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Load Impact Evaluation of Pacific Gas & Electric Company's SmartRate™ Program for 2017

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Opinion Dynamics

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Table of Contents

1. Executive Summary 1
2. Introduction to the SmartRate™ Program 6
3. Study Objectives and Methodology 8
   - **3.1** Key Research Questions 8
   - **3.2** Methodology 8
4. Evaluation Results 28
   - **4.1** Ex-Post Load Impacts 28
   - **4.2** Ex-Ante Load Impacts 38
   - **4.3** Contextualizing Current and Future Load Impacts 41
5. Review of Program Performance 51
   - **5.1** Prior Ex-Post and Current Ex-Post 52
   - **5.2** Prior Ex-Ante and Current Ex-Ante 52
   - **5.3** Prior Ex-Ante and Current Ex-Post 53
   - **5.4** Current Ex-Post and Current Ex-Ante 54
   - **5.5** Recommendations 59

Appendix A. Ex-Post and Ex-Ante Table Generators 61
Appendix B. Bill Protection Analysis Results 62
Appendix C. Multi-Level Model Results 68
Appendix D. Behavioral Spillover Results 75

Table of Tables

Table 1. Average Ex Post Load Impacts for Average Event Day 2
Table 2. Ex-Ante Program and Portfolio-Adjusted Load Impacts for 2019 -- PG&E 1-in-2 Weather for the Summer RA Window (1 – 6pm) 4
Table 3. Average Participant Count for SmartRate™ Program in 2017, by LCA and Enrollment Type 7
Table 4. Summary of SmartRate™ 2017 Ex-Post Key Research Questions and Methods 9
Table 5. Comparison of Average Load Impacts between Ex Post Model and Multi-Level Model 18
Table 6: Summary of SmartRate™ 2017 Ex-Ante Key Research Questions and Methods 21
Table 7. Average 2017 Event-Hour Load Impacts by Event – SmartRate™-Only 29
Table 8. Average Event-Hour Load Impacts by Event – Dually-Enrolled 31
Table 9. Average Event-Hour Load Impacts by LCA – SmartRate™-Only 33
Table 10. Average Event-Hour Load Impacts by LCA – Dually-Enrolled 35
Table 11. SmartRate™-Only and Dually-Enrolled Participants in 2017, by LCA and CARE Status 36
Table 12. SmartRate™-only and Dually-Enrolled Participants in 2017, by LCA and FERA status 37
Table 13. Average Event-Hour Load Impacts by CARE Status 37
Table 14. Average Event-Hour Load Impacts by FERA Status 37
Table 15. SmartRate™ Enrollments (based on month of August) 38
Table 16. Ex-Ante Program and Portfolio-Adjusted Load Impacts for 2019 – PG&E 1-in-2 Weather 39
Table 17. Participant Enrollment, by Customer Type and Year 43
Table 18. Average Per Participant Load Impact, by Year of Enrollment 44
Table 19. SmartRate™ and Dually-Enrolled Average Impacts for Participants On and Off Bill Protection Status 45
Table 20. SmartRate™-Only Participant Enrollment, Mean Behavioral Spillover, and Ex-Post Mean Impact, by LCA 46
Table 21. Distribution of Load Impact Groups by Participant Enrollment Type 48
Table 22. Comparison of Ex-Post Impact Estimates for the Typical Event Day for 2015 - 2017 52
Table 23. Comparison of Prior and Current Ex-Ante Load Impact Forecasts for August Peak Day in 2018 Using the PG&E 1-in-2 Weather Scenario for the RA Window of 1 to 6 pm 53
Table 24. Comparison of Prior Ex-Ante and Current Ex-Post Load Impacts for the Typical Event Day in 2017 for SmartRate™ Event Hours of 2 to 7 pm 54
Table 25. Comparison of Ex-Post Load Impacts for the Typical Event Day in 2017 and Load Forecasts of Impacts for August Peak Day in 2018 Using 1-in-2 PG&E Weather Scenario for SmartRate™ for Event Hours of 2 to 7 pm 54
Table 26. Ex-Post versus Ex-Ante Factors, SmartRate™-Only Customers 55

Table 27. Progression from Ex-Post to Ex-Ante Load Impacts, SmartRate™-Only 57
Table 28. Ex-Post versus Ex-Ante Factors, Dually-Enrolled Customers 58
Table 29. Progression from Ex-Post to Ex-Ante Load Impacts, Dually-Enrolled 59
Table 30. Data Cleaning Steps for Bill Protection Status Analysis 62
Table 31. Share of SmartRate™ and Dually-Enrolled Participants with and without Bill Protection Status 63
Table 32. Bill Changes for SmartRate™ and Dually-Enrolled Bill Protection Status Participants 64
Table 33. Bill Changes for SmartRate™ and Dually-Enrolled Participants without Bill Protection Status 64
Table 34. Bill Changes for All SmartRate™ and Dually-Enrolled Participants 65
Table 35. Average Refund for Bill Protected Participants 65
Table 36. SmartRate™ Bill Impacts by LCA 66
Table 37. SmartRate™ Bill Impacts by CARE Rate Status 66
Table 38. SmartRate™ Bill Impacts by FERA Rate Status 67

Table of Figures

Figure 1. PG&E SmartDays™ in 2017 with Average Maximum Temperatures 2
Figure 2. Event and Non-Event Days, 2017 Summer Period 11
Figure 3. SmartRate™-Only and Matched Comparison Group Load on Non-Event Days 12
Figure 4. Dually-Enrolled SmartRate™ and Matched Comparison Group Load on Non-Event Days 13
Figure 5. Greater Bay Area SmartRate™-only Participant Validation Results 15
Figure 6. Greater Bay Area Dually-Enrolled Participant Validation Results 16
Figure 7. Conceptual Depiction of Behavioral Spillover 19
Figure 8. Relationship between Ex Post Load Impacts and Weather, SmartRate™-Only 22
Figure 9. Relationship between Ex Post Load Impacts and Weather, Dually-Enrolled Only 23
Figure 10. Ex-Ante Predictions of 2016 and 2017 Events Compared to Ex-Post Results for Each Event – Greater Bay Area Dual Enrollees 24
Figure 11. Ex-Ante Predictions of 2016 and 2017 Events Compared to Ex-Post Results for Each Event – Greater Bay Area SmartRate™ Only Enrollees 25
Figure 12. Hourly Loads and Impacts for Average Event - SmartRate™-Only 30
Figure 13. Hourly Load and Load Impacts for Average Event – Dually-Enrolled 32
Figure 14. Average SmartRate™-Only Load Impacts by LCA by Temperature 34
Figure 15. Average Dually-Enrolled Load Impacts by LCA by Temperature 36
Figure 16. Ex-Ante Load Impact Projections by Weather Scenario for SmartDays™ Event and RA Windows for the 2019 August Peak Day – SmartRate™-Only 40
Figure 17. Ex-Ante Load Impact Projections by Weather Scenario for SmartDays™ Event and RA Windows for the 2019 August Peak Day – Dually-Enrolled 40
Figure 18. Annual SmartRate™ and Dually-Enrolled Participation and Aggregate and Per Participant Impacts 41
Figure 19. Historical Aggregate and Per Customer Impacts for SmartRate™ (2013 – 2017) 42
Figure 20. Historical Enrollment Trends 43
Figure 21. Mean Impacts by Length of Enrollment in Program 45
Figure 22. Within-Event and Across-Year Persistence of Load Impacts 50
Figure 23. Average California Temperature (May-September) 51
Figure 24. Greater Bay Area Distribution of Load Impacts, SmartRate™ Only Participants 68
Figure 25. Greater Bay Area Distribution of Load Impacts, Dually-Enrolled Participants 68
Figure 26. Greater Fresno Area Distribution of Load Impacts, SmartRate™ Only Participants 69
Figure 27. Greater Fresno Area Distribution of Load Impacts, Dually-Enrolled Participants 69
Figure 28. Kern Distribution of Load Impacts, SmartRate™ Only Participants 70

Figure 29. Kern Distribution of Load Impacts, Dually-Enrolled Participants 70
Figure 30. Northern Coast Distribution of Load Impacts, SmartRate™ Only Participants 71
Figure 31. Northern Coast Distribution of Load Impacts, Dually-Enrolled Participants 71
Figure 32. Other Distribution of Load Impacts, SmartRate™ Only Participants 72
Figure 33. Other Distribution of Load Impacts, Dually-Enrolled Participants 72
Figure 34. Sierra Distribution of Load Impacts, SmartRate™ Only Participants 73
Figure 35. Sierra Distribution of Load Impacts, Dually-Enrolled Participants 73
Figure 36. Stockton Distribution of Load Impacts, SmartRate™ Only Participants 74
Figure 37. Stockton Distribution of Load Impacts, Dually-Enrolled Participants 74
Figure 38. Greater Bay Area Spillover Baseline and Predicted Load 75
Figure 39. Other Spillover Baseline and Predicted Load 76
Figure 40. Greater Fresno Area Spillover Baseline and Predicted Load 77
Figure 41. Sierra Spillover Baseline and Predicted Load 78
Figure 42. Stockton Spillover Baseline and Predicted Load 79
Figure 43. Kern Spillover Baseline and Predicted Load 80
Figure 44. North Coast and North Bay Spillover Baseline and Predicted Load 81

Table of Equations

Equation 1. Ex-Post Demand Response Regression Model 14
Equation 2. Multi-level Model 17
Equation 3. Load Shift Model Estimating Equation 20
Equation 4. Ex-Ante Demand Response Regression Model 21
Equation 4. Ex-Ante Demand Response Baseline Regression Model 26

1. Executive Summary

This report presents results of the load impact evaluation of the Pacific Gas and Electric Company's (PG&E's) 2017 SmartRate™ program (hereafter referred to as "SmartRate™" or "the Program"). In this report, we provide both ex-post load impacts for the 2017 program year and ex-ante forecasts of load impacts for the years 2018 through 2028.

The overarching objectives of this evaluation are to: (1) estimate ex-post and ex-ante load impacts, and (2) understand who drives impacts and what PG&E can expect in the future. We used SmartMeter™ and customer data, coupled with statistical regression modeling to estimate program impacts. In addition, we conducted a series of analyses to inform Program-level load impacts, including estimating ex-post load impacts by key customer segments (such as Local Capacity Area, CARE customer, and bill protection status), event day, as well as by individual customers. This offered an assessment of the distributional impacts across customers to inform future program delivery and customer targeting. To supplement ex-ante impacts, we also conducted analyses to contextualize what the Program can expect to achieve moving forward, incorporating an estimation of the effects of participants habituating behavioral spillover and non-event load shift, changes in responsiveness to temperature due to participant enrollment characteristics, and changes to enrollment due to the advent of Community Choice Aggregators (CCAs).

SmartRate™ is a rate plan that offers PG&E customers lower electric rates from June 1st through September 30th, except during the hours of 2pm to 7pm on event days (referred to by PG&E as SmartDays™). SmartRate™ is designed to help reduce load on the electric grid on days when resources are constrained, and typically PG&E calls between 9 and 15 SmartDays™ a year when there is high demand and exceptionally hot weather.

Participants in the SmartRate™ program can also enroll in PG&E's SmartAC™ program, which pays customers for allowing PG&E to cycle their air conditioners during times of high system load, as well as during SmartDays™. Customers enrolled in both programs are considered dually-enrolled participants, and we present load impact estimates for these customers throughout the report.

On average, 124,000 customers participated in a SmartDay™ event in 2017. A little over three quarters of participants are SmartRate™-only participants, with the remainder dually-enrolled participants. Participants are also dispersed geographically across PG&E's service territory; however, a little under half (46%) of all participants are concentrated in the Greater Bay Area Local Capacity Area (LCA), followed by Other[1] (21%) and Sierra (11%) LCAs. A little over a quarter (28%) of all participants are CARE customers and less than 1% are FERA customers.

[1] The LCA referred to as "Other" includes PG&E participants who do not reside in the other defined LCAs that are included in PG&E's service territory.

Figure 1 shows the 14 events called in 2017, 9 of which were for both SmartRate™ and SmartAC™ programs. Compared to the temperatures on events in past years, 2017 was one of the hottest summers on record for PG&E's service territory.

Figure 1. PG&E SmartDays™ in 2017 with Average Maximum Temperatures

Ex Post Results

The ex-post aggregate Program load impact for the typical event day in 2017 is 28.1 MW. On average, over 124,000 customers participated in each of the 14 SmartDays™ events. The average per customer impact in 2017 equaled 0.23 kW. Dually-enrolled participants account for more than half (51%) of the aggregate program load impacts, but represent a little under a quarter (23%) of all participants who participated in a SmartDay™ event. Sierra, Kern, Greater Fresno, and Stockton LCAs provide the highest per customer impacts, as found in previous evaluations of the Program. Table 1 presents the aggregate and per customer load impacts for SmartRate™-only and dually-enrolled customer types.

Table 1. Average Ex Post Load Impacts for Average Event Day

Customer Type	Average	Aggregate	Per Customer	% Load	Average

	Event Participation	Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
SmartRate™-Only	95,126	156.5	13.8	1.6	0.14	8.8%	97
Dually-Enrolled	28,923	69.5	14.3	2.4	0.50	20.6%	100

Note: Average event temperatures were mean weighted based on who was enrolled during the event at each weather station.

The ex-post aggregate impacts and enrollment decreased in 2017 compared to 2016 when the program had 146,700 participants and achieved 29.8 MW. Note, however, that the average per customer impacts in 2017 were slightly higher than in 2016 (0.23 kW in 2017 and 0.20 kW in 2016), which to a large degree likely reflects the hotter average event temperature for the typical event day in 2017 compared to the previous year.

Our evaluation included an examination of programmatic spillover and whether it might contribute to declining reference loads, which can affect program event-day impact estimation. In contrast to traditional load control programs, rate-based demand response programs provoke distinct challenges related to developing appropriate baselines for load impact estimates. This is because the program does not solely have an effect on event days, but can have 'spillover' effects on non-event days as well. The time-dependent electricity rates of SmartRate™ therefore can lead customers to shift their electricity use to non-peak hours regardless of whether a SmartDays™ event is in effect.

Our investigation focused on peak-day spillover by looking at the impact of spillover on event days in 2017. As part of our analysis, we found that participants changed their energy consumption behavior on event days and non-event days. In other words, the rate's design provides a price signal to use more energy on non-event days and only to reduce energy usage during peak hours on event days. However, the price signal to reduce energy during event hours was strong enough that some participants lowered their consumption during peak hours on all days (responding more as if they are on a time-of-use (TOU) rate rather than a critical peak pricing (CPP) rate). The size of the spillover varied by customer segment and while not large on a per-participant basis, resulted in potentially 2 MW of additional load impacts in aggregate.

We recommend that PG&E develop additional evidence to support valuing the extent of behavioral spillover load impacts. While the Program is event-based, our analysis indicates that the Program leads to customers habituating load shifting practices on non-event days. Because of the way we estimate load impacts, this evaluation does not incorporate the effect of behavioral spillover in reducing reference loads when calculating load impact estimates. This therefore artificially depresses the reference load used to estimate event day impacts, as well as foregoes valuing the size of impacts for non-event days. In other words, the load impact estimate provided in this report uses a baseline that is estimated based on what would had happened on a non-event day in the same year. Spillover uses a baseline that estimates what would have happened in the absence of the program. Spillover becomes increasingly relevant as residential customers default to TOU rates because we expect more customers to habituate changing their energy consumption practices during the hours of SmartDays™ events on non-event days. Correctly valuing the effect of this spillover and its benefits on hot non-event days may prove instrumental to more effectively manage grid operations. This evaluation estimated spillover on a daily basis, but future research should investigate the effect of spillover on a monthly basis as well as over time.

Ex Ante Results

We estimated ex-ante forecasts for the Program based on four weather scenarios and summarized impacts using the resource adequacy (RA) window.[2] With these results, we forecast lower aggregate impacts in future years, mostly due to the declining forecasts of enrollment in the Program. For the 2019 August peak day using the 1-in-2 PG&E weather scenario, we forecast aggregate impacts of 13 MW for the Program (Table 2).

Table 2. Ex-Ante Program and Portfolio-Adjusted Load Impacts for 2019 – PG&E 1-in-2 Weather for the Summer RA Window (1 – 6pm)

Day Type	Program			Portfolio Adjusted		
	SmartRate™-Only	Dually-enrolled	Total	SmartRate™-Only	Dually-enrolled	Total
January Peak	3.2	2.8	6.0	3.2	2.8	6.0
February Peak	3.2	2.8	6.0	3.2	2.8	6.0
March Peak	3.2	2.8	6.0	3.2	2.8	6.0
April Peak	4.0	3.0	7.0	4.0	3.0	7.0
May Peak	5.0	4.6	9.6	5.0	***0.9***	***5.9***
June Peak	6.5	7.0	13.5	6.5	***1.4***	***7.9***
July Peak	6.5	7.0	13.5	6.5	***1.4***	***7.9***
August Peak	6.3	6.7	**13.0**	6.3	***1.3***	***7.6***
September Peak	5.9	6.0	11.9	5.9	***1.2***	***7.1***
October Peak	4.3	3.3	7.6	4.3	***0.6***	***4.9***
November Peak	3.2	2.8	6.0	3.2	2.8	6.0
December Peak	3.2	2.8	6.0	3.2	2.8	6.0

*Bold italicized numbers reflect the lower impact values when the portfolio-adjustment is made.

The Program has experienced declining enrollment over the past few years and PG&E expects this trend to continue, according to PG&E's enrollment projections. As enrollment declines, we expect lower aggregate impacts for the Program. Key factors driving this decline include:

- The decline in enrollment due to Community Choice Aggregators (CCAs), as PG&E customers become ineligible for the Program when they enroll in a CCA. Though the primary CCA in PG&E's service territory covers the Greater Bay Area where lower load impacts are achieved, the sheer number of customers who are ineligible will continue to affect potential program load impacts. Overall, declines in enrollment due to future CCAs could reduce program load impacts by approximately 12 MW

[2] The Resource Adequacy (RA) window is the set of hours over which we sum load impacts and it differs from PG&E SmartDay™ event hours of 2 – 7pm. The RA window runs from 1 – 6pm during the months of May through October and from 4 – 9pm from November through April.

(applying 2017 multi-level model impacts by 68,000 customers identified as potential future CCA customers).

- The decline in the proportion of dually-enrolled participants. These participants exhibit higher per customer impacts due to the cycling effect of central air conditioners, and therefore decreases in dual enrollment will likely also lead to declines in Program impacts.
- The decline in the proportion of customers who enrolled before 2014. We conducted a multi-level model that allowed us to estimate individual load impacts for each customer. Based on our analysis, we found that newer enrollees contribute smaller load impacts compared to customers who enrolled in the Program in earlier years.

We recommend that PG&E incorporate results from the multi-level modeling analysis to identify existing customers and target future customers who can contribute to load impacts. For existing customers, we recommend reaching out to select under or overperforming customers to provide educational information or behavioral messaging to motivate increasing engagement with the rate. For future customer targeting, we recommend PG&E leverage this research, in addition to prior evaluation findings, to target customers with characteristics known to provide larger load impacts (e.g., climate zone, usage profile, etc.).

We also recommend PG&E consider a process evaluation to gather data from Program participants through a survey effort to gauge their understanding of SmartRate™, whether they receive notification of SmartDay™ events, what changes in electric consumption they make during SmartDay™ event hours to reduce load, and whether they are satisfied with their experience with the Program. This would also present an opportunity to assess whether participants are well informed about how the rate affects their bills while they are bill protected and when bill protection ends.

2. Introduction to the SmartRate™ Program

SmartRate™ is a voluntary critical peak pricing program that overlays lower electric rates on an existing tariff. The Program offers lower electric rates from June 1st through September 30th, except during the hours of 2pm to 7pm on SmartDays™. SmartRate™ is designed to help reduce load on the electric grid on days when resources are constrained. During summer non-event hours, customers receive a credit of approximately $0.024 per kWh and during SmartDays™ event hours, a peak-price adder of $0.60 per kWh.[3] PG&E calls SmartDays™ events when electricity is in high demand and is generally coincident with exceptionally hot weather. PG&E provides day-ahead notification of SmartDays™ via phone, text, and/or email to allow customers to plan for reducing their energy use or shifting their load during event hours. The Program calls a minimum of 9 and a maximum of 15 SmartDays™ in a year. In 2017, PG&E called 14 events. All but one SmartDays™ occurred on weekdays.

PG&E provides newly enrolled participants with bill protection status during their first full summer on SmartRate™ (May through October). Bill protection ensures that if customers are billed more than what they would have been billed on their regular rate plan during this first full summer on the Program, they will receive a credit on their November bill. Customers receive two notifications before their bill protection status ends at the end of their first year in the Program.

Participants of the SmartRate™ program may also enroll in PG&E's SmartAC™ program, which provides customers a payment from PG&E for allowing the utility to control their air conditioners during times of high system load. Customers enrolled in both programs are considered dually-enrolled participants and we present load impact estimates for these customers throughout this report. On SmartDays™, PG&E sends paging signals to participants' programmable communicating air conditioners to use less power during the hours of 2pm and 7pm. This provides additional load reductions for customers who are dually-enrolled in both programs. In 2017, nine of the 14 event days were called for both SmartRate™ and SmartAC™.

Overall, on average 124,000 customers participated in at least one of the 14 SmartDays™. The Program saw an expansion from its modest beginnings, where it had roughly 10,000 participants in 2008. It hit peak enrollment in 2016 with just under 147,000 enrollees and in this past year, enrollment in the program has declined to just over 124,000 participants in 2017. In this report, we define participation as the average participation in a typical SmartDays™ event.

Table 3 provides 2017 SmartRate™ enrollment by LCA and enrollment type (e.g., SmartRate™-only and dually-enrolled SmartRate™ and SmartAC™ participants). SmartRate™-only participants represent over three quarters of all participants (77%), with the remaining 23% dually-enrolled in both SmartRate™ and

[3] PG&E's 2017 SmartRate™ brochure notes the following: "for all rates except E-TOU-B, participants will receive an extra credit of $0.0075 for all usage above baseline (tier 1) from June 1 to September 30. E-TOU-B participants will receive an extra credit of $0.0050 for all usage from June 1 to September 30."

SmartAC™ Programs. By LCA, Greater Bay Area represents a little under half of all enrolled participants (46%), followed by Other (21%) and Sierra (11%).

Table 3. Average Participant Count for SmartRate™ Program in 2017, by LCA and Enrollment Type

LCA	SmartRate™-Only		Dually-Enrolled		Total Participants
	Participants	Percent of All Participants	Participants	Percent of All Participants	
Greater Bay Area	46,992	82%	10,317	18%	57,309
Greater Fresno	9,478	69%	4,338	31%	13,816
Humboldt	44	100%	0	0%	44
Kern	3,328	78%	961	22%	4,289
Northern Coast	1,920	83%	400	17%	2,320
Other	20,701	78%	5,776	22%	26,477
Sierra	8,225	63%	4,921	37%	13,146
Stockton	4,482	67%	2,211	33%	6,693
All	**95,170**	**77%**	**28,924**	**23%**	**124,094**

3. Study Objectives and Methodology

This chapter presents the study objectives that guided our evaluation, research questions we addressed as we conducted our analyses, and detailed methodology used to arrive at our results.

3.1 Key Research Questions

Opinion Dynamics sought to address the following key research questions through this evaluation:

- **What are the ex-post and ex-ante load impacts for SmartDays™?** To address this research question, we estimate the ex-post load impacts of the Program for each event day in 2017 over the 2017 summer season. Additionally, we estimate ex-ante impact projections for 2018–2028 for monthly peak days.
- **Who drives load impacts and what can we expect for the future?** We conducted multi-level modeling to characterize and assess variation in demand reduction responses across Program participants, including an examination of impacts achieved by newer versus continuing enrollees.
- **Why did the Program achieve these results?** We contextualize load reductions by key customer segments (e.g., SmartRate™- only versus dually-enrolled participants, LCAs, CARE), and over time by drawing comparisons to prior evaluation results.

In addition to assessing impacts for 2017, we also incorporate a review of historical trends for the program:

- How has ex-post load impacts changed over time?
- How do prior ex-ante and current ex-post estimates compare?
- Are current ex-post load estimates and current ex-ante load impacts for 2017 in alignment?
- How do prior ex-ante load impact projections match up to current ex-ante load impact projections?

3.2 Methodology

In this section, we provide an overview of our methodological approach to estimating ex-post load impacts for the 2017 SmartRate™ program, as well as the ex-ante load impact projections for 2018-2028. We first present the method we used to estimate ex-post impacts, as well as our approach to assessing variation in demand reduction across participants and analyzing potential behavioral spillover. We subsequently present our approach to estimate ex-ante load impacts. These results are then applied to projected changes in SmartRate™ enrollment, including the effects of customer enrollment changes on ex-ante enrollment projections, such as removal of participants located within a CCA territory, as well as variation in demand reduction based on a change in bill protection status.

3.2.1 Ex-Post Evaluation Methodology

Table 4 provides a summary of our ex-post research questions.

Table 4. Summary of SmartRate™ 2017 Ex-Post Key Research Questions and Methods

Key Research Question	Method
What are the estimated hourly ex-post load impacts of the SmartRate™ program for each 2017 SmartDays™ event? What are the confidence intervals for each hour and average event hour?	Develop matched comparison group and proxy weather days, followed by Difference-in-Differences model for aggregate estimate.
What are the ex-post load impacts for 2017 SmartDays™ events by specific customer segments?	Estimate ex-post impacts by key customer segments: ▪ SmartRate™-only versus dually-enrolled participants, ▪ CARE, ▪ FERA, and ▪ LCAs.
What is the distribution of hourly and average daily impacts by customer segment for the average event?	Conduct multi-level modeling to assess variation in demand reduction across participants.
What effect does behavioral spillover or load shift have on declining reference loads?	Examine the effect of SmartRate™ on customer electricity usage on non-event days to address potential behavioral spillover that may result due to risk aversion, habituation, or other factors influenced by the Program by developing a pre-period baseline and modeling load shift associated with rate.
Does bill protection status affect customer load impacts?	Examine the impacts of participants with and without bill protection status during the summer of 2017 to assess whether there is a difference.

We use a quasi-experimental design to estimate the load impacts of the SmartRate™ program. Our selected approach used non-event days with similar weather to event days, a matched comparison group, and regression modeling to establish the baseline. We selected this approach since neither a matched comparison group nor regression modeling when used in isolation provide a credible baseline. When combined, the regression model can adjust for the small differences between weather response of the comparison group and the participant group, while the comparison group can help adjust for differences between the selected non-event days and the event days.

We assessed a variety of matched comparison group methodologies and selected the most appropriate one to ensure we developed accurate estimates. This was a propensity score approach to select both proxy weather days and the matched comparison group. We used proxy weather days (e.g., non-event days) to help replicate the conditions of event days for electric loads of SmartRate™ program participants and the matched comparison group to replicate the electric loads of non-participants during event days. This information fed into regression models we used to develop baselines that best represent the counterfactual (what would have participant's load have been in the absence of the SmartRate™ program event).

For ex-post estimates, we used a two-way linear fixed-effects regression (LFER) to estimate load reductions and intra-day load shift impacts, with fixed effects for date and customer. To assess variation in impacts between customers, we used a multi-level modeling approach which allows individual impact estimates for each participant while still incorporating information from comparison group customers.

What are the estimated hourly ex-post load impacts for each 2017 SmartDays™ event?

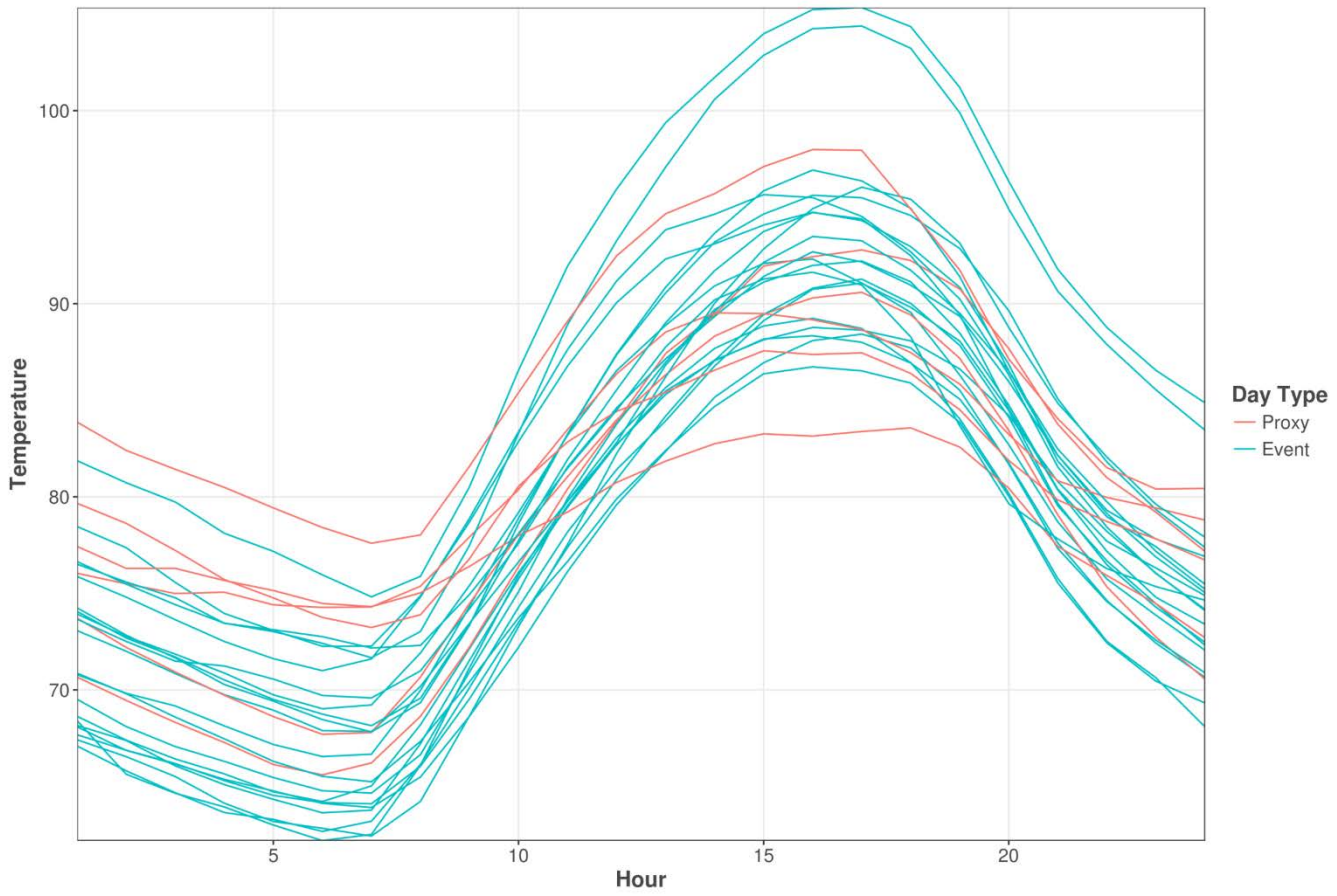
Given the design of the SmartRate™ program, we use a quasi-experimental design to estimate load impacts. This relies on identifying a matched comparison group who have similar peak season load characteristics on event days by identifying non-participating customers with similar hourly usage profiles for each participant on matched non-event days. We selected five non-participating (not SmartRate™ or SmartAC™ participants) customers for each participating customer to form the comparison group.

Energy usage by customers in the matched comparison group helped to establish the "counterfactual" (i.e., the participants' baseline usage in the absence of the SmartRate™ program). A well-matched comparison group helps correct for omitted variable bias, where unmeasured variables (e.g., macroeconomic factors, household size) have an impact on electricity consumption. For this reason, the comparison groups must be as similar as possible to the participants during the matched non-event days so that we can be confident that the behavior and electricity consumption of the comparison group during the event period provides an accurate reflection of participant behavior and electric usage in the absence of the event. Matched comparison groups, on their own, are rarely sufficient to establish a counterfactual, and we used regression models to help adjust for some of the remaining differences between the comparison group and participants.

To develop matches, we first identified non-event days that were similar in terms of their weather patterns to the 14 events that were called during the 2017 period. We used propensity score matching to select six non-event days[4] that are similar in weather profile to the event days. When using propensity score matching, we first build a logistic regression model to estimate each unit's probability of being treated, or propensity score, based on characteristics of interest. We then match each treatment unit to the nearest comparison units in terms of propensity scores (see Figure 2). Notably, given the extremely hot weather conditions in 2017, it was challenging to identify non-event days with similarly hot temperatures for two of the events.

[4] The selected non-event days are all from 2017: June 21, July 17, August 3, August 4, September 3 and September 4.

Figure 2. Event and Non-Event Days, 2017 Summer Period



PG&E provided our team with average hourly load across the six non-event days for each customer from which to select a matched comparison group. We matched each participant to five non-participating customers on aggregate morning load and all afternoon and evening hours on the non-event days selected using a propensity score matching approach after grouping customers by LCA and CARE status. Notably, depending on the quality of the match comparison group for each LCA, we varied the number of matched customers included in our model. We visually inspected our matches by participant enrollment type, since it is not possible to match on enrollment for customers who are not enrolled in the program. Figure 3 and Figure 4 provide the matching results on non-event days by participant type, which indicate that the customers are well matched in terms of usage on similar non-event days.

Figure 3. SmartRate™-Only and Matched Comparison Group Load on Non-Event Days

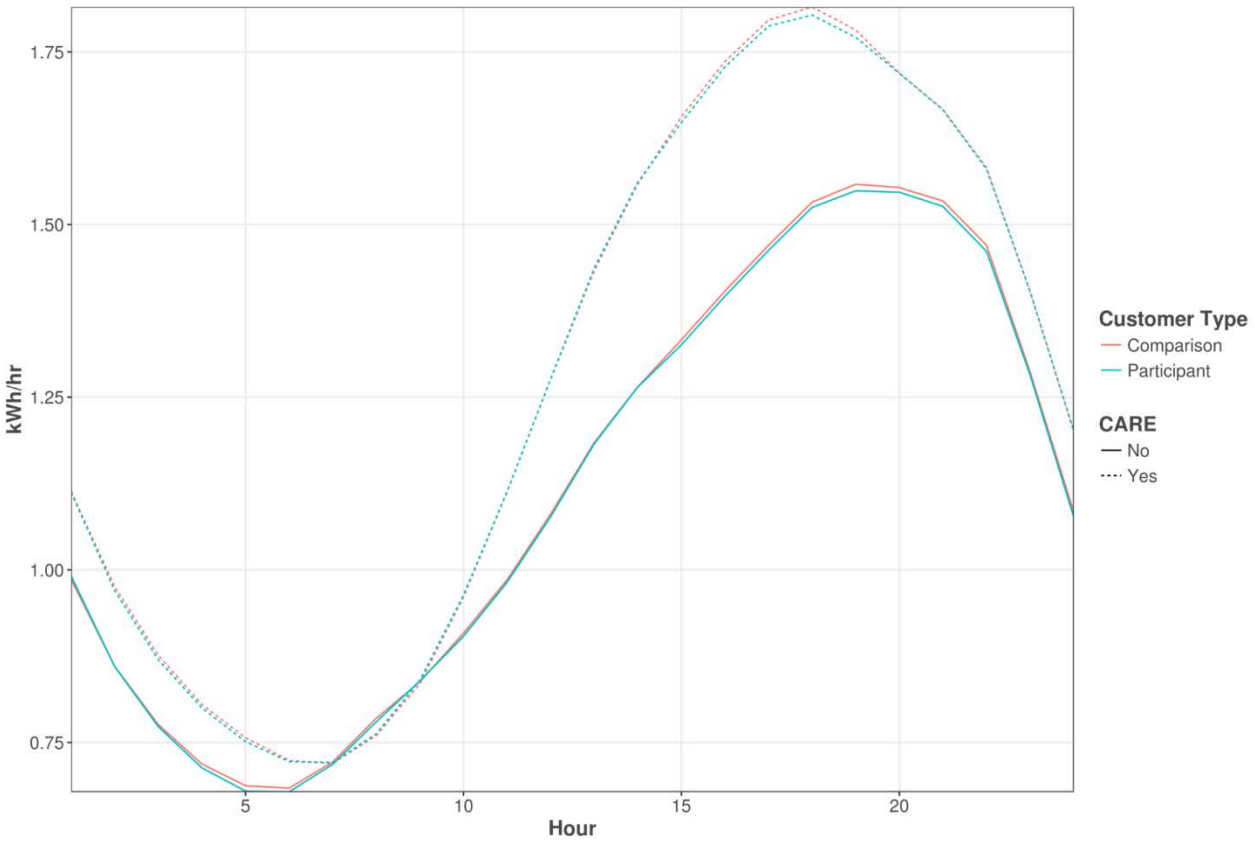
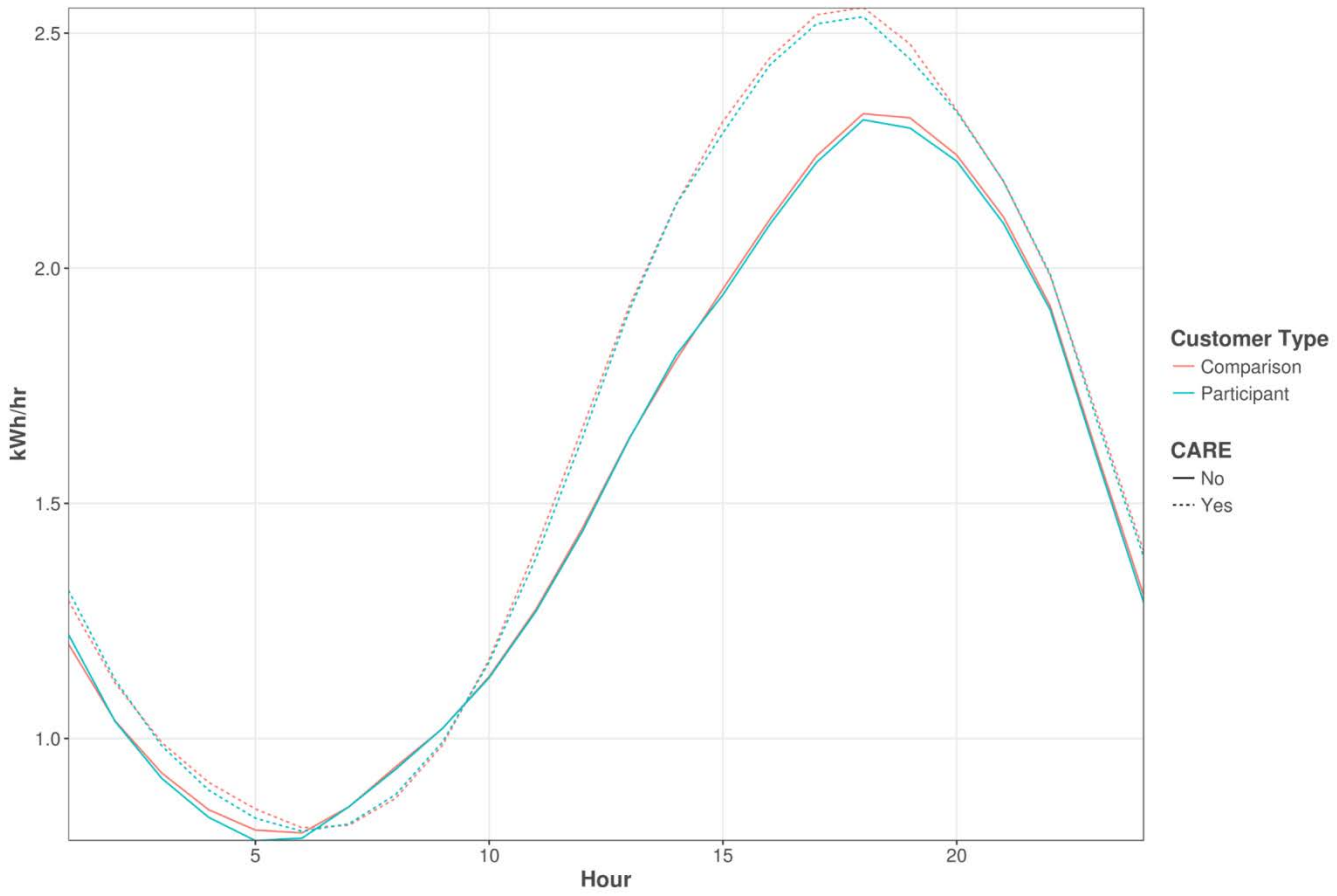


Figure 4. Dually-Enrolled SmartRate™ and Matched Comparison Group Load on Non-Event Days



We also matched customers using simple Euclidian distance, normalized Euclidian distance, and Mahalanobis distance matching. We assessed the performance of all four matching methods before selecting the comparison group. The propensity score matching yielded the best matches. We compared the performance of each matching method in creating a matched comparison group by:

- Calculating the average of the normalized absolute value of differences between pre-period usage for the treatment and comparison group in each of the hours used in matching (evaluating covariate balance).
- Graphically inspecting the similarity of average non-event day load for participants and matched comparison group customers within LCA, CARE and enrollment status, and making comparisons for all hours of non-event days.

We estimated load impacts on event days by modeling the predicted baseline informed by comparison group customer loads and non-event proxy day usage, and subtracting SmartRate™ participant loads. To do so, we used a two-way linear fixed-effects regression (LFER) modeling approach. After testing a variety of models, we selected the following model specification to best predict reference load during event days.

Equation 1. Ex-Post Demand Response Regression Model

$$kw_{it} = \mu_0 + \alpha_i + \alpha_d + \beta_1 Event \cdot Treat + \beta_2 Early\ Afternoon\ Load + \varepsilon_{it}$$

Where:

kw_{it} = Hourly energy consumption kWh/hour in hour *t* for customer *i* (kWh/hr)

μ_0 = Overall mean energy usage

α_i = Participant-specific deviation from mean energy usage

α_d = Day-specific deviation from mean energy usage

ε_{it}= Observation-specific error

$Event$ = Indicator variable for event day

$Treat$ = Indicator variable for program participant

$EarlyAfternoonLoad$ = Average load for each customer on event day from 10AM-1PM

This model specification is similar to prior evaluations, with the exception of incorporating an early afternoon load term. Our team reviewed event day load shapes to assess whether there was evidence of behavioral pre-cooling prior to events.[5] We found no evidence of pre-cooling based on this examination. Further, the early afternoon load term does not incorporate the hour that directly precedes an event, ensuring that the model does not over-correct for pre-cooling behavior. However, if participants were to begin pre-cooling during the 10am-1pm period, the model could introduce bias due to pre-cooling. Incorporating this term is consistent with CPUC Load Impact Protocols and substantively improved the quality of the estimated baseline, verified using cross-validation.

We fit separate regressions for each event by LCA, participant type (e.g., SmartRate™-only and dually-enrolled participants), and CARE status for each hour of each event day.

We report uncertainty using estimated standard errors from the LFER models adjusted for clustering.[6] In addition to testing an array of model specifications, we also validated the model fit by using 10-fold cross validation and adjusted R-squared, consistent with prior evaluation efforts. Validation results suggest that the model does an excellent job predicting usage for both the participants and comparison group on event days on the out of sample customers used for this validation exercise. In this report, we provide SmartRate™-only and dually-enrolled validation results for Greater Bay Area given that this is the largest group of enrolled participants. Both Figure 5 and Figure 6 provide treatment (dotted line) and comparison group (solid line) compared to the actual (red) and predicted (green) baseline and load reduction. As can be seen, the results are essentially identical for each event.

[5] We do not expect any pre-cooling related to enrollment in the SmartAC™ program given the type of equipment used for the program.

[6] We did not adjust for autocorrelation because we ran models separately for each hour.

Figure 5. Greater Bay Area SmartRate™-only Participant Validation Results

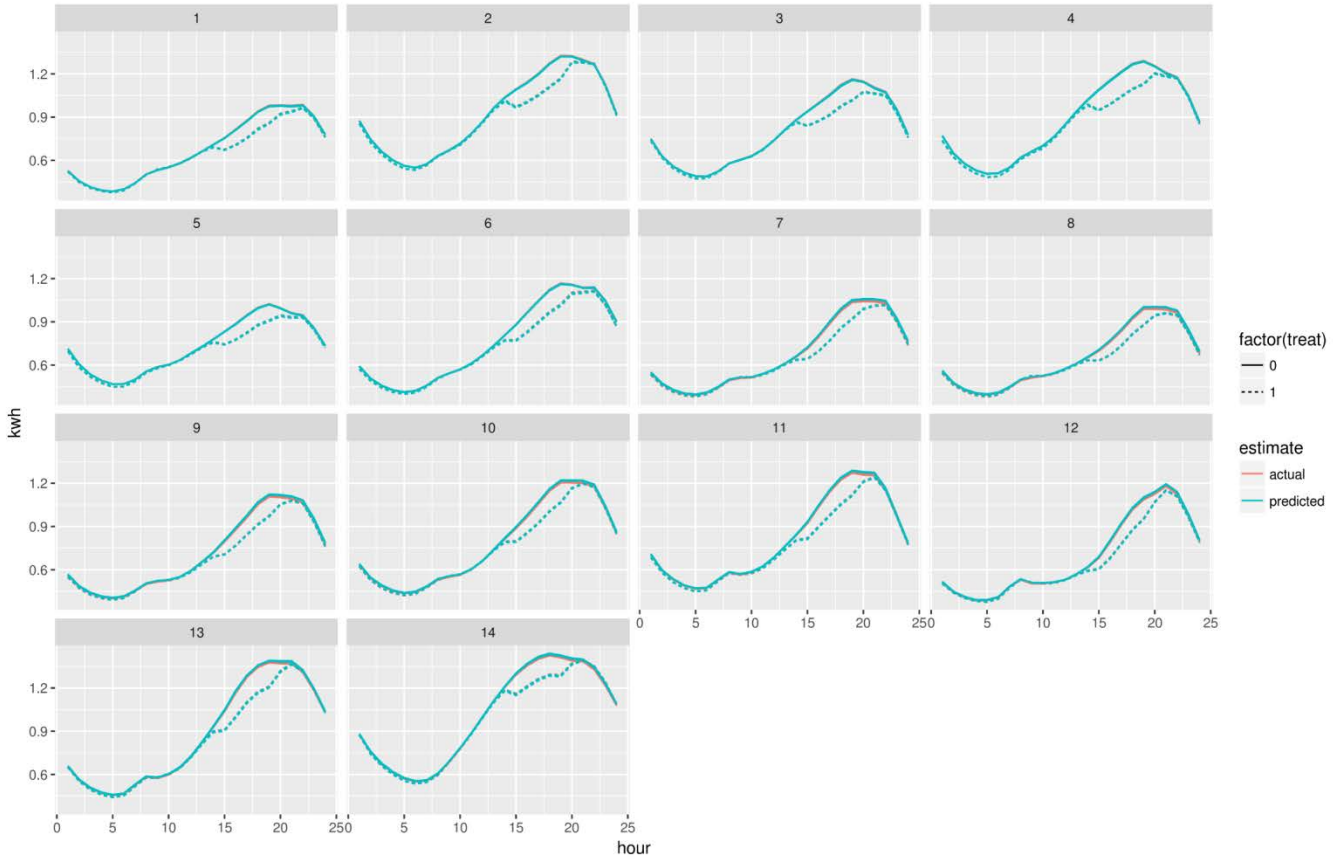
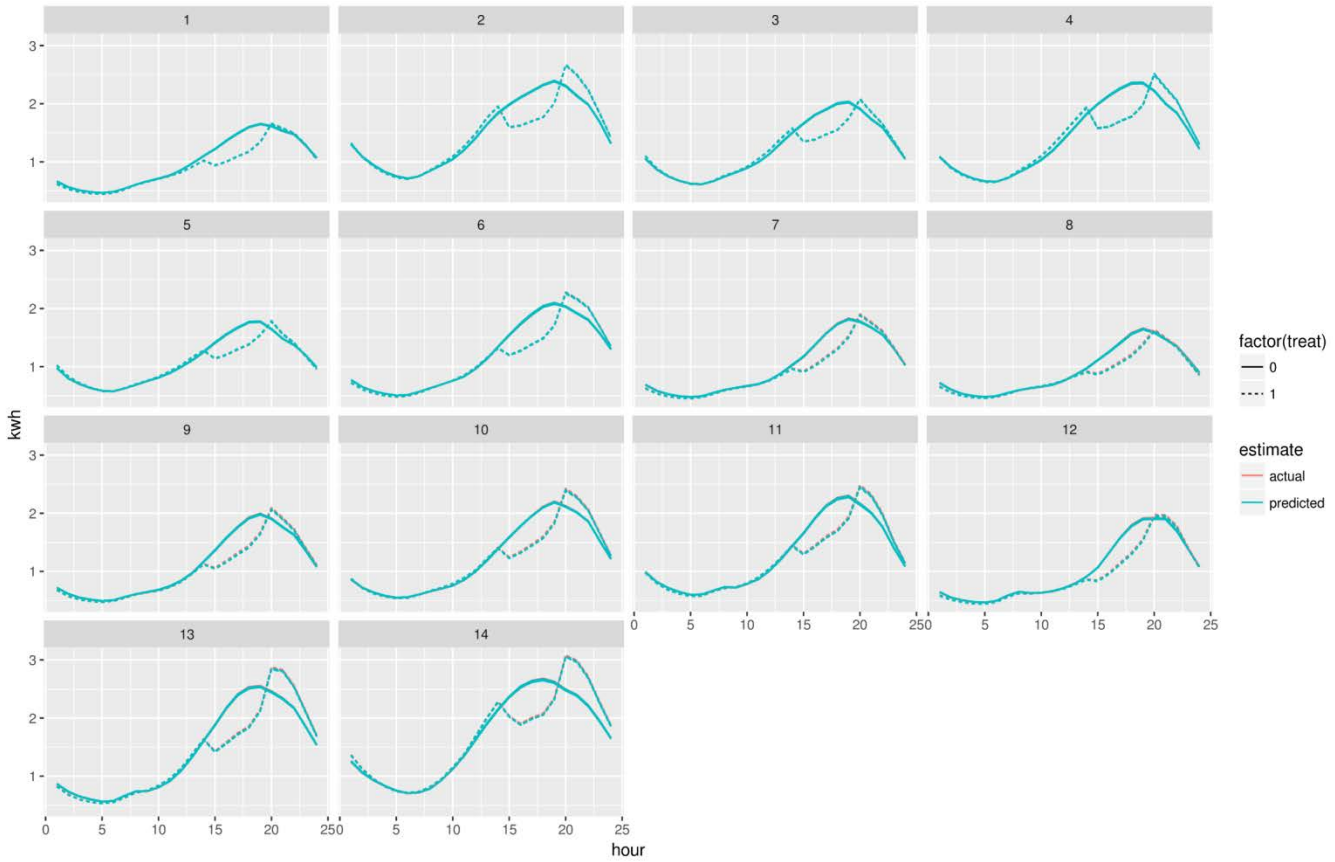


Figure 6. Greater Bay Area Dually-Enrolled Participant Validation Results



What are the ex-post load impacts for 2017 SmartDays™ events by specific customer segments?

We calculated the average load impact and the distribution of load impacts for a variety of segments. This analytical effort examined ex-post load reduction differences between customer segments during SmartDays™ events, by:

- SmartRate™ versus SmartRate™/SmartAC™ dually-enrolled participants,
- FERA,
- CARE; and
- LCAs.

This effort produced load impacts by specific customer segments as well as the distribution of hourly and average daily impacts by customer segment for the average event.

What is the distribution of hourly and average daily impacts by customer segment for the average event?

We use a multi-level model to estimate individual participant's average ex-post impacts. A multi-level model approach is similar to the individual regression approach used in past evaluations, but is less susceptible to high variation in load for individual participants. Instead, when a participant in the model has high variation, estimates for that individual will be closer to the overall average estimate than if the same individual has lower load variation. This adjustment of individual impacts is called regularization and is essentially a borrowing of information from other customers when an individual's load impact is uncertain. Regularization of this type is not possible in individual regression.

We use the results of the participant-specific load impact estimates to examine the distribution of impacts across participants. We also assign participants into negative, below average, above average, and very above average load impact groups. Equation 2 provides the model used for this analysis.

Equation 2. Multi-level Model

$$kW_{it} \sim N\left(\alpha_i + \gamma_d + \theta_i Treatment_t Event_t + \beta_1 CDH_t Event_t + \beta_2 CDH_t Treatment_t Event_t, \sigma_{kW}^2\right),$$

$$for\ t = 1, \dots, t, i = 1, \dots, n;$$

$$\begin{pmatrix} \alpha_i \\ \theta_i \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_\alpha \\ \mu_\theta \end{pmatrix}, \begin{pmatrix} \sigma_\alpha^2 & \rho\sigma_\alpha\sigma_\theta \\ \rho\sigma_\alpha\sigma_\theta & \sigma_\theta^2 \end{pmatrix}\right), for\ i = 1, \dots, n$$

$$\gamma_d \sim N\left(\mu_\gamma, \sigma_\gamma^2\right), for\ d = 1, \dots, D$$

Where:

kW_{it}= Average hourly demand (kWh/hr) for household i at time t

α_i= Household-specific intercept for household i

γ_d= Date-specific intercept for day d

θ_i= Household-specific change in consumption for the treatment group on event days

β_1= Coefficient for CDH on event days

β_2= Coefficient for CDH on event days for the treatment group

β_7= Coefficient for treatment group in the post period by CDD interaction

σ_{kW}^2= Variance of kW

μ_α= Mean of household-specific intercept

μ_γ= Mean of day-specific intercept

μ_θ= Mean of household-specific change in consumption due to treatment

σ_α^2= Variance of household-specific intercept

σ_γ^2= Variance of day-specific intercept

σ_θ^2= Variance of household-specific change in consumption due to treatment

$\rho\sigma_\alpha\sigma_\theta$= Covariance of household-specific intercept and change in consumption

N = Multivariate normal distribution

The multi-level model incorporates both treatment and comparison group customers. As a result, the comparison group controls for exogenous factors that may contribute to load changes. However, because this model does not explicitly control for all non-Program related changes at the individual level, we cannot state results for any given individual are entirely attributable to the Program. As a result, these findings suggest trends that can inform program design enhancements, but are explicitly not used for claiming load impacts.

Table 5. Comparison of Average Load Impacts between Ex Post Model and Multi-Level Model

Participant Type	Ex Post Model Average Load Impact	Multi-Level Model Average Load Impact
SmartRate™-only	0.14	0.14
Dually-Enrolled	0.50	0.52

Multi-level model results do not perfectly align with ex post results given that multi-level modeling uses a different approach to calculate impacts. Even so, the overall average load impacts for each enrollment group are generally in line with the ex post results.

We assigned participants into negative, below average, above average, and very above average load impact groups. We defined these groups based on the mean impacts per enrollment group and LCA. The cutoffs for each group are defined below:

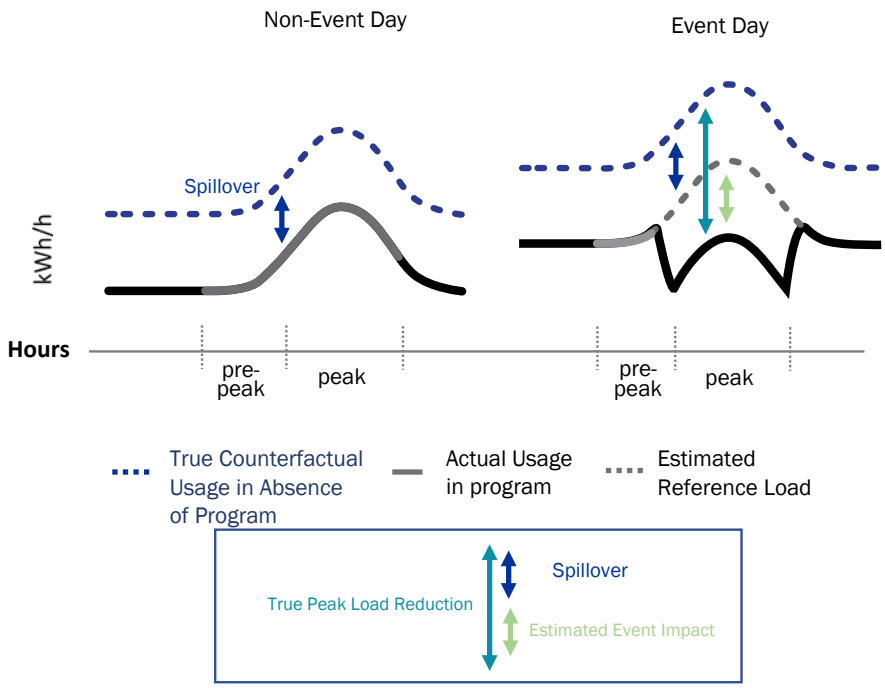
- Negative load impact participants are those that generated a negative average kW reduction.
- Below average load impact participants are those that generated an average kW reduction greater than zero but less than the average kW reduction within their enrollment group and LCA.
- Above average load impact participants are those that generated an average kW reduction greater than the average kW reduction within their enrollment group and LCA but less than the two times the average kW reduction within their enrollment group and LCA.
- Very above average load impact participants are those that generated an average kW reduction greater than two times the average kW reduction within their enrollment group and LCA.

What effect does behavioral spillover or load shift have on declining reference loads?

This analysis estimates the effect behavioral spillover has on declining reference loads. From a methodological standpoint, two baselines support estimation of spillover effects—the 2017 summer event period non-event days and the pre-enrollment summer non-event days. The difference between the two estimates, when controlling for exogenous factors such as weather, will reflect any spillover effects. Notably, we estimate impacts on an hourly basis for the event window.

For this model, we model the non-treatment period (e.g., pre-enrollment non-event days for each customer) and 2017 non-event days for each customer. This model produces an estimated pre-enrollment baseline usage (non-event days) and predicted 2017 usage during non-event days. This allows us to quantify the size of spillover by LCA and customer enrollment type.[7] Figure 7 offers an illustration of behavioral spillover.

Figure 7. Conceptual Depiction of Behavioral Spillover



[7] This effort reflects recent research by LBNL to understand behavioral spillover effects related to rate based designs. Anna Spurlock, Peter Cappers, Ling Jin, Annika Todd, LBNL Patrick Baylis, University of California at Berkeley. "Go for the Silver? Evidence from field studies quantifying the difference in evaluation results between "gold standard" randomized controlled trial methods versus quasi-experimental methods." ACEEE 2016 Summer Study on Energy Efficiency in Buildings. http://aceee.org/files/proceedings/2016/data/papers/2_363.pdf

We tested a range of models with different covariates and interactions, and selected the model with the best fit according to standard econometric and evaluation practices. The final model is:

Equation 3. Load Shift Model Estimating Equation

$$kW_{it} = \alpha + \alpha_i + \beta_{event}Event_t + \beta_{treat\ event}Treatment_i \cdot Event_t + \beta_{CDH}CDH_{it} + \beta_{CDH\ event}CDH_{it} \cdot Event_t + \beta_{CDH\ Treatment}CDH_{it} \cdot Treatment_i + \beta_{CDH\ Treatment\ event}CDH_{it} \cdot Treatment_i \cdot Event_t + \varepsilon_{it}$$

Where:

kW_{it}= Average hourly demand (kWh/hr) for household i at time t

α= Overall intercept

α_i= Household-specific intercept (absorbed)

$Treatment_i$= Indicator variable for inclusion in the treatment group

CDH_{it}= Cooling degree hours for household i at time t

$Event_t$= Indicator for event day at time t

β_x= Model coefficients

ε_{it} = Error term

Do customers on bill protection status contribute to load impacts differently than those who do not?

We use bill charges and credits data to establish bill impacts for all participating customers and to calculate bill protection payments. To more fully understand the bill impacts of the SmartRate™ program, we included summary statistics of overall bill impacts, bill impacts by LCA, and bill impacts by CARE status and FERA status in Appendix B. This analysis then used descriptive statistics to characterize the difference in per customer impacts of participants who were and were not bill protected in 2017.

3.2.2 Ex-Ante Evaluation Methodology

We estimate ex-ante load impacts for 2018 through 2028 for the SmartRate™ program using previous and current evaluated ex post impacts for 2016 through 2017[8], PG&E's enrollment projections, and our

[8] We did not include ex-post impacts from 2011-2015 given how distinct those results were compared to 2016 and 2017 estimates; we did not believe they were reliable for forecasting future ex ante estimates. This is because results from our ex post models suggest that the correlation between temperature and impacts were markedly different in prior years, leading to a potential over estimate of forecasted results (Figure 8 and Figure 9).

comparison of recent ex-post impact results to previous ex-ante load impacts. Table 6 provides a summary of our ex-ante load impact research questions and methodological approach.

Table 6: Summary of SmartRate™ 2017 Ex-Ante Key Research Questions and Methods

Key Research Question	Method
What are the ex-ante load impact projections for a typical event day and for monthly system peak load days in the summer event months under PG&E and CAISO 1-in-2 and 1-in-10 weather conditions?	Estimate overall ex-ante impact projections based on a weather-sensitivity analysis of the 2016 and 2017 per-customer ex-post load impacts and PG&E enrollment forecasts.
What are the ex-ante forecasts of load impacts by specific customer segments?	Estimate ex-ante impacts by key customer segments: ▪ SmartRate™ versus SmartRate™/SmartAC™ dually-enrolled participants, ▪ CARE, ▪ FERA, and ▪ LCAs.
What effect will any changes in customer enrollment forecasts have on predicted load reductions?	Conduct multi-level modeling to assess variation in demand reduction based on customer acquisition type (new or continuing customers) and bill payment status. Customers who opt to be part of a CCA will no longer be eligible for SmartRate™ and we examine how the projected impacts are affected by their removal. Assess persistence of load impacts across multiple years and multiple event days.

What are the ex-ante load impact projections under different weather conditions?

We estimate hourly ex-ante load impacts on an aggregate and per-customer basis for a typical event day and the monthly system peak load day in each month of the year for each LCA. We produce estimates for five sets of weather conditions: PG&E's peaking conditions 1-in-2 and 1-in-10, as well as CAISO's peaking conditions 1-in-2 and 1-in-10, and PG&E's typical event day.

For this task, we use a linear model informed by ex-ante impact estimates from this and previous years' evaluations. We estimate models separately by participant type for each hour of the day. Notably, this effort produces within-event persistence results, (e.g., does the second hour get the same impact as the first hour).

Equation 4. Ex-Ante Demand Response Regression Model

$$Load\ Impact = \beta_0 + \beta_1 mean17_{CDH65} + \sum_{All\ LCAs} \beta_i\ LCA_i + \varepsilon$$

Where:

$Load\ Impact$ = Load Impact in a particular hour for an event day

β_0 = Overall mean load impact

β_1 = Average change in impact for one CDH65 across LCAs

β_i = Average difference from base impact for LCA_i

ε = Observation-specific error

$mean17_CDH65_d$= Indicator variable for mean cooling degree hours from midnight to 5PM at base 65 Fahrenheit

LCA_i= Indicator variable for each LCA

The following figures plot overall average event hour per customer load impacts (kWh/hour) by event-day weather(mean17_CDH65). These results demonstrate that the modeling approach is appropriate for estimating ex ante impacts given the correlation between weather and ex post load impacts. These also demonstrate that over time, customer load impacts have declined for the same weather year over year, which may be due to changes in the customer mix over time. We see similar results for both SmartRate™ only and dually-enrolled participants. Given these results, we used this as an opportunity to identify whether the declining load impacts reflect changes in customer enrollment mix, or changes in participant responsiveness to events. The following plots (see Figure 8 and Figure 9) show that average per-participant impacts have decreased across years despite a record weather year in 2017, and decreased enrollment across program years. The combination of both has led to declining program impacts over time.

Figure 8. Relationship between Ex Post Load Impacts and Weather, SmartRate™-Only

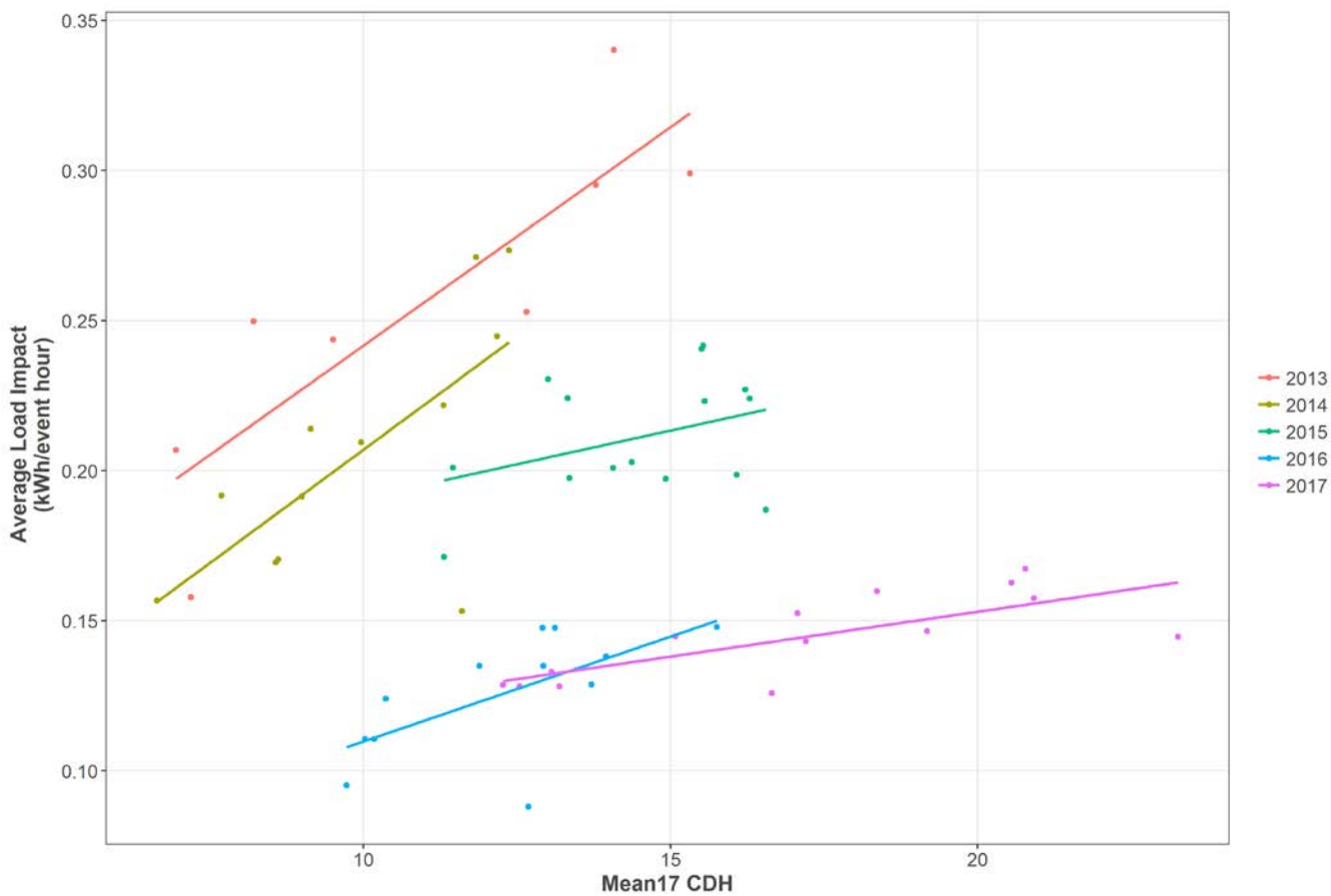
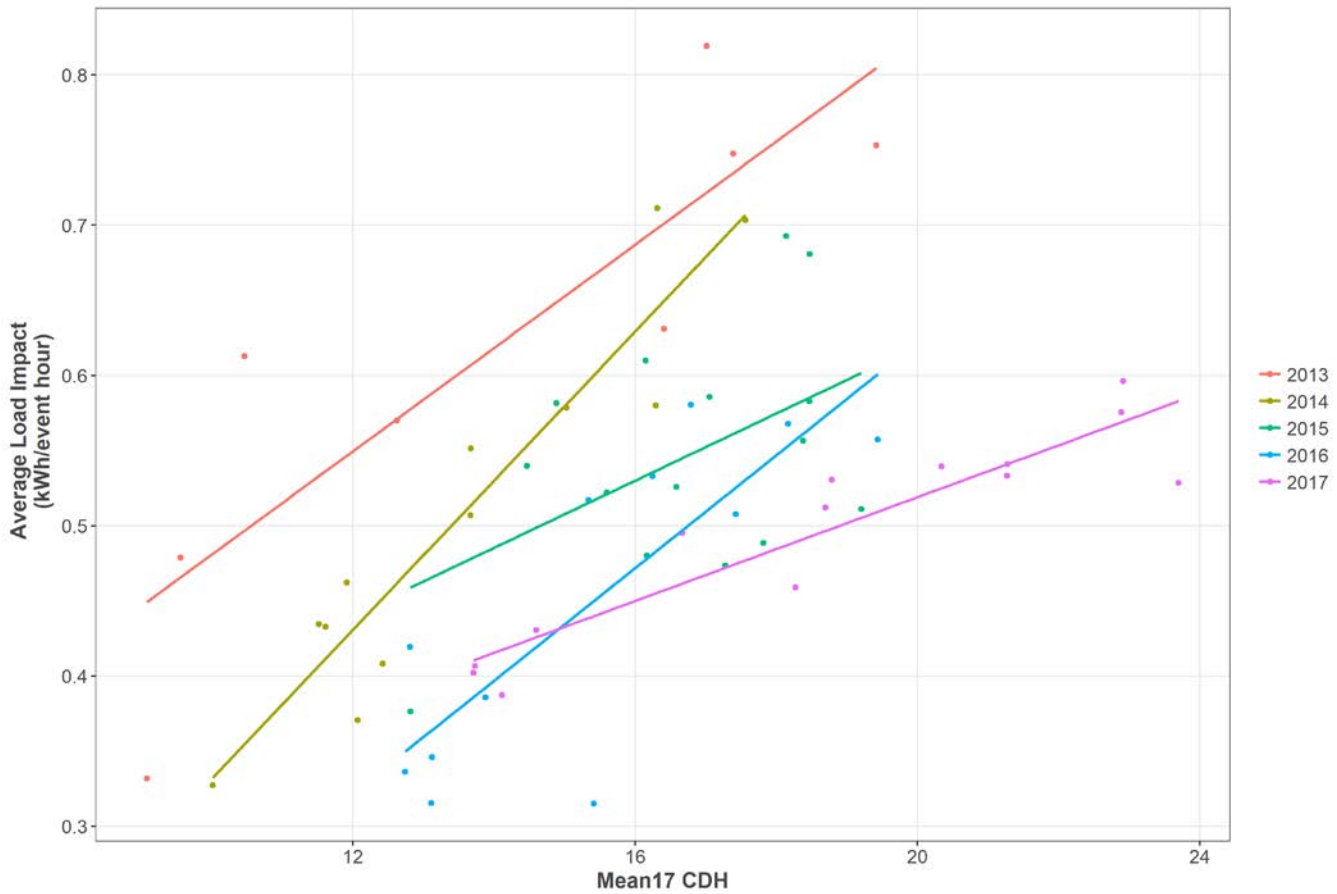


Figure 9. Relationship between Ex Post Load Impacts and Weather, Dually-Enrolled Only



We selected our final model by assessing how well our model predicted historical load for event days. Figure 10 and Figure 11 show that the ex-ante model does well at estimating impacts for all event days except the event on 9/2/2017. This event day was unusually hot, with average temperature of 105 degrees Fahrenheit across all LCAs, much hotter than the CAISO and PG&E 1-in-10 weather day, so we expect the model to perform well for all ex ante day types.[9]

[9] Figure 8 and Figure 9 demonstrate that participant load impacts have declined for the same weather year over year. Further, we found that ex ante model impact estimates for past events are low in earlier years (e.g., 2013-2014), but high in later years (e.g., 2016-2017) when the full set of events (2013-2017) is included in the ex-ante model. As a result, we excluded 2010-2015 from our ex ante model.

Figure 10. Ex-Ante Predictions of 2016 and 2017 Events Compared to Ex-Post Results for Each Event – Greater Bay Area Dual Enrollees

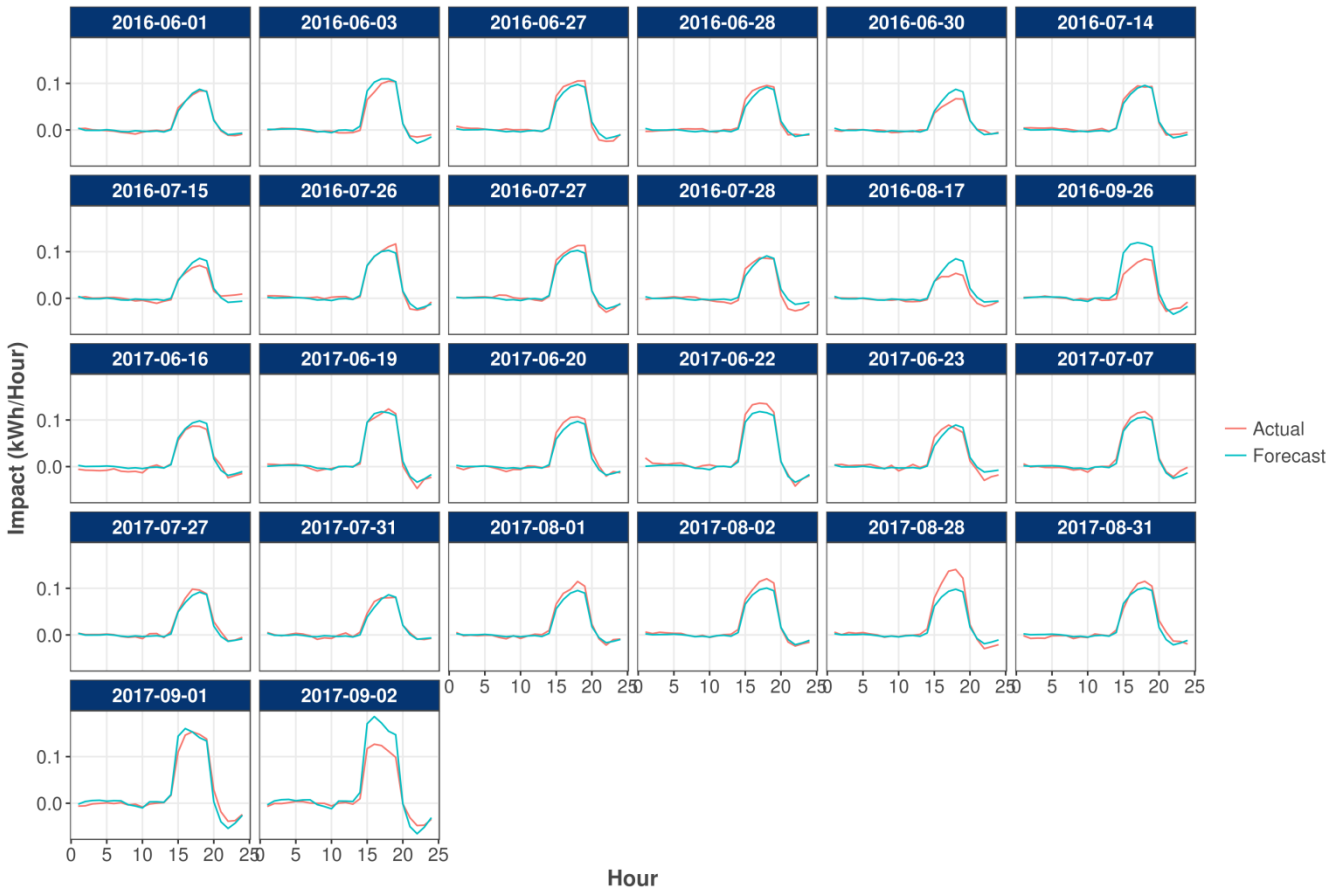
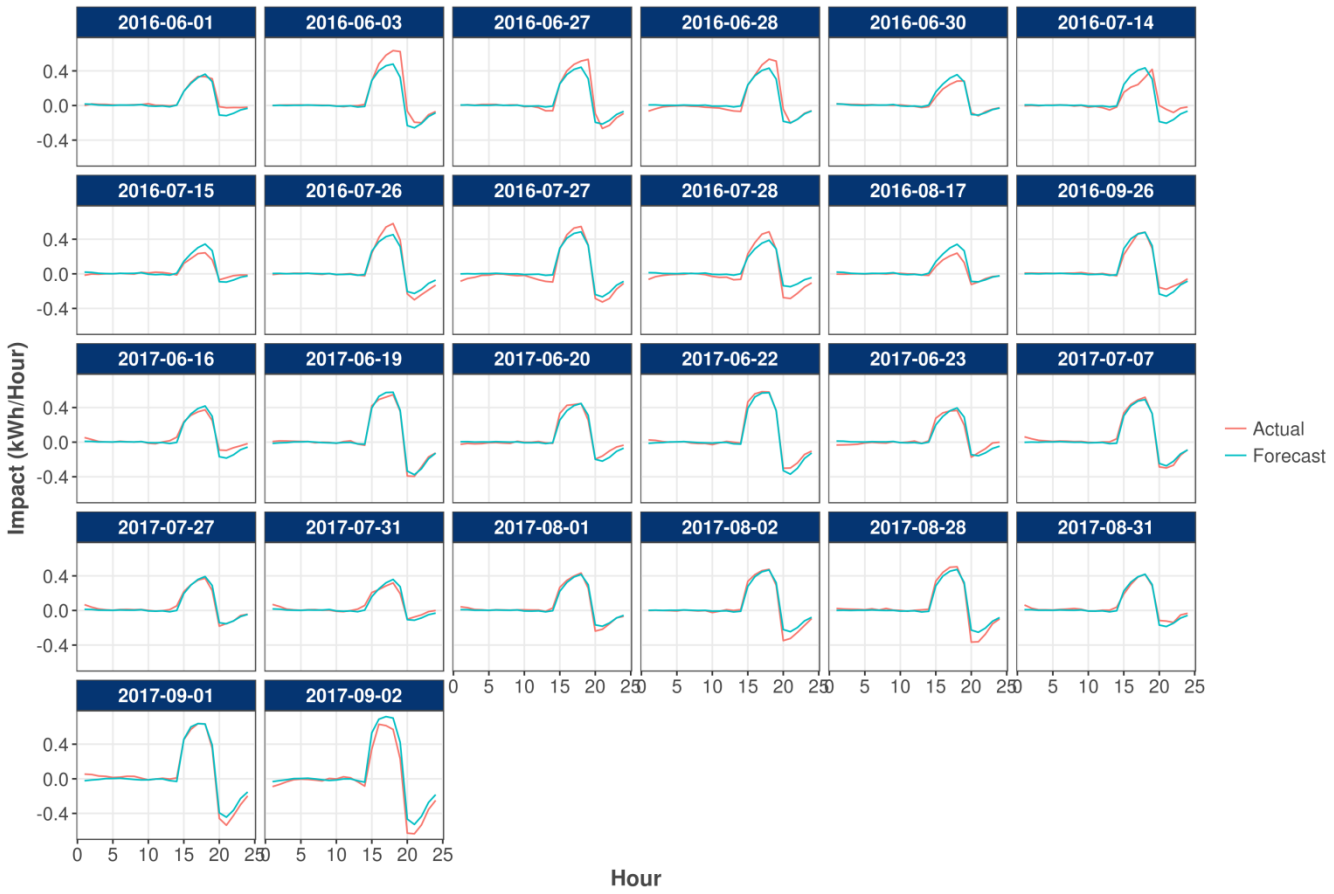


Figure 11. Ex-Ante Predictions of 2016 and 2017 Events Compared to Ex-Post Results for Each Event – Greater Bay Area SmartRate™ Only Enrollees



Notably, ex post estimates reflect event hours (2pm to 7pm), but our ex ante load summer season (April – October) impacts reflect resource adequacy hours (1pm to 6pm) and winter (November – March) resource adequacy hours (4pm to 9pm). To create these ex ante results, we calculated event impacts for the current SmartRate™ window but then report by summarizing ex ante results for the resource adequacy hours. This means the resource adequacy values are lower since the impact from 1pm to 2pm will be effectively 0. All months use the same set of ex ante impact models, since winter weather rarely has non-zero cooling degree hours, the winter ex ante impact estimates are much lower than summer.

To remove impacts where SmartAC™ and SmartRate™ events are called on the same date, we calculate portfolio adjusted impacts (e.g., incremental SmartRate™ impacts above SmartAC™ impacts). We examined the ratio of event period impacts for the event days where SmartAC™ events were called, but SmartRate™ events were not called in 2017 to event impacts on similar SmartRate™ event days. We calculated a multiplier of 19.5% by estimating the difference in event impacts by SmartAC™ only versus SmartRate™ only for the same set of participants (e.g., dually-enrolled participants).

What are the ex-ante baseline projections under different weather conditions?

We estimate May through September hourly ex-ante baselines for the same set of conditions as ex ante impacts using a linear model informed by ex-post baseline estimates from this evaluation. We estimate models separately by participant type for each hour of the day.

Equation 5. Ex-Ante Demand Response Baseline Regression Model

$$Baseline = \beta_0 + \beta_1 mean17_{CDH65} + \sum_{All\ LCAs} \beta_i\, LCA_i + \varepsilon$$

Where:

$Baseline$ = Baseline in a particular hour for a non-event day

β_0 = Overall mean baseline for the hour

β_1 = Average change in baseline for one CDH65 across LCAs

β_i = Average difference from overall mean baseline for LCA_i

ε = Observation-specific error

$mean17_CDH65_d$= Indicator variable for mean cooling degree hours from midnight to 5PM at base 65 Fahrenheit

LCA_i= Indicator variable for each LCA

For non-peak season baseline usage in October through April, we used individual average load projections provided by PG&E for the set of conditions on monthly peak days (CAISO and PG&E, 1-in-2 and 1-in-10 weather years).

What are the ex-ante forecasts of load impacts by specific customer segments?

For this task, we examine ex-ante load reduction differences between LCA, CARE, FERA and customer enrollment type segments during SmartDays™ events**,** producing estimates for all four sets of weather conditions. Estimating ex-ante savings by each LCA allow the models to reflect the variations in behavior, equipment, and household differences that exist.

As part of this effort, we reviewed participation enrollment information supplied by PG&E and applied customer segment specific ex-ante results to projected enrollment forecasts. We used this as an opportunity to identify whether the declining load impacts reflect changes in customers enrollment, or changes in participant responsiveness to events to produce persistence across years.

What effect will any changes in customer enrollment forecasts have on predicted load reductions?

We use the results of our multi-level model from the ex-post analysis to assess variation in load impacts across participants based on key customer enrollment changes. More specifically, we examined the effect of:

- Removing individuals who are part of a community choice aggregator (CCA), as they will no longer be eligible for SmartRate™;
- Customer acquisition type by assessing the changes in load impacts for continuing versus newly enrolled participants to assess how their load impacts change as they participate year over year; and
- Bill payment protection status.

4. Evaluation Results

Below we present evaluation results, including ex-post load impacts, ex-ante load impacts, and contextualizing analyses that provide insights regarding load impact results.

4.1 Ex-Post Load Impacts

In this section, we provide ex-post load impacts for each SmartDays™ event and for the average event day of the 2017 summer season. Additional results from our analysis are available in electronic format in the *Ex-Post Table Generator* provided in Appendix A of this report.

4.1.1 Load Impacts by Event and the Average Event

Opinion Dynamics estimated ex-post impact estimates for each 2017 event day and for the average event day. We provide these results below for participants enrolled in SmartRate™-only, as well as those who are dually-enrolled in SmartRate™ and SmartAC™.

SmartRate™-Only Load Impacts

Table 7 presents the load impacts for SmartRate™-only participants. The number of participants enrolled on the average event day just exceeded 95,000 customers. These participants achieved 13.8 MW in aggregate load reduction and 0.14 kW load reduction per participant, representing an 8.8% reduction from the reference load. The event with the largest aggregate load impact occurred on June 22nd, where SmartRate™-only participants decreased energy usage by 16.4 MW in aggregate and 0.17 kW per participant. June 22nd was not the hottest event in the summer of 2017, but was among the hotter days with an average event temperature of 99 degrees Fahrenheit. The event with the smallest impact occurred on July 31st, where participants achieved a reduction of 11.9 MW in aggregate and 0.13 kW per participant.

Customer enrollment declined as the summer season progressed, starting with 98,143 enrollees during the first event on June 16th, falling to 92,500 enrollees on August 1st, and ending the season with 93,385 enrollees on September 2nd.

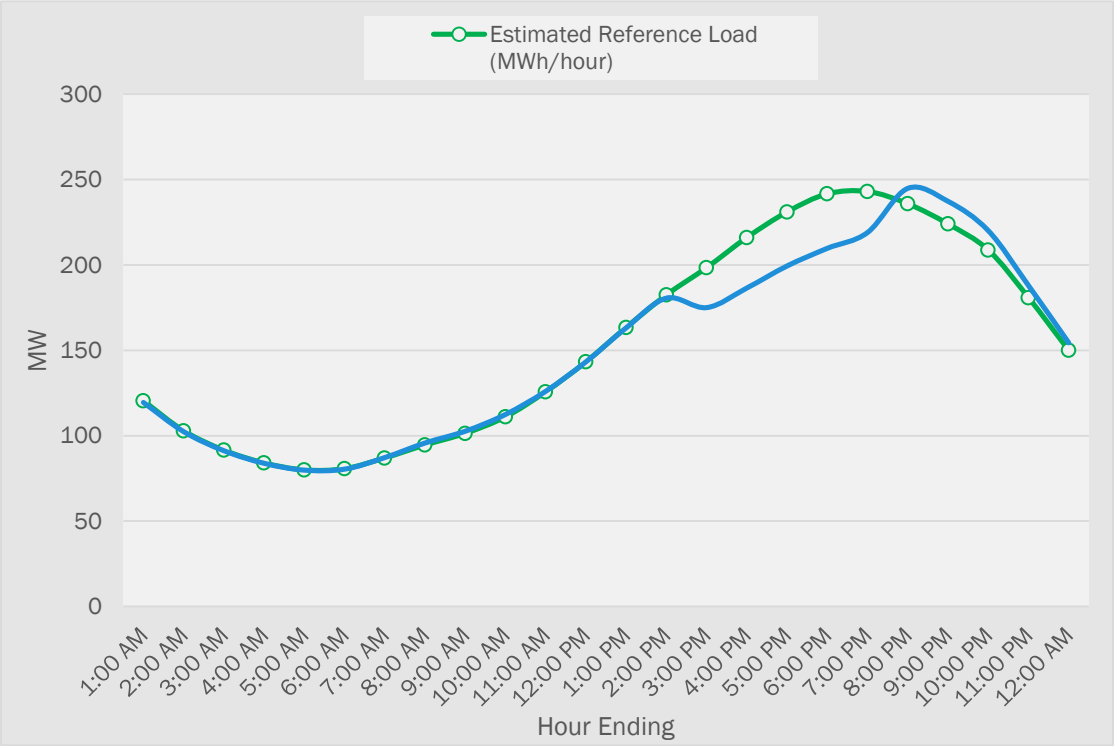
Table 7. Average 2017 Event-Hour Load Impacts by Event – SmartRate™-Only

Events	Number Enrolled	Aggregate		Per Participant		% Load Impact	Average Event Temp.
		Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
16-Jun-17	98,143	127.5	12.6	1.3	0.13	9.9%	91
19-Jun-17	98,098	177.5	15.5	1.8	0.16	8.7%	99
20-Jun-17	98,063	168.1	14.4	1.7	0.15	8.6%	97
22-Jun-17	98,021	176.1	16.4	1.8	0.17	9.3%	99
23-Jun-17	98,020	154.7	12.4	1.6	0.13	8.0%	94
7-Jul-17	96,861	157.6	14.8	1.6	0.15	9.4%	98
27-Jul-17	93,282	137.7	12.0	1.5	0.13	8.7%	94
31-Jul-17	92,790	137.4	11.9	1.5	0.13	8.7%	93
1-Aug-17	92,500	149.0	13.4	1.6	0.14	9.0%	96
2-Aug-17	92,527	154.1	13.3	1.7	0.14	8.6%	94
28-Aug-17	93,387	167.9	14.9	1.8	0.16	8.9%	99
31-Aug-17	93,381	135.3	12.4	1.4	0.13	9.2%	97
1-Sep-17	93,306	164.9	15.2	1.8	0.16	9.2%	103
2-Sep-17*	93,385	182.8	13.5	2.0	0.14	7.4%	105
Average Event Day	**95,126**	**156.5**	**13.8**	**1.6**	**0.14**	**8.8%**	**97**

Note: Average event temperatures were mean weighted based on who was enrolled during the event at each weather station.
*Denotes a weekend event.

Below in Figure 12, we present our estimated aggregate reference and event day loads for the average event day for SmartRate™-only participants. The horizontal axis shows each hour in the day and the vertical axis reflects electric load in MW. The figure clearly shows energy usage reduction occurs when the event starts at 2pm and continues through 7pm.

Figure 12. Hourly Loads and Impacts for Average Event - SmartRate™-Only



Dually-Enrolled Load Impacts

In Table 8, we provide the estimated reference loads and load impacts in aggregate and per participant for dually-enrolled participants for the 2017 event season. The aggregate load impacts for the average event day equaled 14.3 MW and 0.50 kW per participants achieved by just over 28,900 customers. This represents a 20.6% load reduction, which is more than double what was achieved by SmartRate™-only participants. The contribution per dually-enrolled participants is systematically higher for all events than they are for participants only enrolled in SmartRate™ given that air conditioning load are externally controlled through the SmartAC™ Program in addition to the behavioral changes made by Program participants.

The event with the largest aggregate load impact occurred early in the season (June 19th) where dually-enrolled participants decreased energy usage by 17.9 MW in aggregate and 0.60 kW per participant. There were just over 30,000 participants dually-enrolled for this event. The event with the smallest impact occurred on August 31st, where participants achieved a reduction in energy usage of 10.9 MW in aggregate and 0.39 kW per participants.

Compared to 2016, aggregate impacts were smaller (15.8 MW in 2016 compared to 14.3 MW in 2017) for the average event day, though the per participants impact was higher (0.45 kW in 2016 compared to 0.50 in 2017). The number of participants enrolled in 2016 was over 35,000, which explains why the aggregate impact is higher than what was achieved this season, in addition to the record weather experienced by participants in 2017.

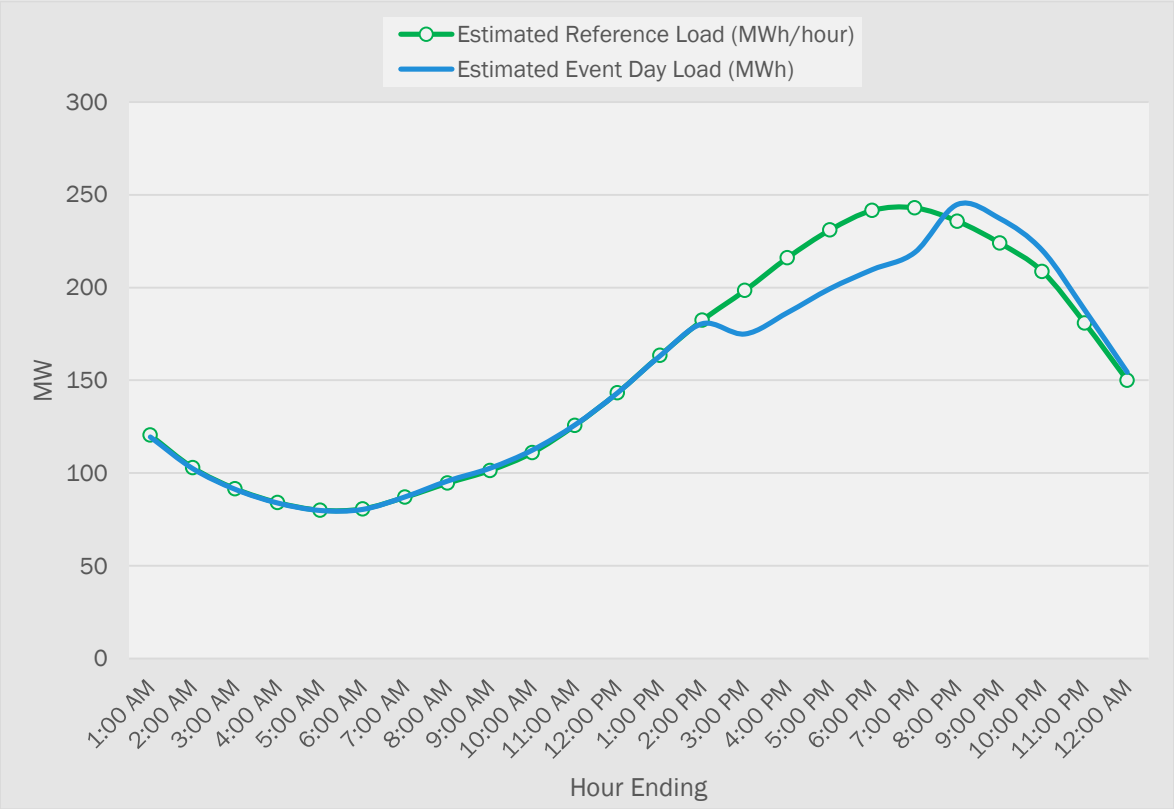
Table 8. Average Event-Hour Load Impacts by Event – Dually-Enrolled

Events	Number Enrolled	Aggregate		Per Participant		% Load Impact	Average Event Temp.
		Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
16-Jun-17	30,115	54.4	12.1	1.8	0.40	22.3%	93
19-Jun-17	30,043	81.7	17.9	2.7	0.60	21.9%	102
20-Jun-17	29,974	76.9	16.2	2.6	0.54	21.1%	100
22-Jun-17	29,906	81.0	17.2	2.7	0.58	21.3%	102
23-Jun-17	29,866	69.6	13.7	2.3	0.46	19.7%	96
7-Jul-17	29,544	71.5	15.7	2.4	0.53	21.9%	101
27-Jul-17	28,508	59.8	12.3	2.1	0.43	20.5%	97
31-Jul-17	28,367	59.1	11.5	2.1	0.41	19.5%	95
1-Aug-17	28,300	66.6	14.0	2.4	0.50	21.0%	99
2-Aug-17	28,276	69.9	14.5	2.5	0.51	20.7%	97
28-Aug-17	28,063	74.2	15.1	2.6	0.54	20.4%	103
31-Aug-17	28,012	56.6	10.9	2.0	0.39	19.2%	99
1-Sep-17	27,974	72.0	14.9	2.6	0.53	20.7%	105
2-Sep-17	27,971	80.0	14.8	2.9	0.53	18.5%	106
Average Event Day	**28,923**	**69.5**	**14.3**	**2.4**	**0.50**	**20.6%**	**100**

Note: Average event temperatures were mean weighted based on who was enrolled during the event at each weather station.

In Figure 13, we present the hourly loads and load impacts for dually-enrolled participants in 2017. In comparison to Figure 12, the impacts on the average event day is clearly larger. In addition, we see snapback after the conclusion of the event, as would be expected given that all participants who are dually-enrolled have central air conditioners that likely return to their regular usage patterns after the end of the event.

Figure 13. Hourly Load and Load Impacts for Average Event – Dually-Enrolled



4.1.2 Load Impacts by Segment

Some of the most informative results that help to maximize program cost-effectiveness through targeted program marketing comes from knowing which segments of the population are most responsive to SmartRate™ price signals, as well as when and for whom to call events. Assessing differences in ex-post load impacts for these groups helps inform which of these attributes are key drivers of load impacts. Below we present load impacts by LCA and CARE status.

Load Impacts by Local Capacity Area

The following tables include enrollment, reference load and load impact in aggregate and per participant for the typical event day by LCA. Table 9 shows the impacts by LCA for SmartRate™-only participants and Table 10 displays these results for dually-enrolled participants. Based on this analysis, we confirm that LCAs with higher temperatures yielded the largest load impacts, as has been the case historically.

LCAs with the most customers are not necessarily the largest contributors to impacts. Greater Bay Area has the most SmartRate™-only enrolled participants (about half of the SmartRate™-only enrolled population), however the per participant load impact is the lowest (0.10 kW) which likely stems from the relatively low reference load that we find mostly due to lower average temperatures in this area.

The LCAs that show higher per participant impacts are those that are in warmer climate zones, such as Sierra, Kern, Greater Fresno, and Stockton. These are the LCAs that have historically shown the largest per participant contributions to load impacts in past studies as well.

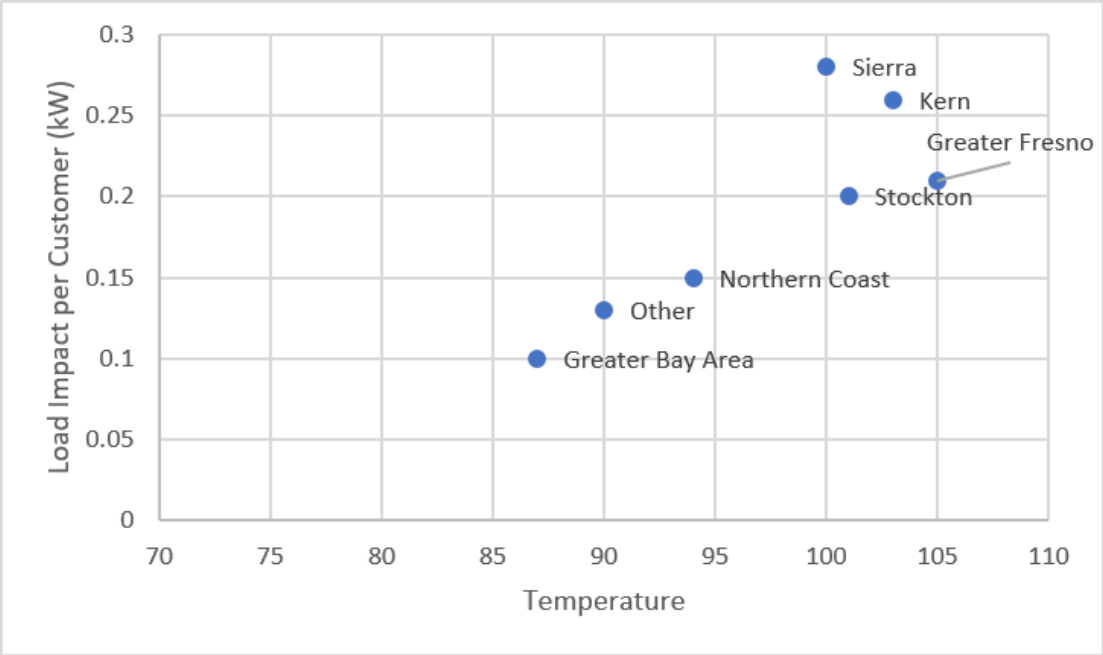
Table 9. Average Event-Hour Load Impacts by LCA – SmartRate™-Only

LCA	Number Enrolled	Aggregate		Per Customer		% Load Impact	Average Event Temp.
		Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
Greater Bay Area	46,992	48.0	4.7	1.0	0.10	9.9%	87
Greater Fresno	9,478	26.9	2.0	2.8	0.21	7.3%	105
Humboldt							
Kern	3,328	9.5	0.9	2.9	0.26	9.0%	103
Northern Coast	1,920	2.6	0.3	1.3	0.15	11.3%	94
Other	20,701	37.4	2.7	1.8	0.13	7.3%	90
Sierra	8,225	20.7	2.3	2.5	0.28	11.0%	100
Stockton	4,482	11.4	0.9	2.5	0.20	8.0%	101
All	**95,170**	**156.5**	**13.8**	**1.6**	**0.14**	**8.8%**	**97**

Note: Average event temperatures were mean weighted based on who was enrolled during the event at each weather station.

Figure 14 provides a visual depiction of average load impacts per participant by temperature across LCAs. As can be seen, those LCAs with higher temperature yielded the largest load impacts. This finding is consistent with prior evaluations since 2014.

Figure 14. Average SmartRate™-Only Load Impacts by LCA by Temperature



For dually-enrolled participants, we see similar trends in per participant impacts, though impacts are generally higher than they are for SmartRate™-only customers. Sierra, followed by Stockton, Kern, and Greater Fresno show the largest per participant load impacts. Unsurprisingly, participants located in hotter regions of PG&E's territory contribute the largest impacts.

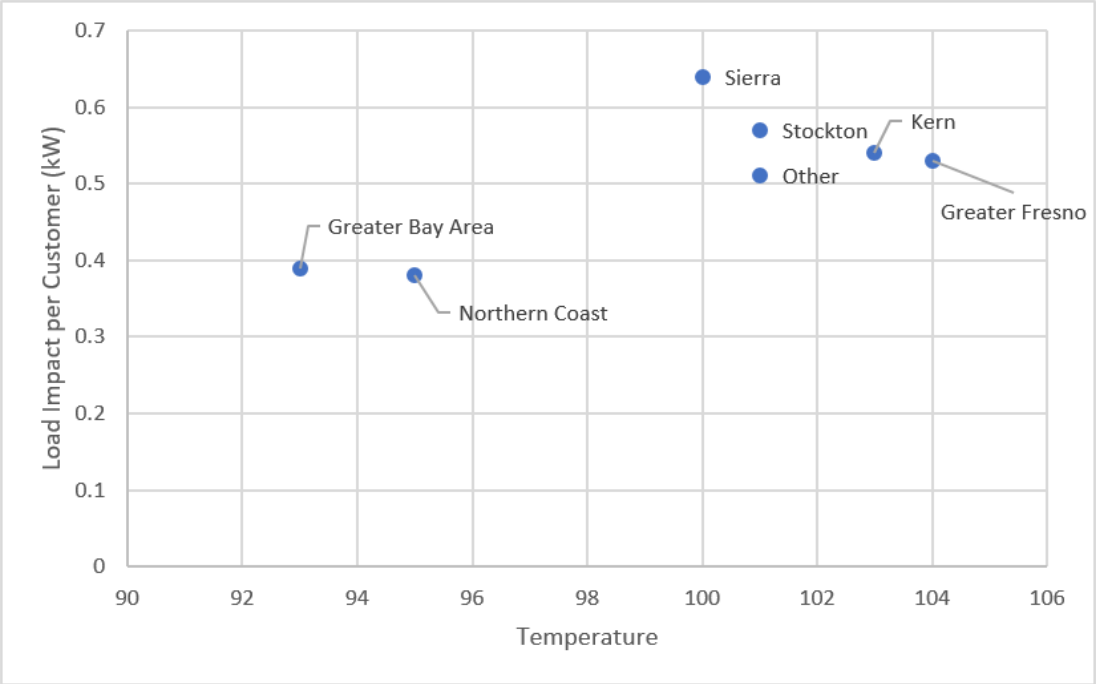
Table 10. Average Event-Hour Load Impacts by LCA – Dually-Enrolled

LCA	Number Enrolled	Aggregate		Per Customer		% Load Impact	Average Event Temp.
		Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
Greater Bay Area	10,317	19.1	4.0	1.9	0.39	20.9%	93
Greater Fresno	4,338	13.0	2.3	3.0	0.53	17.8%	104
Humboldt	0	NA	NA	NA	NA	NA	NA
Kern	961	2.9	0.5	3.0	0.54	17.9%	103
Northern Coast	400	0.7	0.2	1.9	0.38	20.2%	95
Other	5,776	14.6	2.9	2.5	0.51	20.0%	101
Sierra	4,921	13.0	3.2	2.6	0.64	24.3%	100
Stockton	2,211	6.1	1.3	2.7	0.57	20.8%	101
All	**28,923**	**69.5**	**14.3**	**2.4**	**0.50**	**20.6%**	**100**

Note: Average event temperatures were mean weighted based on who was enrolled during the event at each weather station.

Figure 15 presents a visual depiction of average load impacts by temperature across LCAs. Consistent with SmartRate™-only enrolled participants, those LCAs with the highest temperatures tended to have the largest load impacts. However, this figure also suggests that Sierra, and Stockton, despite having lower on average temperatures than Kern and Greater Fresno, resulted in larger load impact results.

Figure 15. Average Dually-Enrolled Load Impacts by LCA by Temperature



Load Impacts by CARE and FERA Status

Overall, 28% of all Program participants are on the CARE rate. While enrollment is down slightly from 2016 (30% of Program participants in 2016), the percentage of CARE and non-CARE Program participants residing in each LCA is roughly similar in comparison to the prior year. Just like in 2016, Greater Bay Area and Other LCAs had the largest proportions of SmartRate™-only CARE customers. For dually-enrolled participants, Greater Fresno has the most participants in 2017. This differs from 2016 where the most participants were in the Other LCA.

Table 11. SmartRate™-Only and Dually-Enrolled Participants in 2017, by LCA and CARE Status

LCA	SmartRate™- Only Participants on CARE	Dually-Enrolled Participants on CARE	Total CARE Participants	Percent of All Participants
Greater Bay Area	8,829	1,306	10,134	8%
Greater Fresno	5,077	2,055	7,132	6%
Humboldt	7	NA	7	0%
Kern	1,766	477	2,243	2%
Northern Coast	588	94	682	1%
Other	7,039	1,961	9,000	7%
Sierra	2,235	975	3,210	3%
Stockton	2,051	852	2,903	2%
All	**27,590**	**7,720**	**35,310**	**28%**

Table 12 presents the number and the proportion of participants on the FERA rate who are enrolled in SmartRate™-only as well as those who are dually-enrolled. FERA status customers represent a little under 1% of all program participants (1,122 customers). Like CARE, the proportion of FERA customers is highest for Greater Bay Area and Other LCAs.

Table 12. SmartRate™-only and Dually-Enrolled Participants in 2017, by LCA and FERA status

LCA	SmartRate™-Only Participants on FERA	Dually-Enrolled Participants on FERA	Total FERA Participants	Percent of All Participants
Greater Bay Area	351	65	416	0.34%
Greater Fresno	110	43	153	0.12%
Humboldt	0	0	0	0.00%
Kern	28	14	42	0.03%
Northern Coast	14	2	16	0.01%
Other	215	62	277	0.22%
Sierra	76	31	107	0.09%
Stockton	68	42	110	0.09%
All	**862**	**260**	**1,122**	**0.90%**

In Table 13, we summarize the participants' enrollment, reference loads and load impacts of customers by CARE and non-CARE status for SmartRate™-only and dually-enrolled participants combined. Load impacts contributed by participants on the CARE rate equal 5.5 MW, with a per participant contribution of 0.16 kW.

Table 13. Average Event-Hour Load Impacts by CARE Status

CARE Status	Number Enrolled	Aggregate		Per Participant		% Load Impact	Average Event Temp.
		Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
Non-CARE	88,783	155.2	22.9	1.7	0.26	14.7%	94
CARE	35,310	71.1	5.5	2.0	0.16	7.7%	96

Table 14 summarizes customer enrollment, reference loads and load impacts by FERA status. Their contribution to the aggregate load impacts is 0.3 MW. The per participant load impact for participants on the FERA rate is 0.28 kW.

Table 14. Average Event-Hour Load Impacts by FERA Status

CARE Status	Number Enrolled	Aggregate		Per Participant		% Load Impact	Average Event Temp.
		Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
Non-FERA	122,970	224	28.1	1.82	0.23	13%	94
FERA	1,122	2.8	0.3	2.46	0.28	12%	98

4.2 Ex-Ante Load Impacts

In the following section, we provide enrollment forecasts and load impacts by month for key weather scenarios. Ex-ante load impact forecasts are the impacts we expect to occur when SmartDays™ are called in future years, under standardized weather conditions. We base our ex-ante impacts for future years on PG&E's forecasts of program enrollment, development of weather-sensitive reference loads, and projections of per- participant load impacts that are estimated based on ex-post load impacts in 2017 and from previous studies.

4.2.1 Enrollment Forecasts

PG&E provided monthly enrollment projections through 2028 that we use in the development of ex-ante load impact projections. Table 15 provides the August enrollment forecasts for 2018 and the average enrollment for the years 2019-2028. Notably, 2017 enrollment is a little under 125,000 participants, projected enrollment steadily declines in 2018 (90,000 participants) and beyond (60,000 participants). This sizable decline in enrollment is exclusively from the Greater Bay Area LCA. The lower projected enrollment from the Greater Bay Area stems from the expectation that some customers will join a Community Choice Aggregator, making them ineligible for SmartRate™. Given that the Greater Bay Area historically has had the largest number of SmartRate™-enrolled participants, we expect forecasts of impacts for the Program to decline.

Table 15. SmartRate™ Enrollments (based on month of August)

LCA	SmartRate™-Only		Dually-Enrolled		Total	
	2018	2019-2028	2018	2019-2028	2018	2019-2028
Greater Bay Area	29,058	3,565	5,280	710	34,338	4,275
Greater Fresno	9,790	9,790	4,066	4,066	13,856	13,856
Humboldt	33	33	0	0	33	33
Kern	3,320	3,320	884	884	4,204	4,204
Northern Coast	1,934	1,934	366	366	2,300	2,300
Other	15,876	15,841	5,222	5,222	21,098	21,064
Sierra	4,968	4,968	2,378	2,378	7,346	7,346
Stockton	4,593	4,593	2,060	2,060	6,653	6,653
Total	**69,572**	**44,044**	**20,257**	**15,686**	**89,829**	**59,731**

4.2.2 Load Impacts by Month

Our *Ex-Ante Table Generator* referenced in Appendix A includes all ex-ante load impact projections based on the four weather scenarios, but as an example, we provide the average hourly ex-ante load impacts for the PG&E 1-in-2 weather scenario in this report. In

Table 16, we present program and portfolio-adjusted impacts[10] by program enrollment type based on the resource adequacy window of 1-6pm for the months of April through October and 4-9pm for the months of November through March for monthly peak days. Portfolio-adjusted impacts (in bold italicized font) are clearly lower (approximately 55 to 60% of program impacts) due to the removal of SmartAC™ impacts from the impacts of SmartRate™ when both events are called for dually-enrolled participants.

Table 16. Ex-Ante Program and Portfolio-Adjusted Load Impacts for 2019 – PG&E 1-in-2 Weather

Day Type	Program			Portfolio		
	SmartRate™-Only	Dually-enrolled	Total	SmartRate™-Only	Dually-enrolled	Total
January Peak	3.2	2.8	6.0	3.2	2.8	6.0
February Peak	3.2	2.8	6.0	3.2	2.8	6.0
March Peak	3.2	2.8	6.0	3.2	2.8	6.0
April Peak	4.0	3.0	7.0	4.0	3.0	7.0
May Peak	5.0	4.6	9.6	5.0	***0.9***	***5.9***
June Peak	6.5	7.0	13.5	6.5	***1.4***	***7.9***
July Peak	6.5	7.0	13.5	6.5	***1.4***	***7.9***
August Peak	6.3	6.7	**13.0**	6.3	***1.3***	***7.6***
September Peak	5.9	6.0	11.9	5.9	***1.2***	***7.1***
October Peak	4.3	3.3	7.6	4.3	***0.6***	***4.9***
November Peak	3.2	2.8	6.0	3.2	2.8	6.0
December Peak	3.2	2.8	6.0	3.2	2.8	6.0

Note: Portfolio-adjusted impacts are in bold italicized font.

Figure 16 graphically depicts the aggregate SmartRate™-only load impacts for SmartDays™ event and resource adequacy event windows based on the four weather scenarios. Figure 17 depicts the same results for dually-enrolled participants. In all scenarios, the event window impacts are larger than the RA window impacts for both SmartRate™-only and dually-enrolled participants since the first hour has no impacts.

[10] When SmartAC™ and SmartRate™ events occur on the same day, the impacts on that day are attributed to SmartAC™, hence an adjustment is made to the SmartRate™ impacts and this is referred to as a portfolio-adjustment.

Figure 16. Ex-Ante Load Impact Projections by Weather Scenario for SmartDays™ Event and RA Windows for the 2019 August Peak Day – SmartRate™-Only

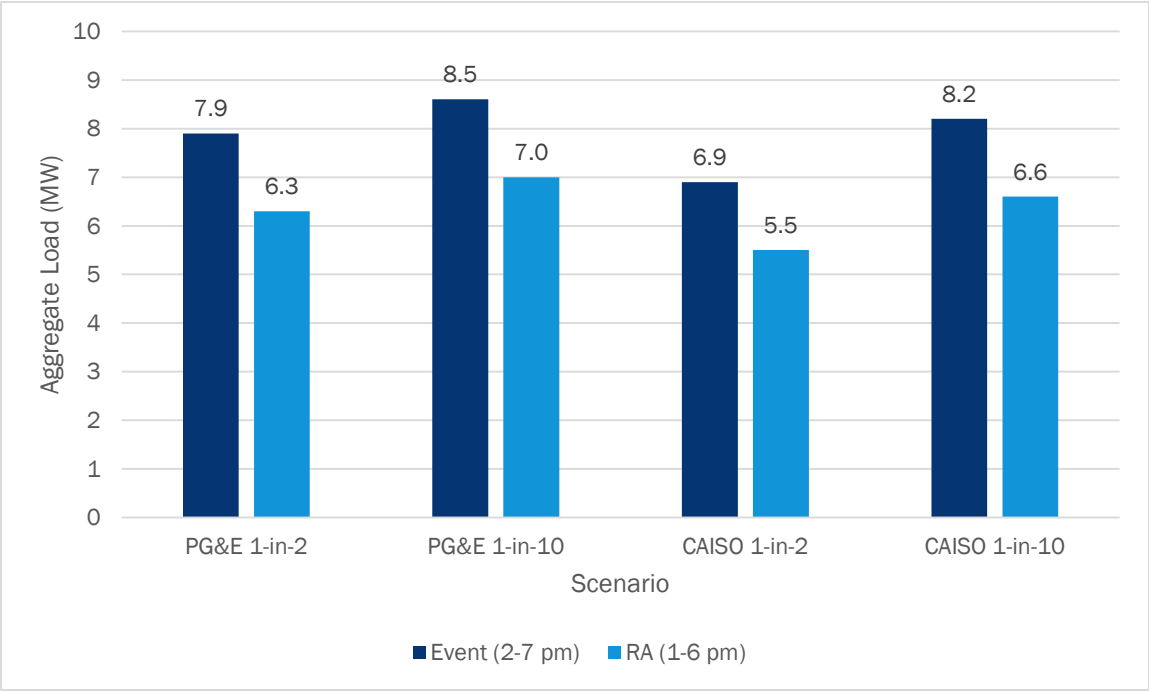
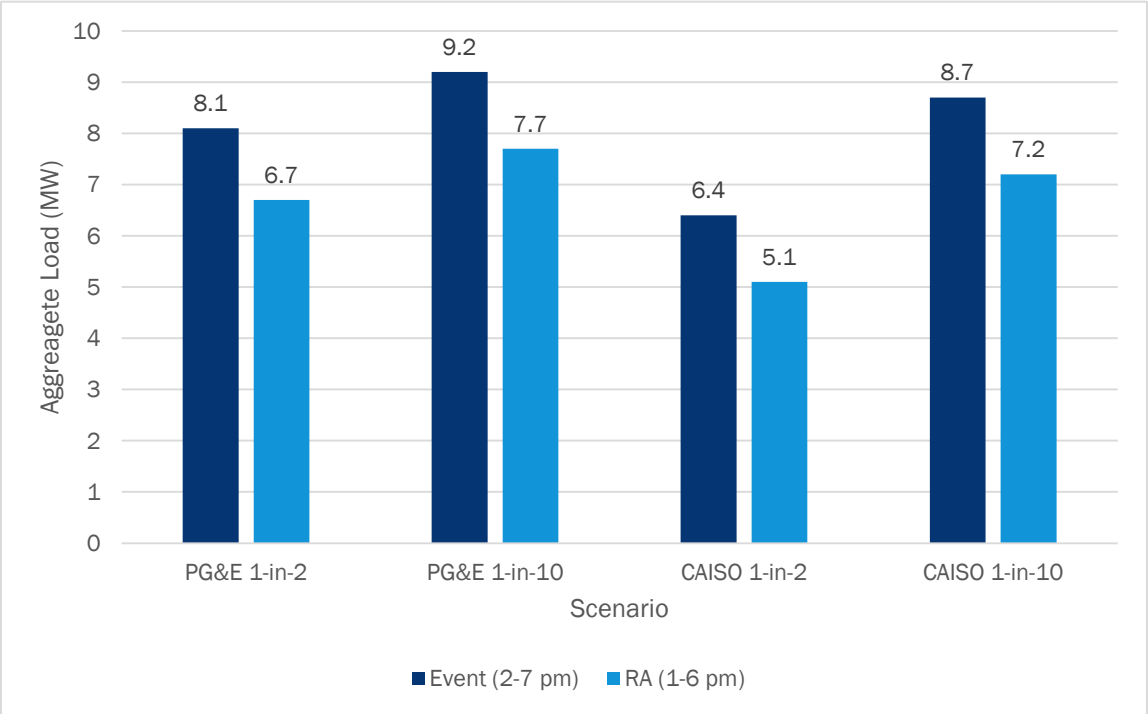


Figure 17. Ex-Ante Load Impact Projections by Weather Scenario for SmartDays™ Event and RA Windows for the 2019 August Peak Day – Dually-Enrolled



4.3 Contextualizing Current and Future Load Impacts

We incorporated a series of additional analyses within the evaluation to contextualize the declining trend in load impacts, and identify the drivers of declining load impacts and their implications on future load impacts. We produce results related to two core research questions: 1) why are load impacts declining, and 2) how will forecasted customer enrollment affect load impacts?

4.3.1 Why are load impacts declining?

Recent evaluations suggest that the program has exhibited a trend of decreasing load impacts, since reaching a peak of 0.37 kW per participant in 2013. Figure 18 shows enrollment, the number of SmartDays™ per year, and aggregate and per participant impacts for SmartRate™-only and dually-enrolled participants.

Figure 18. Annual SmartRate™ and Dually-Enrolled Participation and Aggregate and Per Participant Impacts

	ENROLLMENT			Number of SmartDay™ Events	PROGRAM IMPACTS (MEGAWATTS)			Total Per Customer Impacts (kW)
	In SmartRate™ Only	In SmartRate™ & SmartAC™	Total		SmartRate™ Only	SmartRate™ & SmartAC™	Aggregated Impacts	
2013	79,842	38,302	118,144	8	20.5	23.7	44.2	0.37
2014	89,061	40,279	129,340	12	18.3	20.4	38.7	0.30
2015	92,288	36,598	128, 886	15	19.5	20.0	39.5	0.30
2016	111,389	35,253	146,642	12	14.0	15.8	29.8	0.20
2017	95,126	28,923	124,049	14	13.8	14.3	28.1	0.23

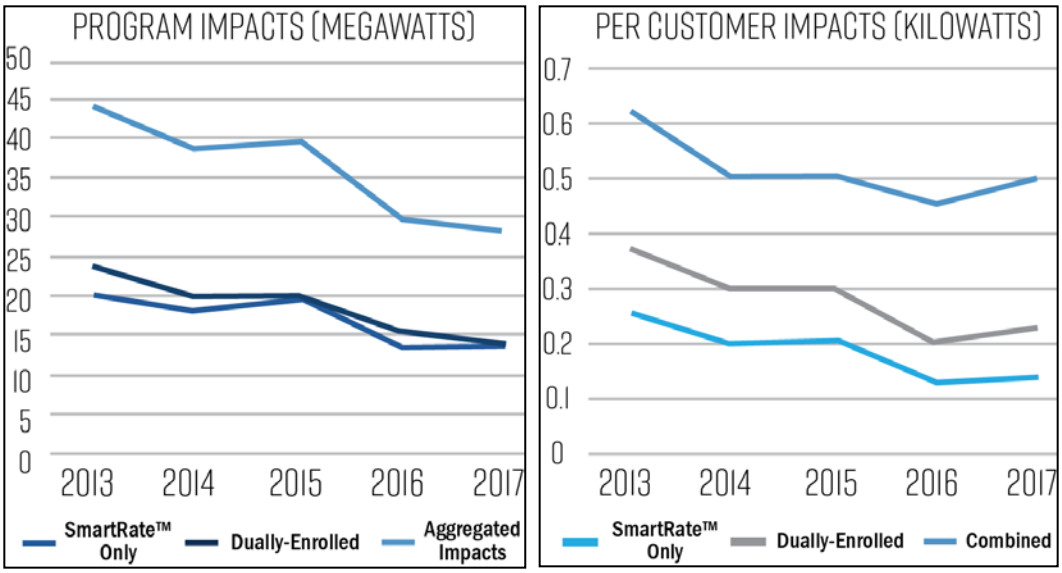
Nexant, Inc., Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-Based Pricing Programs, Final Reports; 2013 (CALMAC Study ID: PGE0352, April 1, 2014) and 2014 (CALMAC Study ID: PGE0352, April 1, 2015)

Christensen Associates Energy Consulting, Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-Based Pricing Programs, Volume 1: Ex-Post and Ex-Ante Reports, 2015 (CALMAC Study ID: PGE0371. April 1, 2016) and 2016 (CALMAC Study ID: PGE0393.01, April 1, 2017)

SmartRate, SmartAC, and SmartDay are trademarks of Pacific Gas and Electric Company

The Program hit peak enrollment in 2016 with just under 147,000 enrollees (including SmartRate™-only and dually-enrolled participants) but has declined to approximately 124,000 participants in 2017. Further, the number of dually-enrolled participants has steadily declined since 2014. Figure 19 shows the aggregate and per customer impacts achieved by customers in the Program also since 2013. Aggregate impacts have been declining over the past five years as have per customer impacts, however in 2017 the per customer impacts were higher than in 2016 (0.23 kW compared to 0.20 kW in 2016).

Figure 19. Historical Aggregate and Per Customer Impacts for SmartRate™ (2013 – 2017)



We identified the following drivers that contextualize lower per-participant load impacts in 2017:

- There are fewer dually-enrolled participants over time (Figure 19), who are known to provide greater per-participant load impacts. Additionally, there are more CARE rate participants over time, who typically offer lower per-participant load impacts (Table 17).[11]
- There are fewer 2017 participants who originally enrolled in 2013 and 2014. These customers tend to have higher per-participant load impacts than customers who enrolled after 2014 (Table 18).
- Responsiveness to temperature has changed over time. Average per-participant impacts have decreased across years despite a record weather year in 2017, and decreased enrollment across program years (Figure 8 and Figure 9). The combination of both has led to declining program impacts over time.
- Customers experience declining reference loads due to behavioral spillover for some LCAs. Though negligible on a per-participant basis, the overall decrease in impacts reflects 2 MW of load Table 20).

Effects of Participant Enrollment Mix

Participant enrollment can have substantive implications in terms of load impacts. We assessed enrollment trends by: proportion of dually-enrolled customers, duration on SmartRate™, and the proportion of

[11] There were no major differences in the proportion of customers enrolled in the SmartRate™ program by LCA from 2013-2017.

customers by LCA and CARE. We understand from prior evaluations that those customers who provide the largest load impacts are typically in warmer climate zones, dually-enrolled, and not on the CARE rate.

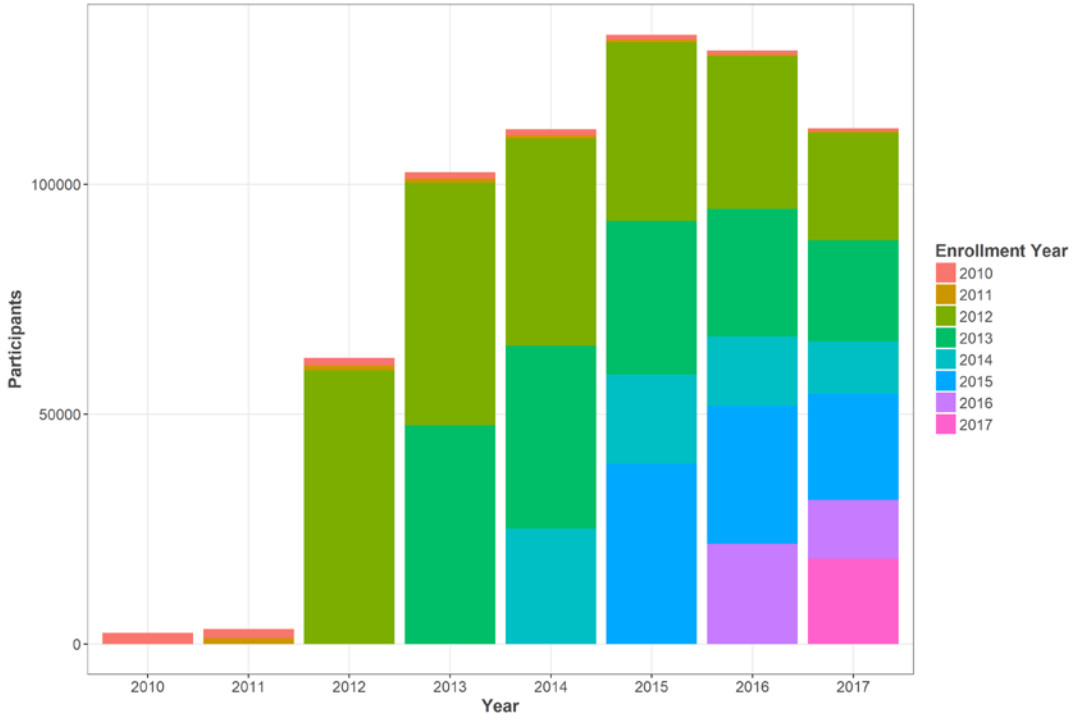
The proportion of customers dually-enrolled in the program has decreased since 2013 (32% of 118,114 participants in 2013, and 23% of 124,049 participants in 2017). Dually-enrolled participants typically achieve substantially larger load impacts than SmartRate™-only participants. Prior research suggests that customers on CARE rates tend to have lower load impacts. Over time, we see that CARE customer enrollment has increased since 2013.

Table 17. Participant Enrollment, by Customer Type and Year

Year	SmartRate™-Only Percent	Dually-Enrolled Percent	CARE Customer Percent
2013	68%	32%	22%
2014	69%	31%	22%
2015	72%	28%	27%
2016	76%	24%	30%
2017	77%	23%	28%

The mix of customers enrolled by duration in the Program reflects a range of enrollment dates, with no particular year of enrollment reflecting the bulk of current participants (Figure 20).

Figure 20. Historical Enrollment Trends



However, the year of enrollment in the program is correlated with load impacts. We found that participants who had enrolled in 2012 had the highest average load impacts compared to other participants. Further, we see a marked decline in average per participant impacts for customers who enrolled after 2014. This decline in average per participant impacts likely results from PG&E's change in marketing. Since 2015, targeted marketing for SmartRate™ has ceased. Additionally, PG&E made a concerted effort in 2013 and 2014 to recruit SmartAC™ customers to dually enroll in SmartRate™, but the effort did not continue beyond this point.

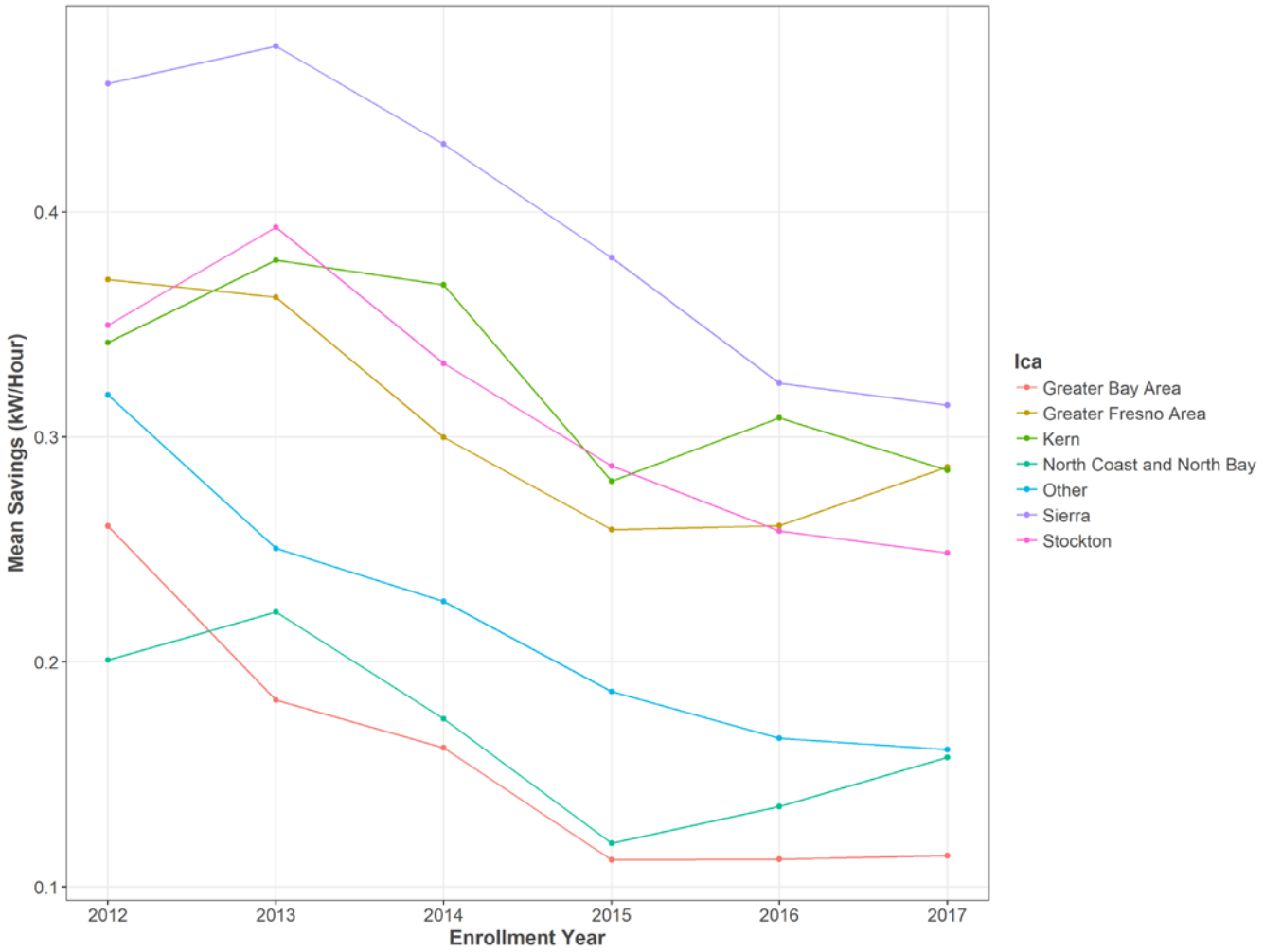
Table 18. Average Per Participant Load Impact, by Year of Enrollment

Year of Enrollment	Average Per Participant Load Impact in 2017*
2010	0.26
2011	0.29
2012	0.32
2013	0.27
2014	0.24
2015	0.18
2016	0.16
2017	0.16

*Reflects kW/hour for the typical event period.

Figure 21 presents mean impacts (kw/hour) for the 2017 summer event period. Each year reflects the date in which a customer enrolled in the program. As can be seen, participants who enrolled in later years had a lower mean load impact than those who enrolled in earlier years across all LCAs.

Figure 21. Mean Impacts by Length of Enrollment in Program



Bill impacts may play a role in declining load impacts over time. Table 19 provides the average 2017 load impact per participant by their bill protection status. The effect of bill protection status is limited for all participants. Notably, we looked at the effect of bill protection status on customers in 2017, not in prior years. Future research may produce additional insights related to bill protection status and declining load impacts.

Table 19. SmartRate™ and Dually-Enrolled Average Impacts for Participants On and Off Bill Protection Status

Program Enrollment	Bill Protected?	Count of Enrolled Participants	2017 Average Load Impact Per Participant (kWh/Hour)
SmartRate™-Only	No	77,355	0.14
	Yes	27,483	0.14
Dually-Enrolled	No	29,311	0.53

	Yes	1,003	0.60

Effects of Behavioral Spillover on Reference Loads

In contrast to traditional load control programs, rate-based DR programs provoke distinct challenges related to developing appropriate baselines for load impact estimates. This is because the program does not solely have an effect on event days, but can have 'spillover' effects on non-event days as well. The time-dependent electricity rates of the SmartRate™ program may lead customers to shift their electricity use to non-peak hours regardless of whether a SmartDays™ event is in effect. We designed our evaluation to include examination of this programmatic spillover, and whether it might contribute to declining reference loads and how these impacts affect estimation of program event-day impacts.

Our investigation focused on peak-day spillover by looking at the impact of spillover on event days in 2017. As part of our analysis, we found that participants changed their energy consumption behavior on event days and non-event days. In other words, the rate's design provides a price signal to use more energy on non-event days and only to reduce energy usage during peak hours on event days. The price signal to reduce energy during event hours was strong enough that risk-averse participants lowered their consumption during peak hours on all days (responding more as if they are on a TOU rate rather than a CPP rate). In Table 20, we present our findings from this analysis by LCA for SmartRate™-only participants. Notably, we excluded dually-enrolled customers as we surmise that many other factors may contribute to pre-enrollment reference loads (either enrolling in the SmartAC™ program or changes to HVAC equipment).

We found that the amount of spillover varies across LCAs with the largest spillover for Greater Bay Area, North Coast and Other. A negative spillover value indicates that customers had lower event hour usage prior to enrolling in the program. We see this to be the case for Greater Fresno, Sierra, and Stockton three LCAs that provide higher per-participant impacts than other LCAs. While negligible at a per-participant level, the effect of behavioral spillover equates to approximately 2 MW. Appendix D provides detailed results by LCA.

Table 20. SmartRate™-Only Participant Enrollment, Mean Behavioral Spillover, and Ex-Post Mean Impact, by LCA

LCA*	Enrollment	Per Participant Mean Spillover (kW)	Per Participant Mean Ex Post Impact (kW)	Aggregate Mean Spillover (MW)	Aggregate Ex Post Impact (MW)
Greater Bay Area	46,992	0.031	0.101	1.46	4.75
Greater Fresno	9,478	-0.011	0.208	-0.10	1.97
Kern	3,328	0.007	0.257	0.02	0.86
Northern Coast	1,920	0.055	0.152	0.11	0.29
Other	20,701	0.025	0.131	0.52	2.71
Sierra	8,225	-0.001	0.275	-0.01	2.26
Stockton	4,482	-0.004	0.203	-0.02	0.91
Total	**95,126**	**0.015**	**0.190**	**1.97**	**13.75**

*Note that we excluded Humboldt given the small number of customers. Mean spillover and impact values are calculated for SmartDay™ event hours between 2pm and 7pm.

The 2016 load impact evaluation report indicates that a growing proportion of customers continue to move to TOU rates (E-6 and historically E-7) reflecting larger policy objectives to move to coupling rates with market prices. These prior SmartRate™ program evaluations suggest that spillover estimates are statistically significant during peak hours on non-event days. These results may be due to permanent load reduction due to technology improvements, spillover effects, or increased use of pre-cooling (e.g., event load shift). This change in energy consumption affects the reference load.

4.3.2 How will forecasted customer enrollment affect load impacts?

As noted in Section 4.2.1, 2017 projected enrollment steadily declines in 2018 (90,000 participants) and beyond (60,000 participants). This sizable decline in enrollment is exclusively from the Greater Bay Area LCA. The lower projected enrollment from the Greater Bay Area stems from the expectation that some customers will join a Community Choice Aggregator, making them ineligible for SmartRate™. Given changes in enrollment over time, as well as the characteristics of customers who contribute load impacts, we conducted the following analytical exercises to assess the effect of changes in customer enrollment forecasts on predicted load reductions.

- We conducted multi-level modeling approach to look at the distribution of savings across customers to see how much of an effect this will have on future load impacts. Overall, declines in enrollment due to CCAs could reduce program load impacts by 12 MW (applying 2017 multi-level model impacts by 68,000 customers identified as potential future CCA customers). As shown in Figure 21 above, newly enrolled customers have lower load impacts than customers who enrolled in earlier years. While there is variation in terms of load impact by bill payment status for dually-enrolled participants (see Table 19), the effect of bill protection status on future load reduction requires running the multi-level model on prior years' impacts. We recommend that PG&E consider running this approach in the next evaluation cycle.

- We reviewed participation enrollment information supplied by PG&E and applied customer segment specific ex-ante results to projected enrollment forecasts to identify whether the declining load impacts reflect changes in customers enrollment, or changes in participant responsiveness to events to produce persistence across years. We found that average per-participant impact has declined over time, but there is no evidence to suggest that there will continue to be a decline. We also found that within events, participants ramp up their load reduction until the final hour of the event. In 2017 the final hour impact drop was slightly larger than previous years.

Distribution of Load Impacts by Participant

Some of the most informative results that help maximize cost-effectiveness through targeted program marketing come from knowing which segments of the population are most responsive to SmartRate™ price

signals, as well as for when and for whom to call events. To this end, we use a multi-level model to estimate individual participant's average ex post impact to support identifying key drivers for load impacts.

We divided Program participants into five savings groups based on the results of our model.[12] We developed five groups to support identifying actionable program design revisions (e.g., to target the very positive and very negative load impacts differently from positive or negative responders). Distinguishing between very positive and very negative responders from the rest of the groups allows PG&E to target participants with much larger changes in load impacts, as well as to better understand trends and specific drivers to load impacts. We ran models by participant enrollment type and LCA.

Table 21 provides the distribution of impacts across participants, which we have assigned into negative[13], below average, above average, and very above average load impact groups. We defined these groups based on the mean impacts per enrollment group and LCA (see Section 3.2.1 for more detail). We found that:

- SmartRate™-only and dually-enrolled participants vary in terms of their kW reduction after enrolling into these programs.
- Very few customers produced negative kW reduction; however, SmartRate™-only participants are more likely to have an increase in load during an event than dually-enrolled participants (15% compared to 5%, respectively).
- 12% of SmartRate™-only participants achieve nearly the same average load reduction as dually-enrolled participants (e.g., very above average customers).

Table 21. Distribution of Load Impact Groups by Participant Enrollment Type

Program Enrollment	Load Impact Group	Number of Participants	Percent of Participants	Average Per-Participant Load Impact (kW)
SmartRate™-Only	Negative	15,372	15%	-0.13
	Below Average	40,642	39%	0.08
	Above Average	36,140	34%	0.19
	Very Above Average	12,684	12%	0.55
Dually-Enrolled	Negative	1,510	5%	-0.17
	Below Average	16,231	54%	0.31
	Above Average	9,663	32%	0.73
	Very Above Average	2,910	10%	1.44

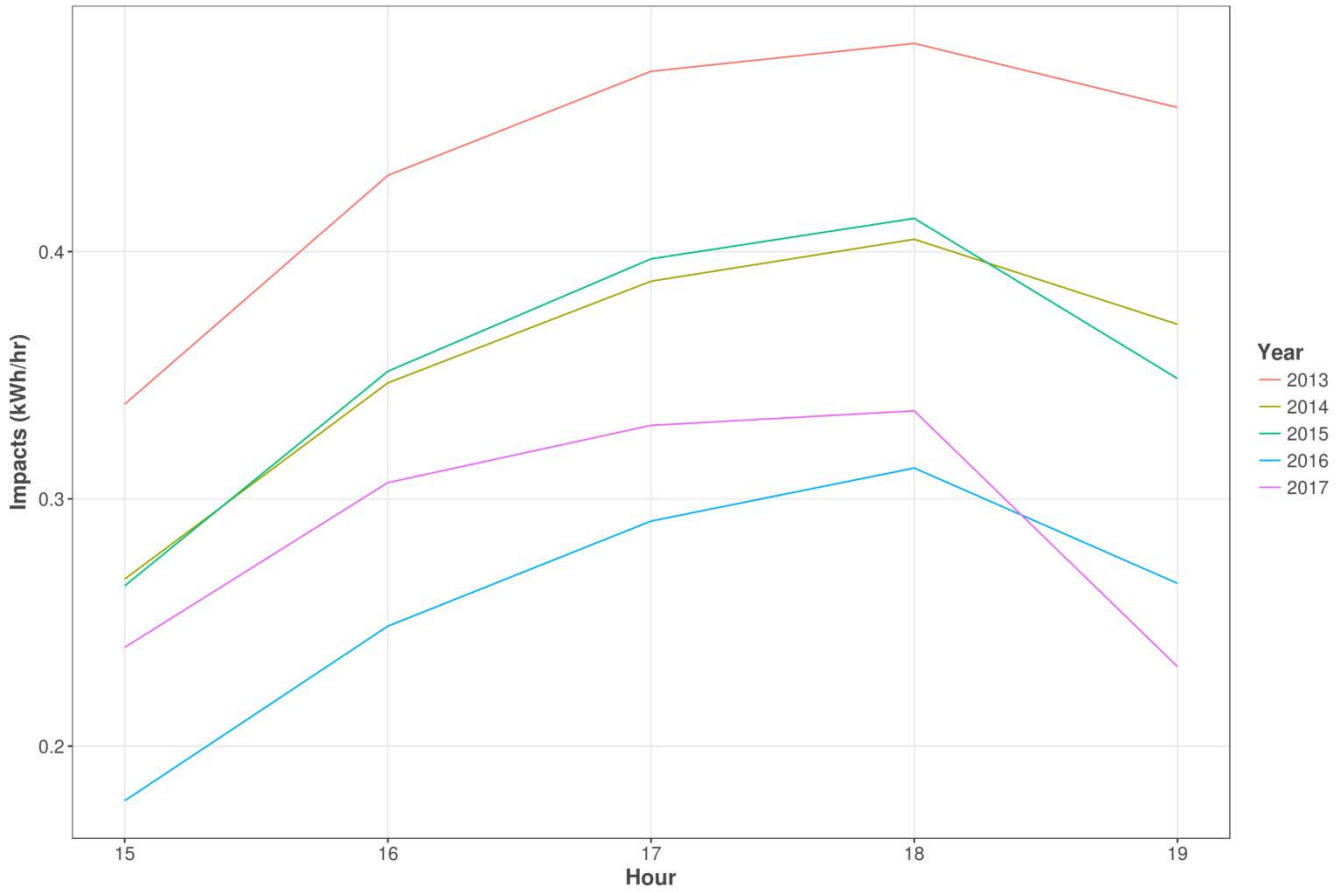
[12] We selected the cut-offs for load impact category to create groups that were actionable for program staff.
[13] A customer with a negative average kW reduction, whom are also in the negative load impact group, are those that increase their consumption after enrolling into SmartRate™-only or both programs.

Load Impact Persistence

Our analysis produces impact persistence within-event as well as across years. It is important to understand impact persistence because changes in customer behavior (such as acclimatization to the rate), equipment operating characteristics (such as reduced impacts for thermostat temperature offsets after the first hour), or removal of bill protection after the first year of being on SmartRate™ can all affect future impacts. As noted earlier, we used modeled results to produce within-event persistence results (e.g., does the second hour get the same impact as the first).

Figure 22 provides both within event and across-year persistence for participants. The figure demonstrates that within an event, customers tend to increase the load reduction until the final hour of the event. Over the years, we find that customers have become less responsive during an event at average historical temperatures, likely due to changing characteristics of customer enrollment and behavioral spillover.

Figure 22. Within-Event and Across-Year Persistence of Load Impacts



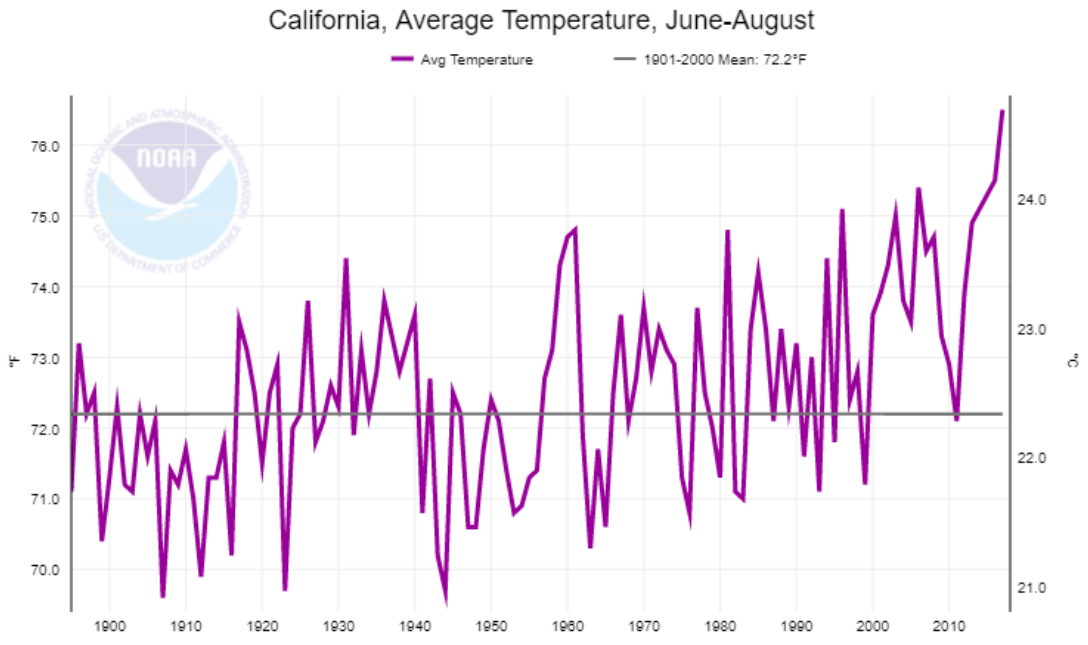
5. Review of Program Performance

In this section, we present comparisons of ex-post impacts and ex-ante projections for the Program. These comparisons help elucidate how projected future impacts align with actual impacts achieved by the Program. We make the following comparisons:

- Ex-post load impacts from this study and previous studies dating back to 2015;
- Ex-ante load forecasts from this study and previous studies;
- Ex-post load impacts from this study and ex-ante projections form previous studies; and
- Ex-post load impacts (for the typical event day) and ex-ante projections (based on 1-in-2 August peak day) from this study.

Overall, we found that Program enrollment is a primary driver in terms of the divergence across actual and predicted aggregate impacts since 2015. As mentioned throughout this report, a growing number of participants located in the Greater Bay Area are opting to join a CCA and this makes them ineligible to participate in SmartRate™. Impact forecasts unsurprisingly continue to decline as enrollment projections account for this phenomenon. Changes in weather is another factor. In 2017, the temperatures in PG&E's service territory were hotter than average, which was not anticipated in previous years when impact forecasts were developed.

Figure 23. Average California Temperature (May-September)



Source: National Oceanic and Atmospheric Administration

5.1 Prior Ex-Post and Current Ex-Post

Table 22 provides a historical comparison of ex-post impact estimates for a typical event day from 2015-2017.[14] Presenting these load estimates together helps to illuminate how the program's load impacts have changed over time and provide insight into the factors (such as weather or enrollment) that contributed to those estimates. Results suggest that there was a decrease in per-participant and aggregate load impacts when comparing 2015 to 2016 and 2017. This is underscored by the percent of load impact, which declines in each subsequent year. Per participant load impact (and reference load for SmartRate™-only participants) are higher in 2017 than in 2016 for customers, which is likely due to higher average event temperature in 2017. As noted earlier, 2017 was one of the hottest summers on record in recent history for PG&E's service territory. In terms of customer enrollment, there was a decline in dually-enrolled participants in each year, and a decline in SmartRate™-only participants since 2016.

Table 22. Comparison of Ex-Post Impact Estimates for the Typical Event Day for 2015 - 2017

Enrollment Type	Year	Enrolled	Aggregate		Per Participant		% Load Impact	Average Event Temp.
			Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
SmartRate™-only	2015	92,288	147.1	19.5	1.59	0.21	13.2%	95
	2016	111,389	155.3	14.0	1.39	0.13	9.0%	94
	2017	95,126	156.5	13.8	1.64	0.14	8.8%	97
Dually - enrolled	2015	36,598	78.7	20.0	2.15	0.55	25.5%	98
	2016	35,253	73.1	15.8	2.07	0.45	21.6%	98
	2017	28,923	69.5	14.3	2.40	0.50	20.6%	100

5.2 Prior Ex-Ante and Current Ex-Ante

We also examined the 2016 and 2017 program and portfolio-adjusted ex ante impacts for a 2018 August peak day based on the 1-in-2 PG&E weather scenario.[15] For dually-enrolled participants, we present program and portfolio adjusted impact forecasts separately because forecasted load impact reductions of participants enrolled in both SmartRate™ and SmartAC™ are attributed to the SmartAC™ program when events are called for both programs.

[14] Christensen Associates Energy Consulting, Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-Based Pricing Programs, Volume 1: Ex-Post and Ex-Ante Reports.2016 Study: CALMAC Study ID PGE0393.01, April 1, 2017 and 2015 Study: CALMAC Study ID 0371, April 1, 2016.

[15] We provide the impacts based on the RA window of 1 to 6pm, because we developed forecasts on the August peak day. Notably, if we had used SmartDay™ event hours, the impacts would be larger, particularly in the month of August.

In Table 23, we see a decrease in aggregate load impacts due to a reduction in anticipated enrollment. This difference in enrollment in the 2017 forecast reflects updated information about the number of participants located in the Greater Bay Area who are selecting to join a Community Choice Aggregator (CCA). Notably, per-participant reference loads do not change for SmartRate™-only participants, but per-participant load impacts increase in 2017, which is likely due to temperature (see Figure 8 for more information on customer responsiveness to temperature over time). Further, percent of load impacts forecasted in 2017 are smaller than forecasted in 2016.

Table 23. Comparison of Prior and Current Ex-Ante Load Impact Forecasts for August Peak Day in 2018 Using the PG&E 1-in-2 Weather Scenario for the RA Window of 1 to 6 pm

Enrollment Type	Typical Event Day in 2018	Year of Forecast	Enrolled	Aggregate		Per Participant		% Load Impact	Average Event Temp.
				Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
SmartRate™-only	Program / Portfolio	2016	78,665	123.3	9.1	1.60	0.10	7.4%	95
		2017	69,572	112.2	8.2	1.60	0.12	7.3%	92
Dually-enrolled	Program	2016	27,929	57.6	11.3	2.10	0.40	19.6%	99
		2017	20,257	45.4	8.0	2.20	0.40	17.7%	98
	Portfolio	2016	27,929	57.6	2.4	2.10	0.10	4.2%	99
		2017	20,257	45.4	1.6	2.20	0.08	3.5%	98

5.3 Prior Ex-Ante and Current Ex-Post

In Table 24, we compare the 2016 ex-ante forecast of load impacts for the typical event day in 2017 with the 2017 ex-post load impacts. For this analysis, we used the event hours of 2 to 7pm to ensure comparability across the ex-ante forecast and our ex-post load impact estimate. Overall, the ex-ante forecasts reflect 2017 ex-post load impact estimates, particularly in terms of per-participant load impacts. However, the ex-ante forecasts for 2017 do not align with the achieved impacts both as a percent of load impact, as well as in aggregate. There may be multiple factors driving this, including changes in reference load, difference in anticipated versus actual enrollment for dually-enrolled participants, and temperature for SmartRate™-only participants.

Table 24. Comparison of Prior Ex-Ante and Current Ex-Post Load Impacts for the Typical Event Day in 2017 for SmartRate™ Event Hours of 2 to 7 pm

Enrollment Type	Typical Event Day in 2017	Enrolled	Aggregate		Per Participant		% Load Impact	Average Event Temp.
			Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
SmartRate™ -only	2016 Ex Ante	92,523	141.7	12.8	1.53	0.14	9.1%	94
	2017 Ex Post	95,126	156.5	14.0	1.64	0.14	8.8%	97
Dually-enrolled	2016 Ex Ante	29,874	65.6	15.1	2.20	0.51	23.0%	99
	2017 Ex Post	28,923	69.5	14.3	2.40	0.50	20.6%	100

5.4 Current Ex-Post and Current Ex-Ante

Below in Table 25, we compare 2017 ex-post estimated load impacts for the typical event day to current ex-ante estimated projections for an August peak day in 2018 using the 1-in-2 PG&E weather scenario to compare the performance of our model specifications. We make this comparison based on estimated ex-post load impacts and ex-ante impact projections for the event hours of 2 to 7pm to ensure comparability across results.

Notably, for the 2018 ex ante forecast, the enrollment projection is substantially lower than the number of enrolled participants for the typical day in 2017 (over 25,500 fewer participants anticipated in 2018 for SmartRate™-only, and 8,000 for dually-enrolled participants). This reflects the expected decrease in enrollment due to CCAs in PG&E's service territory. With this decline in enrollment, we forecast a decline in aggregate load impacts. In addition, the reference load is forecasted to be lower, meaning that load impacts reflect a small share of load. Additionally, the forecasted average event temperature is lower in the 2018 ex-ante forecast scenario.

Table 25. Comparison of Ex-Post Load Impacts for the Typical Event Day in 2017 and Load Forecasts of Impacts for August Peak Day in 2018 Using 1-in-2 PG&E Weather Scenario for SmartRate™ for Event Hours of 2 to 7 pm

Enrollment Type	2017 Typical Event Day/2018 August Peak	Enrolled	Aggregate		Per Participant		% Load Impact	Average Event Temp.
			Reference Load (MW)	Load Impact (MW)	Reference Load (kW)	Load Impact (kW)		
SmartRate™-only	2017 Ex Post	95,126	156.5	14.0	1.64	0.14	8.9%	97.1
	2018 Ex Ante	69,572	118.7	10.2	1.70	0.15	8.6%	91.6
Dually-enrolled	2017 Ex Post	28,923	69.5	14.3	2.40	0.50	20.6%	99.7
	2018 Ex Ante	20,257	48.2	9.70	2.38	0.50	20.2%	98.3

In Table 26, we present the key components that affect the ex-post and ex-ante load impact estimates for SmartRate™-only participants. Weather and enrollment both had sizable effects on the ex-ante impact estimates compared to the ex-post results.

Table 26. Ex-Post versus Ex-Ante Factors, SmartRate™-Only Customers

Factor	Ex Post	Ex Ante	Expected impact
Weather	97.1 degrees Fahrenheit during event hours.	91.9 degrees Fahrenheit during event hours on utility-specific 1-in-2 typical event day	Milder ex-ante weather decreases the forecasted load impact by approximately 6 MW, and participant load impact is 0.02 kW lower for ex-ante relative to ex-post.
Event Window	Hour ending 15-19 for the typical event day.	Hour ending 14-18 in Apr-Oct; Hour ending 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 all enrolled customers are dispatched.
Enrollment	95,126 customers enrolled during the average event day.	Projected enrollment of 69,572 during the average event day.	The decrease in ex-ante enrollments decreases the total load impact relative to ex post.

Table 27 below shows how the SmartRate™-only impacts change as we make adjustments to the ex-post load impact estimates. The second column shows the estimated load impacts by event and for the season overall. Each column to the right of this presents how the load impacts change as we adjust one factor at a time, such as enrollment and hours for which impacts are presented. For example, column 3 shows how the ex-post load impact estimates change when we use August 2018 peak day ex-ante enrollment. Since enrollment is projected to fall, we see a decline in impacts. The next column shows how impacts adjust downward when we use the RA window to estimate impacts instead of SmartDay™ event hours. The last four

columns in the table show the ex-ante load impact estimates for a typical event day in August 2018 for the four weather scenarios.

Table 27. Progression from Ex-Post to Ex-Ante Load Impacts, SmartRate™-Only

Date	Ex Post LI, Event Hours	Ex Post LI @ Ex Ante Enrollment, Event Hours	Ex Post LI @ Ex Ante Enrollment, RA Hours	Ex Ante @ CAISO 1-in-2	Ex Ante @ CAISO 1-in-10	Ex Ante @ PG&E 1-in-2	Ex Ante @ PG&E 1-in-10
6/16/2017	12.6	9.0	7.3	7.4	8.3	8.2	9.2
6/19/2017	15.4	11.0	8.9				
6/20/2017	14.4	10.2	8.4				
6/22/2017	16.4	11.6	9.7				
6/23/2017	12.3	8.8	7.3				
7/7/2017	14.8	10.6	8.8				
7/27/2017	12.0	8.9	7.4				
7/31/2017	11.9	8.9	7.3				
8/1/2017	13.4	10.1	8.2				
8/2/2017	13.3	10.0	8.3				
8/28/2017	14.9	11.1	9.0				
8/31/2017	12.4	9.3	7.5				
9/1/2017	15.2	11.3	9.6				
9/2/2017	13.5	10.1	8.5				
Average Event	**13.8**	**10.1**	**8.3**				

Table 28 presents the key components that affect the ex-post and ex-ante load impact estimates for dually-enrolled participants. Weather does not play as large of a role in this case, but both the adjustment to the RA window and enrollment both had sizable effects on the ex-ante impact estimates compared to the ex-post results.

Table 28. Ex-Post versus Ex-Ante Factors, Dually-Enrolled Customers

Factor	Ex Post	Ex Ante	Expected impact
Weather	99.6 degrees Fahrenheit during event hours.	98.5 degrees Fahrenheit during event hours on utility-specific 1-in-2 typical event day.	Slightly milder ex-ante weather decreases the forecasted load impact by approximately 6 MW, and participant load impact is 0.1 kW lower for ex-ante relative to ex-post.
Event Window	Hour ending 15-19 for the typical event day.	Hour ending 14-18 in Apr-Oct; Hour ending 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 all enrolled customers are dispatched.
Enrollment	28,923 customers enrolled during the average event day.	Projected enrollment of 20,257 during the average event day.	The decrease in ex ante enrollments decreases the total load impact relative to ex-post.

Table 29 below shows how the dually-enrolled impacts change as we adjust the ex-post load impact estimates. In the second column, we present the estimated load impacts by event and for the season overall. The next column to the right shows how the load impacts change when we use August 2018 peak day ex-ante enrollment. Since enrollment is projected to fall, we see a decline in impacts just as we did when we made this same adjustment to the SmartRate™-only impacts. The next column shows how impacts adjust downward when we use the RA window to estimate impacts instead of SmartDay™ event hours. The last four columns in the table show the dually-enrolled ex-ante load impact estimates for a typical event day in August 2018 for the four weather scenarios.

Table 29. Progression from Ex-Post to Ex-Ante Load Impacts, Dually-Enrolled

Date	Ex Post LI, Event Hours	Ex Post LI @ Ex Ante Enrollment, Event Hours	Ex Post LI @ Ex Ante Enrollment, RA Hours	Ex Ante @ CAISO 1-in-2	Ex Ante @ CAISO 1-in-10	Ex Ante @ PG&E 1-in-2	Ex Ante @ PG&E 1-in-10
6/16/2017	12.1	8.2	7.1	6.9	8.1	8.0	9.0
6/19/2017	17.9	12.1	10.0				
6/20/2017	16.2	11	9.4				
6/22/2017	17.2	11.7	9.9				
6/23/2017	13.7	9.3	8.1				
7/7/2017	15.7	10.7	9.1				
7/27/2017	12.3	8.7	7.6				
7/31/2017	11.5	8.2	7.2				
8/1/2017	14.0	10.0	8.6				
8/2/2017	14.5	10.4	8.9				
8/28/2017	15.1	10.9	9.2				
8/31/2017	10.8	7.9	6.8				
9/1/2017	14.9	10.8	9.5				
9/2/2017	14.8	10.7	9.5				
Average Event	**14.3**	**10.0**	**8.6**				

5.5 Recommendations

Based on our evaluation of the 2017 SmartRate™ program, we provide the following recommendations:

- We recommend that PG&E develop additional evidence to support valuing the extent of behavioral spillover load impacts. While the Program is event-based, our analysis indicates that the Program leads to customers habituating load shifting practices on non-event days. Because of the way we estimate load impacts, this evaluation does not incorporate the effect of behavioral spillover in reducing reference loads when calculating load impact estimates. This therefore artificially depresses the reference load used to estimate event day impacts, as well as foregoes calculating impacts for non-event days. Correctly valuing the effect of this spillover and its benefits on hot non-event days may prove instrumental to more effectively manage grid operations. This evaluation estimated spillover on a daily basis, but we recommend future research to investigate the effect of spillover on a monthly basis as well as over time.

- We recommend that PG&E incorporate results from the multi-level modeling analysis to identify existing customers and target future customers who can best contribute to load impacts. For existing customers, we recommend reaching out to select under or overperforming customers to provide educational information or behavioral messaging to motivate increasing engagement with the rate. For future customer targeting, we recommend PG&E leverage this research, in addition to prior

evaluation findings, to target customers with characteristics known to provide larger load impacts (e.g., climate zone, usage profile, etc.).

- We recommend PG&E consider a process evaluation to gather data from Program participants through a survey effort to gauge their understanding of SmartRate™, whether they receive notification of SmartDay™ events, what changes in electric consumption they make during SmartDay™ event hours to reduce load, and whether they are satisfied with their experience with the Program. This would also present an opportunity to assess whether participants are well informed about how the rate affects their bills while they are bill protected and when bill protection ends.

- We recommend PG&E consider resuming targeted marketing to recruit customers who have the potential to make a larger contribution to load impacts. We recommend that when considering targeted marketing, that PG&E balance the cost of targeted marketing for this program compared to achieving a portfolio level load reduction from other types of programs. These would include customers in hotter locations, such as Greater Fresno, Stockton, and Sierra LCAs. Additionally, since dually-enrolled customers contribute larger per customer impacts relative to those who participate in SmartRate™-only, we recommend PG&E encourage participants to enroll in both programs.

Appendix A. Ex-Post and Ex-Ante Table Generators

Ex-post and ex-ante table generators are provided separately as Excel files:

- PGE_2017_SmartRate_Ex_Post_PUBLIC_20180329.xlsm
- PGE_2017_SmartRate_Ex_Ante_PUBLIC_20180329.xlsm

Appendix B. Bill Protection Analysis Results

During the first full summer participants are enrolled in SmartRate™ (May through October), PG&E provides them with bill protection status. Bill protection means that if participants are charged more than what they would have been billed on their regular rate plan during this first full summer on the Program, they will receive a credit at the end of the summer period (which occurs on their November bill). The credit received is for the difference in what they would have been charged had they not been on SmartRate™ and what they were charged while enrolled in the program. After the first full summer, participants are charged for their electric usage based on SmartRate™.

For all SmartRate™-enrolled participants, PG&E provided bill data for May 2017 through October 2017 that allowed us to determine whether participants were bill protected (in other words, whether they were enrolled in their first full summer on the Program), along with customer charges associated with customer electric usage during event hours on event days and credits associated with customer usage on summer non-event days. For bill protected participants, the data also include the refunds received by bill protected participants, where applicable. We merged the bill data with the Program participant list of participants who were enrolled in SmartRate™ for the summer of 2017.

We developed a master list of SmartRate™ program participants which contained any PG&E customer who was enrolled in the Program in 2017. From this list we identified the participants we could use in the bill protection analysis based on the length of time they were enrolled in the Program, the dates during which they were enrolled, and whether they had sufficient data. The following table shows the initial starting count of participants and reasons why participants were dropped. After we completed our data cleaning steps, we ended up with a dataset of 116,929 customers for the bill impacts analysis (see Table 30).

Table 30. Data Cleaning Steps for Bill Protection Status Analysis

Dropped from Analysis Reasons	Number of Participants
After merging billing data with master participant list, starting count:	142,793
Drop Reason 1: Missing from billing data	3,736
Drop Reason 2: Missing from AMI data	2,141
Drop Reason 3: Less than 90 days of billing data	17,457
Drop Reason 4: Enrolled in the program for less than 90 days	50
Drop Reason 5: Enrolled too late for Summer 2017 period	2,475
Drop Reason 6: Dropped out before the start of summer 2017	5
Final Count for Bill Protection Analysis	**116,929**

Proportion of Bill Protected Customers and Average Refunds

A little under a quarter (21%) of SmartRate™-only participants and 3% of dually-enrolled participants were bill protected during the summer of 2017 (see column 4 of Table 31, which shows the proportion of bill protected and unprotected participants who are enrolled in SmartRate™-only and who are dually-enrolled). Of all Program participants, approximately 17% received bill protection status in 2017. In 2016, approximately 20% of participants received bill protection status.

Table 31. Share of SmartRate™ and Dually-Enrolled Participants with and without Bill Protection Status

Program Enrollment	Bill Protection Status	Count of Participants	% of Population by Program Enrollment	% of Total Population
SmartRate™-Only	Yes	18,962	21%	16%
	No	69,765	79%	60%
	Total	**88,727**	**100%**	**76%**
Dually-Enrolled	Yes	762	3%	1%
	No	27,440	97%	23%
	Total	**28,202**	**100%**	**24%**
All	Yes	19,724	17%	17%
	No	97,205	83%	83%
	Total	**116,929**	**100%**	**100%**

Over three quarters of bill protected participants (76%) experienced reduced bills (shown as negative bill changes in Table 32) regardless of whether they were enrolled in SmartRate™-only or were dually-enrolled, however the average bill reduction was larger for dually-enrolled program participants (approximately $41) compared to SmartRate™–only participants ($24). For those participants who would have experienced higher bills if they were not bill protected (those with positive bill changes in the last column of the table below), the bill increases were of similar magnitude to the decreases for SmartRate™-only participants ($23.90 and $22.35, for SmartRate™-only and dually-enrolled participants). Overall, the average change in bills for bill protected participants was a bill reduction of $13.50.

Table 32. Bill Changes for SmartRate™ and Dually-Enrolled Bill Protection Status Participants

Program	Bill Change Type	Number of Participants	Percent Change	Avg. Bill Change
SmartRate™-Only	Decreased Bill	14,496	76%	-$24.31
	Increased Bill	4,466	24%	$23.90
	All	**18,962**	**100%**	**-$13.09**
Dually-Enrolled	Decreased Bill	547	72%	-$40.76
	Increased Bill	215	28%	$22.35
	All	**762**	**100%**	**-$23.21**
All	Decreased Bill	15,043	76%	-$24.93
	Increased Bill	4,681	24%	$23.82
	All	**19,724**	**100%**	**-$13.50**

Table 33 presents the proportion of Program enrolled participants who had been enrolled longer than a full summer and therefore did not have bill protection status. Again, a larger proportion of participants experienced bill reductions (66%) than those who incurred higher bills (34%). In this case, the average change in bills for all non-bill protected participants is an approximate $7.50 reduction in their bill.

Table 33. Bill Changes for SmartRate™ and Dually-Enrolled Participants without Bill Protection Status

Program	Bill Change Type	Number of Participants	Percent Change	Avg. Bill Change
SmartRate™-Only	Decreased Bill	48,496	70%	-$24.62
	Increased Bill	21,269	30%	$30.17
	All	**69,765**	**100%**	**-$7.98**
Dually-Enrolled	Decreased Bill	16,067	59%	-$30.06
	Increased Bill	11,373	41%	$27.56
	All	**27,440**	**100%**	**-$6.24**
All	Decreased Bill	64,563	66%	-$25.98
	Increased Bill	32,642	34%	$29.26
	All	**97,205**	**100%**	-$7.49

When we combine all the SmartRate™ and dually-enrolled participants, regardless of bill protection status, we find that average bill reductions and increases are comparable for both SmartRate™ and dually-enrolled participants, ranging from $24.55 to $30.44. Further, SmartRate™ and dually-enrolled participants experience a bill reduction of $8.52 on average, though the SmartRate™-only customers saw a slightly larger average reduction in their bills than did dually-enrolled participants ($9.09 versus $6.72). Finally, 68% of participants received lower bills (see Table 34).

Table 34. Bill Changes for All SmartRate™ and Dually-Enrolled Participants

Program	Bill Change Type	Number of Participants	Percent Change	Avg. Bill Change
SmartRate™-Only	Decreased Bill	62,992	71%	-$24.55
	Increased Bill	25,735	29%	$29.07
	All	**88,727**	**100%**	**-$9.09**
Dually-Enrolled	Decreased Bill	16,614	59%	-$30.44
	Increased Bill	11,588	41%	$27.46
	All	**28,202**	**100%**	**-$6.72**
All	Decreased Bill	79,606	68%	-$25.78
	Increased Bill	37,323	32%	$28.57
	All	**116,929**	**100%**	-$8.52

In Table 35, we present the average refund received by SmartRate™-only and dually-enrolled participants who were eligible to receive them. Of the 19,724 who were bill protected during the summer of 2017, 14% of SmartRate™-only participants and 17% of dually-enrolled participants received refunds. We found similar results for 2016--last year's analysis showed approximately 10% of SmartRate™-only participants and 19% of dually-enrolled participants received refunds.

Table 35. Average Refund for Bill Protected Participants

Program	Received Refund?	Count of Participants	% of Bill Protected Participants	Average Refund
SmartRate™-Only	No	16,276	86%	$ -
	Yes	2,686	14%	$ 24.47
	Total	18,962	100%	$ -
Dually-Enrolled	No	633	83%	$ -
	Yes	129	17%	$ 21.15
	Total	762	100%	$ -

Bill Impacts by Customer Segment

Below we present the average effects on customer bills by LCA and for participants who are on CARE and FERA rates. Table 36 shows the proportion of participants in each LCA who are on SmartRate™ or are dually-enrolled, as well as information about their average bill changes. Additionally, we calculated the share of participants who experienced bill reductions in each LCA and the average bill reduction these participants. For all LCAs, the average bill changes for participants enrolled in SmartRate™ or dually-enrolled in SmartRate™ and SmartAC™ were negative, except for SmartRate™-only customers located in Stockton. The average bill change was positive for these participants, meaning they paid more than they would have had they not been enrolled in SmartRate™.

Further examination of Table 36 shows the larger average bill changes for SmartRate™-only participants occurred for customers in Northern Coast. For dually-enrolled participants, the largest average bill change was in Kern, followed far behind by Greater Fresno and Sierra.

Table 36. SmartRate™ Bill Impacts by LCA

Enrollment Status	LCA	% of Participants	Average Bill Change
SmartRate™-Only	Greater Bay Area	47%	-$10.64
	Greater Fresno	8%	-$5.91
	Humboldt		
	Kern	7%	-$10.69
	Northern Coast	2%	-$16.59
	Other	22%	-$10.60
	Sierra	6%	-$7.41
	Stockton	7%	$6.01
	Total	**100%**	
Dually-Enrolled	Greater Bay Area	34%	-$5.21
	Greater Fresno	11%	-$10.81
	Humboldt		
	Kern	6%	-$21.71
	Northern Coast	2%	-$5.77
	Other	22%	-$2.79
	Sierra	12%	-$10.31
	Stockton	12%	-$3.68
	Total	**100%**	

When assessing impacts by CARE status (as shown in Table 37), it is interesting to note that customers who are on CARE rates experience smaller average bill changes than those who are not. The average change in electric bills for Program participants is negative, which means on average, the participants' bills are lower than when they were not enrolled.

Table 37. SmartRate™ Bill Impacts by CARE Rate Status

Enrollment Status	CARE Status	Number of Participants	% of Participants	Average Bill Change
SmartRate™-Only	Yes	26,690	23%	-$1.61
	No	62,037	53%	-$12.29
Dually-Enrolled	Yes	7,698	7%	-$2.12
	No	20,504	18%	-$8.45

We also provide bill impacts by FERA status and as Table 38 shows, there are far fewer participants on this rate relative to those on the CARE rate. Unlike participants on the CARE rate, those on the FERA rate experience larger average bill changes than those who are not. The average bill change is negative, which means that when we average participants' monthly bill changes, they are less than when they were not enrolled in the Program. This holds regardless of whether participants are enrolled in SmartRate™-only or are dually-enrolled.

Table 38. SmartRate™ Bill Impacts by FERA Rate Status

Enrollment Status	FERA Status	Number of Participants	% of Participants	Average Bill Change
SmartRate™-Only	Yes	870	1%	-$10.87
	No	87,857	75%	-$9.07
Dually-enrolled	Yes	269	0%	-$14.22
	No	27,933	24%	-$6.65

Appendix C. Multi-Level Model Results

This appendix provides the distribution of load impacts by participant for each LCA and enrollment type. Overall, the distribution of load impacts per participant vary across the LCAs.

Figure 24. Greater Bay Area Distribution of Load Impacts, SmartRate™ Only Participants

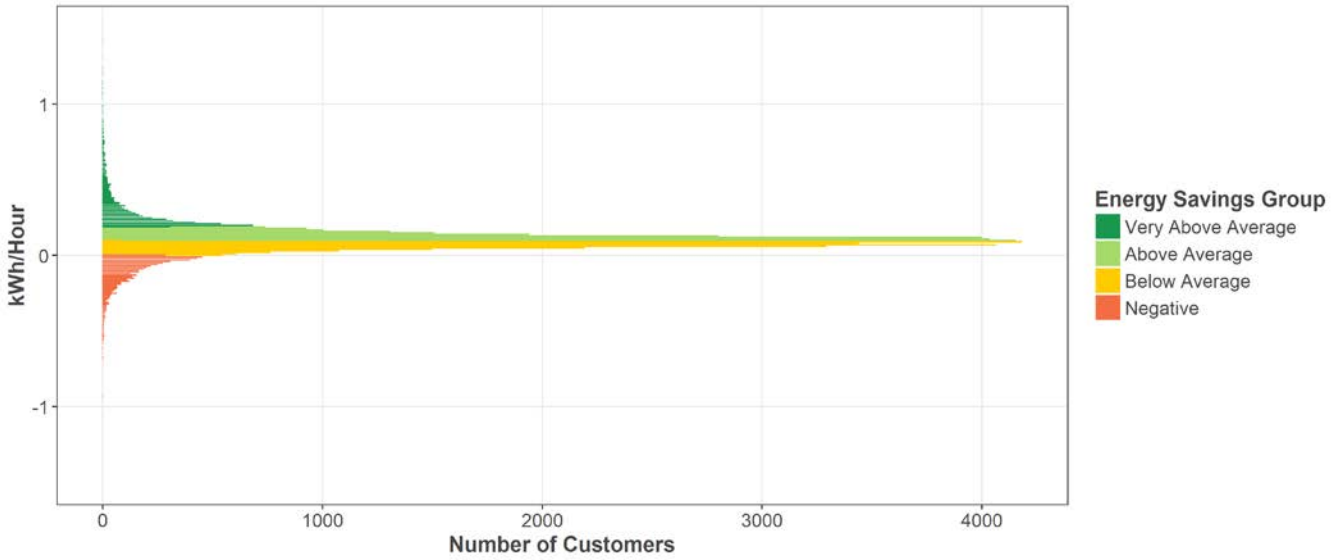


Figure 25. Greater Bay Area Distribution of Load Impacts, Dually-Enrolled Participants

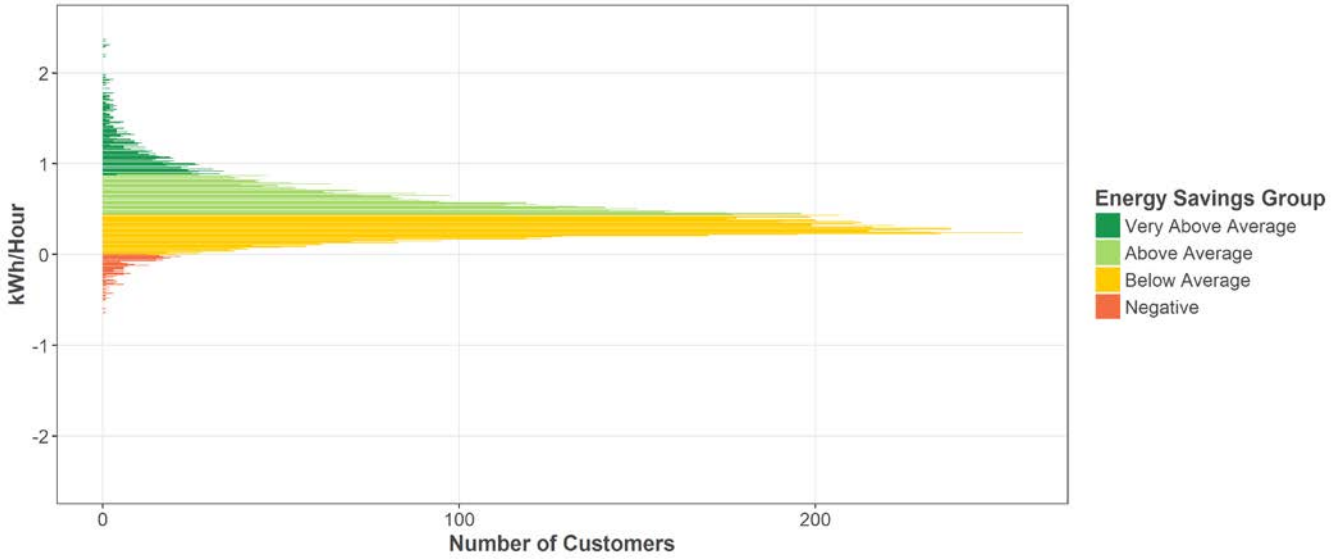


Figure 26. Greater Fresno Area Distribution of Load Impacts, SmartRate™ Only Participants

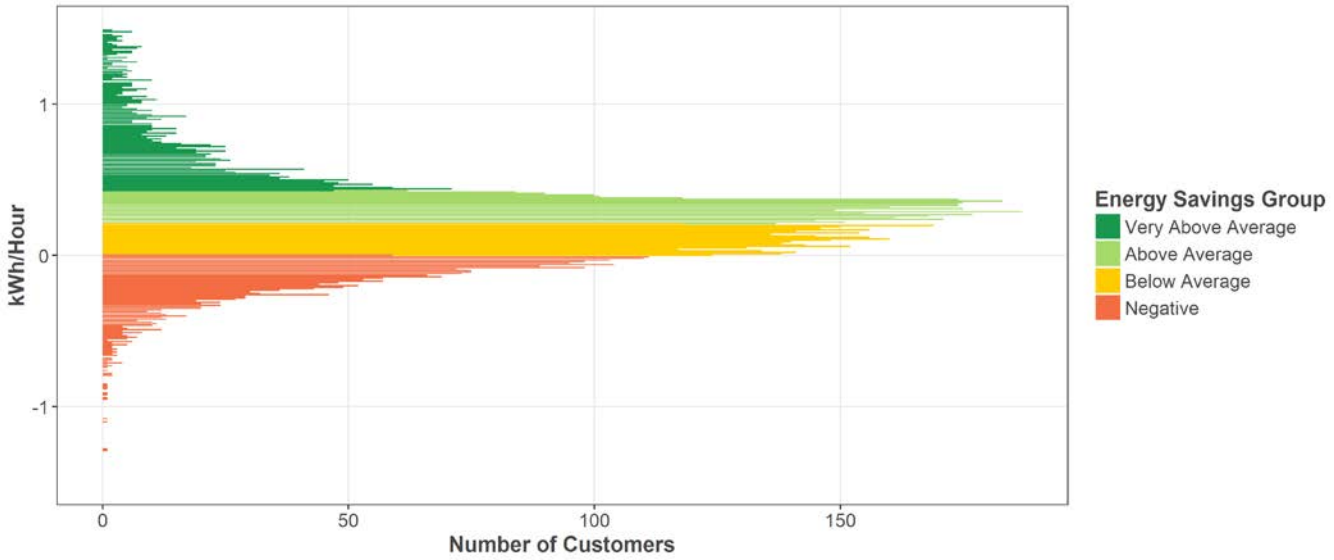


Figure 27. Greater Fresno Area Distribution of Load Impacts, Dually-Enrolled Participants

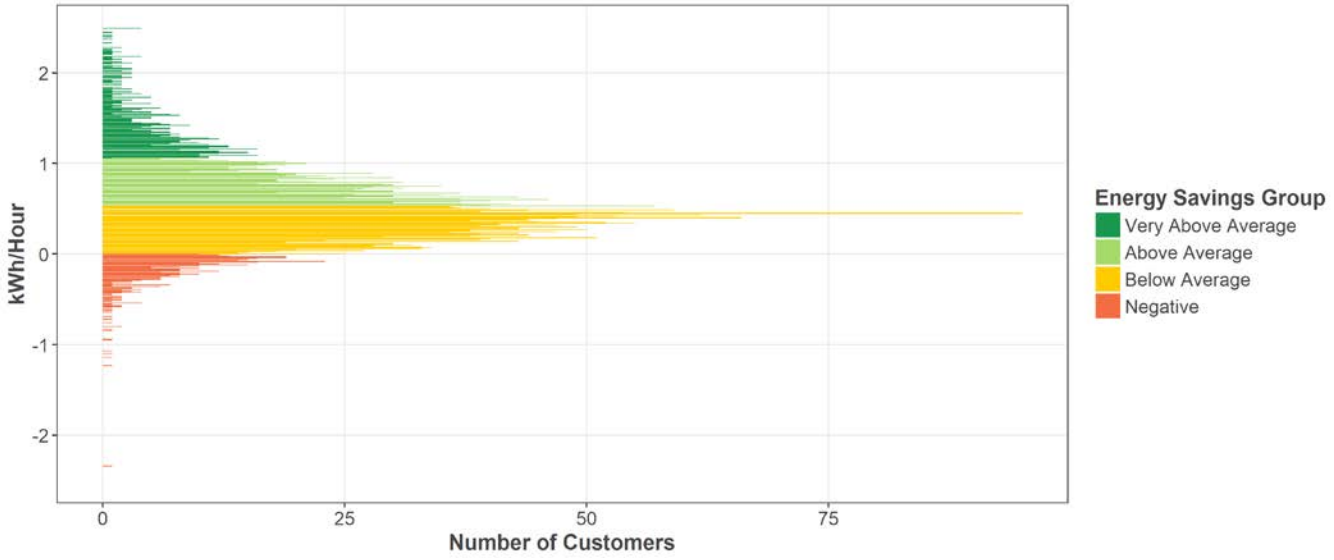


Figure 28. Kern Distribution of Load Impacts, SmartRate™ Only Participants

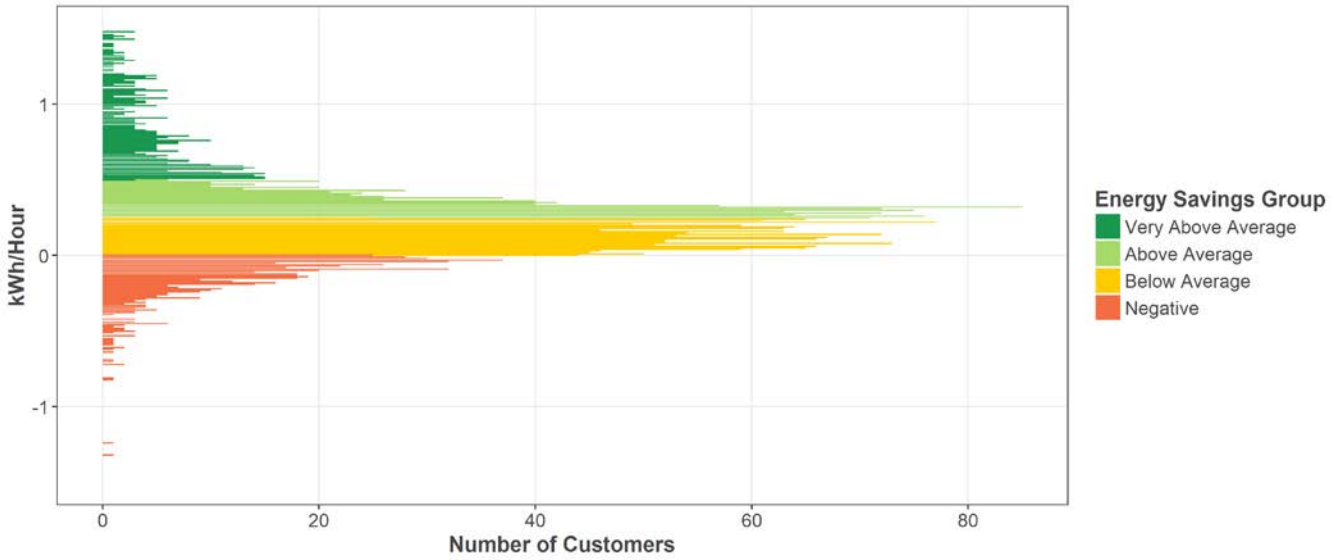


Figure 29. Kern Distribution of Load Impacts, Dually-Enrolled Participants

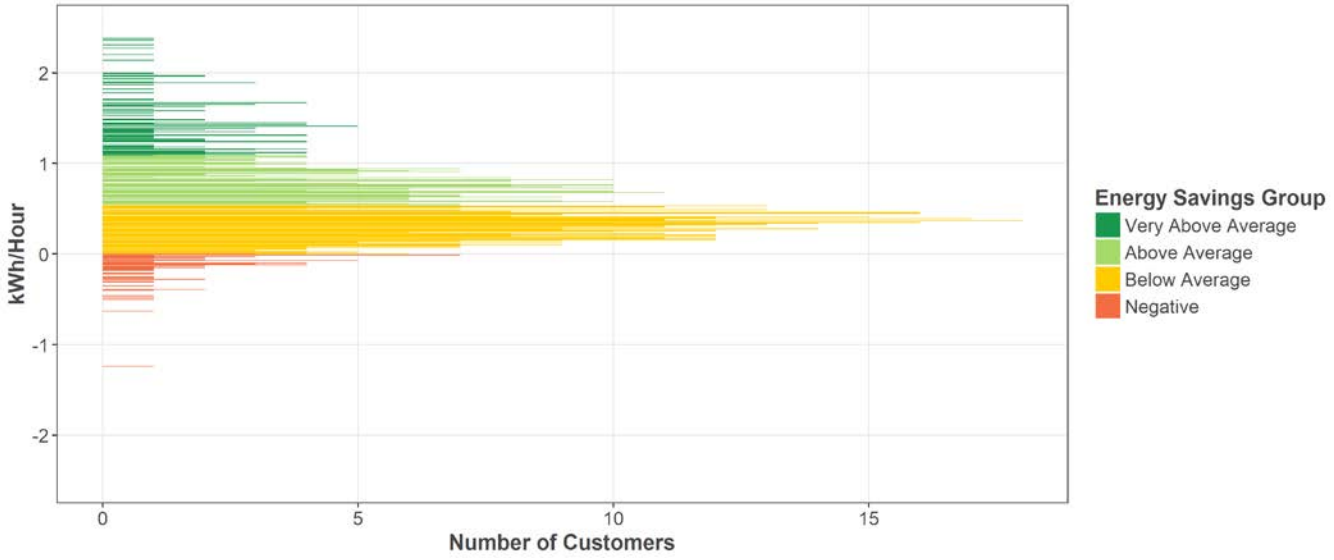


Figure 30. Northern Coast Distribution of Load Impacts, SmartRate™ Only Participants

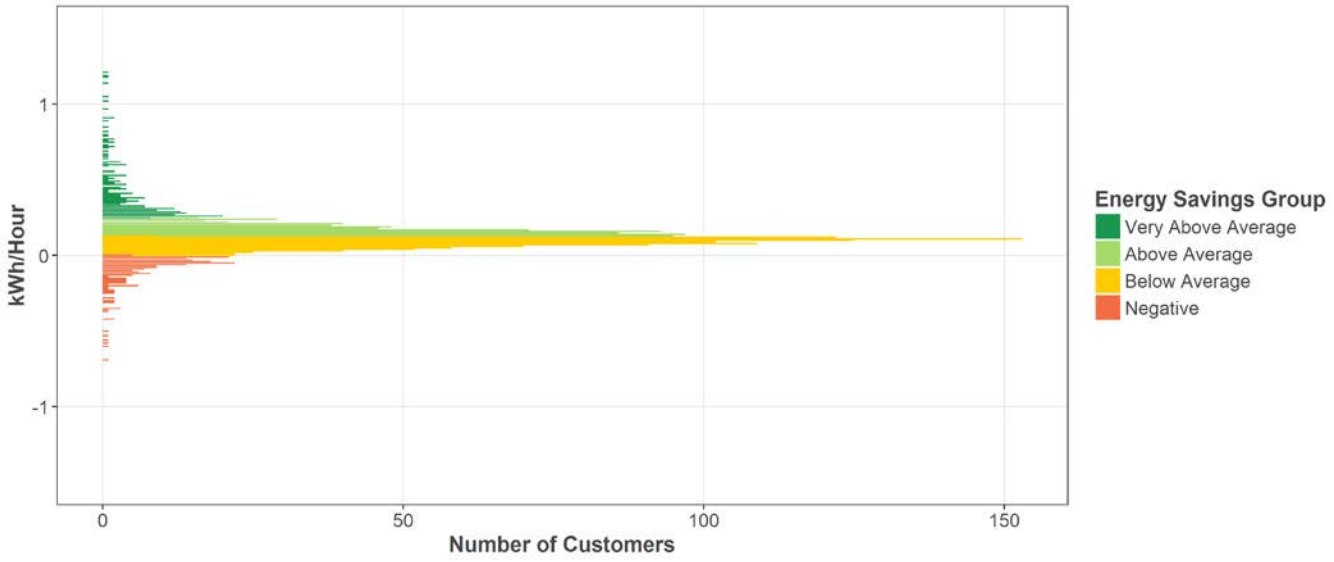


Figure 31. Northern Coast Distribution of Load Impacts, Dually-Enrolled Participants

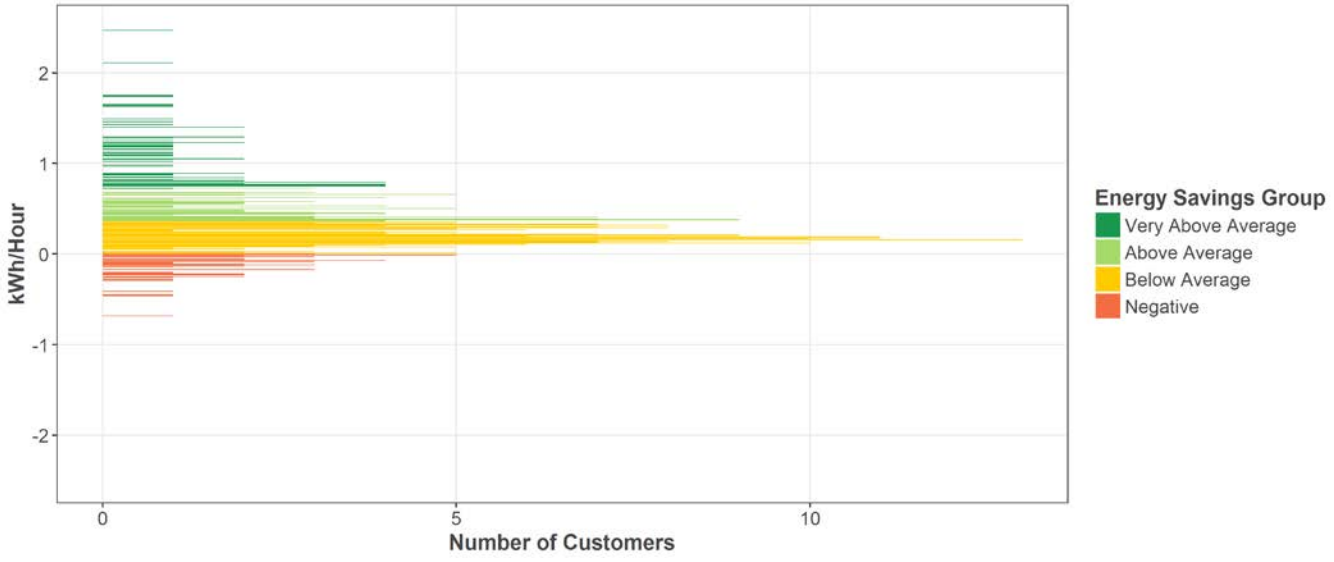


Figure 32. Other Distribution of Load Impacts, SmartRate™ Only Participants

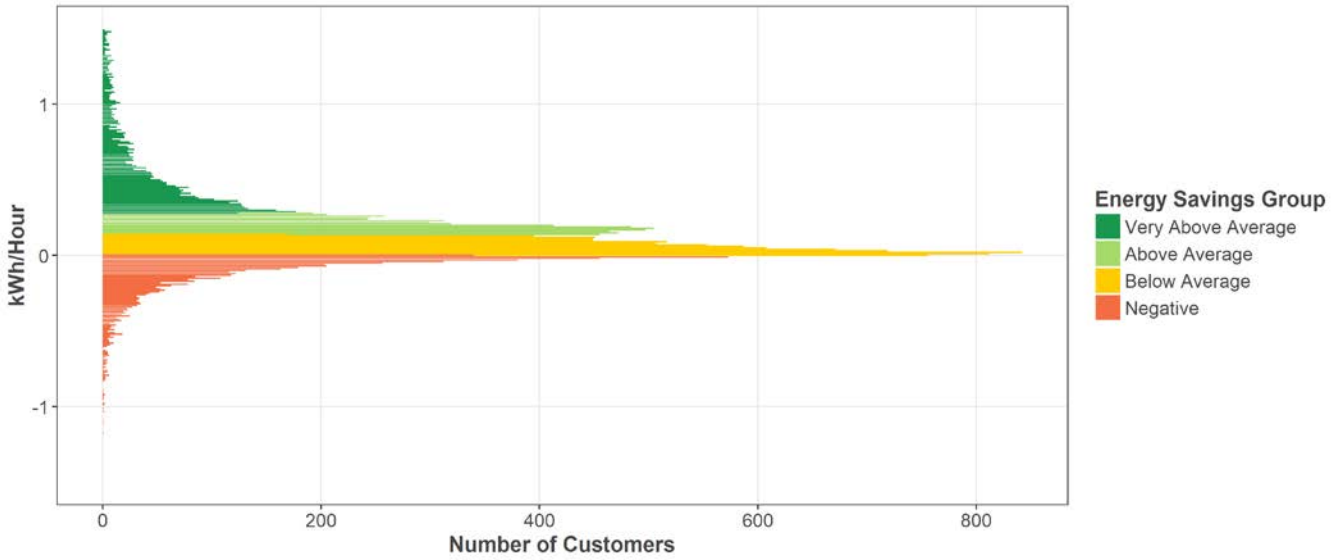


Figure 33. Other Distribution of Load Impacts, Dually-Enrolled Participants

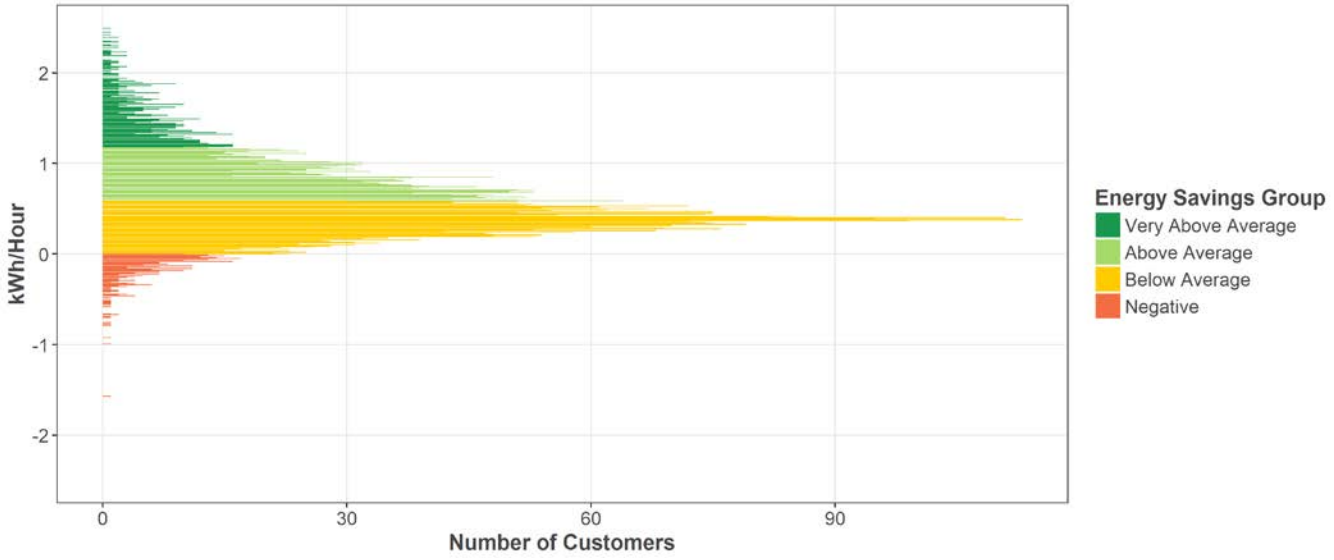


Figure 34. Sierra Distribution of Load Impacts, SmartRate™ Only Participants

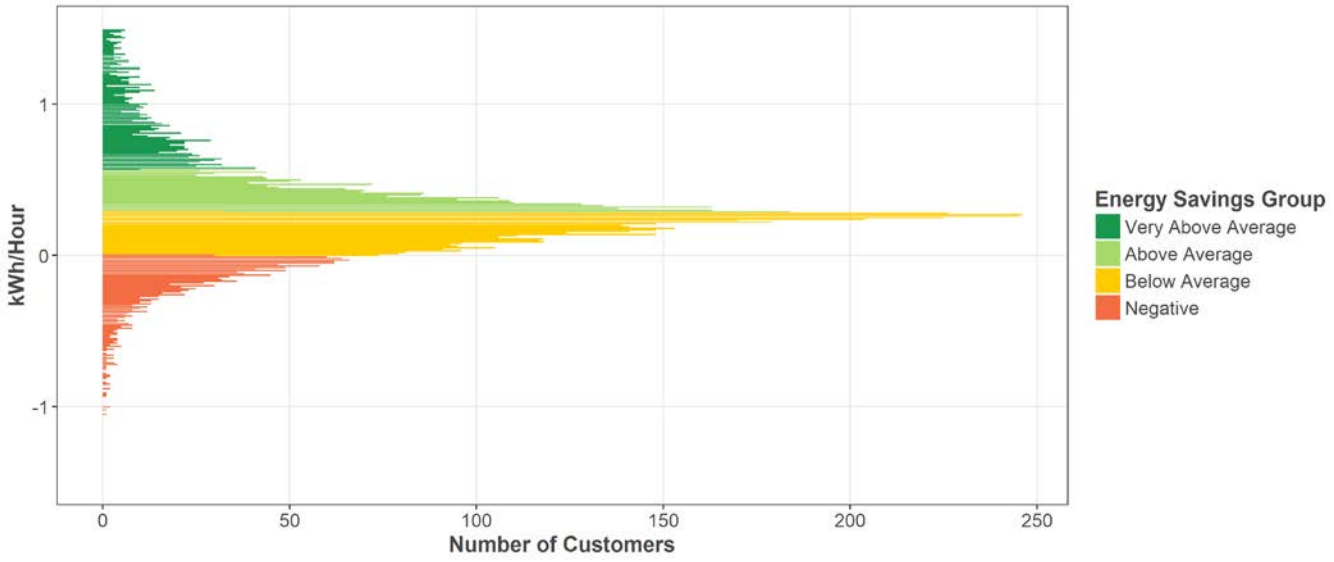


Figure 35. Sierra Distribution of Load Impacts, Dually-Enrolled Participants

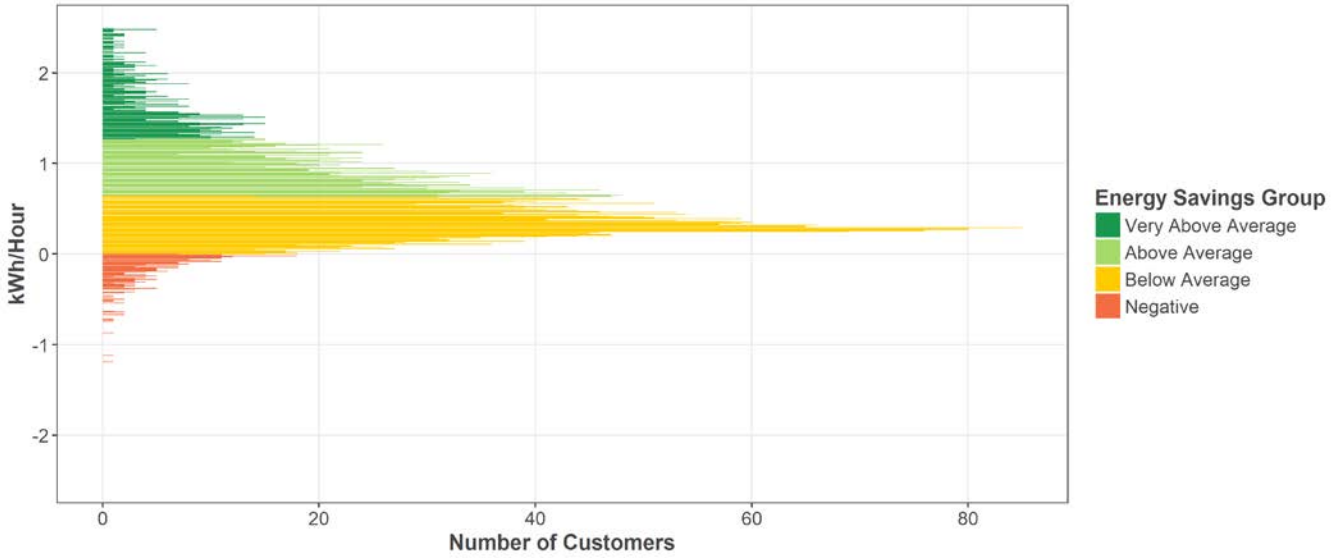


Figure 36. Stockton Distribution of Load Impacts, SmartRate™ Only Participants

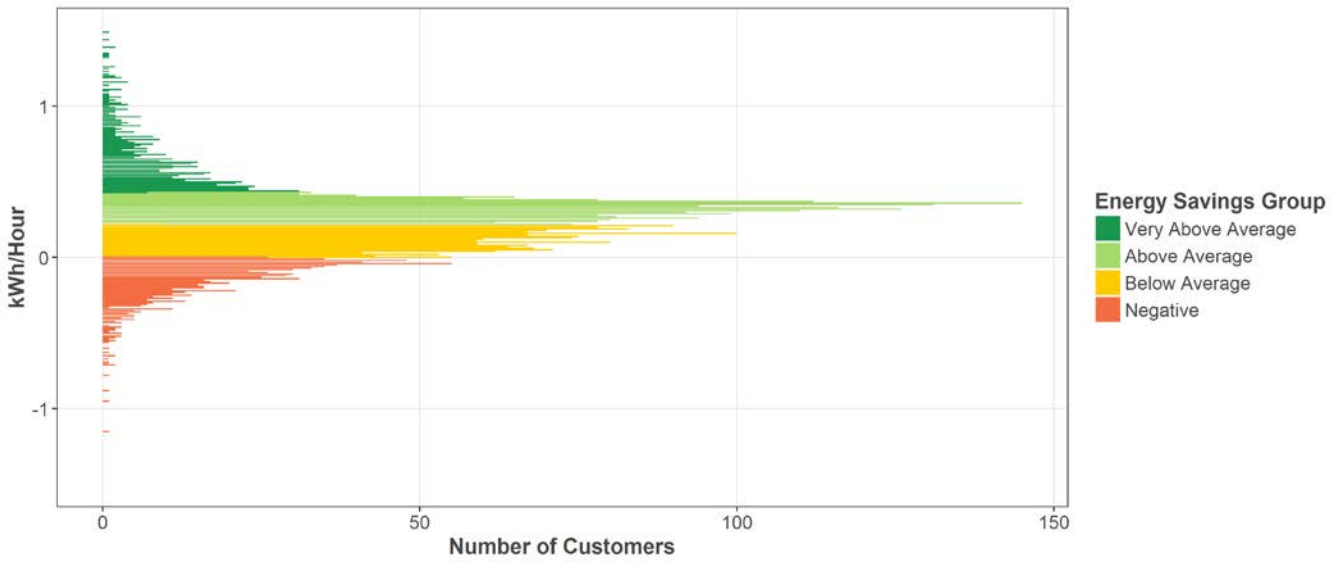
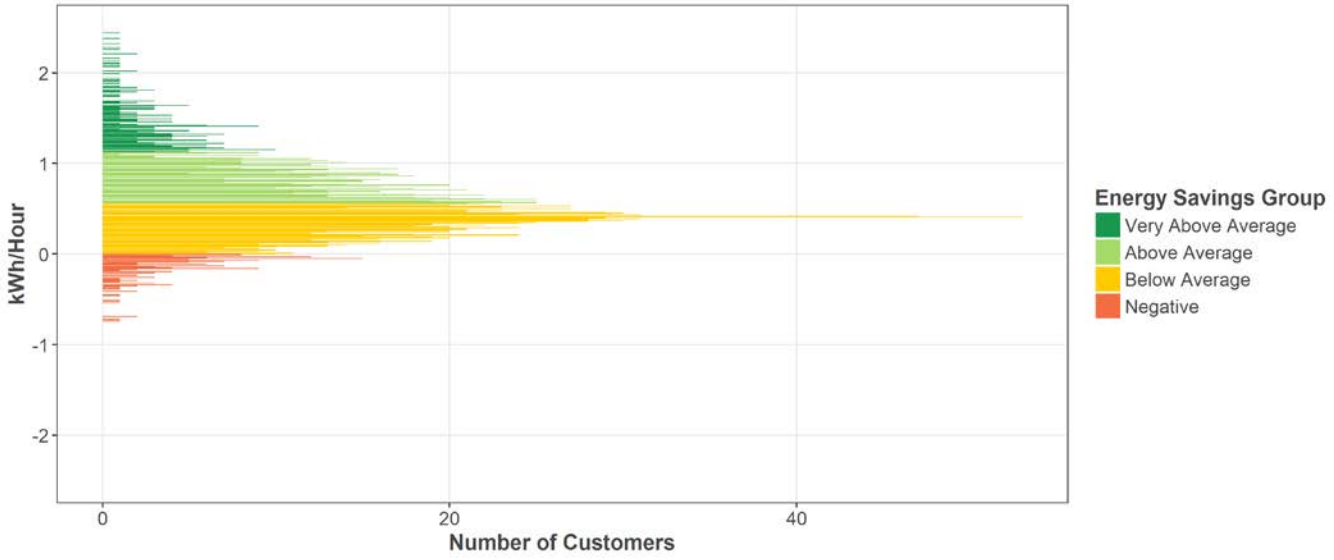


Figure 37. Stockton Distribution of Load Impacts, Dually-Enrolled Participants



Appendix D. Behavioral Spillover Results

The following figures provide results related to behavioral spillover effects. The red line shows the estimated pre-period usage compared to the predicted 2017 usage (blue line). The amount of spillover varies across LCA's with the largest spillover for Greater Bay Area, North Coast and Other.

Figure 38. Greater Bay Area Spillover Baseline and Predicted Load

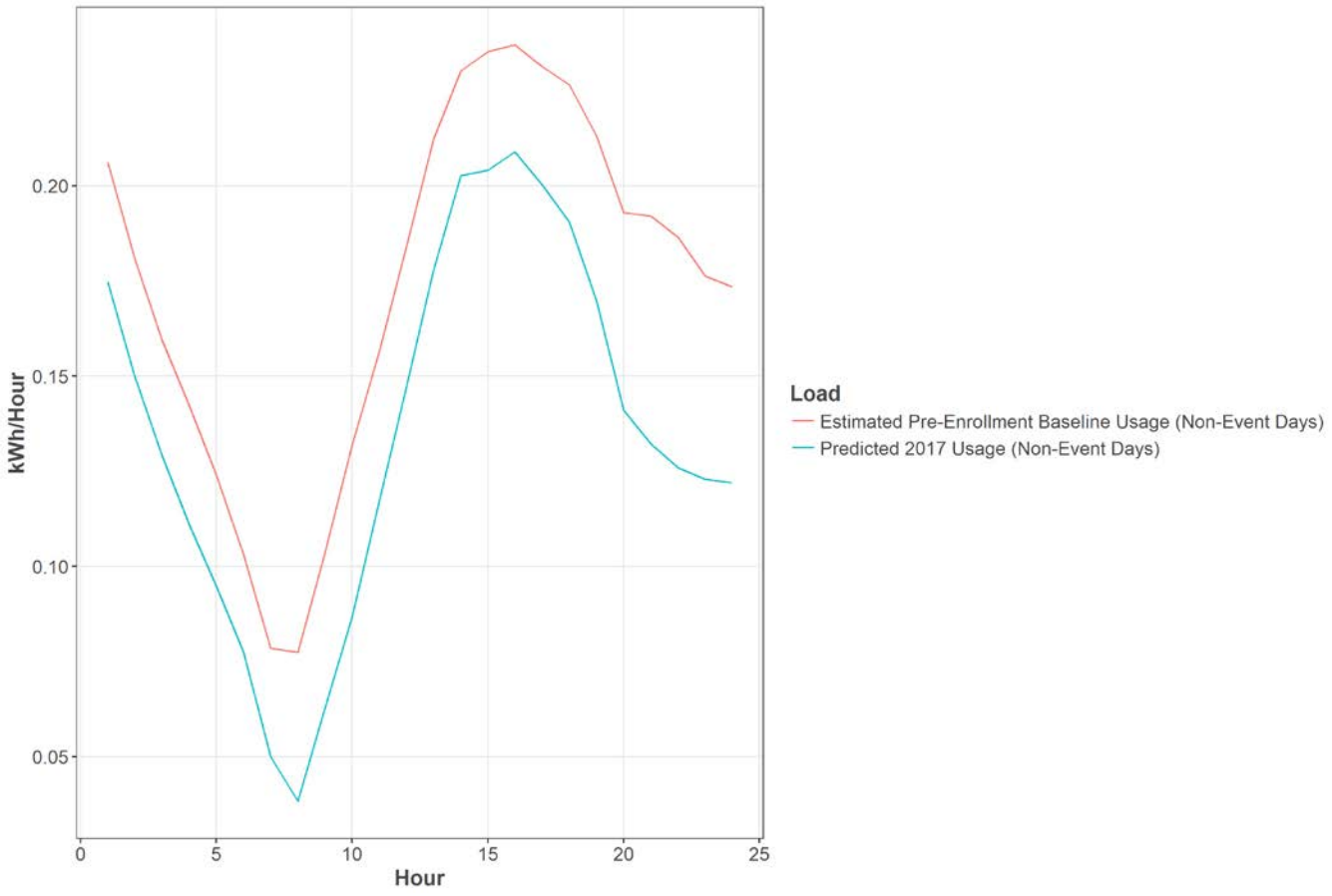


Figure 39. Other Spillover Baseline and Predicted Load

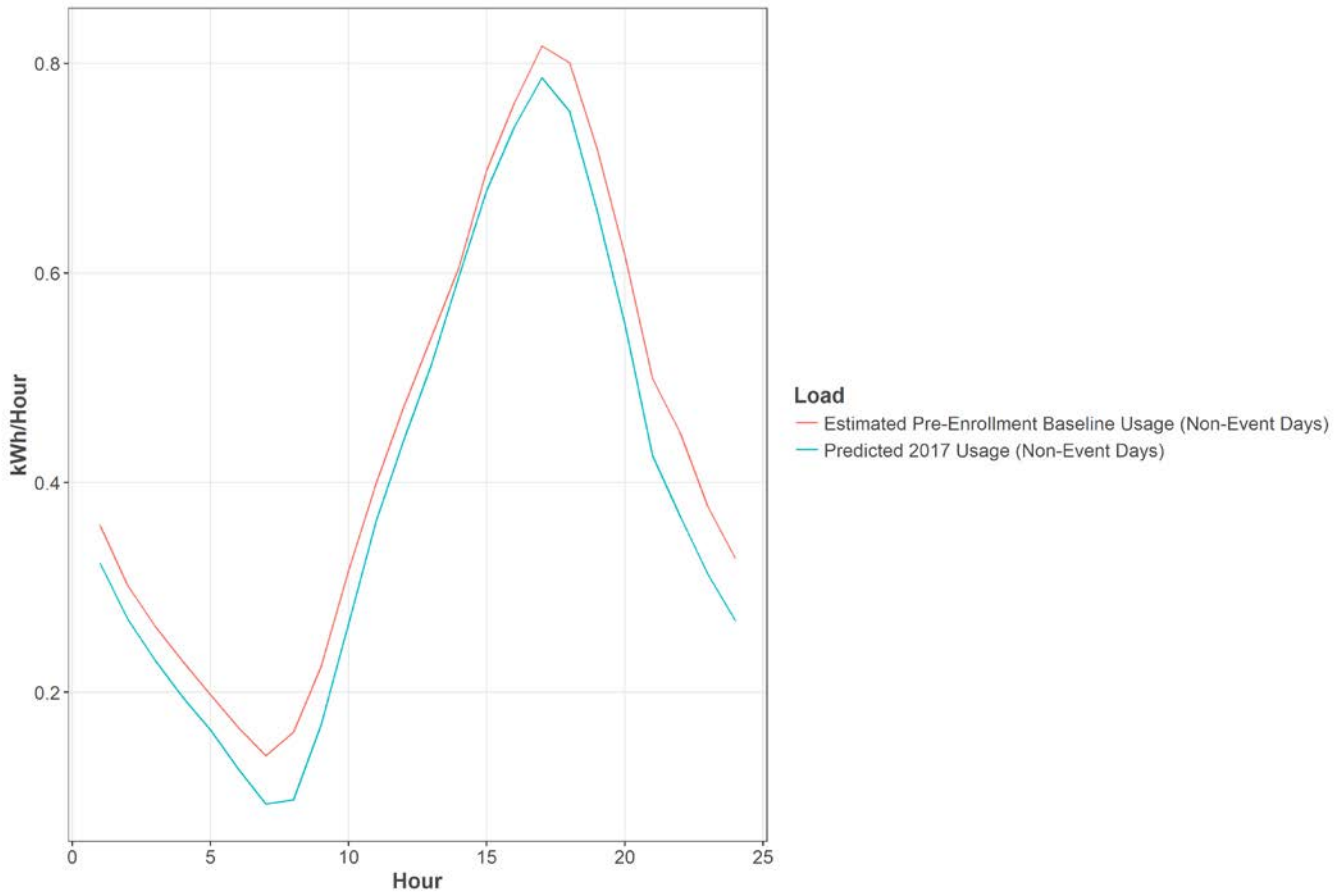


Figure 40. Greater Fresno Area Spillover Baseline and Predicted Load

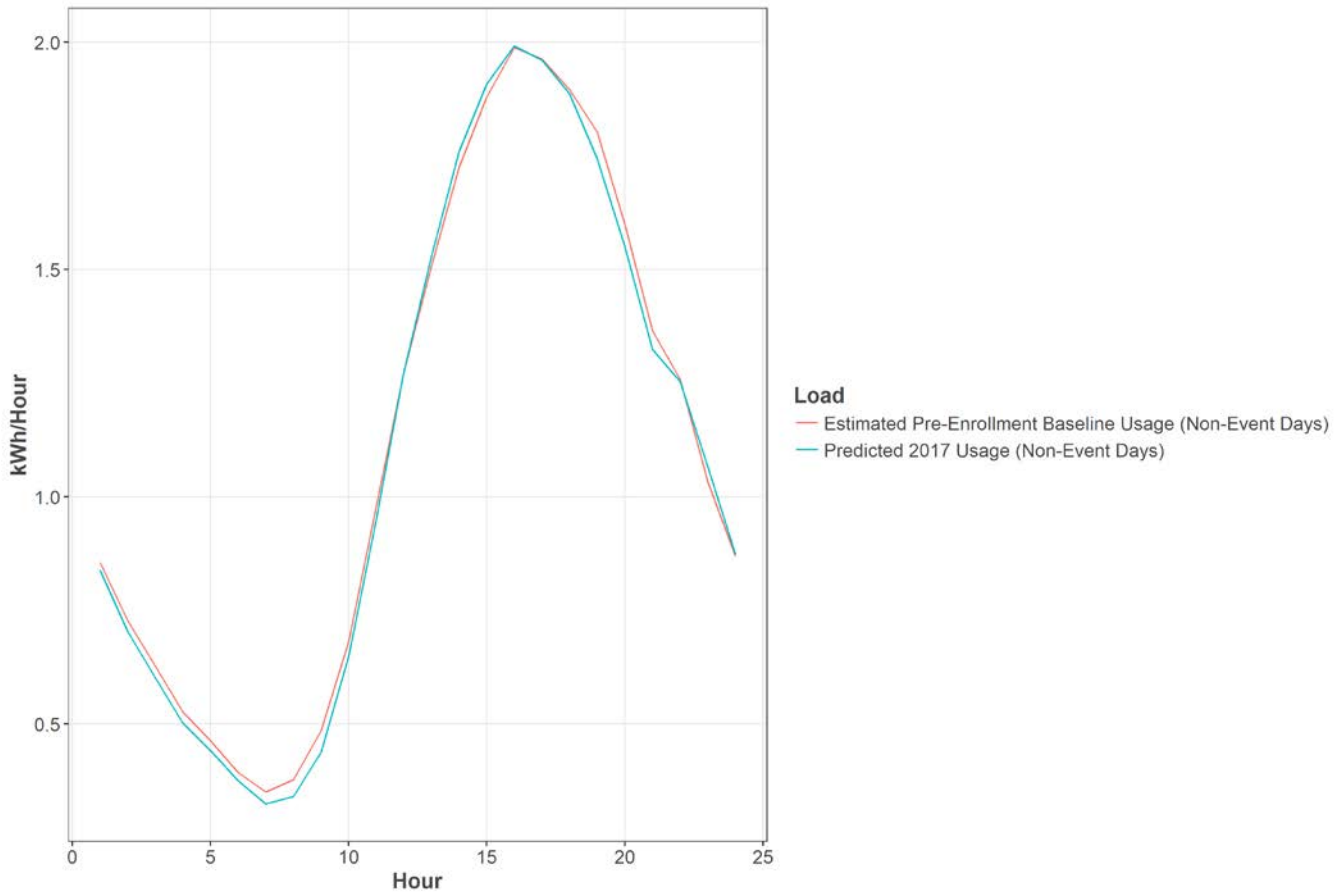


Figure 41. Sierra Spillover Baseline and Predicted Load

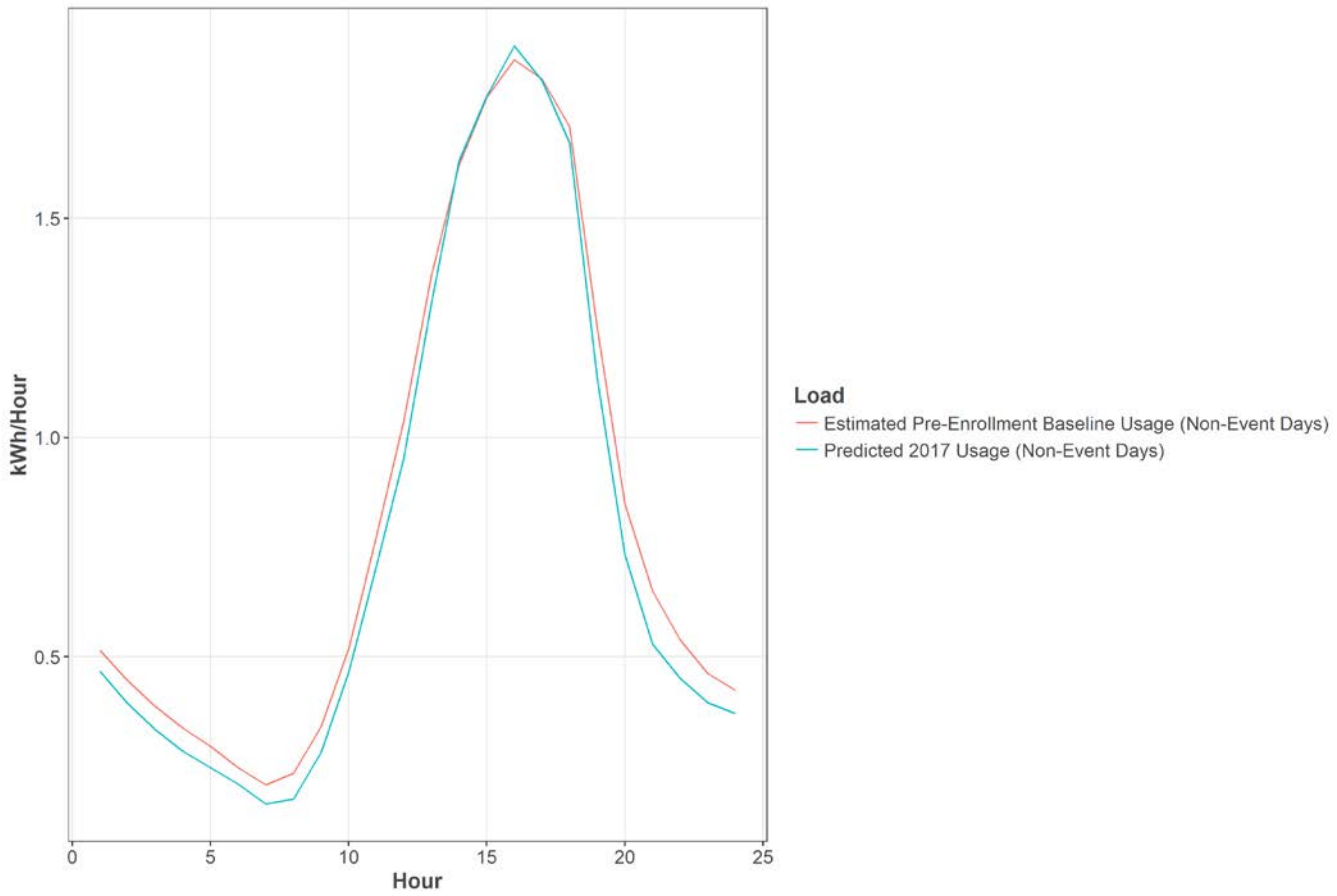


Figure 42. Stockton Spillover Baseline and Predicted Load

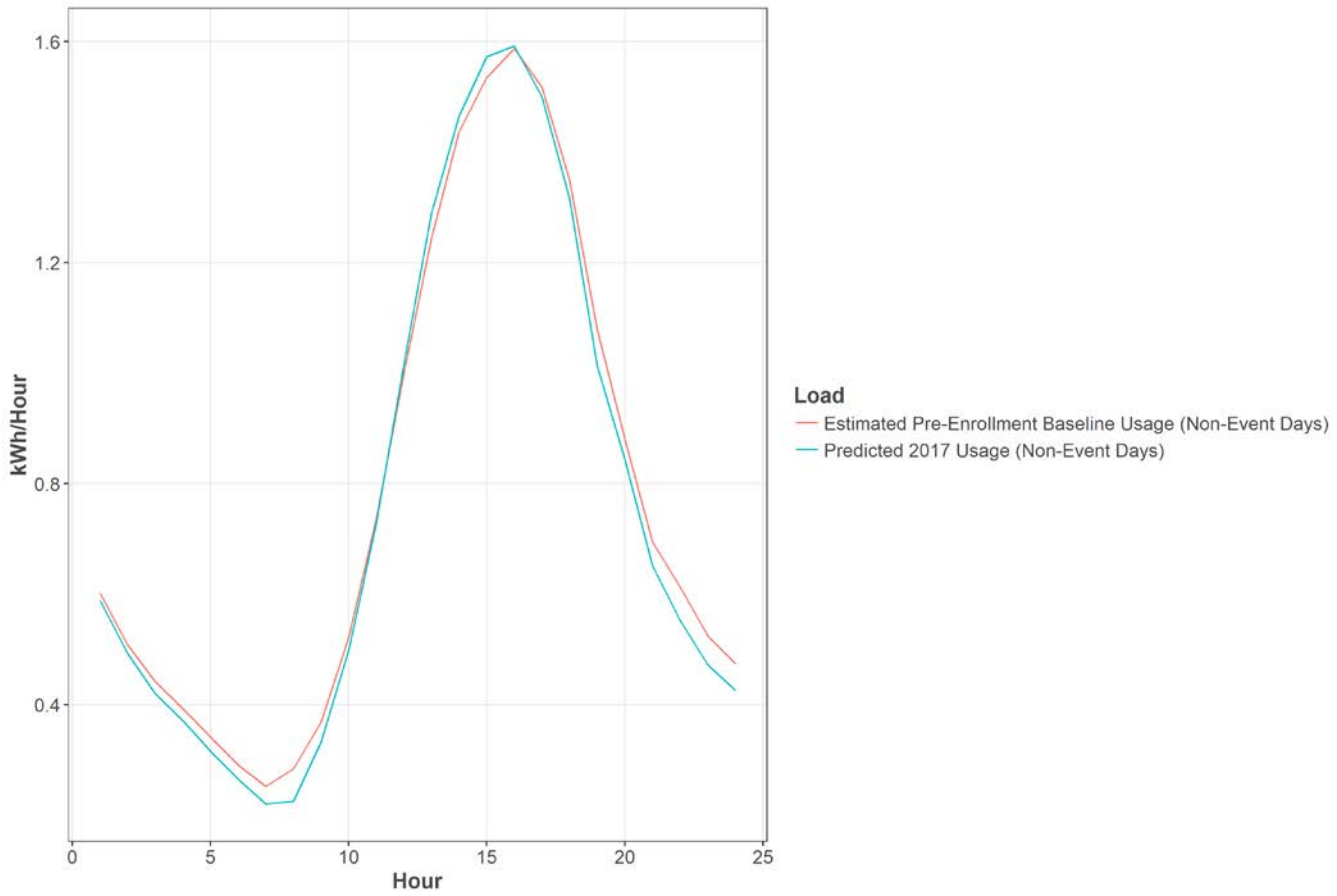


Figure 43. Kern Spillover Baseline and Predicted Load

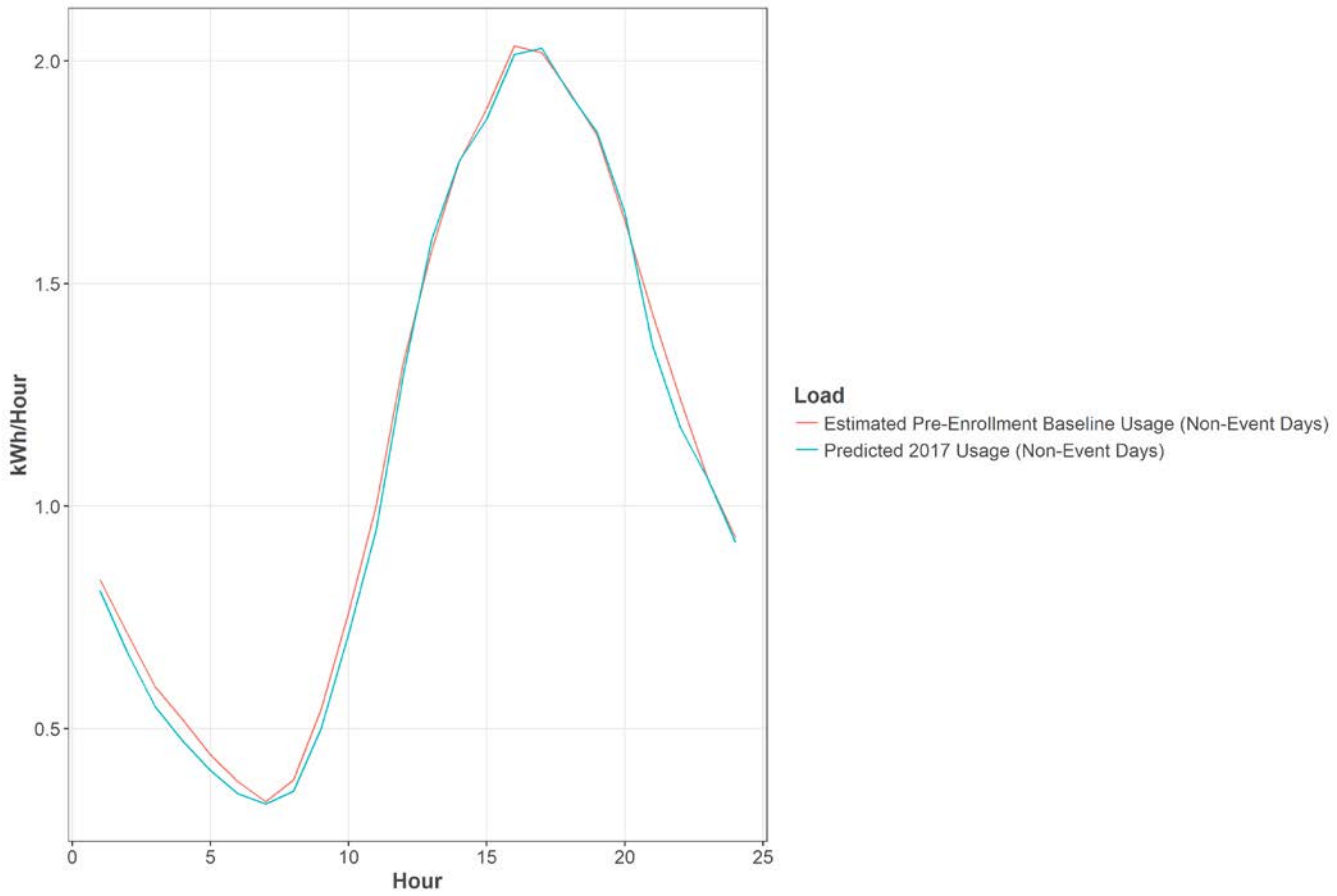
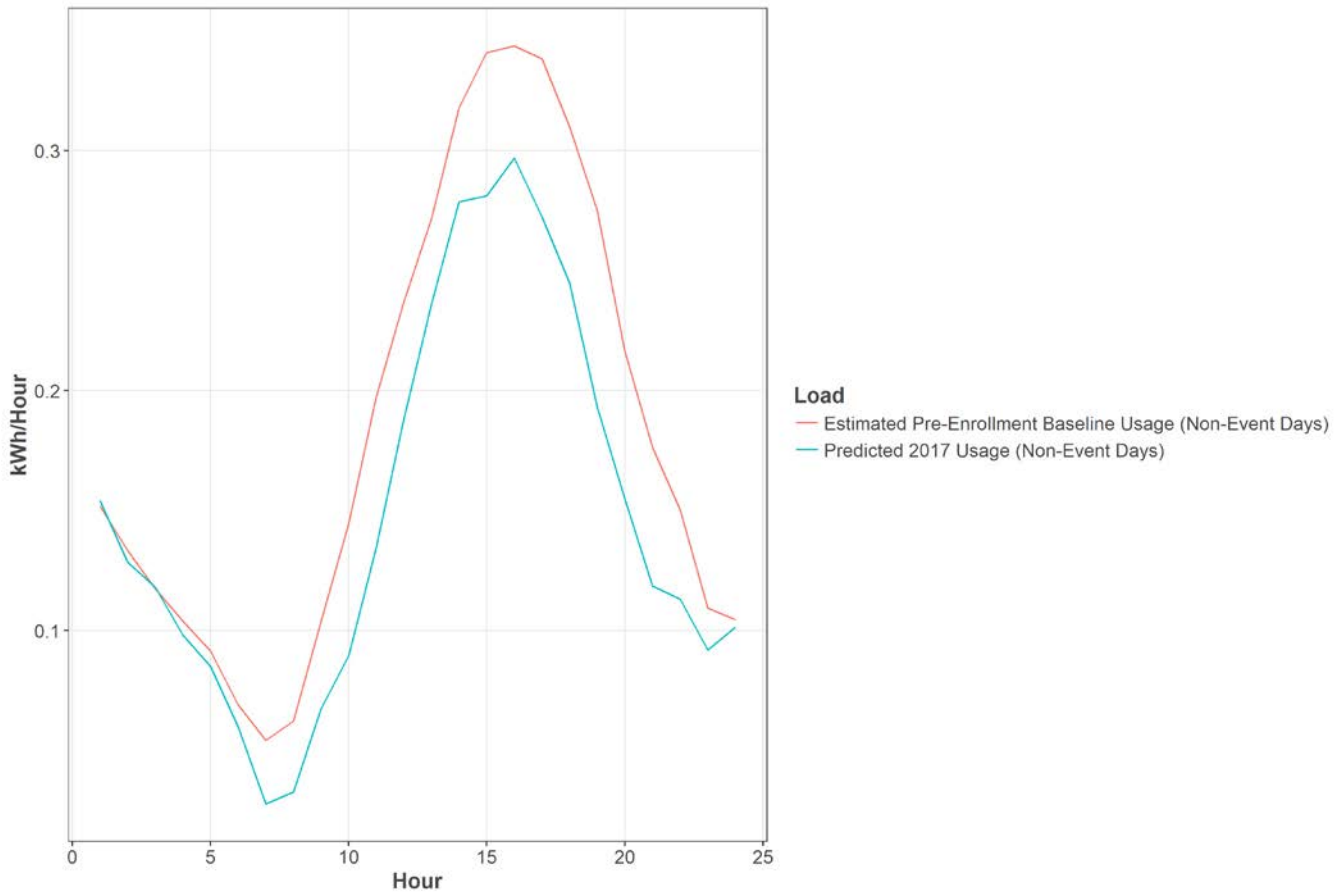


Figure 44. North Coast and North Bay Spillover Baseline and Predicted Load



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