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2020 Load Impact Evaluation for Pacific Gas & Electric Company's SmartAC™ Program

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Executive Summary

This report documents *ex-post* and *ex-ante* load impact evaluations of Pacific Gas and Electric's (PG&E) SmartAC™ program for 2020. The evaluation produces estimates of the *ex-post* load impacts for each hour of each event called in 2020, and it develops *ex-ante* load impact forecasts for the program through 2031.

ES.1 Resources Covered

SmartAC™ is a direct load control central air conditioner (AC) cycling program for residential customers that was integrated into the CAISO wholesale market in program year 2018. SmartAC™ program participants receive a one-time incentive for allowing PG&E to cycle their AC for up to 6 hours per day in response to CAISO market awards, during periods of system or local area emergencies for PG&E capacity, or for limited testing for a maximum of 100 hours per summer (May 1 through October 31). Upon enrollment in SmartAC™, PG&E installs an AC control switch (*i.e.*, Energate LC2200) on the participant's central AC unit that communicates bi-directionally over the AMI network. Legacy technology, installed prior to August 2017, is capable of one-way communication over commercial paging systems and includes programmable communicating thermostats (PCT) and switches. When events are called, PG&E sends signals to the PCTs and switches.

PG&E employs a combination of events including system-wide serial events or at the Sub-Load Aggregation Point (sub-LAP) level. System-wide events include all participants and can be initiated based on CAISO or PG&E emergencies or for testing purposes. System-wide test events generally call all SmartAC™ customers throughout the service territory except for a random sample of SmartAC™ customers that serve as the control group based on the last digit of the factory programmed serial number of their installed device (*i.e.*, one or two serial groups are withheld from the event). During sub-LAP level events all SmartAC™ participants with devices that are associated with a given sub-LAP are dispatched for the event. One of the events during PY2020 was a serial test event, while the remaining fourteen events were CAISO market awards.

The primary goals of the evaluation include:

1. Estimate hourly *ex-post* load impacts for the 2020 program year, including:
    a. Hourly and average daily load impacts for each event;
    b. The distribution of hourly and average daily load impacts by customer segment, including: sub-LAP, CARE/non-CARE customers, net-metering solar customers (NEM), housing type (*i.e.*, single family vs. multifamily customers), AC usage intensity, and device type (*i.e.*, Two-way vs. One-way; by One-way device type: UtilityPro, Gen 1, and Gen 2);
    c. Load Impact estimates for SmartAC™-only customers as compared to customers who are dually enrolled in SmartAC™ and SmartRate™;

   d. The opt-out/override rate by customer segment; and
   e. The persistence of load reductions across event-hours for multiple hour events.
2. Produce *ex-ante* load impact forecasts for 2021-2031 by local capacity area (LCA) on an aggregate and per customer basis for a typical event day and the monthly system peak load day for May through October. Forecasts are based on the following four sets of weather conditions:
   a. PG&E's peaking conditions in a 1-in-2 weather year;
   b. PG&E's peaking conditions in a 1-in-10 weather year;
   c. CAISO peaking conditions in a 1-in-2 weather year; and
   d. CAISO peaking conditions in a 1-in-10 weather year.

ES.2 Evaluation Methodologies

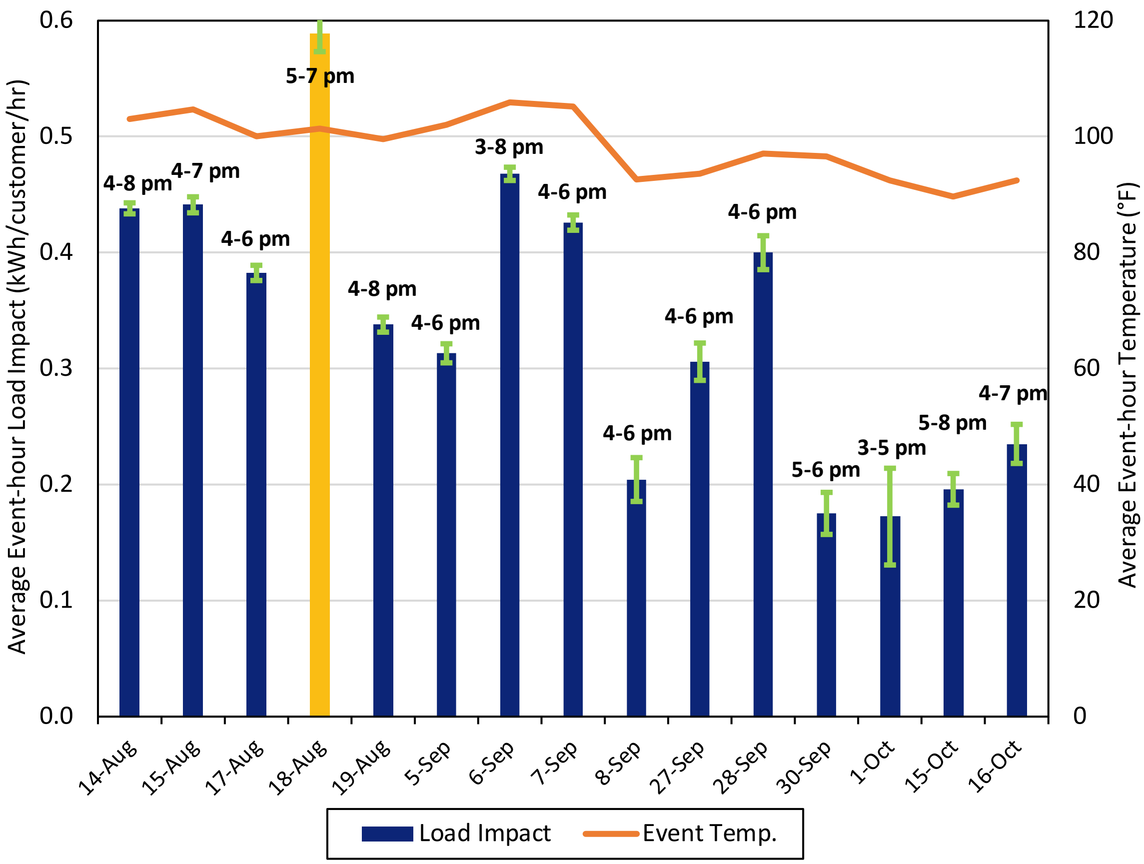
In this evaluation, we estimate load impacts by comparing SmartAC™ customer loads to that of a control group on event days, net of the differences in loads on non-event days with comparable weather conditions. For system-wide serial test events where at least one serial group is withheld from the event, we use this random sample of SmartAC™ customers as the control group. Otherwise we use a matched control group consisting of residential customers who are not enrolled in SmartAC™ or SmartRate™. Matched control group customers are selected based on the similarity of available customer characteristics (*e.g.*, sub-LAP, AC usage, CARE status, NEM status) as well as usage patterns on non-event days.

We then estimate event-day load impacts using a regression-based difference-in-differences method, which produces estimates of standard errors, and thus confidence intervals around the estimated event-hour or event-day usage reductions. This approach also adjusts for differences in usage between the treated SmartAC™ customers and the control group on event-like non-event days, thus representing a difference-in-differences evaluation approach.

ES.3 Ex-Post Load Impacts

Figure ES.1 summarizes the *ex-post* load impact estimates (in kWh/customer/hour) for the average event-hour for all fifteen SmartAC™ events in PY2020, along with an 80 percent confidence interval (corresponding to the 10th and 90th percentile uncertainty-adjusted load impacts). The gold bar indicates the serial test event, while the blue bars correspond to the fourteen sub-LAP event days. These results indicate that SmartAC™ customers had statistically significant load reductions on each of the fifteen event days, ranging from 0.17 to 0.59 kWh/customer/hour. Differences in event temperatures, the sub-LAPS called for events, and variation in sub-LAP performance are driving the variation of average load impacts across events. Moreover, load impacts were not lower during the three weekend events and the holiday event (August 15th, September 5th, September 6th, and September 27th) than weekday events with comparable temperatures. Finally, the load impacts are higher during the serial test event on August 18th, consistent with previous evaluations.

Figure ES.1: Average Event-Hour Load Impacts by Event



In addition to the overall load impacts, we examined patterns of load impacts at the sub-LAP level for sub-LAP events and at the LCA level for serial events. We also examined how load impacts are distributed across customer subgroups. Our results were largely consistent with previous findings, however this year load impacts were not significantly different for one-way and two-way devices during the serial event.

ES.4 Ex-Ante Load Impacts

Ex-ante load impacts represent forecasts of load impacts that are expected to occur when program events are called in future years under standardized weather conditions.

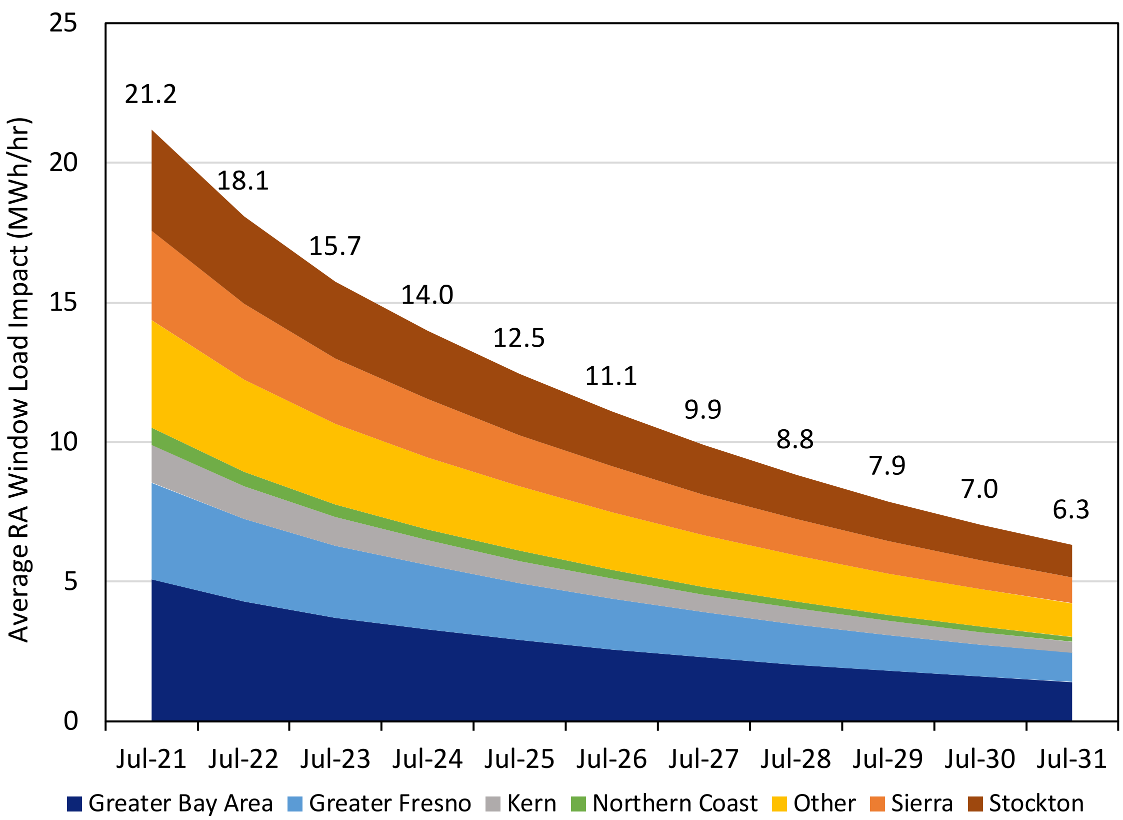
Estimating *ex-ante* load impacts requires three key pieces of information:

1. An *enrollment forecast* provided by PG&E for relevant components of the program, which consists of forecasts of the number of customers by required type of customer;

2. *Reference loads* by customer type, simulated from regression models plus *ex-ante* weather conditions provided by PG&E; and
3. A forecast of *load impacts per customer*, again by relevant customer type, where the load impact forecast also varies with weather conditions and is based on *ex-post* results from current or past program years.

Figure ES.2 summarizes the *ex-ante* load impact forecast for 2021 to 2031 for SmartAC™ customers by plotting the average aggregate load impacts for the Resource Adequacy (RA) window over time by LCA. For this comparison we use the PG&E 1-in-2 scenario for July peak days. The large declines in aggregate load impacts over time are being driven by the enrollment forecast provided by PG&E, which assumes consistent program attrition of approximately 11 percent per year from 2021 to 2031. Overall, load impacts decline by more than 70 percent from 21.2 MWh/hour in 2021 to 6.3 MWh/hour in 2031.

Figure ES.2: Aggregate Load Impacts over RA Window 2021-2031 for PG&E 1-in-2 July Peak Scenario



1. Introduction and Purpose of the Study

This report documents *ex-post* and *ex-ante* load impact evaluations of Pacific Gas and Electric's (PG&E) SmartAC™ program for 2020. The evaluation produces estimates of the *ex-post* load impacts for each hour of each event called in 2020, and it develops *ex-ante* load impact forecasts for the program through 2031.

SmartAC™ is a direct load control central air conditioner (AC) cycling program for residential customers that was integrated into the CAISO wholesale market in program year 2018. SmartAC™ program participants receive a one-time incentive for allowing PG&E to cycle their AC for up to 6 hours per day in response to CAISO market awards, during periods of system or local area emergencies for PG&E capacity, or for limited testing for a maximum of 100 hours per summer (May 1 through October 31).

Upon enrollment in SmartAC™, PG&E installs an AC control switch (*i.e.*, Energate LC2200) on the participant's central AC unit that communicates bi-directionally over the AMI network. Legacy technology, installed prior to August 2017, is capable of one-way communication over commercial paging systems and includes programmable communicating thermostats (PCT) and switches. When events are called, PG&E sends signals to the PCTs and switches. As dictated by the tariff, PG&E cycles the AC unit for residential customers for approximately 50% of the compressor run-time during each half-hour. Switches and some PCTs are cycled using adaptive algorithms.

PG&E employs a combination of events including system-wide serial events or at the Sub-Load Aggregation Point (sub-LAP) level. System-wide events include all participants and can be initiated based on CAISO or PG&E emergencies or for testing purposes. System-wide test events generally call all SmartAC™ customers throughout the service territory except for a random sample of SmartAC™ customers that serve as the control group based on the last digit of the factory programmed serial number of their installed device (*i.e.*, one or two serial groups are withheld from the event). During sub-LAP level events all SmartAC™ participants with devices that are associated with a given sub-LAP are dispatched for the event. Historically, sub-LAP "addressing" was done by sending a signal to new SmartAC™ devices after installation to associate these devices with the appropriate sub-LAP. Since the CAISO wholesale market integration of the SmartAC™ program in 2018, a majority of SmartAC™ events are sub-LAP-level events, while a select number of serial events are called for testing purposes.

Table 1-1 shows the details for each event in program year 2020 (PY2020). There were 25 SmartAC™ events called across 15 event days in 2020. One of the events, on August 18th was a serial test event, while the remaining fourteen event days were CAISO market awards. August 14th included a combination of CAISO market award events for some sub-LAPs as well as an emergency event, where all sub-LAPs were dispatched at some point during the hours from 5:38 p.m. to 8:22 p.m. There were six SmartAC™ sub-LAP event days on August 14th, August 15th, August 19th, September 6th, October 15th, and October 16th, during which the event hours differed across sub-LAPs. Otherwise, sub-LAPs were dispatched for the same event hours. There were also events on August 14th, August 18th, and August 19th that were dispatched for partial event hours.

Table 1-1: PY2020 SmartAC™ Events

<table>
<tr><th>Date</th><th>Smart-Rate™ Event?</th><th>Reason</th><th>Event Hours (p.m.)</th><th>Sub-LAPs/Serial Groups Dispatched</th><th># Customers Dispatched</th></tr>
<tr><td rowspan="5">8/14</td><td rowspan="5">Yes</td><td>Market</td><td>4:00-6:00</td><td rowspan="2">PGEB, PGKN, PGNB, PGNC, PGNP, PGP2, PGST, PGZP</td><td rowspan="2">43,604</td></tr>
<tr><td>Emergency</td><td>6:05-8:22</td></tr>
<tr><td>Market</td><td>5:00-7:00</td><td rowspan="2">PGCC, PGF1, PGSI</td><td rowspan="2">26,550</td></tr>
<tr><td>Emergency</td><td>7:05-8:22</td></tr>
<tr><td>Emergency</td><td>5:38-8:21</td><td>PGFG, PGSB</td><td>9,384</td></tr>
<tr><td rowspan="2">8/15</td><td rowspan="2">No</td><td rowspan="2">Market</td><td>4:00-6:00</td><td>PGCC, PGEB, PGF1, PGKN, PGNC, PGNP, PGP2, PGST</td><td>62,555</td></tr>
<tr><td>5:00-7:00</td><td>PGNB, PGSI</td><td>15,870</td></tr>
<tr><td>8/17</td><td>Yes</td><td>Market</td><td>4:00-6:00</td><td>PGEB, PGF1, PGKN, PGNB, PGNC, PGNP, PGSI, PGST, PGZP</td><td>65,780</td></tr>
<tr><td>8/18</td><td>Yes</td><td>Test</td><td>4:19-7:00</td><td>All Sub-LAPs, Serial Group 7 withheld</td><td>71,444</td></tr>
<tr><td rowspan="3">8/19</td><td rowspan="3">Yes</td><td rowspan="3">Market</td><td>4:00-6:00</td><td>PGEB, PGF1, PGKN, PGNB, PGP2, PGSI, PGST, PGZP</td><td>58,120</td></tr>
<tr><td>5:09-6:00</td><td>PGCC</td><td>241</td></tr>
<tr><td>6:00-8:00</td><td>PGNC</td><td>547</td></tr>
<tr><td>9/5</td><td>No</td><td>Market</td><td>4:00-6:00</td><td>PGEB, PGF1, PGSI</td><td>47,526</td></tr>
<tr><td rowspan="2">9/6</td><td rowspan="2">Yes</td><td rowspan="2">Market</td><td>3:00-6:00</td><td>PGCC, PGEB, PGKN, PGNB, PGNC, PGNP, PGP2, PGSI, PGST, PGZP</td><td>55,853</td></tr>
<tr><td>5:00-8:00</td><td>PGF1</td><td>12,904</td></tr>
<tr><td>9/7</td><td>No</td><td>Market</td><td>4:00-6:00</td><td>PGEB, PGF1, PGKN, PGNB, PGNC, PGNP, PGSI, PGST, PGZP</td><td>75,122</td></tr>
<tr><td>9/8</td><td>No</td><td>Market</td><td>4:00-6:00</td><td>PGNB, PGST</td><td>7,775</td></tr>
<tr><td>9/27</td><td>No</td><td>Market</td><td>4:00-6:00</td><td>PGCC, PGP2, PGSB</td><td>11,160</td></tr>
<tr><td>9/28</td><td>No</td><td>Market</td><td>4:00-6:00</td><td>PGCC, PGFG, PGNC, PGP2, PGSB</td><td>13,593</td></tr>
<tr><td>9/30</td><td>No</td><td>Market</td><td>5:00-6:00</td><td>PGSI</td><td>14,173</td></tr>
<tr><td>10/1</td><td>No</td><td>Market</td><td>3:00-5:00</td><td>PGFG</td><td>1,817</td></tr>
<tr><td rowspan="2">10/15</td><td rowspan="2">No</td><td rowspan="2">Market</td><td>5:00-7:00</td><td>PGFG, PGP2</td><td>5,185</td></tr>
<tr><td>6:00-8:00</td><td>PGCC, PGSB</td><td>7,786</td></tr>
<tr><td rowspan="2">10/16</td><td rowspan="2">No</td><td rowspan="2">Market</td><td>4:00-6:00</td><td>PGSB</td><td>7,545</td></tr>
<tr><td>5:00-7:00</td><td>PGFG</td><td>1,817</td></tr>
</table>

SmartAC™ customers have historically been eligible to also enroll in the SmartRate™ program. A CPUC decision permits the legacy dual participants if they enrolled before October 26, 2018, but subsequent new dual participation is prohibited. As of May 2020, SmartAC™ had over 90,000 active enrolled residential customers; approximately 10,700 of these customers were dually enrolled in SmartAC™ and SmartRate™. On days when both a SmartAC™ event and a SmartRate™ event is called, the SmartRate™ customers are withheld from our summary of SmartAC™ events and the response from dually enrolled customers is attributed to the SmartRate™ program.

The primary goals of the evaluation include:

1. Estimate hourly *ex-post* load impacts for the 2020 program year, including:
    a. Hourly and average daily load impacts for each event;
    b. The distribution of hourly and average daily load impacts by customer segment, including: sub-LAP, CARE/non-CARE customers, net-metering solar customers (NEM), housing type (*i.e.*, single family vs. multifamily customers), AC usage intensity, and device type (*i.e.*, Two-way vs. One-way; by One-way device type: UtilityPro, Gen 1, and Gen 2)[1];
    c. Load Impact estimates for SmartAC™-only customers as compared to customers who are dually enrolled in SmartAC™ and SmartRate™;
    d. The opt-out / override rate by customer segment[2]; and
    e. The persistence of load reductions across event-hours for multiple hour events.
2. Produce *ex-ante* load impact forecasts for 2021-2031 by LCA on an aggregate and per customer basis for a typical event day and the monthly system peak load day for May through October. Forecasts are based on the following four sets of weather conditions:
    a. PG&E's peaking conditions in a 1-in-2 weather year;
    b. PG&E's peaking conditions in a 1-in-10 weather year;
    c. CAISO peaking conditions in a 1-in-2 weather year; and
    d. CAISO peaking conditions in a 1-in-10 weather year.

The evaluation conforms to the Load Impact Protocols adopted by the California Public Utilities Commission (CPUC) in April 2008 (D.08-04-050).

This report is organized as follows: Section 2 describes the evaluation methods used in the study; Section 3 contains *ex-post* load impact results; Section 4 contains *ex-ante* forecasts; Section 5 compares *ex-post* and *ex-ante* estimates to those from previous years; and Section 6 provides recommendations. Appendices describe the results of our control-group matching process, approaches used to evaluate the quality of results, and contain electronic versions of the required Protocol table generators.

[1] Previous evaluations examined load impacts for ExpressStat devices as well, however, there were only six SmartAC™ customers in PY2020 with ExpressStat devices. We are not able to provide reliable results for small subgroup sample sizes, hence we exclude this group from the PY2020 analysis.

[2] The opt-out rate is the portion of program participants who request by phone or website to override the control of their AC device during specific events.

2. Study Methodology

The primary objectives of this evaluation were outlined in Section 1. This section describes the data and methods used to produce *ex-post* load impacts and *ex-ante* forecasts.

2.1 Ex-post Load Impact Evaluation: Sub-LAP Events

For the sub-LAP events, we estimate load impacts by comparing SmartAC™ customer loads to that of a quasi-experimental matched control group of non-SmartAC™ customers on event days, net of the differences in loads on event-like non-event days. This regression-based approach, known as the difference-in-differences (D-in-D) method, can be used to produce estimates of standard errors to develop confidence intervals about the estimated event-hour or event-day load impacts. The eligible control-group customers consist of residential customers who are not enrolled in SmartAC™ or SmartRate™. We match control-group customers based on the similarity of available customer characteristics (*e.g.*, sub-LAP, AC usage, CARE status, NEM status) as well as usage patterns on non-event days.

2.1.1 Data

To address each of the load impact objectives listed in Section 1, the following data is required:

- *Customer* information for SmartAC™ customers and potential control-group customers (*e.g.*, sub-LAP, LCA, weather station, AC usage level, housing type, CARE status, NEM status);
- Billing-based *interval load data* (*i.e.*, hourly loads for each treatment and potential control group customer) for PY2020 (May 1 through October 31);
- *Weather data* (*i.e.*, hourly temperatures and other variables for PY2020, by weather station);
- *Program event data* (*i.e.*, dates and hours of SmartAC™ and SmartRate™ events and a list of SmartAC™ customers who are dually enrolled in both programs); and
- *Device Information* for SmartAC™ customers (*i.e.*, the type and number of devices installed at each premise and the serial number to determine treatment and control groups for the serial event) as well as SmartAC™ customer opt-outs on each date.

2.1.2 Control Group Selection for Sub-LAP events

The objective in selecting a quasi-experimental matched control group is to identify a group of customers that are as similar as possible to treatment customers, particularly in terms of their hourly load profiles. Due to the high number of potential control customers, we perform the matching in two stages. In the first stage, we use nearest neighbor matching to identify three control customers for each treatment customer that have the closest match in terms of average daily usage (based on monthly billing data), weather station and average cooling degree days, and customer characteristics such as CARE status, NEM status, dwelling type, AC usage, and rate schedule. Following the first-stage matching, we obtain interval load data for the treatment customers and the pared-down set of matched control customers.

The first-stage matching allows for a more tractable matching process in the second stage using the interval load data. The second-stage matching process uses propensity score matching to find a single control customer for each SmartAC™ customer with the closest hourly load profile on a selection of non-event, non-holiday weekdays. Moreover, to ensure that customers are matched based on the sensitivity of their energy usage to weather conditions, we perform this matching process using two 24-hour load profiles drawn from different temperature profiles. The first 24-hour load profile reflects usage patterns during the hottest 10 percent of non-event days. The second 24-hour load profile reflects usage over a set of cooler days taken from the middle 50 percent of non-event days. In addition to two 24-hour load profiles, customers are also matched based on CARE status, NEM status, dwelling type, and AC usage level.[3] Finally, we require that SmartAC™ customers are matched to a control customer residing in the same sub-LAP area.

Propensity score matching involves estimating a regression to determine each customer's probability (*i.e.*, "propensity") of being assigned treatment based upon observable characteristics. Each SmartAC™ customer is then matched to the control customer with the nearest value in terms of their predicted probability, also known as their "propensity score". For the second stage matching, we assume the probability model is a logistic function of the following form:

$$logit(SmartAC_c) = \beta_0 + \sum_{h=1}^{24} \beta_{1,h} avgkW_{c,h} + \sum_{all\ j} \beta_{2,j} X_{c,j} + \varepsilon_c$$

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

Table 2-1: Propensity Score Model Terms

Symbol	Description
$SmartAC_c$	Variable indicating whether customer c is a SmartAC (1) or Control (0) customer
$avgkW_{c,h}$	Average load during hour h for customer *c*
$X_{c,j}$	The value of characteristic j for customer c
β_0	Estimated constant coefficient
$\beta_{1,h}$	Estimated coefficient for hour h of 24-hour load profile
$\beta_{2,i}$	Estimated coefficient for customer characteristic j
ε_c	Error term for customer c

We estimate a logistic regression that includes two 24-hour profiles: one that averages customer load across hot days (*i.e.*, the hottest 10 percent of non-event days) and one that averages customer load across a random selection of cooler days (*i.e.*, days that fall

[3] Propensity score matching does not guarantee that treatment customers are matched with a control that has the same CARE status, NEM status, *etc*. However, this approach leads to a similar distribution across these characteristics for the treatment group and control group.

between the 25th and 75th percentile of non-event days based on average temperature). Furthermore, we include indicators for CARE status, NEM status, type of dwelling, and AC usage level as customer characteristics in the regression. This model is estimated separately for each sub-LAP.

To assess the validity of the control-group matching processes, we compare the characteristics and non-event-day load profiles of the matched control-group and treatment customers. More details about our matching process, including evaluation of match quality, are provided in Section 3.1 and Appendix A.

2.1.3 Analysis Methods

To produce estimates of *ex-post* load impacts for the sub-LAP events, we estimate the following panel model for each hour of the day and sub-LAP:

$$kW_{c,d} = \beta_0 + \sum_{i=1}^{n}(\beta_{1,i} \times SmartAC_{c,d} \times Evt_{i,d}) + \sum_{all\ j} \beta_{2,j} X_{c,d,j} + C_c + D_d + \varepsilon_{c,d}$$

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

Table 2-2: *Ex-Post* Load Impacts Model Terms

Symbol	Description
$kW_{c,d}$	Load during a given hour for customer *c* on day *d*
$SmartAC_{c,d}$	Variable indicating whether customer *c* is a SmartAC (1) or Control (0) customer
$Evt_{i,d}$	Variable indicating that day *d* is the i^{th} event day (1) or not (0)
$X_{c,d,j}$	The value of weather variable j on day d for customer c
β_0	Estimated constant coefficient
$\beta_{1,i}$	Estimated load impact for event *i*
$\beta_{2,i}$	Estimated coefficient for customer characteristic j
C_c	Customer fixed effects
D_d	Date fixed effects
$\varepsilon_{c,d}$	Error term (correlated at the customer level)

The model includes date and customer fixed effects to account for factors that commonly affect all customers over time (*e.g.*, weather) and time-invariant customer characteristics (*e.g.*, home size). In addition, the model includes time variant weather controls such as the mean temperature across the first 17 hours of the day[4]. The $\beta_{1,i}$ coefficients represent the estimated load impacts for each hour of every event day.

We estimate this model separately for each hour of the day using only event and event-like non-event days (*i.e.*, the hottest 10% of non-event days). The distribution of load impacts across different customer subgroups is reserved for the serial test event on August 15, 2020, since this allows for a system-wide comparison of treatments and controls with the same subgroup status. As previously mentioned, the matching procedure used for sub-LAP events does not guarantee that the dispatched sub-LAPs are representative of the system-wide results nor that treatments and matched controls have the same subgroup status. For sub-LAP events we estimate the load impacts by

[4] The inclusion of weather variables may improve the effectiveness of the date fixed effects, particularly in models that include customers in different weather regions (*e.g.*, models by sub-LAP).

sub-LAP and for customers who are dually enrolled in SmartRate™ compared to customers who are only enrolled in the SmartAC™ program.

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. Thus, in addition to producing point estimates of the *ex-post* load impacts, we show the uncertainty around the estimated impacts. These methods use the estimated load-impact parameter values and the associated variances to derive scenarios of hourly load impacts. Due to variation in event hours across event days, we are not able to estimate the uncertainty associated with the typical event day.

We validated the *ex-post* load impact estimates against simple difference-in-difference calculations from load data. Specifically, for each sub-LAP and event day, we compared the average treatment customer hourly loads to the average control-group hourly loads. The comparisons included events during which the sub-LAP was not dispatched, which allowed us to ensure that the event information we were provided was correct and that our methods did not produce "false positives" (*i.e.*, estimated load impacts for dates/locations in which customers were not dispatched).

2.2 Ex-post Load Impact Evaluation: Serial Events

For the system-wide test event on August 18th, in which the control group consists of SmartAC™ customers with device serial numbers ending in 7 (*i.e.*, serial group 7 was not dispatched for the event), we can estimate load impacts by simply comparing the treatment and control customer usage during each hour of the day. This approach relies upon treatment and control-group customer load profiles being statistically equal during pre-event hours. Although this is generally the case for a large number of customers, when estimating load impacts for smaller subgroups significant differences can arise.[5] A D-in-D approach, similar to the model presented in Section 2.1.3, can be used to control for any remaining differences in pre-event hour loads. This approach subtracts the difference between treatment and control loads (SmartAC™ customers in serial group 7) on select non-event days with comparable weather profiles from the difference on the serial event day.

Consistent with previous evaluations of serial test events, we use a simple D-in-D approach to estimate load impacts. In order to obtain standard errors for the uncertainty-adjusted load impacts, we implement this by estimating a regression model with each customer's usage during a given hour as the dependent variable and with the explanatory variables limited to a constant term and variables indicating 1) customers who are in the treatment group, 2) the day where the event is called, and 3) the treatment customers on the event day. The coefficient on the latter variable is the D-in-D load impact estimate. Once again, we use the estimated load-impact parameter values and the associated variances to derive uncertainty-adjusted load impacts for the Load Impact Protocols.

[5] This issue was discussed at length in the PY2017 evaluation.

We estimate this model separately for each hour of the day using only event and event-like non-event days. The distribution of load impacts across different customer subgroups is explored by estimating the above model separately for each subgroup when there are sufficient treatment and control customers in the subgroup. These variables include CARE status, NEM status, housing type, AC usage level, and device type (*i.e.*, Two-way vs. One-way; by One-way device type: UtilityPro, Gen 1, and Gen 2). Since the serial test event in 2020 was also a SmartRate™ event, we are not able to compare load impacts for customers who are dually enrolled in SmartRate™ to load impacts for SmartAC™ only customers using this method, because the dually enrolled customers in the control group have their devices signaled as part of the SmartRate™ event. Essentially there is no randomized control group for the dually enrolled customers for this event. Instead we use the matched control group approach described in Section 2.1 for this comparison.

2.3 Developing Ex-Ante Load Impacts

Ex-ante load impacts represent forecasts of load impacts that are expected to occur when program events are called in future years under standardized weather conditions.

Estimating *ex-ante* load impacts requires three key pieces of information:

1. An *enrollment forecast* for relevant components of the program, which consists of forecasts of the number of customers by required type of customer;
2. *Reference loads* by customer type; and
3. A forecast of *load impacts per customer*, again by relevant customer type, where the load impact forecast also varies with weather conditions (if applicable), as determined in the *ex-post* evaluation.

Ex-ante load impacts are developed for the years 2021 through 2031, both for the monthly system peak load as well as a typical event day, under the four scenarios defined by both utility-specific and CAISO peaking conditions in both 1-in-2 (normal) and 1-in-10 (extreme) scenarios. Furthermore, *ex-ante* load impacts are developed for the following subgroups of customers:

1. LCA;
2. Customers enrolled in only SmartAC™ vs. customers dually enrolled in SmartAC™ and SmartRate™; and
3. Busbar (by November 1, 2021).

PG&E provided the enrollment forecasts and *ex-ante* weather conditions for each required scenario.

2.3.1 Reference Loads

The *per-customer reference loads* are simulated based on regression models, which reflect customer load patterns on non-event days and estimate the relationship between load patterns and weather. Reference loads are simulated using the appropriate weather scenario data (*i.e.*, the 1-in-2 and 1-in-10 weather-year conditions provided by the utilities) and month.

The regression model uses data for treatment customers from all non-holiday weekdays that do not coincide with SmartAC™ or SmartRate™ events from May 1 to October 31 in 2020. Average load profiles are created for each LCA and enrollment segment (*i.e.*, SmartAC™-only and dually enrolled customers). The regressions account for differences in loads by hour, day-of-week, or month by including various indicator control variables.

The *ex-ante* reference load regression model is as follows:

$$avgkW_{d,h} = \beta_0 + \sum_{h=1}^{24} \beta_{1,h}(CDD60_d \times H_h) + \sum_{h=1}^{24} \beta_{2,h} H_h + \sum_{h=1}^{24} \beta_{3,h}(Mon_d \times H_h) + \sum_{h=1}^{24} \beta_{4,h}(Fri_d \times H_h) + D_d + M_d + \varepsilon_{d,h}$$

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

Table 2-3: *Ex-Ante* Reference Loads Model Terms

Symbol	Description
$avgkW_{d,h}$	Average load (kWh/customer/hour) on day *d* during hour *h*
$CDD60_d$	The cooling degrees on day *d*
$B_{1,h}$	Estimated increase in average load during hour *h* from an increase of one cooling degree
$B_{2,h}$	Estimated average load during hour *h*
$B_{3,h}$	Estimated difference in average load during hour *h* on Mondays
$B_{4,h}$	Estimated difference in average load during hour *h* on Fridays
H_h	Variable indicating that the hour is *h* (1) or not (0)
Mon_d	Variable indicating that day *d* is a Monday (1) or not (0)
Fri_d	Variable indicating that day *d* is a Friday (1) or not (0)
D_d	Day of the week fixed effects
M_d	Month of the year fixed effects
$\varepsilon_{d,h}$	Error term (robust)

The model includes hour fixed effects to allow loads to vary by hour of the day. Monday and Friday hourly fixed effects allow for differences in load profiles on Mondays and Fridays. Day of the week fixed effects allow the daily load level to vary by day of the week. Month fixed effects allow the daily load level to vary by month of the year. The $\beta_{1,h}$ coefficients represent the estimated increase in average loads during hour *h* due to a one cooling degree day increase. We estimate this model separately for each sub-LAP and enrollment segment to be consistent with the load impact model described in Section Load Impacts. We then aggregate results from the sub-LAP level models to LCA based on the share of customers in each sub-LAP and LCA in PY2020.

Reference loads are simulated by applying the cooling degree days from the weather scenarios provided by PG&E to the estimated $\beta_{1,h}$ coefficients along with the other relevant load shape variables and fixed effects. The estimated reference loads for each month and weather scenario are assumed to be the monthly system peak load (or typical event day) for a Wednesday event.

2.3.2 Load Impacts

The *per-customer load impacts* are derived from an analysis of the current and previous *ex-post* load impact evaluations, with a focus on the effect of weather on the estimated load impacts. The resulting per-customer load impacts are then coupled with the appropriate reference loads to develop the forecasted load impacts and event-day reference load profiles.

In previous evaluations, *ex-ante* load impacts were based entirely on program performance during serial events. The *ex-ante* forecast simulated program performance during system-wide emergency events, where devices are signaled similar to a serial test event, but without a withheld control group. As such, the forecast represented maximal performance of the SmartAC™ program if called for emergency purposes. Another reason for using serial test events was that they allowed for estimates to easily be produced by LCA, as is required by the Protocols. Serial events have rarely been called since SmartAC™ was integrated into the CAISO wholesale market in 2018 and CAISO market awards are dispatched at the sub-LAP level. As previously documented, the load impacts for sub-LAP events consistently underperform those of serial events because the legacy paging devices have historical issues with sub-LAP dispatch.

In response to the changing nature of SmartAC™ events, we have changed the approach for developing the *ex-ante* load impacts for the PY2020 evaluation, at the direction of PG&E staff. For this evaluation, we develop an *ex-ante* forecast that is designed to project program performance during sub-LAP events. To accomplish this goal, we include load impacts from all sub-LAP events in PY2020 in addition to the serial events from PY2019 and PY2020. We develop a model that estimates the relationship between *ex-post* load impacts (for both serial and sub-LAP events) and event temperatures and simulate the model results for sub-LAP events.

We modeled the relationship between load impacts and weather conditions as follows:

$$\begin{aligned}\%\,Impact_{s,h,evt\,i} = \beta_0 + \beta_1 Temp_{s,h,evt\,i} + \beta_{2,s} Mean8_{s,evt\,i} \times subLAP_s +\\ \delta_s Serial_{evt\,i} \times subLAP_s + subLAP_s + H_h + \varepsilon_{s,h,evt\,i}\end{aligned}$$

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

Table 2-4: *Ex-Ante* Load Impacts Model Terms

Symbol	Description
% Impact$_{s,h,evt\,i}$	Estimated load impact divided by reference load in sub-LAP *s* during hour *h* on event *i*
Temp$_{s,h,evt\,i}$	Average temperature in subLAP *s* during hour *h* on event *i*
Mean8$_{s,evt\,i}$	Average temperature in subLAP *s* over the first eight hours of the day on event *i*
β_1	Estimated increase in percent load impact from a 1 degree increase in average hourly temperature
$\beta_{2,s}$	Estimated increase in percent load impact in subLAP *s* from a 1 degree increase in average temperature over the first eight hours of the day
δ_s	Estimated difference in percent load impacts in subLAP *s* during serial events
Serial$_{evt\,i}$	Variable indicating if event *i* is a serial event (1) or not (0)
subLAP$_s$	Variable indicating if the subLAP is s (1) or not (0)
H_h	Variable indicating if the hour is *h* (1) or not (0)
$\varepsilon_{s,h,evt\,i}$	Error term (robust)

The model includes sub-LAP and hour fixed effects to allow load impacts to vary by sub-LAP and hour of the day. The β coefficients represent the estimated increase in percent load impacts that results from a one-degree increase in temperature, either hourly or the average of the first eight hours of the event day. The δ coefficient measures the additional load impacts during serial events, which may vary by sub-LAP. The simulated *ex-ante* results in percentage terms are multiplied by the *ex-ante* reference loads to arrive at the per-customer *ex-ante* load impacts (in kWh/customer/hour). The standard errors from this model are the basis for the uncertainty-adjusted load impacts.

We build our *ex-ante* load impact forecasts based on a combination of serial events called in 2019 and 2020 as well as all sub-LAP events called in 2020. In an effort to ensure the load impact forecast reflects current program performance, we give the PY2020 load impacts twice the weight in our regressions as the PY2019 load impacts. Moreover, the simulations produced from this model are only for sub-LAP events to reflect the nature of how events will be called for the SmartAC™ program in future program years.[6]

In addition, we use load impacts that correspond to SmartAC™-only customers, consistent with how this analysis was done in previous reports. We use the same load impacts for dually enrolled customers, based on our examination of the relationship between SmartAC™-only customers and dually enrolled customers during the sub-LAP events in PY2020. As we discuss in Section 3.5.2, load impacts are higher for dually enrolled customers for some SmartAC™-only events and lower for others. On average the performance is comparable during sub-LAP events.

The snapback in the three hours following the event (when the customer's AC unit is running more than it would have in the absence of the event day to bring the home's temperature back to the thermostat's set point) is modeled as a share of the total event-hour load impact, by LCA. That is, larger event-hour load impacts are associated with higher post-event snapback.

As in all recent load impact evaluations, we present results of analyses of the relationship between current *ex-post* and *ex-ante* load impacts, focusing on key factors causing differences between them (*e.g.*, differences between observed temperatures in 2020 and the temperatures in the various weather scenarios). We will also compare current and previous *ex-post* load impacts, and current and previous *ex-ante* load impacts.

2.3.3 Adjustments due to the COVID-19 Pandemic

The statewide shelter-in-place (SIP) orders enacted to address the global pandemic in 2020 led to increased residential loads primarily during the midday hours. PG&E provided us with a forecast of its expected COVID effects on customer load, which we have incorporated in the forecast.

[6] To simulate the load impacts for sub-LAP events, we set $Serial_{evt\ i}$ equal to zero so that the incremental load impact during serial events is not included in the simulated load impacts.

To make these adjustments to the *ex-ante* forecast, we estimate the impact of SIP on reference loads for SmartAC™-only customers by comparing reference loads from PY2019 and PY2020 for the subset of customers enrolled during both program years. We estimate a model similar to the reference load model detailed in Section 2.3.1 that also includes an interaction term between the hour of the day and observations that occur during PY2020. This allows us to estimate the impact of SIP on average hourly loads for SmartAC™ customers for each hour of the day by sub-LAP. We normalize these results to conform with the levels assumed in PG&E's SIP forecast adjustments.

3. *Ex-Post* Load Impacts

This section documents the findings from the *ex-post* load impact analysis. The primary load impact results include estimates of the aggregate and per-customer event-hour load impacts for each event. Due to the nature of sub-LAP events (fourteen out of fifteen events), where different sub-LAPs are dispatched for different events and, in some cases, different event hours, we are not able to present results for the typical event day. Instead, we average the hourly load impacts across all potential, full event hours, or in some cases choose an illustrative event hour or event day. Our main findings are summarized in this section in various figures and data tables, while detailed results for each hour, event, and sub-LAP or LCA are available in electronic form in Protocol table generators provided along with this report.

As described in Section 2, all results presented in this section are derived from D-in-D regression analyses of hourly data for SmartAC™ customers and a control group. In addition to the controls described in the estimated model in Section 2.1.3, we control for the five concurrent SmartRate™ events by including separate indicators for customers who are dually enrolled in SmartAC™ and SmartRate™. Furthermore, we drop SmartRate™-only events from the pool of SmartAC™ non-event days to ensure that non-event loads are comparable between SmartAC™ customers and controls on all non-event days.

In previous evaluations, net hourly loads were used for all analyses, which subtracts received loads (produced by NEM customers and exported to the grid) from delivered loads (produced by PG&E). For the PY2020 evaluation, we use only delivered loads for our analysis, in an effort to align with CAISO's DR settlement processes, which only counts curtailed delivered loads in the load impacts and does not credit exported (negative) loads. However, a comparison of both approaches for events in PY2019 did not show a significant impact on load impacts. The load shape of overall reference loads was impacted during the midday hours, however most SmartAC™ events occurred during later hours, which were not affected.

3.1 Control Group Matching Results

In this section, we present summaries of our control group matching process used to create a control group for the fourteen sub-LAP events, including the emergency event on August 14^{th}. Our validity assessment focuses on comparisons of treatment and control-group loads for selected event-like non-event days. We also report statistics such as the mean absolute percentage error (MAPE) and mean percent error (MPE), which provide measures of accuracy and bias in the matches, respectively.[7]

Table 3-1 provides the mean percentage error (MPE) and mean absolute percentage error (MAPE) calculated across the average 24-hour load profile as well over the RA window. We evaluate match quality based on the two 24-hour load profiles that we used in matching. The first corresponds to the average load profile over the hottest 10 percent of event-like non-event days, while the second corresponds to a random sample of cooler days taken from the middle 50 percent of days based on temperature. We also evaluate the match quality of the cooler days (*i.e.*, the middle 50 percent of days based on temperature) that were not sampled for use in matching and the weekend non-event days, which helps assess whether there is good match quality on out-of-sample days. Additional results by sub-LAP are presented in Appendix A.

Table 3-1: Match Quality Statistics

Comparison Days	MPE	MAPE	MPE RA Window	MAPE RA Window
Hot Days	0.5%	0.6%	0.7%	0.7%
Cool Days	0.4%	0.5%	0.8%	0.8%
Non-Matching Cool Days	0.6%	0.7%	1.5%	1.5%
Weekend Days	0.8%	0.8%	1.0%	1.0%

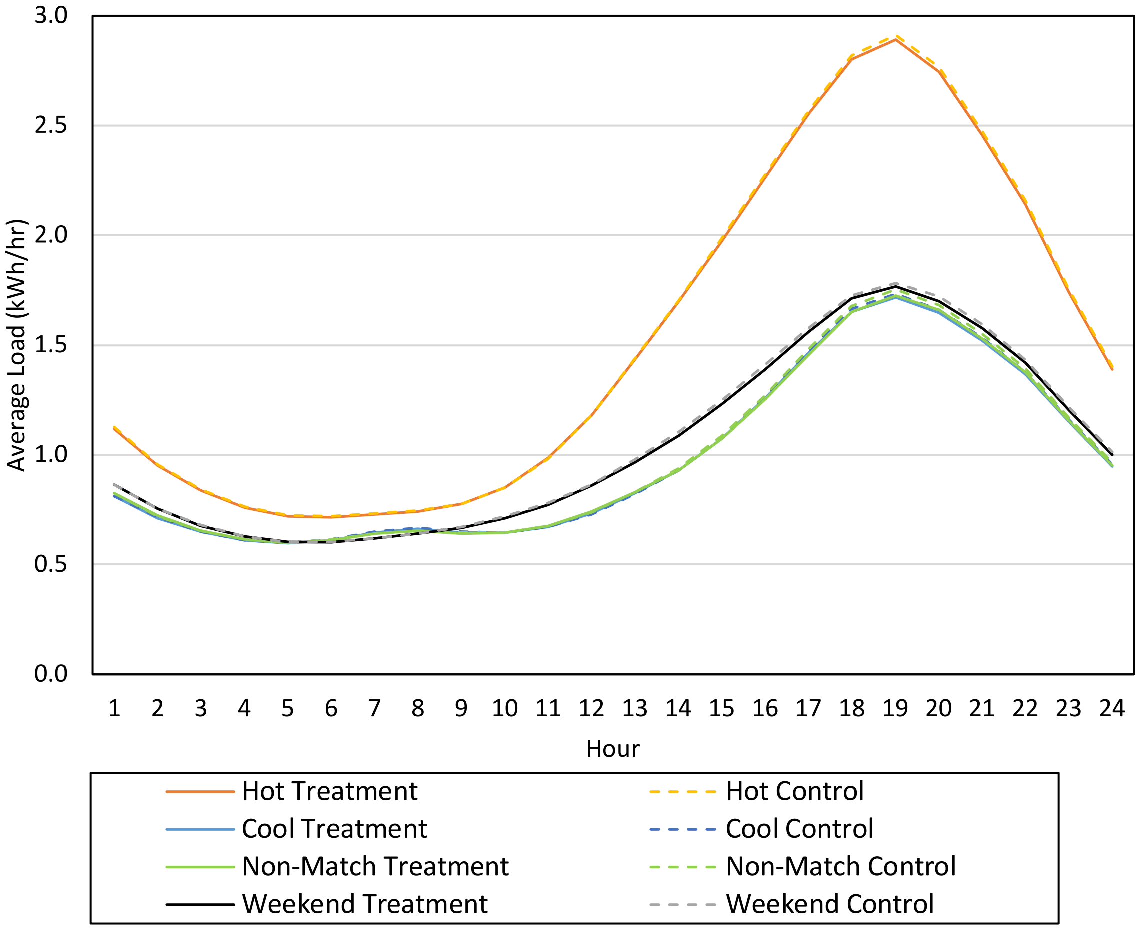
Figure 3-1 illustrates the matched load profiles for selected event-like days. This figure contains the average hourly profiles for the treatment and matched control-group customers by day type including hot days, cooler days that were used in matching, the cooler days that were not used in matching, and weekend days (not used in matching). The solid lines represent the average usage of treatment customers on hot days (red), cooler matching days (blue), cooler non-matching days (green), and weekend days (black). Similarly, the dashed lines represent the average usage of the matched control customers on hot days (yellow), cooler matching days (blue), cooler non-matching days (green), and weekend days (gray). Regardless of the comparison day, the average load profiles are nearly identical between treatment and control. Cool days that are used in matching have comparable loads to cool days that are not used in matching and the control loads on each type of day tracks the treatment loads very closely. Moreover, weekend loads have a comparable load shape to cool weekdays. These results also suggest that matches based on weekdays are appropriate for estimating load impacts for the frequent weekend and holiday events dispatched in PY2020.

Figure 3-1 also shows how load shapes are impacted by using only delivered loads during PY2020. Previously, the load shapes dipped down between 8 a.m. and 4 p.m. due to the impact of exported loads from NEM customers. The load shapes during PY2020 do not dip down during these hours and have a more traditional shape. Figure 3-1 also

[7] Note that "biased" matches do not necessarily adversely affect the estimated load impacts, as we employ a difference-in-differences estimation methodology that accounts for load differences during the matching period.

shows the impact of SIP on reference loads. During PY2020 reference loads peak at 2.9 kWh/customer/hour during hot non-event days, compared to a peak of 2.6 kWh/customer/hour in PY2019.

Figure 3-1: Treatment and Control Non-Event Day Load Profiles



3.2 Overall Load Impacts

This section summarizes overall results for all SmartAC™ events. In later sections, we focus attention on sub-LAP events, serial events, and discuss how these load impacts are distributed across subgroups of interest, including for customers who are dually enrolled in SmartRate™.

The *ex-post* load impacts are summarized for all fifteen events in Figure 3-2.[8] The bars indicate the magnitude of the average per customer load impact (in kWh/customer/hour) during the full event hours dispatched for each event, while the labels show the maximal range of full event hours over which all customers were

[8] The load impacts do not include partial event hours. For example, including partial event hours lowers the average event-hour load impact on August 14th to 0.32 kWh per-customer per-hour.

dispatched.[9] The gold bar indicates the serial event on August 18th, while the blue bars correspond to the fourteen sub-LAP events. The green bands correspond to 80 percent confidence intervals around these estimates (*i.e.*, the 10th and 90th percentile scenarios from the uncertainty-adjusted load impacts). The orange line represents the average temperatures experienced by the customers during the event.

Overall results range from 0.17-0.59 kWh/customer/hour

These results indicate that SmartAC™ customers had statistically significant load reductions on each of the fifteen event days, ranging from 0.17 to 0.59 kWh/customer/hour.

Temperatures explain most of the variation in per-customer load impacts

Figure 3-2 also shows that events with lower load impacts correspond to cooler event temperatures. Differences in event temperatures explain most of the variation of average load impacts across events. Differences in the sub-LAPs called and variation in sub-LAP performance are another big factor driving load impact variation across events.

Weekend and Holiday events do not have lower load impacts

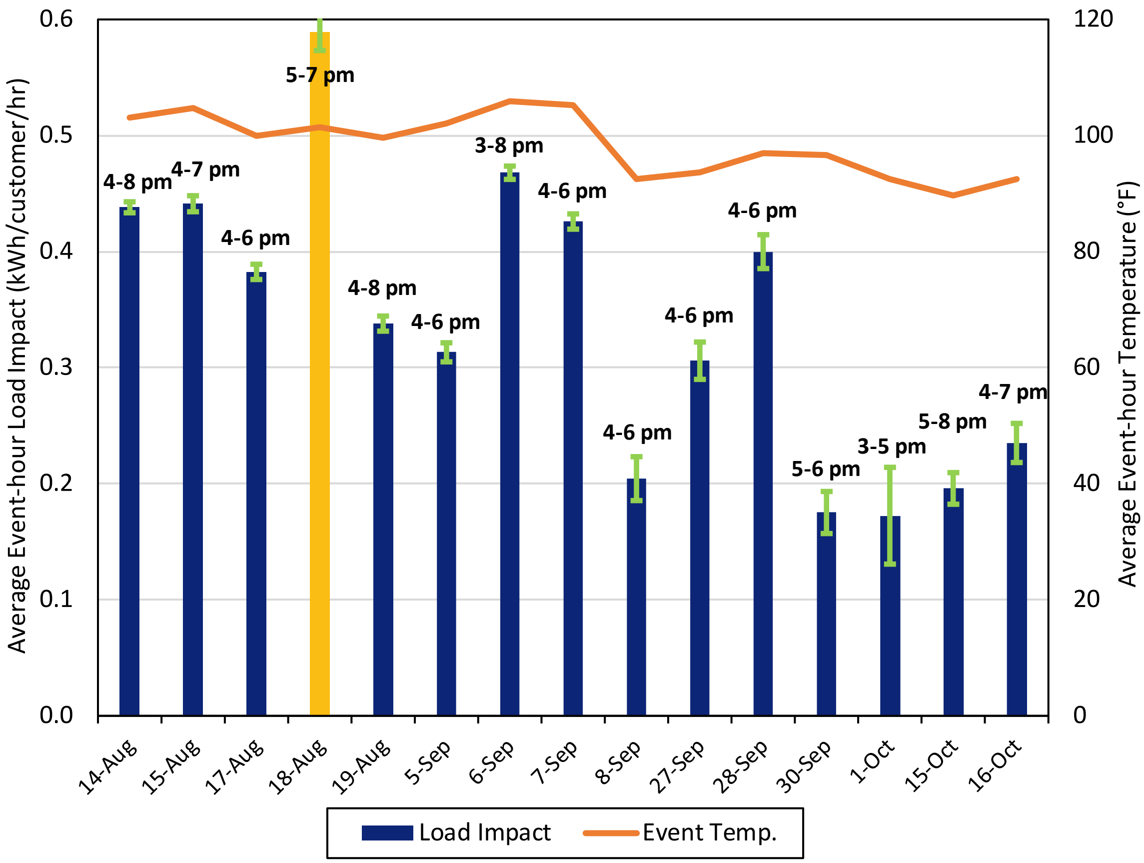
The weekend events on August 15th, September 5th, September 6th, and September 27th and the holiday event on September 7th have some of the highest load impacts out of the sub-LAP events in PY2020. The holiday weekend events from September 5th through September 7th were called during a period of extremely high temperatures, explaining the high per-customer load impacts. The August 15th event has comparable load impacts to the August 14th event. The event on September 27th had much lower temperatures compared to the other weekend events. Overall, these results suggest that the SmartAC™ program performs comparably on weekend and holiday events.

The serial event has higher per-customer load impact than sub-LAP events

The average load impact across serial event hours was 0.59 kWh/customer/hour while the average load impact across sub-LAP event hours was 0.32 kWh/customer per hour. Historically load impacts for SmartAC™ serial test events have been higher than load impacts for sub-LAP events, since factory programmed addressing, used for serial event dispatch, is more reliable than sub-LAP addressing. While previous analyses have suggested that this difference would shrink as new two-way devices replace old devices, there has been less comprehensive replacement of one-way devices than previously anticipated. Indeed, there was less of a gap between serial and sub-LAP event load impacts in PY2019. That evaluation found average per-customer load impacts across all serial event hours was 0.51 kWh/customer/hour compared to 0.37 kWh/customer/hour across all sub-LAP event hours.

[9] On the August 15th, October 15th, and October 16th sub-LAP events, sub-LAPs were called for different event hours. In Figure 3-2, we aggregate across hours during which customers were called, while in the protocol table generators the hourly load impacts are aggregated across all called sub-LAPs for each hour of the day. This can dampen the estimated load impacts during hours where only a subset of called sub-LAP areas are called during the hour.

Figure 3-2: Average Event-Hour Load Impacts by Event



The number of dispatched customers and average event temperature drive large variation in aggregate event impacts

Table 3-2 presents a more complete summary of event information, including the sub-LAPs dispatched, the sub-LAP-specific event hours, the type of event, and the number customers dispatched, as well as average load impacts (per customer and in aggregate), reference loads, and percentage load impacts across the full event hours for which each sub-LAP was dispatched (in the case of sub-LAP events) for each event day. The number of dispatched customers and average event temperatures explain 82 percent of the variation in aggregate load impacts. The number of dispatched customers varies dramatically across events, with 1,817 customers dispatched for the sub-LAP event on October 1, 2020 to 79,538 customers during the emergency event hours on August 14, 2020. Aggregate load impacts, which averaged 14.18 MWh/hour, ranged from 0.31 MWh/hour on October 1st to 42.08 MWh/hour on August 18th.

Table 3-2: Average Event-Hour Load Impacts by Event

Date	Smart-Rate™ Event?	Type of Event	Event Hours (p.m.)	Sub-LAPs/Serial Groups Dispatched	# Called	Average Event Hour				
						Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
8/14	Yes	Market, Emergency	4:00-8:22	PGEB, PGKN, PGNB, PGNC, PGNP, PGP2, PGST, PGZP	79,538	3.34	0.44	13.1%	29.89	103.1
			5:00-8:22	PGCC, PGF1, PGSI						
			5:38-8:21	PGFG, PGSB						
8/15	No	Market	4:00-6:00	PGCC, PGEB, PGF1, PGKN, PGNC, PGNP, PGP2, PGST	78,425	3.37	0.44	13.1%	23.07	104.7
			5:00-7:00	PGNB, PGSI						
8/17	Yes	Market	4:00-6:00	PGEB, PGF1, PGKN, PGNB, PGNC, PGNP, PGSI, PGST, PGZP	65,780	3.17	0.38	12.1%	25.16	100.0
8/18	Yes	Test	4:19-7:00	All Sub-LAPs (Serial Group 7 withheld)	71,444	3.41	0.59	17.3%	42.08	101.4
8/19	Yes	Market	4:00-6:00	PGEB, PGF1, PGKN, PGNB, PGP2, PGSI, PGST, PGZP	58,361	2.84	0.34	11.9%	9.93	99.5
			5:09-6:00	PGCC						
			6:00-8:00	PGNC						
9/5	No	Market	4:00-6:00	PGEB, PGF1, PGSI	47,526	2.87	0.31	10.9%	14.89	102.1
9/6	Yes	Market	3:00-6:00	PGCC, PGEB, PGKN, PGNB, PGNC, PGNP, PGP2, PGSI, PGST, PGZP	68,757	3.25	0.47	14.4%	19.30	105.9
			5:00-8:00	PGF1						
9/7	No	Market	4:00-6:00	PGEB, PGF1, PGKN, PGNB, PGNC, PGNP, PGSI, PGST, PGZP	75,122	3.30	0.43	12.9%	31.99	105.2
9/8	No	Market	4:00-6:00	PGNB, PGST	7,775	2.16	0.20	9.5%	1.59	92.6
9/27	No	Market	4:00-6:00	PGCC, PGP2, PGSB	11,160	1.97	0.31	15.5%	3.41	93.6
9/28	No	Market	4:00-6:00	PGCC, PGFG, PGNC, PGP2, PGSB	13,593	2.41	0.40	16.6%	5.44	97.0
9/30	No	Market	5:00-6:00	PGSI	14,173	2.15	0.18	8.1%	2.48	96.6
10/1	No	Market	3:00-5:00	PGFG	1,817	1.39	0.17	12.4%	0.31	92.5
10/15	No	Market	5:00-7:00	PGFG, PGP2	12,971	1.90	0.20	10.3%	1.69	89.7
		Market	6:00-8:00	PGCC, PGSB						
10/16	No	Market	4:00-6:00	PGSB	9,362	1.89	0.24	12.4%	1.47	92.4
		Market	5:00-7:00	PGFG						

Percentage load impacts range from 8.1 percent to 17.3 percent

There is wide variation in the percentage load impacts ranging from 8.1 percent of reference loads for the sub-LAP event on September 30th to 17.3 percent for the serial event on August 18th. The sub-LAP events on September 27th and September 28th also had relatively high percentage load impacts of 15.5 and 16.6 percent, respectively. Percentage load impacts are not correlated with event temperatures and depend largely on which sub-LAPs are called for events.

Load Impacts are persistent across event hours for multiple hour events

Table 3-3 compares average per-customer load impacts and hourly temperatures across hours within each event to analyze whether load impacts persist across event hours.[10] Load impacts are comparable in magnitude across event hours within each event, suggesting that load impacts are persistent across multiple hour events. For most events, the load impact during the second event hour exceeds the load impacts during the first event hour. In all cases where load impacts are lower during the second hour of the event, the hourly temperatures are also cooler. The third hour of the August 14th event has a lower load impacts than the first two hours possibly due to a five minute gap between the end of the market award event and the start of the emergency event for sub-LAPs dispatched for both events. By contrast, the load impacts are comparable during the second and third hours of the event on September 6th.

Table 3-3: Persistence of Load Impacts Across Consecutive Events

Date	Full Event Hours (p.m.)	SmartRate™ Event?	Impact (kW/Cust)				Avg. Temp (°F)			
			Hour 1	Hour 2	Hour 3	Hour 4	Hour 1	Hour 2	Hour 3	Hour 4
8/14	4:00-8:00	Yes	0.44	0.50	0.37	0.41	103.4	103.2	103.2	102.0
8/15	4:00-7:00	No	0.41	0.47			104.8	104.7		
8/17	4:00-6:00	Yes	0.38	0.39			100.8	99.2		
8/18	5:00-7:00	Yes	0.63	0.55			102.2	100.6		
8/19	4:00-8:00	Yes	0.34	0.34			100.0	99.1		
9/5	4:00-6:00	No	0.30	0.32			101.8	102.3		
9/6	3:00-8:00	Yes	0.42	0.50	0.48		105.1	106.4	106.3	
9/7	4:00-6:00	No	0.38	0.47			105.5	105.0		
9/8	4:00-6:00	No	0.23	0.18			93.5	91.6		
9/27	4:00-6:00	No	0.31	0.31			93.1	94.0		
9/28	4:00-6:00	No	0.39	0.41			97.9	96.1		
9/30	5:00-6:00	No	0.18				96.6			
10/1	3:00-5:00	No	0.12	0.22			92.0	93.0		
10/15	5:00-8:00	No	0.24	0.15			91.4	88.0		
10/16	4:00-7:00	No	0.23	0.24			93.6	91.2		

[10] On August 15th, August 19th, September 6th, October 15th, and October 16th sub-LAPs are called for two-hour events, but different sub-LAPs have different event hours. The hours in Table 3-3 reflect the full span of all sub-LAP event hours for these events.

3.3 Sub-LAP Event Load Impacts

Next, we examine the results for sub-LAP events at the sub-LAP level. Figure 3-3 summarizes the sub-LAP level *ex-post* load impacts by event for two sub-LAP events in which a large share of sub-LAPs was dispatched on August 14th and September 6th. The bars indicate the magnitude of the average per customer load impacts (in kWh/customer/hour) across the sub-LAP-specific event hours. The green bands correspond to 80 percent confidence intervals around these estimates (*i.e.*, the 10th and 90th percentile scenarios from the uncertainty-adjusted load impacts). The orange scatter plot represents the average temperatures experienced by the customers in each sub-LAP during the event hours.

Sub-LAP event load impacts range from 0.14 to 0.78 kWh/customer/hour

Figure 3-3 illustrates that there is considerable variation across sub-LAP areas within the same event, as well as within sub-LAP across events. There was a dispatch issue with PGCC on August 14th, which we discuss later. Normal sub-LAP event load impacts range from 0.14 kWh/customer/hour for PGZP on August 14th to 0.78 kWh/customer/hour for PGCC on September 6th. Most sub-LAPs experienced hotter temperatures on September 6th, which explains the higher overall load impacts. Several sub-LAPs that achieve the highest per-customer load impacts include PGCC, PGEB, PGKN, PGNB, PGP2, and PGST.

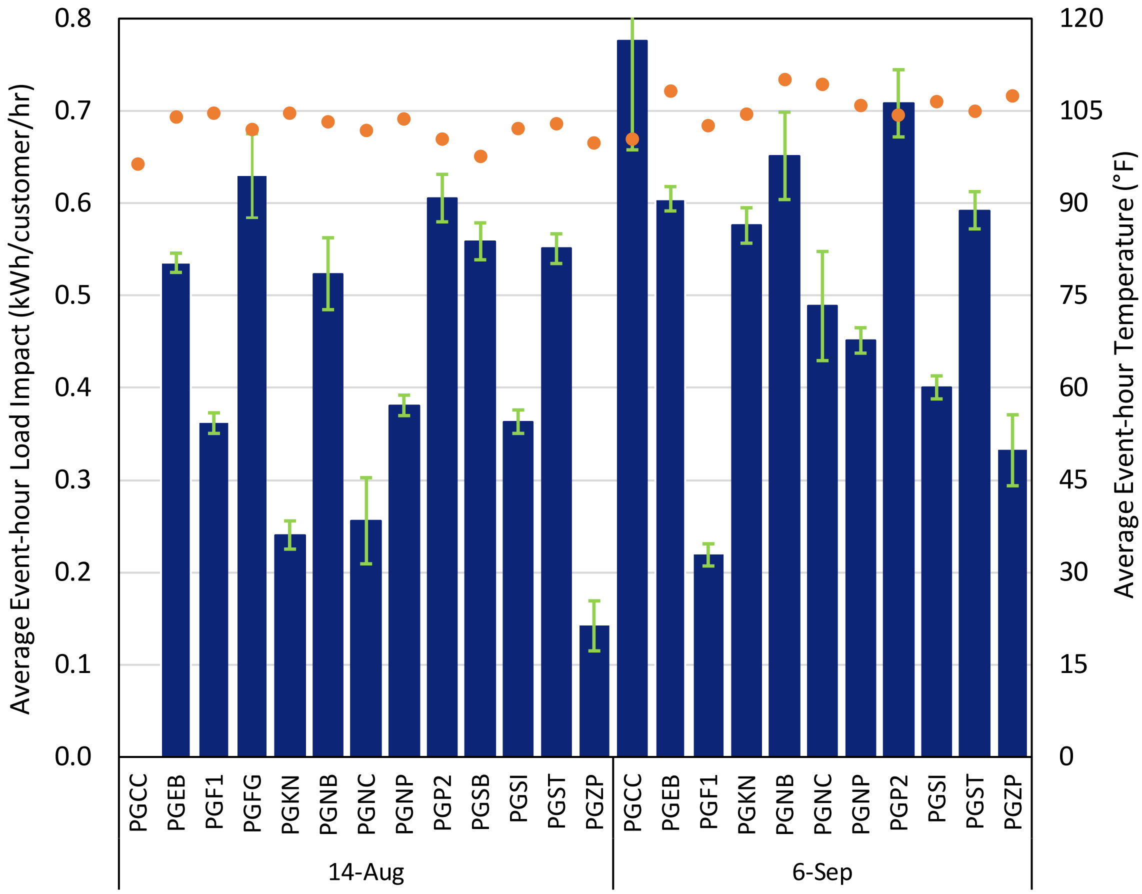
PGKN had lower load impacts on August 14th despite comparable temperatures

PGKN experienced lower load impacts due to the loss of one-way paging towers during previous program years, which led PG&E to replace numerous devices in PY2018, greatly improving load impact results in PY2019. The sub-LAP had significantly lower per-customer load impacts on August 14th compared to the load impacts on September 6th despite comparable event temperatures. Load impacts were 58 percent lower on August 14th, suggesting that there is a new technical issue for this sub-LAP.

PGCC had dispatch issues during the August 14th and 15th events

PG&E discovered a programming issue with PGCC after the first two events, which was rectified for subsequent events. As a result, customers were not dispatched for the August 14th and 15th events in PGCC, although PG&E still received a CAISO market award for this sub-LAP event. Figure 3-3 and Table 3-4 include placeholders for PGCC, but load impact estimates are not reported.

Figure 3-3: Average Event-Hour Load Impacts by Sub-LAP for Sub-LAP Events



PGEB has the highest aggregate load impacts

Table 3-4 provides the detailed information underlying Figure 3-3 for all sub-LAP events, including the number customers dispatched, the average event load impacts (per customer and in aggregate), reference loads, and percentage load impacts for each sub-LAP for each event. The number of dispatched customers varies dramatically across sub-LAPs leading to aggregate load impacts that range from 0.04 MWh/hour for PGNC to 10.21 MWh/hour for PGEB. In percentage terms, the load impacts range from 3.1 percent of reference loads for PGNC on August 19th to 28.3 percent of reference loads for PGCC on September 27th. While the per-customer and percentage load impacts for PGCC are very high for several events, the estimates have large standard errors due to the low number of customers in this sub-LAP. In general, sub-laps with fewer customers such as PGCC and PGNC have less reliable load impact estimates.

Table 3-4: Average Event-Hour Load Impacts by Sub-LAP and Event for Sub-LAP Events

Date	Sub-LAP	Full Event Hours (p.m.)	SmartRate Event?	# Called	Average Event Hour				
					Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
8/14	PGCC	5:00-8:00	Yes	246	3.46	N/A	N/A	N/A	96.4
	PGEB	4:00-8:00		17,079	3.43	0.54	15.6%	9.14	104.1
	PGF1	5:00-8:00		13,181	3.48	0.36	10.4%	4.77	104.7
	PGFG	6:00-8:00		1,785	3.36	0.63	18.7%	1.12	102.0
	PGKN	4:00-8:00		4,037	3.51	0.24	6.9%	0.97	104.8
	PGNB	4:00-8:00		1,208	3.14	0.52	16.7%	0.63	103.3
	PGNC	4:00-8:00		555	2.87	0.26	8.9%	0.14	101.9
	PGNP	4:00-8:00		10,513	3.32	0.38	11.5%	4.00	103.7
	PGP2	4:00-8:00		3,431	3.48	0.61	17.4%	2.08	100.4
	PGSB	6:00-8:00		7,599	3.16	0.56	17.7%	4.25	97.7
	PGSI	5:00-8:00		13,123	3.05	0.36	11.9%	4.77	102.2
	PGST	4:00-8:00		5,217	3.50	0.55	15.7%	2.87	102.9
	PGZP	4:00-8:00		1,564	3.06	0.14	4.6%	0.22	99.9
8/15	PGCC	4:00-6:00	No	245	3.38	N/A	N/A	N/A	93.6
	PGEB	4:00-6:00		18,713	3.43	0.51	14.9%	9.54	105.6
	PGF1	4:00-6:00		15,175	3.21	0.35	11.0%	5.36	105.4
	PGKN	4:00-6:00		4,638	3.15	0.19	6.1%	0.88	100.0
	PGNB	5:00-7:00		1,345	3.30	0.48	14.4%	0.64	103.4
	PGNC	4:00-6:00		634	2.98	0.33	11.0%	0.21	103.4
	PGNP	4:00-6:00		13,097	3.29	0.36	11.0%	4.73	106.4
	PGP2	4:00-6:00		3,445	3.40	0.59	17.4%	2.04	97.4
	PGSI	5:00-7:00		14,525	3.56	0.51	14.4%	7.45	105.2
	PGST	4:00-6:00		6,608	3.50	0.57	16.4%	3.80	104.7
8/17	PGEB	4:00-6:00	Yes	16,917	3.02	0.38	12.6%	6.44	96.6
	PGF1	4:00-6:00		12,999	3.63	0.48	13.1%	6.19	105.8
	PGKN	4:00-6:00		3,998	3.50	0.35	10.0%	1.39	106.0
	PGNB	4:00-6:00		1,192	2.65	0.44	16.7%	0.53	93.9
	PGNC	4:00-6:00		548	1.72	0.28	16.5%	0.16	79.4
	PGNP	4:00-6:00		10,407	2.92	0.38	12.9%	3.91	98.4
	PGSI	4:00-6:00		13,031	2.93	0.32	10.9%	4.15	98.1
	PGST	4:00-6:00		5,142	3.51	0.40	11.4%	2.07	102.3
	PGZP	4:00-6:00		1,546	3.40	0.21	6.3%	0.33	103.9
8/19	PGCC	5:00-6:00	Yes	241	2.86	0.26	9.2%	0.06	83.4
	PGEB	4:00-6:00		16,870	3.09	0.47	15.3%	8.00	101.7
	PGF1	4:00-6:00		12,991	2.68	0.20	7.3%	2.54	99.6
	PGKN	4:00-6:00		3,992	3.22	0.52	16.2%	2.08	105.0
	PGNB	4:00-6:00		1,190	2.36	0.27	11.3%	0.32	95.1
	PGNC	6:00-8:00		547	2.16	0.07	3.1%	0.04	88.8
	PGP2	4:00-6:00		3,390	2.71	0.34	12.6%	1.16	89.6
	PGSI	4:00-6:00		13,009	2.67	0.27	10.1%	3.49	98.2
	PGST	4:00-6:00		5,135	2.88	0.37	13.0%	1.92	100.3
	PGZP	4:00-6:00		1,543	2.84	0.20	6.9%	0.30	101.0

Date	Sub-LAP	Full Event Hours (p.m.)	SmartRate Event?	# Called	Average Event Hour				
					Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
9/5	PGEB	4:00-6:00	No	18,379	2.78	0.38	13.5%	6.90	103.2
	PGF1	4:00-6:00		14,866	3.14	0.25	8.1%	3.79	103.4
	PGSI	4:00-6:00		14,281	2.71	0.29	10.9%	4.20	99.3
9/6	PGCC	3:00-6:00	Yes	241	3.75	0.78	20.7%	0.19	100.4
	PGEB	3:00-6:00		16,723	3.39	0.60	17.8%	10.11	108.3
	PGF1	5:00-8:00		12,904	3.24	0.22	6.8%	2.83	102.6
	PGKN	3:00-6:00		3,956	3.24	0.58	17.8%	2.28	104.5
	PGNB	3:00-6:00		1,174	3.48	0.65	18.7%	0.76	110.1
	PGNC	3:00-6:00		546	3.04	0.49	16.1%	0.27	109.4
	PGNP	3:00-6:00		10,304	3.20	0.45	14.1%	4.65	105.9
	PGP2	3:00-6:00		3,371	3.59	0.71	19.8%	2.39	104.4
	PGSI	3:00-6:00		12,895	2.95	0.40	13.6%	5.16	106.6
	PGST	3:00-6:00		5,111	3.31	0.59	17.9%	3.03	105.1
	PGZP	3:00-6:00		1,532	3.42	0.33	9.7%	0.51	107.4
9/7	PGEB	4:00-6:00	No	18,338	3.55	0.56	15.7%	10.21	108.2
	PGF1	4:00-6:00		14,857	3.45	0.36	10.5%	5.38	105.5
	PGKN	4:00-6:00		4,533	3.09	0.43	14.0%	1.96	102.2
	PGNB	4:00-6:00		1,311	3.42	0.48	14.0%	0.63	106.6
	PGNC	4:00-6:00		625	3.11	0.30	9.8%	0.19	106.4
	PGNP	4:00-6:00		12,843	3.23	0.36	11.0%	4.58	104.2
	PGSI	4:00-6:00		14,269	2.86	0.37	12.8%	5.23	102.5
	PGST	4:00-6:00		6,473	3.51	0.50	14.3%	3.24	105.9
	PGZP	4:00-6:00		1,873	3.25	0.31	9.5%	0.58	105.7
9/8	PGNB	4:00-6:00	No	1,309	1.98	0.23	11.7%	0.30	89.9
	PGST	4:00-6:00		6,466	2.20	0.20	9.1%	1.29	93.1
9/27	PGCC	4:00-6:00	No	241	2.83	0.80	28.3%	0.19	91.0
	PGP2	4:00-6:00		3,370	2.00	0.24	12.2%	0.82	93.0
	PGSB	4:00-6:00		7,549	1.94	0.32	16.4%	2.40	93.9
9/28	PGCC	4:00-6:00	No	241	2.38	0.36	15.0%	0.09	89.5
	PGFG	4:00-6:00		1,819	1.98	0.28	14.3%	0.51	89.6
	PGNC	4:00-6:00		620	2.01	0.27	13.4%	0.17	95.3
	PGP2	4:00-6:00		3,369	2.60	0.36	13.9%	1.21	98.3
	PGSB	4:00-6:00		7,544	2.47	0.46	18.6%	3.45	98.6
9/30	PGSI	5:00-6:00	No	14,173	2.15	0.18	8.1%	2.48	96.6
10/1	PGFG	3:00-5:00	No	1,817	1.39	0.17	12.4%	0.31	92.5
10/15	PGCC	6:00-8:00	No	241	2.22	0.24	10.8%	0.06	85.4
	PGFG	5:00-7:00		1,817	2.29	0.34	15.0%	0.62	94.0
	PGP2	5:00-7:00		3,368	1.91	0.17	8.7%	0.56	91.1
	PGSB	6:00-8:00		7,545	1.79	0.17	9.7%	1.30	88.1
10/16	PGFG	5:00-7:00	No	1,817	2.35	0.25	10.7%	0.45	95.5
	PGSB	4:00-6:00		7,545	1.78	0.23	13.0%	1.75	91.7

Load impacts are similar across sub-LAP event hours with large post-event snapback

Figure 3-4 shows an example of the aggregate hourly reference loads, observed loads, and estimated load impacts using the September 7th sub-LAP event, in which 85 percent enrolled SmartAC™ customers were dispatched for the same event hours from 4 to 6 p.m. Table 3-5 contains the hourly results for September 7th in the manner required by the Protocols, including hourly temperatures and uncertainty adjusted load impacts. Notice that the load impacts peak at 35.1 MWh during the second hour of this event (5:00 to 6:00 p.m.). Furthermore, there is statistically significant post-event snapback, when loads increase by 19.1 MWh the first hour after the event. The snapback declines over the course of the evening.

Figure 3-4: Hourly Load Impacts and on September 7, 2020

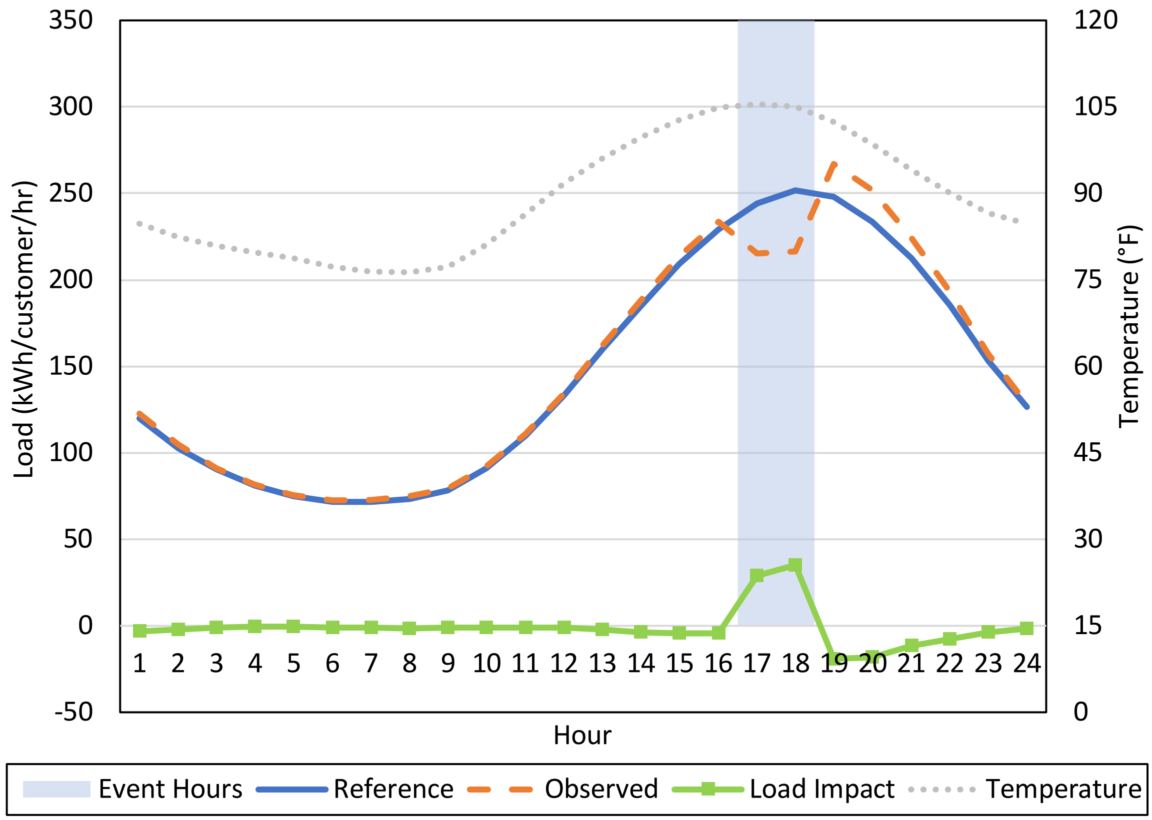


Table 3-5: Hourly Load Impacts and Uncertainty Adjusted Estimates-on September 7, 2020

Hour Ending	Reference Load (MWh/hour)	Event Day Load (MWh/hour)	Estimated Load Impact (MWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (MWh/hour)- Percentiles				
					10^{th}%ile	30^{th}%ile	50^{th}%ile	70^{th}%ile	90^{th}%ile
1	119.9	122.9	-3.03	84.8	-3.55	-3.24	-3.03	-2.82	-2.51
2	102.8	104.9	-2.09	82.4	-2.56	-2.28	-2.09	-1.90	-1.62
3	90.4	91.3	-0.87	80.8	-1.30	-1.05	-0.87	-0.70	-0.45
4	81.1	81.5	-0.49	79.8	-0.87	-0.64	-0.49	-0.33	-0.10
5	75.0	75.4	-0.32	78.8	-0.67	-0.47	-0.32	-0.18	0.03
6	71.6	72.5	-0.87	77.3	-1.20	-1.00	-0.87	-0.73	-0.54
7	71.7	72.9	-1.22	76.4	-1.55	-1.35	-1.22	-1.08	-0.88
8	73.1	74.7	-1.63	76.3	-2.00	-1.78	-1.63	-1.49	-1.27
9	78.5	79.4	-0.94	77.3	-1.36	-1.11	-0.94	-0.77	-0.52
10	91.3	92.1	-0.76	81.1	-1.24	-0.96	-0.76	-0.56	-0.27
11	109.8	110.8	-1.00	86.3	-1.55	-1.22	-1.00	-0.77	-0.44
12	133.3	134.5	-1.15	91.7	-1.78	-1.41	-1.15	-0.90	-0.53
13	159.7	161.8	-2.10	96.1	-2.77	-2.37	-2.10	-1.82	-1.42
14	184.8	188.4	-3.60	99.7	-4.30	-3.88	-3.60	-3.31	-2.89
15	209.0	213.6	-4.58	102.7	-5.30	-4.88	-4.58	-4.29	-3.86
16	229.4	233.8	-4.42	104.9	-5.15	-4.72	-4.42	-4.12	-3.69
17	244.1	215.3	28.84	105.5	28.14	28.56	28.84	29.13	29.55
18	251.7	216.6	35.14	105.0	34.45	34.86	35.14	35.43	35.84
19	247.9	267.0	-19.11	102.4	-19.80	-19.39	-19.11	-18.82	-18.41
20	233.4	251.9	-18.49	98.5	-19.15	-18.76	-18.49	-18.22	-17.82
21	212.3	224.0	-11.69	94.1	-12.32	-11.95	-11.69	-11.43	-11.06
22	185.2	193.0	-7.74	90.1	-8.33	-7.98	-7.74	-7.49	-7.14
23	153.2	157.3	-4.06	86.6	-4.60	-4.28	-4.06	-3.83	-3.51
24	126.3	128.0	-1.72	84.8	-2.22	-1.92	-1.72	-1.52	-1.22
By Period:	Estimated Reference Energy Use (MWh/hour)	Observed Event Day Energy Use (MWh/hour)	Estimated Change in Energy Use (MWh/hour)	Cooling Degree Hours (Base 75°F)	Uncertainty Adjusted Impact (MWh/hour) - Percentiles				
					10th	30th	50th	70th	90th
Daily	3,535.8	3,563.7	-27.87	343.6	-34.51	-30.59	-27.87	-25.16	-21.23
Avg. Event Hour	247.9	215.9	31.99	60.5	31.50	31.79	31.99	32.20	32.49

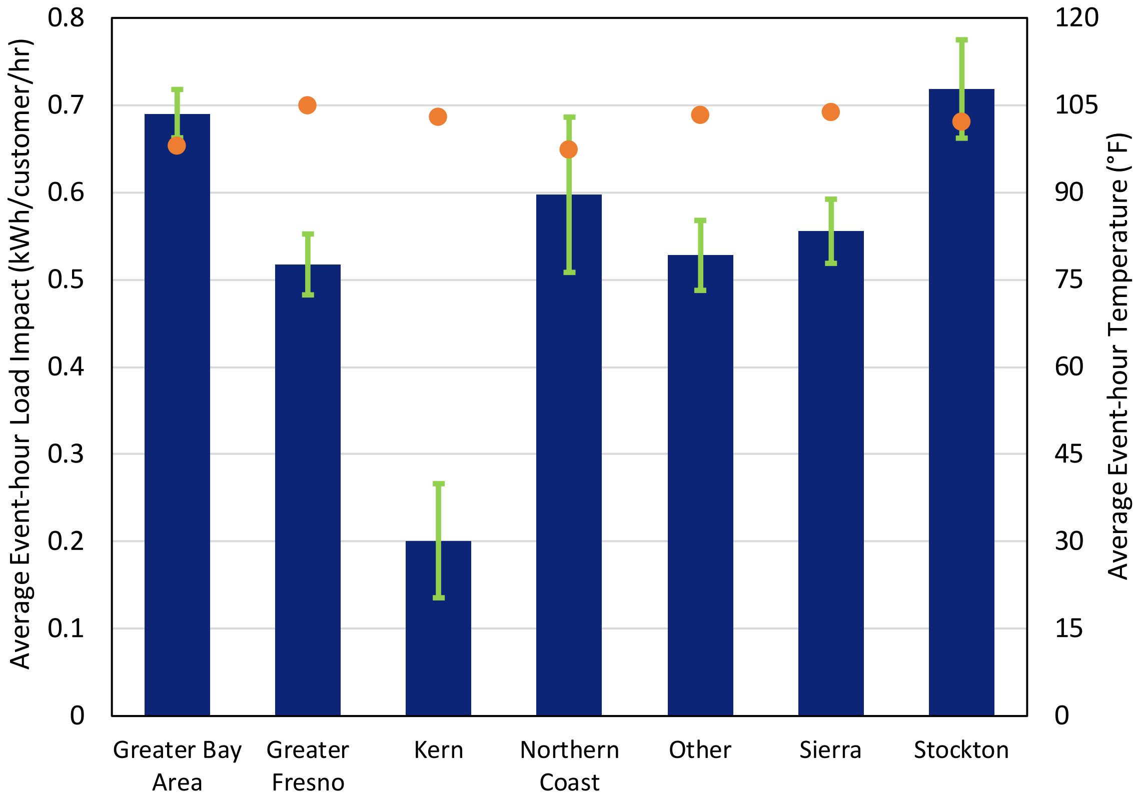
3.4 Serial Event Load Impacts

Next, we examine the results for the serial event on August 18th by LCA. Figure 3-5 summarizes the LCA level *ex-post* load impacts. The bars indicate the magnitude of the average per customer load impacts (in kWh/customer/hour) across the full event hours during which customers were dispatched (5 to 7 p.m.). The green bands correspond to 80 percent confidence intervals around these estimates (*i.e.*, the 10th and 90th percentile scenarios from the uncertainty-adjusted load impacts). The orange scatter plot represents the average temperatures experienced by the customers in each LCA during the event hours.

Serial event load impacts range from 0.20 to 0.72 kWh/customer/hour

Figure 3-5 illustrates that there is more consistency in per-customer load impacts across LCAs for serial events, with the exception of Kern, which is significantly lower despite having comparably high temperatures. Load impacts range from 0.20 to 0.72 kWh/customer/hour for serial event.

Figure 3-5: Average Event-Hour Load Impacts by LCA for the Serial Event



Greater Bay Area has the highest aggregate load impacts

Table 3-6 provides the detailed information underlying Figure 3-5, including the number customers dispatched, the average event load impacts (per customer and in aggregate), reference loads, and percentage load impacts for each LCA for each serial event. Greater Bay Area has by far the highest number of customers leading to the highest aggregate load impacts of 17.68 MWh/hour on August 18th. Greater Bay Area also has the highest load impacts in percentage terms with load impacts that are 20.7 percent of reference loads.

Kern had significantly lower load impacts than the other LCAs despite comparable temperatures

Kern also shows evidence of technical issues during the serial test event in 2020. The load impacts for Kern were significantly in lower per-customer terms compared to the other LCAs despite comparable event temperatures. Load impacts were 61 percent lower than the next lowest LCA, Greater Fresno. This contrasts the comparable performance of these LCAs during the serial events in 2019.

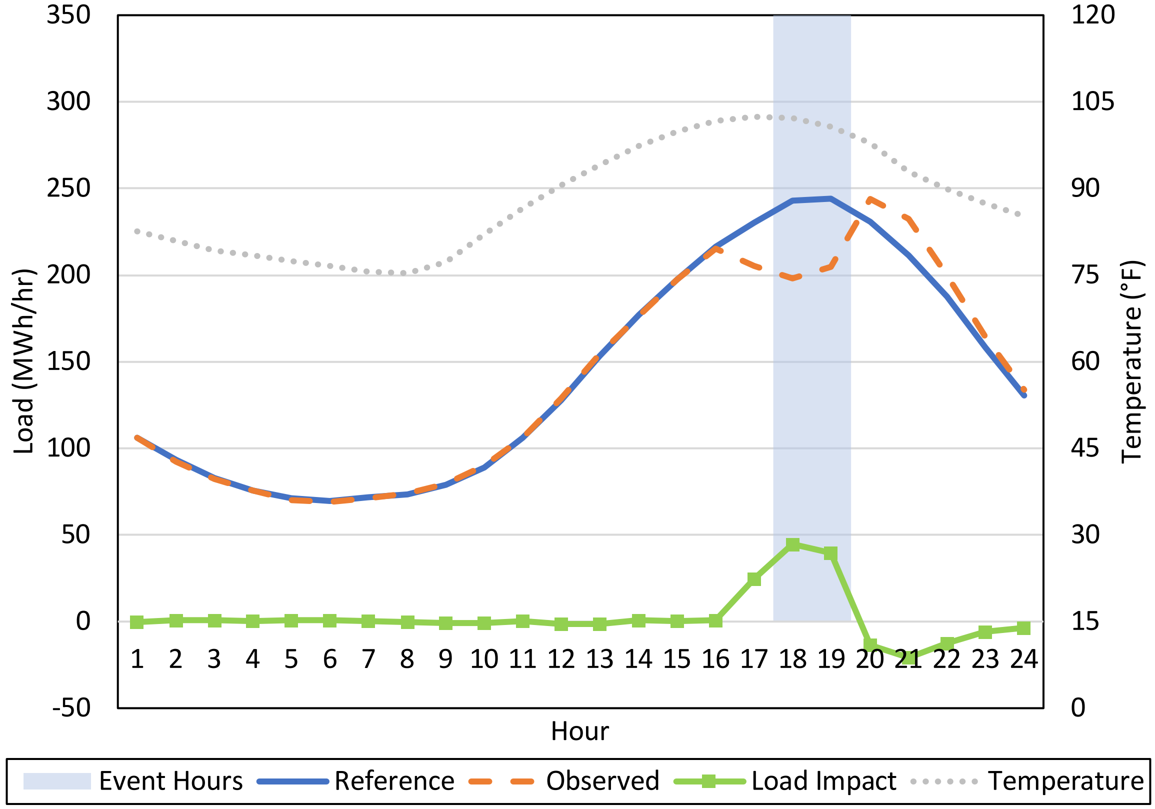
Table 3-6: Average Event-Hour Load Impacts by LCA for the Serial Event

LCA	Event Hours (p.m.)	Smart-Rate Event?	# Called	Average Event Hour				
				Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
Greater Bay Area	4:19-7:00	Yes	25,614	3.34	0.69	20.7%	17.68	98.0
Greater Fresno			11,505	3.61	0.52	14.3%	5.95	104.9
Kern			3,346	3.44	0.20	5.8%	0.67	103.0
Northern Coast			3,070	2.91	0.60	20.5%	1.83	97.3
Other			11,323	3.41	0.53	15.5%	5.98	103.3
Sierra			11,822	3.35	0.56	16.6%	6.57	103.8
Stockton			4,804	3.69	0.72	19.5%	3.45	102.2

Load impacts for serial events peak during the second hour and decline during third hour of event

Figure 3-6 shows the average aggregate hourly reference loads, observed loads, and estimated load impacts using the serial event. Table 3-7 contains the hourly results in the manner required by the Protocols, including hourly temperatures and uncertainty adjusted load impacts. Notice that the load impacts peak at 44.7 MWh during the first full hour of this event (5:00 to 6:00 p.m.) and are lower during the second full hour of the event (6:00 to 7:00 p.m.) at 39.5 MWh.

Figure 3-6: Hourly Load Impacts on August 18, 2020



Post-event snapback for serial events is lower as a share of event load impacts

Figure 3-6 also illustrates that there is significant post-event snapback for serial events, when loads increase by 13.4 MWh the first hour after the event and decline over the course of the evening. Moreover, post-event snapback as a share of event load impacts is lower for serial events compared to the sub-LAP event example in Figure 3-4. For the two serial events, the peak post-event snapback from 7 to 8 p.m. is 30 percent of the peak load impacts during 5 to 6 p.m. For the sub-LAP event on September 7th, the peak post-event snapback during 6 to 7 p.m. is 54 percent of the peak load impact during 5 to 6 p.m.

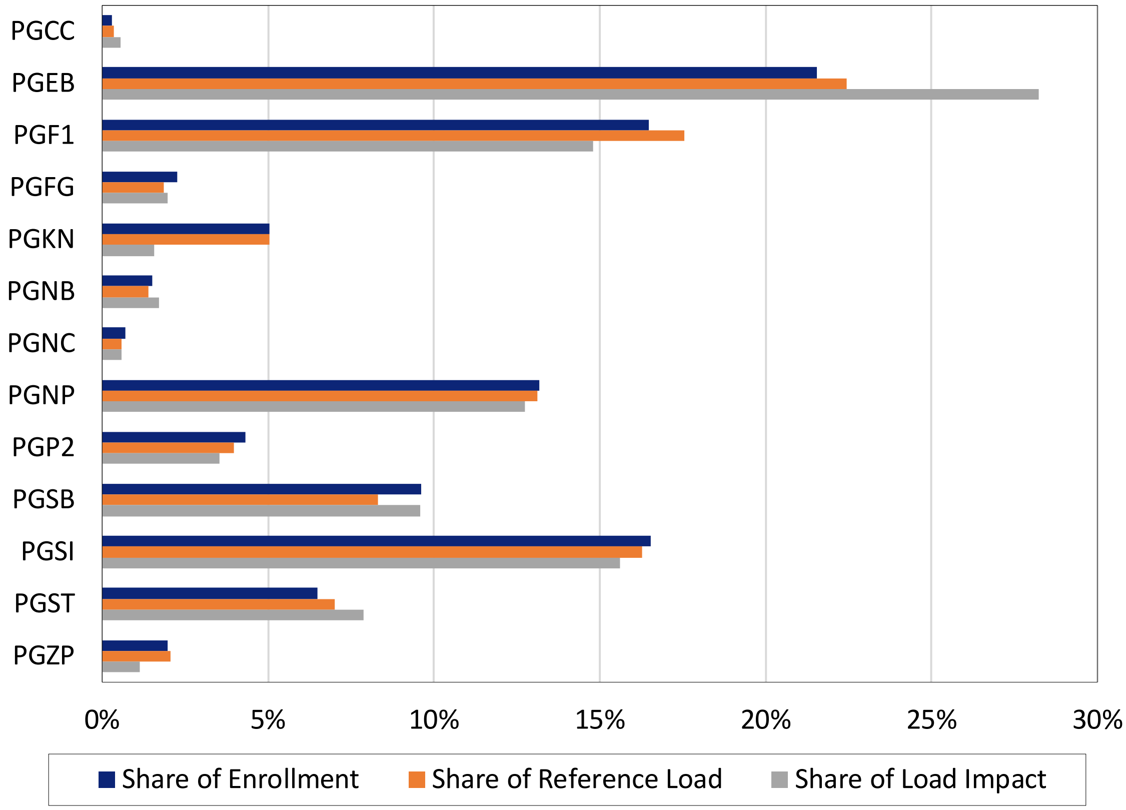
Table 3-7: Hourly Load Impacts and Uncertainty Adjusted Estimates-August 18, 2020

Hour Ending	Reference Load (MWh/hour)	Event Day Load (MWh/hour)	Estimated Load Impact (MWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (MWh/hour)- Percentiles				
					10th%ile	30th%ile	50th%ile	70th%ile	90th%ile
1	106.1	106.2	-0.11	82.6	-1.21	-0.56	-0.11	0.34	0.99
2	93.1	92.5	0.61	80.9	-0.40	0.19	0.61	1.02	1.62
3	83.0	82.4	0.57	79.2	-0.40	0.18	0.57	0.97	1.54
4	75.6	75.4	0.22	78.4	-0.69	-0.15	0.22	0.59	1.13
5	71.0	70.3	0.71	77.5	-0.13	0.37	0.71	1.06	1.56
6	69.6	69.1	0.55	76.6	-0.25	0.22	0.55	0.88	1.35
7	71.6	71.1	0.51	75.6	-0.32	0.17	0.51	0.84	1.33
8	73.5	73.8	-0.27	75.3	-1.19	-0.65	-0.27	0.11	0.66
9	78.8	79.4	-0.63	77.3	-1.66	-1.05	-0.63	-0.21	0.39
10	89.1	89.8	-0.64	82.0	-1.80	-1.12	-0.64	-0.17	0.51
11	106.4	106.2	0.18	86.5	-1.14	-0.36	0.18	0.72	1.50
12	127.7	129.1	-1.34	90.6	-2.74	-1.91	-1.34	-0.76	0.07
13	153.0	154.1	-1.13	94.1	-2.63	-1.74	-1.13	-0.51	0.38
14	177.3	176.6	0.72	97.4	-0.84	0.08	0.72	1.36	2.29
15	197.8	197.4	0.39	99.8	-1.20	-0.26	0.39	1.04	1.98
16	216.2	215.2	1.01	101.7	-0.59	0.35	1.01	1.66	2.60
17	230.1	205.2	24.84	102.4	23.24	24.18	24.84	25.49	26.43
18	242.8	198.0	44.71	102.2	43.11	44.06	44.71	45.37	46.31
19	244.1	204.5	39.56	100.7	38.00	38.92	39.56	40.20	41.13
20	230.6	243.9	-13.36	97.8	-14.87	-13.97	-13.36	-12.74	-11.84
21	211.4	232.2	-20.83	93.0	-22.27	-21.42	-20.83	-20.24	-19.39
22	187.7	199.9	-12.28	90.0	-13.68	-12.86	-12.28	-11.71	-10.89
23	158.3	164.1	-5.76	87.4	-7.08	-6.30	-5.76	-5.22	-4.44
24	130.2	133.9	-3.66	85.2	-4.86	-4.15	-3.66	-3.17	-2.46
By Period:	Estimated Reference Energy Use (MWh/hour)	Observed Event Day Energy Use (MWh/hour)	Estimated Change in Energy Use (MWh/hour)	Cooling Degree Hours (Base 75°F)	Uncertainty Adjusted Impact (MWh/hour) - Percentiles				
					10th	30th	50th	70th	90th
Daily	3,424.9	3,370.3	54.58	314.2	39.77	48.52	54.58	60.65	69.40
Avg. Event Hour	243.4	201.3	42.14	52.8	41.02	41.68	42.14	42.60	43.26

PGEB, PGF1, PGNP and PGSI produced 71 percent of the PY2020 load reductions

Next, we look at how load impacts are distributed across sub-LAPs. We focus this analysis on the load impacts from the serial event on August 18th, because all sub-LAPs were dispatched for this event during the same event hours. Figure 3-7 compares the sub-LAP shares of estimated aggregate event-hour load impacts, reference loads, and enrollments. The load impacts for SmartAC™ customers are mainly driven by four sub-LAPs (PGEB, PGF1, PGNP, and PGSI), which collectively produced 71 percent of the PY2020 load reductions. Furthermore, PGEB has a considerably higher share of load impacts than of enrollments or reference loads, while PGKN and PGF1 have appreciably lower shares of load impacts compared to the share of enrollments and reference loads.

Figure 3-7: Share of Load Impacts by Sub-LAP for the Serial Event on August 18th



3.5 Subgroup Load Impacts

This section summarizes how SmartAC™ load impacts are distributed across subgroups of interest including: CARE/non-CARE customers, NEM/non-NEM customers, housing type, AC usage intensity, and device type (one-way versus two-way and by one-way device type).[11] Typically, we also compare the load impacts for customers who are only enrolled in SmartAC™ to customers who are also enrolled in SmartRate™, but the only system-wide events in PY2020 were dual events, so that comparison is not possible in this program year. As a result, all comparisons include SmartAC™-only customers, with no dually-enrolled customers in these analyses.[12] These comparisons are based on load impacts from the serial event on August 18th during the two full event hours from 5 to 7 p.m. Additional results for these subgroups, including the load profiles, can be found in electronic form in Protocol table generators provided along with this report.

[11] There is no analysis of ExpressStat customers because there are too few customers in this subgroup enrolled on the system-wide event. PG&E has been systematically replacing or decommissioning ExpressStat devices, leading to few devices remaining for this estimation. Additionally, there is no cohort analysis because that is no longer included in the program evaluation plan with PG&E.

[12] The analysis comparing results for SmartAC™-only and dually enrolled customers is in Section 3.5.2.

The *ex-post* load impacts for the August 18th serial test event are summarized for each subgroup in Figure 3-8. The blue and gray bars indicate the magnitude of the average per customer load impact (in kWh/customer/hour) within each subgroup. The green bands correspond to 80 percent confidence intervals around these estimates. The orange scatter plot represents the average temperatures experienced by customers in each subgroup.

Most subgroup comparisons are consistent with PY2019 results

Figure 3-8 shows that there are statistically significant load impacts for every subgroup during the serial event. Furthermore, the average event-hour temperatures are comparable across subgroups. The pattern of load impacts is similar to subgroup comparisons from the PY2019 report, including the following:

- NEM customers had comparable load impacts to non-NEM customers; there were no statistically significant differences in load impacts between these two subgroups.
- Gen 1 and Gen 2 switches had significantly higher load impacts than UtilityPro thermostats. Load impacts for UtiliPro thermostats decreased from 0.38 kWh/customer/hour in PY2019 to 0.2 kWh/customer/hour in PY2020, which suggests that UtilityPro thermostats have diminishing performance due to increasing device obsolescence.
- Detached residences (single family) have significantly higher load impacts compared to Shared Wall residences (multi-family).[13]
- Load impacts increase with AC usage intensity, with high AC usage having significantly higher load impacts than medium and low AC usage.

CARE and non-CARE customers have comparable load impacts

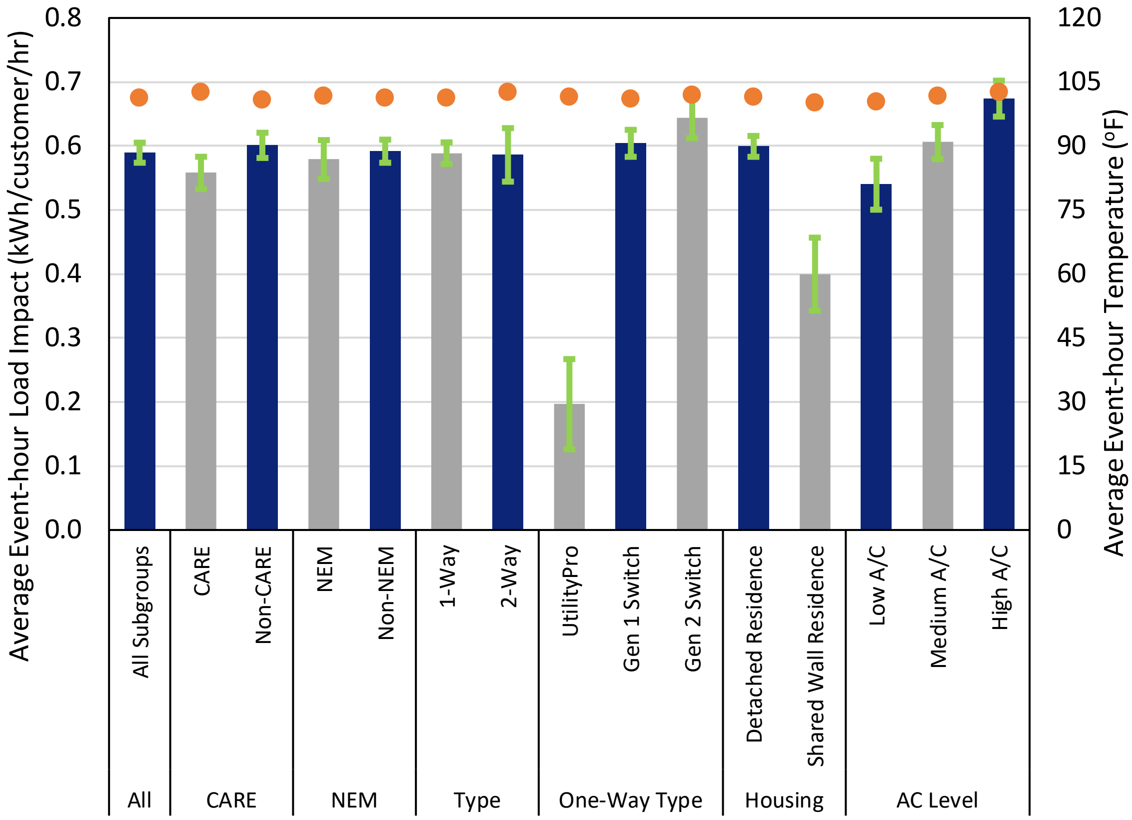
There was no statistically significant difference in load impacts between CARE and non-CARE customers for the serial event in 2020 in contrast to the PY2019 evaluation, which found that CARE customers had significantly higher load impacts.

One-way and two-way devices have comparable load impacts

During the serial event in 2020, one-way and two-way devices led to similar per-customer load impacts that were not statistically different. This contrasts the PY2019 evaluation where two-way devices generated substantially higher load impacts, which may be due to poor performance for PGKN during this event due to technical issues. We present further device type analysis in Section 3.5.1.

[13] There is also a category called common area, but there are very few SmartAC™ customers classified as common area, which prevents the reliable estimation of results for this subgroup.

Figure 3-8: Average Event-Hour Load Impacts by Subgroup on-August 18, 2020



Comparing subgroups by percentage load impacts can lead to different results

Table 3-8 provides the detailed information underlying Figure 3-8, including the number of customers dispatched for the August 18th event, the total number of enrolled customers in each subgroup, the average load impacts, reference loads, percentage load impacts, and temperatures. While comparisons by percentage load impacts mostly follow the same patterns as per-customer load impacts, a different pattern emerges by AC usage intensity. Percentage load impacts decrease with higher levels of AC usage due to the fact that reference loads increase more substantially than load impacts for higher AC usage levels.

Table 3-8: Average Event-Hour Load Impacts by Subgroup-August 18, 2020

Subgroup	# Called	Enrolled Customers	Average Load Impacts (5-7 p.m.)				
			Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
All SmartAC™ Customers	71,484	78,713	3.41	0.59	17.31%	42.14	101.4
CARE	21,932	24,290	3.40	0.56	16.39%	12.24	102.8
Non-CARE	49,550	54,421	3.41	0.60	17.64%	29.78	100.8
NEM	21,285	23,311	3.46	0.58	16.72%	12.32	101.8
Non-NEM	50,197	55,400	3.38	0.59	17.50%	29.71	101.3
1-Way	62,873	69,056	3.37	0.59	17.48%	37.02	101.2
2-Way	8,611	9,603	3.65	0.59	16.05%	5.05	102.6
UtilityPro	3,420	3,722	3.37	0.20	5.83%	0.67	101.6
Gen 1 Switch	43,274	47,491	3.35	0.60	18.01%	26.15	101.0
Gen 2 Switch	14,973	16,525	3.39	0.64	18.96%	9.64	102.0
Detached Residence	67,680	74,505	3.47	0.60	17.29%	40.57	101.6
Shared Wall Residence	3,751	4,149	2.43	0.40	16.45%	1.50	100.2
Low A/C	11,533	12,692	2.94	0.54	18.40%	6.23	100.3
Medium A/C	21,754	24,009	3.45	0.61	17.59%	13.18	101.9
High A/C	25,013	27,500	4.12	0.67	16.37%	16.86	102.7

3.5.1 Two-way Devices

This section compares results for customers with two-way communicating devices to customers with legacy technology capable of one-way communication including thermostats and Gen1 and Gen2 switches. We contrast results for each device type for the average event-hour for serial test events compared to sub-LAP events.

Table 3-9 summarizes the per-customer and aggregate results for customers with two-way and one-way devices for serial and sub-LAP type events, including the number of customers dispatched and enrolled on average, the average event load impacts (per customer and in aggregate), reference loads, and percentage load impacts. Only 12 percent of SmartAC™ customers had two-way devices during PY2020, which accounts for the large aggregate load impacts for one-way devices compared to two-way devices.

While two-way devices led to comparable per-customer load impacts for the serial event, the load impacts were significantly higher for two-way devices during sub-LAP events. Two-way devices generated per-customer load impacts of 0.58 kWh/customer/hour during serial events compared to 0.59 kWh/customer/hour for one-way devices and 0.57 kWh/customer/hour during sub-LAP events compared to 0.38 kWh/customer/hour for one-way devices. Since paging for one-way devices differs between serial events (*i.e.*, based on factory programmed addressing) and sub-LAP events (*i.e.*, based on sub-LAP addressing after device installation), we would expect more of a performance advantage for two-way devices relative to one-way devices on sub-LAP events compared to serial events. Indeed, average per-customer load impacts are 0.19 kWh/customer/hour higher for two-way devices relative to one-way devices on sub-LAP events compared to a negligible difference for serial events. In percentage terms, per-customer load impacts for one-way devices are 67 percent of the per-customer load impacts for two-way devices on sub-LAP events, despite comparable event temperatures.

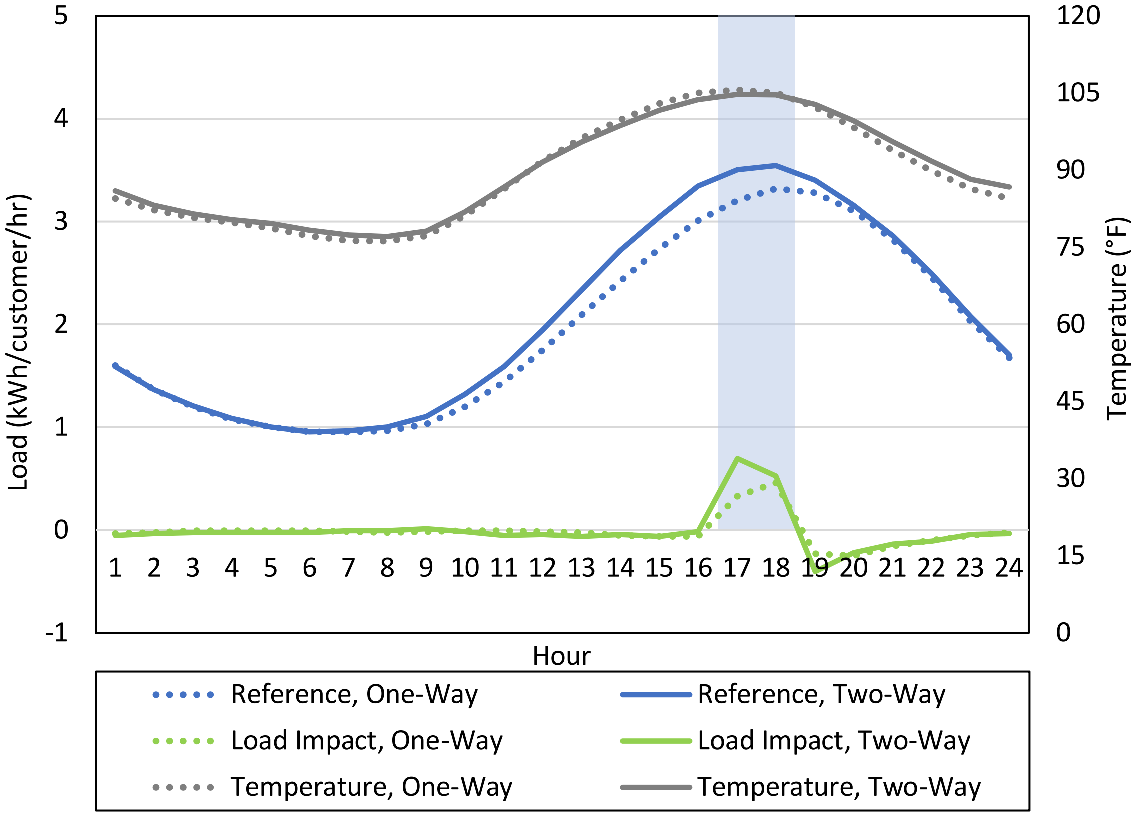
The results are roughly consistent with those presented in the PY2019 report. Across all device and event types, per-customer load impacts are slightly higher in 2020 as are average event temperatures. An exception is two-way devices during the serial event, for which PY2020 impacts are slightly lower than PY2019 impacts (0.58 vs. 0.62 kWh/customer/hour) despite higher temperatures in PY2020. As mentioned in Section 3.4, possible dispatch issues that could have affected both one-way and two-way devices may explain the poor performance for Kern during the serial event.

Table 3-9: Average Event-Hour Load Impacts by Device Type and Event Type

Event Type	Device Type	Avg. # Called	Avg. # Enrolled	Average Event Hour				
				Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
Serial Test Event	One-Way	62,834	69,056	3.37	0.59	17.5%	36.94	101.2
	Two-Way	8,610	9,603	3.65	0.58	15.9%	5.00	102.6
Sub-LAP Event	One-Way	33,981	74,516	3.06	0.38	12.3%	12.79	102.2
	Two-Way	4,889	10,786	3.37	0.57	16.8%	2.77	102.9

Figure 3-9 illustrates differences in the per-customer hourly reference loads and estimated load impacts between one-way and two-way devices during the sub-LAP event on September 7th. The dotted lines show the results for one-way customers, while the solid lines show the results for two-way customers. The grey lines show that the temperature profiles are similar for one-way and two-way customers on this date, while the reference loads are higher for customers with two-way devices. Two-way devices are more likely to be installed on properties with high levels of AC usage. The one-way devices have a higher load impact during the second hour of the event, while the two-way devices peak in the first hour and decline during the second hour. Load impacts are comparable between one-way and two-way devices during the second hour of the event. The differences in load shapes and the pattern of event load impacts are consistent with patterns shown on other sub-LAP event in PY2020.

Figure 3-9: Hourly Load Impacts on September 7, 2020, One-way vs. Two-way devices



3.5.2 Dually Enrolled Customers

This section compares results for customers who are only enrolled in the SmartAC™ program to customers who are dually enrolled in SmartAC™ and SmartRate™. We present results for the average full event-hour for each event day. On dual event days we limit the comparison to hours where events overlap for the two programs. Additional results for these customers can be found in electronic form in Protocol table generators provided along with this report.

Table 3-10 summarizes the per-customer and aggregate results for SmartAC™-only and dually enrolled customers for each event, including the number of customers dispatched, the average event load impacts (per customer and in aggregate), reference loads, and percentage load impacts. The serial test event is shaded blue. Fewer than 12 percent of SmartAC™ customers were dually enrolled in SmartRate™ during PY2020, which explains the higher aggregate load impacts for SmartAC™-only customers.

On a per-customer basis, the load impacts are higher for dually enrolled customers than SmartAC™-only customers during dual sub-LAP events but are lower during the dual serial event and some of the SmartAC™-only sub-LAP events. Due to the low number of dually enrolled customers dispatched by sub-LAP, the sub-LAP-level results are unreliable for dually enrolled customers in several sub-LAPs, including PGFG, PGNB, PGNC, PGP2, and PGSB. The sub-LAPs listed are exclusively dispatched for the events on September 27th and 28th and October 1st, 15th, and 16th, making the overall load impact estimates for dually enrolled customers for these events unreliable. A comparison across the remaining SmartAC™-only sub-LAP events suggests that per-customer load impacts for dually enrolled customers are comparable to SmartAC™-only customers on average. We build this assumption into the *ex-ante* forecast described in Section 2.3.2.

Table 3-10: Average Event-Hour Load Impacts by Event, SmartAC™-only vs. Dually Enrolled

Enrollment Segment	Date	SmartRate™ Event?	# Called	Average Event Hour				
				Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
Dually Enrolled	8/14	Yes	10,526	2.87	0.56	19.4%	5.2	103.9
	8/15	No	9,974	2.99	0.36	12.1%	2.4	105.1
	8/17	Yes	10,194	2.79	0.58	20.8%	5.9	100.7
	8/18	Yes	9,380	2.86	0.46	16.1%	4.3	102.7
	8/19	Yes	7,526	2.45	0.43	17.7%	2.2	100.0
	9/5	No	4,980	2.54	0.34	13.4%	1.7	102.1
	9/6	Yes	10,058	2.86	0.64	22.3%	4.5	106.2
	9/7	No	10,031	2.96	0.46	15.4%	4.6	105.0
	9/8	No	1,507	1.95	0.12	6.4%	0.2	92.9
	9/27	No	121	1.18	-0.17	-14.2%	0.0	93.7
	9/28	No	278	1.61	0.14	8.8%	0.0	95.5
	9/30	No	1,357	1.81	0.23	13.0%	0.3	95.7
	10/1	No	77	[redacted]				
	10/15	No	198	1.31	0.08	6.1%	0.0	90.7
	10/16	No	178	1.28	0.00	0.0%	0.0	93.4
SmartAC™ Only	8/14	Yes	79,538	3.36	0.47	14.0%	30.3	103.7
	8/15	No	68,451	3.42	0.45	13.2%	20.6	104.7
	8/17	Yes	65,780	3.17	0.39	12.2%	25.4	100.0
	8/18	Yes	71,444	3.41	0.59	17.3%	42.1	101.4
	8/19	Yes	58,361	2.85	0.34	12.0%	13.3	99.6
	9/5	No	42,546	2.90	0.31	10.5%	13.0	102.1
	9/6	Yes	68,757	3.26	0.50	15.3%	24.1	106.2
	9/7	No	65,091	3.35	0.42	12.5%	27.2	105.3
	9/8	No	6,268	2.20	0.22	9.9%	1.4	92.5
	9/27	No	11,039	1.98	0.31	15.6%	3.4	93.6
	9/28	No	13,315	2.43	0.40	16.6%	5.4	97.0
	9/30	No	12,816	2.18	0.16	7.4%	2.1	96.8
	10/1	No	1,740	1.41	0.17	12.3%	0.3	92.5
	10/15	No	12,773	1.91	0.20	10.3%	1.7	89.6
	10/16	No	9,184	1.90	0.24	12.5%	1.5	92.4

3.6 Event Override Rate

Customers can override (opt-out of) SmartAC™ events. Table 3-11 summarizes the number of overrides by event day, including the number of enrolled customers in the sub-LAPs dispatched for each event. Although the number of overrides includes all SmartAC™ customers who opt-out on a given event day, including some customers who were not dispatched for the event, over 86 percent of the overrides correspond to customers dispatched for events. In total, the overrides correspond to only 0.2 percent of dispatched customers during PY2020 events. There were no events with high override rates, all were below one percent.

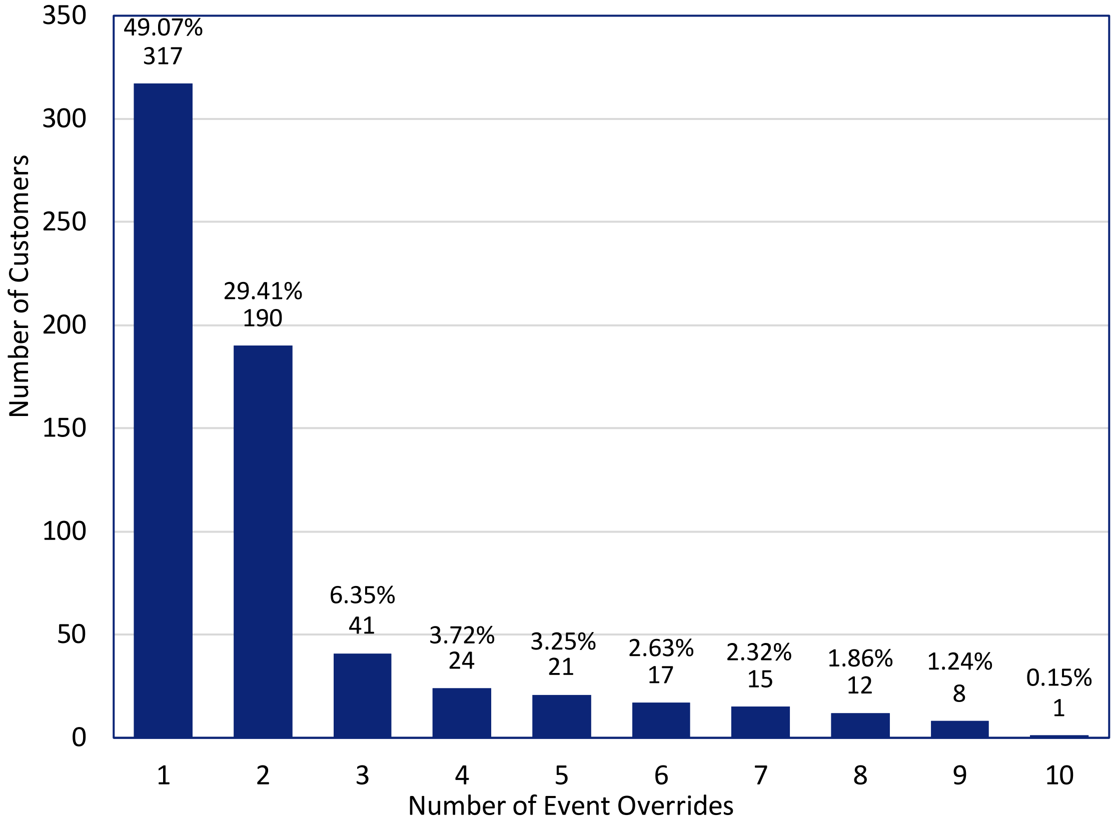
Additional tables in the appendix break down the override rates by location for each event. Table B-1 shows the override rates by sub-LAP for the 14 sub-LAP events and Table B-2 shows the override rates by LCA for the serial event. Most sub-LAPs and LCAs had override rates well below 1 percent.

Table 3-11: Customer Overrides by Event Day

Date	Full Event Hours (p.m.)	Sub-LAPs Called	Smart-Rate™ Event?	# Over-rides	# Called	Over-ride Rate
8/14	4:00-8:00	PGCC, PGEB, PGF1, PGFG, PGKN, PGNB, PGNC, PGNP, PGP2, PGSB, PGSI, PGST, PGZP	Yes	361	79,538	0.5%
8/15	4:00-7:00	PGCC, PGEB, PGF1, PGKN, PGNB, PGNC, PGNP, PGP2, PGSI, PGST	No	169	78,425	0.2%
8/17	4:00-6:00	PGEB, PGF1, PGKN, PGNB, PGNC, PGNP, PGSI, PGST, PGZP	Yes	109	65,780	0.2%
8/18	5:00-7:00	All Sub-LAPs (Serial Group 7 withheld)	Yes	134	71,444	0.2%
8/19	4:00-8:00	PGCC, PGEB, PGF1, PGKN, PGNB, PGNC, PGP2, PGSI, PGST, PGZP	Yes	95	58,361	0.2%
9/5	4:00-6:00	PGEB, PGF1, PGSI	No	53	47,526	0.1%
9/6	3:00-8:00	PGCC, PGEB, PGF1, PGKN, PGNB, PGNC, PGNP, PGP2, PGSI, PGST, PGZP	Yes	164	68,757	0.2%
9/7	4:00-6:00	PGEB, PGF1, PGKN, PGNB, PGNC, PGNP, PGSI, PGST, PGZP	No	111	75,122	0.1%
9/8	4:00-6:00	PGNB, PGST	No	3	7,775	0.0%
9/27	4:00-6:00	PGCC, PGP2, PGSB	No	7	11,160	0.1%
9/28	4:00-6:00	PGCC, PGFG, PGNC, PGP2, PGSB	No	16	13,593	0.1%
9/30	5:00-6:00	PGSI	No	3	14,173	0.0%
10/1	3:00-5:00	PGFG	No	0	1,817	0.0%
10/15	5:00-8:00	PGCC, PGFG, PGP2, PGSB	No	109	12,971	0.8%
10/16	4:00-7:00	PGFG, PGSB	No	72	9,362	0.8%
			Total	**1,406**	**615,804**	**0.2%**

Figure 3-10 illustrates the extent to which customers opted-out of multiple events. Nearly half of the customers (49 percent) exercised the ability to override during only one event, while an additional 29 percent overrode only two events. Only 15 percent of customers opt-out during four or more events.

Figure 3-10: Number of Event Day Overrides by Customer



4. *Ex-Ante* Load Impacts

This section provides the SmartAC™ *ex-ante* load impact forecast for the period from 2021 to 2031. The forecasts are based on analyses of per-customer load impacts from *ex-post* evaluations, weather-sensitive reference loads, and incorporation of PG&E's forecasts of program enrollments and SIP adjustments. Differing from previous evaluations, the PY2020 *ex-ante* forecast reflects load impacts that represent sub-LAP events, which have lower impacts than the serial event dispatches on which forecasts have been based historically. This is driven by the SmartAC™ program's integration into the CAISO market, where most events are now called though market dispatches at the sub-LAP level.

Results are presented for customers who are enrolled in SmartAC™-only and for customers who are dually enrolled in SmartAC™ and SmartRate™. We present the following: a figure showing the PG&E's enrollment forecast by LCA; a table and figures showing the hourly reference loads and load impacts on a typical event day; a figure summarizing how *ex-ante* load impacts vary by month and weather scenario; and a figure showing the share of load impacts on a typical event day by LCA. Detailed results for each hour, weather scenario, month, forecast year, and enrollment segment (*i.e.*, SmartAC™-only and dually enrolled customers) are available in electronic form in Protocol table generators provided along with this report.

The enrollment forecast provided by PG&E anticipates a high level of program attrition throughout 2021 to 2031 of approximately 11 percent per year due to PG&E's decision to minimize marketing efforts to back-fill attrition. Figure 4-1 illustrates this attrition over the forecast period for the July peak month by LCA. Enrollments are expected to decline across all LCAs. Moreover, dually enrolled customers, which are not depicted here, are expected to maintain a proportionate share of declining SmartAC™ enrollments over the forecast period.

Figure 4-1: Changes in Enrollment by LCA (2021-2031)

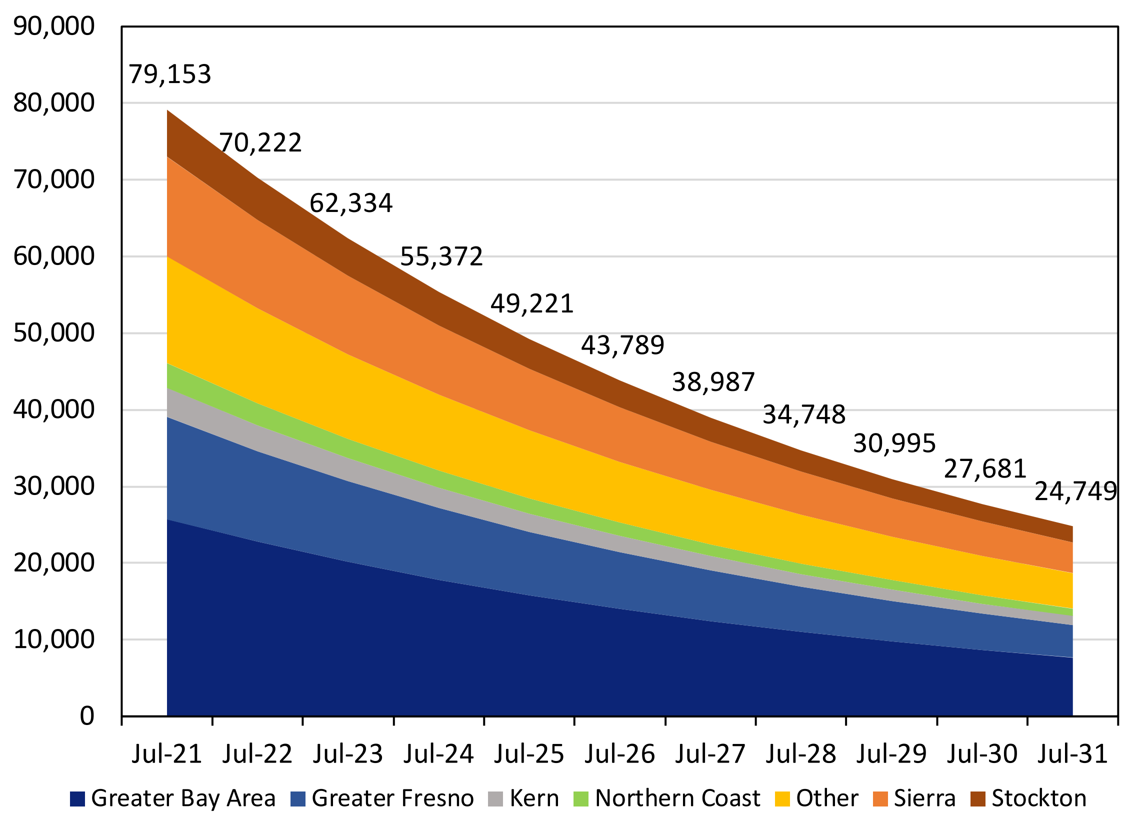


Figure 4-2 illustrates the changes in aggregate load impacts during the Resource Adequacy (RA) window (4 to 9 p.m.) over the forecast period by comparing load impacts for all SmartAC™ customers by LCA for the PG&E 1-in-2 scenario for a July peak day. Aggregate load impacts decline by approximately 11 percent per year after 2022, commensurate with the decline in enrollments. Overall, load impacts decline by more than 70 percent from 21.2 MWh/hour in 2021 to 6.3 MWh/hour in 2031.

Figure 4-2: Changes in Aggregate Load Impacts over RA Window by LCA for PG&E 1-in-2 July Peak Scenario (2021-2031)

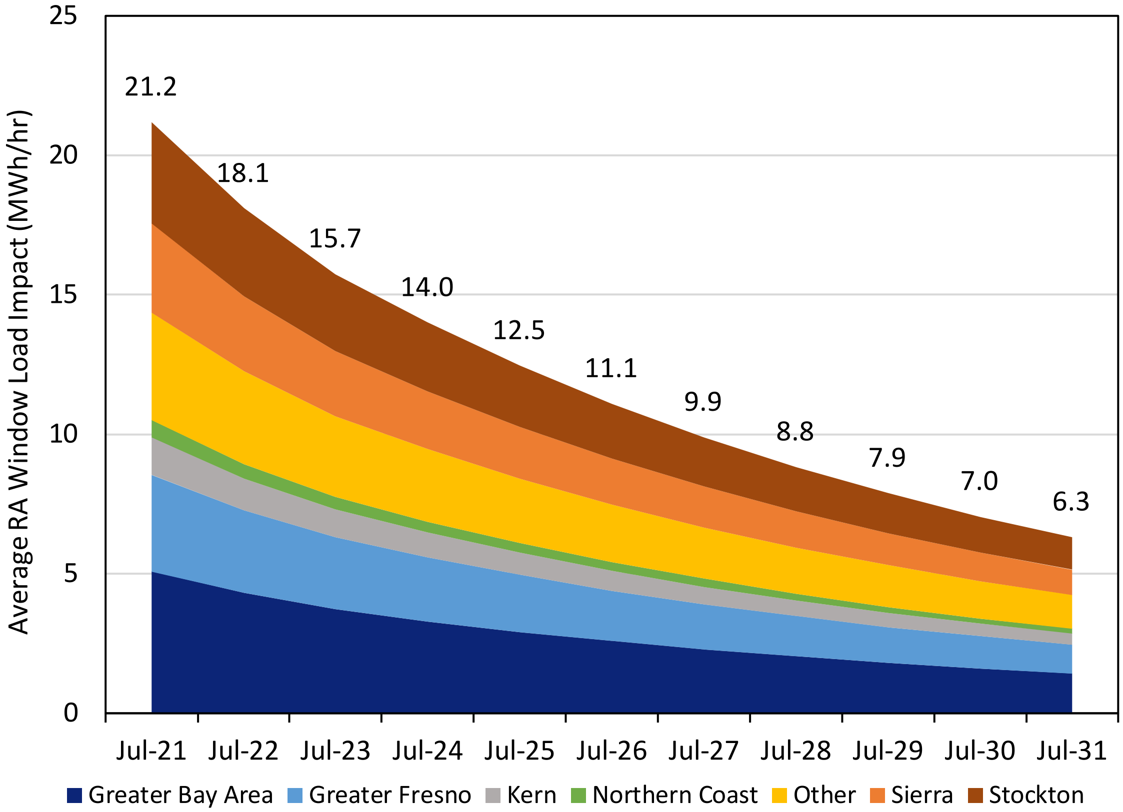


Figure 4-3 illustrates the aggregate reference load, observed load, and load impact for all SmartAC™ customers on a July peak day in 2021 for the PG&E 1-in-2 weather scenario. *Ex-ante* load impacts peak during the second event hour, similar to the pattern observed during sub-LAP events in PY2020, illustrated in Figure 3-4. The shape of the event load impacts is flatter due to the longer duration of the RA window. Furthermore, the *ex-ante* loads and load impacts are smaller in magnitude than those presented in Figure 3-4 due to declining program enrollments and SIP adjustments. The average RA window load impact is 21.2 MWh/hour, or 10 percent of the average RA window reference loads.

Figure 4-3: Aggregate Hourly Loads and Load Impacts for July Peak, *PG&E 1-in-2 Scenario* in 2021-All SmartAC™ customers

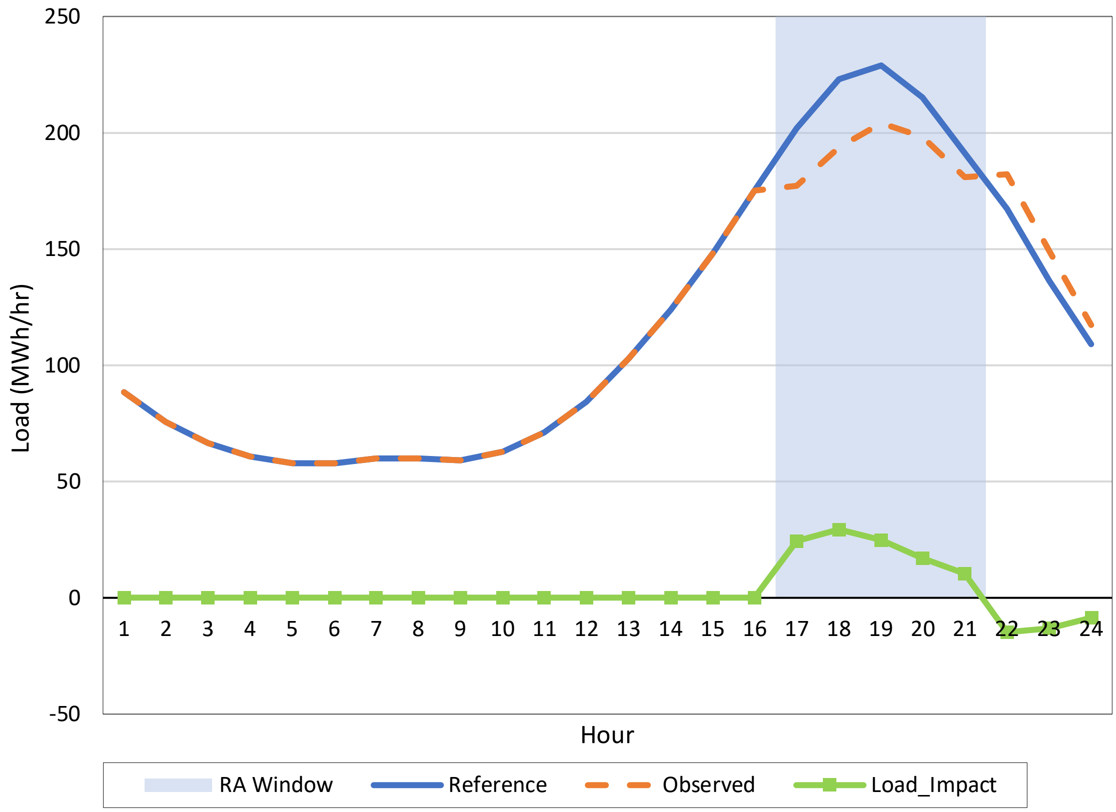


Figure 4-4 illustrates the aggregate reference load, observed load, and load impacts for SmartAC™-only customers on a July peak day in 2021 for the PG&E 1-in-2 weather scenario. The shape of the *ex-ante* loads and load impacts is similar to the results for all SmartAC™ program customers. The average RA window load impact is 18.4 MWh/hour, or 9.7 percent of the average RA window reference loads.

Figure 4-4: Aggregate Hourly Loads and Load Impacts for July Peak, *PG&E 1-in-2* Scenario in 2021: SmartAC™-only customers

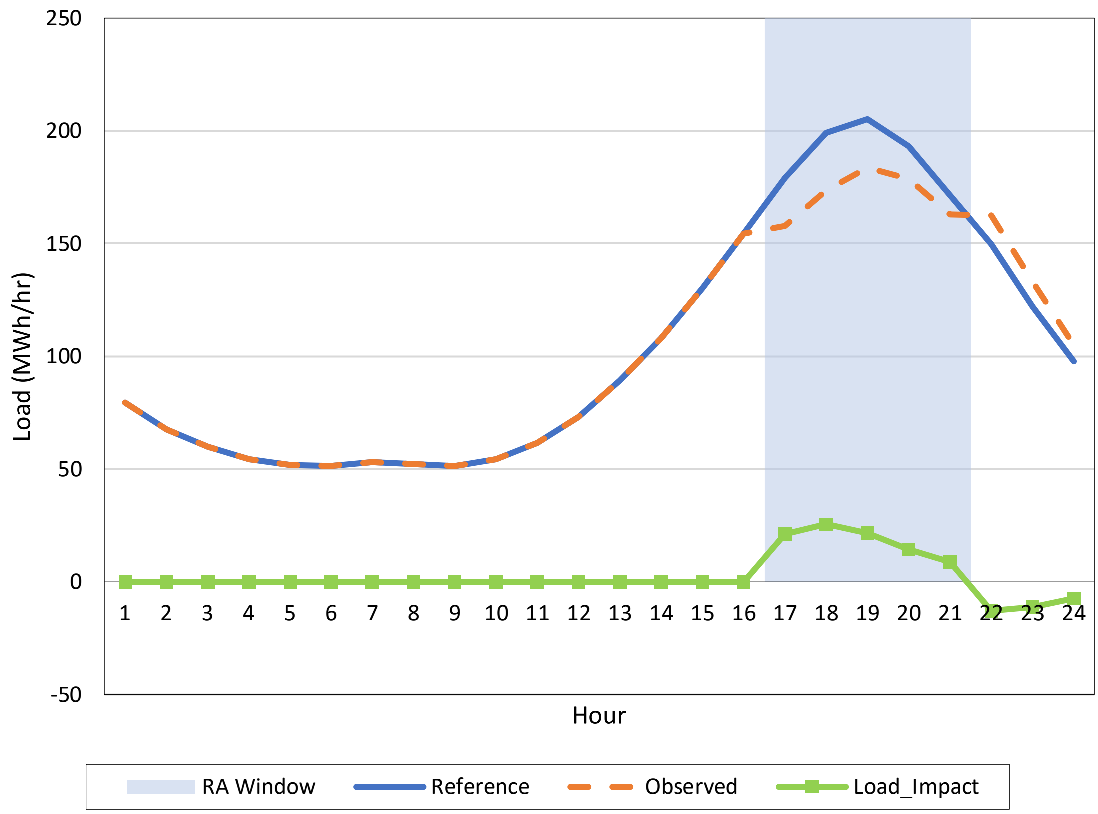


Figure 4-5 illustrates the aggregate reference load, observed load, and load impact for customers who are dually enrolled in SmartAC™ and SmartRate™ on a July peak day in 2021 for the PG&E 1-in-2 weather scenario. The shape of the *ex-ante* reference load is flatter than for SmartAC™-only customers, with a slightly less pronounced peak. The magnitude of the aggregate loads and load impacts is much smaller compared to SmartAC™-only customers due to lower dual enrollments. However, per-customer load impacts are the same for dually enrolled customers. The average RA window load impact is 2.8 MWh/hour, or 12.5 percent of the average RA window reference loads.

Figure 4-5: Aggregate Hourly Loads and Load Impacts for July Peak, *PG&E 1-in-2* Scenario in 2021-Dually Enrolled Customers

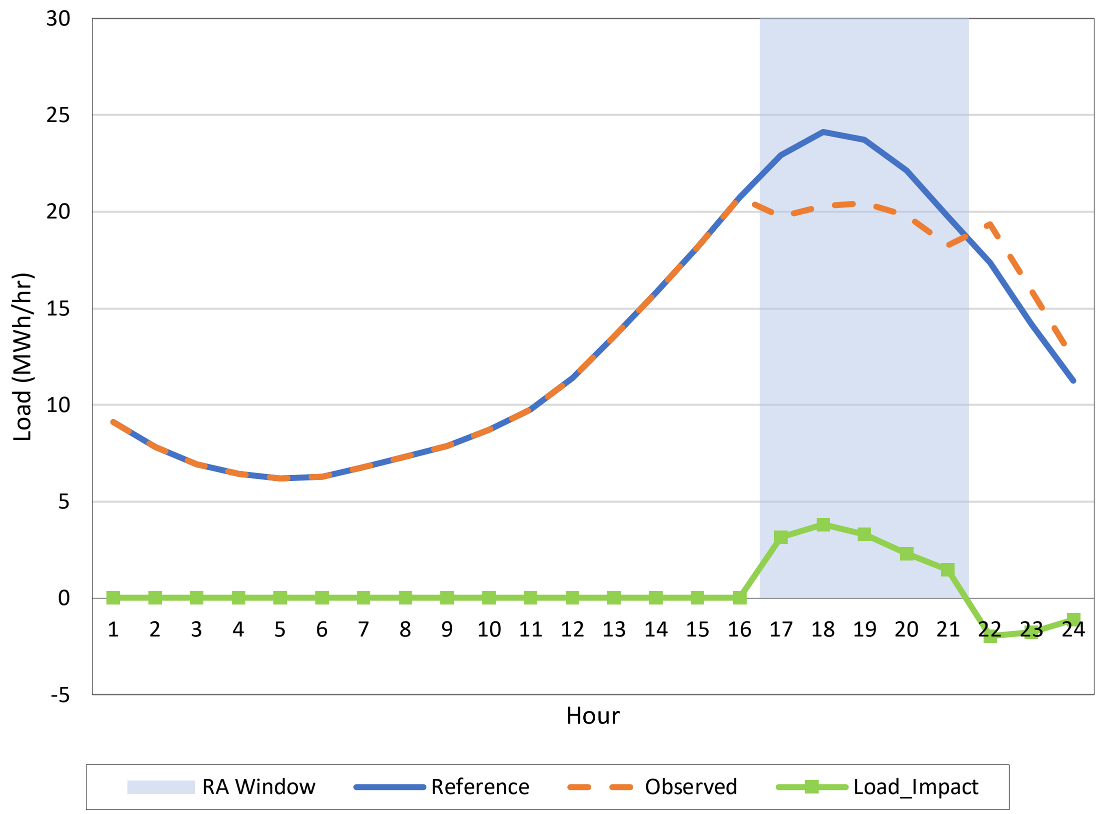


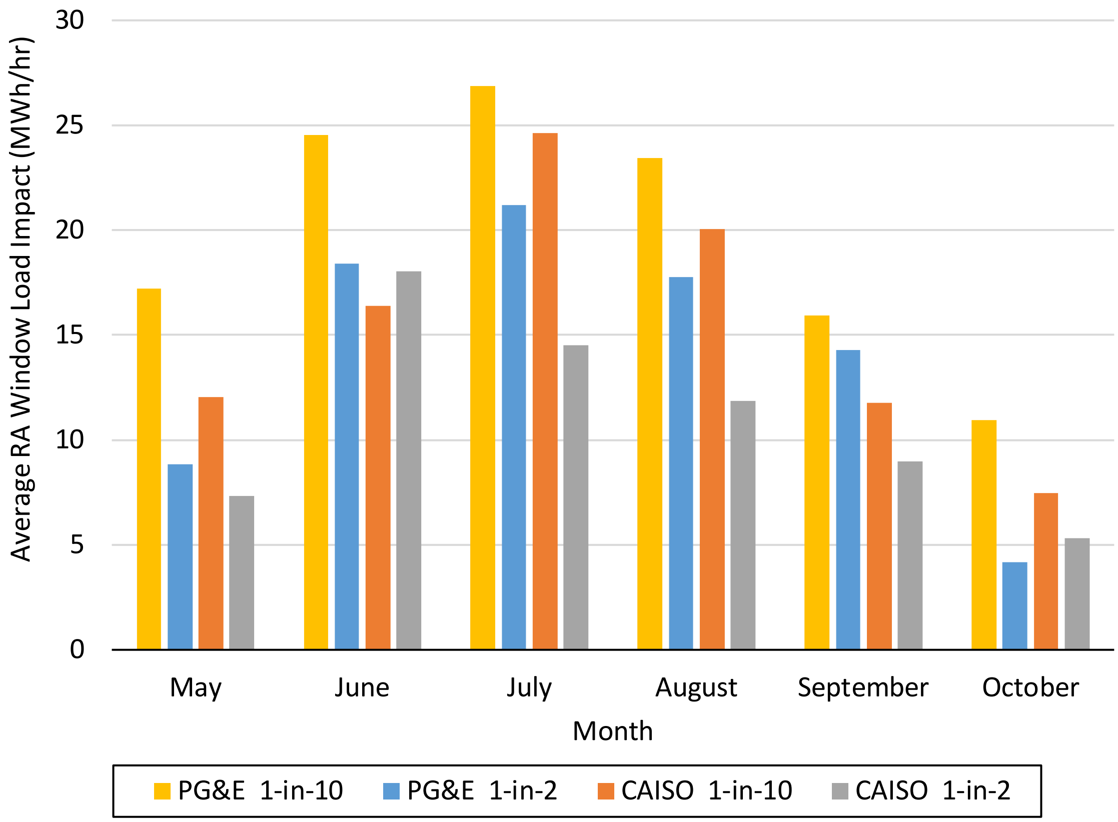
Table 4-1 summarizes average loads and load impacts, percentage load impacts, and average temperature for the RA window on a July peak day in 2021 for the PG&E 1-in-2 weather scenario by LCA and enrollment segment. Per-customer load impacts, which are identical for SmartAC™-only and dually enrolled customers, range from 0.19 (kWh/customer/hour) for Northern Coast to 0.59 for Stockton. There is large variation in aggregate load impacts due to the distribution of enrolled customers across LCAs. The Greater Bay Area will have the largest aggregate load impacts of 5.1 MWh/hour and the largest percentage reduction of 21.4 percent from dually enrolled customers in Stockton.

Table 4-1: Average RA Window Load Impacts for *PG&E 1-in-2* July Peak Day by LCA and Enrollment Segment

Enrollment Segment	LCA	Enrolled	Average RA Window Hour				
			Reference (kW/Cust)	Impact (kW/Cust)	% Load Impact	Aggregate Impact (MW)	Avg. Temp (°F)
All	Greater Bay Area	25,725	2.21	0.20	9.0%	5.1	89.9
	Greater Fresno	13,344	3.26	0.26	7.9%	3.5	103.8
	Kern	3,801	3.22	0.36	11.1%	1.4	102.8
	Northern Coast	3,216	2.04	0.19	9.3%	0.6	88.7
	Other	13,967	2.74	0.28	10.0%	3.8	100.2
	Sierra	12,950	2.72	0.25	9.1%	3.2	98.5
	Stockton	6,150	3.16	0.59	18.6%	3.6	100.0
	Total	**79,153**	**2.68**	**0.27**	**10.0%**	**21.2**	**96.8**
Dually Enrolled	Greater Bay Area	1,623	1.91	0.20	10.3%	0.3	89.9
	Greater Fresno	1,765	2.83	0.26	9.1%	0.5	103.8
	Kern	485	2.94	0.36	12.2%	0.2	102.8
	Northern Coast	223	1.56	0.19	12.2%	0.0	88.7
	Other	2,728	2.31	0.28	11.9%	0.8	100.2
	Sierra	1,268	2.22	0.25	11.1%	0.3	98.5
	Stockton	1,287	2.75	0.59	21.4%	0.8	100.0
	Total	**9,379**	**2.40**	**0.30**	**12.5%**	**2.8**	**98.7**
SmartAC™ Only	Greater Bay Area	24,102	2.23	0.20	8.9%	4.8	89.9
	Greater Fresno	11,579	3.33	0.26	7.8%	3.0	103.8
	Kern	3,316	3.26	0.36	11.0%	1.2	102.8
	Northern Coast	2,993	2.08	0.19	9.2%	0.6	88.7
	Other	11,239	2.85	0.28	9.7%	3.1	100.2
	Sierra	11,682	2.77	0.25	8.9%	2.9	98.5
	Stockton	4,863	3.27	0.59	18.0%	2.9	100.0
	Total	**69,774**	**2.72**	**0.26**	**9.7%**	**18.4**	**96.6**

Figure 4-6 illustrates the seasonality and variation by weather scenario in the forecasted load impacts by comparing aggregate load impacts for the average hour in the Resource Adequacy (RA) window in 2021 across months and weather scenarios. The load impact is highest in July in three out of the four weather scenarios, with a maximum load impact of 26.9 MWh/hour from the PG&E 1-in-10 scenario. For the CAISO 1-in-2 scenario, the load impacts are highest in June (18 MWh/hour). The loads impacts are always the lowest in October, with a minimum of 4.2 MWh/hour from the PG&E 1-in-2 scenario.

Figure 4-6: Aggregate Load Impacts over RA Window in 2021 by Month and Weather Scenario



While this year's *ex-ante* forecast represents estimated sub-LAP event performance, the program can still be called for emergency events through a serial dispatch or less commonly for serial test events. For comparison, we show what the aggregate load impacts would be if the forecast was designed to simulate serial event load impacts rather than sub-LAP event load impacts. Figure 4-7 shows aggregate load impacts for the average hour in the Resource Adequacy (RA) window in 2021 across months and weather scenarios for a serial event simulation. In the case of a full system dispatch, the total potential load reduction during the July Peak in 2021 would be 38.8 MWh/hour.

Figure 4-7: Aggregate Load Impacts over RA Window in 2021 by Month and Weather Scenario for Serial Event Simulation

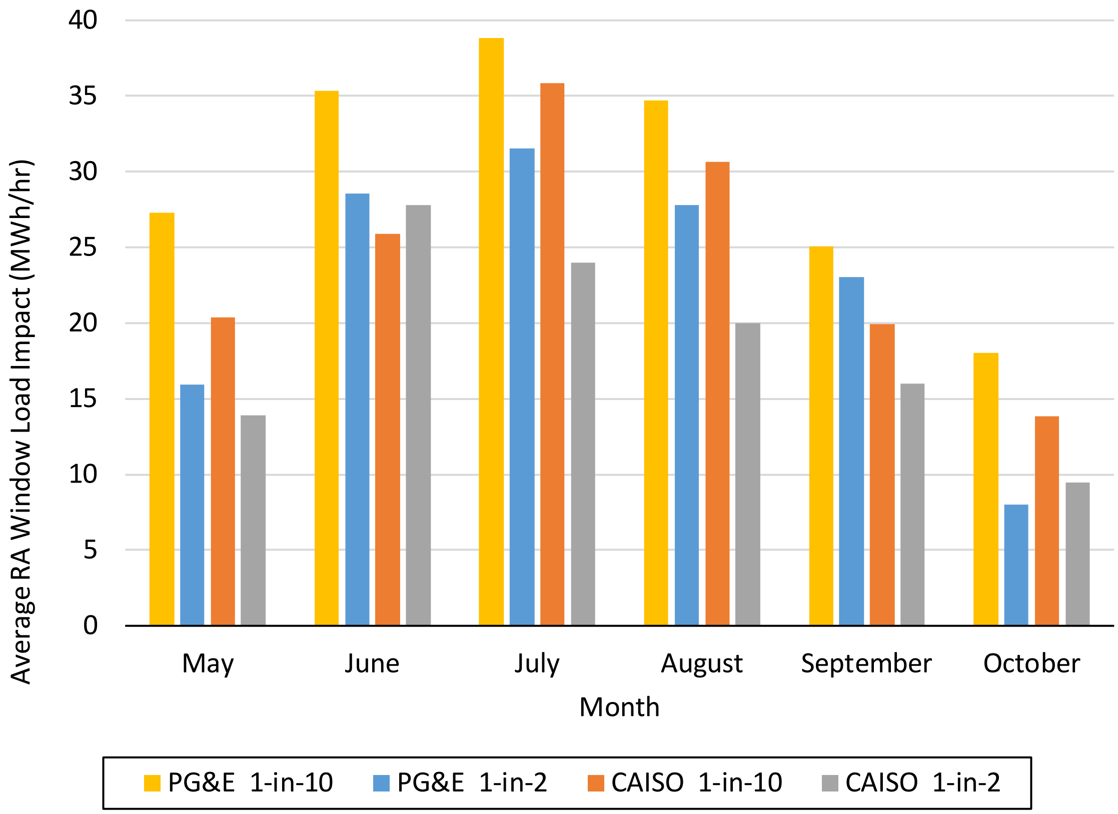
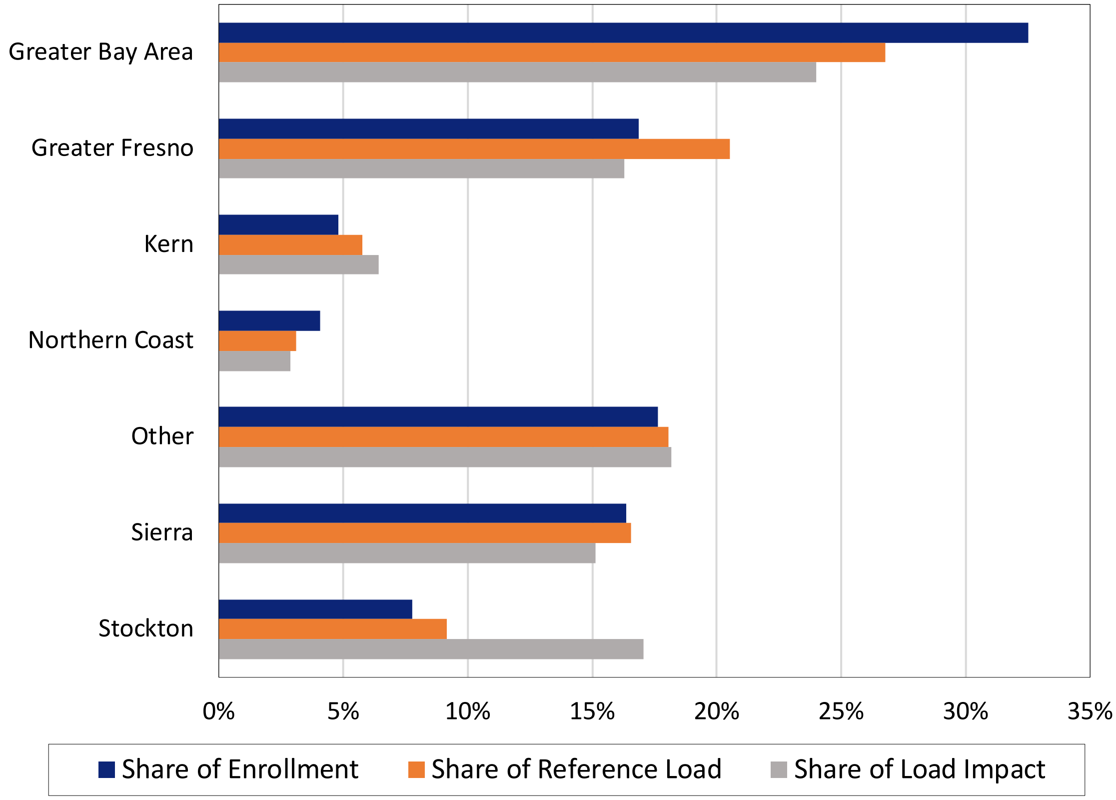


Figure 4-8 compares the LCA shares of average RA window load impacts, reference loads, and enrollments on a July peak day for the PG&E 1-in-2 scenario in 2021. The load impacts for the SmartAC™ program are highest in the Greater Bay Area with 24 percent of aggregate load impacts, 32.5 percent of enrolled customers, and 26.8 percent of reference loads. The top four LCAs, including the Greater Bay Area, Greater Fresno, Other, and Stockton, contribute 75.6 percent of the aggregate load reductions for SmartAC™. Kern, Other, and Stockton have a higher share of load impacts compared to the share of enrollments or reference loads, suggesting that these LCAs are relatively more responsive on a per-customer basis. The remaining LCAs have a lower share of load impacts compared to enrollments or reference loads.

Figure 4-8: RA Window Load Impacts for *PG&E 1-in-2* Typical Event Day by LCA



5. Load Impact Reconciliations

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

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

The term "current" refers to the present study, which includes *ex-post* and *ex-ante* results for PY2020. The term "previous" refers to findings in reports for PY2019. In the final comparison above, we illustrate the linkage between the PY2020 *ex-post* load impacts and the "current" *ex-ante* forecast for 2020.

5.1 Previous vs. Current Ex-Post

In this section we compare *ex-post* load impacts from the current and previous studies. We compare results for sub-LAP and serial events to the results from PY2019.

Table 5-1 compares the average per-customer reference loads, load impacts, and temperatures for sub-LAP events for the current and previous program years across the most common event hours from 4 to 6 p.m. For the eleven sub-LAPs that had sub-LAP events in both years, the load impacts were higher in PY2020 compared to PY2019 for six sub-LAPs, while temperatures were hotter for 10 sub-LAPs. PGF1, PGKN, PGSI, and PGZP had lower load impacts in PY2020 despite higher event temperatures, while PGSB had lower load impacts and lower temperatures. PGNB and PGP2 had higher load impacts despite comparable event temperatures.

The bottom row of the table compares average load impacts across sub-LAPs that had events in both years. About 4,300 fewer customers were dispatched for sub-LAP events in 2020 relative to 2019 due to program attrition. There was an increase in per-customer reference loads due to higher event temperatures and potential SIP impacts. Load impacts were comparable despite the higher temperatures in PY2020, suggesting that aging devices and technical issues may have dampened load impacts. The combination of higher reference loads and the same magnitude load impacts led to a decrease in percentage load impacts from 14.9 to 13.1 percent of reference loads.

Table 5-1: Current vs. Previous *Ex-Post* Load Impacts for sub-LAP events (4-6 p.m.)

sub-LAP	Avg. # called		Reference (kW/cust)		Load Impact (kW/cust)		Avg Temp (°F)	
	PY2019	PY2020	PY2019	PY2020	PY2019	PY2020	PY2019	PY2020
PGCC		242		3.11		0.36		93.2
PGEB	20,123	18,477	2.62	3.24	0.40	0.50	100.2	104.1
PGF1	17,990	14,966	3.04	3.25	0.34	0.33	102.6	104.2
PGFG		1,818		2.05		0.30		93.2
PGKN	5,154	4,586	2.82	3.28	0.48	0.39	100.8	103.7
PGNB	1,346	1,317	2.63	2.91	0.40	0.46	100.3	100.6
PGNC	618	626	2.29	2.63	0.31	0.32	97.8	99.8
PGNP	11,355	12,970	2.63	3.20	0.37	0.39	100.0	104.0
PGP2	3,656	3,391	2.53	2.90	0.46	0.48	97.3	97.1
PGSB	8,218	7,546	2.27	2.06	0.39	0.34	97.3	94.7
PGSI	14,345	14,300	2.63	2.88	0.43	0.35	99.0	101.2
PGST	5,907	6,516	2.78	3.19	0.46	0.47	98.6	102.0
PGZP	2,169	1,873	2.38	3.20	0.32	0.25	94.2	104.2
Common Sub-LAPs	**90,881**	**86,568**	**2.68**	**3.05**	**0.40**	**0.40**	**99.84**	**102.28**

Table 5-2 compares the average per-customer reference loads, load impacts, and temperatures for serial events during full dispatch hours (4 to 6 p.m.) for the current program year to PY2019 by LCA. This comparison is for SmartAC™-only customers, since the serial event in PY2020 was a dual SmartRate™ event. Overall, reference loads and load impacts have increased since 2019, due to hotter event temperatures in 2020. Kern is the exception to this trend. Despite comparable event temperatures, average load impacts go from being the highest at 0.73 kWh/customer/hour in 2019 to the lowest in 2020 at 0.21 kWh/customer/hour. This trend for Kern is consistent with technical and device failure issues, as in previous program years.

The bottom row of the table compares average load impacts across all LCAs. In addition to increasing per-customer load impacts and reference loads there is a sharp decline in program enrollments of 11 percent between PY2019 and PY2020. Overall serial event load impacts increased by 0.1 kWh/customer/hour (18 percent) from 2019 to 2020, which is likely driven by hotter event temperatures in 2020. At the same time, percentage load impacts have decreased from 19.1 percent to 18.5 percent in 2020, due to a large increase in reference loads.

Table 5-2: Current vs. Previous *Ex-Post* Load Impacts for serial events by LCA (4-6 p.m.)

sub-LAP	Avg. # enrolled		Reference (kW/cust)		Load Impact (kW/cust)		Avg Temp (°F)	
	PY2019	PY2020	PY2019	PY2020	PY2019	PY2020	PY2019	PY2020
Greater Bay Area	30,808	28,119	2.54	3.32	0.53	0.73	97.9	98.8
Greater Fresno	15,197	12,707	3.08	3.62	0.48	0.57	104.1	105.4
Kern	4,112	3,712	3.02	3.46	0.73	0.21	104.2	104.0
Northern Coast	3,769	3,367	2.55	2.94	0.52	0.66	97.7	98.4
Other	13,710	12,469	2.83	3.39	0.49	0.54	102.2	104.2
Sierra	14,427	13,015	2.81	3.33	0.54	0.59	101.0	104.5
Stockton	6,266	5,322	2.99	3.68	0.58	0.76	100.9	102.7
All LCA	**88,287**	**78,711**	**2.78**	**3.40**	**0.53**	**0.63**	**100.64**	**102.18**

5.2 Previous vs. Current Ex-Ante

In this section, we compare the *ex-ante* forecast from the previous study to the *ex-ante* forecast contained in the current study. We focus on average load impacts across the RA window from 4 to 9 p.m.

Table 5-3 reports the average event-hour load impacts for the July 2021 peak day under PG&E 1-in-2 weather conditions. The aggregate load impact forecast decreases dramatically across program years from 43.7 MWh/hour in the previous study to 21.2 MWh/hour in the current study, a 51 percent decrease. This change is primarily due to shifting the objective for the *ex-ante* forecast from predicting load impacts during system-wide events to predicting load impacts during sub-LAP events. Per-customer load impacts decrease by 48 percent from the 2019 forecast to the 2020 forecast, despite comparable temperatures. For comparison, if we use the *ex-ante* model described in Section 2.3.2 to simulate a serial event rather than a sub-LAP event, the *ex-ante* load impacts would be 31.6 MWh/hour. This scenario would still lead to a decrease in per-customer load impacts from 0.52 to 0.4 kWh/customer/hour, because there are several sub-LAPs that likely have technical and device failure issues, which is reflected in the forecast. Another factor explaining the decrease in aggregate load impacts is the updated enrollment forecast, which predicts a further six percent decline in enrollments by 2021 compared to the PY2019 forecast. A final component explaining the lower aggregate load impacts in the PY2020 forecast is the SIP adjustments. Recall that the forecast uses percent load impact estimates, which are applied to the *ex-ante* reference loads to produce *ex-ante* load impacts. Despite declines in load impacts, reference loads are expected to increase, both at the per-customer level and in aggregate, due to continued SIP impacts.

Table 5-3: Previous vs. Current *Ex-Ante* Load Impacts, *PG&E 1-in-2 July 2021 Peak Day*

Level	Outcome	PY2019	PY2020
Total	Enrollments	84,393	79,153
	Reference (MW)	205.8	212.1
	Load Impact (MW)	43.7	21.2
	Avg. Temp (°F)	97.8	97.7
	% Load Impact	21.2%	10.0%
Per Participant	Reference (kW)	2.44	2.68
	Load Impact (kW)	0.52	0.27

5.3 Previous Ex-ante vs. Current Ex-Post

In this section, we compare the *ex-ante* forecast from the previous study to the *ex-post* results from the serial event contained in the current study. We limit the load impacts to the serial event hours during PY2020 from 4 to 6 p.m., which fall within the RA window from 4 to 9 p.m.

Table 5-4 provides a comparison of the *ex-ante* forecast of 2020 load impacts for the PG&E 1-in-10 scenario for the typical event day from the previous study to the *ex-post* load impacts for serial events estimated as part of the current study. This scenario was chosen because the scenario temperature was closest to serial event temperatures in 2020. There were many events in 2020 that had higher temperatures than the hottest *ex-ante* weather scenario. The serial event had slightly higher temperatures compared to the weather scenario.

Overall, the per-customer *ex-post* load impacts are comparable to the previous *ex-ante* forecast, while per-customer reference loads were considerably higher. As a result, load impacts during 2020 were much lower as a percent of reference loads compared to the forecast. The aggregate load impacts are 14 percent lower than forecasted, mainly as a result of approximately 13,000 fewer customers enrolled compared to the enrollment forecast.

Table 5-4: Comparison of Previous *Ex-Ante* and Current *Ex-Post* Impacts (4-6 p.m.)

Level	Outcome	PY2019 Forecast of 2020	PY2020 Serial Event Load Impacts
Total	Enrollments	91,783	78,711
	Reference (MW)	237.19	267.34
	Load Impact (MW)	57.50	49.22
	Avg. Temp (°F)	101.7	102.2
	% Load Impact	24.2%	18.4%
Per Participant	Reference (kW)	2.58	3.40
	Load Impact (kW)	0.63	0.63

5.4 Current Ex-Post vs. Current Ex-Ante

In this section, we compare the *ex-post* findings from the current study to the *ex-ante* forecast contained in the current study in a similar fashion as the previous comparison during the event hours from 4 to 6 p.m.

Table 5-5 compares the *ex-post* load impacts from the fourteen sub-LAP events in 2020 to the *ex-ante* load impact forecast for an August Peak day for the PG&E 1-in-10 weather conditions. The event temperatures and the *ex-post* per-customer load impacts are the similar, while the reference loads are slight lower in the forecast. Percentage load impacts are also comparable between the forecast and the *ex-post* results. The main difference is due to enrollments, which are forecast to be 12 percent lower in 2021. This leads to lower aggregate load impacts and reference loads in the forecast compared to the *ex-post* results. Aggregate load impacts are expected to decrease by 4.1 MWh/hour over the next year.

Table 5-5: Comparison of Current *Ex-Post* and *Ex-Ante* Load Impacts (4-6 p.m.)

Level	Outcome	PY2020 Forecast of 2021	PY2020 Serial Event Load Impacts
Total	Enrollments	78,367	88,628
	Reference (MW)	232.49	268.27
	Load Impact (MW)	31.02	35.12
	Avg. Temp (°F)	102.5	102.1
	% Load Impact	13.3%	13.1%
Per Participant	Reference (kW)	2.97	3.03
	Load Impact (kW)	0.40	0.40

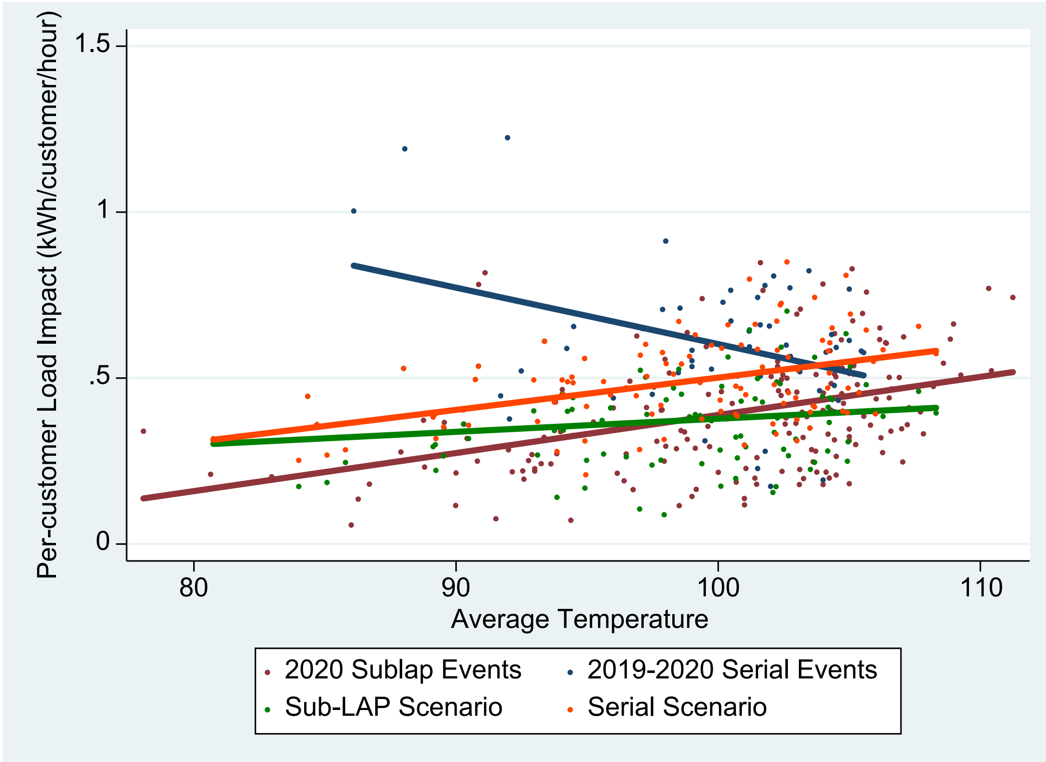
To further demonstrate the consistency between the *ex-post* load impacts on which the *ex-ante* load impact is based and the resulting *ex-ante* forecast, Figure 5-1 shows a scatterplot of hourly *ex-post* and *ex-ante* load impacts compared to average temperatures from PY2020 for all sub-LAPs. Appendix C shows similar comparisons by sub-LAP. The red dots show the *ex-post* load impacts from sub-LAP events in 2020, while the red line shows the linear relationship between sub-LAP load impacts and hourly temperatures. The blue dots and line show the *ex-post* load impacts for serial events from 2019 and 2020. The green dots and line show the *ex-ante* load impacts from the PY2020 forecast, which is designed to simulate sub-LAP event load impacts. The orange dots and line show an alternative forecast that is designed to simulate load impacts during system-wide and serial test events. The results are limited to the hours where *ex-post* and *ex-ante* have overlapping event hours from 4 to 8 p.m. For the *ex-ante* load impacts we use the June and July peak month weather conditions for the PG&E 1-in-10 weather scenario for 2021.[14]

Figure 5-1 illustrates how load impacts during serial events were hotter on average than during sub-LAP events at for comparable temperatures.[15] Figure 5-1 also shows how the PY2020 *ex-ante* forecast (in green) is comparable to the range of *ex-post* load impacts for sub-LAP events (in red). The forecast of serial events (in orange) predicts larger load impacts on average, but these are still in the range of most sub-LAP load impacts, and lower than some of the serial event load impacts. While these results are pooled across all sub-LAPs, the *ex-ante* models were estimated for each sub-LAP. Appendix C shows the relationship between the two *ex-ante* forecasts and the *ex-post* load impacts for each sub-LAP.

[14] The *ex-ante* load impacts do not include any SIP adjustments, which would decrease the load impacts by a negligible amount.

[15] The three load impacts that are greater than 1 kWh/customer/hour are outlier load impacts from PGCC, which are unreliable due to the lower number of customers in this sub-LAP as previously explained. Otherwise there is a positive relationship between load impacts and temperature during serial events.

Figure 5-1: Scatterplot of Hourly Load Impacts vs. Average Temperature, All Sub-LAPs



6. Recommendations

Aging devices, such as the UtilityPro thermostats, have led to lower load impacts in PY2020. Device obsolescence is anticipated to increase in future program years across the one-way device population. Moreover, technical issues, such as the problems experienced in PGKN, further contributed to lower load impacts for some sub-LAPs in PY2020. Continued repair and replacement of old failing one-way devices with new two-way devices would improve per-customer load impacts for sub-LAP events in future program years, making the SmartAC™ program a more dependable resource in the CAISO wholesale market. Performance should be monitored after early season events to identify dispatch issues and remedy technical problems before remaining events are dispatched.

While we understand that sub-LAP events are the source of value from CAISO market awards, we recommend that there continue to be some system-wide or serial events called going forward. This would allow for more representative subgroup comparisons across PG&E's system rather than across the subset of dispatched sub-LAPs.

Appendices

The following Appendices accompany this report. Appendix A presents further information about how we evaluated the quality of our *ex-post* load impact evaluation and *ex-ante* forecast. The additional appendices consist of Excel files that can produce the tables required by the Protocols.

Appendix D 4a. PGE_2020_SAC_Ex_Post_PUBLIC

Appendix E 4b. PGE_2020_SAC_Ex_Ante_PUBLIC

Appendix A. Additional Control Group Matching Results

Table A-1 provides the mean percentage error (MPE) and mean absolute percentage error (MAPE) calculated across the average 24-hour load profile as well over the RA window. Also included are the mean error (ME) and mean absolute error (MAE) which show the errors in terms of kWh/customer/hour differences rather than percentage differences. Again, we evaluate match quality based on 24-hour load profiles for hot days and cooler days used in matching as well as days not using in matching.

The MPE and MAPE are higher by sub-LAP than the overall results. The average MAPE is 1.5 percent for all hours and 1.29 percent for the RA window. Table A-1 demonstrates that all ME and MAE values are less than 0.05 kWh/customer/hour. Moreover, hot non-event days generally have lower MAPEs, which average 1.3 percent for all hours and 1 percent for the RA window.

Table A-1: Match Quality Statistics by Sub-LAP

Sub-LAP	Comparison Days	24 Hour Load Profile				RA Window			
		MPE (%)	ME (kW)	MAPE (%)	MAE (kW)	MPE (%)	ME (kW)	MAPE (%)	MAE (kW)
PGCC	Hot Days	-1.4%	-0.01	3.3%	0.04	1.8%	0.02	1.8%	0.03
	Cool Days	-2.6%	-0.01	3.8%	0.03	2.6%	0.01	2.6%	0.02
	Non-Matching Cool Days	-1.5%	0.00	4.3%	0.03	4.0%	0.02	4.0%	0.02
	Weekend Days	-0.4%	0.00	4.6%	0.04	3.2%	0.02	3.2%	0.02
PGEB	Hot Days	0.5%	0.01	0.5%	0.01	0.5%	0.02	0.5%	0.03
	Cool Days	1.0%	0.01	1.0%	0.01	1.6%	0.01	1.6%	0.02
	Non-Matching Cool Days	1.5%	0.02	1.6%	0.02	3.0%	0.02	3.0%	0.02
	Weekend Days	1.1%	0.01	1.2%	0.01	1.6%	0.02	1.6%	0.02
PGF1	Hot Days	0.7%	0.01	0.8%	0.01	0.9%	0.02	0.9%	0.03
	Cool Days	0.7%	0.01	0.9%	0.01	1.0%	0.01	1.0%	0.02
	Non-Matching Cool Days	1.1%	0.02	1.1%	0.02	2.1%	0.02	2.1%	0.02
	Weekend Days	0.9%	0.01	0.9%	0.01	1.2%	0.02	1.2%	0.02
PGFG	Hot Days	0.9%	0.01	1.3%	0.02	1.0%	0.02	1.0%	0.03
	Cool Days	0.3%	0.00	1.3%	0.01	0.3%	0.01	0.7%	0.02
	Non-Matching Cool Days	0.0%	0.00	1.2%	0.01	0.6%	0.02	1.1%	0.02
	Weekend Days	1.4%	0.01	1.7%	0.02	1.5%	0.02	1.5%	0.02
PGKN	Hot Days	0.6%	0.01	0.7%	0.01	0.5%	0.02	0.5%	0.03
	Cool Days	0.4%	0.00	0.6%	0.01	0.3%	0.01	0.3%	0.02
	Non-Matching Cool Days	0.9%	0.01	0.9%	0.01	1.0%	0.02	1.0%	0.02
	Weekend Days	0.5%	0.01	0.5%	0.01	0.7%	0.02	0.7%	0.02
PGNB	Hot Days	0.4%	0.01	1.8%	0.02	1.6%	0.02	1.6%	0.03
	Cool Days	0.0%	0.00	1.6%	0.01	0.7%	0.01	0.9%	0.02
	Non-Matching Cool Days	-0.1%	0.00	1.8%	0.01	1.5%	0.02	1.5%	0.02
	Weekend Days	0.9%	0.01	1.3%	0.01	1.8%	0.02	1.8%	0.02

Sub-LAP	Comparison Days	24 Hour Load Profile				RA Window			
		MPE (%)	ME (kW)	MAPE (%)	MAE (kW)	MPE (%)	ME (kW)	MAPE (%)	MAE (kW)
PGNC	Hot Days	-1.4%	-0.01	1.9%	0.02	0.6%	0.02	1.0%	0.03
	Cool Days	-2.6%	-0.02	3.0%	0.02	0.7%	0.01	1.0%	0.02
	Non-Matching Cool Days	-2.6%	-0.01	3.7%	0.03	2.6%	0.02	2.7%	0.02
	Weekend Days	-0.6%	0.00	1.1%	0.01	-0.5%	0.02	0.6%	0.02
PGNP	Hot Days	-0.2%	0.00	0.3%	0.00	-0.2%	0.02	0.2%	0.03
	Cool Days	-0.2%	0.00	0.4%	0.00	-0.3%	0.01	0.3%	0.02
	Non-Matching Cool Days	-0.3%	0.00	0.4%	0.00	-0.1%	0.02	0.2%	0.02
	Weekend Days	0.1%	0.00	0.4%	0.00	-0.2%	0.02	0.3%	0.02
PGP2	Hot Days	1.6%	0.03	1.7%	0.03	2.5%	0.02	2.5%	0.03
	Cool Days	0.9%	0.01	1.2%	0.01	2.2%	0.01	2.2%	0.02
	Non-Matching Cool Days	0.7%	0.01	1.3%	0.01	2.1%	0.02	2.1%	0.02
	Weekend Days	0.8%	0.01	1.8%	0.02	2.7%	0.02	2.7%	0.02
PGSB	Hot Days	-0.3%	0.00	1.0%	0.01	0.7%	0.02	0.7%	0.03
	Cool Days	-0.6%	0.00	1.2%	0.01	1.0%	0.01	1.0%	0.02
	Non-Matching Cool Days	-0.5%	0.00	1.6%	0.01	1.7%	0.02	1.7%	0.02
	Weekend Days	-0.5%	0.00	1.5%	0.01	1.3%	0.02	1.3%	0.02
PGSI	Hot Days	0.9%	0.01	0.9%	0.01	0.7%	0.02	0.7%	0.03
	Cool Days	0.2%	0.00	0.6%	0.01	0.5%	0.01	0.5%	0.02
	Non-Matching Cool Days	0.9%	0.01	1.0%	0.01	1.8%	0.02	1.8%	0.02
	Weekend Days	1.0%	0.01	1.2%	0.01	1.0%	0.02	1.0%	0.02
PGST	Hot Days	0.7%	0.01	0.8%	0.01	0.7%	0.02	0.7%	0.03
	Cool Days	1.1%	0.01	1.1%	0.01	0.9%	0.01	0.9%	0.02
	Non-Matching Cool Days	0.5%	0.00	0.7%	0.01	0.3%	0.02	0.4%	0.02
	Weekend Days	1.8%	0.02	1.8%	0.02	1.2%	0.02	1.2%	0.02
PGZP	Hot Days	0.5%	0.01	1.5%	0.02	0.8%	0.02	0.8%	0.03
	Cool Days	-0.2%	0.00	1.5%	0.01	-0.2%	0.01	0.5%	0.02
	Non-Matching Cool Days	-1.0%	-0.01	1.9%	0.02	-0.9%	0.02	0.9%	0.02
	Weekend Days	0.1%	0.00	1.4%	0.01	-0.4%	0.02	0.8%	0.02

Appendix B. Event Overrides by Event and Location

Table B-1 shows customers overrides by sub-LAP for sub-LAP events and Table B-2 displays overrides by LCA for the serial event. Most override rates are below one percent, with the exception of some sub-LAPs during the last two events, October 15th and October 16th. PGCC and PGFG had more customers opt-out than normal during these events relative to the small number of customers in those sub-LAPs, leading to override rates that range between 3 and 5 percent.

Table B-1: Overrides by Sub-LAP and Event for Sub-LAP events

Date	Sub-LAP	Full Event Hours (p.m.)	SmartRate™ Event?	# Overrides	# Called	Override Rate
8/14	PGCC	5:00-8:00	Yes	1	246	0.4%
	PGEB	4:00-8:00		139	17,079	0.8%
	PGF1	5:00-8:00		26	13,181	0.2%
	PGFG	6:00-8:00		6	1,785	0.3%
	PGKN	4:00-8:00		8	4,037	0.2%
	PGNB	4:00-8:00		10	1,208	0.8%
	PGNC	4:00-8:00		0	555	0.0%
	PGNP	4:00-8:00		57	10,513	0.5%
	PGP2	4:00-8:00		26	3,431	0.8%
	PGSB	6:00-8:00		22	7,599	0.3%
	PGSI	5:00-8:00		29	13,123	0.2%
	PGST	4:00-8:00		28	5,217	0.5%
	PGZP	4:00-8:00		9	1,564	0.6%
8/15	PGCC	4:00-6:00	No	1	245	0.4%
	PGEB	4:00-6:00		72	18,713	0.4%
	PGF1	4:00-6:00		17	15,175	0.1%
	PGKN	4:00-6:00		2	4,638	0.0%
	PGNB	5:00-7:00		4	1,345	0.3%
	PGNC	4:00-6:00		2	634	0.3%
	PGNP	4:00-6:00		22	13,097	0.2%
	PGP2	4:00-6:00		16	3,445	0.5%
	PGSI	5:00-7:00		20	14,525	0.1%
	PGST	4:00-6:00		10	6,608	0.2%
8/17	PGEB	4:00-6:00	Yes	34	16,917	0.2%
	PGF1	4:00-6:00		18	12,999	0.1%
	PGKN	4:00-6:00		3	3,998	0.1%
	PGNB	4:00-6:00		2	1,192	0.2%
	PGNC	4:00-6:00		0	548	0.0%
	PGNP	4:00-6:00		22	10,407	0.2%
	PGSI	4:00-6:00		20	13,031	0.2%
	PGST	4:00-6:00		5	5,142	0.1%

Date	Sub-LAP	Full Event Hours (p.m.)	Smart-Rate™ Event?	# Overrides	# Called	Override Rate
	PGZP	4:00-6:00		4	1,546	0.3%
8/19	PGCC	5:00-6:00	Yes	0	241	0.0%
	PGEB	4:00-6:00		38	16,870	0.2%
	PGF1	4:00-6:00		10	12,991	0.1%
	PGKN	4:00-6:00		4	3,992	0.1%
	PGNB	4:00-6:00		4	1,190	0.3%
	PGNC	6:00-8:00		1	547	0.2%
	PGP2	4:00-6:00		4	3,390	0.1%
	PGSI	4:00-6:00		21	13,009	0.2%
	PGST	4:00-6:00		4	5,135	0.1%
	PGZP	4:00-6:00		4	1,543	0.3%
9/5	PGEB	4:00-6:00	No	35	18,379	0.2%
	PGF1	4:00-6:00		5	14,866	0.0%
	PGSI	4:00-6:00		13	14,281	0.1%
9/6	PGCC	3:00-6:00	Yes	1	241	0.4%
	PGEB	3:00-6:00		68	16,723	0.4%
	PGF1	5:00-8:00		14	12,904	0.1%
	PGKN	3:00-6:00		4	3,956	0.1%
	PGNB	3:00-6:00		3	1,174	0.3%
	PGNC	3:00-6:00		2	546	0.4%
	PGNP	3:00-6:00		23	10,304	0.2%
	PGP2	3:00-6:00		13	3,371	0.4%
	PGSI	3:00-6:00		22	12,895	0.2%
	PGST	3:00-6:00		6	5,111	0.1%
	PGZP	3:00-6:00		7	1,532	0.5%
9/7	PGEB	4:00-6:00	No	50	18,338	0.3%
	PGF1	4:00-6:00		12	14,857	0.1%
	PGKN	4:00-6:00		2	4,533	0.0%
	PGNB	4:00-6:00		2	1,311	0.2%
	PGNC	4:00-6:00		0	625	0.0%
	PGNP	4:00-6:00		22	12,843	0.2%
	PGSI	4:00-6:00		13	14,269	0.1%
	PGST	4:00-6:00		6	6,473	0.1%
	PGZP	4:00-6:00		4	1,873	0.2%
9/8	PGNB	4:00-6:00	No	1	1,309	0.1%
	PGST	4:00-6:00		2	6,466	0.0%
9/27	PGCC	4:00-6:00	No	0	241	0.0%
	PGP2	4:00-6:00		3	3,370	0.1%
	PGSB	4:00-6:00		4	7,549	0.1%
9/28	PGCC	4:00-6:00	No	0	241	0.0%

Date	Sub-LAP	Full Event Hours (p.m.)	Smart-Rate™ Event?	# Overrides	# Called	Override Rate
	PGFG	4:00-6:00		1	1,819	0.1%
	PGNC	4:00-6:00		0	620	0.0%
	PGP2	4:00-6:00		5	3,369	0.1%
	PGSB	4:00-6:00		7	7,544	0.1%
9/30	PGSI	5:00-6:00	No	3	14,173	0.0%
10/1	PGFG	3:00-5:00	No	0	1,817	0.0%
10/15	PGCC	6:00-8:00	No	7	241	2.9%
	PGFG	5:00-7:00		80	1,817	4.4%
	PGP2	5:00-7:00		14	3,368	0.4%
	PGSB	6:00-8:00		8	7,545	0.1%
10/16	PGFG	5:00-7:00	No	63	1,817	3.5%
	PGSB	4:00-6:00		9	7,545	0.1%

Table B-2: Overrides by LCA and Event for Serial Events

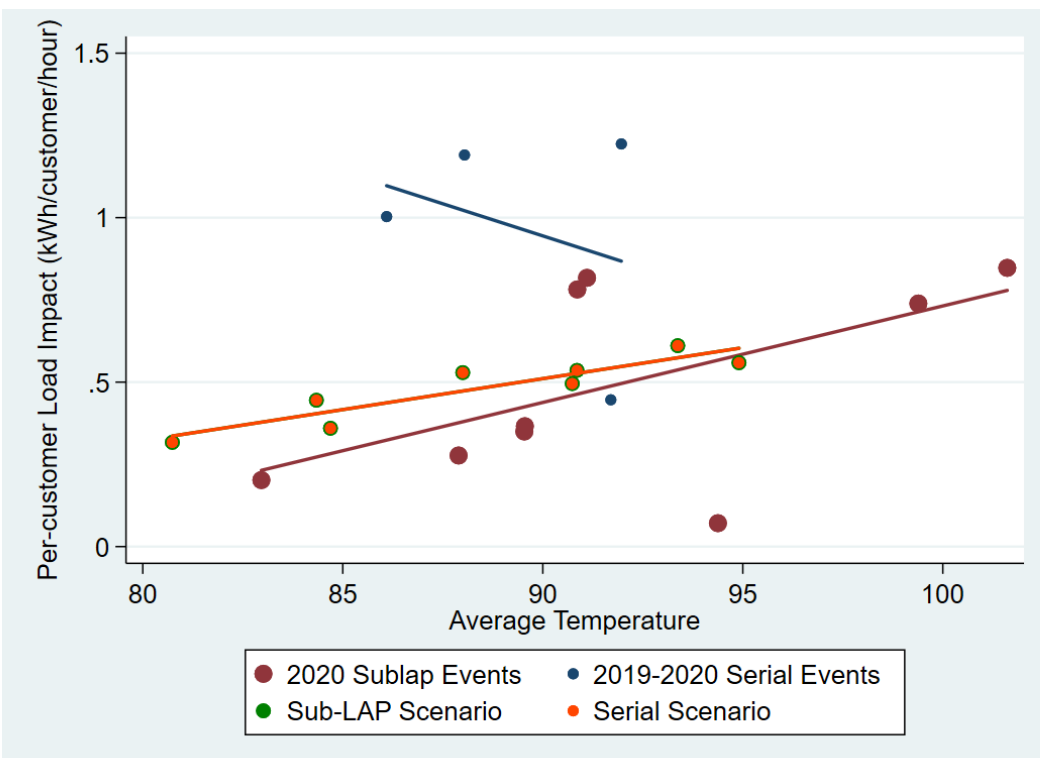
Date	Event Hours	LCA	Overrides	# Called	Override Rate
8/18	4:19 to 7 pm	Greater Bay Area	62	25,614	0.24%
		Greater Fresno	13	11,505	0.11%
		Kern	2	3,346	0.06%
		Northern Coast	6	3,070	0.20%
		Other	26	11,323	0.23%
		Sierra	19	11,822	0.16%
		Stockton	6	4,804	0.12%
Total			**134**	**71,484**	**0.19%**

Appendix C. Scatterplots of Load Impacts and Temperature

Figures C-1 through C-13 show scatterplots of hourly *ex-post* and *ex-ante* load impacts compared to average temperatures from PY2020 for all sub-LAPs. The red dots show the *ex-post* load impacts from sub-LAP events in 2020, while the red line shows the linear relationship between sub-LAP load impacts and hourly temperatures. The blue dots and line show the *ex-post* load impacts for serial events from 2019 and 2020. The green dots and line show the *ex-ante* load impacts from the PY2020 forecast, which is designed to simulate sub-LAP event load impacts. The orange dots and line show an alternative forecast that is designed to simulate load impacts during system-wide and serial test events. The results are limited to the hours where *ex-post* and *ex-ante* have overlapping event hours from 4 to 8 p.m. For the *ex-ante* load impacts we use the June and July peak month weather conditions for the PG&E 1-in-10 weather scenario for 2021.[16]

For most sub-LAPs the serial event load impacts (blue) are above the range for sub-LAP event load impacts (red). The higher serial event forecast scenario (orange) reflects this difference. For all sub-LAPs, the sub-LAP event forecast scenario (green) is in line with the *ex-post* sub-LAP load impacts. Several sub-LAPs experienced high temperatures during sub-LAP events in 2020 that are far outside the range of the hottest temperatures available in the weather scenarios including PCGG, PBEB, PGNB, PGNC, PGP2, PGSI, and PGZP.

Figure C-1: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGCC



[16] The *ex-ante* load impacts do not include any SIP adjustments, which would decrease the load impacts by a negligible amount.

Figure C-2: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGEB

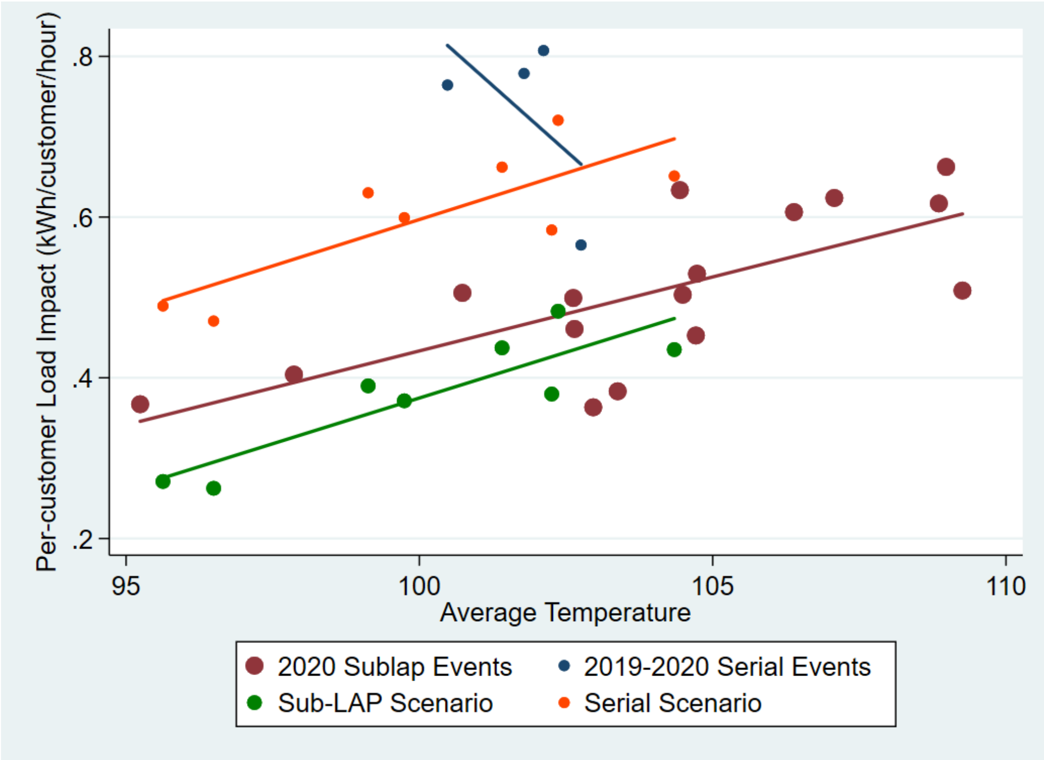


Figure C-3: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGF1

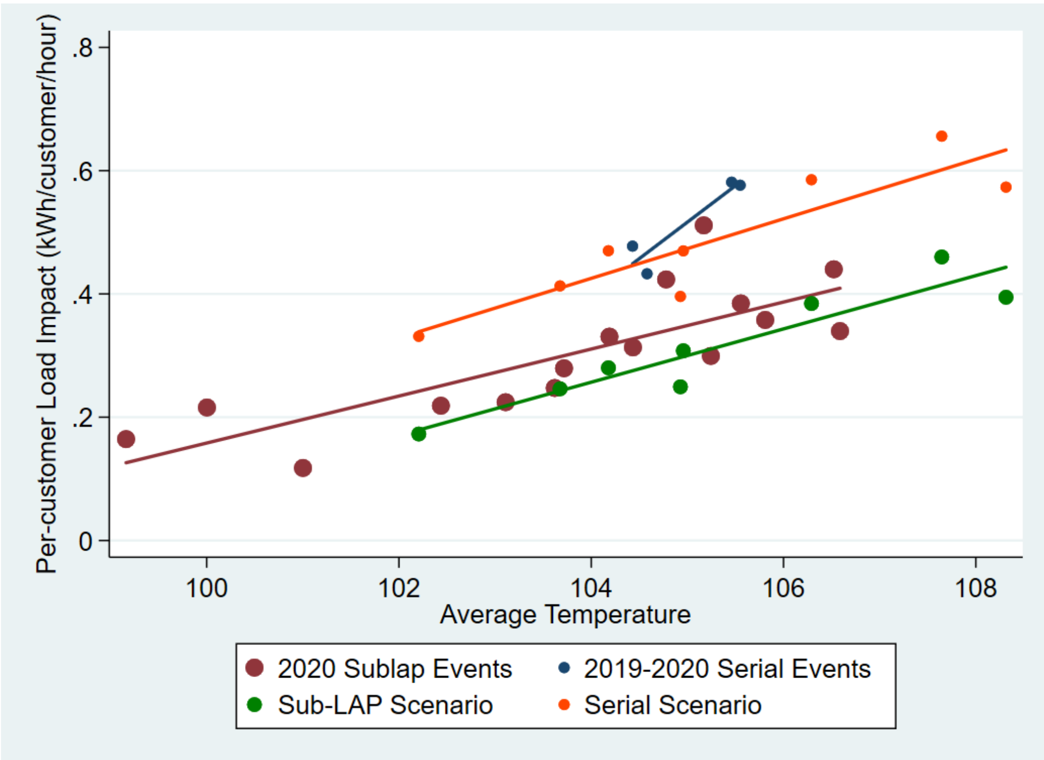


Figure C-4: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGFG

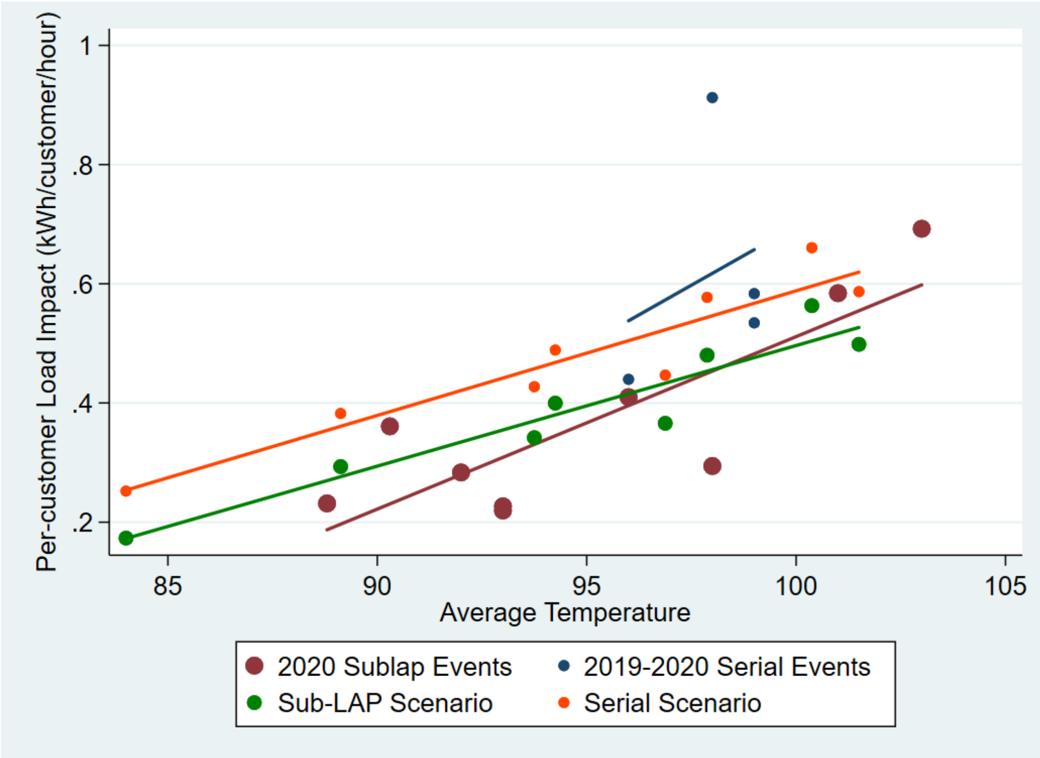


Figure C-5: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGKN

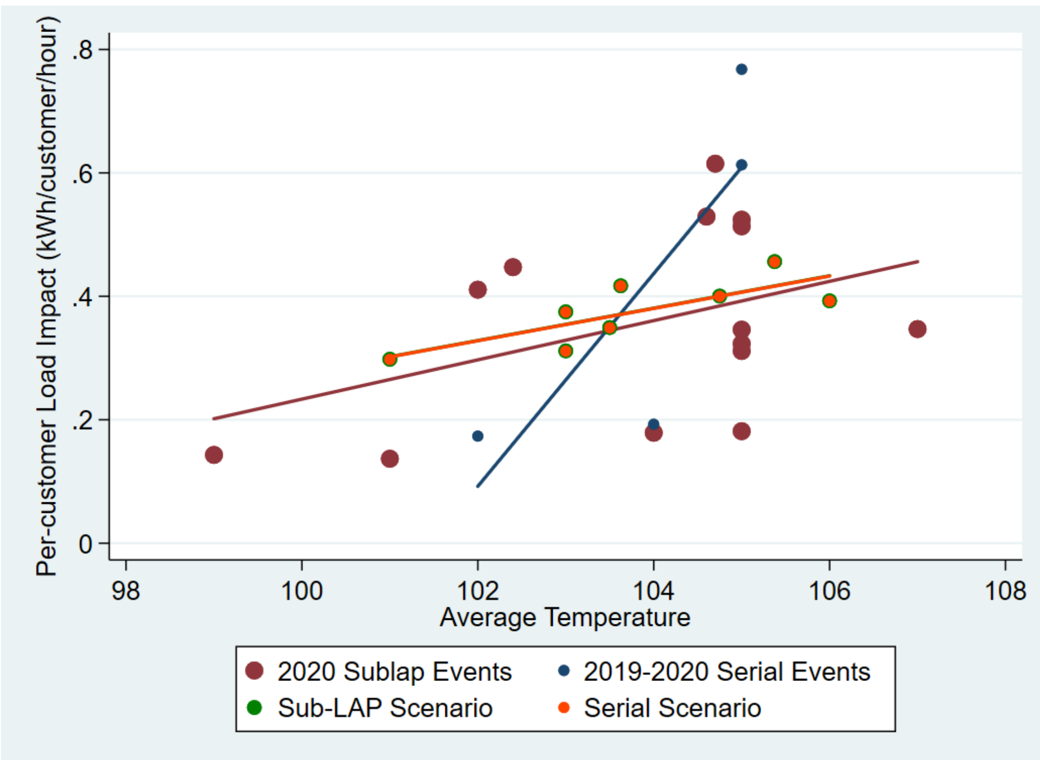


Figure C-6: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGNB

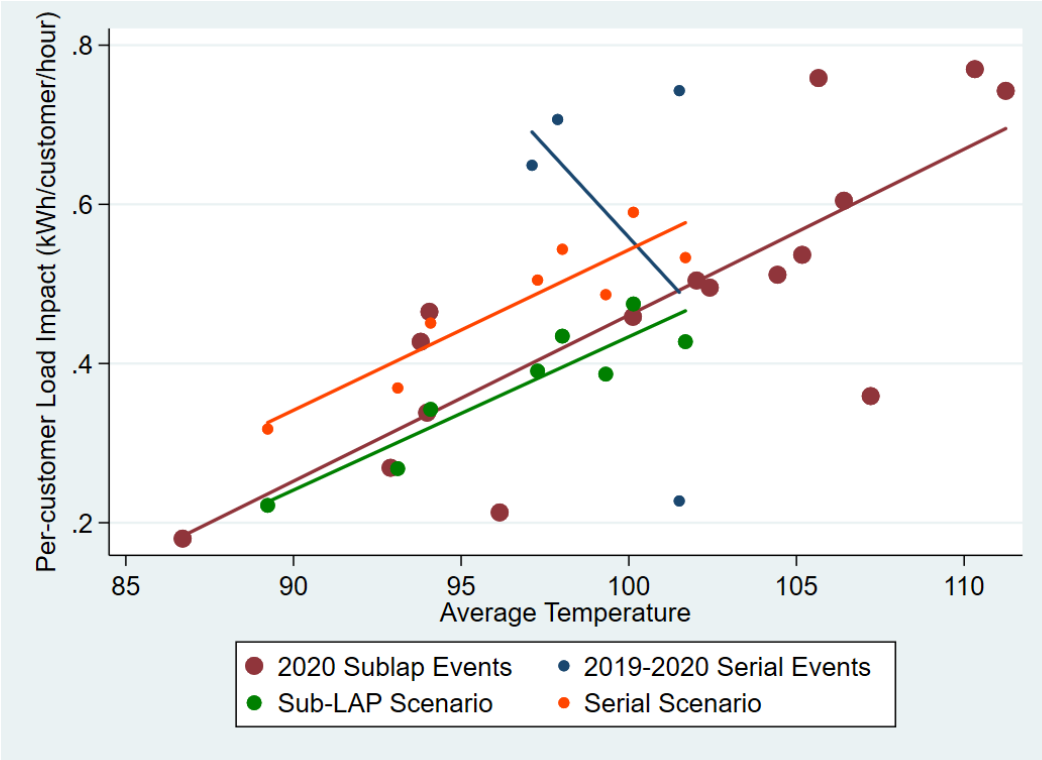


Figure C-7: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGNC

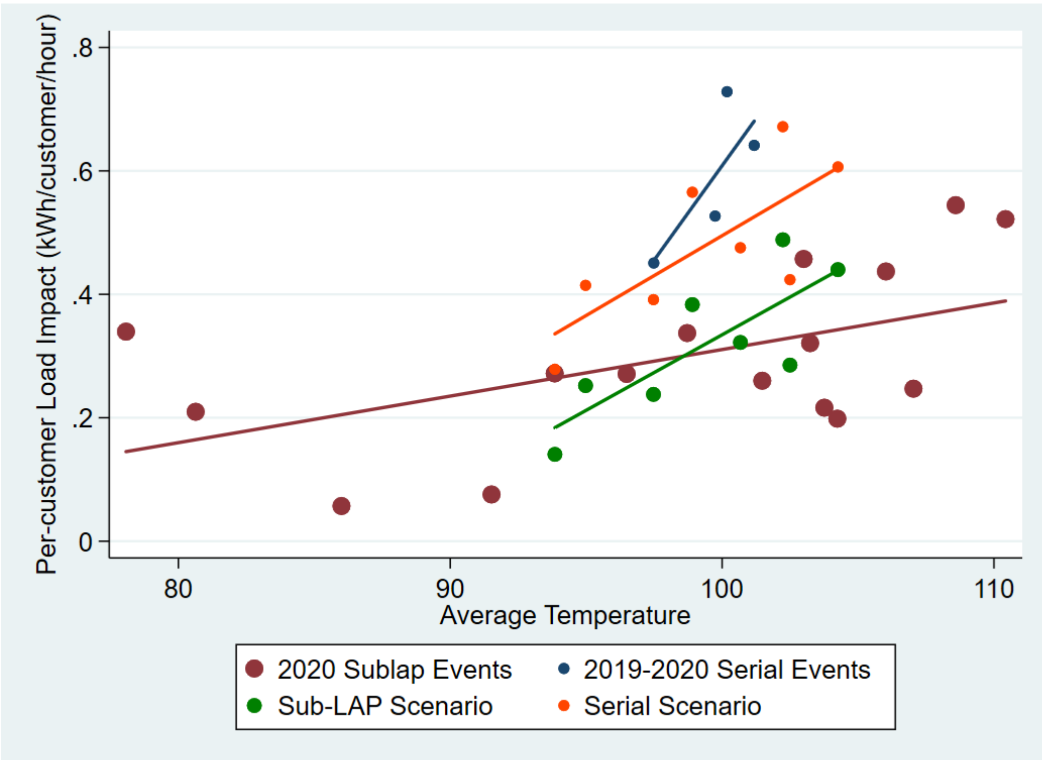


Figure C-8: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGNP

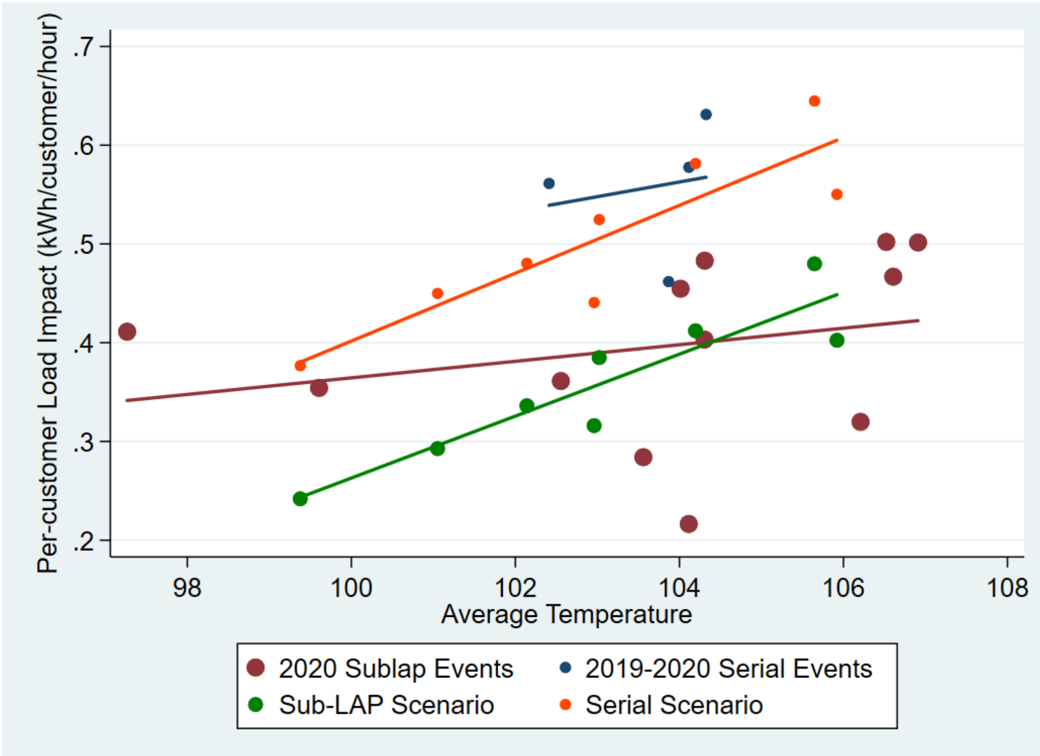


Figure C-9: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGP2

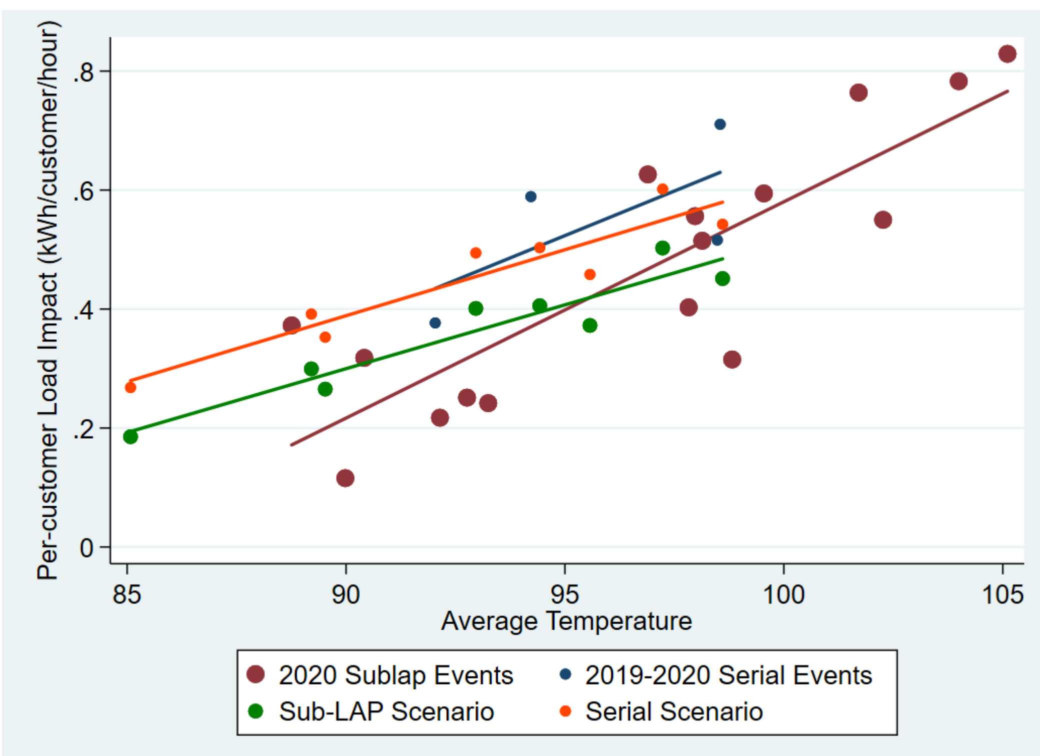


Figure C-10: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGSB

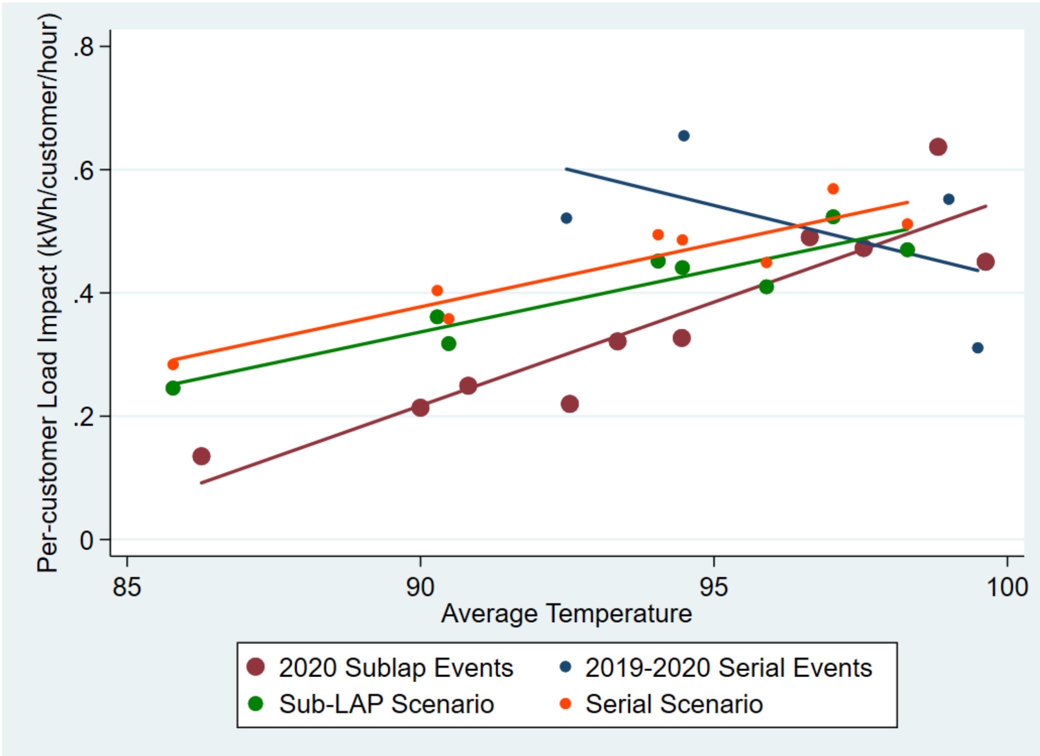


Figure C-11: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGSI

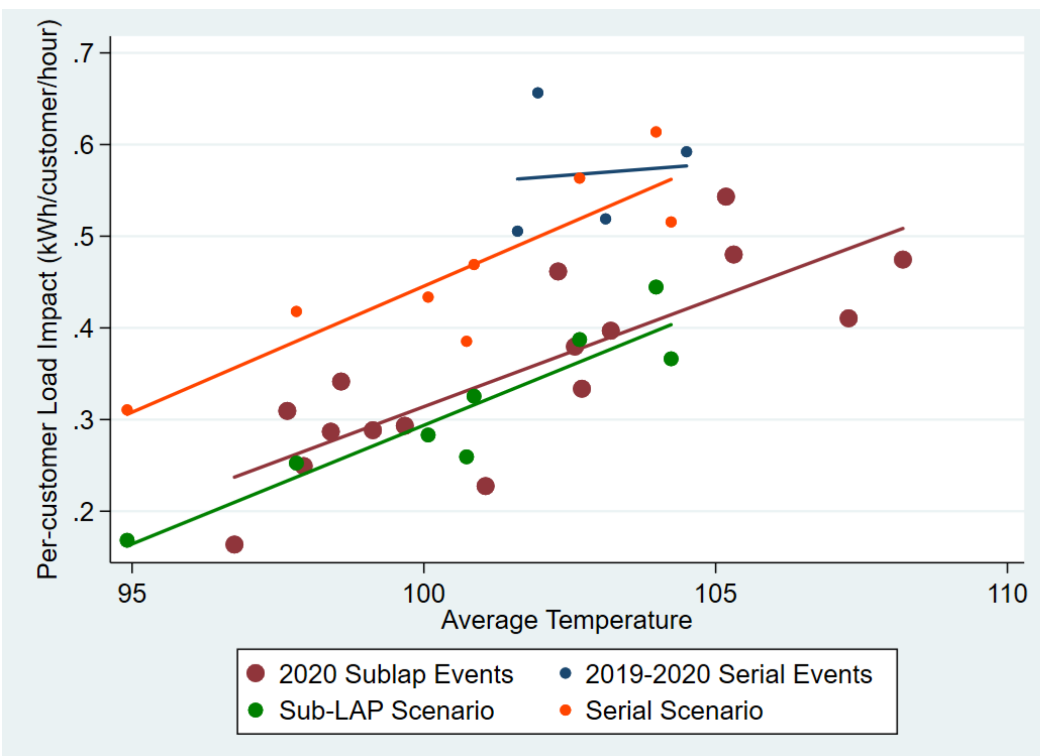


Figure C-12: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGST

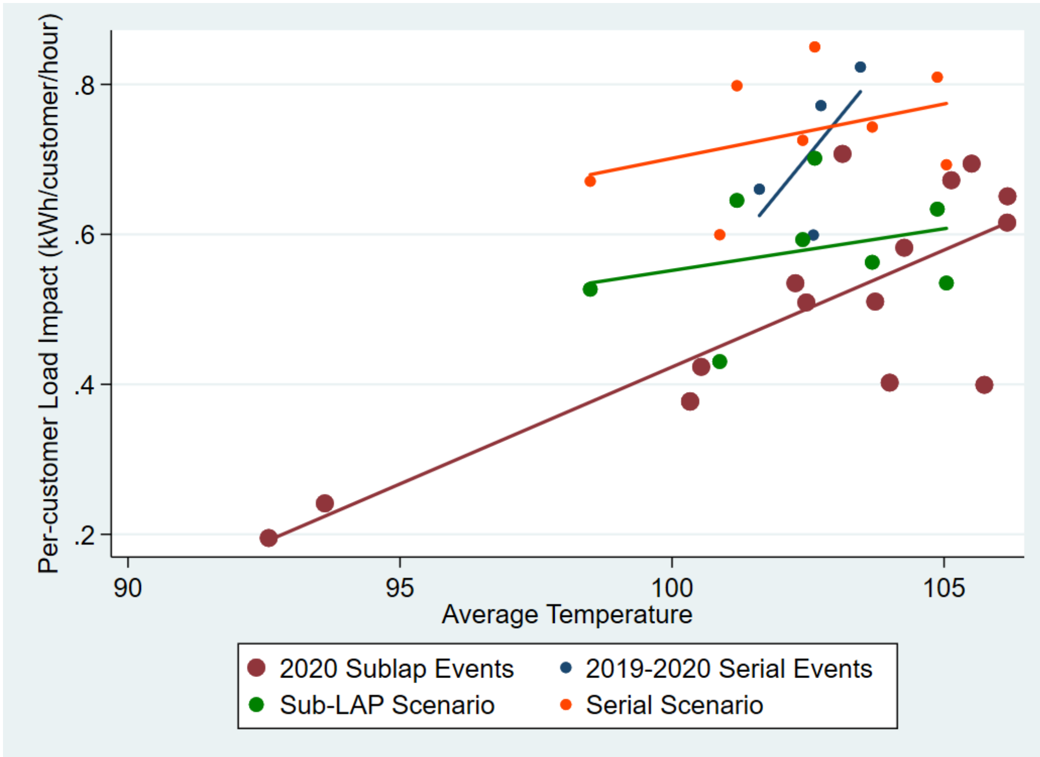


Figure C-13: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGZP