Public Version. Redactions in 2020 Load Impact Evaluation for Pacific Gas & Electric Company's SmartRate™ Program and Appendices

Applied Energy Group

2020 LOAD IMPACT EVALUATION OF PG&E SMARTRATE™ PROGRAM

Ex-Post and Ex-Ante Load Impacts

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[redacted] *Confidential content removed and blacked out.*

Report prepared for:
PACIFIC GAS & ELECTRIC COMPANY

Energy Solutions. Delivered.

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ABSTRACT

This report documents the load impact evaluation of the residential SmartRate™ program operated by Pacific Gas and Electric (PG&E) for Program Year 2020 (PY2020). The primary goals of this evaluation study are to 1) estimate the ex-post load impacts for PY2020, and 2) estimate ex-ante load impacts for the programs for years 2021 through 2031.

SmartRate™ is a voluntary critical peak pricing program that overlays a customer's existing electric rate. The peak pricing signals are designed to lower summer electricity costs for customers and conserve California's power grid. During the summer season (June through September), customers receive an energy credit for usage on non-event day off-peak hours. On SmartDays™ (i.e., SmartRate™ events), participants are charged a peak price over their regular rate during the peak period (2 to 7 PM). During their first full summer season of program enrollment (and any preceding partial season), customers are backed by PG&E's Bill Protection Guarantee that refunds customers if their SmartRate™ costs are more than their regular residential pricing plan.

The program calls a minimum of 9 and a maximum of 15 SmartDays™ in a year. SmartDays™ can be called year-round but are typically called on summer weekdays. In PY2020, PG&E called 12 events occurring between June and September. PG&E provides customers with day-ahead notification of SmartDays™ via phone, text, or email to allow customers to plan for reducing their energy use or shifting their load during event hours.

AEG estimated hourly ex-post load impacts for each event during 2020, using regression analysis of subgroup-level hourly load, weather, and event data. The estimated load impacts are reported for each event and the average event day. Load impacts are also reported by CAISO local capacity area (LCA), dual enrollment to SmartAC™, bill protection status, CARE enrollment, medical baseline status, and TOU enrollment. The estimated aggregate ex-post load impact for an average event day is 12.3 MW.

AEG developed ex-ante load impact forecasts by combining enrollment forecasts provided by PG&E and per customer load impacts generated from the analysis of current ex-post load impact estimates. The forecast numbers of enrolled service accounts and aggregate ex-ante load impacts presented in the report reflect several program changes expected to take place beginning in 2022. AEG also estimated and incorporated the current and future impacts of COVID-19 conditions in the ex-ante forecast. The estimated aggregate ex-ante load impacts for a typical event day in 2021 for a PG&E 1-in-2 weather scenario is 4.8 MW during the resource adequacy (RA) window (4 to 9 PM).

EXECUTIVE SUMMARY

This report documents the load impact evaluation of the residential SmartRate™ program operated by Pacific Gas and Electric (PG&E) for Program Year 2020 (PY2020). SmartRate™ is a voluntary critical peak pricing program that overlays a customer's electric rate designed to lower summer electricity costs for customers and conserve California's power grid. During the summer season (June through September), customers receive an energy credit for usage on non-event day off-peak hours. On SmartDays™ (i.e., SmartRate™ events), participants are charged a peak price over their regular rate during the peak period (2 to 7 PM). The program calls a minimum of 9 and a maximum of 15 SmartDays™ in a year. SmartDays™ can be called year-round but are typically called on summer weekdays. PG&E provides customers with day-ahead notification of SmartDays™ via phone, text, or email to allow customers to plan for reducing their energy use or shifting their load during event hours.

Research Objectives

The study's key objectives are to estimate both ex-post and ex-ante load impacts for the residential SmartRate™ program, complying with the California DR Load Impact Protocols.[1] More specifically,

- This report presents PY2020 hourly and daily ex-post load impact estimates for each SmartDay™ for the average customer and all participants in aggregate. Ex-post results also include impacts at the program level and the following: dual enrollment in SmartAC™, each local capacity area (LCA), CARE enrollment, bill protection status, TOU enrollment, and medical baseline status, along with the distribution of impacts for each segment.
- This report presents ex-ante impact estimates for each year over an 11-year time horizon based on PG&E's and CAISO's 1-in-2 and 1-in-10 weather conditions for a typical event day and each monthly system peak day both at the program and portfolio[2] level. Ex-ante results also include impact estimates at the program level and the following: LCA and dual enrollment in SmartAC™ for both an average participant and all participants in aggregate for all program operating hours and the resource adequacy (RA) window (4 PM to 9 PM).

In addition to this study's key objectives, PG&E expressed interest in the following issues:

- Potential effects of Shelter-in-Place (SIP) conditions on both ex-post and ex-ante load impacts;
- The effect of bill protection on load impacts and bill impacts; and
- Further exploration of load impacts from TOU enrollment.

Program Description

SmartRate™ is a voluntary critical peak pricing program that overlays a customer's electric rate and is designed to lower summer electricity costs for customers and conserve California's power grid. Customers receive a credit of approximately $0.024 per kWh from June 1 to September 30 except for SmartDays™ (i.e., SmartRate™ events) between 2 PM and 7 PM. On SmartDays™, customers are charged a peak-price of $0.60 per kWh over their regular rate during peak periods (2 to 7 PM). Customers receive an extra

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[1] *Attachment A. Load Impact Estimation for Demand Response: Protocols and Regulatory Guidance*, California Public Utilities Commission, Energy Division, April 2008.

[2] Portfolio level impacts exclude the load impacts from dually enrolled participants attributed to concurrent SmartAC events.

participation credit of $0.0075 for all usage above baseline (Tier 1) during the billing cycles, including June 1 through September 30. These credits are adjusted slightly for customers on an E-TOU-B rate.

PG&E provides customers with day-ahead notification of SmartDays™ via phone, text, or email to allow customers to plan for reducing their energy use or shifting their load during event hours. During their first full summer season (May through October) of program enrollment (and any preceding partial season), customers are backed by PG&E's Bill Protection Guarantee that refunds customers if their SmartRate™ costs are more than their regular residential pricing plan. PG&E would credit the difference on the customer's November bill if they did not save on SmartRate™.

Table ES-1 PY2020 SmartDays™

Date	Day of Week
June 24	Wednesday
June 25	Thursday
July 27	Monday
July 28	Tuesday
July 30	Thursday
August 10	Monday
August 13	Thursday
August 14	Friday
August 17	Monday
August 18	Tuesday
August 19	Wednesday
September 6	Sunday

The program calls a minimum of 9 and a maximum of 15 SmartDays™ in a year. SmartDays™ can be called year-round but are typically called on summer weekdays. Table ES-1 to the right summarizes the events called by PG&E in PY2020. PG&E called a total of 12 SmartDays™ between June 1st and September 30th, including one weekend event on September 6th (highlighted in red font). High temperatures, CAISO alerts, and other factors, including Public Safety Power Shutoff (PSPS) activity (to minimize demands on the customer service center, web, and meteorology teams and avoid unnecessary communications with impacted customers), influence event dispatches.

Changes anticipated to impact the SmartRate™ program are as follows:

- SmartRate™ is currently available to customers both on the standard rate (E-1) and some TOU rates. Residential customers are in the process of defaulting onto the TOU rate. In PY2021, customers will transition to the TOU rate in waves of around 250k per month. All residential customers (excluding customers that opt-out) are expected to be on the TOU rate by PY2022. SmartRate™ participants for PY2020 and PY2021 receive service under a combination of underlying rates, while majority of participants will be on a TOU rate by PY2022.
- The SmartRate™ event window is already approved to shift to 5 PM – 8 PM, but this change is not effective until PY2022.[3] The event window will remain at 2 PM –7 PM in PY2020 and PY2021.

[3] Pending CPUC decision for R.20-11-003, the SmartRate™ event window is expected to be modified to 4 to 9 PM at a later point.

Ex-Post Load Impacts

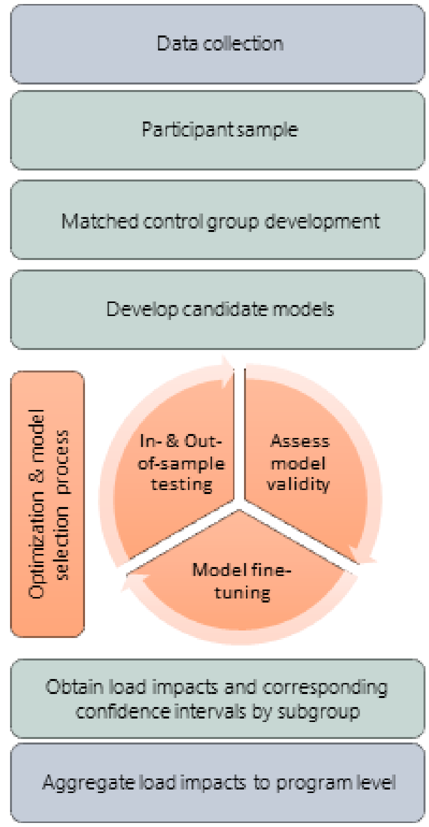
The study method and summary results of the ex-post analysis are presented below.

Methods

Figure ES-1 to the right outlines our approach to the ex-post analysis. The basic structure is one that we've used in previous California Statewide C&I DR evaluations; however, we implemented several modifications appropriate to a residential DR program and to account for PY2020's unique conditions:

- We limited data used to PY2020 data (June 2020 – September 2020) to estimate PY2020 ex-post impacts to account for the unique circumstances due to COVID-19 and SIP conditions.
- We utilized a sampling approach to limit the amount of data required to perform the analysis. AEG used a segmented sampling approach aligned with the chosen regression modeling approach. We also used a segmented approach in matched control group development.
- We used a simplified version of the optimization process compared to the method used in C&I DR evaluations. The optimization process served as a starting point to our model selection, leveraging automated algorithms that we have developed for previous C&I DR evaluations. The optimization process also played a crucial role in assessing model validity.

Figure ES-1 Ex-Post Analysis Approach



Results

Table ES-2 below summarizes the overall program level event-hour impacts on each event, including the number of participants enrolled during each SmartDay™, the aggregate reference load and load impacts, the percent impact, and the average temperature. Load impacts as a percent of the reference load were 8.0%, on average, across the twelve events.

Table ES-2 All Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
June 24	65,761	145.2	11.0	7.6%	93
June 25	65,685	152.9	11.2	7.3%	94
July 27	65,023	140.6	10.8	7.7%	92
July 28	64,993	144.1	10.9	7.6%	93
July 30	64,950	138.8	10.7	7.7%	92

Event Date	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
August 10	64,608	149.1	10.9	7.3%	93
August 13	64,553	135.6	11.5	8.5%	96
August 14*	64,530	172.4	16.4	9.5%	102
August 17*	64,414	168.6	13.3	7.9%	97
August 18*	64,347	176.8	14.2	8.0%	100
August 19*	64,295	149.8	12.7	8.5%	96
September 6*	63,864	171.9	14.5	8.4%	104
Typical Event Day	**64,752**	**153.8**	**12.3**	**8.0%**	**96**

* Concurrent SmartAC events were called for various combinations of Sub-LAPs and event hours.

Figure ES-2 presents the average event-hour ex-post load impacts for each event day for all SmartRate™ participants. The green bars indicate the magnitude of the aggregate load impact, and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours. These results indicate that participants had statistically significant load reductions on all twelve SmartDays™, ranging from 10.7 to 16.4 MW. These results also demonstrate weather-sensitivity, with the green bars moving up/down with the orange line. The average load impact was 12.3 MW, with five out of twelve event days having a load impact greater than 12 MW. These five high-performing SmartDays™ had concurrent SmartAC™ events and called for various combinations of Sub-LAPs and event hours. These five events are highlighted in a light gray box in the figure below.

Figure ES-2 All Participants: Average Event-Hour Impacts by Event

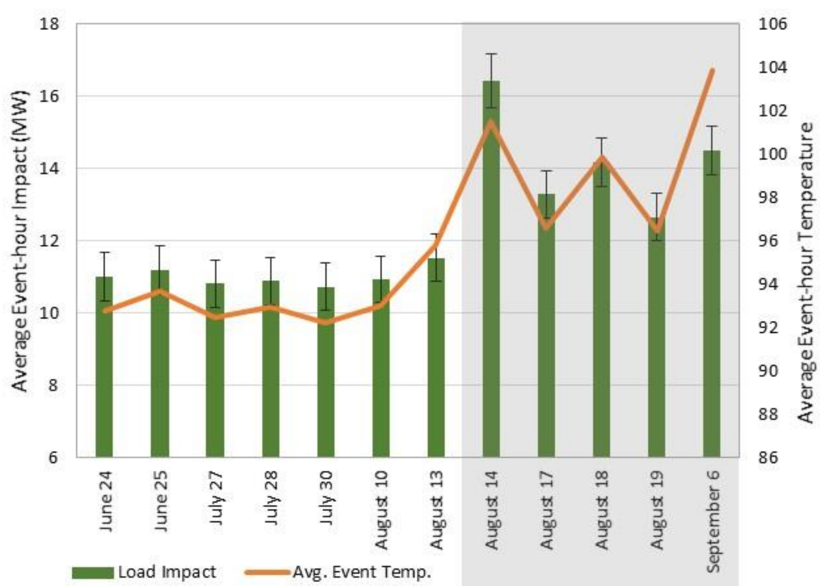


Figure ES-3 presents the total load impact contributions by LCA on a typical event day. The "Other or Unknown" category contributes the most load impacts (3.5 MW), on average, followed by the Greater Fresno Area (2.9 MW).

Figure ES-3 Contributions by LCA on a Typical Event Day

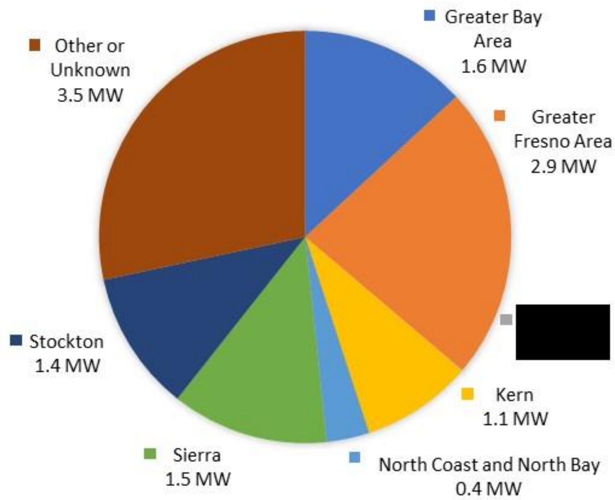
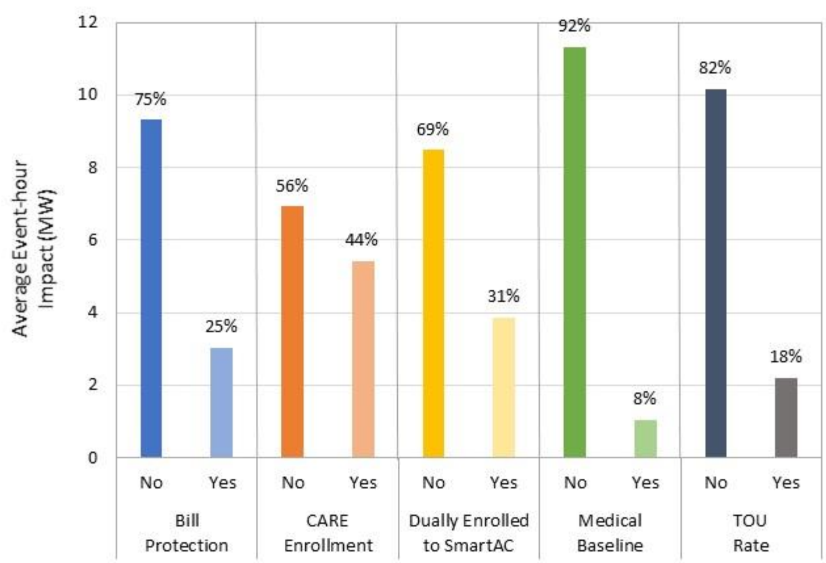


Figure ES-4 presents the total load impact contributions and the corresponding percentages, based on status ("yes" vs. "no") within each subgroup on a typical event day. For each subgroup, the share of aggregate load impacts is driven mainly by enrollment regardless of differences in per customer load impacts. The analysis showed differences in per customer impacts due to bill protection status, dual enrollment in SmartAC™, and TOU enrollment. The study showed minimal[4] differences in per customers impacts due to CARE enrollment and medical baseline status.

Figure ES-4 Contributions by Subgroup on a Typical Event Day



[4] CARE enrollment showed no statistically significant difference in per customer load impacts, while medical baseline status showed very small yet statistically significant differences in per customer load impacts.

Ex-Ante Load Impacts

The study method and summary results of the ex-ante analysis are presented below.

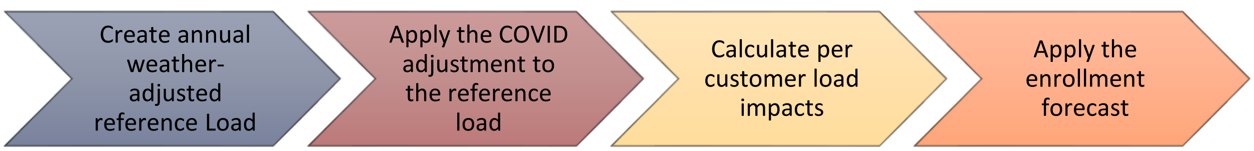
Methods

The uniqueness of 2020 added to the complexity of developing 11-year forecasts. AEG first performed a comparative analysis between PY2019 and PY2020, focusing on both the per customer impacts and the reference loads. The results of the comparative analysis informed the ultimate ex-ante approach presented in Figure ES-5 below.

Implications of Shelter-in-Place (SIP) Conditions. We performed a comparative analysis to understand the potential effects of COVID-19 and SIP conditions on SmartDays™ by looking at the differences in impacts and reference loads between PY2019 and PY2020. This analysis provided insight into both the development of the enrollment forecast and the appropriateness of PY2020 ex-post impacts in forecast development. Results from the comparative analysis indicated the following:

- AEG did not find significant differences in participant load impacts and did not make any additional adjustments to account for COVID-19 and SIP conditions.
- AEG found that the overall average customer usage (reference loads) increased due to COVID-19 and SIP conditions. AEG incorporated PG&E's internal forecast that removes the COVID effect over time.

Figure ES-5 Ex-Ante Analysis Approach



Ex-Ante Analysis. As noted above, the analyses of SIP implications, current events, and internal PG&E forecasts determined that additional adjustments on the average customer reference load were appropriate. AEG made adjustments as follows:

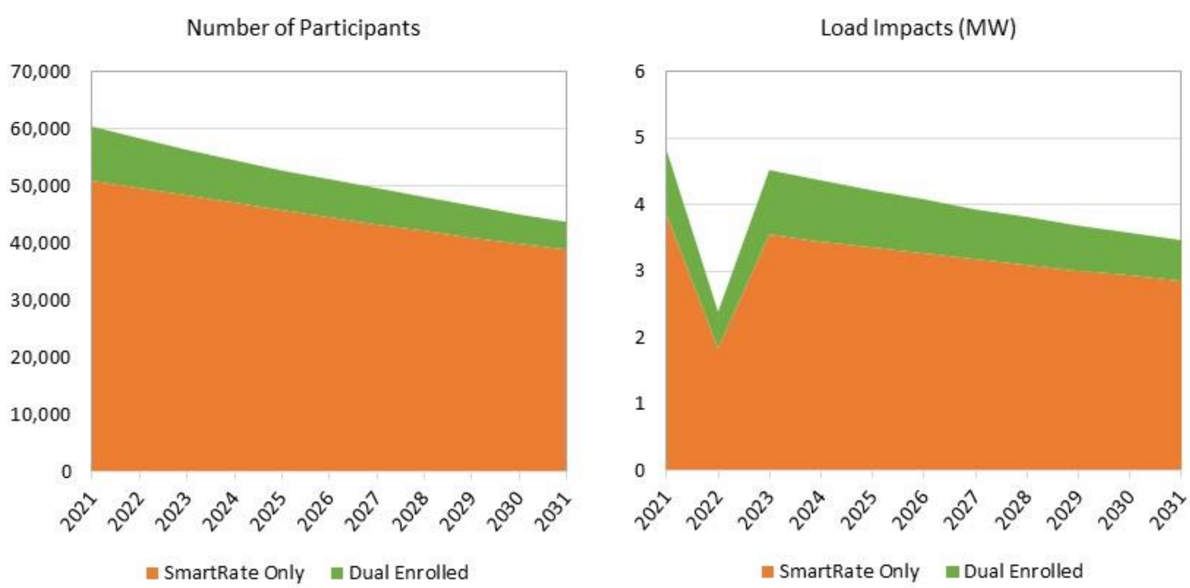
- Calculated the average customer pre-SIP reference load for each day type and weather condition.
- Applied PG&E's residential COVID adjustment to determine the adjusted average customer reference load for each year, day type, and weather condition.
- Adjusted the average customer load impact for each year, day type, and weather condition as a percent of the adjusted customer reference load.
- Shifted the event window to 5 to 8 PM starting April 2022.
- Multiplied the annual per customer impacts by the enrollment forecast to arrive at an aggregate forecast.

Results

While the analysis of COVID-19 and SIP conditions on SmartRate™ participants did not show evidence of significant differences in participant load impacts, we found that SmartRate™ participants, like most residential customers, saw an overall increase in their regular usage, i.e., reference loads. AEG estimated the effect of COVID-19 and SIP conditions on the per customer reference loads and used the estimated effect to adjust the ex-ante forecast of the reference load. The purpose of the adjustment is to bring the reference load back to a level representing a no-COVID world over time. The adjusted reference load decreases relative to the unadjusted load in later years, representing a return to "normal" or a no-COVID state.

In Figure ES-6 below, we present side-by-side comparisons of PG&E's 11-year annual enrollment and impact forecasts for the PG&E 1-in-2 weather scenario on a typical event day. The forecast is segmented by enrollment: singly versus dually enrolled. PG&E expects a decrease in enrollment over time with no marketing-derivied enrolled expected for future years.[5] PG&E forecasts approximately 61k participants in 2021, slowly decreasing to 44k participants in 2031. Under PG&E 1-in-2 weather conditions, PG&E estimates a 4.8 MW total load impact during the RA window on a typical event day in 2021. Also, effective in April 2022 is a new event window that is shifted but still three hours coincident with the RA window. We assume a 50% decrease in load impacts in the first year of the new event window to account for the "learning curve" as participants adjust their behaviors. From the second year, 2023, we assume that load impacts will return to normal levels.

Figure ES-6 Enrollment and Impact Forecast: PG&E 1-in-2, Typical Event Day, 2021 - 2031



Recommendations

AEG developed the following recommendations for future research and evaluation related to PG&E's residential SmartRate™ program.

- Incorporate TOU enrollment as a sampling and modeling segment as TOU defaulting rolls out and the share of TOU enrollment increases among SmartRate™ participants. This modification can

[5] PG&E plans to reengage marketing efforts in PY2022, but it is not currently reflected in the enrollment forecast.

accommodate additional ex-post modeling assumptions, i.e., accounting for different TOU peak periods, which can produce more accurate load impact estimates.

- Use LCA definitions instead of weather station assignments for matched control group development. LCA definitions accomplish similar geographically-targeted matching done by weather station assignments while also allowing analysis flexibility in LCA-specific reporting.
    - Attempt to correctly classify participants in the "Other or Unknown" category to allow more accurate LCA-specific reporting.
- Remove medical baseline status as a sampling and modeling segment since the ex-post analysis did not find significantly different responses from the medical baseline participants.
- Utilize year-round hourly usage data for more accurate ex-ante load impact estimates in the non-summer months.

AEG also developed one programmatic recommendation for PG&E's consideration in future program years.

- PG&E's program management team may wish to consider the cost-effectiveness of enabling SmartRate™ event signals to communicate with smart thermostats such as Nest and Ecobee to facilitate thermostat setbacks during events. The additional technological assistance will enhance impacts and expand the existing savings strategies already employed by thermostat vendors to facilitate shifting on TOU rates. These setback strategies will also increase impacts at the population level that may be falling over time, given that new dual enrollment in SmartAC is no longer available.

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1

INTRODUCTION

This report documents the program year 2020 (PY2020) load impact evaluation of the residential SmartRate™ program offered by Pacific Gas & Electric (PG&E).

Research Objectives

The study's key objectives are to estimate both ex-post and ex-ante load impacts for the residential SmartRate™ program, complying with the California DR Load Impact Protocols.[6] More specifically,

- This report presents PY2020 hourly and daily ex-post load impact estimates for each SmartDay™ for the average customer and all participants in aggregate. Ex-post results also include impacts at the program level and the following: dual enrollment in SmartAC™, each local capacity area (LCA), CARE enrollment, bill protection status, TOU enrollment, and medical baseline status, along with the distribution of impacts for each segment.
- This report presents ex-ante impact estimates for each year over an 11-year time horizon based on PG&E's and CAISO's 1-in-2 and 1-in-10 weather conditions for a typical event day and each monthly system peak day both at the program and portfolio[7] level. Ex-ante results also include impact estimates at the program level and the following: LCA and dual enrollment in SmartAC™ for both an average participant and all participants in aggregate for all program operating hours and the resource adequacy (RA) window (4 PM to 9 PM).

Additional Research Objectives

In addition to this study's key objectives, PG&E expressed interest in the following issues:

- Potential effects of Shelter-in-Place (SIP) conditions on both ex-post and ex-ante load impacts;
- The effect of bill protection on load impacts and bill impacts; and
- Further exploration of load impacts from TOU enrollment.

The methods used in addressing these additional issues are described in Section 3. Results are presented in Sections 4 and 5, as appropriate. Findings related to additional analyses are presented in Section 6.

The Conservation Effect

The scope outlined in the request for proposal (RFP) also expressed interest in estimating the conservation effect or the impacts on non-SmartDays™ due to SmartRate™ enrollment. After conversations with PG&E and reevaluation of the methodology, the research team decided to delay this analysis for the following reasons.

- Matched control group development based on 2019 data may introduce bias given that customers potentially changed their overall usage patterns under SIP conditions. In other words, a participant's pretreatment period match may not result in an appropriate PY2020 match.

[6] *Attachment A. Load Impact Estimation for Demand Response: Protocols and Regulatory Guidance*, California Public Utilities Commission, Energy Division, April 2008.

[7] Portfolio level impacts exclude the load impacts from dually enrolled participants attributed to concurrent SmartAC events.

- Attempts to estimate the conservation effect based on PY2020 usage can potentially result in zero or negative impacts since analyses of SIP conditions indicate an overall increase in residential consumption.
- Finally, isolating behavioral effects like the conservation effect will be extremely difficult due to simultaneous behavioral changes driven by different factors.

AEG will work with PG&E to determine the appropriate approach and timing[8] of addressing this research objective.

Report Organization

The remainder of this report is organized into the following sections:

- Section 2 describes the SmartRate™ program as PG&E implements it. The section also presents information regarding the total number of accounts enrolled in the program.
- Section 3 describes the methods used to estimate the ex-post and ex-ante impacts for the 2020 program year.
- Section 4 presents the ex-post impact evaluation results.
- Section 5 presents the ex-ante impact evaluation results.
- Section 6 presents key findings and recommendations.

[8] This research objective can potentially be addressed outside of the evaluation season or in succeeding program years (PY2021 or PY2022) under AEG's current contractual agreement.

2

PROGRAM DESCRIPTION

This section describes the PY2020 SmartRate™ program implementation along with any changes to the program since PY2019. We also present information regarding the PY2020 event days and the total number of participants.

Program Implementation

SmartRate™ is a voluntary critical peak pricing program that overlays a customer's electric rate designed to lower summer electricity costs for customers and conserve California's power grid. Customers receive a credit of approximately $0.024 per kWh from June 1 to September 30 except for SmartDays™ (i.e., SmartRate™ events) between 2 pm and 7 pm. On SmartDays™, customers are charged a peak-price of $0.60 per kWh over their regular rate during peak periods (2 to 7 PM). Customers receive an extra participation credit of $0.0075 for all usage above baseline (Tier 1) during the billing cycles, including June 1 through September 30. These credits are adjusted slightly for customers on an E-TOU-B rate.

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Table 2-1 PY2020 SmartDays™

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PY2020 Event Days

Table 2-1 to the right summarizes the events called by PG&E in PY2020. PG&E called a total of 12 SmartDays™ between June 1st and September 30th, including one weekend event on September 6th (highlighted in red font).

Program Changes

Changes anticipated to impact the SmartRate™ program are as follows:

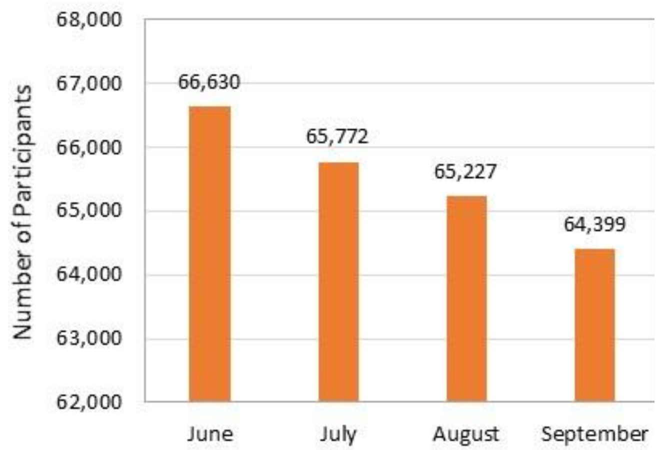
- SmartRate™ is currently available to customers both on the standard rate (E-1) and some TOU rates. Residential customers are in the process of defaulting onto the TOU rate. In PY2021, will transition to the TOU rate in waves of around 250k per month. All residential customers (excluding customers that opt-out) are expected to be on the TOU rate by PY2022. SmartRate™ participants for PY2020 and PY2021 receive service under a combination of underlying rates, while majority of participants will be on a TOU rate by PY2022.

- The SmartRate™ event window is already approved to shift to 5 PM – 8 PM, but this change is not effective until PY2022.[9] The event window will remain at 2 PM –7 PM in PY2020 and PY2021.

PY2020 Participation

A total of 68,209 unique customers participated in at least one SmartDay™ in the PY2020 season. SmartRate™ saw an average of 500 new enrollments and 1,000 unenrollments[10] each month, showing a slight decrease in participation through the season, as shown in Figure 2-1.

Figure 2-1 SmartRate™ PY2020 Monthly Enrollment

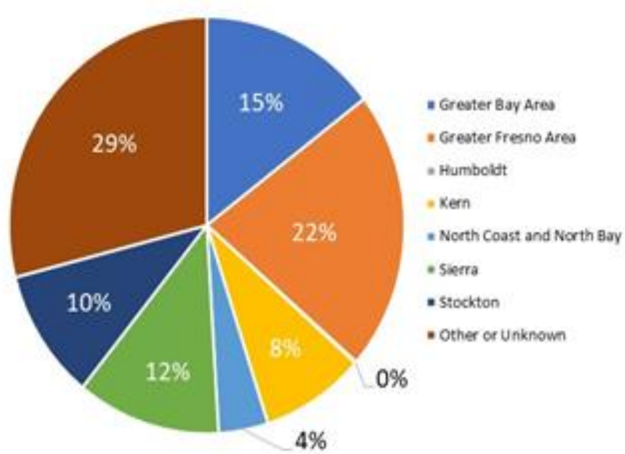


Next, we present the enrollment distribution of SmartRate™ participants in each of PG&E's eight local capacity areas or LCA. As shown in Table 2-2 and Figure 2-2, the Greater Fresno Area has the largest share of SmartRate™ enrollment (22%). Notably, 29% of participants are categorized as "Other or Unknown."

Table 2-2 Enrollment by LCA

LCA	# of Accounts
Greater Bay Area	9,976
Greater Fresno Area	14,843
Humboldt	76
Kern	5,801
North Coast and North Bay	2,761
Sierra	8,028
Stockton	6,927
Other or Unknown	19,797

Figure 2-2 Enrollment by LCA



Finally, we present the enrollment distribution of SmartRate™ participants in each subgroup of interest: bill protection status, CARE enrollment, dual enrollment[11] to SmartAC™, medical baseline status, and TOU enrollment.

[9] Pending CPUC decision for R.20-11-003, the SmartRate™ event window is expected to be modified to 4 to 9 PM at a later point.

[10] CCA customers are ineligible to participate in SmartRate™.

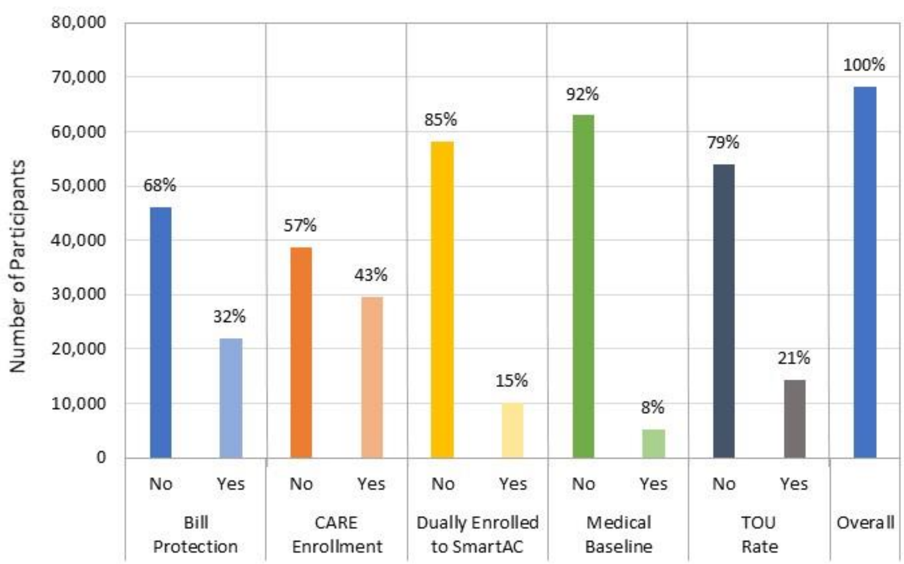
[11] Dual enrollment is not currently available to new participants. All dually enrolled participants enrolled in both programs before October 26th, 2018.

Table 2-3 shows the counts of unique participants by subgroup. Figure 2-3 illustrates the share of enrollment and the corresponding percent of total enrollment by subgrouping. For reference, the overall enrollment count is also shown (100%).

Table 2-3 Enrollment by Subgroup

Subgroup	Status	# of Accts
Bill Protection	No	46,199
	Yes	22,010
CARE Enrollment	No	38,671
	Yes	29,538
Dually Enrolled in SmartAC™	No	58,126
	Yes	10,083
Medical Baseline	No	62,978
	Yes	5,231
TOU Rate	No	53,909
	Yes	14,300

Figure 2-3 Enrollment by Subgroup



3

STUDY METHODS

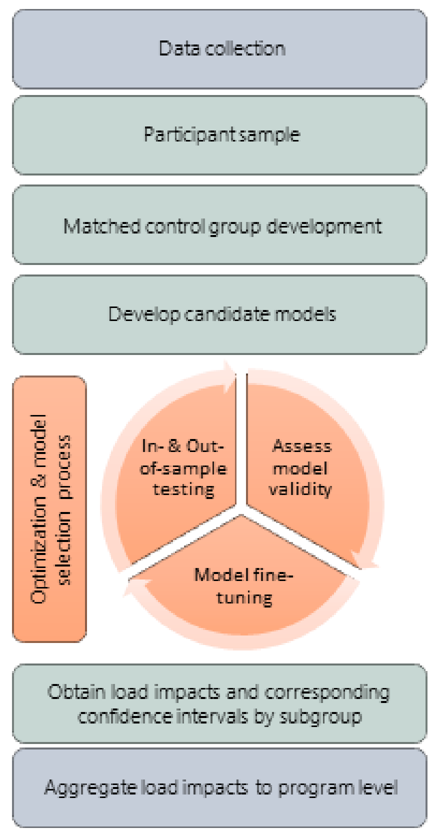
Overall Method

In this section, we first describe AEG's approach to the analysis at a high-level. Then, we present our detailed approach.

Overview of the Ex-post Analysis

Figure 3-1 to the right outlines our approach to the ex-post analysis. The basic structure is one that we've used in previous California Statewide C&I DR evaluations; however, we modified the system to be appropriate to a residential DR program, including simplifying and streamlining the approach to leverage tried-and-true algorithms, without over-complicating the modeling process. For each of the steps outlined in the figure, the following are the essential modifications that make our approach unique to the SmartRate™ program. We discuss each step in detail in subsequent sections.

Figure 3-1 Ex-Post Analysis Approach



Data Collection. We limited the data used in the study to PY2020 data (June 2020 – September 2020). The limitation allowed us to treat PY2020 as a unique period, estimating the impacts of SmartRate™ relative to current conditions.

Participant Sample Development. PY2020 had approximately 65k participants in the SmartRate™ program. We utilized a sampling approach to limit the amount of data required to perform the analysis. AEG used a segmented sampling approach aligned with the chosen regression modeling approach. The sample included the following segments: medical baseline status, bill protection status, dual enrollment to SmartAC™, and single enrollment to SmartRate™.

Matched Control Group Development. To create the matched control group, we used a Stratified Euclidean Distance Matching (SEDM) technique. Working with PG&E, AEG used weather station and CARE status as strata within each sample segment (above). AEG requested an eligible control pool with a 1:10 participant to control ratio within each stratum based on participant sample counts.

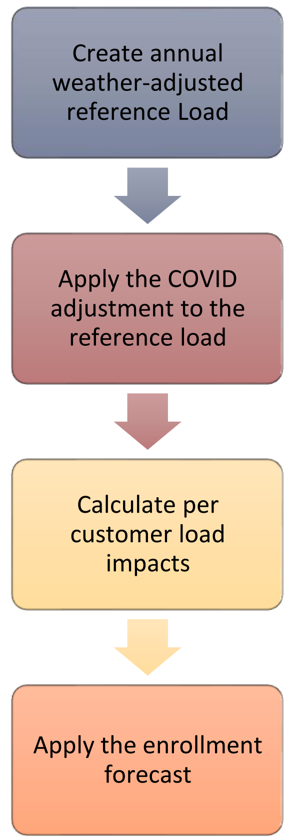
Model Optimization and Selection Process. We used a simplified version of the optimization process wherein each model segment needed approximately five candidate models, and the "best" model served as a starting point to our model selection. The optimization process also played a crucial role in assessing model validity to justify our confidence in our impact estimates.

Obtaining Impact Estimates and Confidence Intervals. The methodology for obtaining estimates is relatively straightforward, we leveraged algorithms designed specifically to address the CPUC LI Protocol requirements.

Overview of the Ex-ante Analysis

The uniqueness of 2020 added to the complexity of developing 11-year forecasts. AEG first performed a comparative analysis between PY2019 and PY2020, focusing on both the per customer impacts and the reference loads. The comparative analysis results informed the ultimate ex-ante approach presented in Figure 3-2 to the right.

Figure 3-2 Ex-Ante Analysis Approach



Implications of Shelter-in-Place (SIP) Conditions. We performed a comparative analysis to understand the potential effects of COVID-19 and SIP conditions on SmartDays™ by looking at the differences in impacts and reference loads between PY2019 and PY2020. This analysis provided insight into both the development of the enrollment forecast and the appropriateness of PY2020 ex-post impacts in forecast development. Results from the comparative analysis indicated the following:

- AEG did not find significant differences in participant load impacts and did not make any additional adjustments to account for COVID-19 and SIP conditions.
- AEG found that the overall average customer usage, i.e., participant reference loads, increased due to COVID-19 and SIP conditions. AEG incorporated PG&E's internal forecast that removes the COVID effect over time.

Ex-Ante Analysis. As noted above, the analyses of SIP implications, current events, and internal PG&E forecasts determined that additional adjustments on the average customer reference load were appropriate. AEG made adjustments as follows:

- Calculated the average customer pre-SIP reference load for each day type and weather condition.
- Applied PG&E's residential COVID adjustment to determine the adjusted average customer reference load for each year, day type, and weather condition.
- Adjusted the average customer load impact for each year, day type, and weather condition as a percent of the adjusted customer reference load.
- Shifted the event window to 5 to 8 PM starting April 2022.
- Multiplied the annual per customer impacts by the enrollment forecast to arrive at an aggregate forecast.

Ex-Post Load Impact Analysis

In the subsections that follow, we describe the ex-post analysis steps in more detail.

Data Collection and Validation

The comprehensive data provided by PG&E included the following items:

- SmartRate™ participant and eligible control group customer information: DR program enrollment, LCA indicator, CARE-status, bill protection status, and weather station indicator,
- Billing data: tariff, billed consumption, billed amount, and program credits,
- Participant and eligible control group hourly interval data that has undergone standard billing VEE processes during the appropriate program periods,
- Outage or PSPS day data,
- Hourly weather data for the appropriate program periods by weather station,
- SmartRate™ and SmartAC™ event data,
- Monthly peak day and typical event day hourly weather for PG&E and CAISO 1-in-2 weather year and 1-in-10 weather year, and
- Eleven-year enrollment forecast data by LCA and dual enrollment to SmartAC™.

Data Validation. We reviewed the data received from PG&E to make sure it corresponded to the data request and was complete. We also validated all interval data using algorithms we developed to detect issues such as zero intervals, missing intervals, peaks, valleys, and erroneous intervals.

Sample Development

In the interest of efficiency, AEG utilized a sampling approach to limit the amount of data requested and received. Since regression models were estimated at the segment level, the sample was designed based on this subgrouping. We pulled a sample of 3,000 customers from each of the following segments:

- Participants identified as medical baseline,
- Participants under Bill Protection Guarantee,
- Participants dually enrolled in SmartAC™, and
- Participants singly enrolled in SmartRate™.

Matched Control Group Development

Event-like Day Selection

The selection of comparable non-SmartDays™ or event-like days is essential to several of the evaluation activities. These days are used in the matched control group development and the out-of-sample testing in model optimization and validation.

The event-like days included twelve days comparable to called SmartDays™ in weather, day of the week and month of the year. We use these days to match treatment customers to control customers with similar usage on event-like days and therefore also on SmartDays™. Due to the unique circumstances in PY2020, we selected the event-like days within the same year.[12]

We used a Euclidean distance metric (similar to what we describe below) to select days that are as similar as possible to actual SmartDays™ using multiple weather-based criteria.[13]

Matched Control Group

To create the matched control group, we used a Stratified Euclidean Distance Matching (SEDM) technique. The necessary steps are as follows.

Step 1 is to define both the participant and non-participant populations and the treatment and pre-treatment periods[14] for each participant. Once the participant and non-participant populations are identified, both populations can be assigned to strata or filters that are categorical in nature. For SmartRate™ participants, we used weather station assignment and CARE status as filters. This ensured that customers with similar usage characteristics were matched to one another, capturing some of the unobservable attributes that affect how customers use energy.

Step 2 is to perform the one-to-one match based on hourly demand data of comparable event-like days. To determine how close each participant is to a potential match, we used a Euclidean distance metric. The Euclidean distance is defined as the square root of the sum of the squared differences between the matching variables. Any number of relevant variables could be included in the Euclidean distance. For this one-to-one match, we included three types of demand variables:

- The average demand on event-like days during the event window,
- The demand on event-like days during the typical system peak hour (HE18),
- And the average demand on event-like days during the hours outside[15] the event window.

We then weighted the variables to reflect the relative importance of the estimates, with the typical system peak hour having the most weight and the average demand outside the typical event window having the least weight. The Euclidean distance for this set of variables can be calculated using the equation below.

$$ED = \sqrt{\begin{array}{r} w_1(avgevnt_{Ti} - avgevnt_{Ci})^2 + \; w_2(systempeak_{Ti} - systempeak_{Ci})^2 \\ + \, w_3(avgnonevnt_{Ti} - avgnonevnt_{Ci})^2 \end{array}}$$

After calculating each group's distance metric for each possible combination of participant and control customer, the control customer with the smallest distance is matched to each participant without replacement. We can then select the closest matches[16] for each of our participants, creating a one-to-one

[12] AEG also selected nine PY2019 event-like days that will be used in the SIP Impact Analysis under the Ex-ante Analysis. These were selected from PY2019 non-SmartDays™ based on their match to PY2019 SmartDays™.

[13] We included three weather variables in the Euclidean distance metrics calculation to select similar non-event days: (1) daily maximum temperature; (2) daily minimum temperatures; and (3) average daily temperature. We will work with each IOU to determine which weather variables are best suited for selecting days that are most similar to event days. In PY2019, the Euclidean distance metric used was calculated by the following equation:

$$ED = \sqrt{(MaxTemp_{event} - MaxTemp_{non-event})^2 + (MinTemp_{event} - MinTemp_{non-event})^2 + (MeanTemp_{event} - MeanTemp_{non-event})^2}$$

[14] We define the treatment periods as the event days and the pre-treatment period as the event-like days.

[15] The window can be one or more of the following: HE5-HE8, HE9-HE13, HE15-HE19, HE20-HE21, and HE23-HE24.

[16] The closest match is defined by a control customer with an ED with the smallest distance to a participant's ED. If two or more participants share the same closest match, the participant that is "worst off" will "win" its closest match. This is determined by checking the ED's for the second closest matches for each participant.

match of control customers to participants. Once the matching process is complete, we validate the match by using the appropriate t-tests and visual inspection of the event-like day load shapes.

Develop Candidate Regression Models

AEG estimated hourly regression models, which allowed us to estimate the impact of SmartDays™ independently in each hour. For all 24 fitted models, we used the same set of independent variables and referred to them as one model. This approach allowed us to estimate seasonality[17] consistently through each hour of the day and estimate seasonality independently in each hour.

We can think of regression models as being made up of building blocks, including one or more explanatory variables. These different sets of variables can be combined in various ways to represent different types of customers. The blocks can be generally categorized into either "baseline" variables or "impact" variables and could consist of a single variable (e.g., cooling degree hours, CDH) or groups of variables (e.g., days of the week). The baseline portion of the model explains variation in usage unrelated to demand response events, while the impact portion explains the variation in use related to a DR event.[18]

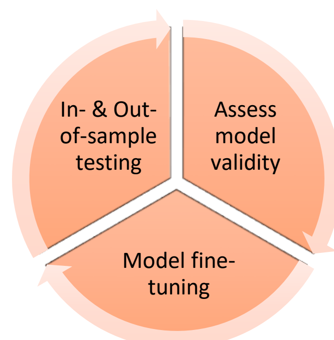
The building blocks were combined in various ways to create a set of candidate models representing a wide variety of customers and their impacts. We used our judgment and experience and worked closely with PG&E to develop an initial set of 5 to 10 models.

Optimization and Model Selection Process

Our optimization process included the validation of the hourly segment regression models and was designed to:

- Accurately predict the actual participant load on SmartDays™, and
- Accurately predict the reference load, or what customers would have used on SmartDays™ in the absence of an event.

Figure 3-3 Model Optimization and Selection Process



To meet these two specific goals, the optimization process included a three-part cycle consisting of the following steps: (1) In-sample and out-of-sample testing; (2) assessing model validity; and (3) model fine-tuning. After fitting each candidate model to a segment, we selected the best model through an optimization process described below. Results were estimated at the smallest segment level required in the CPUC LI Protocols and aggregated to the various segments of interest.

In-Sample and Out-of-Sample Testing

We used in-sample tests to show how well each model performs on the actual SmartDays™, helping us understand how well the model matched the actual load. We used out-of-sample tests to show how well each of the candidate models could predict a customer's load on non-SmartDays™ that were as similar as

[17] An example of seasonality would be using weekday v. weekend indicators in all hourly models. This means that we are assuming all hours have weekday v. weekend usage patterns, but the magnitude, i.e., coefficient estimate, of the weekday v. weekend usage patterns are unique to each hour.

[18] Any unexplained variation will end up in the error term.

possible to actual SmartDays™, giving us an estimate of how well each model could predict the reference load.

To perform the in-sample test, we fit each candidate model to the entire data set. The results of these fitted models predict the usage on SmartDays™. Then we assessed the accuracy and bias of the predictions by calculating the mean absolute percent error (MAPE)[19] and mean percent error (MPE)[20], respectively. We refer to these metrics as the in-sample MAPE and MPE.

To perform the out-of-sample test, we first identified the out-of-sample event-like days as several days similar to SmartDays™. For efficiency and consistency, we used the same event-like days used in matched control group development. After identifying the event-like days, we removed them from the analysis dataset and fit the candidate models to the remaining data. We used the results of these fitted models to predict the usage on event-like days. Lastly, we assessed the accuracy and bias of the event-like day predictions by calculating the MAPE and MPE, respectively. Similarly, we refer to these metrics as the out-of-sample MAPE and MPE.

These two tests result in several in-sample and out-of-sample metrics. Recall that the tests' goal is to find the best model for each segment in terms of its ability to predict the reference load and the actual load for each segment. Therefore, we combined the two tests into a single metric. The metric used is defined as follows:

$$\boldsymbol{metric_{ic}} = (0.4 * MAPE_{in}) + (0.4 * MAPE_{out}) + (0.1 * |MPE_{in}|) + (0.1 * |MPE_{out}|)$$

We computed the metric for each segment and candidate model combination and then selected the best model by choosing the specification with the smallest overall metric.

Assessing Model Validity

After selecting the best model for each segment by minimizing the smallest overall metric, AEG assessed model validity at the program level by calculating the weighted average MAPE and MPE at the program level. We describe the steps in more detail and go over program metrics in the model validity subsection (see Appendix B).

Model Fine-Tuning

We also used visual inspection of the results as a simple but highly effective tool. We looked for specific aspects of the segment-level predicted and reference load shapes to tell us how well the models performed during the inspection. We used observations derived from these inspections to make edits to the model specifications obtained from the optimization process. For example:

- We checked that the reference load is closely aligned with the actual and predicted loads during the early morning and late evening hours when there is likely little effect from the event. Significant differences can indicate a problem with the reference load either over or underestimating usage in the absence of the rate.
- We closely examined the reference load for odd increases or decreases that could indicate an effect is not adequately captured in the model.

[19] The mean absolute percent error (MAPE) is defined as: $MAPE = \frac{100\%}{n}\sum_{h=1}^{n}\left|\frac{Actual_h - Estimate_h}{Actual_h}\right|$

[20] The mean percent error (MPE) is defined as: $MPE = \frac{100\%}{n}\sum_{h=1}^{n}\frac{Actual_h - Estimate_h}{Actual_h}$

- We also looked for bias both visually and mathematically. Identification of bias and its source allowed us to adjust the models to capture and isolate the bias-inducing effects within the model specification.

Obtain Load Impacts and Confidence Intervals by Reporting Subgroup

For each of four model segments, the final model selected is the following:

$$kwh_{it} = \beta_0 + \beta_1 trt_i + \beta_b(\delta_t + CDH_t + AvgLoad_i) + \beta_a EVNT_i(1 + CDH_t + Aug14_{it} + SR\_SAC_{it} + SAC_{it}) + \varepsilon_{it}$$

Where:

kwh_{it} is the consumption of customer i in hour t.

βs are the model intercept and the coefficient estimates.

trt_i is a dummy variable indicating that a customer i is a SmartRate™ participant.

δ_t is a vector of seasonal indicators, i.e. month and day of week.

CDH_t represents the cooling degree hours for hour t.

$AvgLoad_i$ represents the average hourly load for a specified window[21] for customer i.

$EVNT_i$ is a dummy variable indicating a SmartDay™ for customer i.

$Aug14_{it}$ is a dummy variable indicating Aug 14th for customer i.[22]

SR_SAC_{it} is a dummy variable indicating a simultaneous SmartAC™ event for customer i on hour t.

SAC_{it} is a dummy variable indicating a SmartAC™ event for customer i on hour t.

ε_{it} is the error for participant i in time t.

To illustrate a simplified process of estimating the impacts from the final model for a single subgroup, we simplify the model above to be the following:

$$kwh_{it} = \beta_0 + \beta_1 trt_i + \beta_b(base_{it}) + \beta_a EVNT_i(impact_{it}) + \varepsilon_{it}$$

Where, $base_{it} = \delta_t + CDH_t + AvgLoad_i$ and $impact_{it} = 1 + CDH_t + Aug14_{it} + SR\_SAC_{it} + SAC_{it}$.

In the simplified example above, trt_i and $base_{it}$ make up the baseline blocks of the model, and explain variation in kwh_{it} unrelated to demand response events. The remaining variables, $EVNT_i(impact_{it})$, make up the impact blocks and explain the variation in kwh_{it} related to a SmartDay™.[23] An hourly model like the equation above can be equivalently estimated as one model with hourly dummy variables or as 24 separate hourly models.

This type of time-series data is likely both autocorrelated and heteroskedastic. To address autocorrelation, we utilize two techniques: (1) estimate 24 separate models for each hour to remove autocorrelation from hour-to-hour; and (2) incorporate seasonal indicators to minimize autocorrelation. To address heteroskedasticity, we simply use the Huber-White robust error correction.

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[21] The specified window can be one or more of the following: HE3-HE5 or HE11-HE13.

[22] August 14th showed participant loads that were visually different from other SmartDays™, It was also a SmartAC™ event.

[23] Any unexplained variation will end up in the error term.

We used the model above to estimate the load impacts as follows:

- First, we obtained the actual and predicted load for each customer on each hour and SmartDay™ based on the specification defined in the equation above.
- Next, we used the estimated coefficients and the baseline portion of the model to predict what this customer would have used on each day and hour if there had been no events. We call this prediction the reference load.
- We calculated the difference between the reference load (the estimate based on the baseline blocks) and the predicted load (the estimate based on the baseline + impact blocks) on each SmartDay™. This difference represents our estimated load impact for each customer.

To show the observed load (and avoid confusion associated with the predicted load), we re-estimated the reference load as the sum of the observed load and the load impact.

Although we fitted models at the segment level, we estimated the impact at the smallest reporting subgroup level required in the CPUC LI Protocols and aggregated the results for each subgroup to represent impacts for each of the reporting subgroups required by the CPUC LI Protocols. This included analysis of impacts for each LCA, CARE status, bill protection status, TOU enrollment, medical baseline status, and dual enrollment in SmartAC™.

Because the impacts are statistical estimates, it is important to establish a range or confidence interval around the estimates resulting in the uncertainty-adjusted load impacts required by the CPUC LI Protocols. We used a statistical package to output the standard errors of the point estimates. The standard errors were then used to calculate a confidence interval at various levels (e.g., 50%, 70%, 90%, etc.) for each customer. Then, because the subgroup-specific estimates are independent across customers, the variance of the sum is the sum of the variances. A similar process was repeated to obtain confidence intervals for each segment.

Ex-Ante Load Impact Analysis

The primary goal of the ex-ante analysis is to produce an annual 11-year forecast of the load impacts expected from the SmartRate™ program. We created a set of impacts under each of the required weather scenarios (monthly peak day and typical event day for both PG&E's and CAISO's 1-in-2 and 1-in-10 weather conditions), presented at the program level, for each LCA, and for dually enrolled participants, for both an average participant and all participants in aggregate, for all program operating hours and the resource adequacy (RA) window (4 PM to 9 PM). A portfolio forecast that excludes the incremental load impacts of dually enrolled customers was also provided.

The uniqueness of 2020 adds to the complexity of developing forecasts. As a result, in addition to the conventional factors contributing to ex-ante analysis (i.e., anticipated program changes, enrollment trends, and weather-adjusted ex-post impacts), we incorporated current and anticipated conditions related to COVID-19 and SIP. This additional analysis looked specifically at the implications of COVID-19 and SIP conditions on the SmartRate™ program and helped us make more informed decisions on assumptions regarding the ex-ante impact estimates.

Additionally, the SmartRate™ event window is shifting to 5 PM to 8 PM effective April 2022. We describe the assumptions used to incorporate this program change in a subsection below.

Shelter-in-Place Impact Analysis

To understand SIP conditions' potential effects on the SmartRate™ program, AEG performed a two-part comparative analysis on the differences between PY2019 and PY2020. The comparative analysis accomplished the following goals:

- Assisted in the development of the enrollment forecast by providing insight on changes in participant enrollment distributions and enrollment trends, and
- Assessed the appropriate assumptions necessary in developing a 11-year ex-ante load impact forecast.

The two-part comparative analysis is as follows:

Performed a direct comparison of PY2019 and PY2020 that focused on these two items:

- Participant enrollment distributions to capture any changes in participant enrollment trends attributed to 2020 circumstances. This comparison found that two subgroup distributions changed in PY2020:
    - The share of dually enrolled participants decreased due to a change in program eligibility, not due to SIP conditions.
    - The share of CARE program enrollment increased, potentially as a result of SIP conditions.
- Per customer reference loads, load impacts, and impacts as a percentage of reference loads to perform an initial check on the differences in magnitude between the two years. This comparison found that:
    - As expected, the average customer reference loads are higher in PY2020, with most residents being primarily in their homes.
    - There are minor magnitude differences in average load impacts (absolute and as a percent of the reference load). However, these changes may not necessarily be an effect of SIP conditions, which we validated in the second part of the comparative analysis.

Performed difference-in-differences regression analyses using PY2019 and PY2020 data to perform additional comparisons on PY2019 and PY2020 reference loads and load impacts while allowing us to control for differences in weather. For these analyses, we restricted the data to only PY2020 participants, using event-like days in both program years in lieu of the matched control group data.[24] AEG performed the following two analyses:

- A simple regression model to estimate the effect of SIP conditions on the per customer load impacts. This model utilizes both SmartDays™ and event-like days from PY2019 and PY2020.

$$kwh_{it} = \beta_0 + \beta_1 CDH_t + \beta_2 PY_t + \beta_3 EVNT_t + \beta_4 (PY_t * EVNT_t) + \varepsilon_{it}$$

- A simple regression model to estimate the effect of SIP conditions on the per customer reference loads. This model utilizes only event-like days from PY2019 and PY2020.

$$kwh_{it} = \beta_0 + \beta_1 CDH_t + \beta_2 PY_t + \varepsilon_{it}$$

Where:

[24] Doing so eliminates the need to re-validate the match under the assumption that SIP conditions changed participants' overall usage patterns, i.e., their PY2020 match may not necessarily be their PY2019 match.

kwh_{it} is the average event window consumption of customer i on day t

β_0 is the intercept

CDH_t represents the cooling degree hours for day t

PY_t is a dummy variable indicating that day t is in PY2020

$EVNT_t$ is a dummy variable indicating that day t is a SmartDay™

$PY_t * EVNT_t$ is an interaction variable indicating that day t is a PY2020 SmartDay™

ε_{it} is the error for customer i on day t

Altogether, results from the comparative analysis indicated the following:

- AEG did not find significant differences in participant load impacts and did not make any additional adjustments to account for COVID-19 and SIP conditions.
- AEG found that the overall average customer usage (participant reference loads) increased due to COVID-19 and SIP conditions. AEG incorporated PG&E's internal forecast that removes the COVID effect over time.

Weather-Adjusted and COVID-Adjusted Load Impacts

The comparative analysis on the implications of COVID-19 and SIP conditions determined the appropriate approach and assumptions in estimating the ex-ante load impacts, shown in Figure 3-4. The figure below provides an overview of the ex-ante analysis approach, including the four key steps of the analysis. Estimation of the reference load is presented in teal, estimation of the load impacts is presented in yellow, and application of the enrollment forecast is highlighted in orange.

Figure 3-4 Overview of the Ex-Ante Analysis Approach

Create Annual Weather-Adjusted Reference Load

- Estimate the weather-adjusted per customer reference loads using the coefficients from the ex-post models and inputs from the weather scenarios.
    - Where winter data is unavailable, PY2019 ex-ante per customer reference loads were used.

Apply the COVID adjustment to Reference Load

- The effect of COVID-19 conditions is estimated using a simple regression approach.
- Apply the effect to the reference load using PG&E factors to remove the effect of COVID-19 conditions over time.

Calculate the Per Customer Load Impacts

- Estimate the weather-adjusted per customer load impacts using the coefficients from the ex-post models and inputs from the weather scenarios.
- Incorporate the COVID adjustment by calculating the new load impacts as a percent of the new (COVID-adjusted) reference load.

Apply the enrollment forecast

- Multiply annual per customer impacts by enrollment forecast to arrive at aggregate forecast.

Each step is described below:

Weather-Adjusted and COVID-Adjusted Reference Loads

This step aims to determine a no-COVID case for each of the required weather scenarios and apply the PG&E factors that remove the effect of COVID-19 and SIP conditions over time.

To determine the no-COVID case for each weather scenario, we did the following steps:

- For June through September, the weather-adjusted reference load is estimated using the coefficients from the ex-post models and the inputs from the required weather scenarios.
- We estimated SIP conditions' effect on the per customer reference loads using a simple regression analysis (performed in the SIP Impact Analysis).
- We compared these weather-adjusted reference loads to the PY2019 monthly per customer reference loads from the ex-ante analysis and found that our estimated COVID effect from the SIP impact analysis quantified an extreme effect, i.e., the effect on the hottest days or event-like days.
- Without substantial changes in the participant population, we determined that the PY2019 ex-ante reference loads were appropriate for the no-COVID case for non-summer months. For the summer months, we used the estimated COVID effect to determine the no-COVID case.

Once the no-COVID case was developed for each of the required monthly scenarios, we applied the PG&E residential factors to remove the COVID effect over time. The COVID-adjusted reference loads are presented at the beginning of the ex-ante section.

Per Customer Load Impacts

The next step in the ex-ante analysis was to use the ex-post regression models to predict weather-adjusted impacts. The prediction produced a set of impacts under each of the required weather scenarios. To do this, we carried out the following steps:

- The analysis begins with the coefficients estimated in the segment regression models developed for the ex-post analysis.
- Then, the actual weather from the program year is replaced with the 1-in-2 and 1-in-10 weather data to predict an average customer's load for each of these scenarios assuming no events are called. The result was a weather-adjusted reference load for an average customer for each weather scenario required.
- Next, the weather-adjusted event day load is predicted by again applying the coefficients from the ex-post models to both the 1-in-2 and 1-in-10 weather data. However, in this prediction, we assumed that events were called by changing the event indicator variables from zero to one.
- The weather-adjusted load impact for an average customer is calculated by subtracting the weather-adjusted event-day load from the weather-adjusted reference load.
- For PY2020, we calculated the COVID-adjusted load impacts as a percent[25] of COVID-adjusted reference loads. This will allow the impacts to decrease proportionally to the reference loads as usage returns to a no-COVID case.

[25] Percentage is determined using the weather-adjusted estimates, i.e., weather-adjusted load impacts divided by weather-adjusted reference loads.

Event Window Shift

Effective April 2022, SmartRate™'s event window will be from 5 to 8 PM. [26] To incorporate these expected changes into the forecast, AEG used the following assumptions:

- We maintained the 2 to 7 PM event window in the 2020 "back-cast" and January 2021 through March 2022 monthly peak scenario forecast.
- Starting from the 2022 April monthly peak scenario, we shifted the event window to 5 to 8 PM by applying the hourly percent impacts to the hourly reference load. We did this for the event window, one pre-event hours, and two post-event hours.
    - We used percent impacts to account for the change in available load under the new event window, which was adjusted according to PG&E residential factors to remove the COVID effect over time.
    - We included the pre-event and post-event hours to incorporate any pre-cooling and snapback behaviors, which are evident in some participant segments.
- We assumed a 50% decrease in load impacts during the first year of the event window shift, to account for the "learning curve" as participants adjust their behavior to the new event window. Load impacts are assumed to be 100% or "back to normal" from the second year through the remainder of the forecast.

Portfolio-Adjusted Load Impacts

Portfolio-adjusted load impacts exclude the load impacts from dually enrolled participants attributed to concurrent SmartAC™ events. In other words, SmartAC™ takes precedence over SmartRate™, and to avoid double counting, the dually enrolled customer load impacts are removed in the portfolio-adjusted scenarios. However, we assume a portion of the load impacts for dually-enrolled customers on dual-event days is attributable to SmartRate™ because those customers exhibit higher impacts on dual-event days than on SmartAC™-only event days. We believe the incremental impact is due to a price response over and above the effect of the SmartAC™ switch.

In previous program years, estimates of the incremental effect of the SmartRate™ price incentive have been provided when there are sufficient SmartAC™-only and system-wide events called. In PY2020, SmartAC™ events were called for a variety of subsets of SmartAC™ customers and for different sets of event hours. This provided some additional limited basis for estimating incremental SmartRate™ impacts on SmartAC™ event days, and we found estimates of incremental SmartRate™ impacts varied, ranging from 16% to 30%. As a result, for this study, we have maintained the PY2019 assumption that SmartRate™ portfolio load impacts are 18% percent of program load impacts.

11-Year Annual Load Impact Forecasts and Uncertainty Estimates

Once the annual per customer load impact estimates were determined, we multiplied the per customer impacts by the number of participants for each year specified by the enrollment forecast.

Confidence intervals are provided for each hour as well as for an average event hour. Uncertainty in the ex-ante forecasts comes from modeling error, both from the hourly regression models and the weather adjustment to the 1-in-2 and 1-in-10 weather years. Though there is also error in the enrollment forecast, the confidence intervals do not include the enrollment forecast uncertainty.

[26] Pending CPUC decision for R.20-11-003, the SmartRate™ event window is expected to be modified to 4 to 9 PM at a later point.

4

EX-POST RESULTS

This section presents the PY2020 ex-post impacts for PG&E's Residential SmartRate™ Program.

Summary of Load Impacts

Table 4-1 below summarizes the overall program level event-hour impacts on each event, including the number of participants enrolled during each SmartDay™, the aggregate and per customer reference load and load impacts, the percent impact, and the average temperature. Note that in PY2020, PG&E called one weekend event on September 6th.

Load impacts as a percent of the reference load were 8.0% on average across the twelve events. Note that enrollment dropped slightly over time from 65,761 participants during the first event on June 24th to 63,864 participants during the September 6th event.

Table 4-1 All Participants: Average Event-Hour Impacts by Event

Event Date	# of Accts	Aggregate (MW)		Per Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
June 24	65,761	145.2	11.0	2.21	0.17	7.6%	93
June 25	65,685	152.9	11.2	2.33	0.17	7.3%	94
July 27	65,023	140.6	10.8	2.16	0.17	7.7%	92
July 28	64,993	144.1	10.9	2.22	0.17	7.6%	93
July 30	64,950	138.8	10.7	2.14	0.17	7.7%	92
August 10	64,608	149.1	10.9	2.31	0.17	7.3%	93
August 13	64,553	135.6	11.5	2.10	0.18	8.5%	96
August 14*	64,530	172.4	16.4	2.67	0.25	9.5%	102
August 17*	64,414	168.6	13.3	2.62	0.21	7.9%	97
August 18*	64,347	176.8	14.2	2.75	0.22	8.0%	100
August 19*	64,295	149.8	12.7	2.33	0.20	8.5%	96
September 6*	63,864	171.9	14.5	2.69	0.23	8.4%	104
Typical Event Day	**64,752**	**153.8**	**12.3**	**2.38**	**0.19**	**8.0%**	**96**

* Concurrent SmartAC events were called for various combinations of Sub-LAPs and event hours.

Figure 4-1 presents the average event-hour ex-post load impacts for each event day for all SmartRate™ participants. The green bars indicate the magnitude of the aggregate load impact, and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

These results indicate that participants had statistically significant load reductions on all twelve SmartDays™, ranging from 10.7 to 16.4 MW. The average load impact was 12.3 MW, with five out of twelve event days having a load impact greater than 12 MW. These five high-performing SmartDays™ had concurrent SmartAC™ events and called for various combinations of Sub-LAPs and event hours. These five events are highlighted in a light gray box in the figure below.

Figure 4-1 All Participants: Average Event-Hour Impacts by Event

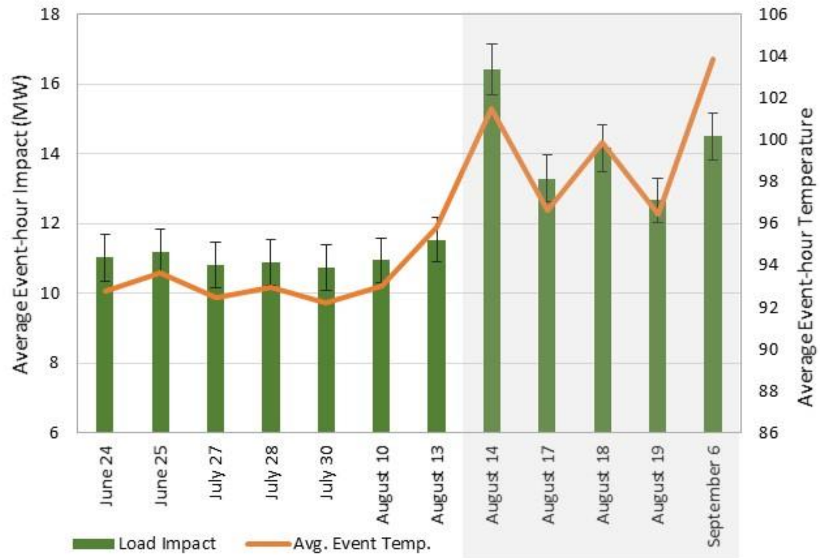
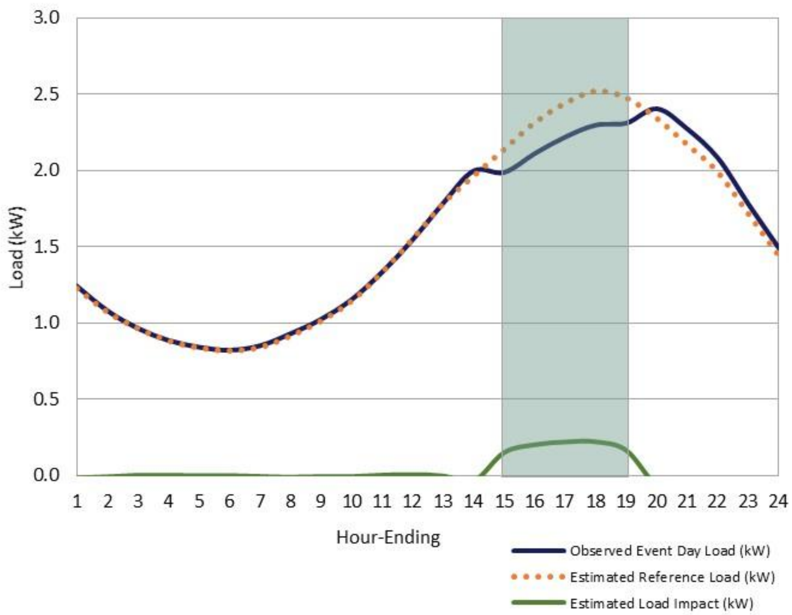


Figure 4-2 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. On average, SmartRate™ participants have a relatively flat event response, reaching the highest impact during the third event hour (HE17). Also, hourly load impacts show very minimal signs of pre-cooling or post-event snapback. This response is typical of programs where participants do not have a technology-enabled device to assist in event response. We will discuss this more in a subsequent section on the impacts of dual enrollment in SmartAC™.

Figure 4-2 All Participants: Hourly Typical Event Day Load Impacts



Comparison of Ex-Post Impacts

Table 4-2 and Table 4-3 below present the comparison of current ex-post impacts to previous ex-post impacts and current ex-post impacts to prior ex-ante impacts. These comparisons give the reader a sense of how the program has performed over time and how the program has performed relative to the most recent forecast.

Table 4-2 Current Ex-Post v. Previous Ex-Post, Typical Event Day

Year	# of Accts	Aggregate Impact (MW)		Per Customer Impact (kW)		% Impact	Temp (F)
		Reference Load	Impact	Reference Load	Impact		
2019	66,504	143.7	14.9	2.16	0.22	10%	97
2020	**64,752**	**153.8**	**12.3**	**2.38**	**0.19**	**8%**	**96**

Table 4-2 presents the ex-post impacts over time. PG&E's SmartRate™ program saw a slight decrease in participants' total impacts and per customer impacts in PY2020. However, the average customer reference load is slightly higher in PY2020, a consistent trend in residential customers, and likely a direct result of SIP conditions. We will discuss this in more detail in Section 5 (Ex-Ante Results). Note also the minimal decrease in participant counts, indicating a slow rate of attrition.

In Table 4-3Table 4-3 below, we present the PY2020 ex-post impacts compared to prior ex-ante impacts. In this comparison, we see the same trends discussed above. We also see that PY2020, on average, experienced temperatures that are slightly milder than 1-in-2 weather conditions, potentially causing slightly lower per customer impacts of 0.19 kW compared to 0.23 kW in PY2019's 2020 forecast. However, the critical difference is that in PY2019, PG&E anticipated a small growth in participant enrollment instead of the decline that occurred in PY2020, resulting in a 2.8 MW difference in the two load impact estimates.

Table 4-3 Current Ex-Post (Typical Event Day) v. Prior Ex-Ante (PG&E 1-in-2, August Peak, 2020), 2 PM to 7 PM

Estimate	# of Accts	Aggregate Impact (MW)		Per Customer Impact (kW)		% Impact	Temp (F)
		Reference Load	Impact	Reference Load	Impact		
Prior Ex-Ante	65,519	129.6	15.1	1.95	0.23	12%	99
Ex-Post 2020	**64,752**	**153.8**	**12.3**	**2.38**	**0.19**	**8%**	**96**

Distribution of Program Impacts

Impacts by Local Capacity Area

Next, we look at load impacts for by LCA. Table 4-4 summarizes aggregate event-hour results for the typical event day for PG&E's eight LCAs. The tables include the number of enrolled customers, the reference loads and load impacts, the estimated load impacts as a percentage of the reference load, and the average event temperature.

As one might expect, enrollments are concentrated in the Greater Bay and Fresno Areas, with 36% of all participants coming from the two areas combined. However, the largest subgroup of customers (29%) is in the "Other or Unknown" category, and accordingly, the highest estimated load impacts, 3.5 MW, come from the "Other or Unknown" category. The second-largest estimated load impacts come from the Greater Fresno Area, which tends to experience more extreme summer heat, as shown by the greater average event temperatures (See Table 4-4).

Table 4-4 Average Event-Hour Impacts by LCA on a Typical Event Day

LCA	# of Accts	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
Greater Bay Area	9,300	16.6	1.6	9.8%	92
Greater Fresno Area	14,083	39.7	2.9	7.2%	101
Humboldt	73	[redacted]	[redacted]	[redacted]	70
Kern	5,517	16.2	1.1	6.7%	102
North Coast and North Bay	2,654	3.8	0.4	11.0%	93
Sierra	7,617	18.3	1.5	8.3%	98
Stockton	6,673	17.3	1.4	7.9%	97
Other or Unknown	18,835	41.9	3.5	8.4%	95

In Figure 4-3, we present the share of the total enrollment, impacts, and reference load by LCA. This figure demonstrates that the share of impacts is similar to the share of enrollment, resulting from small differences between each LCA's per customer impacts. The Greater Bay Area's share of impacts is notable, being proportional to its share of enrollment while having a lower share of the reference load. This indicates that participants in the Greater Bay Area are still strong responders despite their lower average usage and milder weather.

Figure 4-3 Contributions by LCA on a Typical Event Day

Impacts by Other Subgroups

Next, we look at load impacts for other subgroups of interest. Table 4-5 summarizes average event-hour results for the typical event day for each of the following subgroups: bill protection status, CARE enrollment status, dual enrollment to SmartAC™, medical baseline status, and TOU enrollment. The tables include the number of enrolled customers, the aggregate and per customer reference loads and load impacts, the estimated load impacts as a percentage of the reference load, and the average event temperature.

Table 4-5 Average Event-Hour Impacts by Event by Subgroup

Subgroup	Status	# of Accts	Aggregate (MW)		Per Customer (kW)		% Load Impact	Avg. Event Temp.
			Ref. Load	Load Impact	Ref. Load	Load Impact		
Bill Protection	No	44,992	107.3	9.3	2.38	0.21	8.7%	97
	Yes	19,760	46.5	3.0	2.36	0.15	6.5%	95
CARE Enrollment	No	36,575	80.5	6.9	2.20	0.19	8.6%	95
	Yes	28,177	73.4	5.4	2.60	0.19	7.4%	97
Dually Enrolled in SmartAC™	No	54,645	130.2	8.5	2.38	0.16	6.5%	95
	Yes	10,107	23.6	3.9	2.34	0.38	16.4%	98
Medical Baseline	No	59,681	139.3	11.3	2.33	0.19	8.1%	96
	Yes	5,071	14.5	1.0	2.87	0.20	7.1%	96
TOU Rate	No	51,303	123.0	10.2	2.40	0.20	8.3%	96
	Yes	13,449	30.8	2.2	2.29	0.16	7.1%	95

Figure 4-4 presents the total load impact contributions based on status ("yes" vs. "no") within each subgroup on a typical event day and the corresponding percentages. As expected, for each subgroup, the share of load impacts is mostly driven by the share of enrollment. For example, participants singly enrolled in SmartRate™ is 54k out of 64k total enrollment and contributes to 69% of total MW impacts despite having much lower per customer impacts relative to participants dually enrolled in SmartAC™.

Figure 4-4 Contributions by Subgroup on a Typical Event Day

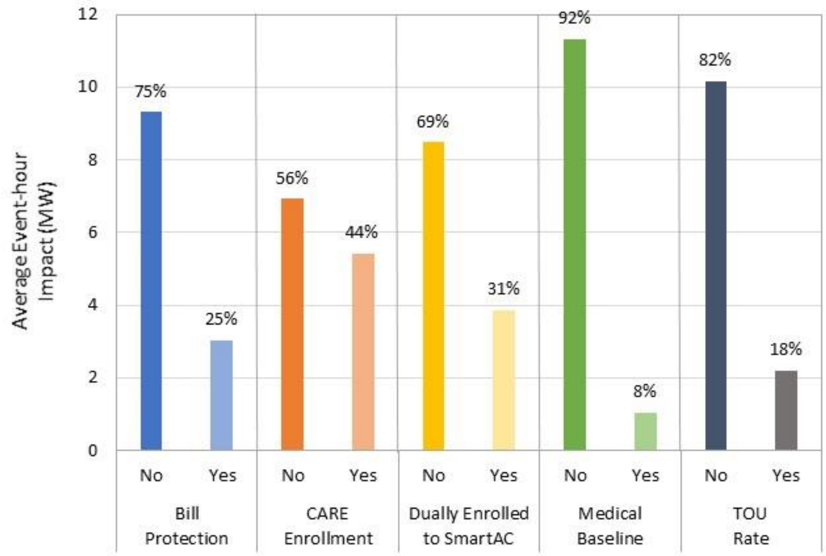


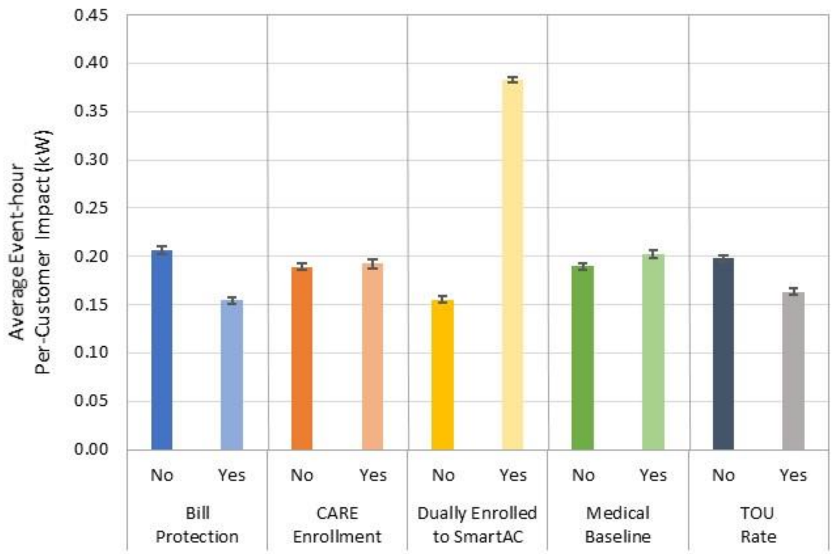
Figure 4-5 presents the per customer impacts by subgroup on a typical event day. The black bands correspond to 90 percent confidence intervals around these estimates. Notably, we see differences in per customer impacts due to bill protection status, dual enrollment to SmartAC™, and TOU enrollment. These differences are discussed in subsequent sections.[27] On the other hand, we see minimal differences in per customers impacts due to CARE enrollment[28] and medical baseline status[29].

[27] Differences in TOU enrollment are discussed in Section 6 along with additional analyses in relation to TOU enrollment.

[28] No statistically significant difference.

[29] Statistically significant difference.

Figure 4-5 Per Customer Impacts by Subgroup on a Typical Event Day



Dual Enrollment in SmartAC™

Next, we present the implications of dual enrollment in SmartAC™. As mentioned above, around 16% of PY2020 SmartRate™ participants are dually enrolled in SmartAC™. These participants contribute, on average, 31% of total MW impacts.

Customers enrolled in the SmartAC™ program have a device installed on their air conditioner (AC), allowing PG&E to signal AC units to run at a lower capacity remotely. SmartAC™ events are emergency-based and Sub-LAP-level events, lasting between one to six hours a day. During SmartDays™, PG&E also remotely controls participants' AC Units via the SmartAC™ devices. In other words, dually enrolled participants experience control of their AC units during both SmartAC™ and SmartRate™ events. Dual enrollment is not currently available to new participants. All dually enrolled participants enrolled in both programs before October 26th, 2018.

Table 4-6 presents the per customer reference loads and load impacts by SmartAC™ enrollment on a typical event day. When we compare the results from these two groups, we can see that the key difference is the magnitude of load impacts. Dually enrolled participants save 16.4%, on average, compared to 6.5% for singly enrolled participants. These differences in magnitude can be directly attributed to the SmartAC™ devices, which allow participants to respond to events with minimal to no impact on customer behavior.

Both groups are very comparable in customer size, with reference loads at 2.38 kW and 2.34 kW for singly and dually enrolled, respectively.

Table 4-6 Per Customer Impacts by SmartAC™ Enrollment: Typical Event Day

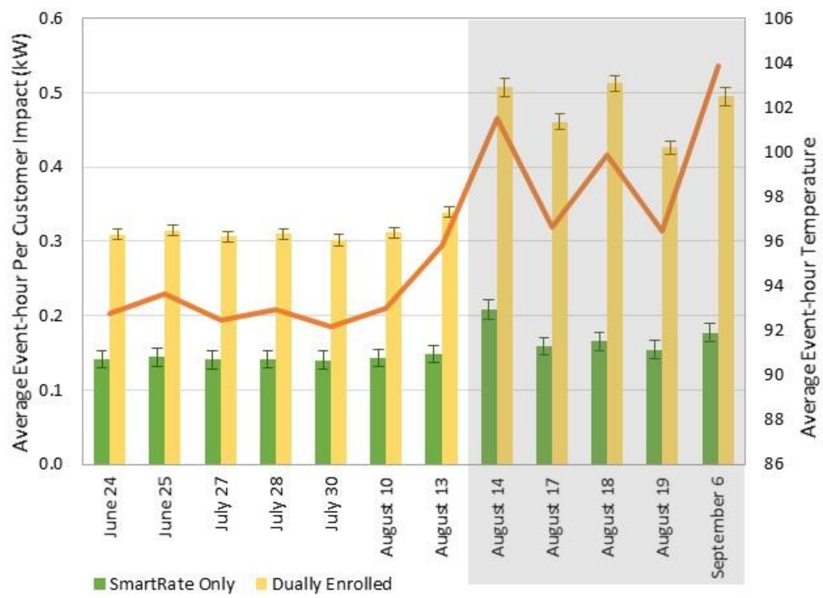
Subgroup	# of Accts	Per Customer Ref. Load (kW)	Per Customer Load Impact (kW)	Aggregate Load Impact (MW)	% Load Impact
SmartRate™ Only	54,645	2.38	0.16	8.5	6.5%
Dually Enrolled in SmartAC™	10,107	2.34	0.38	3.9	16.4%

In Figure 4-6, we present the share of the total enrollment, impacts, and reference load by SmartAC™ enrollment.

Figure 4-6 Contributions by SmartAC™ Enrollment on a Typical Event Day

Figure 4-7 compares the average event-hour ex-post load impacts for singly and dually enrolled customers for each event day. The green and yellow bars indicate the magnitude of the per customer load impact, and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by all participants during the event hours. The events inside a light gray box are events with concurrent SmartAC™ events for some or all dually enrolled participants.

Figure 4-7 SmartRate™ Only v. Dually Enrolled in SmartAC™: Average Event-Hour Per Customer Impacts



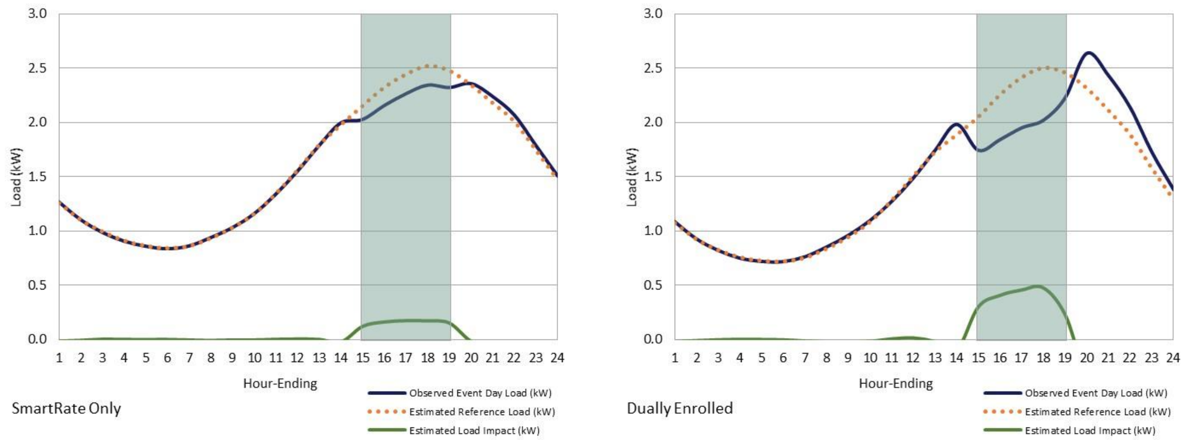
From Figure 4-7, we can observe the following:

- As we have previously discussed, dually enrolled participants have higher per-participant impacts relative to singly enrolled participants.
- Both groups show some correlation between impacts and temperatures, with the highest impacts on August 14th, August 18th, and September 6th.
- Dually enrolled participants have substantially higher impacts on SmartDays™ with concurrent SmartAC™ events, suggesting that dually enrolled participants have an incremental impact[30] attributed to SmartRate™ in addition to impacts attributed to SmartAC™ devices.

Figure 4-8 compares the per customer hourly reference loads, observed loads, and estimated load impacts on the typical event day for singly and dually enrolled participants.

[30] We discuss this further under the portfolio adjusted ex-ante impacts in Section 5.

Figure 4-8 SmartRate™ Only v. Dually Enrolled in SmartAC™: Hourly Typical Event Day Load Impacts



From Figure 4-8, we can observe the following:

- Singly enrolled participants show minimal impacts outside the event window, indicating consistent load reductions without shifting load into non-event hours.
- On the other hand, dually enrolled participants have clear pre-cooling and snapback usage patterns, typical of technology-enabled participants.
- And again, the magnitude difference in per customer impacts is clearly shown in these comparison figures.

Bill Protection Guarantee

During their first full summer season (May through October) of program enrollment (and any preceding partial season), customers are backed by PG&E's Bill Protection Guarantee that refunds customers if their SmartRate™ costs are more than their regular residential pricing plan. PG&E credits the difference on the customer's November bill if they did not save on SmartRate™. This section explores any implications of PG&E's Bill Protection Guarantee on load impacts.

As mentioned above, around 31% of PY2020 SmartRate™ participants are under the Bill Protection Guarantee. These participants contribute, on average, 25% of total MW impacts.

Table 4-7 presents the per customer reference loads and load impacts by bill protection status on a typical event day. When we compare the results from these two groups, we can see that the key difference is the magnitude of load impacts. On average, participants under bill protection save 6.5%, compared to 8.7% for participants not on bill protection. These differences in magnitude can be attributed to one or more of the following:

- Customer "complacency" due to the absence of cost impacts from the Bill Protection Guarantee.
- First season "learning curve" where participants have yet to adjust their behaviors to respond to events adequately.
- Absence of technology-enabled participants in the bill-protected group since dual enrollment in SmartAC™ is closed to new customers.

Both groups are comparable in customer size, with reference loads at 2.36 kW and 2.38 kW for bill-protected and not bill-protected participants, respectively.

Table 4-7 Per Customer Impacts by Bill Protection Status: Typical Event Day

Subgroup	# of Accts	Per Customer Ref. Load (kW)	Per Customer Load Impact (kW)	Aggregate Load Impact (MW)	% Load Impact
No Bill Protection	44,992	2.38	0.21	9.3	8.7%
Bill Protection	19,760	2.36	0.15	3.0	6.5%

In Figure 4-9, we present the share of the total enrollment, impacts, and reference load by bill protection status.

Figure 4-9 Contributions by Bill Protection Status on a Typical Event Day

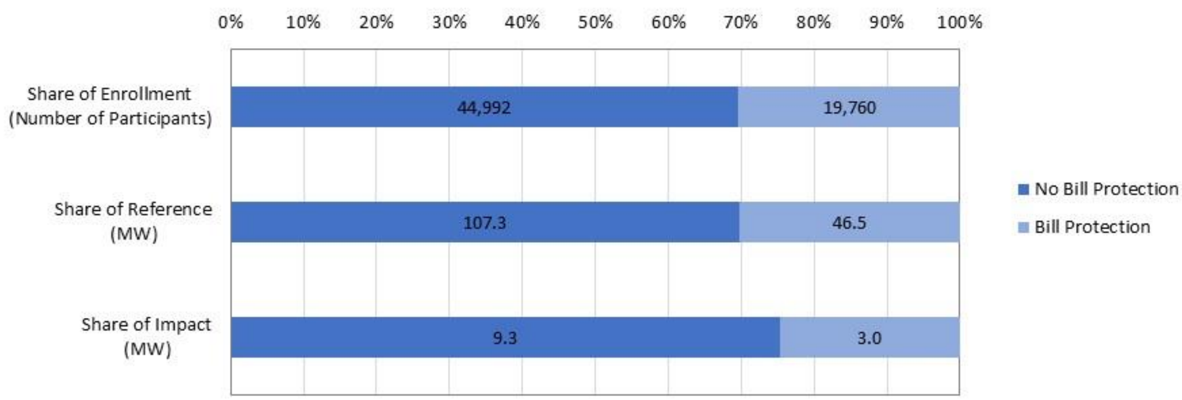
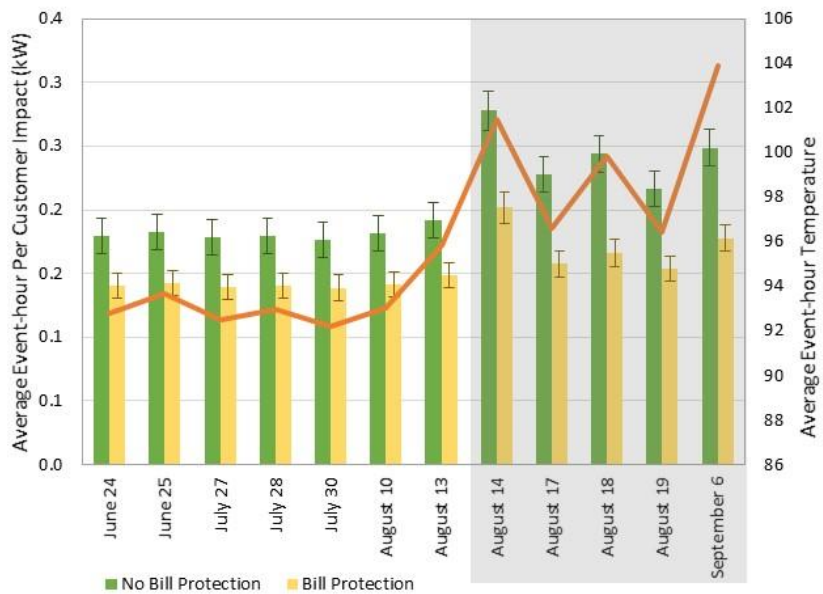


Figure 4-10 compares the average event-hour ex-post load impacts for each event day for bill-protected and not bill-protected (continuing) participants. The green and yellow bars indicate the magnitude of the per customer load impact, and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by all participants during the event hours. The events inside a light gray box are events with concurrent SmartAC™ events for some or all dually enrolled participants. Note that because dual enrollment in SmartAC™ is closed to new customers, there are no SmartAC™ participants in the bill-protected group, while about 22% of the continuing group are dually enrolled.

Figure 4-10 Continuing SmartRate™ v. Bill Protected Participants: Average Event-Hour Per Customer Impacts

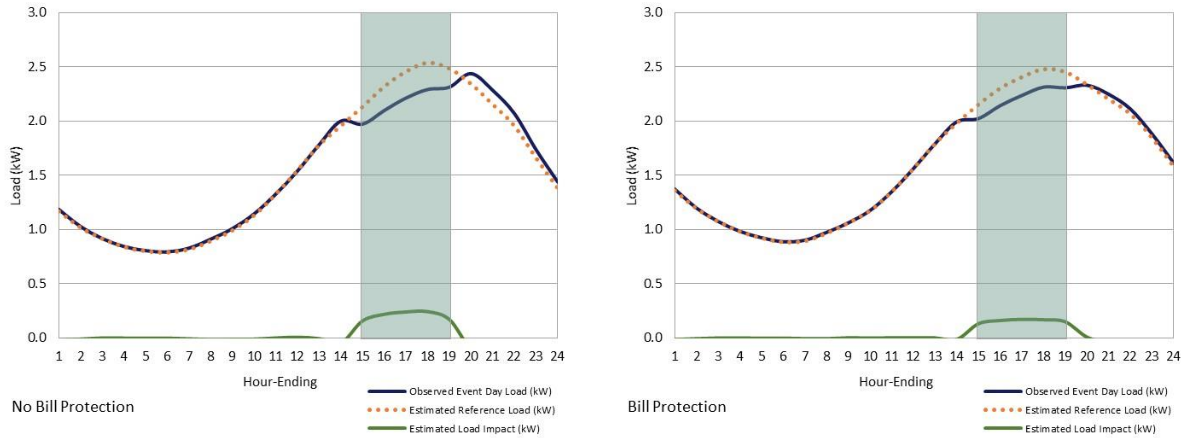


From Figure 4-10, we can observe the following:

- Again, participants under the Bill Protection Guarantee have lower per-participant impacts relative to continuing SmartRate™ participants.
- Both groups show some correlation between impacts and temperatures, with the highest impacts on August 14th and September 6th.
- Dually enrolled participants make up only 22% of continuing SmartRate™ participants. However, the higher impacts of dually enrolled participants are still apparent, showing higher impacts on SmartDays™ with concurrent SmartAC™ events.

Figure 4-11 compares the per customer hourly reference loads, observed loads, and estimated load impacts on the typical event day for both continuing and bill-protected participants.

Figure 4-11 Continuing SmartRate™ v. Bill Protected Participants: Hourly Typical Event Day Load Impacts



From Figure 4-11, we can observe the following:

- Both groups show minimal impact outside the event window, indicating consistent load reductions without shifting load into non-event hours.
- Continuing participants show a presence of technology-enabled participants with slight indications of snapback usage patterns.
- And again, the magnitude difference in per customer impacts is clearly shown in these comparison figures.

TOU Enrollment

SmartRate™ is currently available to customers both on the standard rate and TOU rates. Residential customers are currently defaulting onto the TOU rate in waves of around 250k customers per month throughout PY2021. All residential customers (minus opt-outs) are expected to be on the TOU rate by PY2022. SmartRate™ participants for PY2020 and PY2021 should be a combination of different rates, with the majority/all expected to be on a TOU rate by PY2022.

For the PY2020 evaluation, we grouped all currently enrolled TOU rate participants together since the TOU participants collectively make up only 21% of the overall PY2020 SmartRate™ participants. It is important to note that the participants reported as TOU-enrolled experience different TOU periods: TOU-A, TOU-B, TOU-C, and HE-6. TOU-C is the rate that will become the default rate. The current TOU-C customers were either defaulted as part of the 2018 pilot study or voluntarily enrolled starting in 2019. TOU-C customers make up 12% of the overall PY2020 SmartRate™ participants.

It is also important to note that TOU-B customers, despite being opt-in customers, have a very similar TOU experience to TOU-C customers. TOU-B customers make up 8% of the overall PY2020 SmartRate™ participants. Collectively, the TOU-B and TOU-C customers make up 20% of the overall PY2020 SmartRate™ participants, and the majority of what is presented in this study as TOU rate participants. Granted that opt-in and defaulted customers tend to have different behavior/responses, the definition of TOU enrollment in this analysis is a representation of a mixed population (opt-ins and defaults) under the 4 to 9 PM peak period.

For reference, the TOU periods of the different rates mentioned above are as follows.

- TOU-A: Peak pricing on weekdays from 3 to 8 PM.
- TOU-B: Peak pricing on weekdays from 4 to 9 PM.
- TOU-C: Peak pricing every day from 4 to 9 PM.
- HE-6: Peak pricing on weekdays from 1 to 7 PM, partial peak pricing on weekdays from 10 AM to 1 PM and 7 to 9 PM, and partial peak pricing on weekends from 5 to 8 PM.

Table 4-8 presents the per customer reference loads and load impacts by TOU enrollment on a typical event day. When we compare the results from these two groups, we can see differences in the magnitude of both the reference load and load impacts.

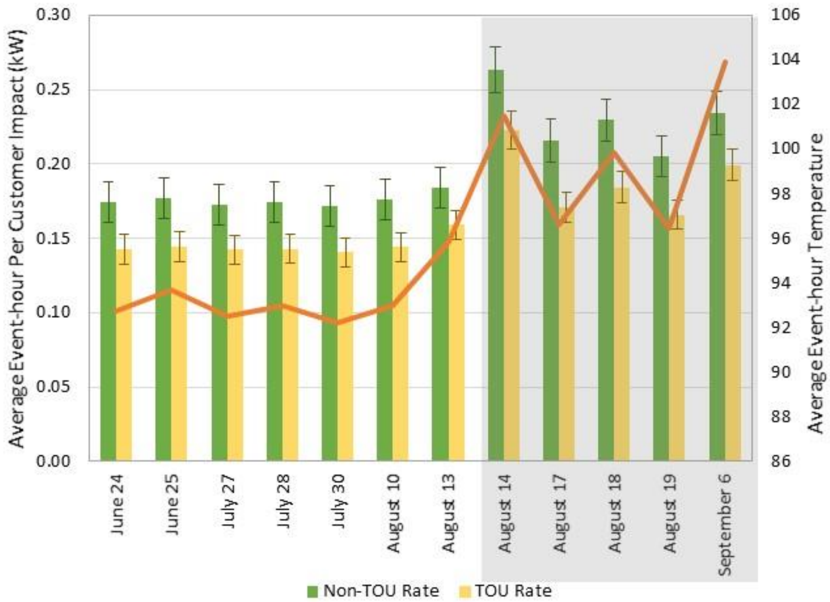
Participants on a TOU rate save 7.1%, on average, compared to 8.3% for participants on a standard rate. Participants on a TOU rate also have lower per customer reference loads at 2.29 kW, on average, compared to 2.40 kW for participants on a standard rate. These differences are likely attributable to the shifting behavior of the TOU participants. Participants on a TOU rate are already shifting some portion of their usage outside of the on-peak window on all summer weekdays, which overlaps with the SmartDay™ event window. This shift in usage results in lower on-peak reference loads and correspondingly lower impacts relative to participants on a standard rate.

Table 4-8 Per Customer Impacts by TOU Enrollment: Typical Event Day

Subgroup	# of Accts	Per Customer Ref. Load (kW)	Per Customer Load Impact (kW)	Aggregate Load Impact (MW)	% Load Impact
Non-TOU Rate	51,303	2.40	0.20	10.2	8.3%
TOU Rate	13,449	2.29	0.16	2.2	7.1%

Figure 4-12 compares the average event-hour ex-post load impacts for each event day for non-TOU rate and TOU rate participants. The green and yellow bars indicate the magnitude of the per customer load impact, and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by all participants during the event hours. The events inside a light gray box are events with concurrent SmartAC™ events for some or all dually enrolled participants.

Figure 4-12 Non-TOU Rate v. TOU Rate: Average Event-Hour Per Customer Impacts

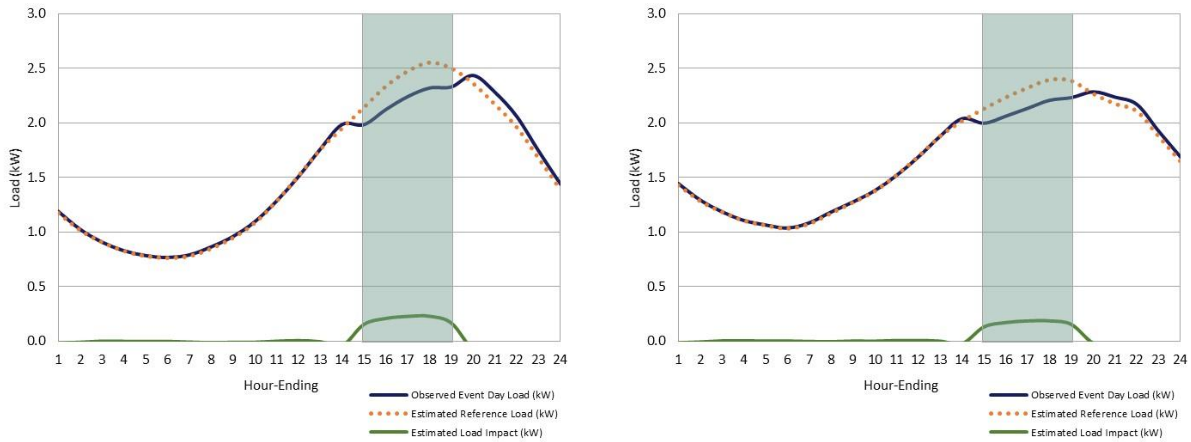


From Figure 4-12, we can observe the following:

- As noted above, non-TOU rate participants show higher per-participant impacts relative to TOU rate participants.
- Both groups show some correlation between impacts and temperatures, with the highest impacts on August 14th, August 18th, and September 6th.
- Dually enrolled participants make up only 17% and 7% of non-TOU rate and TOU rate participants, respectively. However, in both groups, the higher impacts of dually enrolled participants are still apparent, showing higher impacts on SmartDays™ with concurrent SmartAC™ events.

Figure 4-13 compares the per customer hourly reference loads, observed loads, and estimated load impacts on the typical event day for both non-TOU rate and TOU rate participants.

Figure 4-13 Non-TOU Rate v. TOU Rate: Hourly Typical Event Day Load Impacts



From Figure 4-13, we can observe the following:

- Neither group shows evidence of impacts outside the event window, indicating consistent load reductions without shifting event reductions into non-event hours.
- The TOU group shows significant flattening during the on-peak period relative to the non-TOU group, again likely attributable to daily shifting behavior in response to the TOU rate.
- The difference in per customer impacts is clearly shown in these comparison figures, with slightly higher impacts from the non-TOU vs. TOU group.

5

EX-ANTE RESULTS

This section presents the ex-ante results, which include the load impact forecasts for the 1-in-2 and 1-in-10 weather conditions for PG&E and CAISO. We first present a summary of the effect of COVID-19 and SIP conditions and the accompanying adjustment. Next, we summarize the enrollment forecast and load impacts for both program and portfolio-adjusted forecasts. Finally, we discuss the ex-ante impacts relative to current ex-post estimates and previous ex-ante results.

It should be noted that the resource adequacy (RA) window (4 to 9 PM) does not coincide with the SmartRate™ event window (2 to 7 PM), which means that the SmartRate™ program is only available during the first three hours of the RA window and the two remaining hours are post-event hours. This results in slightly lower (and sometimes even negative) impacts within the RA window. Effective April 2022, the SmartRate™ event window is shifting to 5 to 8 PM[31], which still gives three coincident hours between the SmartRate™ event and RA window.

Ex-Ante Enrollment and Load Impact Summary

Table 5-1 summarizes the average event-hour load impact forecasts for SmartRate™ participants on a typical event day in 2021. The table includes impact forecasts under the 1-in-2 and 1-in-10 weather scenarios and the PG&E peak and the CAISO peak. As noted in the ex-post analysis, dually enrolled participants show higher per customer load impacts. However, singly enrolled participants make up the majority of SmartRate™ enrollment (85% of enrollment) and contribute more to the aggregate impact (approximately 79% of impacts).

Table 5-1 Typical Event Enrollment and Impacts by Dual Enrollment: 2021

	# of Accts	Aggregate Impact (MW)				Per Customer Impact (kW)			
		Utility Peak		CAISO Peak		Utility Peak		CAISO Peak	
		1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
SmartRate™ Only	50,992	3.83	3.83	3.75	3.82	0.08	0.08	0.07	0.07
Dually Enrolled	9,321	0.96	0.93	0.93	0.96	0.10	0.10	0.10	0.10
Total	**60,313**	**4.80**	**4.76**	**4.68**	**4.78**	**0.08**	**0.08**	**0.08**	**0.08**

[31] Pending CPUC decision for R.20-11-003, the SmartRate™ event window is expected to be modified to 4 to 9 PM at a later point.

Figure 5-1 shows the distribution of estimated typical event day load impacts by LCA. This is shown for the 2021 forecast under the PG&E 1-in-2 weather conditions. The LCA distribution of load impacts is similar to what we see in the ex-post analysis, since PG&E does not expect any substantial changes in participant enrollment by LCA.

Table 5-2 below shows the program level impacts by month for a PG&E 1-in-2 weather year for 2021, 2024, and 2031. Enrollment shows small fluctuations across months, which is expected in typical participant enrollment and attrition. Impacts are weather-sensitive, with the highest impacts occurring in the summer months

Figure 5-1 PG&E 1-in-2 Typical Event Day Aggregate Load Impacts by LCA: 2021

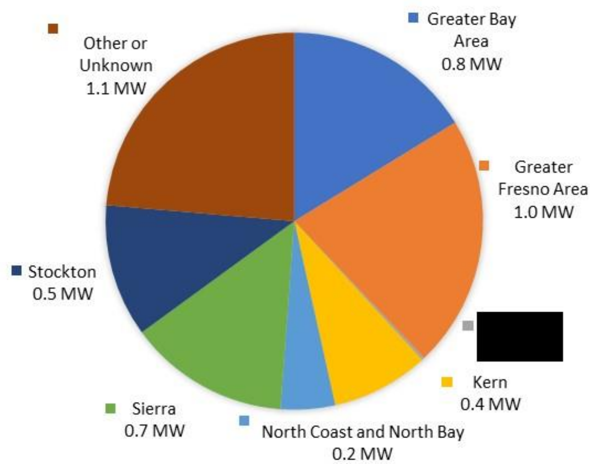


Table 5-2 Monthly Program Level Enrollment and Impacts for Selected Years: PG&E 1-in-2

Month	2021		2024		2031	
	Enrollment	Impact (MW)	Enrollment	Impact (MW)	Enrollment	Impact (MW)
January	61,550	2.26	55,582	2.39	44,585	1.90
February	61,372	2.26	55,429	2.38	44,472	1.89
March	61,193	2.25	55,277	2.38	44,359	1.89
April	61,015	3.23	55,126	2.97	44,249	2.35
May	60,839	4.16	54,974	3.83	44,138	3.03
June	60,664	5.16	54,824	4.84	44,026	3.82
July	60,487	4.72	54,673	4.63	43,917	3.65
August	60,313	4.82	54,526	4.35	43,808	3.44
September	60,142	5.81	54,376	5.00	43,698	3.95
October	59,968	3.54	54,229	3.10	43,588	2.45
November	59,796	2.17	54,084	2.32	43,480	1.85
December	59,624	2.15	53,934	2.32	43,372	1.84

In Figure 5-2 below, we present side-by-side comparisons of PG&E's 11-year annual enrollment and impact forecasts for the PG&E 1-in-2 weather scenario on a typical event day. The forecast is broken down by program enrollment: singly versus dually enrolled. PG&E expects a decrease in enrollment over time with no marketing-derived enrollments expected for future years.[32] Also, effective in April 2022 is a new event window that is shifted but still three hours coincident with the RA window. We assume a 50% decrease in load impacts in the first year of the new event window to account for the "learning curve" as participants

[32] PG&E plans to reengage marketing efforts in PY2022, but it is not currently reflected in the enrollment forecast.

adjust their behaviors. From the second year, 2023, we assume that load impacts will return to normal levels.

Figure 5-2 Enrollment and Impact Forecast: PG&E 1-in-2, Typical Event Day, 2021 - 2031

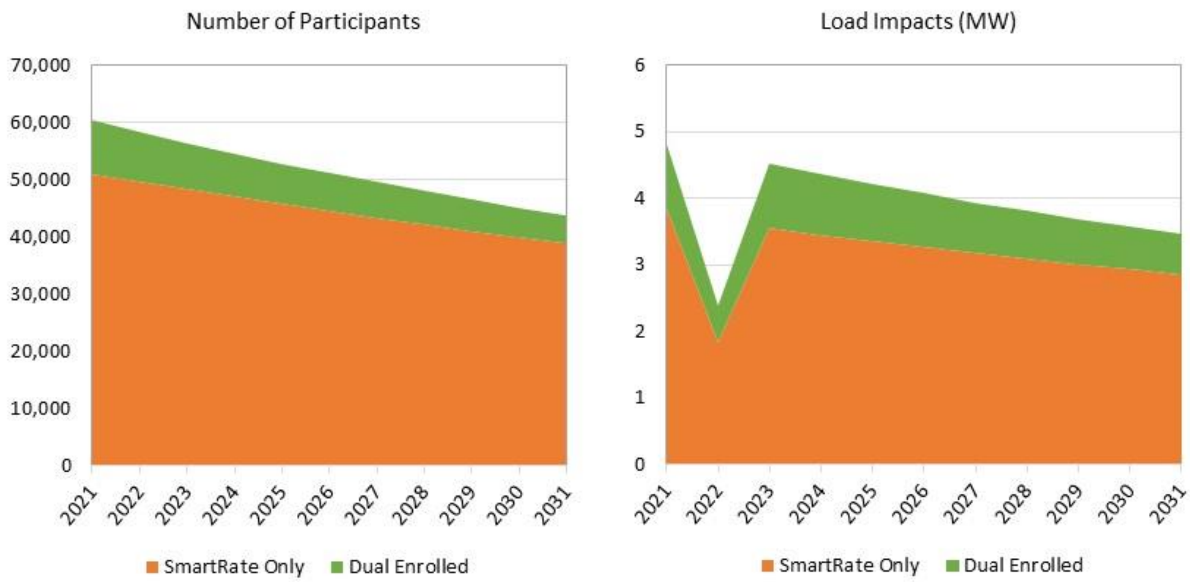
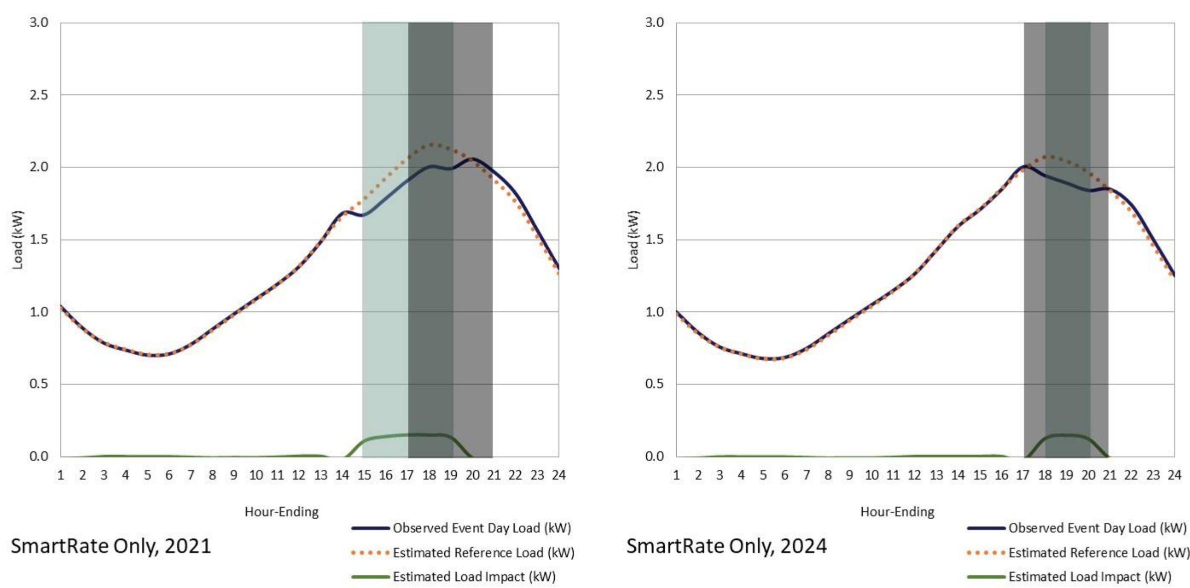


Figure 5-3 and Figure 5-4, below, present side-by-side comparisons of the SmartRate™ hourly load impacts under the two event windows, 2 to 7 PM in 2021 and 5 to 8 PM in 2024, for singly and dually enrolled participants. The areas shaded green represent the effective SmartRate™ event window and the areas shaded grey represent the RA window. The overlapping area in dark-green represent the coincident hours between the event and the RA window.

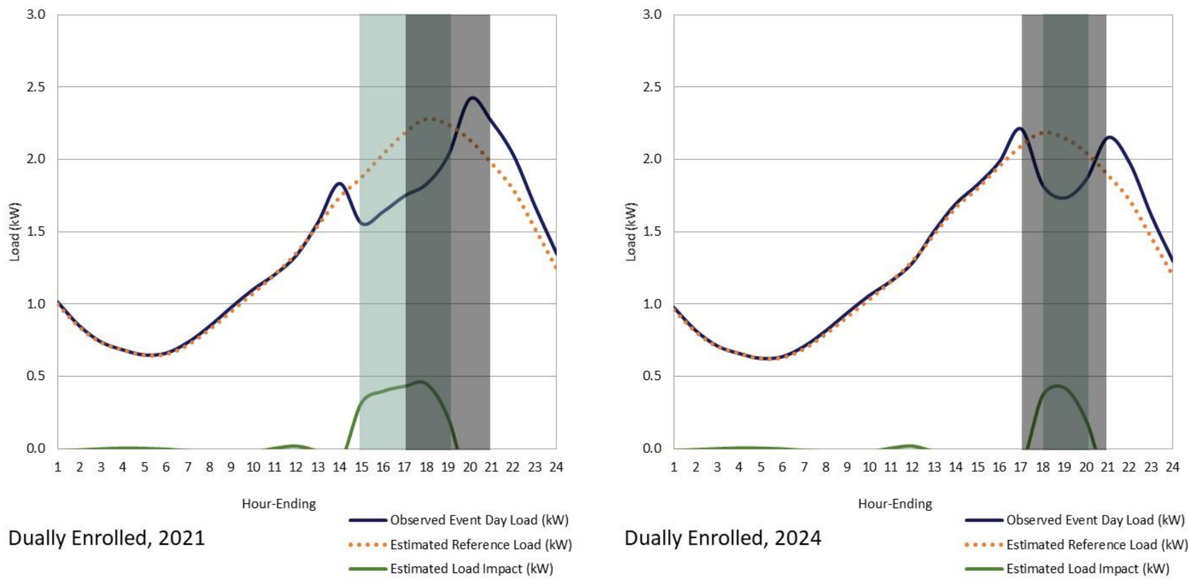
Figure 5-3 SmartRate™ Only Hourly Load Impacts: PG&E 1-in-2, Typical Event Day, 2021 v. 2024



Since both event windows have three hours coincident with the RA window, the event window shift shows very little effect in the RA window load impacts. Dually enrolled participants show slightly higher RA window impacts since the event window shift results in only one post-event hour coincident with the RA window. This results in less snapback behavior included in the RA window load impact, which is more substantial in the dually enrolled participants.

Note that we see a slight decrease in per-customer reference loads (from 2021 to 2024) due to COVID adjustments to the reference loads, forecasting a "return to normal" in overall customer usage.

Figure 5-4 Dually Enrolled in SmartAC™ Hourly Load Impacts: PG&E 1-in-2, Typical Event Day, 2021 v. 2024



In Section 3, we discuss the methodology used to determine the portfolio-adjusted impact forecast. Portfolio-adjusted results assume all of the forecasted impacts from SmartRate™ only participants and 18% of the forecasted impacts from the dually enrolled participants. In other words, during events when both SmartRate™ and SmartAC™ programs are called to respond, we are estimating that 18% of impacts can be attributed to SmartRate™, i.e., the incremental effect of the SmartRate™ price incentive. Table 5-3 shows the program and portfolio-adjusted impacts for the PG&E 1-in-2 weather scenario by program enrollment.

Table 5-3 Program Level vs. Portfolio-Adjusted Load Impacts: PG&E 1-in-2, Monthly Peak Day, 2021

Month	Program Level Load Impacts (MW)			Portfolio-Adjusted Load Impacts (MW)		
	SmartRate™ Only	Dually Enrolled	Total	SmartRate™ Only	Dually Enrolled	Total
January	1.93	0.33	2.26	1.93	0.06	1.99
February	1.93	0.33	2.26	1.93	0.06	1.99
March	1.92	0.33	2.25	1.92	0.06	1.98
April	2.62	0.61	3.23	2.62	0.11	2.73
May	3.34	0.82	4.16	3.34	0.15	3.49
June	4.15	1.01	5.16	4.15	0.18	4.33
July	3.81	0.91	4.72	3.81	0.16	3.97
August	3.85	0.97	4.82	3.85	0.17	4.02
September	4.53	1.27	5.81	4.53	0.23	4.76
October	2.83	0.71	3.54	2.83	0.13	2.96
November	1.86	0.31	2.17	1.86	0.06	1.91
December	1.85	0.30	2.15	1.85	0.05	1.91

Comparison of Ex-Ante Impacts

In Table 5-4 below, we compare the current ex-post with the current ex-ante. This comparison shows the average estimates for the SmartRate™ event window (2 to 7 PM). This comparison highlights the effect of adjusting the impacts and reference loads to reflect the various weather scenarios required in the analysis. Here, we compare the ex-post to a 1-in-2 weather year. The results indicate that the ex-post impacts, while experiencing some extreme weather in parts of PG&E's territory, were on the whole slightly below normal, with the 1-in-2 impacts being just a bit higher than the ex-post impacts across the board.

Table 5-4 Current Ex-Post (Typical Event Day) and Current Ex-Ante (PG&E 1-in-2, Typical Event Day, 2020), 2 to 7 PM

		# Enrolled	Aggregate (MW)		Per Customer (kW)		% Load Impact	Avg. Event Temp.
			Ref. Load	Load Impact	Ref. Load	Load Impact		
Current Ex-Post	SmartRate™ Only	54,645	130.2	8.5	2.38	0.16	6.5%	95
	Dually Enrolled	10,107	23.6	3.9	2.34	0.38	16.4%	98
	Total	**64,752**	**153.8**	**12.3**	**2.38**	**0.19**	**8.0%**	**96**
Current Ex-Ante	SmartRate™ Only	52,144	120.5	8.3	2.31	0.16	6.9%	98
	Dually Enrolled	10,076	24.1	4.1	2.39	0.41	17.0%	100
	Total	**62,220**	**144.6**	**12.4**	**2.32**	**0.20**	**8.6%**	**98**

In Table 5-5, we compare the previous ex-ante forecast from PY2019 to the current ex-ante forecasts from PY2020 in both 2021 and 2024. We include both years because 2021 is still affected by COVID conditions, while by 2024, we start to see a return to a no-COVID case and a new event window in effect. A couple of key highlights include the following.

- Comparing the aggregate load impacts in MW between the two 2021 forecasts, we see a decrease from 8.3 MW to 4.8 MW. This is coming primarily from the decrease in per customer impacts during the RA window, which could be from lower impacts in the later hours of the SmartRate™ event or a larger snapback effect in the post-event hours. We also see a decrease in forecasted enrollment for 2021 at 60k participants, previously 65k participants in PY2019.
- Comparing the per-customer load impacts between the PY2020 2021 and PY2020 2024 forecasts, we see the following observations due to the event window shift:
  - Very little change in the SmartRate™ only partcipants, since both scenarios have three event hours coincident with the RA window and the SmartRate™ only partcipants have very little pre-cooling and snapback behavior.
  - A slight increase in the dually enrolled participants, since the event window shift results in only one post-event hour coincident with the RA window. This results in less snapback behavior included in the RA window load impact, which is more substantial in the dually enrolled participants.
- Comparing the reference loads between the PY2019 – 2021 forecast and PY2020 - 2024 forecasts, we see that the per customer reference loads are closer to PY2019 (pre-COVID) levels as a result of the COVID adjustments.

Table 5-5 Previous and Current Ex-Ante, PG&E 1-in-2, Typical Event Day

		# Enrolled	Aggregate (MW)		Per Customer (kW)		% Load Impact	Avg. Event Temp.
			Ref. Load	Load Impact	Ref. Load	Load Impact		
Prev. Ex-Ante (2021)	SmartRate™ Only	53,792	107.8	5.9	2.00	0.11	5.5%	96
	Dually Enrolled	11,881	24.7	2.3	2.08	0.20	9.5%	96
	Total	**65,673**	**133.1**	**8.3**	**2.03**	**0.13**	**6.2%**	**96**
Current Ex-Ante (2021)	SmartRate™ Only	50,992	105.1	3.8	2.06	0.08	3.6%	96
	Dually Enrolled	9,321	20.1	1.0	2.16	0.10	4.8%	96
	Total	**60,313**	**125.3**	**4.8**	**2.08**	**0.08**	**3.8%**	**96**
Current Ex-Ante (2024)	SmartRate™ Only	47,004	93.1	3.4	1.98	0.07	3.7%	96
	Dually Enrolled	7,522	15.6	0.9	2.08	0.12	5.9%	96
	Total	**54,526**	**108.7**	**4.4**	**1.99**	**0.08**	**4.0%**	**96**

6

KEY FINDINGS AND RECOMMENDATIONS

In this section, we present the evaluation key findings and recommendations for future research.

Key Findings

The ex-post analysis resulted in the following key findings:

- SmartRate™ participants deliver highly weather-sensitive load impacts, showing an increase in load impacts on hotter days with or without technology assistance, i.e., for both singly enrolled in SmartRate™ and dually enrolled in SmartAC™. The average load impact was 12.3 MW in the 2020 season.
- Dual enrolled participants (SmartAC™ enrollment) deliver substantially higher load impacts per customer with 16.4% average event impacts compared to 6.5% for singly enrolled participants. These higher load impacts can be directly attributed to the SmartAC™ devices, which allow participants to respond to events with minimal to no effort or change in behavior. Since dual enrollment in SmartAC™ is no longer allowed for new participants, the higher load impacts from SmartAC™ devices will slowly decline as natural participant attrition occurs.
- Participants under the Bill Protection Guarantee deliver lower load impacts per customer with 6.5% average event impacts compared to 8.7% for participants no longer eligible for bill protection. This can be attributed to one or more of the following: (1) customer "complacency" due to the absence of cost impacts from the Bill Protection Guarantee; (2) the first season "learning curve" where participants have yet to adjust their behaviors to respond to events adequately; and (3) the absence of technology-enabled participants in the bill protected group since dual enrollment in SmartAC™ is closed to new customers.
- Participants with an underlying TOU rate deliver lower load impacts per customer with 7.1% average event impacts compared to 8.3% for participants with an underlying standard rate. This is likely due to participants having lower reference loads during the event window attributable to daily shifting behavior in response to the TOU rate. Although the current participants with an underlying TOU rate are a mix of opt-ins and defaults, which can potentially have different customer behaviors, lower per customer load impacts (maybe in a lesser magnitude) will likely be seen as TOU defaulting rolls out in 2021-2022 and learned behaviors are acquired.

The ex-ante analysis resulted in the following key findings:

- COVID-19 and SIP conditions did not have significant effects on participant load impacts but instead caused an overall increase in their regular usage, i.e., reference loads. For SmartRate™ participants, the COVID effect is estimated to be a 17% increase in reference load during the RA window (4 to 9 PM). This resulted in PG&E's development of a secondary forecast that estimates the persistence of the COVID effect on residential reference loads through 2022.
- Ex-ante load impacts indicate an 8.5% average load reduction during the SmartRate™ event window (2 to 7 PM) and a 3.8% average load reduction during the RA window on a typical event

day. Under the PG&E 1-in-2 weather conditions, this is equivalent to 10.4 MW and 4.8 MW in 2021 for the event window and RA window, respectively.

- The event window shift shows very little effect in the RA window load impacts, since both event windows (2 to 7 PM v. 5 to 8 PM) have three hours coincident with the RA window. Dually enrolled participants show slightly higher RA window impacts since the shift results in only one post-event hour coincident with the RA window. This results in less snapback behavior included in the RA window load impact, which is more substantial in the dually enrolled participants.
- PG&E estimates a slow decrease in SmartRate™ enrollment through 2031. Partnered with a slow decrease (or a return to a no-COVID case) in overall usage, this results in a reduced ex-ante forecast of 3.45 MW (RA window) in 2031 for a typical event day under the PG&E 1-in-2 weather conditions.

Recommendations

AEG developed the following recommendations for future research and evaluation related to PG&E's residential SmartRate™ program.

- Incorporate TOU enrollment as a sampling and modeling segment as TOU defaulting rolls out and the share of TOU enrollment increases among SmartRate™ participants. This modification can accommodate additional ex-post modeling assumptions, i.e., accounting for different TOU peak periods, which can produce more accurate load impact estimates.
- Use LCA definitions instead of weather station assignments for matched control group development. LCA definitions accomplish similar geographically-targeted matching done by weather station assignments while also allowing analysis flexibility in LCA-specific reporting.
    - Attempt to correctly classify participants in the "Other or Unknown" category to allow more accurate LCA-specific reporting.
- Remove medical baseline status as a sampling and modeling segment since the ex-post analysis did not find significantly different responses from the medical baseline participants.
- Utilize year-round hourly usage data for more accurate ex-ante load impact estimates in the non-summer months.

AEG also developed one programmatic recommendation for PG&E's consideration in future program years.

- PG&E's program management team may wish to consider the cost-effectiveness of enabling SmartRate™ event signals to communicate with smart thermostats such as Nest and Ecobee to facilitate thermostat setbacks during events. The additional technological assistance will enhance impacts and expand the existing savings strategies already employed by thermostat vendors to facilitate shifting on TOU rates. These setback strategies will also increase impacts at the population level that may be falling over time, given that new dual enrollment in SmartAC is no longer available.

A

TABLE GENERATORS

SmartRate™ Ex-Post Table Generator

SmartRate™ Ex-Ante Table Generator

B

MODEL VALIDITY

We selected and validated subgroup level regression models during our optimization process; participants are grouped based on segments presented in Section 3. The subgroup models are designed to be able to:

- Accurately predict the actual participant load on event days, and
- Accurately predict the reference load, or what customers would have used on event days, in absence of an event.

To meet these two specific goals, our optimization process included an analysis of both the in-sample and out-of-sample mean absolute percent error (MAPE) and mean percent error (MPE) for each of the candidate regression models for each group. We used the out-of-sample tests to show how well each of the candidate models could predict a customer's load on non-event days that were as similar as possible to actual event days; this test gave us an estimate of how well each model could predict the reference load. We used the in-sample tests to show how well each model performed on the actual event days; therefore, it helped us understand how well the model was able to match the actual load.

As described in Section 3, our optimization procedure has three key steps: (1) in-sample and out-of-sample testing; (3) assessing model validity; and, (4) model fine-tuning. This section presents metrics related to steps 1 and 2, specifically:

- Selection of event-like days used in out-of-sample testing.
- Metrics from in-sample and out-of-sample tests from the final models of the ex-post analysis: MAPE, MPE, and comparison load graphs.

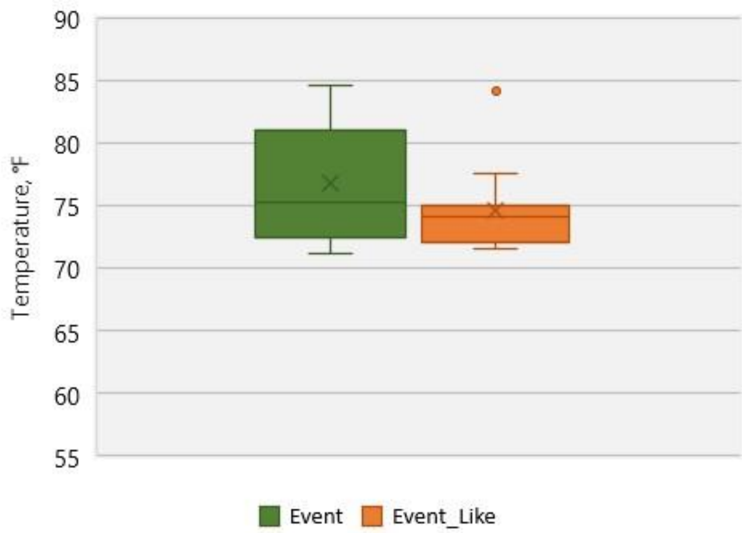
Selecting Event-Like Days

To select similar non-event days, we used a Euclidean Distance matching approach. Euclidean distance is a simple and highly effective way of creating matched pairs. To determine how close event day temperature is to a potential event-like day, we calculated a Euclidean distance metric defined as the square root of the sum of the squared differences between the matching variables. Any number of relevant variables could be included in the Euclidean distance; in this program year, we included three weather variables in the Euclidean distance metrics calculation to select similar non-event days: (1) daily maximum temperature; (2) daily minimum temperatures; and (3) average daily temperature. The Euclidean distance metric used can be calculated by Equation B1 below.

$$ED = \sqrt{\begin{gathered}(MaxTemp_{event} - MaxTemp_{non-event})^2 + (MinTemp_{event} - MinTemp_{non-event})^2 \\ + (MeanTemp_{event} - MeanTemp_{non-event})^2\end{gathered}} \quad \text{(B1)}$$

In Figure B-1, we show a comparison of the distributions of average daily temperature of event days and event-like days. We show a single program level comparison because these dates were chosen at the program level, i.e. all subgroups have the same set of event and event-like dates.

Figure B-1 Average Daily Temperatures of Event Days v. Event-Like Days



Optimization Process and Results

Next, we estimated the MAPE and MPE, for the entire day, for each subgroup, and for each candidate model, both for the in-sample and the out-of-sample scenarios:

- To perform the in-sample test, we fitted each candidate model to the entire data set. The results of these fitted models are used to predict the usage on event days. Then we assessed the accuracy and bias of the predictions by calculating the in-sample MAPE and in-sample MPE, respectively.
- To perform the out-of-sample test, we remove the out-of-sample event-like days from the analysis dataset and the candidate models are fitted to the remaining data. Then we assessed the accuracy and bias of the predictions by calculating the out-of-sample MAPE and out-of-sample MPE, respectively.

These two tests resulted in several in-sample and out-of-sample metrics. Recall that the goal of the tests is to find the best model for each subgroup in terms of its ability to predict the reference load and the actual load for each subgroup. Therefore, for each subgroup, we combined the two tests into a single metric, giving each candidate model a single metric. The metric is defined in as follows:

$$\boldsymbol{metric_{ic}} = (0.4 * MAPE_{in}) + (0.4 * MAPE_{out}) + \big(0.1 * abs(MPE_{in})) + (0.1 * abs(MPE_{out})\big)$$

Where,

$$MAPE = \frac{100\%}{n}\sum_{h=1}^{n}\left|\frac{Actual_h - Estimate_h}{Actual_h}\right|, \qquad MPE = \frac{100\%}{n}\sum_{h=1}^{n}\frac{Actual_h - Estimate_h}{Actual_h}$$

Once we have a single metric for each subgroup and candidate model combination, we selected the best model for each subgroup by choosing the model specification with the smallest overall metric. The results of the optimization process are shown in the following tables and figures.

Table B-1 presents the weighted average MAPE and MPE for the final set of models for each subgroup. All subgroups have MAPE and MPE estimates below 3.5%. We see very see very small MPE values, especially in the in-sample MPEs, which indicate relatively low level of bias.

Table B-1 Weighted Average MAPE and MPE by Subgroup

Subgroup	Out-of-Sample		In-Sample	
	MAPE	MPE	MAPE	MPE
Bill Protected	2.26%	1.04%	1.89%	0.28%
Dual Enrolled	3.24%	2.32%	2.65%	-0.24%
Medical Baseline	2.21%	1.11%	1.98%	-0.00%
SmartRate Only	3.14%	1.90%	2.26%	0.34%

Figure B-2 and Figure B-3 presents the average predicted loads (dotted lines) and actual loads (solid lines) from the in-sample and out-of-sample tests by subgroup. In each case, the predicted load is very close to the actual load. This tells us that on average, the customer-specific regression models do a very good job estimating what customer loads would be like on event-like days and event days, and therefore are able to produce very accurate reference loads.

Figure B-2 Actual and Predicted Loads: Event-like Days

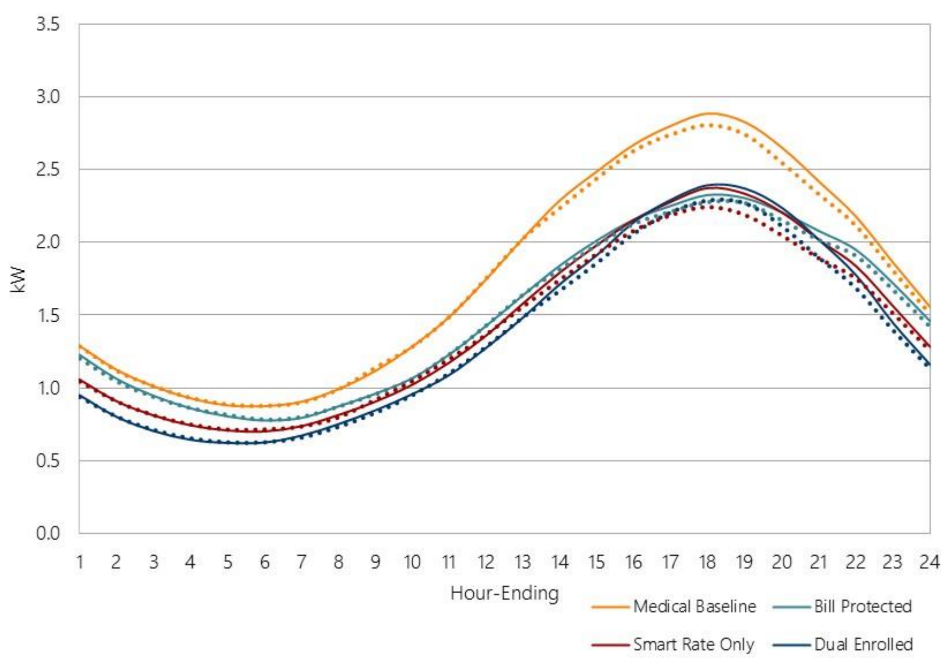
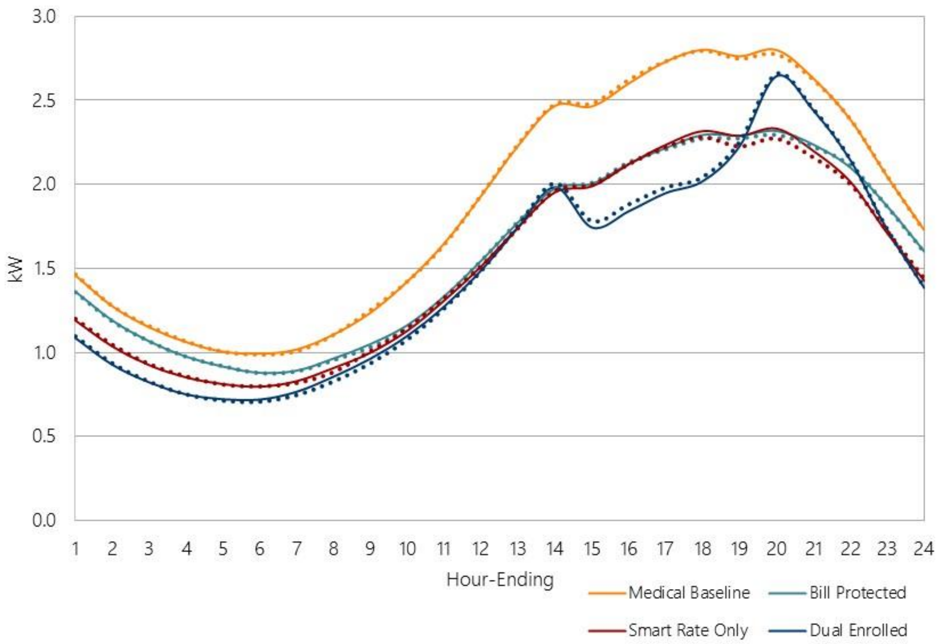


Figure B-3 Actual and Predicted Loads: Event Days



Additional Checks

Visual inspection can be a simple but highly effective tool. During the inspection, we looked for specific aspects of the predicted and reference load shapes to tell us how well the models performed. For example,

- We checked to make sure that the reference load is closely aligned with the actual and predicted loads during the early morning and late evening hours when there is likely to be little effect from the event. Large differences can indicate that there is a problem with the reference load either over- or under-estimating usage in absence of the event.
- We closely examined the reference load for odd increases or decreases in load that could indicate an effect that is not properly being captured in the models. If we found such an increase or decrease, we investigated the cause and attempted to control for the effect in the models.
- We also looked for bias, both visually and mathematically. Bias is the consistent over- or under-prediction of the actual load. We may see bias that is temperature-related, under-predicting on hot days, and over-predicting on cool days. We have also seen bias that is time-based, over-predicting in the beginning of the year, and under-predicting at the end of the year. Identification of bias and its source often allows us to adjust the models to capture and isolate the bias-inducing effects within the model specification.

C

BILL IMPACT ANALYSIS

PG&E provided billing data with program specific credits and charges for all PY2020 SmartRate™ participants[33]. This included billing impacts for May 2020 through November 2020 billing periods.

During their first full summer season of program enrollment (and any preceding partial season), customers are backed by PG&E's Bill Protection Guarantee that refunds customers if their SmartRate™ costs are more than their regular residential pricing plan. PG&E credits the difference on the customer's November bill if they did not save on SmartRate™.

AEG analyzed the data to understand the impact on customer bills for the whole program and for customers that qualify for bill protection. Consistent with the PY2019 analysis, AEG included customers that are defined as PY2020 participants and had at least 3 months of billing data between May and September 2020. This left AEG a working sample of 64,159 customers out of the 68,209 unique PY2020 participants.

The following sections discuss the findings of the bill impact analysis.

Average Billing Impact Across all Participants

The table below presents the average billing impacts in PY2020. Across all 64,159 participants, the average participant saved $20.81. SmartRate™ only participants averaged slightly higher reductions compared to dually enrolled participants with $21.08 versus $19.35 reductions.

Table C-1 Bill Impacts for All Participants

Enrollment Status	Impact	Count of Participants	% of Population	Average Bill Change
SmartRate™ Only	Increased Bill	14,424	22%	$17.73
	Decreased Bill	39,699	62%	-$35.19
	All SR Only	**54,123**	**84%**	**-$21.08**
Dually Enrolled	Increased Bill	2,853	4%	$17.86
	Decreased Bill	7,183	11%	-$34.13
	All Dual	**10,036**	**16%**	**-$19.35**
All	Increased Bill	17,277	27%	$17.75
	Decreased Bill	46,882	73%	-$35.03
	All	**64,159**	**100%**	**-$20.81**

Bill Protection Guarantee

Overall, 31% of PY2020 participants qualified for the Bill Protection Guarantee during the PY2020 SmartRate™ season. This is higher compared to PY2019 with only 22% of participants with bill protection. However, similar to prior years, almost all of those under bill protection are singly enrolled or SmartRate™ only. This is because dual enrollment is not currently available to new participants with all dually enrolled participants having enrolled in both programs before October 26th, 2018.

[33] Defined as participants enrolled between June 1, 2020 and September 30, 2020 and participated in at least one SmartDay™.

Table C-2 Participant Distribution by Bill Protection Status

Enrollment Status	Protection Status	Count of Participants	% of Enrollment Status	% of Population
SmartRate™ Only	Unprotected	34,576	64%	54%
	Protected	19,547	36%	30%
	All SR Only	**54,123**	**100%**	**84%**
Dually Enrolled	Unprotected	9,935	99%	15%
	Protected	101	1%	0%
	All Dual	**10,036**	**100%**	**16%**
All	Unprotected	44,511	69%	69%
	Protected	19,648	31%	31%
	All	**64,145**	**100%**	**100%**

Of those who were eligible for the Bill Protection Guarantee (19,547 participants), 78% experienced reductions in their bill. The average bill reduction total across the PY2020 season was $37.47, but the small number of dually enrolled participants who experienced a bill reduction saw an even larger reduction, on average, with a $45.19 reduction.

On the other hand, 22% of participants under bill protection saw an increase in their billing total with a $15.00 average increase. Since these participants are eligible for a refund under the Bill Protection Guarantee, this would be equivalent to the average refund received by protected participants at the end of the PY2020 season.

Table C-3 Bill Impacts for Participants under the Bill Protection Guarantee

Enrollment Status	Impact	Count of Participants	% of Bill Protected	Average Bill Change
SmartRate™ Only	Increased Bill	4,262	22%	$14.98
	Decreased Bill	15,285	78%	-$37.43
	All SR Only	**19,547**	**99%**	**-$26.00**
Dually Enrolled	Increased Bill	15	0%	$18.48
	Decreased Bill	86	0%	-$45.19
	All Dual	**101**	**1%**	**-$35.73**
All	Increased Bill	4,277	22%	$15.00
	Decreased Bill	15,371	78%	-$37.47
	All	**19,648**	**100%**	**-$26.05**

Billing Impacts by Participant Segment

This section presents billing impacts for other participant segments.

As comparison to participants under the Bill Protection Guarantee, the table below presents the billing impacts for participants that have been enrolled in SmartRate™ for more than a full summer and are no longer eligible for the Bill Protection Guarantee. Within this segment, 71% of participants experienced a reduction in their billing total and the average reduction was slightly lower than participants under bill protection ($33.83 versus $37.47).

Table C-4 Bill Impacts for Participants without the Bill Protection Guarantee

Enrollment Status	Impact	Count of Participants	% of Not Bill Protected	Average Bill Change
SmartRate™ Only	Increased Bill	10,162	23%	$18.88
	Decreased Bill	24,414	55%	-$33.78
	All SR Only	**34,576**	**78%**	**-$18.31**
Dually Enrolled	Increased Bill	2,838	6%	$17.86
	Decreased Bill	7,097	16%	-$33.99
	All Dual	**9,935**	**22%**	**-$19.18**
All	Increased Bill	13,000	29%	$18.66
	Decreased Bill	31,511	71%	-$33.83
	All	**44,511**	**100%**	**-$18.50**

The next table presents the average billing impacts by LCA. Each LCA shows an average reduction in billing totals with the largest reduction experienced by participants in Humboldt, followed by participants in North Coast and North Bay. The smallest reductions were seen in the Stockton LCA.

Table C-5 Bill Impacts by LCA

LCA	Count of Participants	% of Population	Average Bill Change
Greater Bay Area	9,069	14%	-$20.72
Greater Fresno Area	14,032	22%	-$21.92
Humboldt	[redacted]	[redacted]	[redacted]
Kern	5,484	9%	-$24.32
North Coast and North Bay	2,520	4%	-$26.26
Sierra	7,577	12%	-$20.97
Stockton	6,642	10%	-$15.83
Other	18,765	29%	-$19.87
All	**64,159**	**100%**	**-$20.81**

The next table presents average billing impacts by CARE enrollment. Customers on CARE status experienced lower billing reductions, on average, compared to non-CARE customers.

Table C-6 Bill Impacts by CARE Status

CARE Status	Impact	Count of Participants	% of Populaiton	Average Bill Change
Non-CARE	Increased Bill	8,955	14%	$18.24
	Decreased Bill	27,206	42%	-$37.14
	All Non-CARE	**36,161**	**56%**	**-$23.43**
CARE	Increased Bill	8,322	13%	$17.23
	Decreased Bill	19,676	31%	-$32.10
	All CARE	**27,998**	**44%**	**-$17.44**

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