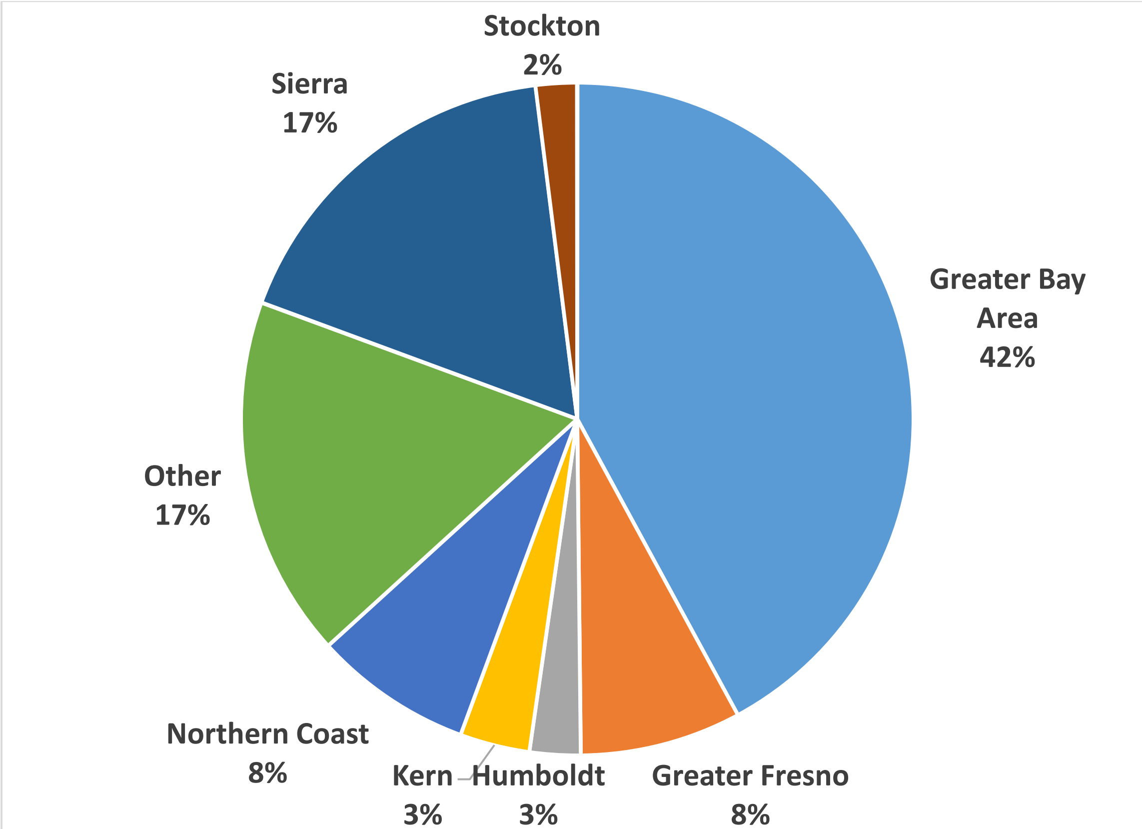


Figure 8.4 shows the distribution of E-6 load impacts by LCA in August 2017 (for the PG&E 1-in-2 weather scenario). It happens to be the case that the distribution is the same for the E-6 incremental and embedded customers. The Greater Bay Area has the largest share of load impacts.

Figure 8.4: E-6 Load Impacts by LCA, August 2017 PG&E 1-in-2



8.2.2 E-TOU-A and E-TOU-B *ex-ante* load impacts

Both the E-TOU-A and E-TOU-B *ex-ante* load impacts are presented in this section. Table 8.4 shows the E-TOU-A load impacts, averaged during the RA window. The table shows monthly load impacts in 2017 associated with each of the four weather scenarios. As one might expect, summer load impacts are higher than winter load impacts. The differences in load impacts across weather scenarios are not large, as our methodology assumes the same percentage load impact across all scenarios.

Table 8.4: E-TOU-A *Ex-Ante* Load Impacts – 2017 Monthly Peak Day during RA Window (MWh / hour)

Month	CAISO 1-in-10	CAISO 1-in-2	PG&E 1-in-10	PG&E 1-in-2
January	0.03	0.03	0.03	0.03
February	0.03	0.03	0.03	0.03
March	0.02	0.03	0.02	0.03
April	0.01	0.01	0.01	0.01
May	0.02	0.01	0.02	0.02
June	0.18	0.18	0.20	0.18
July	0.20	0.18	0.21	0.18
August	0.18	0.16	0.20	0.18
September	0.17	0.16	0.18	0.17
October	0.02	0.02	0.02	0.02
November	0.02	0.02	0.03	0.03
December	0.03	0.03	0.04	0.03

Figure 8.5 shows the hourly load impacts associated with one of the cells in Table 8.4 – the August PG&E 1-in-2 scenario. Note the “regularity” of the load impacts relative to the E-6 patterns. This is the case because the E-6 load impacts are based on *ex-post* estimates, while the E-TOU-A load impacts are based on a CES-based simulation model (no *ex-post* impacts exist because it is a new rate). Therefore, the typical pattern of peak-period load reductions and off-peak-period load increases emerges. However, the load impacts are not particularly large (0.9 percent during the summer peak period) due to a relatively low peak to off-peak price ratio.

Figure 8.5: E-TOU-A *Ex-Ante* Load Impacts, 2017 August PG&E 1-in-2 Peak Day

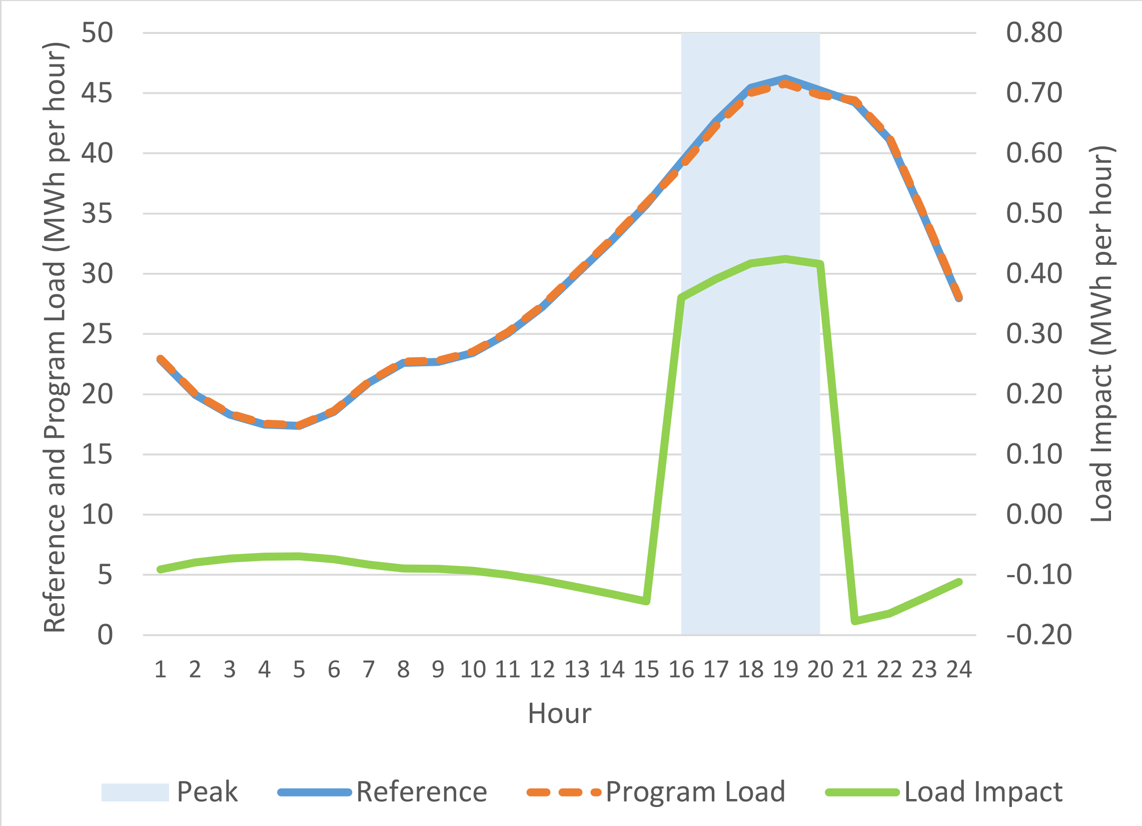


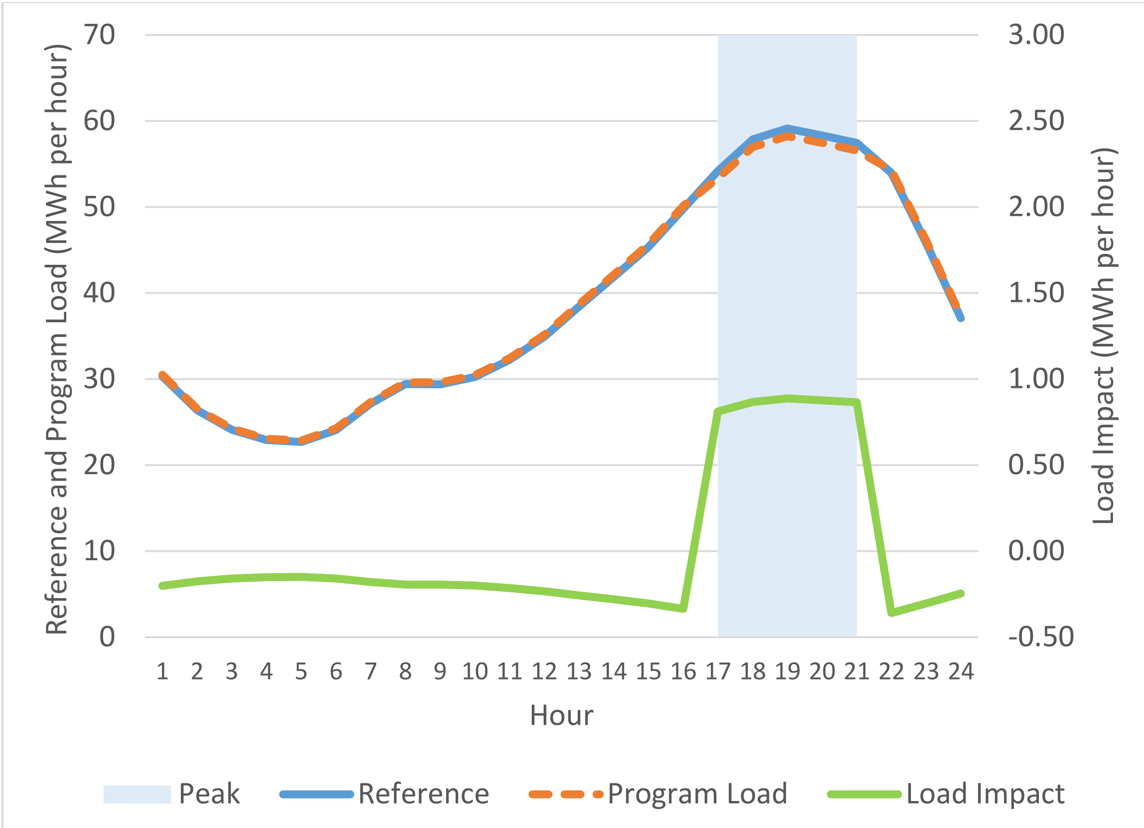
Table 8.5 shows the E-TOU-B load impacts, averaged during the RA window. The table shows monthly load impacts in 2017 associated with each of the four weather scenarios. The load impacts have the same basic pattern as the E-TOU-A load impacts, though the E-TOU-A load impacts are somewhat higher due to the fact that the RA window excludes one hour of the E-TOU-A peak period, but two hours of the E-TOU-B peak period. Two factors offset this effect: E-TOU-B leads to larger peak-period load reductions because the peak to off-peak price ratio is higher than it is for E-TOU-A; and E-TOU-B has slightly higher enrollment during that year.

Table 8.5: E-TOU-B *Ex-Ante* Load Impacts – 2017 Monthly Peak Day during RA Window (MWh / hour)

Month	CAISO 1-in-10	CAISO 1-in-2	PG&E 1-in-10	PG&E 1-in-2
January	0.07	0.07	0.08	0.07
February	0.07	0.07	0.07	0.07
March	0.06	0.07	0.06	0.07
April	0.01	0.01	0.01	0.01
May	0.01	0.01	0.02	0.01
June	0.14	0.14	0.15	0.14
July	0.16	0.14	0.16	0.15
August	0.15	0.14	0.16	0.15
September	0.15	0.14	0.16	0.15
October	0.02	0.02	0.02	0.02
November	0.09	0.09	0.09	0.10
December	0.13	0.12	0.13	0.12

Figure 8.6 shows the hourly load impacts associated with one of the cells in Table 8.5 – the August PG&E 1-in-2 scenario. As with the E-TOU-A load impacts, these load impacts display the typical pattern of peak-period load reductions and off-peak-period load increases. In this case, the average peak-hour percentage load impact is 1.5 percent (versus 0.9 percent for E-TOU-A).

Figure 8.6: E-TOU-B *Ex-Ante* Load Impacts, 2017 August PG&E 1-in-2 Peak Day



Figures 8.7 and 8.8 show the shares of load impacts by LCA for E-TOU-A and E-TOU-B, respectively. In both cases, the load impacts correspond to the August 2017 PG&E 1-in-2 peak day. The shares are quite similar for the two rates, with the Greater Bay Area having the largest share of load impacts.

Figure 8.7: E-TOU-A *Ex-Ante* Load Impacts by LCA, 2017 August PG&E 1-in-2 Peak Day

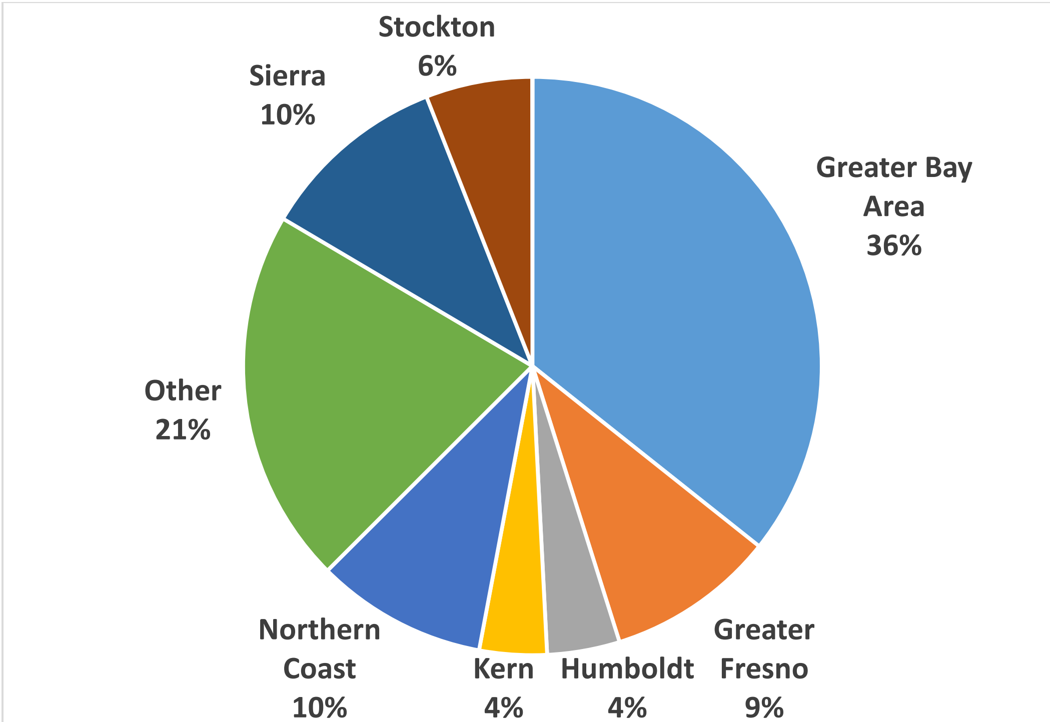
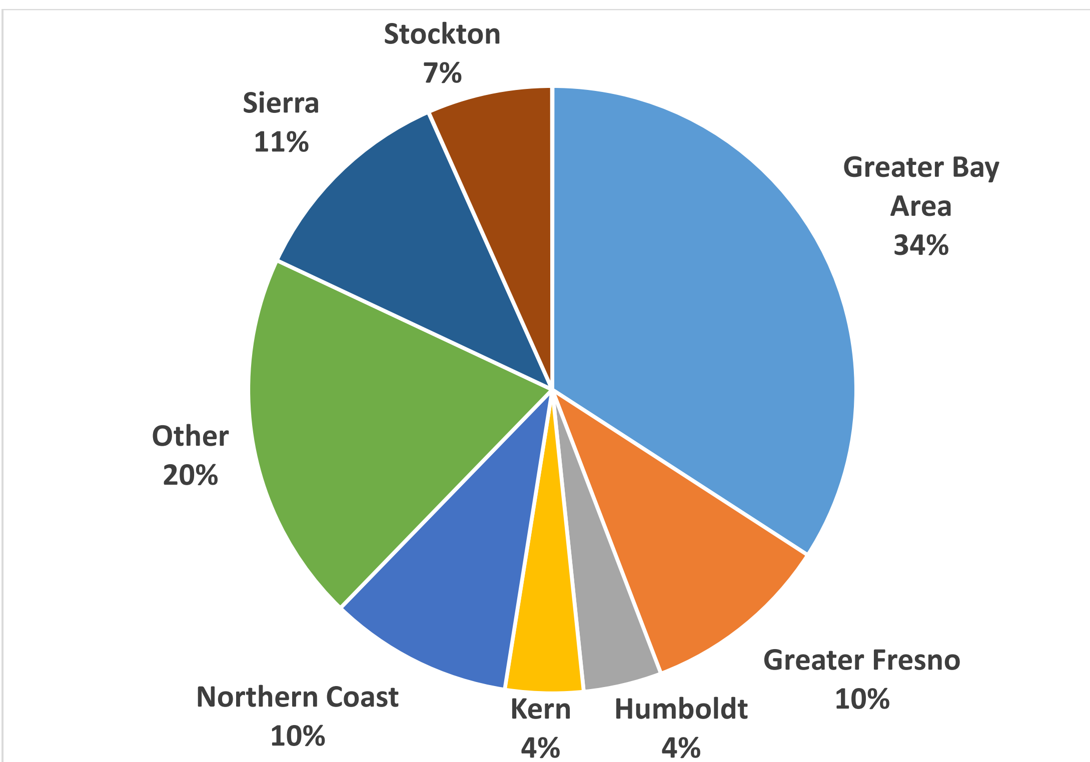


Figure 8.8: E-TOU-B *Ex-Ante* Load Impacts by LCA, 2017 August PG&E 1-in-2 Peak Day



9. Comparisons of Results

In a continuing effort to clarify the relationships between *ex-post* and *ex-ante* results, this section compares several sets of estimated load impacts for SmartRate and the TOU rates, including the following:

- *Ex-post* load impacts from the current and previous studies;
- *Ex-ante* load impacts from the current and previous studies;
- Current *ex-post* and previous *ex-ante* load impacts; and
- Current *ex-post* and *ex-ante* load impacts.

The term "current" refers to the present study, which includes *ex-post* and *ex-ante* results for PY2015. The term "previous" refers to findings in reports for PY2014, and in some cases earlier. In the final comparison above, we illustrate the linkage between the PY2015 *ex-post* load impacts and the *ex-ante* forecast (of the 1-in-2 August peak day) for 2016. Only the SmartRate, E-6, and E-7 forecasts are included in this section. The E-TOU-A and E-TOU-B forecasts are excluded because they are new to this study and there is no transition from *ex-post* to *ex-ante* load impacts to describe (because there no estimates of *ex-post* load impacts at this time).

9.1 SmartRate

9.1.1 Previous versus current *ex-post*

Table 9.1 compares the estimated *ex-post* load impacts for the average event from the current and previous two studies, for SmartRate-only and dually-enrolled customers. The findings from the current (2015) study are shown in the last row of the two blocks of values. Findings from the previous studies (2013 and 2014) were prepared by Nexant. Some high-level similarities and differences across the results include the following:

- Enrollment in SmartRate-only has increased somewhat over the past three years, while dual enrollment in SmartRate and SmartAC has fallen somewhat after an increase in 2014.[32]
- Per-customer load impacts and percentage load impacts for both SmartRate-only and dually-enrolled customers have declined from their 2013 values.
- The average event temperature was considerably warmer in 2015 than the two previous years for SmartRate-only, although temperatures for the dually-enrolled group were quite similar.[33]
- Because the temperatures during the PY2015 events were higher, the weather-adjusted load impacts for PY2015 were significantly lower than those of PY2014.
- There is some evidence that dually enrolled customers engaged in more pre-cooling in PY2015 (not shown in Table 9.1). The average percentage load impact

[32] As shown in Table 4.5, there is a fair amount of customer turnover, which could lead changes in customer mix over time. For example, 25,000 customers dropped out of SmartRate in 2014/2015, while nearly 30,000 new customers enrolled. Similar findings were reported in 2014.

[33] The values shown are customer-weighted temperatures by weather station, and thus reflect the geographical distribution of the customers enrolled in both categories.

in the three hours preceding the event is 2.8 percent (load increase) versus 2.0 percent in PY2014. Pre-cooling is more likely to occur when the prior day was also an event day (on average, the pre-cooling is 2 percentage points higher on consecutive event days).

Table 9.1: Current vs. Previous *Ex-Post* Load Impacts for Average Event

Enrollment Type	Year	Enrolled	Aggregate: Ref. Load (MW)	Aggregate: Load Impact (MW)	Per-Customer: Ref. Load (kW)	Per-Customer: Load Impact (kW)	% Load Impact	Ave. Event Temp.
SmartRate-only	2013	79,842	126.6	20.5	1.59	0.26	16.1%	88
	2014	89,061	135.2	18.3	1.52	0.21	13.6%	87
	2015	92,288	147.1	19.5	1.59	0.21	13.2%	95
Dually-enrolled	2013	38,302	81.7	23.7	2.13	0.60	28.3%	94
	2014	40,279	80.0	20.4	1.99	0.51	25.4%	93
	2015	36,598	78.7	20.0	2.15	0.55	25.5%	95

Expanding on the final point above, we explored the differences between PY2014 and PY2015 load impacts by estimating a regression model of average event-hour per-customer load impacts by event as a function of the following explanatory variables: CDD65; an indicator for whether the previous day was also an event day (this was more common in PY2015 than PY2014); an indicator variable for whether the date is earlier than mid-June or later than mid-August (because it appears that customer usage is different during the school year); and an indicator for whether the event is in PY2015. Table 9.2 contains the estimated coefficients with the p-value in parentheses.

Table 9.2: Meta-analysis of PY2014 vs. PY2015 SmartRate *Ex-Post* Load Impacts

Variable	SmartRate Only	SmartRate + SmartAC
CDD65	0.013 (0.000)	0.041 (0.000)
Consecutive Event	0.009 (0.356)	0.017 (0.471)
School	-0.026 (0.009)	-0.054 (0.026)
PY2015 Event	-0.061 (0.001)	-0.105 (0.002)
Constant	0.064 (0.047)	-0.110 (0.246)

The coefficients in Table 9.2 show the following:

- Load impacts are weather sensitive, and the dually enrolled customers are much more weather sensitive than the SmartRate-only customers;
- Load impacts are not statistically significantly different when the previous day was an event day;
- Load impacts are lower when school is in session;
- After controlling for the factors listed above, PY2015 per-customer load impacts are lower than PY2014 load impacts.

Our analysis has demonstrated that some factors, such as weather and timing within the summer period, have statistically significant effects on the magnitude of load impacts across events. However, they don't explain the difference between PY2014 and PY2015 load impacts (*i.e.*, it's not weather or the fact that PY2015 had more consecutive event days). Thus, we don't have any positive indication of why PY2015 load impacts are lower than they were in PY2014. [34,35] We conducted a parallel analysis with the average event-hour reference load as the dependent variable (in place of the average event-hour load impact) and did not find a statistically significant difference between PY2014 and PY2015, controlling for other included factors.

9.1.2 Previous versus current *ex-ante*

Table 9.3 compares the *ex-ante* load impact forecasts from the previous and current studies, for an August 2016 peak day in utility-specific 1-in-2 weather conditions. The values shown are averages across the RA hours of 1 to 6 p.m., which has the effect of reducing the average load impact value since it includes the non-event hours of 1 to 2 p.m., which has a zero or near-zero load impact. Separate portfolio-level results are shown for the dually-enrolled category, reflecting the fact that the majority of summer load impacts are attributed to SmartAC in cases where events for both programs are called.

One major difference between the two forecasts is that enrollment for SmartRate-only is anticipated to increase more rapidly, and dual enrollment to fall compared to the previous forecast. The most significant difference between the two forecasts is the reduction in per-customer load impacts in the current study. This is directly related to the *ex-post* load impact differences described in Section 9.1.1. Note that the prior study

[34] Note that we also tested different matching methods, looking at matches within LCA as well as matches within LCA and climate zone, and the alternative methods made very little difference in the estimated load impacts despite the fact that many of the selected matches changed. Therefore, we believe our results are robust to the methodology employed.

[35] We also tested whether customers who joined SmartRate were less responsive than the customers who were in SmartRate during both PY2014 and PY2015. While the newly enrolled customers were more likely to be enrolled in SmartRate only, once we account for the dual enrollment status the new customers have load impacts that are very close to those of the existing customers. This rules out one aspect of customer composition changes as an explanation for lower load impacts in PY2015. It is possible that the customers who left SmartRate after PY2014 were especially responsive, but it seems unlikely that such an effect would be large enough (if it even exists) to fully explain the load impact difference across program years.

(following PY2014) based its *ex-ante* load impacts on the *ex-post* load impacts from PY2013 and PY2014, which further increases the *ex-ante* load impacts relative to the current study (because PY2013 load impacts were higher than those of PY2014).[36,37]

Table 9.3 Previous vs. Current *Ex-Ante* Load Impacts – *PG&E 1-in-2 August 2016 Peak Day (RA Window, 1 to 6 p.m.)*

Enrollment Type	Program/ Portfolio	Year of Forecast	Enrollment	Aggregate Ref. Load (MW)	Aggregate Load Impact (MW)	Per-Customer Ref. Load (kW)	Per-Customer Load Impact (kW)	% Load Impact	Ave. Event Temp.
SmartRate-only	Program/ Portfolio	2014	93,800	145.3	18.4	1.55	0.20	12.7%	91
		2015	110,289	149.2	18.3	1.35	0.17	12.6%	94
Dually-enrolled	Program	2014	46,200	95.7	22.6	2.07	0.49	23.7%	97
		2015	34,605	59.6	15.9	1.72	0.46	26.7%	98
	Portfolio	2014	46,200	95.7	6.3	2.07	0.14	6.6%	97
		2015	34,605	59.6	3.3	1.72	0.10	5.8%	98

9.1.3 Previous *ex-ante* versus current *ex-post*

Table 9.4 compares the previous study's typical event day *ex-ante* forecast for 2015 for utility 1-in-2 weather year to the *ex-post* load impacts estimated in this study. The previous forecast enrollment was close to the actual enrollment for the average event in 2015 for SmartRate-only, though somewhat high for dually-enrolled. The forecast load impact forecasts shown in bold have been adjusted to reflect the actual event hours of 2 to 7 p.m. rather than the RA hours required in the *ex-ante* forecasts, so as to make them more comparable to the *ex-post* values (the average RA values for an August peak day are shown in Table 9.3).[38] After the adjustment, the per-customer load impacts and percentage load impacts are somewhat higher than the *ex-post* values found for 2015. This is consistent with the differences we described earlier, showing that *ex-post* load impacts were lower in PY2015 than in previous years.

[36] The per-customer reference loads in the current study are also somewhat lower than those of the prior study. However, the level of the reference loads in this study has no effect on the forecast load impacts. That is, we simulate the per-customer hourly load impacts using a method that only includes information from the *ex-post* load impact estimates (as described in Section 7.1.1). These load impacts are paired up with the corresponding reference loads to complete the *ex-ante* study, but the level of the *ex-ante* load impacts is not dependent on the level of the *ex-ante* reference loads in any way.

[37] We only included current-year load impacts in this year's forecast because it would have been difficult for us to account for the change in customer composition. That is, we did not have the ability to exclude customers who left SmartRate following PY2014 from the analysis. In addition, the downward trend in *ex-post* load impacts estimated in recent years indicates that current-year *ex-post* load impacts may be the best available proxy for *ex-ante* load impacts.

[38] The adjusted load impacts were calculated by applying the average percentage load impact over the four hours from 2 to 6 p.m. to the reference load for the hour ending at 7 p.m., and then averaging the resulting load impacts over hours 2 to 7 p.m. This approach was required since Nexant characterized a synthetic *ex-ante* event that has a rebound load increase in the hour after the RA window rather than a load reduction that would normally be seen in an event ending at 7 p.m.

Table 9.4 Previous *Ex-Ante* vs. Current *Ex-Post* Load Impacts

Enrollment Type	Typical Event Day in 2015	Enrollment	Aggregate Ref. Load (MW)	Aggregate Load Impact (MW)	Per Customer Ref. Load (MW)	Per Customer Load Impact (MW)	% Load Impact	Ave. Event Temp.
SmartRate Only	2014 ExA	91,618	148.9	**22.7**	1.63	**0.25**	**15.3%**	90
	2015 ExP	92,288	147.1	19.5	1.59	0.21	13.2%	95
Dually Enrolled	2014 ExA	43,423	104.3	**29.9**	2.40	**0.69**	**28.7%**	97
	2015 ExP	36,598	78.7	20.0	2.15	0.55	25.5%	95

9.1.4 Current *ex-post* versus current *ex-ante*

Table 9.5 compares the *ex-post* load impacts for 2015 and *ex-ante* load impacts for 2016 from this study, both for a typical event day. The *ex-ante* load impacts are averaged over the RA window rather than the actual event hours. Since our *ex-ante* load impacts are built on the 2015 *ex-post* values, the per-customer load impacts are otherwise similar (the use of the RA window reduces load impacts by approximately 20 percent).

Table 9.5 *Ex-Post* vs. Incremental *Ex-Ante* Load Impacts

Enrollment Type	Typical Event Day	Enrollment	Aggregate Ref. Load (MW)	Aggregate Load Impact (MW)	Per-Customer Ref. Load (kW)	Per-Customer Load Impact (kW)	% Load Impact	Avg. Event Temp.
SmartRate Only	2015 ExP	92,288	147.1	19.5	1.59	0.21	13.2%	94.9
	2016 ExA	110,289	147.9	18.1	1.34	0.16	12.3%	93.9
Dually Enrolled	2015 ExP	36,598	78.7	20.0	2.15	0.55	25.5%	97.6
	2016 ExA	34,605	59.3	15.8	1.71	0.46	26.6%	98.3

Table 9.6 compares the key components of the two analyses for the SmartRate-only customers. As the table describes, the two largest sources of differences between the *ex-post* and *ex-ante* load impacts are the enrollment level and the summary over the RA window for *ex-ante* versus the actual event hours for the *ex-post* impacts.

Table 9.6: *Ex-Post* versus *Ex-Ante* Factors, SmartRate-only Customers

Factor	*Ex-Post*	*Ex-Ante*	Expected Impact
Weather	94.9 degrees Fahrenheit during event hours.	93.9 degrees Fahrenheit during event hours on utility-specific 1-in-2 typical event day.	Slightly milder *ex-ante* weather decreases the forecast load impact somewhat, though the effect is not large for SmartRate-only customers.
Event window	HE 15-19 for the typical event day.	HE 14-18 in Apr-Oct; HE 17-21 in Nov-Mar.	The difference between the RA window used in *ex-ante* and the actual event window used in *ex-post* reduces the *ex-ante* load impacts relative to *ex-post*. From April to October, one RA window hour is a non-event hour; and two RA window hours are non-event hours from November to March.
% of resource dispatched	The entire program was dispatched on all of the typical event days.	Assume all customers are called.	None. The *ex-ante* method assumes that all enrolled customers are dispatched.
Enrollment	92,288 SAIDs during the average event day.	110,289 SAIDs.	The increase in *ex-ante* enrollments increases the total load impact proportionately relative to *ex-post*.
Methodology	LCA-specific regressions using a matched control-group and difference-in-differences analysis.	Load impacts are forecast directly from LCA-specific regression models of *ex-post* load impacts as a function of weather and whether school is expected to be in session.	Small. The regression-based method of simulating *ex-ante* load impacts ensures consistency with the *ex-post* impacts on a per-customer basis.

Table 9.7 shows how the SmartRate-only load impacts change as we make various adjustments to the *ex-post* load impacts. The table shows the *ex-post* load impacts at the far left. The next column adjusts those load impacts to account for *ex-ante* enrollments (in August 2017). The column to the right of that further adjusts the load impacts (downward) to account for the change from the event window to the RA window (which includes one hour that is not an event hour, thus producing lower average load impacts). Finally, the four rightmost columns show the *ex-ante* load impacts for the typical event day in August 2017 by weather scenario.

Table 9.7: Progression from *Ex-post* to *Ex-ante* Load Impacts, SmartRate Only

Date	*Ex-post* LI, Event Hrs.	*Ex-post* LI @ *ex-ante* enroll., Event Hrs.	*Ex-post* LI @ *ex-ante* enroll., RA Hrs.	*Ex-ante* @ CAISO 1-in-10	*Ex-ante* @ CAISO 1-in-2	*Ex-ante* @ Utility 1-in-10	*Ex-ante* @ Utility 1-in-2
6/12/2015	17.9	22.1	17.5	18.6	16.8	21.2	18.1
6/25/2015	19.8	24.6	19.5				
6/26/2015	17.8	22.0	17.9				
6/30/2015	21.2	26.4	21.1				
7/1/2015	17.5	21.8	17.8				
7/28/2015	20.6	25.3	20.1				
7/29/2015	21.7	26.5	21.4				
7/30/2015	17.7	21.6	17.5				
8/17/2015	21.2	24.7	19.6				
8/18/2015	16.1	18.5	14.9				
8/27/2015	19.5	22.0	17.8				
8/28/2015	18.1	20.3	16.5				
9/9/2015	21.8	24.3	19.3				
9/10/2015	21.9	24.3	19.8				
9/11/2015	19.3	21.4	17.5				
Avg. Evt.	**19.5**	**23.0**	**18.6**				

Table 9.8 compares the key components of the two analyses for the dually enrolled customers. As with the SmartRate-only customers, the two largest sources of differences between the *ex-post* and *ex-ante* load impacts are the enrollment level and the summary over the RA window for *ex-ante* versus the actual event hours for the *ex-post* impacts.

Table 9.8: *Ex-Post* versus *Ex-Ante* Factors, Dually Enrolled Customers

Factor	*Ex-Post*	*Ex-Ante*	Expected Impact
Weather	97.6 degrees Fahrenheit during event hours.	98.3 degrees Fahrenheit during event hours on utility-specific 1-in-2 typical event day.	Slightly hotter *ex-ante* weather increases the forecast load impact somewhat.
Event window	HE 15-19 for the typical event day.	HE 14-18 in Apr-Oct; HE 17-21 in Nov-Mar.	The difference between the RA window used in *ex-ante* and the actual event window used in *ex-post* reduces the *ex-ante* load impacts relative to *ex-post*. From April to October, one RA window hour is a non-event hour; and two RA window hours are non-event hours from November to March.
% of resource dispatched	The entire program was dispatched on all of the typical event days.	Assume all customers are called.	None. The *ex-ante* method assumes that all enrolled customers are dispatched.
Enrollment	36,598 SAIDs during the average event day.	34,605 SAIDs.	The decrease in *ex-ante* enrollments increases the total load impact proportionately relative to *ex-post*.
Methodology	LCA-specific regressions using a matched control-group and difference-in-differences analysis.	Load impacts are forecast directly from LCA-specific regression models of *ex-post* load impacts as a function of weather and whether school is expected to be in session.	Small. The regression-based method of simulating *ex-ante* load impacts ensures consistency with the *ex-post* impacts on a per-customer basis.

Table 9. shows how the dually enrolled customer load impacts change as we make various adjustments to the *ex-post* load impacts. The table shows the *ex-post* load impacts at the far left. The next column adjusts those load impacts to account for *ex-ante* enrollments (in August 2017). The column to the right of that further adjusts the load impacts (downward) to account for the change from the event window to the RA window (which includes one hour that is not an event hour, thus producing lower average load impacts). Finally, the four rightmost columns show the *ex-ante* load impacts for the typical event day in August 2017 by weather scenario.

Table 9.9: Progression from *Ex-post* to *Ex-ante* Load Impacts, Dually Enrolled

Date	*Ex-post* LI, Event Hrs.	*Ex-post* LI @ *ex-ante* enroll., Event Hrs.	*Ex-post* LI @ *ex-ante* enroll., RA Hrs.	*Ex-ante* @ CAISO 1-in-10	*Ex-ante* @ CAISO 1-in-2	*Ex-ante* @ Utility 1-in-10	*Ex-ante* @ Utility 1-in-2
6/12/2015	20.3	18.7	14.9	16.1	13.6	18.5	15.9
6/25/2015	22.7	21.2	16.6				
6/26/2015	21.8	20.3	16.2				
6/30/2015	25.2	23.7	18.3				
7/1/2015	18.9	17.8	13.9				
7/28/2015	21.3	20.2	15.5				
7/29/2015	25.3	24.1	18.9				
7/30/2015	19.1	18.1	13.9				
8/17/2015	21.2	20.3	16.5				
8/18/2015	13.7	13.0	10.8				
8/27/2015	17.4	16.7	13.9				
8/28/2015	17.7	17.0	14.4				
9/9/2015	19.0	18.3	14.9				
9/10/2015	20.1	19.3	16.1				
9/11/2015	17.1	16.5	14.1				
Avg. Evt.	**20.0**	**19.0**	**15.2**				

9.2 Residential TOU, E-6

Given the many changes scheduled to take place for the residential TOU rates, the only case in which *ex-ante* forecasts are produced based on estimated *ex-post* results is the E-6 incremental group. This section focuses on those results. The next section addresses the comparisons that can be made for E-7 customers (for which there is no *ex-ante* forecast).

9.2.1 Previous versus current *ex-post*

Table 9.10 shows the average peak-hour reference loads and load impacts for the August average weekday during the current and previous program years. In the previous evaluation, the *ex-post* load impacts were scaled to represent all non-NEM E-6 customers. In PY2015, the enrollment level represents only the customers who joined E-6 on or after October 1, 2014. In both cases, the load impacts represent estimates from recent adopters using a difference-in-differences methodology with a matched control group. Because of the different enrollment levels, the per-customer results allow for the most appropriate comparison across years.

Table 9.10: Comparison of Average August Weekday Peak-period *Ex-Post* Impacts (in MW) in PY 2014 and PY 2015

Level	Outcome	PY2014	PY2015
Total	# SAIDs	8,644	6,469
	Reference (MW)	7.86	5.34
	Load Impact (MW)	1.22	0.51
	Avg. Temp.	77.0	82.7
Per SAID	Reference (kW)	0.91	0.83
	Load Impact (kW)	0.14	0.08
	% Load Impact	15.5%	9.5%

Table 9.10 shows that the per-customer reference loads, load impacts, and percentage load impact were all somewhat lower in PY2015 versus PY2014. The higher reference loads in PY2014 are not explained by weather (it was cooler in PY2014) or the distribution of customers across LCAs (applying PY2014 enrollments by LCA to PY2015 reference loads by LCA only increases the average reference load from 0.83 to 0.87 kWh per hour). We note that the customers analyzed in the two years are completely separate from one another. That is, the PY2015 customers joined E-6 after the PY2014 analysis was conducted. It could just be that lower-use (and lower load impact) customers tended to join E-6 in PY2015 relative to PY2014.

9.2.2 Previous versus current *ex-ante*

In this sub-section, we compare the *ex-ante* forecast prepared following PY2014 (the "previous study") to the *ex-ante* forecast contained in this study (the "current study"). Table 9.11 contains this comparison for the August 2016 average weekday under PG&E 1-in-2 peak weather conditions. In the PY2014 study, the E-6 incremental and embedded customer counts were combined in the enrollment forecast. In this study, we kept the two groups separate, but the only difference between the two forecasts is in the enrollment levels (*i.e.*, the E-6 incremental and embedded forecasts have the same per-customer load impacts by LCA). Table 9.11 shows the current study's E-6 embedded forecast, which has enrollments that are more comparable to last year's forecast for 2016.

Table 9.11: Comparison of Average August 2016 Weekday Peak-period *Ex-Ante* Impacts (in MW) in PY 2014 and PY 2015 Studies

Level	Outcome	Previous Study - 2016	Current Study - 2016
Total	# SAIDs	12,889	18,057
	Reference (MW)	12.64	14.14
	Load Impact (MW)	2.15	1.42
	Avg. Temp.	80.1	80.6
Per SAID	Reference (kW)	0.98	0.78
	Load Impact (kW)	0.17	0.08
	% Load Impact	17.0%	10.1%

The differences in the per-customer reference loads and load impacts are consistent with the *ex-post* differences described in the previous sub-section.

9.2.3 Previous *ex-ante* versus current *ex-post*

Table 9.12 provides a comparison of the *ex-ante* forecast of August 2015 average weekday load impacts prepared following PY2014 and the *ex-post* PY2015 load impacts estimated as part of this study. The *ex-ante* forecast shown in the table represents the August average weekday during a PG&E 1-in-2 weather year. As above, the enrollments are different primarily by construction (the previous *ex-ante* enrollment represents all E-6 customers while the current *ex-post* represents only the E-6 customers joining since October 2014). The per-customer reference loads and load impacts are smaller in the current *ex-post* study, which is consistent with the findings presented in the previous sub-sections.

Table 9.12 Comparison of Previous *Ex-Ante* and Current *Ex-Post* Impacts

Level	Outcome	*Ex-Ante* for Aug. 2015 Avg. Weekday from PY2014 Study	*Ex-Post* for Aug. 2015 Avg. Weekday from PY2015 Study
Total	# SAIDs	10,355	6,469
	Reference (MW)	10.15	5.34
	Load Impact (MW)	1.73	0.51
	Avg. Temp.	80.1	82.7
Per SAID	Reference (kW)	0.98	0.83
	Load Impact (kW)	0.17	0.08
	% Load Impact	17.0%	9.5%

9.2.4 Current *ex-post* versus current *ex-ante*

Table 9.13 compares the PY2015 *ex-post* load impacts for the August average weekday to the corresponding *ex-ante* forecast for 2016 produced in this study. In each case, the load impacts represent the E-6 incremental customers.

Table 9.13 Comparison of Current *Ex-Post* and *Ex-Ante* Load Impacts

Level	Outcome	*Ex-Post* for Aug. 2015 Avg. Weekday from PY2015 Study	*Ex-Ante* for Aug. 2016 Avg. Weekday from PY2015 Study
Total	# SAIDs	6,469	1,825
	Reference (MW)	5.34	1.43
	Load Impact (MW)	0.51	0.14
	Avg. Temp.	82.7	80.6
Per SAID	Reference (kW)	0.83	0.78
	Load Impact (kW)	0.08	0.08
	% Load Impact	9.5%	10.1%

As Table 9.13 shows, the *ex-ante* load impacts are lower in total due to lower forecast enrollment, but the per-customer load impacts are similar. The *ex-ante* reference load is somewhat lower than the *ex-post* because of the milder temperatures.

Table 9.14 reviews the potential sources of differences between PY 2015 *ex-post* August average weekday load impacts and the corresponding *ex-ante* load impacts. The most significant difference between the two is the enrollments that scale the per-customer *ex-ante* load impacts to the program level. Because the per-customer *ex-ante* load impacts are derived from a modified version of the model used to estimate the *ex-post* load impacts, the results are quite similar at the per-customer level.

Table 9.14: E-6 Incremental *Ex-Post* versus *Ex-Ante* Factors

Factor	*Ex-Post*	*Ex-Ante*	Expected Impact
Weather	82.7 degrees Fahrenheit during the RA window of the August 2015 average weekday.	80.6 degrees Fahrenheit during the RA window on utility-specific 1-in-2 August average weekday.	Milder *ex-ante* weather decreases the reference load and load impact slightly, but the effect is small.
Enrollment	6,469 SAIDs during the August 2015 average weekday.	1,825 SAIDs in August 2016.	The enrollment level directly scales the per-customer *ex-ante* load impacts.
Methodology	LCA-specific difference-in-differences estimates using a matched control group.	Adds weather interactions to the *ex-post* regression models to allow for simulated load impacts at *ex-ante* weather conditions.	The modification of the *ex-post* regression model allows us to simulate the required weather conditions, but errors in that model may lead to minor differences between *ex-post* and *ex-ante* load impacts.

9.3 Residential TOU, E-7

In this section, we compare *ex-post* and *ex-ante* load impacts for customers on the E-7 TOU rate. Because this rate is closing in May 2016, we only conduct two comparisons: previous versus current *ex-post* load impacts; and previous *ex-ante* versus current *ex-post* load impacts. There is no current *ex-ante* forecast for E-7 because the rate is closing.

9.3.1 Previous versus current *ex-post*

Table 9.15 shows the average peak-hour reference loads and load impacts for the August average weekday during the current and previous program years. As in the previous evaluation, the *ex-post* load impacts represent only non-NEM E-7 customers. The number of customers is somewhat lower in PY2015, while the reference loads and load impacts are somewhat higher, perhaps in part due to hotter temperatures.

Table 9.15: Comparison of Average August Weekday Peak-period *Ex-Post* Impacts (in MW) in PY 2014 and PY 2015, E-7

Level	Outcome	PY2014	PY2015
Total	# SAIDs	50,621	47,777
	Reference (MW)	68.3	67.7
	Load Impact (MW)	5.8	8.0
	Avg. Temp.	80.8	85.6
Per SAID	Reference (kW)	1.35	1.42
	Load Impact (kW)	0.11	0.17
	% Load Impact	8.4%	11.8%

9.3.2 Previous *ex-ante* versus current *ex-post*

Table 9.16 provides a comparison of the *ex-ante* forecast of August 2015 average weekday load impacts prepared following PY2014 and the *ex-post* PY2015 load impacts estimated as part of this study. The *ex-ante* forecast shown in the table represents the August average weekday during a PG&E 1-in-2 weather year. In this case, the reference loads and load impacts are averaged across the RA window (1 to 6 p.m.) rather than the E-7 peak hours. The enrollment forecast used in the prior study was quite close to the enrollments that occurred in PY2015. However, the *ex-ante* weather was somewhat hotter than occurred in PY2015 and percentage load impacts were higher in the current *ex-post* study.

Table 9.16 Comparison of Previous *Ex-Ante* and Current *Ex-Post* Impacts, E-7

Level	Outcome	*Ex-Ante* for Aug. 2015 Avg. Weekday from PY2014 Study	*Ex-Post* for Aug. 2015 Avg. Weekday from PY2015 Study
Total	# SAIDs	47,647	47,777
	Reference (MW)	78.7	70.2
	Load Impact (MW)	7.6	8.5
	Avg. Temp.	90.7	86.3
Per SAID	Reference (kW)	1.65	1.47
	Load Impact (kW)	0.16	0.18
	% Load Impact	9.6%	12.2%

10. Recommendations

As described in Section 9.1.1, we have not been able to find an explanation for why SmartRate load impacts declined in the 2015 program year, after also declining between the 2013 and 2014 program years. It would be useful to explore this issue in greater detail, perhaps by analyzing customers who have remained enrolled in the program for all three years, or surveying participating customers to determine whether they self-report any changes in behavior across years. For example, it is possible that estimated load impacts have declined over time because customers are setting their thermostat set points higher, reducing the amount of cooling load available to reduce. This type of behavior is difficult to detect in our analysis, but may be revealed through survey research.

Appendices

Appendix A	SmartRate *Ex-Post* Load Impact Tables
Appendix B	SmartRate *Ex-Ante* Load Impact Tables
Appendix C	E-6 Incremental *Ex-Post* Load Impact Tables
Appendix D	E-7 Embedded *Ex-Post* Load Impact Tables
Appendix E	E-6 Incremental *Ex-Ante* Load Impact Tables
Appendix F	E-6 Embedded *Ex-Ante* Load Impact Tables
Appendix G	E-TOU-A *Ex-Ante* Load Impact Tables
Appendix H	E-TOU-B *Ex-Ante* Load Impact Tables