**Executive Summary of the**

**2015 SDG&E Measurement and Evaluation**

**Load Impact Reports**

**April 1st, 2016**

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# SDG&E’s 2015 Load Impact Executive Summary Background

In Decision (D.) 08-04-050 the Commission required the investor owned utilities (IOUs) - San Diego Gas & Electric Company (SDG&E), Southern California Edison (SCE) and Pacific Gas and Electric (PG&E) to perform annual studies of its demand response (DR) activities in accordance with the load impact protocols and to file the load impact reports by April 1st each year. The load impact protocols require the preparation of a voluminous amount of tables that resulted in the load impact reports being too large to be filed in hard copy.  On April 6th 2009 the investor owned utilities (IOUs) filed a petition to modify D.08-41-050.  The petition asked for two things:  1) the removal of the requirement to file the load impact reports in their entirety and 2) to provide the reports to the energy division of the CPUC.  On April 8th 2010 D.10-04-006 granted the utilities requests, which meant that they were not required to file the load impact reports in their entirety.  This new decision also directed the utilities to file an executive summary of the load impact reports.

SDG&E submits this executive summary in accordance with D.10-04-006. This report contains a summary of the ex-post and ex-ante load impacts of the SDG&E Capacity Bidding Program (CBP), Critical Peak Pricing Default (CPP-D), Base Interruptible Program (BIP), Demand Bidding Program (DBP), Summer Saver program, Residential Peak Time Rebate Program and Small Commercial Technology deployment program (SCTD), Permanent Load Shifting program (PLS), Non-Residential SPP Rates, and the Commercial Thermostat Program. This report includes a summary of the ex-ante forecasts for these new demand response activities. The summary ex-ante tables that include the 12-year forecast (from 2015 through 2026) for the 1 in 2 individual program scenario, the 1 in 2 portfolio scenario, the 1 in 10 individual program scenario, and the 1 in 10 portfolio scenario are provided in a separate document named Appendix A. The ex-ante starts in 2015 for the purpose of ex-post and ex-ante comparison.

Note that all ex-ante summaries in this report are averaged over the current Resource Adequacy (RA) hours of 1pm-6pm in the summer (Apr-Oct) and 4pm-9pm all other months. The RA hours may change in future years as more renewable generation comes online but this report uses current RA hours.

# Summary of SDG&E’s Capacity Bidding Program Report

## CBP Program Description

CBP program provides monthly capacity payments ($/kW) to participants based on the nominated kW load, the specific operating month, and the program notice option Day Ahead (DA) or Day Of (DO). The program has two options Capacity Bidding Program day-ahead (CBP DA) and Capacity Bidding Program day-of (CBP DO). Customers may also choose a maximum event length of 4 hour, 6 hour, or 8 hours. CBP events may be called on non-holiday weekdays in the months of May through October, between the hours of 11 a.m. and 7 p.m., with a maximum of forty-four event hours per month. Customers enrolled in CBP may participate in another DR program, so long as it is an energy-payment program and does not have the same advanced notification (*i.e.*, day-ahead or day-of). SDG&E added a 30-minute notice option to the DO product in 2015 and opened up the CBP program to small customers of less than 20 kW enrolled on a time of use rate.

## CBP Ex-Post Evaluation Methodology

The program year 2015 ex-post analysis was designed specifically to meet each of the following goals:

1. To develop hourly and daily load impact estimates for each event in the 2015 program year.

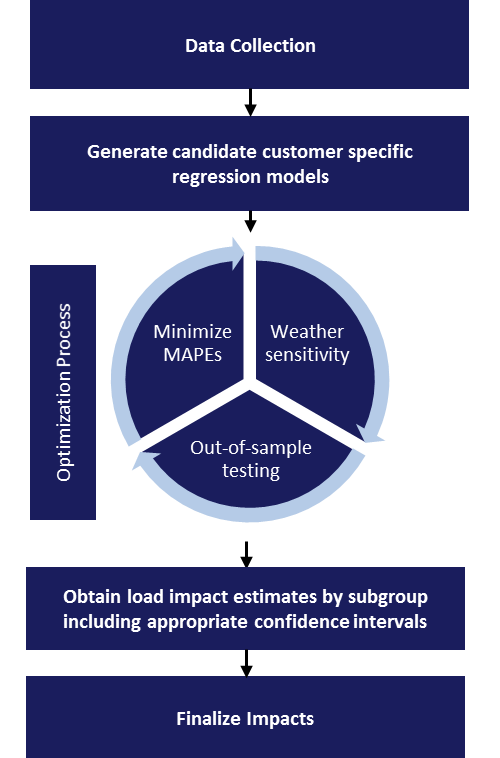
2. To provide these estimates by various segments, i.e., IOU, program, LCA, industry group, TA&TI participation, and notification type.

3. To estimate the distribution of load impacts by customer segment for the average event.

Applied Energy Group (AEG) used a candidate model optimization process to select the best model for each participant.

Figure 2-1 illustrates a high-level overview of the approach AEG used to develop ex-post impacts.

Figure 2‑1 Ex-Post Analysis Approach



### Develop Candidate Customer-Specific Regression Models

Table 2-1 presents the different explanatory variables that were used to create approximately 35 different candidate models for the CBP and AMP participants.

Table 2‑1. Explanatory Variables Included in Candidate Regression Models

|  |  |  |
| --- | --- | --- |
| **Variable Name** | **Variable Description** | |
|  | *Baseline Variables* | |
| Weatheri,d | Weather related variables including average daily temperature, multiple cooling degree hour (CDH) terms with base values of 75, 70, and 65 depending on service territory, and lagged versions of various weather related variables | |
| Monthi,d | A series of indicator variables for each month | |
| DayOfWeeki,d | A series of indicator variables for each day of the week | |
| Yeari,d | An indicator for the year 2015 | |
| OtherEvti,d | Equals one on event days of other demand response programs in which the customer is enrolled | |
| MornLoadi,d | The average of each day’s load in hours 5 am through 10 am | |
|  | | *Impact Variables* |
| Pt,d | An indicator variable for aggregator program event days | |
| P \* Weathert,d | An indicator variable for aggregator program event days interacted with weather terms | |
| P \* Yeari,d | An indicator variable for aggregator program event days interacted with the year 2015 | |
| P\*NonTypEventi,d | An indicator variable for aggregator program event days interacted with an indicator for non-typical event windows (outside of HE 16-19) | |

AEG used the different variables presented above to create sets of candidate models that represent a wide variety of customers and their impacts. Each IOU has customized sets of candidate models, but in general, the candidate models fit into two basic categories with a total of approximately 25 weather sensitive models, and 10 non-weather sensitive models:

* Weather-sensitive models that include weather effects and calendar effects. These models are less likely to require a morning load adjustment due to much of the variation in load on a day-to-day basis being captured by weather terms.
* Non-weather sensitive models that include the morning load adjustment and calendar effects.

### Optimization Process

After developing a set of candidate models, the single “best” model for each customer was selected. The final model was selected to minimize error and bias through a series of out-of-sample tests and MAPE (mean absolute percentage error) and MPE (mean percentage error) comparisons. [[1]](#footnote-1)

Below the two final model examples are presented, one for a weather sensitive customer, and one for a non-weather sensitive customer. For both types of models identically specified models for each hour of the day were used.

Simple weather sensitive example:

(2.1)

where:

is the customer’s consumption in hour i, on day d.

is the intercept.

is the error for participant in hour i on day d.

and, all other terms are defined in Table 2‑1 above.

Simple non-weather sensitive example:

(2.2)

where:

is the customer’s consumption in hour i, on day d.

is the intercept.

is the error for participant in hour i on day d.

and, all other terms are defined in Table 2‑1 above.

AEG used the “best” model selected for each customer to calculate the customer-specific impact as follows:

1. Obtained the actual and predicted load on each hour and day based on the best model specification for each customer.
2. Used the estimated coefficients and the baseline portion of the model to predict what this customer would have used on each day and hour, if there had been no events. This is called prediction the reference load.
3. Calculated the difference between the reference load (the estimate based on the baseline variables) and the predicted load (the estimate based on the baseline + impacts variables) on each event day. This difference represents our estimated load impact.

### Obtain Load Impacts and Confidence Intervals by Subgroup

Because AEG estimated an impact for each customer, the model results are easily aggregated to represent impacts for each of the required subpopulations of participants for each of the three IOUs. This includes analysis of incremental impacts for TA&TI and Auto-DR participants and participants dually enrolled in other utility DR programs, and the distinction between DO and DA notification.

## CBP Ex-Post Load Impact Estimates

Table 2-2 below presents a summary of the 2015 events for SDG&E’s CBP program by product. The table includes the definition of an average event day. The DO participants experienced a total of 24 events over the course of the program year, while DA participants experienced 42 events. Typical events were those called during hours-ending 16-19. For the DA product, approximately 70 accounts under a single aggregator were removed from the total number of accounts beginning in August of 2015 due to the fact that they changed their nomination to 0 MW for the remainder of the year.

**Table 2-2: Number of Accounts nominated by event – *SDG&E CBP***

| **Date** | **Day of Week** | **Event Hours (HE)** | **# Accounts DO 1-4 Hour** | **# Accounts DO 2-6 Hour** | **# Accounts DA 1-4 Hour** |
| --- | --- | --- | --- | --- | --- |
| Avg. Event | - | 16-19 | 160 | 63 | 122 |
| 5/1/2015 | Friday | 16-19 | 173 | 70 | 123 |
| 6/9/2015 | Tuesday | 16-19 | 194 | 70 | 131 |
| 6/16/2015 | Tuesday | 16-19 | - | - | 131 |
| 6/17/2015 | Wednesday | 16-19 | - | - | 131 |
| 6/22/2015 | Monday | 16-19 | - | - | 131 |
| 6/24/2015 | Wednesday | 16-19 | 194 | 70 | 131 |
| 6/25/2015 | Thursday | 16-19 | 194 | 70 | 131 |
| 6/26/2015 | Friday | 16-19 | 194 | 70 | 131 |
| 6/29/2015 | Monday | 16-19 | 194 | 70 | - |
| 6/30/2015 | Tuesday | 16-19 | 194 | 70 | 131 |
| 7/1/2015 | Wednesday | 16-19 | 168 | 70 | 130 |
| 7/16/2015 | Thursday | 16-19 | - | - | 130 |
| 7/28/2015 | Tuesday | 16-19 | - | - | 130 |
| 7/29/2015 | Wednesday | 16-19 | 168 | 70 | - |
| 7/30/2015 | Thursday | 16-19 | - | - | 130 |
| 7/31/2015 | Friday | 16-19 | - | - | 130 |
| 8/5/2015 | Wednesday | 16-19 | 156 | 60 | - |
| 8/6/2015 | Thursday | 16-19 | - | - | 61 |
| 8/11/2015 | Tuesday | 16-19 | - | - | 61 |
| 8/12/2015 | Wednesday | 15-18 | - | - | 61 |
| 8/13/2015 | Thursday | 16-19 | 156 | 60 | 61 |
| 8/21/2015 | Friday | 15-18 | - | - | 61 |
| 8/25/2015 | Tuesday | 16-19 | 156 | 60 | 61 |
| 8/26/2015 | Wednesday | 16-19 | 156 | 60 | 61 |
| 8/27/2015 | Thursday | 16-19 | 156 | 60 | 61 |
| 8/28/2015 | Friday | 16-19 | 156 | 60 | 61 |
| 9/8/2015 | Tuesday | 16-19 | 155 | 60 | - |
| 9/9/2015 | Wednesday | 16-19 | 155 | 60 | 59 |
| 9/10/2015 | Thursday | 16-19 | 155 | 60 | 59 |
| 9/11/2015 | Friday | 16-19 | 155 | 60 | 59 |
| 9/21/2015 | Monday | 16-19 | 155 | 60 | - |
| 9/23/2015 | Wednesday | 16-19 | - | - | 59 |
| 9/24/2015 | Thursday | 16-19 | - | - | 59 |
| 9/25/2015 | Friday | 16-19 | - | - | 59 |
| 9/29/2015 | Tuesday | 16-19 | - | - | 59 |
| 9/30/2015 | Wednesday | 16-19 | - | - | 59 |
| 10/8/2015 | Thursday | 16-19 | - | - | 58 |
| 10/9/2015 | Friday | 16-19 | 158 | 60 | 58 |
| 10/12/2015 | Monday | 16-19 | 158 | 60 | 58 |
| 10/13/2015 | Tuesday | 16-19 | 158 | 60 | 58 |
| 10/14/2015 | Wednesday | 16-19 | 158 | 60 | 58 |
| 10/21/2015 | Wednesday | 16-19 | - | - | 58 |
| 10/22/2015 | Thursday | 16-19 | - | - | 58 |
| 10/23/2015 | Friday | 16-19 | - | - | 58 |
| 10/27/2015 | Tuesday | 16-19 | - | - | 58 |
| 10/28/2015 | Wednesday | 16-19 | - | - | 58 |
| 10/30/2015 | Friday | 16-19 | - | - | 58 |

Table 2-3 to Table 2-5 show the average event-hour impacts for each event and for each product, both at the average per-customer level and in aggregate. The tables include results for the average event day.

In Table 2-4 the average event-hour impacts for the CBP DO 1-4 hour participants are presented. Of the three products offered under SDG&E’s CBP, the DO 1-4 has the most participants. The highest per-customer impacts (31.6 kW) and highest overall aggregate impacts (4.9 MW) occurred during the event on September 10, 2015. The impacts represent a 15% reduction over the reference load and a total of 155 nominated service accounts. The lowest impacts occurred during the first event which was on May 1, 2015 when impacts of only 11.3 kW (per-customer) and 2 MW (aggregate) were achieved.

Table 2‑3: SDG&E CBP Day-Of 1-4 Hour: Impacts by Event

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **# of**  **Accts** | **Nominated Capacity (MW)** | **Per Customer Impact (kW)** | | **Aggregate Impact**  **(MW)** | |  |  |
| **Event** | **Reference Load** | **Impact** | **Reference Load** | **Impact** | **% Impact** | **Temp (˚F)** |
| Avg. Event | 160 | 4.4 | 182.8 | 21.9 | 29.2 | 3.5 | 12% | 81 |
| 5/1/2015 | 173 | 2.9 | 110.6 | 11.3 | 19.1 | 2.0 | 10% | 76 |
| 6/9/2015 | 193 | 4.7 | 144.8 | 16.0 | 27.9 | 3.1 | 11% | 70 |
| 6/24/2015 | 193 | 4.7 | 151.6 | 14.5 | 29.3 | 2.8 | 10% | 76 |
| 6/25/2015 | 193 | 4.7 | 147.2 | 15.1 | 28.4 | 2.9 | 10% | 74 |
| 6/26/2015 | 193 | 4.7 | 144.5 | 15.4 | 27.9 | 3.0 | 11% | 74 |
| 6/29/2015 | 193 | 4.7 | 154.0 | 16.1 | 29.7 | 3.1 | 10% | 74 |
| 6/30/2015 | 193 | 4.7 | 159.2 | 15.8 | 30.7 | 3.1 | 10% | 81 |
| 7/1/2015 | 168 | 4.4 | 167.8 | 18.3 | 28.2 | 3.1 | 11% | 76 |
| 7/29/2015 | 168 | 4.4 | 158.1 | 17.4 | 26.6 | 2.9 | 11% | 76 |
| 8/5/2015 | 156 | 4.4 | 189.1 | 19.9 | 29.5 | 3.1 | 11% | 80 |
| 8/13/2015 | 156 | 4.4 | 198.2 | 21.2 | 30.9 | 3.3 | 11% | 82 |
| 8/25/2015 | 156 | 4.4 | 174.1 | 17.2 | 27.2 | 2.7 | 10% | 78 |
| 8/26/2015 | 156 | 4.4 | 190.2 | 22.1 | 29.7 | 3.4 | 12% | 84 |
| 8/27/2015 | 156 | 4.4 | 197.4 | 23.2 | 30.8 | 3.6 | 12% | 87 |
| 8/28/2015 | 156 | 4.4 | 202.7 | 26.5 | 31.6 | 4.1 | 13% | 90 |
| 9/8/2015 | 155 | 3.6 | 192.5 | 27.4 | 29.8 | 4.2 | 14% | 88 |
| 9/9/2015 | 155 | 3.6 | 204.8 | 30.7 | 31.8 | 4.8 | 15% | 94 |
| 9/10/2015 | 155 | 3.6 | 218.0 | 31.6 | 33.8 | 4.9 | 15% | 90 |
| 9/11/2015 | 155 | 3.6 | 194.0 | 23.8 | 30.1 | 3.7 | 12% | 84 |
| 9/21/2015 | 155 | 3.6 | 176.1 | 24.1 | 27.3 | 3.7 | 14% | 78 |
| 10/9/2015 | 158 | 2.8 | 195.1 | 27.6 | 30.8 | 4.4 | 14% | 95 |
| 10/12/2015 | 158 | 2.8 | 194.1 | 28.5 | 30.7 | 4.5 | 15% | 88 |
| 10/13/2015 | 158 | 2.8 | 193.3 | 26.6 | 30.5 | 4.2 | 14% | 82 |
| 10/14/2015 | 158 | 2.8 | 188.0 | 23.2 | 29.7 | 3.7 | 12% | 80 |

In Table 2-4 the average event-hour impacts for the CBP DO 2-6 hour participants are presented. In this case, the highest per-customer impacts occurred during August, with a maximum per-customer impact of 40.5 kW on August 5, 2015 representing 60 service accounts and an average 14% reduction over the reference load. The largest aggregate impacts occurred on June 26, 2015 at 2.7 MW representing a total of 70 service accounts and a 15% reduction over the reference load. The lowest impacts occurred on May 1, 2015. On that day 70 service accounts provided a total of 1.1 MW of load reduction.

Table 2‑4: SDG&E CBP Day-Of 2-6 Hour: Impacts by Event

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **# of**  **Accts** | **Nominated Capacity (MW)** | **Per Customer Impact (kW)** | | **Aggregate Impact**  **(MW)** | |  |  |
| **Event** | **Reference Load** | **Impact** | **Reference Load** | **Impact** | **% Impact** | **Temp (˚F)** |
| Avg. Event | 63 | 1.7 | 273.3 | 34.8 | 17.2 | 2.2 | 13% | 82 |
| 5/1/2015 | 70 | 2.2 | 188.5 | 15.9 | 13.2 | 1.1 | 8% | 76 |
| 6/9/2015 | 70 | 2.0 | 236.6 | 33.6 | 16.6 | 2.3 | 14% | 71 |
| 6/24/2015 | 70 | 2.0 | 249.9 | 37.7 | 17.5 | 2.6 | 15% | 76 |
| 6/25/2015 | 70 | 2.0 | 247.9 | 37.8 | 17.4 | 2.6 | 15% | 74 |
| 6/26/2015 | 70 | 2.0 | 252.7 | 38.1 | 17.7 | 2.7 | 15% | 74 |
| 6/29/2015 | 70 | 2.0 | 249.4 | 37.0 | 17.5 | 2.6 | 15% | 74 |
| 6/30/2015 | 70 | 2.0 | 260.3 | 35.3 | 18.2 | 2.5 | 14% | 81 |
| 7/1/2015 | 70 | 2.0 | 240.6 | 25.9 | 16.8 | 1.8 | 11% | 76 |
| 7/29/2015 | 70 | 2.0 | 246.4 | 35.1 | 17.2 | 2.5 | 14% | 76 |
| 8/5/2015 | 60 | 1.7 | 297.9 | 40.5 | 17.9 | 2.4 | 14% | 80 |
| 8/13/2015 | 60 | 1.7 | 278.1 | 38.2 | 16.7 | 2.3 | 14% | 82 |
| 8/25/2015 | 60 | 1.7 | 276.0 | 40.3 | 16.6 | 2.4 | 15% | 78 |
| 8/26/2015 | 60 | 1.7 | 276.7 | 36.1 | 16.6 | 2.2 | 13% | 84 |
| 8/27/2015 | 60 | 1.7 | 274.9 | 34.7 | 16.5 | 2.1 | 13% | 88 |
| 8/28/2015 | 60 | 1.7 | 281.7 | 33.7 | 16.9 | 2.0 | 12% | 90 |
| 9/8/2015 | 60 | 1.7 | 283.5 | 33.0 | 17.0 | 2.0 | 12% | 88 |
| 9/9/2015 | 60 | 1.7 | 279.8 | 31.3 | 16.8 | 1.9 | 11% | 94 |
| 9/10/2015 | 60 | 1.7 | 296.9 | 31.8 | 17.8 | 1.9 | 11% | 90 |
| 9/11/2015 | 60 | 1.7 | 289.2 | 32.9 | 17.4 | 2.0 | 11% | 84 |
| 9/21/2015 | 60 | 1.7 | 288.9 | 39.6 | 17.3 | 2.4 | 14% | 78 |
| 10/9/2015 | 60 | 1.7 | 306.8 | 33.6 | 18.4 | 2.0 | 11% | 95 |
| 10/12/2015 | 60 | 1.7 | 302.8 | 34.9 | 18.2 | 2.1 | 12% | 88 |
| 10/13/2015 | 60 | 1.7 | 311.9 | 36.0 | 18.7 | 2.2 | 12% | 82 |
| 10/14/2015 | 60 | 1.7 | 308.1 | 35.2 | 18.5 | 2.1 | 11% | 80 |

Table 2-5 presents the average event-hour impacts for the CBP DA 1-4 hour participants.[[2]](#footnote-2) The highest per-customer impacts and aggregate impacts occurred in August, with a maximum per-customer impact of 148.7 kW and 9.1 MW on August 12, 2015 representing 61 service accounts and an average 55% reduction over the reference load. The lowest impacts occurred on October 30, 2015. On that day 58 service accounts provided a total of 0.3 MW of load reduction.

Table 2‑5: SDG&E CBP Day-Ahead 1-4 Hour: Impacts by Event

|  | **# of**  **Accts** | **Nominated Capacity (MW)** | **Per Customer Impact (kW)** | | **Aggregate Impact**  **(MW)** | |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Event** | **Reference Load** | **Impact** | **Reference Load** | **Impact** | **% Impact** | **Temp (˚F)** |
| Avg. Event | 122 | 7.3 | 148.0 | 64.1 | 18.1 | 7.8 | 43% | 80 |
| 5/1/2015 | 123 | 8.0 | 202.2 | 68.7 | 24.9 | 8.5 | 34% | 76 |
| 6/9/2015 | 131 | 7.8 | 195.5 | 64.7 | 25.6 | 8.5 | 33% | 70 |
| 6/16/2015 | 131 | 7.8 | 199.4 | 69.5 | 26.1 | 9.1 | 35% | 70 |
| 6/17/2015 | 131 | 7.8 | 200.6 | 68.7 | 26.3 | 9.0 | 34% | 73 |
| 6/22/2015 | 131 | 7.8 | 203.6 | 66.1 | 26.7 | 8.7 | 32% | 76 |
| 6/24/2015 | 131 | 7.8 | 204.4 | 65.1 | 26.8 | 8.5 | 32% | 75 |
| 6/25/2015 | 131 | 7.8 | 188.2 | 64.2 | 24.7 | 8.4 | 34% | 74 |
| 6/26/2015 | 131 | 7.8 | 187.0 | 64.1 | 24.5 | 8.4 | 34% | 73 |
| 6/30/2015 | 131 | 7.8 | 205.7 | 65.1 | 27.0 | 8.5 | 32% | 81 |
| 7/1/2015 | 130 | 7.9 | 189.2 | 62.8 | 24.6 | 8.2 | 33% | 75 |
| 7/16/2015 | 130 | 7.9 | 185.8 | 65.5 | 24.1 | 8.5 | 35% | 74 |
| 7/28/2015 | 130 | 7.9 | 193.4 | 64.7 | 25.1 | 8.4 | 33% | 75 |
| 7/30/2015 | 130 | 7.9 | 194.5 | 61.9 | 25.3 | 8.0 | 32% | 76 |
| 7/31/2015 | 130 | 7.9 | 195.4 | 62.7 | 25.4 | 8.1 | 32% | 76 |
| 8/6/2015 | 61 | 7.3 | 249.0 | 130.6 | 15.2 | 8.0 | 52% | 77 |
| 8/11/2015 | 61 | 7.3 | 242.9 | 137.0 | 14.8 | 8.4 | 56% | 74 |
| 8/12/2015 | 61 | 7.3 | 270.1 | 148.7 | 16.5 | 9.1 | 55% | 81 |
| 8/13/2015 | 61 | 7.3 | 242.8 | 129.1 | 14.8 | 7.9 | 53% | 83 |
| 8/21/2015 | 61 | 7.3 | 263.1 | 137.2 | 16.0 | 8.4 | 52% | 77 |
| 8/25/2015 | 61 | 7.3 | 247.4 | 130.8 | 15.1 | 8.0 | 53% | 79 |
| 8/26/2015 | 61 | 7.3 | 264.5 | 127.7 | 16.1 | 7.8 | 48% | 85 |
| 8/27/2015 | 61 | 7.3 | 244.7 | 125.3 | 14.9 | 7.6 | 51% | 89 |
| 8/28/2015 | 61 | 7.3 | 260.8 | 123.1 | 15.9 | 7.5 | 47% | 91 |
| 9/9/2015 | 59 | 7.3 | 245.1 | 124.2 | 14.5 | 7.3 | 51% | 95 |
| 9/10/2015 | 59 | 7.3 | 231.9 | 118.4 | 13.7 | 7.0 | 51% | 91 |
| 9/11/2015 | 59 | 7.3 | 230.9 | 121.1 | 13.6 | 7.1 | 52% | 86 |
| 9/23/2015 | 59 | 7.3 | 236.1 | 132.1 | 13.9 | 7.8 | 56% | 79 |
| 9/24/2015 | 59 | 7.3 | 245.6 | 131.5 | 14.5 | 7.8 | 54% | 83 |
| 9/25/2015 | 59 | 7.3 | 238.9 | 128.4 | 14.1 | 7.6 | 54% | 84 |
| 9/29/2015 | 59 | 7.3 | 231.9 | 132.1 | 13.7 | 7.8 | 57% | 79 |
| 9/30/2015 | 59 | 7.3 | 242.1 | 134.1 | 14.3 | 7.9 | 55% | 81 |
| 10/8/2015 | 58 | 7.1 | 234.2 | 137.3 | 13.6 | 8.0 | 59% | 81 |
| 10/9/2015 | 58 | 7.1 | 228.9 | 134.9 | 13.3 | 7.8 | 59% | 96 |
| 10/12/2015 | 58 | 7.1 | 253.9 | 123.7 | 14.7 | 7.2 | 49% | 89 |
| 10/13/2015 | 58 | 7.1 | 248.3 | 125.8 | 14.4 | 7.3 | 51% | 83 |
| 10/14/2015 | 58 | 7.1 | 298.3 | 129.7 | 17.3 | 7.5 | 43% | 81 |
| 10/21/2015 | 58 | 7.1 | 239.9 | 139.3 | 13.9 | 8.1 | 58% | 74 |
| 10/22/2015 | 58 | 7.1 | 234.8 | 139.0 | 13.6 | 8.1 | 59% | 74 |
| 10/23/2015 | 58 | 7.1 | 230.6 | 140.5 | 13.4 | 8.2 | 61% | 75 |
| 10/27/2015 | 58 | 7.1 | 227.8 | 138.5 | 13.2 | 8.0 | 61% | 78 |
| 10/28/2015 | 58 | 7.1 | 229.6 | 141.4 | 13.3 | 8.2 | 62% | 76 |
| 10/30/2015 | 58 | 7.1 | 92.1 | 4.7 | 5.3 | 0.3 | 5% | 78 |

## CBP Ex-Ante Evaluation Methodology

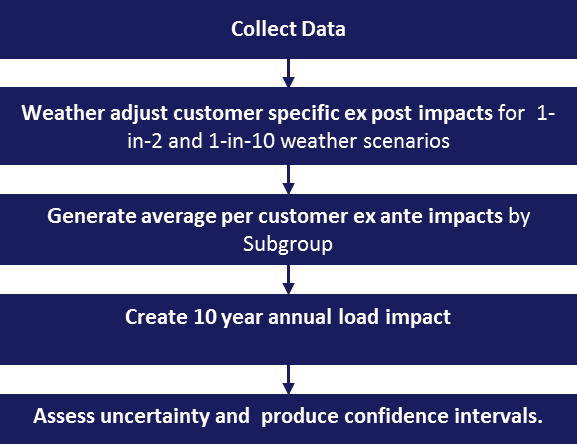
The main goal of the ex-ante analysis is to produce an annual ten-year forecast of the load impacts expected from CBP programs.

AEG developed the ex-ante forecasts using the following steps:

1. AEG first provided the IOUs with the appropriate weather-adjusted, per-customer impacts for each year of the forecast and each subgroup.
2. The IOUs used the per-customer impacts, along with contractual MW agreements and adjustments based on actual load reduction performance, to determine the enrollment forecasts.
3. AEG then used the enrollment forecasts and the per-customer ex-ante impacts to develop the 10-year annual load impact forecasts for the participant populations and subgroups.

Figure 2-2 provides an overview of the ex-ante analysis approach which includes four basic steps after assembling the required data: 1) prediction of weather-adjusted impacts for each customer; 2) generation of per-customer average impacts by subgroup; 3) creation of annual load impact forecasts over the next 10 years; and 4) an assessment of uncertainty and the development of confidence intervals.

Figure 2‑2 Ex-Ante Analysis Approach



### 2.4.1 Weather-Adjusted Impacts for Each Customer

The first step in the ex-ante analysis is to use the customer-specific regression models to predict weather-adjusted per-customer average impacts for each IOU and for each of the appropriate subgroups (LCA, size, and industry segment). This produces a set of impacts under each of the different monthly weather conditions: 1-in-2 CAISO peak; 1-in-10 CAISO peak; 1-in-2 IOU peak; and 1-in-10 IOU peak. To do this, we completed the following steps:

After creating the weather adjusted per-customer impacts a counter-intuitive result was discovered in several of the subgroups: the predicted impacts under 1-in-10 conditions were actually lower than the predicted impacts under 1-in-2 conditions. Upon further investigation, the weather interaction term that was added to the impact portion of the model was in some cases identifying an inverse relationship between weather and impacts. While this result is not typical, it is not uncommon in commercial customers. Unfortunately there was not enough time during the evaluation to thoroughly investigate this finding, and AEG was unable to confirm that it was truly a significant weather response rather than customer fatigue, an artifact of the model, or customer behavior. As a result, it was decided jointly with the IOUs to 1) set the 1-in-10 impacts equal to the 1-in-2 impacts, and 2) apply the impacts predicted under July 1-in-2 weather conditions to each month so that the impacts would not vary by month in a given forecast year.

### 2.4.2 Generation of Per-Customer Average Impacts by Subgroup

Once weather-adjusted impacts have been predicted for each customer, for each of the desired event day types, it becomes a relatively simple exercise to average the individual impacts and generate per-customer average impacts by subgroup. For example, the average impact for a particular LCA is the average of the impacts predicted for each customer in that LCA. At this stage, we also worked with the IOUs to determine the best way to account for dual participation between programs to ensure that they are not double-counted in the forecast. Since CBP and AMP are capacity-payment programs, the IOUs allocate the full load impacts from the dual participants of CBP/AMP and other energy-payment programs to CBP/AMP. Therefore, the CBP and AMP impacts for dual participants do not require adjustments.

### 2.4.3 Creation of 10-Year Annual Load Impact Forecasts

AEG provided the IOUs with the per-customer average ex-ante impacts by year and subgroup. The IOUs used the per-customer impacts—along with contractual MW agreements and adjustments that reflect actual vs. contractual load reduction performance—to determine the enrollment forecasts. AEG used the enrollment forecasts and set of per-customer average ex-ante impacts to create the annual forecast of load impacts over the next 10 years.

## CBP Ex-Ante Load Impact Estimates

SDG&E forecasts the CBP nominations to stay constant across the 2016-2026 horizon, with an estimated 122 service accounts for the DA product, 160 for the DO 1-4 hour product, and 60 for the DO 2-6 hour product during May through October. These enrollment forecasts are lower than those estimated in PY2014, which were held constant at 159 service accounts for the DA product and increased from 239 to 284 for the DO 1-4 hour and 2-6 hour products combined.

The ex-ante impact results also forecast constant annual CBP load impacts across the 2016-2026 horizon for the DA and DO products. In addition, the impacts are expected to remain constant during the months of May through October.

Table 2-6 summarizes the average event-hour load impact forecasts for the DA and DO products on an August peak day in 2016.[[3]](#footnote-3) The table includes impact forecasts under the 1-in-2 and 1-in-10 weather scenarios and for the utility peak and the CAISO peak. The ex-ante impacts are assumed to be the same under both 1-in-2 and 1-in-10 weather conditions. The assumption is not unreasonable, as the load impacts should be a function of the monthly nomination, which is not weather-dependent within a given month. The table shows that per-customer impacts for CBP DA are 62.87 kW under the utility peak weather conditions and 62.82 kW under the CAISO peak conditions. For CBP DO, the per-customer impacts are 20.69 kW and 20.66 kW for utility peak and CAISO peak weather, respectively. Aggregate impacts for the CBP DA product are 7.67 MW under utility peak weather and 7.66 MW under CAISO peak weather for DA, and are 4.55 MW under utility peak weather and 4.54 MW under CAISO peak weather for DO.

Table 2-6: SDG&E CBP: Average Event-Hour Ex-Ante Impacts for an August Peak Day, 2016

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **Per Customer Impact (kW)** | | | | **Aggregate Impact (MW)** | | | |
|  |  | **Utility Peak** | | **CAISO Peak** | | **Utility Peak** | | **CAISO Peak** | |
| **Notice** | **Accts** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** |
| **Total DA** | **122** | **62.87** | **62.87** | **62.82** | **62.82** | **7.67** | **7.67** | **7.66** | **7.66** |
| DO, 1-4 Hour | 160 | 14.60 | 14.60 | 14.23 | 14.23 | 2.34 | 2.34 | 2.28 | 2.28 |
| DO, 2-6 Hour | 60 | 36.95 | 36.95 | 37.79 | 37.79 | 2.22 | 2.22 | 2.27 | 2.27 |
| **Total DO** | **220** | **20.69** | **20.69** | **20.66** | **20.66** | **4.55** | **4.55** | **4.54** | **4.54** |

## CBP Comparisons of Ex-Post and Ex-Ante Results

In response to the request to improve the transparency of the linkage between ex-post and ex-ante results, the following two sections compare the estimated load impacts.

### Ex-post load impacts from the current and previous studies

Table 2-7 summarizes the CBP DA and DO average event-hour ex-post load impact results for the past four years for an average event day. The table includes the number of participating accounts, the average event-hour reference loads, and average event temperature. Both per-customer and aggregate results are presented.

For the CBP DA product, the number of accounts decreased from 163 in 2014 to 122 in 2015. The aggregate impacts were also smaller in 2015 (7.8 MW) than in 2014 (9.9 MW). However, on a percent impact basis, 2015 realized 43%, while the 2014 program yielded 25%, which can be explained by the significant decrease in reference load between 2014 and 2015.

For the CBP DO product, the number of accounts decreased from 237 to 223 between 2014 and 2015. The aggregate load impact also decreased, falling from 8.8 MW in 2014 to 5.7 MW in 2015. The percent impacts in 2015 were 12% in 2015 compared to 16% in 2014.

Table 2-7: SDG&E CBP: Previous and Current Ex-Post, Average Event Day

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  | **Per Customer (kW)** | | **Aggregate (MW)** | |  |  |
| **Ex-Post Year** | **Accounts** | **Reference Load** | **Load Impact** | **Reference Load** | **Load Impact** | **% Impact** | **Event Temp (˚F)** |
| DA | 2012 | 78 | 320 | 82 | 25.0 | 6.4 | 25% | 83 |
| 2013 | 142 | 305 | 76 | 43.2 | 10.8 | 25% | 88 |
| 2014 | 163 | 247 | 61 | 40.4 | 9.9 | 25% | 87 |
| 2015 | 122 | 148 | 64 | 18.1 | 7.8 | 43% | 80 |
| DO | 2012 | 321 | 230 | 31 | 73.7 | 9.8 | 13% | 86 |
| 2013 | 260 | 235 | 40 | 61.1 | 10.5 | 17% | 87 |
| 2014 | 237 | 229 | 37 | 54.1 | 8.8 | 16% | 87 |
| 2015 | 223 | 208 | 26 | 46.4 | 5.7 | 12% | 81.5 |

### Previous and Current Ex-Ante and Ex-Post

Table 2-8 compares the current year’s analysis with the previous year’s analysis of CBP ex-post and ex-ante average event-hour impacts. To make the comparison as consistent as possible, the ex-post and ex-ante results represent events on monthly system peak days in August, unless otherwise noted.[[4]](#footnote-4) In addition, the ex-ante results reflect the utility peak 1-in-2 weather scenario.[[5]](#footnote-5)

Table 2-8: SDG&E CBP: Previous and Current Ex-Ante and Ex-Post, August Peak Day, 2016

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  | **Per Customer (kW)** | | **Aggregate (MW)** | |  | **Event Temp (˚F)** |
|  | **Model** | **Year** | **Day** | **Accts** | **Ref. Load** | **Impact** | **Ref. Load** | **Impact** | **% Impact** |
| DA | Current | Ex-Post 2015 | Jun 30[[6]](#footnote-6) | 131 | 205.7 | 65.1 | 27.0 | 8.5 | 31.6% | 80.5 |
| Ex-Ante 2016 | Aug Peak | 122 | 213.5 | 62.9 | 26.0 | 7.7 | 29.5% | 81.0 |
| Previous | Ex-Post 2014 | Aug 1 | 161 | 251.4 | 63.4 | 40.5 | 10.2 | 25.2% | 80.8 |
| Ex-Ante 2015/16 | Aug Peak | 159 | 269.4 | 74.8 | 42.8 | 11.9 | 27.8% | 81.0 |
| DO | Current | Ex-Post 2015 | Aug 26 | 216 | 214.2 | 25.9 | 46.3 | 5.6 | 12.1% | 83.7 |
| Ex-Ante 2016 | Aug Peak | 220 | 187.0 | 20.7 | 41.2 | 4.6 | 11.1% | 81.3 |
| Previous | Ex-Post 2014 | Avg. Event[[7]](#footnote-7) | 237 | 228.5 | 37.0 | 54.1 | 8.8 | 16.0% | 87.0 |
| Ex-Ante 2015/16 | Aug Peak | 284 | 216.8 | 36.6 | 61.5 | 10.4 | 16.9% | 81.5 |

# Summary of SDG&E’s Critical Peak Pricing Default Report

## CPP Rate Description

Critical Peak Pricing is an electric rate in which the utility charges a higher price for consumption of electricity during peak hours on selected days, referred to as critical peak days or event days. The higher price during peak hours on critical event days is designed to encourage reductions in demand and reflects the fact that electric demand during those hours drives a substantial portion of electric infrastructure costs. The CPPD schedule is the default commodity rate for customers currently receiving bundled utility service whose maximum demand is equal to or exceeds or is expected to equal or exceed 20 kW for twelve consecutive months. At SDG&E, customers are locked into the CPP rate for a full year if they do not opt out prior to going on the default rate; events for the SDG&E CPP-D rate last from 11am-6pm and can be called on any day of the year.

All customers have the ability to hedge part or all of their demand against higher CPP prices, a feature known as a capacity reservation (CR). The capacity reservation option, which is a type of insurance contract in which a customer pays a fee (paid per kW) to set a level of demand below which it will be charged the non-CPP, TOU price during event periods. The company charges $6.33 per kW per month, year-round, for this option and the default level for customers is 50% of a customer’s maximum on-peak demand from the prior summer. Default CRLs are set to zero for those customers with no SDG&E summer usage history.

In addition, the program offers customers CPP bill protection during their default year, which ensures that the customer does not pay more for the energy commodity under CPP than they would have under the otherwise applicable tariff (OAT).

## CPP-D Ex-Post Evaluation Methodology

To calculate load reductions for demand response programs, customers’ load patterns in the absence of higher event-day prices—the reference load—must be estimated. Load impacts are estimated for 2015 using a combination of customer specific regressions and difference-in-differences. For the majority of customers we estimate difference-in-differences panel regressions that make use of both an external control group and non-event day data. However, for CPP customers for which a similar control customer is unavailable, we estimate customer specific regressions—that is, we rely exclusively on each customer’s electricity usage patterns on non-event days to estimate reference load for event days.

The subsections that follow describe the work to select a matching model and the subsequent control group selection.

### Proxy Day Selection

Proxy event days are selected by matching historical events to non-event days based on system loads, temperature conditions, month and day of week. CPP event days tend to differ from typical days. System loads are typically higher, the days are hotter and they are more likely to fall on specific weekdays. Most event days were matched to similar non-event days; however, comparable non-event days are not available for some of the days with the most extreme weather.

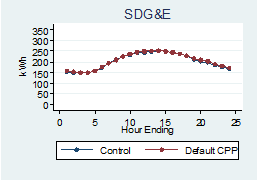
### Matching Model Selection

Propensity score matching using a probit model was used to select valid control groups for each utility and relevant customer segment. This method is a standard approach for identifying statistical look-alikes from a pool of control group candidates and is typically used to address self-selection based on observable differences between CPP participants and non-participants.

### Control group selection

The control group was selected from customers who were not on CPP rates, but were on the otherwise applicable TOU tariff. The best performing probit model and caliper were used to select customers from the control pool. The majority of CPP customers were successfully matched i.e. 93% for SDG&E. Customers who were not matched were moved to the individual customer regression group. Some control group customers were selected more than once—that is, if customer A was the best match for both customer B and customer C, it was chosen twice. Figure 3-1 shows load for the matched treatment and control customers on the average proxy event day. The loads match closely, particularly during event hours.

Figure 3-1: Comparison of Matched Treatment and Control Group Load on Average Proxy Event Day



### Difference-in-difference

Using the matched control groups, 2015 ex-post CPP load impacts were estimated for the majority of customers with the difference-in-differences approach.

The difference-in-differences calculation refines the impact estimates by netting out the small differences between the two groups observed during proxy event days (when CPP prices were not in effect for either group).

The regression analysis in the table below was employed to net out the differences between the participant and control customers. The model includes customer fixed effects and time effects .

|  |  |
| --- | --- |
| Avg. Event Equation: |  |
| Individual Event Equation: |  |

|  |  |
| --- | --- |
| Variable | Definition |
| *i, t, n* | Indicate observations for each individual *i*, date *t* and event number *n*, where the number of events varies by utility and is denoted *max* |
| *a* | The model constant |
| *b* | Pre-existing difference between treatment and control customers |
| *c* | The difference between event and non-event days common to both CPP participants and control group members[[8]](#footnote-8) |
| *d* | The net difference between CPP and control group customers during event days – this parameter represents the difference-in-differences |
| *u* | Time effects for each date that control for unobserved factors that are common to all treatment and control customers but unique to the time period |
| *v* | Customer fixed effects that control for unobserved factors that are time-invariant and unique to each customer; fixed effects do not control for fixed characteristics such as air conditioning that interact with time varying factors like weather |
| *Ε* | The error for each individual customer and time period |
| *Treatment* | A binary indicator or whether or not the customer is part of the treatment (CPP) or control group |
| *Event* | A binary indicator of whether an event occurred that day – impacts are only observed if the customer is on CPP (*Treatment* = 1) and it was an event day |

### Individual Customers Regressions

This type of analysis consists of applying regression models to the hourly load data for each individual customer. The estimated coefficients vary for each customer, as does the amount of data used for each customer. The fact that each customer has its own parameters automatically accounts for variables that are constant for each customer, such as industry and geographic location.

Customer specific regressions were only used for customers who an adequate control group match could not be found.

## CPP-D Ex-Post Load Impacts Estimates

This section summarizes the ex-post load impact evaluation for customers on SDG&E’s CPP tariff. SDG&E called five CPP events in 2015. The first event occurred on August 27 and the last was held on September 11. On average, there were 1,207 accounts enrolled on SDG&E’s tariff in 2015.

Table 3-1 shows the ex-post load impact estimates for each event day and for the average event in 2015. On the average event day, the average participant reduced peak period load by 8.3%, or 21.0 kW. In aggregate, SDG&E’s CPP customers reduced load by 25.3 MW on average across the five events in 2015.

Table 3-1: Default CPP Ex-Post Load Impact Estimates by Event Day  
SDG&E 2015 CPP Events (11 AM to 6 PM)

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Event Date** | **Day of Week** | **Accounts** | **Avg. Customer Reference Load** | **Avg. Customer Load w/ DR** | **Average Customer**  **Impact** | **Aggregate Impact** | **% Reduction** | **Avg. Temp.** | **Daily Maximum Temp.** |
| **(kW)** | **(kW)** | **(kW)** | **(MW)** | **%** | **°F** | **°F** |
| 8/27/2015 | Thu | 1,207 | 240.6 | 223.1 | 17.5 | 21.1 | 7.3% | 88.5 | 91.2 |
| 8/28/2015 | Fri | 1,206 | 240.8 | 219.5 | 21.3 | 25.7 | 8.8% | 91.2 | 92.2 |
| 9/9/2015 | Wed | 1,209 | 270.7 | 241.0 | 29.7 | 35.9 | 11.0% | 94.6 | 95.9 |
| 9/10/2015 | Thu | 1,209 | 267.4 | 244.6 | 22.8 | 27.5 | 8.5% | 92.6 | 95.1 |
| 9/11/2015 | Fri | 1,208 | 245.8 | 232.2 | 13.5 | 16.4 | 5.5% | 87.3 | 89.7 |
| **Avg. Event** | | **1,207** | **253.1** | **232.1** | **21.0** | **25.3** | **8.3%** | **90.8** | **91.6** |

## CPP-D Ex-Ante Evaluation Methodology

Ex ante impacts are designed to reflect demand reduction capabilities under a standard set of peak hours, 1 to 6 PM for the summer season, under both 1-in-2 and 1-in-10 weather conditions.

The process to estimate ex-ante load impacts differed for large C&I customers (peak demands above 200 kW) and small/medium customers (peak demands between 20 and 200 kW). For large customers, the ex-ante estimation process began by re-estimating ex-post load impacts for customers with data for all events, using the same estimation model. Then modeled reference loads for 1-in-2 and 1-in-10 weather conditions. Reference loads are estimated separately for the large and small/medium C&I customer classes. For the large C&I customer class, hourly default CPP customer load, by LCA, is modeled as a function of temperature and month. For the small/medium C&I customer class, hourly load for a representative sample of small/medium C&I customers is modeled by LCA as a function of temperature and month. Temperature is represented by daily average of the first 17 hours (mean17), which is used to capture heat buildup in the daylight hours.

The next step in ex-ante estimation is modeling the relationship of ex-post load impacts to temperature conditions. This step is only performed for large customers. Load impacts from 2014 and 2015 for large persistent customers were modeled as a function of temperature for each LCA. Just as in the reference load modeling, temperature is represented by mean17, which is used to capture heat buildup in the daylight hours.

## CPP-D Ex-Ante Load Impacts Estimates

This section presents ex-ante load impact estimates for SDG&E's non-residential CPP tariff. As discussed in Section 3, the main purpose of ex-ante load impact estimates is to reflect the load reduction capability of a demand response resource under a standard set of conditions that align with system planning. These estimates are used in assessing alternatives for meeting peak demand, cost-effectiveness comparisons and long-term planning. The ex-ante impact estimates for SDG&E are based on ex-post load impacts of CPP events that occurred in 2014 and 2015. In total, load impact estimates 11 events were used as input to the ex-ante model. All load impact estimates presented here are incremental to the effects of the underlying TOU rates.

### Large C&I Ex-Ante Impacts

The ex-ante load impact estimates for large C&I customers are based on a regression model that relates impacts to weather conditions using the ex-post impacts and weather data for 2014 and 2015 to estimate model coefficients.

Table 3-2 shows SDG&E’s enrollment projections for large C&I CPP customers through 2026. Overall, 1,207 large customers were enrolled in default CPP in 2015.[[9]](#footnote-9) The forecasted year-to-year change in enrollment is a gradual increase which simply reflects the expected growth of SDG&E’s large customer population.

Table 3-2: SDG&E Enrollment Projections for Large C&I CPP Customers by

Forecast Year and Month

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | | **Jan.** | **Feb.** | **Mar.** | **Apr.** | **May** | **Jun.** | **Jul.** | **Aug.** | **Sep.** | **Oct.** | **Nov.** | **Dec.** |
| 2016 | 1,263 | | 1,264 | 1,265 | 1,266 | 1,267 | 1,268 | 1,270 | 1,271 | 1,272 | 1,273 | 1,274 | 1,275 |
| 2017 | 1,276 | | 1,277 | 1,278 | 1,278 | 1,279 | 1,280 | 1,281 | 1,282 | 1,283 | 1,283 | 1,284 | 1,285 |
| 2018 | 1,286 | | 1,288 | 1,289 | 1,290 | 1,291 | 1,293 | 1,294 | 1,295 | 1,296 | 1,298 | 1,299 | 1,300 |
| 2019 | 1,301 | | 1,303 | 1,304 | 1,305 | 1,307 | 1,308 | 1,310 | 1,311 | 1,312 | 1,314 | 1,315 | 1,316 |
| 2020 | 1,318 | | 1,319 | 1,320 | 1,321 | 1,322 | 1,323 | 1,324 | 1,326 | 1,327 | 1,328 | 1,329 | 1,330 |
| 2021 | 1,331 | | 1,333 | 1,334 | 1,335 | 1,336 | 1,338 | 1,339 | 1,340 | 1,342 | 1,343 | 1,344 | 1,345 |
| 2022 | 1,347 | | 1,348 | 1,349 | 1,351 | 1,352 | 1,353 | 1,354 | 1,356 | 1,357 | 1,358 | 1,360 | 1,361 |
| 2023 | 1,362 | | 1,364 | 1,365 | 1,366 | 1,367 | 1,369 | 1,370 | 1,371 | 1,373 | 1,374 | 1,375 | 1,377 |
| 2024 | 1,378 | | 1,379 | 1,381 | 1,382 | 1,383 | 1,385 | 1,386 | 1,387 | 1,389 | 1,390 | 1,391 | 1,393 |
| 2025 | 1,394 | | 1,395 | 1,397 | 1,398 | 1,399 | 1,401 | 1,402 | 1,403 | 1,405 | 1,406 | 1,407 | 1,409 |
| 2026 | 1,410 | | 1,411 | 1,413 | 1,414 | 1,415 | 1,417 | 1,418 | 1,419 | 1,421 | 1,422 | 1,424 | 1,425 |

#### Monthly System Peak Day Impacts

Table 3-3 summarizes the aggregate load impact estimates for large customers on SDG&E’s CPP tariff for each forecast year under both 1-in-2 and 1-in-10 year weather conditions based on both SDG&E and CAISO weather scenarios. The table shows the average load reduction across the 1 PM to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on SDG&E-specific, 1-in-2 year weather conditions, load reductions will grow from roughly 22 MW to 25 MW between 2016 and 2026. Impacts based on 1-in-10 year SDG&E weather conditions equal roughly 25 MW in 2016 and will grow to 28 MW by 2026. These estimates equal roughly 8% of the aggregate reference load for large C&I customers. Impact estimates based on CAISO-specific, 1-in-2 year weather conditions are roughly 5% larger than the estimates based on SDG&E weather. The CAISO 1-in-10 year weather values produce a load reduction that is about 6% less than the 1-in-10 year SDG&E estimates in aggregate terms. These differences were driven by underlying differences in the weather forecast temperatures across the four scenarios that impact both the estimated reference loads as well as impact estimates.

Table 3-3: Default CPP Ex-Ante Load Impact Estimates by Weather   
Scenario for Large C&I  
SDG&E August System Peak Day (1PM to 6 PM)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Type** | **Weather Year** | **Year** | **Enrolled Accounts** | **Aggregate Reference Load** | **Aggregate Estimated Load w/ DR** | **Aggregate Load Impact** | **% Load Reduction** | **Weighted Temp.** |
| **(MW 1–6 PM)** | **(MW 1–6 PM)** | **(MW 1–6 PM)** | **(%)** | **(°F)** |
| SDG&E | 1-in-10 | 2016 | 1271 | 302.0 | 276.9 | 25.1 | 8.3% | 86.6 |
| 2017 | 1282 | 304.6 | 279.3 | 25.3 | 8.3% | 86.6 |
| 2026 | 1419 | 337.2 | 309.2 | 27.9 | 8.3% | 86.6 |
| 1-in-2 | 2016 | 1271 | 286.8 | 264.7 | 22.1 | 7.7% | 81.2 |
| 2017 | 1282 | 289.3 | 267.0 | 22.3 | 7.7% | 81.2 |
| 2026 | 1419 | 320.2 | 295.6 | 24.6 | 7.7% | 81.2 |
| CAISO | 1-in-10 | 2016 | 1271 | 293.3 | 269.9 | 23.4 | 8.0% | 83.8 |
| 2017 | 1282 | 295.9 | 272.3 | 23.6 | 8.0% | 83.8 |
| 2026 | 1419 | 327.5 | 301.5 | 26.0 | 8.0% | 83.8 |
| 1-in-2 | 2016 | 1271 | 291.1 | 268.1 | 22.9 | 7.9% | 83.5 |
| 2017 | 1282 | 293.6 | 270.5 | 23.1 | 7.9% | 83.5 |
| 2026 | 1419 | 325.0 | 299.5 | 25.6 | 7.9% | 83.5 |

#### Comparison of 2014 and 2015 Ex-Ante Estimates

Table 3-4 compares the ex-ante estimates produced for the 2014 evaluation to those presented earlier in this report. Because ex-ante impacts take into account changes in utility enrollment forecasts, program design and customer mix as well as additional experience, the forecasts are adjusted each year. In general, forecasts a year out are more reliable while forecasts further into the future are less certain. The largest changes observed in Table 3-6 are the decreases in predicted reference loads between the 2014 CPP evaluation and this year due to smaller average 2015 reference loads in the persistent customers used to estimate the ex-ante reference loads. Percent impacts for both evaluations are roughly the same, with the net effect that this year’s forecast for 2016 is 25.1 MW, which is 7% lower than last year’s forecast of 27.1MW.

Table 3-4: Comparison of Ex-Ante Estimates to Prior Year Estimates

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Year** | **Year** | **Accounts** | | **Reference Loads (MW)** | | **Percent Reductions** | | **Aggregate Impacts (MW)** | |
| **2014 Estimates** | **2015 Estimates** | **2014 Estimates** | **2015 Estimates** | **2014 Estimates** | **2015 Estimates** | **2014 Estimates** | **2015 Estimates** |
| 1-in-10 | 2016 | 1267 | 1271 | 254.6 | 237.7 | 8.4% | 8.3% | 27.1 | 25.1 |
| 2017 | 1283 | 1282 | 254.6 | 237.6 | 8.4% | 8.3% | 27.5 | 25.3 |
| 2025 | 1405 | 1403 | 254.3 | 237.6 | 8.3% | 8.3% | 29.8 | 27.6 |
| 1-in-2 | 2016 | 1267 | 1271 | 243.5 | 225.7 | 7.9% | 7.7% | 24.5 | 22.1 |
| 2017 | 1283 | 1282 | 243.5 | 225.7 | 7.9% | 7.7% | 24.8 | 22.3 |
| 2025 | 1405 | 1403 | 243.2 | 225.6 | 7.9% | 7.7% | 26.9 | 24.4 |

#### Relationship Between Ex-Post and Ex-Ante Estimates

This section discusses the impact of each of these factors on the difference between ex-post and ex-ante impact estimates.

Table 3-5 summarizes key factors that lead to differences between ex-post and ex-ante estimates for CPP and the expected influence that these factors have on the relationship between ex-post and ex-ante impacts. Given that the CPP load impacts are sensitive to variation in weather, even small changes in *mean17* between ex-post and ex-ante weather conditions can produce differences in load impacts. For the typical event day, ex-ante impacts are significantly lower than the ex-post values when based on SDG&E ex-ante weather and also lower than the ex-post values when based on CAISO weather conditions. This is primarily due to the difference in summer season weather observed in the ex-post and ex-ante results. The average midnight to 5pm (mean17) weather in all four of the ex-ante weather scenarios are all lower than the lower end the mean17 weather experienced in 2015 season. This change decreases the ex-ante impacts by roughly 20% for the typical event day under 1-in-2 SDG&E weather conditions, compared with the average 2015 event day. Changes in enrollment between the values used for ex-post estimation and the 2016 enrollment values increase impact estimates by about 5%. Finally, the fact that the ex-ante model is based on ex-post impacts from both 2014 and 2015 for persistent customers, which exhibit a stronger relationship with temperature, will result in slightly higher ex-ante load impacts at higher temperature values than ex-post impacts at similar values.

Table 3-5: Summary of Factors Underlying Differences Between Ex-Post and Ex-Ante Impacts for the Default CPP Customers for the Ex-Ante Typical Event Day

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex-Post | Ex-Ante | Expected Impact |
| Weather | Default CPP customers:  79.9 < event day mean17 < 86.3  Average event day mean17 = 83.2 | Program specific mean17 for 1-in-2 typical event day = 72.5 and 73.2 for SDG&E and CAISO weather, respectively  Program specific mean17 for 1-in-10 typical event day = 77.5 and 76.0 for SDG&E and CAISO weather, respectively | Ex ante estimates are sensitive to variation in mean17 – impacts will be lower based on both SDG&E weather and CAISO weather |
| Enrollment | Enrollment remained fairly constant over the 2015 summer | 2016 enrollment is forecast to be about 5% higher | Ex ante estimates will be about 5% higher than ex-post |
| Methodology | 2015 impacts based on combination of matched control groups and individual customer regressions | Impacts: regression of ex-post percent impacts against mean17 for each hour using two years’ worth of ex-post impacts for persistent customers  Reference Load: regression of kW against mean17 and date variables for each hour using default cpp population | Pooled impacts from 2014 and 2015 for persistent customers exhibit a stronger temperature relationship than those for all customers. Impacts will be higher at higher temperatures and lower or similar at lower temperatures.  Reference load of the ex-ante population is similar to that of the ex-post population. |

Table 3-6 shows how aggregate load impacts change for large default CPP customers as a result of differences in the factors underlying ex-post and ex-ante estimates. The third column uses the 2015 ex-post impacts and the projected enrollment for August of 2016 to produce a scaled-up ex-post impact estimate, which is approximately the same as the average ex-post impact since enrollment grew very little. The next column shows what the ex-ante model would produce using the same August 2016 enrollment figures and the ex-post weather conditions for each event day. The final four columns show how aggregate load reductions vary with the different ex-ante weather scenarios. The impacts are similar across SDG&E and CAISO weather scenarios. On average across all event days, the impacts derived from the 1-in-10 conditions are most similar to those derived using the 2015 SDG&E ex-post weather conditions, although the impacts are still lower than the average ex-post day by about 12%.

Table 3-6: Differences in Large C&I Ex-Post and Ex-Ante Impacts Due to Key Factors

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **Mean 17** | **Ex-Post Impact** | **Ex-Post Impact with Ex-Ante Enrollment** | **Ex-Ante Model Ex-Post Weather** | **CAISO 1-in-2** | **SDG&E 1-in-2** | **CAISO 1-in-10** | **SDG&E 1-in-10** |
| **(F)** | **(MW)** | **(MW)** | **(MW)** | **(MW)** | **(MW)** | **(MW)** | **(MW)** |
| 8/27/2015 | 79.9 | 21.1 | 22.3 | 25.6 | 20.8 | 20.6 | 21.8 | 22.4 |
| 8/28/2015 | 82.0 | 25.7 | 27.1 | 27.3 |
| 9/9/2015 | 86.3 | 35.9 | 37.8 | 30.8 |
| 9/10/2015 | 85.1 | 27.5 | 29.0 | 29.8 |
| 9/11/2015 | 82.4 | 16.4 | 17.2 | 27.6 |
| Avg. | 83.2 | 25.3 | 26.7 | 28.2 |

## Medium C&I Ex-Ante Impacts

Overall, there is greater uncertainty regarding medium C&I customer impacts under default CPP. Only one year of data is available for default SMB CPP rates for California customers; at PG&E, not SDG&E. While some SDG&E medium customers volunteered onto CPP rates, their mix and demand reductions are not representative of the current and future medium default customer population. 2015 was the first year of PG&E’s small and medium business default CPP enrollment, while SDG&E will begin defaulting SMB customers in early 2016 before the typical CPP event season. For this reason, the initial results from PG&E’s program are being used to estimate SDG&E’s ex-ante impacts.

To estimate impacts for the larger SMB population, Nexant used the PG&E Medium CPP percent reductions as the estimate for SDG&E defaulted medium customers, yielding percent reductions of 0.9%. The reference loads were developed by using interval data for customers that are eligible to be defaulted in March 2016. Table 3-9 presents SDG&E's enrollment projections for medium C&I customers through 2026. While the number of eligible customers is due to increase over the next ten years due to growth in accounts, higher levels of opt-out to a TOU rate reduce the CPP enrollment forecast over time. Of the customers who were already defaulted in March 2016, 16,260 customers are projected to remain on CPP in March 2026.

Table 3-7: SDG&E Enrollment Projections for Medium C&I CPP Customers

by Forecast Year and Month

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Year | Jan. | Feb. | Mar. | Apr. | May | Jun. | Jul. | Aug. | Sep. | Oct. | Nov. | Dec. |
| 2016 | 19,308 | 19,308 | 19,308 | 19,308 | 19,308 | 19,308 | 19,308 | 19,308 | 19,308 | 19,308 | 19,308 | 19,308 |
| 2017 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 |
| 2026 | 16,260 | 16,260 | 16,260 | 16,260 | 16,260 | 16,260 | 16,260 | 16,260 | 16,260 | 16,260 | 16,260 | 16,260 |

### Monthly System Peak Day Impacts

Table 3-8 summarizes the aggregate load impact estimates for medium C&I customers on SDG&E’s CPP rate for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios based on both SDG&E and CAISO weather scenarios. The table shows the average load reduction across the 1 PM to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on SDG&E-specific weather, August load reductions decrease from 4.4 MW in 2016 to 3.9 MW in 2017 under 1-in-10 weather conditions, and then increase to 4.8 MW in 2026. Once default CPP is fully implemented, medium customers are forecasted to reduce less than 1% of their demand under all weather conditions. based on the PG&E default CPP results. Underlying the enrollment of SDG&E customers on to the CPP rate are both the aggregate number of eligible accounts, forecasted to rise over time, and the rate at which they opt out of default CPP on to a TOU rate only. This forecasted opt-out rate is the reason why enrollment declines slowly over the first three years of the forecast, then flattens out in the later years. In the meantime, the awareness factor increases as described above. Together these conflicting influences cause the drop in aggregate impacts in the short to mid term, but then increase in the later years of the forecast period.. Impact estimates based on CAISO weather 1-in-2 year conditions are the same as under SDG&E scenarios. Reference loads under the SDG&E-specific 1-in-10 year weather are higher than CAISO-specific, while CAISO-specific weather yields higher reference loads in the 1-in-2 year weather scenario. In both cases, reference loads do not vary by more than 3% between the two scenarios.

Table 3-8: Aggregate Default CPP Ex-Ante Load Impact Estimates by Weather Scenario for Medium C&I, SDG&E August System Peak Day (1 PM to 6 PM)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Type** | **Weather Year** | **Year** | **Enrolled Accounts** | **Aggregate Reference Load** | **Aggregate Estimated Load w/ DR** | **Aggregate Load Impact** | **% Load Reduction** | **Weighted Temp.** |
| **(MW 11 AM–6 PM)** | **(MW 11 AM–6 PM)** | **(MW 11 AM–6 PM)** | **(%)** | **(°F)** |
| SDG&E | 1-in-10 | 2016 | 19,308 | 676.2 | 669.9 | 6.2 | 0.92% | 91.0 |
| 2017 | 17,276 | 605.0 | 599.4 | 5.6 | 0.92% | 91.0 |
| 2026 | 16,260 | 569.4 | 564.2 | 5.2 | 0.92% | 91.0 |
| 1-in-2 | 2016 | 19,308 | 631.6 | 625.8 | 5.8 | 0.92% | 83.5 |
| 2017 | 17,276 | 565.1 | 559.9 | 5.2 | 0.92% | 83.5 |
| 2026 | 16,260 | 531.9 | 527.0 | 4.9 | 0.92% | 88.5 |
| CAISO | 1-in-10 | 2016 | 19,308 | 656.2 | 650.2 | 6.0 | 0.92% | 88.5 |
| 2017 | 17,276 | 587.2 | 581.8 | 5.4 | 0.92% | 88.5 |
| 2026 | 16,260 | 552.6 | 547.5 | 5.1 | 0.92% | 88.5 |
| 1-in-2 | 2016 | 19,308 | 649.8 | 643.8 | 6.0 | 0.92% | 88.1 |
| 2017 | 17,276 | 581.4 | 576.1 | 5.4 | 0.92% | 88.1 |
| 2026 | 16,260 | 547.2 | 542.2 | 5.0 | 0.92% | 88.1 |

# Summary of SDG&E’s Base Interruptible Program Report

## BIP Program Description

SDG&E’s BIP is a voluntary program that offers participants a monthly capacity bill credit in exchange for committing to reduce their demand to a contracted FSL on short notice during emergency situations. Non-residential customers who can commit to curtail 15 percent of monthly peak demand with a minimum load reduction of 100 kW are eligible for the program. Customers are notified no later than 30 minutes before the event. Monthly incentive payments are $12 per kW during May through October and $2 per kW during all other months. Curtailment events for an individual BIP customer are limited to a single 4-hour event per day, no more than 10 events per month and no more than 120 event hours per calendar year. A curtailment event may be called under BIP at any time during the year.

Participation in SDG&E’s program has been low, consistent with the California Public Utilities Commission (“Commission” or “CPUC”) direction to focus marketing efforts on price responsive programs. There were no participants in 2006, three participants in 2007, five participants in 2008, 20 in 2009, 19 customers in 2010, 21 customers in 2011, 11 in 2012,[[10]](#footnote-10) seven participants in 2013 and 2014, and five participants in 2015.

## BIP Ex-Post Evaluation Methodology

We estimated *ex-post* hourly load impacts using regression equations applied to customer-level hourly load data. The regression equation models hourly load as a function of a set of variables designed to control for factors affecting consumers’ hourly demand levels, such as:

* Seasonal and hourly time patterns (*e.g.*, year, month, day-of-week, and hour, plus various hour/day-type interactions);
* Weather, including hour-specific weather coefficients;
* Event variables. A series of dummy variables was included to account for each hour of each event day, allowing us to estimate the load impacts for all hours across the event days.

The models use the level of hourly demand (kW) as the dependent variable and a separate equation is estimated for each enrolled customer. As a result, the coefficients on the event day/hour variables are direct estimates of the *ex-post* load impacts. For example, a BIP hour 15 event coefficient of -100 would mean that the customer reduced load by 100 kWh during hour 15 of that event day relative to its normal usage in that hour. Weekends and holidays were excluded from the estimation database.[[11]](#footnote-11)

### Regression Model

A modified model was used for SDG&E customers. To better capture the greatly shifting load profiles across months of a few relatively large customers, an interaction term between month and hour was added. To address the potential for overfitting with this near doubling of the total number of estimated coefficients, the interaction terms between specific days of the week (Monday and Friday) and hour were removed.



Table 4.1: Descriptions of Variables included in the *Ex-post* Regression Equation

|  |  |
| --- | --- |
| **Variable Name** | **Variable Description** |
| *Qt* | the demand in hour *t* for a BIP customer |
| The various *b*’s | the estimated parameters |
| *hi,t* | an indicator variable for hour *i*, equal to one when *t* corresponds to hour *i* of a given day |
| *BIPt* | an indicator variable for program event days |
| *E* | the number of program event days that occurred during the program year |
|  | an indicator variable for event day *DR* of other demand response programs in which the customer is enrolled (e.g. *DR* = DBP Event 1, DBP Event 2, ...) |
| *Weathert* | the weather variables selected using our model screening process |
| *MornLoadt* | a variable equal to the average of the day’s load in hours 1 through 10 |
| *MornLoadAltt* | a variable equal to the average of the day’s load in hours 9 through 12 |
| *DTYPEj,t* | a series of indicator variables for each day of the week |
| *MONt, FRIt*, | indicator variables for Monday and Friday |
| *MONTHj,t* | a series of indicator variables for each month |
| *SUMMERt* | an indicator variable for the summer pricing season[[12]](#footnote-12) |
| *et* | the error term |

The *OtherEvt* variables help the model explain load changes that occur on event days for programs in which the BIP customers are dually enrolled. (In the absence of these variables, any load reductions that occur on such days may be falsely attributed to other included variables, such as weather condition or day type variables.) The “morning load” variables are included in the same spirit as the day-of adjustment to the 10-in-10 baseline settlement method used in some DR programs (*e.g.*, Demand Bidding Program, or DBP). That is, those variables help adjust the reference loads (or the loads that would have been observed in the absence of an event) for factors that affect pre-event usage, but are not accounted for by the other included variables.

The model allows for the hourly load profile to differ by: day of week, with separate profiles for Monday, Tuesday through Thursday, and Friday; and by pricing season (*i.e.*, summer versus winter), in order to account for potential customer load changes in response to seasonal changes in rates.

Separate models were estimated for each customer. The load impacts were aggregated across customer accounts as appropriate to arrive at program-level load impacts, as well as load impacts by industry group and local capacity area (LCA).

A parallel set of winter models was estimated for each customer. The structure matches the model described above, with the appropriate month indicators substituted in.

## BIP Ex-Post Load Impact Estimates

One BIP event was called on August 28th 2015 from The average load reduction was 1.5 MW.

## BIP Ex-Ante Evaluation Methodology

This section describes the methods used to develop the relevant groups of customers, to develop reference loads for the relevant customer types and event-day types, and to develop load impacts for a typical event day.

### Development of Reference Loads and Load Impacts

Reference loads and load impacts for all of the above factors were developed in the following series of steps:

1. Define data sources;
2. Estimate *ex-ante* regressions and simulate reference loads by service account and scenario;
3. Calculate historical FSL achievement rates from *ex-post* results;
4. Apply achievement rates to the reference loads; and
5. Scale the reference loads using enrollment forecasts.

Each of these steps is described below.

1. *Define data sources*

The reference loads are developed using data for customers enrolled in BIP at the start of the 2016 program year. The load impacts are developed using the historical FSL achievement rates of customers remaining enrolled at the start of the 2016 program year, based on their estimated *ex-post* load impacts during program year 2015.

1. *Simulate reference loads*

In order to develop reference loads, we first re-estimated regression equations for each enrolled customer account using data for the current program year. The resulting estimates were used to simulate reference loads for each service account under the various scenarios required by the Protocols (*e.g.*, the typical event day in a utility-specific 1-in-2 weather year).

For the summer months, the re-estimated regression equations were similar in design to the *ex-post* load impact equations described in Section 3.2, differing in two ways. First, the *ex-ante* models excluded the morning-usage variables. While these variables are useful for improving accuracy in estimating *ex-post* load impacts for particular events, they complicate the use of the equations in *ex-ante* simulation. That is, they would require a separate simulation of the level of the morning load. The second difference between the *ex-post* and *ex-ante* models is that the *ex-ante* models do not use weather variables using information from prior days.[[13]](#footnote-13) The primary reason for this is that the *ex-ante* weather days were not selected based on weather from the prior day, restricting the use of lagged weather variables to construct the *ex-ante* scenarios.

Because BIP events may be called in any month of the year, we estimated separate regression models to allow us to simulate winter reference loads. The winter model is shown below. This model is estimated separately from the summer *ex-ante* model. It only differs from the summer model in two ways: it includes different weather variables; and the month dummies relate to a different set of months. Table 4.2 describes the terms included in the equation.[[14]](#footnote-14)



Table 4.2: Descriptions of Terms included in the *Ex-ante* Regression Equation

|  |  |
| --- | --- |
| **Variable Name** | **Variable Description** |
| *Qt* | the demand in hour *t* for a customer enrolled in BIP prior to the last event date |
| The various *b*’s | the estimated parameters |
| *hi,t* | an indicator variable for hour *i*, equal to one when *t* corresponds to hour *i* of a given day |
| *BIPt* | an indicator variable for program event days |
| *E* | the number of program event days that occurred during the program year |
|  | an indicator variable for event day *DR* of other demand response programs in which the customer is enrolled (e.g. *DR* = DBP Event 1, DBP Event 2, ...) |
| *Weathert* | the weather variables selected using our model screening process |
| *DTYPEj,t* | a series of indicator variables for each day of the week |
| *MONt, FRIt*, | indicator variables for Monday and Friday |
| *MONTHj,t* | a series of indicator variables for each month |
| *et* | the error term |

Once these models were estimated, we simulated 24-hour load profiles for each required scenario. The typical event day was assumed to occur in August. In 2014, two sets of 1-in-2 and 1-in-10 weather years were introduced in the load impact analyses. The sets are differentiated according to whether they correspond to utility-specific conditions or CAISO-coincident conditions. The weather conditions used in prior evaluations corresponded to the utility-specific scenarios.

1. *Calculate forecast load impacts*

Each service account’s achievement rate is defined as the estimated load impact divided by the difference between the reference load and the FSL. A result of 100 percent implies that the customer dropped its load exactly to its FSL. Values greater than 100 percent imply event-day loads lower than the FSL, and values less than 100 percent imply event-day loads higher than the FSL.[[15]](#footnote-15)The achievement rates are based on the estimates for the most recent observed event day.

Because the forecast event window (1:00 to 6:00 p.m. in April through October; and 4:00 to 9:00 p.m. in all other months) differs from the historical event window (which can vary across event days), we needed to adjust the historical load impacts for use in the *ex-ante* study. Load impacts are assumed to be zero until the hour prior to the beginning of the event, at which time we apply historical load impacts to the forecast window to best represent the pattern of customer response given the limitations of the observed events. We develop forecast load impacts through the end of the event day because customers load reductions often persist well after the end of the event hours.

1. *Apply achievement rates to reference loads for each event scenario*.

In this step, the customer-specific achievement rates are applied to the reference loads for each scenario to produce all of the required estimated event-day loads and load impacts. For customers for which an achievement rate cannot be calculated, either because they were not enrolled in 2015 or because their reference loads were below their FSLs, the average achievement rate among all customers is used.

1. *Apply forecast enrollments to produce program-level load impacts*.

The SDG&E enrollment forecast projects that enrollment will grow from 5 accounts in 2015 to 7 accounts in 2016 and that and remain constant throughout the remainder of the forecast period. (2016-2026)

## BIP Ex-Ante Load Impacts

The ex-ante forecast for BIP is shown in table 4-2 below.

Table 4-3 SDG&E BiP Ex-Ante Forecast

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| 0.53 | 0.33 | 0.67 | 2.33 | 2.14 | 2.16 | 1.63 | 1.44 | 1.67 | 1.96 | 0.39 | 0.17 |

## BIP Comparison of current Ex-Post versus Ex-Ante

Table 4.4 below describes the factors that differ between the *ex-post* and *ex-ante* load impacts for SDG&E. Note that portions of the table have been removed due to confidentiality concerns.

The *ex-ante* forecast is based on the *ex-post* achievement (*i.e.*, observed loads) relative to the FSL during event hours. So in terms of achievement relative to the FSL, the *ex-post* and *ex-ante* load impacts for the five continuing customers match by design. However, the forecast reference loads differ from the ex-post event-hour reference loads for various reasons. For instance, forecast reference loads are lower partly due to a difference in event windows, as the historical event occurred from 1:00 to 5:00 p.m., ending one hour earlier than *ex-ante* event window, which also includes the relatively low loads of hour 18. In addition ex-post reference loads for the five original customers are higher than they are in the ex-ante analysis due to the unusually high reference load of the largest customer, on the event day

However, the addition of two new customers to the 2016 forecast almost completely cancels out the effect of the above factors on aggregate ex-ante load impact. These new customers increase the aggregate reference load even more, resulting in a higher ex-ante aggregate reference load overall despite the above factors working in the opposite direction. These new customers slightly decrease the per-customer load impact despite increasing the per-customer reference load.

Table 4.4: SDG&E BIP *Ex-post* versus *Ex-ante* Factors, Typical Event Day

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex-Post | Ex-Ante | Expected Impact |
| Weather | 88.5 degrees Fahrenheit during HE 14-17 on the August 28th event day | 79.6 degrees Fahrenheit during HE 14-18 on utility-specific 1-in-2 typical event day | Program load is not very weather sensitive, so a small effect. |
| Event window | HE 14-17 | HE 14-18 in Apr-Oct. | Reference loads are substantially lower by 5 p.m. relative to earlier in the day, so the inclusion of hour-ending 18 tends to drag down the average *ex-ante* reference loads and load impacts relative to *ex-post*. |
| % of resource dispatched | All | All | None |
| Enrollment | 5 service accounts | 7 service accounts |  |
| Methodology | SAID-specific regressions using own within-subject analysis. | Reference loads are simulated from SAID-specific regressions. |  |

Table 4.5: SDG&E Ex-Ante versus Ex-Post Results

|  |  |  |
| --- | --- | --- |
| Program | 2015 Ex-Post Load Impact (MW) | 2016 Ex-Ante Load Impact August (MW) |
| BIP | 1.5 | 1.4 |

# Summary of SDG&E’s Demand Bidding Program Report

## DBP Program Description

SDG&E has two Demand Bidding Programs described below:

Schedule DBP-DA: Schedule DBP-DA provides day-ahead notice of event days. This program is applicable to customers who are capable of providing at least a 2 MW load reduction based on the customer’s specific baseline. The DBP-DA incentive is $0.40 per kWh for customers who purchase commodity from the utility (bundled customers).

Schedule DBP-DO: Demand/energy bidding program offers incentives to nonresidential customers for reducing energy consumption and demand during a specific Demand Bidding Event. This program is applicable to customers who are capable of providing at least a 5 MW load reduction based on the customer’s specific baseline. The DBP-DA incentive is $0.50 per kWh for customers who purchase commodity from the Utility (bundled customers).

Schedule DBP-DO and DBP-DA programs are available year-round and there is no limit to the number of Demand Bidding Events per month or per year. A customer may not participate simultaneously in DBP-DA or DBP-DO and any other Demand Response rate or program. SDG&E will end these programs in 2016.

## DBP Ex-Post Load Impacts Estimates

SDG&E did not call any DBP event days during the 2015 program year.

## DBP Ex-Ante Evaluation Methodology

According to the current tariff the both the DBP day-ahead and the DBP day-of programs end in December of 2016 and SDG&E has not proposed to extend the programs. Therefore the ex-ante forecast for 2017-2026 is zero.

# Summary of the Summer Saver Program

## Summer Saver Program Description

The Summer Saver program is a San Diego Gas and Electric Co. (SDG&E) demand response resource based on central air conditioning (CAC) load control. It is implemented through an agreement between SDG&E and Alternative Energy Resources (AER), a subsidiary of Comverge, Inc., and is expected to continue to be implemented at SDG&E through 2016.

The Summer Saver program is classified as a day-of program and is available to both residential and nonresidential customers, where eligible nonresidential customers are subject to a demand limit; only those nonresidential customers with average monthly peak demand up to a maximum of 100 kW over a 12-month period may participate. Summer Saver events may only be called during the months of May through October. Load control events must run for at least two hours but may also not run for more than four hours. Participants’ air conditioners cannot be cycled for more than four hours in any event day and events cannot be triggered for more than 40 hours per month or 120 hours per year. Load control events can occur on weekends but not on holidays and cannot be called more than three days in any calendar week. These program rules apply to both residential and nonresidential customers alike.

There are two enrollment options for both residential and nonresidential participants. Residential customers can choose to have their CAC units cycled 50% or 100% of the time during an event. The incentive paid for each option varies; the 50% cycling option pays $11.50 per ton per year of CAC capacity and the 100% cycling option pays $30 per ton per year. A residential customer with a four-ton CAC unit would be paid the following in the form of an annual credit on their SDG&E bill:

$46 for 50% cycling; or

$120 for 100% cycling.

Nonresidential customers have the option of choosing 30% or 50% cycling. The incentive payment for 30% cycling is $9 per ton per year and $15 per ton per year for the 50% cycling option. A nonresidential customer with five tons of air conditioning would be paid the following in the form of an annual credit on their SDG&E bill:

$45 for 30% cycling; or

$75 for 50% cycling.

Table 6-1: Summer Saver Enrollment, September 2015

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Customer Type** | **Cycling Option** | **Enrolled Customers** | **Enrolled Control Devices** | **Enrolled Tons** |
| Commercial | 30% | 1,137 | 3,324 | 12,871 |
| 50% | 3,515 | 7,750 | 29,704 |
| Total | 4,652 | 11,074 | 42,575 |
| Residential | 50% | 12,474 | 14,540 | 51,053 |
| 100% | 9,260 | 11,432 | 41,623 |
| Total | 21,734 | 25,972 | 92,677 |
| **Grand Total** | | **26,386** | **37,046** | **135,252** |

## Summer Saver Ex-Post Evaluation Methodology

The primary task in developing ex post load impacts is to estimate a reference load for each event. The reference load is a measure of what participant demand would have been in the absence of the CAC cycling during an event.

Two separate approaches were used for estimating the reference loads: a randomized controlled trial (RCT) design and a propensity score matching (PSM) design. All residential customer impacts were estimated using a randomized controlled trial. The non-residential customer impacts were estimated by pooling a small RCT with a larger PSM study.

An RCT is an experimental research approach where customers are randomly assigned to treatment and control conditions so that the only difference between the two groups, other than random chance, is the existence of the treatment condition. In this context, half of the roughly 2,000 customers in the residential sample and half of the approximately 300 customers in the nonresidential sample had their CAC unit cycled while the remaining customers served as the control group. The group that received the event signal alternated from event to event. This design has significant advantages in providing fast, reliable impact estimates if sample sizes are large enough.

Those non-residential Summer Saver customers who were not sampled for the RCT all had their CAC units cycled. Because a sample size of 150 customers per nonresidential sub-segment is not large enough to reliably estimate load impacts, a matched control group was selected for the remaining nonresidential program population, whereby one matched non-participant was selected for each participant on each event. The entire small commercial customer class was made available for the statistical matching analysis. Each matched customer was chosen because they most closely resembled their matched participant in terms of their propensity score, where the propensity score calculates the likelihood that a customer is a Summer Saver participant given that they have certain characteristics. In this case, those characteristics were typical peak demand on hot non-event days and demand in the morning and early afternoon prior to the event. This approach minimizes the differences between participants and matched non-participants.[[16]](#footnote-16)

## Summer Saver Ex-Post Load Impact Estimates

This section contains the ex-post load impact estimates for program year 2015. Residential estimates are provided first, followed by nonresidential estimates.

### Summer Saver Residential Ex-Post Load Impact Estimates

Fifteen Summer Saver events were called in 2015, and each one lasted for four hours, except for the event called on September 20. This event was called for an emergency and only lasted two hours, from 1:35 to 3:35 PM. For the remaining fourteen events, nine were called from 3 to 7 PM, and the others were called from 2 to 6 PM and 4 to 8 PM, respectively. Table 6-2 presents ex post load impacts for the residential program segment for program years 2015.

Table 6-2: Summer Saver Residential Ex Post Load Impact Estimates

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | **Date** | **Impact** | | | | | **Mean17 (°F)[[17]](#footnote-17)** | |
| **Per CAC Unit (kW)** | | **Per Premise (kW)** | | **Aggregate (MW)** |
| 2015 | 8/13/2015 | 0.42 | 0.50 | | 10.5 | | 78 | |
| 8/14/2015 | 0.36 | 0.43 | | 9.0 | | 79 | |
| 8/16/2015 | 0.70 | 0.84 | | 17.8 | | 82 | |
| 8/26/2015 | 0.35 | 0.42 | | 9.0 | | 80 | |
| 8/27/2015 | 0.54 | 0.64 | | 13.7 | | 82 | |
| 8/28/2015 | 0.59 | 0.70 | | 14.9 | | 84 | |
| 9/9/2015 | 0.68 | 0.81 | | 17.2 | | 88 | |
| 9/10/2015 | 0.45 | 0.54 | | 11.4 | | 86 | |
| 9/11/2015 | 0.51 | 0.61 | | 13.0 | | 84 | |
| 9/20/2015\*\* | 0.34 | 0.41 | | 8.7 | | 84 | |
| 9/24/2015 | 0.48 | 0.58 | | 12.2 | | 78 | |
| 9/25/2015 | 0.40 | 0.47 | | 10.1 | | 79 | |
| 10/9/2015 | 0.43 | 0.51 | | 10.8 | | 81 | |
| 10/10/2015 | 0.45 | 0.54 | | 11.4 | | 88 | |
| 10/13/2015 | 0.30 | 0.36 | | 7.6 | | 82 | |
| Average\*\*\* | 0.53 | 0.63 | | 13.3 | | 83 | |
| \*Reflects the average 4-hour event from 2-6 PM | | | | | | | |
| \*\*Reflects the emergency event called from 1:35 to 3:35 PM | | | | | | | |
| \*\*\*Reflects the average 4-hour weekday event from 3-7 PM | | | | | | | |

### Summer Saver Nonresidential Ex-Post Load Impact Estimates

Table 6-3 presents ex post load impact estimates for nonresidential customers for each 2015 event day and an average event day across the nine Summer Saver events in 2015 with common event hours from 3 to 7 PM. Nonresidential customers represent 17.6% of total Summer Saver participants and 31% of enrolled CAC tonnage.

Table 6-3: Summer Saver Nonresidential Ex Post Load Impact Estimates

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Year** | **Date** | **Impact** | | | **Mean17 (°F)** |
| **Per CAC Unit (kW)** | **Per Premise (kW)** | **Aggregate (MW)** |
| 2015 | 13-Aug-15 | 0.12 | 0.28 | 1.3 | 77 |
| 14-Aug-15 | 0.08 | 0.19 | 0.8 | 78 |
| 16-Aug-15 | 0.12 | 0.29 | 1.3 | 80 |
| 26-Aug-15 | 0.09 | 0.21 | 1.0 | 79 |
| 27-Aug-15 | 0.12 | 0.30 | 1.3 | 80 |
| 28-Aug-15 | 0.10 | 0.25 | 1.1 | 83 |
| 9-Sep-15 | 0.11 | 0.26 | 1.2 | 87 |
| 10-Sep-15 | 0.15 | 0.36 | 1.7 | 85 |
| 11-Sep-15 | 0.14 | 0.34 | 1.6 | 83 |
| 20-Sep-15 | 0.06 | 0.14 | 0.6 | 83 |
| 24-Sep-15 | 0.23 | 0.54 | 2.5 | 77 |
| 25-Sep-15 | 0.20 | 0.47 | 2.1 | 78 |
| 9-Oct-15 | 0.14 | 0.34 | 1.6 | 80 |
| 10-Oct-15 | 0.15 | 0.35 | 1.6 | 87 |
| 13-Oct-15 | 0.04 | 0.08 | 0.4 | 81 |
| Average\*\* | 0.13 | 0.30 | 1.4 | 82 |
| \*Reflects the average 4-hour event from 2-6 PM | | | | | |
| \*\*Reflects the average 4-hour weekday event from 3-7 PM | | | | | |

## Summer Saver Ex-Ante Evaluation Methodology

Calculating the ex ante load impacts is a multi-step process, but is driven by a straightforward approach to modeling load impacts as a function of weather. Briefly, load impacts from the 2015 plus the previous five years of Summer Saver events were modeled as a function of temperature and then applied to ex ante weather conditions to predict ex ante load impacts. This section presents a detailed description of the ex ante methodology.

Ex ante load impacts were developed by using the available ex post data. For both residential and nonresidential customers, load impacts for a common set of hours across all ex post events from 2010 through 2015 were used in the estimation database for developing the ex ante model. Only the hours from 3 to 5 PM were used for the analysis because these hours were common across the greatest number of ex post event days. Certain prior Summer Saver event days were not used in the ex ante regression analysis because of atypical circumstances surrounding the event. September 8 and 9, 2011 were excluded as they were associated with a regional system outage. August 10, 2012 and September 20, 2015 were excluded because those events only had one hour during the period 2 to 5 PM. The May 2014 events were excluded because of wildfires in the San Diego region in addition to unusually high temperatures, attributable to Santa Ana wind conditions, that were recorded during those events which were further coupled with unusually low load impacts.

The average load reduction from 3 to 5 PM was modeled as a function of the average temperature for the first 17 hours of each event day, midnight to 5 PM, (mean17). This 17-hour average was used to capture the impact of heat buildup leading up to and including the event hours. Per ton load impacts were used so that the load impacts would be scalable to ex ante scenarios where the tonnage and number of devices per premise may be different. The models were run separately by customer type (residential and nonresidential) and cycling strategy. The estimated parameters from the models were used to predict load impacts under 1-in-2 and 1-in-10 year ex ante weather conditions. The final regressions only included one explanatory variable because more complicated models were not found to perform better in cross-validations done in previous Summer Saver evaluations. The model that was used to predict average ex post impacts was:

Table 6‑4: Ex Ante Regression Variables

| Variable | Description |
| --- | --- |
| *Impactd* | Average per ton ex post load impact for each event day from 2 to 5 PM |
|  | Estimated constant |
|  | Estimated parameter coefficient |
|  | Average temperature over the 17 hours prior to the start of the event for each event day |
|  | The error term for each day *d* |

After the ex ante impacts have been estimated for the 3 to 5 PM period, the next step is to predict impacts for the additional hours covered by the CPUC resource adequacy window from 1 to 6 PM.

The average ex ante load impacts were estimated directly based on ex post impacts. However, the CPUC Load Impact Protocols require that ex ante reference loads also be estimated even though they may not always be necessary for load impact estimation, as is true here. To meet this requirement, reference loads were estimated in a manner similar to the approach used for ex ante impact estimation. Models for estimating reference loads were estimated separately by customer type and cycling strategy. The following steps were used:

* Average control group usage during the 3 to 5 PM time period on 2011–2015[[18]](#footnote-18) event days was modeled as a function of mean17;
* The parameters from this regression were used to predict average usage from 3 to 5 PM under ex ante weather conditions;
* A ratio between each ex ante prediction and average 2014 control group usage from 2 to 5 PM across all days was calculated; and

Average control group load profiles for the entire average event day 2011–2015 were adjusted by the ratio specific to each set of ex ante weather conditions to produce the final ex ante reference loads.

## Summer Saver Ex-Ante Load Impact Estimates

The model described in the previous section was used to estimate load impacts based on ex ante event weather conditions and enrollment projections for the years 2016–2026. Enrollment in the Summer Saver program is not expected to change over the forecast horizon so the tables in this section represent predictions for each of the 11 years from 2016 to 2026, under the assumption that the program would continue to be operated as it is currently throughout that period of time.

September ex ante conditions are much hotter than typical event day conditions. The residential program is estimated to provide an average impact of 14.6 MW over the 5-hour event window from 1 to 6 PM on a 1-in-10 September monthly system peak day and 11.1 MW on the September monthly system peak day under 1-in-2 year weather conditions for SDG&E-specific peaking conditions. Under CAISO peak conditions, residential aggregate load reduction on a September monthly system peak day is 11.9 MW for 1-in-2 and 14.7 MW for 1-in-10.

There is significant variation in load impacts across months and weather conditions. Based on 1-in-2 year weather, the low temperatures in May and June typically experienced in San Diego result in the smallest average and aggregate load impacts. The May and June 1-in-2 year impacts for residential customers are only about 60% of the September estimate, which is the highest of any month under 1-in-2 year weather conditions. For residential customers, the May and June 1-in-10 year estimates are 1.7 times greater than the 1-in-2 year estimates as a result of the 1‑in-10 year temperatures being much warmer than the 1-in-2 year temperatures for May and June.

The nonresidential segment of the program is less weather sensitive than the residential segment. For example, May 1-in-2 load impacts are 74% of the September 1-in-2 load impacts, and May 1-in-10 load impacts are about 1.4 times as large as May 1-in-2 load impacts.

On a per premise basis, the nonresidential segment provides more load impacts than residential customers. But in aggregate, the residential segment provides far more MW of load reduction due to the much greater numbers of residential participants than nonparticipants.

Table 6-5: Summer Saver Ex Ante Load Impact Estimates by CAISO and SDG&E-specific Weather and Day Type (1 to 6 PM, 1-in-10 Conditions)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Customer Type** | **Day Type** | **Per Premise Impact (kW)** | | **Aggregate Impact (MW)** | |
| **CAISO** | **SDGE** | **CAISO** | **SDGE** |
| Residential | Typical Event Day | 0.53 | 0.58 | 11.6 | 12.6 |
| May Monthly Peak | 0.45 | 0.53 | 9.8 | 11.4 |
| June Monthly Peak | 0.45 | 0.46 | 9.7 | 10.0 |
| July Monthly Peak | 0.47 | 0.58 | 10.1 | 12.7 |
| August Monthly Peak | 0.55 | 0.60 | 11.9 | 13.1 |
| September Monthly Peak | 0.68 | 0.67 | 14.7 | 14.6 |
| October Monthly Peak | 0.49 | 0.54 | 10.5 | 11.6 |
| Non-Residential | Typical Event Day | 0.66 | 0.67 | 3.1 | 3.1 |
| May Monthly Peak | 0.63 | 0.66 | 3.0 | 3.1 |
| June Monthly Peak | 0.63 | 0.63 | 3.0 | 3.0 |
| July Monthly Peak | 0.64 | 0.67 | 3.0 | 3.1 |
| August Monthly Peak | 0.66 | 0.68 | 3.1 | 3.2 |
| September Monthly Peak | 0.69 | 0.69 | 3.2 | 3.2 |
| October Monthly Peak | 0.65 | 0.66 | 3.0 | 3.1 |

## Comparison of Ex-Ante and Ex-Post results

Ex post and ex ante load impacts may differ for a variety of reasons, including differences in weather conditions, the timing and length of the event window, and other factors such as changes in expected enrollment. Table 5-8 below presents an overall comparison of 2015 ex post load impacts and the ex ante load impacts as estimated for years 2016 through 2026.

Table 6-6: Comparison of 2015 Ex Post Load Impacts to Ex Ante Load Impacts by Month

|  |  |  |
| --- | --- | --- |
| **Month** | **Ex Post Average Aggregate Impacts\* (MW)** | **Ex Ante Impact\*\* CAISO  1-in-2 (MW)** |
|
| August | 13.9 | 14.5 |
| September | 14.2 | 15.0 |
| October | 11.4 | 9.3 |
| \*Average of 2015 events by month | | |
| \*\*For RA hours of 1-6 PM | | |

# Opt-in Peak Time Rebate Program (PTR) and Residential Small Customer Technology Deployment (SCTD) Program

## Program Overview

### Opt-in PTRProgram Description

The program provides customers with notification on a day-ahead basis that a PTR event will occur on the following day. In emergency situations, a PTR event can be called on a day-of basis to help address an emergency, but day-of events are not the primary design or intended use of the program. PTR is a two-level incentive program, providing a basic incentive level ($0.75/kWh) to customers that reduce energy use through manual means and a premium incentive ($1.25/kWh) to customers that reduce energy use through automated demand response (DR) enabling technologies. The PTR bill credit is calculated based on their event day reduction in electric usage below their established customer-specific reference level (CRL). The program is marketed under the name Reduce Your Use (RYU) and is an opt-in program for residential customers. CPUC Decision D-13-07-003 directed SDG&E to require residential customers to enroll in PTR to receive a bill credit beginning in 2014. Prior to 2014, the PTR program was a default program for all SDG&E residential customers with an opt-in component whereby customers could receive notification of events.

### SCTD Program Description

The program provides demand response enabling technology to residential customers. In 2014 the enabling technology was offered free of charge and customers received bill credits through the PTR program. The enabling technology offered in 2014 was the Ecobee Smart Si thermostat These thermostats are signaled by SDG&E through Wi-Fi. Two cycling strategies were being tested. The first strategy is a four degree thermostat setback and the other is a 50% AC cycling strategy. Customers were randomly assigned to one of the two strategies. Although PTR events are seven hours long SCTD participant’s thermostats were curtailed for 4 hours, typically from 2 p.m. – 6 p.m.

Since PTR is opt-in a customer must enroll to receive a bill credit. Not all SCTD customers enrolled themselves in PTR. If the customers did not enroll in PTR their thermostat was curtailed but they did not receive a bill credit.

SDG&E also offers an air-conditioning cycling program called Summer Saver. Residential customers are either enrolled on a 50% cycling option or a 100% cycling option. Some of these customers are also enrolled in PTR and receive the higher bill credit of $1.25. The Summer Saver program is run by a third party aggregator and the contract expires after summer of 2016.

## PTR and SCTD Residential Ex-Post Evaluation Methodology and Validation

To estimate ex post load impacts for the PTR opt-in and SCTD programs, regression-based models were developed using a difference in differences (DiD) format, comparing participant and reference aggregate hourly residential loads. The reference loads for these models were calculated from matched control groups selected from SDG&E’s population of non-program participants. The methods for the matching and ex post estimations are described in detail below.

### Control Group Selection

Control groups were used to measure impacts from the PTR and SCTD programs due to the following conditions: a) few events, with the potential of these events being the hottest days during the summer, b) some events occurring during non-cooling months and/or months where hot weather is not typical, and c) small average impacts relative to the overall size of the average participant load during the events. To develop control groups for this evaluation, a Stratified Propensity Score Matching (SPSM) method was used.

### Pre-Matching Stratification and Design

Prior to generating propensity scores, the participant sites were stratified to control for variables that may observationally influence participation. Strata were defined using a combination of climate zone (coastal and inland) and annual usage group (small, medium, and large). Low income, Net Energy Metering (NEM), Summer Saver, and electric vehicle charging participants were each handled separately as they required non-participant populations that were equivalent for control group matching. In total, this provided 25 different strata from which to develop control groups:

PTR – Coastal (Small/Medium/Large) and Inland (Small/Medium/Large),

Low Income – Coastal (Small/Medium/Large) and Inland (Small/Medium/Large),

SCTD – Coastal (Small/Medium/Large) and Inland (Small/Medium/Large),

Electric Vehicles, and

NEM – Coastal (Small/Medium/Large) and Inland (Small/Medium/Large).

Using these customer segments and strata, the SPSM methodology used a logistic regression (logit) model to estimate the probability of participation within each stratum. The matching routine paired each participant with a non-participant that had the most similar estimated probability of participation.

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The control group selection was based on a two-stage approach. In the first stage, PSM was used to identify an initial set of ten control group candidate premises for every participant based on variables calculated using 2014 monthly billing data. After requesting the hourly interval data for these candidate premises, a second stage of PSM selected the final control group using variables developed from interval data. Second-stage matching was done separately for all PTR participants, as well as for the other various participant subgroups, namely, NEM, electric vehicle (EV), SCTD, Summer Saver, and Low Income.

After experimenting with various combinations, the final set of variables chosen for the first stage’s logit model included: monthly kWh usage, average monthly kWh, correlation coefficients between monthly CDD65 and kWh usage for summer and winter months, coefficient of variation of kWh usage, ratio of average monthly usage between summer and winter months, ratio of summer kWh usage to total CDD65, and dummy variables for Low Income and Summer Saver customers. Also, accounts were compared to databases of 2013-2014 tracking data for energy efficiency programs and Energy Savings Assistance Programs (ESAP) to create an additional dummy variable for EE program participation for matching.

The second stage of matching saw the additional inclusion of hourly kWh usage during the event hours for summer hot days[[19]](#footnote-19), correlation coefficient of usage and cooling degree hours (CDH65) on hot days, coefficient of variation of kWh usage during event hours, as well as monthly event hour kWh usage.

### Propensity Score Matching Results

One of the key methods of assessing the effectiveness of the PSM is to conduct t-tests on the independent variables used in the logistic regression for the groups both before and after matching. If the matching is successful, the participant and control groups should not be statistically significantly different for these variables. The results of the t-tests for both stages of the PTR and SCTD participant PSM matching show that none of the PSM variables had a statistically significant difference after selecting the control premise candidates. A final assessment of the efficacy of the PSM is a graphical comparison of the annual load profiles of the participant premises with the control premises before and after matching.

### PTR Ex-Post Methodology

A number of different combinations of specifications were tested in developing the aggregate *ex post* model. The final model specifications used for the analysis included variables for hour, day of the week, month, cooling degree hours (CDH65), [[20]](#footnote-20)and event indicators. Additionally, because enrollment increased during the summer, the model included a binary variable to indicate whether a participant was “active,” meaning that they had opted in to the program by the date in question. This means that for periods prior to enrollment, some participants were effectively part of the control group.

Expressed symbolically, the model is as follows:

Where

|  |  |
| --- | --- |
|  | Is the kWh in hour t |
|  | Is the intercept |
|  | Is the set coefficient for day of week (DOW) d |
|  | Is the set of coefficient for month m |
|  | Is the set of coefficients for hour h |
|  | Is the set of coefficients for the interaction of hour h and DOW d |
|  | Is the set of coefficients for the interaction of hour h and month m |
|  | Is the coefficient for cooling degree hours (CDH) |
|  | Is the set of coefficients for CDH interacted with hour h |
|  | Is the set of coefficients for the interaction of CDH with event days |
|  | Is the set of coefficients for interaction of CDH with hour h and event days for inactive participants |
|  | Is the set of coefficients for interaction of CDH with hour h and event days for active participants |
|  | Is the error |

The program impacts were based on the interaction of four variables: the event day flag, the active participant flag, the hour, and the cooling degree hours (CDH). The interaction with CDH served two purposes. First, it allowed for the estimation of savings for individual events, since temperatures were obviously not the same. Second, it allows for the use of the results to develop ex ante impacts. The remainder of the variables allowed controlling for weather and other periodic factors that determine aggregate customer loads.

### SCTD Residential Ex-Post Methodology

The model used to estimate savings for the SCTD participants was nearly identical to that applied to the PTR opt-in alert customers. Using the population of SCTD participants and its associated matched control group, ex post impacts were estimated in an analogous fashion to the PTR groups. Each set of estimated impacts were grouped by SCTD cycling strategy (4 degree setback or 50% cycling) as well as overall.

## PTR and SCTD Residential Ex-Post Load Impact Estimates

## Summary of 2015 PTR and SCTD Events

Table 7-1 presents the ex post load impacts for PTR participants without any load control (SCTD or Summer Saver), including those that are Net Energy Metered. These results are presented by each of the four event days in 2015. Table 7-2 presents the ex post load impacts for all SCTD participants by event date.

Table 7-1: PTR with No Load Control (including NEM) Ex Post Load Impact Estimates –

By Event Date (11 a.m. to 6 p.m.)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Event Date | Active Participants | Mean Reference Load (kW) | Mean Observed Load (kW) | Mean Impact (kW) | % Load Reduction | Aggregate Load Reduction (MW) | Mean °F |
| August 28th, 2015 | 71,497 | 1.40 | 1.32 | 0.08 | 5.4% | 5.37 | 90.66 |
| September 9th, 2015 | 71,497 | 1.52 | 1.44 | 0.08 | 5.6% | 6.08 | 94.10 |
| September 10th, 2015 | 71,497 | 1.46 | 1.38 | 0.08 | 5.5% | 5.73 | 92.46 |
| September 11th, 2015 | 71,497 | 1.40 | 1.33 | 0.06 | 4.6% | 4.59 | 86.86 |
| Average 2015 Event | 71,497 | 1.44 | 1.37 | 0.08 | 5.3% | 5.44 | 91.02 |

Table 7‑2: SCTD Overall Ex Post Load Impact Estimates –

**By Event Date (2 p.m. to 6 p.m.)**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Event Date | Active Participants | Mean Reference Load (kW) | Mean Observed Load (kW) | Mean Impact (kW) | % Load Reduction | Aggregate Load Reduction (MW) | Mean °F |
| August 28th, 2015 | 6,531 | 2.53 | 1.88 | 0.65 | 26.0% | 4.25 | 92.2 |
| September 9th, 2015 | 6,616 | 2.57 | 1.97 | 0.60 | 23.5% | 3.96 | 95.0 |
| September 10th, 2015 | 6,625 | 2.35 | 2.04 | 0.30 | 13.1% | 2.02 | 93.3 |
| September 11th, 2015 | 6,635 | 2.36 | 1.83 | 0.53 | 22.5% | 3.50 | 87.8 |
| Average 2015 Event | 6,602 | 2.45 | 1.93 | 0.52 | 21.4% | 3.44 | 92.1 |

Table 7‑3 PTR Dually Enrolled in Summer Saver Ex Post Load Impact Estimates –

Average 2015 Event (3 p.m. to 6 p.m.)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Customer Category | Mean Active Participants | Mean Reference Load (kW) | Mean Observed Load (kW) | Mean Impact (kW) | % Load Reduction | Aggregate Load Reduction (MW) | Mean °F |
| All | 4,179 | 1.84 | 1.57 | 0.27 | 14.7% | 1.13 | 92.5 |
| Summer Saver – 50% Cycling | 1,487 | 2.09 | 2.10 | -0.01 | -0.4% | -0.01 | 92.9 |
| Summer Saver – 100% Cycling | 2,690 | 1.69 | 1.27 | 0.42 | 24.8% | 1.12 | 92.3 |

## PTR Ex-Ante Evaluation Methodology

Ex ante impacts for the PTR program for four participant segments (Opt-In PTR-Only, PTR Dually Enrolled in Summer Saver, PTR Dually Enrolled in SCTD, and SCTD-Only) were estimated by combining the regression model results from the ex post impacts with two other sources of data. The first data source was a 10-year forecast of enrollment for four separate participant segments. The second data source was two separate versions of weather scenarios containing hourly weather for different types of weather years and day types for each month of the year, one from SDG&E and the second from CAISO. The results presented in this section use the weather conditions based on SDG&E estimates.

The ex ante estimation process was relatively straightforward, involving two main steps. The first step required taking the model parameters from the ex post regression model and combining them with the weather scenarios to calculate per participant average reference loads, observed loads, and load impacts. Because the impacts were based on variables that were interacted with temperature variables, they can be applied to the weather data from the various year and day types to generated estimated savings for those scenarios. The standard errors from the impact variable parameters from the ex post model were used to calculate the uncertainty estimates. The second step was to combine estimated per-participant impacts for the different weather scenarios and multiply them by the forecast of enrolled participants to generate the total program impacts. SDG&E forecasts that the PTR, Summer Saver, and SCTD programs will continue to grow. By the end of 2017, the PTR program is expected to grow to over 83,000 participants (including dual enrollments in the other programs), while the SCTD program is expected to grow to over 15,000 participants. These projections are then expected to remain constant throughout the remainder of the ex ante forecast period.

While this process was straightforward, there were some nuances to the data that call for additional discussion. First, the enrollment forecasts were based on total participants by participant segment, whereas the weather scenarios and estimated impacts have more detailed information. Consequently, the alignment of these data sources called for making certain assumptions about the allocation of program participants. Total participants from the forecast were allocated to climate zones and, for the SCTD and Summer Saver groups, to the cycling strategies based on the relative shares as of the last event day from 2015. Additionally, since the weather scenarios were provided by climate zone, an average weather scenario was created using an average where the same participant shares were used as weights. Note that this weighting was program segment specific. For example, the overall weather for the SCTD 100% cycling participants was based on the shares by climate zone for that particular group. The shares used for the allocation of the enrollment forecast are presented in Table7-4.

Table 7‑4: Shares for Allocation of Enrollment Forecast

| **Participant Segment** | | **Coastal** | **Inland** | **All** |
| --- | --- | --- | --- | --- |
| **PTR-Only** | **All** | 54% | 46% | 100% |
| **PTR Dually Enrolled in Summer Saver** | **100% Cycle** | 18% | 46% | 64% |
| **50% Cycle** | 5% | 31% | 36% |
| **All** | 23% | 77% | 100% |
| **PTR Dually Enrolled in SCTD** | **4 Degree Setback** | 22% | 33% | 55% |
| **50% Cycle** | 16% | 29% | 45% |
| **All** | 37% | 63% | 100% |
| **SCTD-Only** | **4 Degree Setback** | 18% | 34% | 52% |
| **50% Cycle** | 17% | 31% | 48% |
| **All** | 35% | 65% | 100% |

## 7.6 PTR Ex-Ante Load Impact Estimates

### PTR Only

Table 7-5 shows the ex ante load impact estimates for the average PTR-only customer on an average weekday, monthly system peak day, and a typical event day based on 1-in-2 and 1-in-10 weather year conditions for 2017. The average weekday and monthly system peak days are presented for June, July, and August, while the typical event day is presented for the month of August. For a 1-in-2 typical event day, the estimated load reduction for the average participant is 0.039 kW during the resource adequacy (RA) availability hours (1:00pm to 6:00 pm). The average estimated aggregate load reduction under this scenario is 3.91 MW. For a 1-in-10 typical event day, the estimated load reduction is higher, at 0.09 kW. The average estimated aggregate reduction is 3.71 MW. These estimates represent approximately 3.3% and 3.8% of the reference load, respectively for each weather scenario.

Table 7‑5: Ex Ante Hourly Load Impact Results – PTR-Only

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Day / Type** | **Month** | **1-in-10** | | | | | **1-in-2** | | | | |
| **Avg. Hourly Reference Load (kWh)** | **Average Hourly Observed Load (kWh)** | **Average Hourly Impact (kWh)** | **Percent Load Reduc-tion** | **Average Total Hourly Impact (MWh)** | **Avg. Hourly Reference Load (kWh)** | **Avg. Hourly Observed Load (kWh)** | **Avg. Hourly Impact (kWh)** | **Percent Load Reduc-tion** | **Avg. Total Hourly Impact (MWh)** |
| **ALL** | **Average Weekday** | **Jun** | 0.88 | 0.86 | 0.025 | 2.9% | 1.76 | 0.68 | 0.66 | 0.013 | 2.0% | 0.91 |
| **Jul** | 0.96 | 0.93 | 0.029 | 3.0% | 2.02 | 0.84 | 0.82 | 0.022 | 2.6% | 1.54 |
| **Aug** | 1.09 | 1.05 | 0.034 | 3.1% | 2.33 | 0.96 | 0.94 | 0.026 | 2.7% | 1.83 |
| **Monthly System Peak Day** | **Jun** | 1.19 | 1.15 | 0.044 | 3.7% | 3.03 | 0.90 | 0.87 | 0.027 | 3.0% | 1.83 |
| **Jul** | 1.32 | 1.27 | 0.051 | 3.9% | 3.54 | 1.07 | 1.03 | 0.035 | 3.3% | 2.43 |
| **Aug** | 1.43 | 1.38 | 0.054 | 3.8% | 3.77 | 1.20 | 1.16 | 0.041 | 3.4% | 2.81 |
| **Typical Event Day** | **Aug** | 1.42 | 1.36 | 0.053 | 3.8% | 3.71 | 1.17 | 1.13 | 0.039 | 3.3% | 2.67 |

### PTR Dually Enrolled in Summer Saver

Table 7-6 shows the ex ante load impact estimates for the average PTR customer dually enrolled in Summer Saver for the various combinations of day types and weather scenarios for 2017. For a 1-in-2 typical event day, the estimated load reduction for the average participant is 0.16 kW during event hours. For a 1-in-10 typical event day, the estimated load reduction is higher, at 0.23 kW. These estimates are higher than the PTR-only. The average estimated aggregate load reductions are 0.72 MW (11.7%) and 1.02 MW (13.1%), respectively.

The 100% cycling group has an estimated load reduction during event hours of 0.23 kW under the 1-in-2 scenario, representing a 17.4% reduction from the reference load. Under the 1-in-10 conditions, this group has an estimated event hour load reduction of 0.32 kW, or 19.6%. The 50% cycling group has much lower estimated load reductions of 0.04 kW (2.6%) and 0.06 kW (3.0%) for the 1-in-2 and 1-in-10 scenarios, respectively.

Table 7‑6: Ex Ante Hourly Load Impact Results – PTR Dually Enrolled in Summer Saver

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Day / Type** | **Month** | **1-in-10** | | | | | **1-in-2** | | | | |
| **Average Hourly Reference Load (kWh)** | **Average Hourly Observed Load (kWh)** | **Average Hourly Impact (kWh)** | **Percent Load Reduc-tion** | **Average Total Hourly Impact (MWh)** | **Average Hourly Reference Load (kWh)** | **Average Hourly Observed Load (kWh)** | **Average Hourly Impact (kWh)** | **Percent Load Reduc-tion** | **Average Total Hourly Impact (MWh)** |
| **Monthly System Peak Day** | **Jun** | 1.45 | 1.25 | 0.195 | 13.5% | 0.85 | 1.03 | 0.91 | 0.118 | 11.4% | 0.51 |
| **Jul** | 1.63 | 1.41 | 0.219 | 13.5% | 0.96 | 1.25 | 1.10 | 0.153 | 12.2% | 0.67 |
| **Aug** | 1.77 | 1.54 | 0.231 | 13.1% | 1.01 | 1.42 | 1.26 | 0.167 | 11.7% | 0.73 |

### PTRR Dually Enrolled in SCTD

Table 7-7 shows the *ex ante* load impact estimates for the average PTR customer dually enrolled in SCTD for the various combinations of day types and weather scenarios for 2017. For a 1-in-2 typical event day, the estimated load reduction for the average dual PTR-SCTD participant is 0.36 kW during resource availability hours.

Table 7‑7: Ex Ante Hourly Load Impact Results – PTR Dually Enrolled in SCTD

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Day / Type** | **Month** | **1-in-10** | | | | | **1-in-2** | | | | |
| **Average Hourly Reference Load (kWh)** | **Average Hourly Observed Load (kWh)** | **Average Hourly Impact (kWh)** | **Percent Load Reduction** | **Average Total Hourly Impact (MWh)** | **Average Hourly Reference Load (kWh)** | **Average Hourly Observed Load (kWh)** | **Average Hourly Impact (kWh)** | **Percent Load Reduction** | **Average Total Hourly Impact (MWh)** |
| **Monthly System Peak Day** | **Jun** | 1.74 | 1.32 | 0.421 | 24.2% | 3.38 | 1.21 | 0.95 | 0.259 | 21.4% | 2.08 |
| **Jul** | 1.92 | 1.43 | 0.486 | 25.3% | 3.99 | 1.47 | 1.14 | 0.333 | 22.7% | 2.74 |
| **Aug** | 2.02 | 1.51 | 0.510 | 25.2% | 4.28 | 1.59 | 1.21 | 0.375 | 23.6% | 3.15 |

### SCTD Only

Table 7-8 shows the *ex ante* load impact estimates for the average customer only enrolled in the SCTD program for the various combinations of day types and weather scenarios for 2017. For a 1-in-2 typical event day, the estimated load reduction for the average SCTD-only participant is 0.22 kW during the resource availability hour. For a 1-in-10 typical event day, the estimated load reduction is 0.31 kW. The average estimated aggregate load reductions are 1.29 MW (13.7%) and 1.81 MW (14.9%), respectively. As the enrollment in the SCTD programs continues to grow, these aggregate estimates will increase.

Table 7‑8: 2017 Ex Ante Hourly Load Impact Results - SCTD Only

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  | | | | |  | | | | |
| **Average Hourly Reference Load (kWh)** | **Average Hourly Observed Load (kWh)** | **Average Hourly Impact (kWh)** | **Percent Load Reduction** | **Average Total Hourly Impact (MWh)** | **Average Hourly Reference Load (kWh)** | **Average Hourly Observed Load (kWh)** | **Average Hourly Impact (kWh)** | **Percent Load Reduction** | **Average Total Hourly Impact (MWh)** |
| **Monthly System Peak Day** | **Jun** | 1.77 | 1.51 | 0.251 | 14.2% | 1.43 | 1.24 | 1.08 | 0.156 | 12.5% | 0.88 |
| **Jul** | 1.94 | 1.65 | 0.292 | 15.0% | 1.69 | 1.50 | 1.30 | 0.197 | 13.1% | 1.14 |
| **Aug** | 2.05 | 1.74 | 0.303 | 14.8% | 1.80 | 1.61 | 1.39 | 0.223 | 13.9% | 1.33 |

### Comparison of 2015 and 2014 Ex Ante Estimates

Table 7-9 shows the comparisons between the ex ante estimates in the current evaluation and those reported in the previous evaluation for the forecast year 2017. The current *ex ante* estimates are lower for the PTR-only group – the current estimates are 0.04 kW for a 1-in-2 event day and 0.05 kW for a 1-in-10 event day, while the previous estimates were 0.07 kW and 0.09 kW, respectively. The percentage load reductions are also lower, from approximately 6% in the previous analysis to approximately 4% in the current analysis for a 1-in-10 year. This may be largely due to the lower modeled impacts for the PTR events in the current evaluation cycle. Two out of the four events this year were called on a Friday, which generally shows smaller impacts than other weekday events. In addition, one of these Friday events was the third consecutive event day, which may also lend itself to customer fatigue and therefore less load shedding or shifting.

The estimates for the group dually enrolled in Summer Saver are not entirely comparable because the current evaluation focused on quantifying the incremental impact of the PTR program for those dually enrolled in Summer Saver over and above those enrolled in Summer Saver alone. This ensures that there is no double counting of the Summer Saver impacts as they are covered by a separate evaluation. Subsequent evaluations will use this incremental approach, which will allow for a more meaningful comparison of PTR ex ante estimates.

The estimates for the SCTD participants in the current analysis are similar to the previous analysis, but slightly lower in absolute terms. For the dually enrolled participants, the previous analysis found estimates of 0.43 kW on 1-in-2 event days and 0.60 kW on 1-in-10 event days. The current analysis projects 0.36 kW on 1-in-2 event days and 0.51 kW on 1-in-10 event days. The percentage load reduction estimates under the current analysis are higher. For example, in the 1-in-2 year, the previous results had load reductions of 21.3%, while the current estimates are 23.4%. For the SCTD-only participants, the current forecasts are lower in both absolute and percentage terms. The previous analysis found estimates of 0.34 kW (15.8%) on 1-in-2 event days and 0.46 kW (17.1%) on 1-in-10 event days. The current analysis projects 0.22 kW (13.7%) on 1-in-2 event days and 0.30 kW (14.9%) on 1-in-10 event days.

Table 7‑9: Comparison of 2015 and 2014 Ex Ante Estimates – Forecast Year 2017

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Participant Segment** | **Weather Year** | **Day / Type** | **Current** | | | | **Previous** | | | |
| **Average Hourly Reference Load** | **Average Hourly Observed Load** | **Average Hourly Impact** | **Percent Load Reduction** | **Average Hourly Reference Load** | **Average Hourly Observed Load** | **Average Hourly Impact** | **Percent Load Reduction** |
| **PTR Only** | **1-in-10** | **Monthly System Peak Day** | 1.43 | 1.38 | 0.05 | 3.8% | 1.59 | 1.50 | 0.09 | 5.8% |
| **Typical Event Day** | 1.42 | 1.36 | 0.05 | 3.8% | 1.57 | 1.48 | 0.09 | 5.8% |
| **1-in-2** | **Monthly System Peak Day** | 1.20 | 1.16 | 0.04 | 3.4% | 1.39 | 1.32 | 0.07 | 5.0% |
| **Typical Event Day** | 1.17 | 1.13 | 0.04 | 3.3% | 1.37 | 1.30 | 0.07 | 4.8% |
| **PTR/SS** | **1-in-10** | **Monthly System Peak Day** | 1.77 | 1.54 | 0.23 | 13.1% | 2.31 | 1.66 | 0.66 | 28.4% |
| **Typical Event Day** | 1.79 | 1.55 | 0.23 | 13.1% | 2.30 | 1.65 | 0.64 | 28.0% |
| **1-in-2** | **Monthly System Peak Day** | 1.42 | 1.26 | 0.17 | 11.7% | 1.94 | 1.47 | 0.48 | 24.5% |
| **Typical Event Day** | 1.41 | 1.24 | 0.16 | 11.7% | 1.91 | 1.44 | 0.47 | 24.4% |
| **PTR/SCTD** | **1-in-10** | **Monthly System Peak Day** | 2.02 | 1.51 | 0.51 | 25.2% | 2.64 | 2.03 | 0.61 | 23.1% |
| **Typical Event Day** | 2.02 | 1.51 | 0.51 | 25.3% | 2.62 | 2.01 | 0.60 | 23.1% |
| **1-in-2** | **Monthly System Peak Day** | 1.59 | 1.21 | 0.38 | 23.6% | 2.09 | 1.64 | 0.45 | 21.5% |
| **Typical Event Day** | 1.55 | 1.19 | 0.36 | 23.4% | 2.04 | 1.60 | 0.43 | 21.3% |
| **SCTD Only** | **1-in-10** | **Monthly System Peak Day** | 2.05 | 1.74 | 0.30 | 14.8% | 2.74 | 2.27 | 0.47 | 17.2% |
| **Typical Event Day** | 2.04 | 1.74 | 0.30 | 14.9% | 2.72 | 2.25 | 0.46 | 17.1% |
| **1-in-2** | **Monthly System Peak Day** | 1.61 | 1.39 | 0.22 | 13.9% | 2.19 | 1.84 | 0.35 | 15.8% |
| **Typical Event Day** | 1.58 | 1.36 | 0.22 | 13.7% | 2.13 | 1.79 | 0.34 | 15.8% |

## Relationship between Ex Post and Ex Ante Estimates

Table 7-10 shows comparisons between the *ex ante* and *ex post* estimates from this evaluation. For all of the groups, and similar to the previous evaluation, it seems that the weather in 2015 was particularly hot, and thus the results are more aligned with 1-in-10 weather conditions.

For the overall PTR-only group, the *ex post* results show an average event hour load reduction of 0.06 kW, while the 1-in-10 *ex ante* estimates show average event hour load reductions of 0.05 kW, both around 4% of the reference load. The predicted 1-in-10 average event hour load reductions for the overall PTR-Summer Saver dually enrolled group (0.27 kW, or 13.8%) are very similar, but slightly higher than the *ex post* impacts (0.23 kW, or 13.1%). The same relationship exists for the 50% and 100% cycling sub-groups. For the dually enrolled PTR-SCTD group, the *ex post* and 1-in-10 *ex ante* estimates are essentially identical, at 0.52 and 0.51 kW, respectively. These represent approximately 22% and 25% of the reference load. The estimates for the load control sub-groups are also similar. The 4 degree setback group’s 1-in-10 *ex ante* estimate 0.01 kW lower than the *ex post* estimate, while the 50% cycling group’s is the same. As with the other groups, the SCTD-only *ex post* estimates are similar to the 1-in-10 *ex ante* estimates. The overall event hour load reduction estimate is 0.28 kW (11.9%) for the *ex post* and 0.30 kW (14.9%) for the 1-in-10 *ex ante*. The 50% cycling sub-group has lower *ex post* estimates, with averages of 0.20 kW (8.9%) for *ex post* and 0.24 (12.1%) for the 1-in-10 *ex ante* estimate. The 4 degree setback has *ex post* estimate of 0.34 kW, compared to the *ex ante* average of 0.35 for the 1-in-10 typical event day.

Table 7‑10: Comparison of Ex Ante and Ex Post Estimates

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Participant Segment** | **Control Strategy** | **Weather Year** | **Day / Type** | **Average Hourly Reference Load** | **Average Hourly Observed Load** | **Average Hourly Impact** | **Percent Load Reduction** | **Average °F** |
| **PTR Only** |  | **1-In-10** | **Monthly System Peak Day** | 1.43 | 1.38 | 0.05 | 3.8% | 86.97 |
| **Typical Event Day** | 1.42 | 1.36 | 0.05 | 3.8% | 86.59 |
| **1-In-2** | **Monthly System Peak Day** | 1.20 | 1.16 | 0.04 | 3.4% | 81.37 |
| **Typical Event Day** | 1.17 | 1.13 | 0.04 | 3.3% | 80.59 |
| **Ex Post** | **Ex Post Average Event Day** | 1.59 | 1.52 | 0.06 | 4.0% | 90.94 |
| **PTR/SS** | **100** | **1-In-10** | **Monthly System Peak Day** | 1.63 | 1.31 | 0.32 | 19.7% | 89.01 |
| **Typical Event Day** | 1.64 | 1.32 | 0.32 | 19.6% | 89.18 |
| **1-In-2** | **Monthly System Peak Day** | 1.33 | 1.10 | 0.23 | 17.5% | 82.45 |
| **Typical Event Day** | 1.31 | 1.08 | 0.23 | 17.4% | 82.05 |
| **Ex Post** | **Ex Post Average Event Day** | 1.80 | 1.42 | 0.37 | 20.9% | 93.06 |
| **50** | **1-In-10** | **Monthly System Peak Day** | 2.01 | 1.95 | 0.06 | 2.8% | 90.10 |
| **Typical Event Day** | 2.04 | 1.98 | 0.06 | 3.0% | 90.57 |
| **1-In-2** | **Monthly System Peak Day** | 1.58 | 1.54 | 0.04 | 2.7% | 83.03 |
| **Typical Event Day** | 1.57 | 1.53 | 0.04 | 2.6% | 82.83 |
| **Ex Post** | **Ex Post Average Event Day** | 2.20 | 2.14 | 0.07 | 3.0% | 93.80 |
| **ALL** | **1-In-10** | **Monthly System Peak Day** | 1.77 | 1.54 | 0.23 | 13.1% | 89.40 |
| **Typical Event Day** | 1.79 | 1.55 | 0.23 | 13.1% | 89.69 |
| **1-In-2** | **Monthly System Peak Day** | 1.42 | 1.26 | 0.17 | 11.7% | 82.66 |
| **Typical Event Day** | 1.41 | 1.24 | 0.16 | 11.7% | 82.33 |
| **Ex Post** | **Ex Post Average Event Day** | 1.95 | 1.68 | 0.27 | 13.8% | 93.33 |
| **PTR/SCTD** | **4 Degree Setback** | **1-In-10** | **Monthly System Peak Day** | 2.07 | 1.50 | 0.57 | 27.4% | 88.27 |
| **Typical Event Day** | 2.06 | 1.50 | 0.57 | 27.5% | 88.24 |
| **1-In-2** | **Monthly System Peak Day** | 1.62 | 1.21 | 0.42 | 25.7% | 82.06 |
| **Typical Event Day** | 1.59 | 1.18 | 0.40 | 25.4% | 81.52 |
| **Ex Post** | **Ex Post Average Event Day** | 2.40 | 1.82 | 0.58 | 24.0% | 92.34 |
| **50% Cycle** | **1-In-10** | **Monthly System Peak Day** | 1.97 | 1.53 | 0.44 | 22.1% | 88.35 |

Table 7-10: (Cont’d) Comparison of Ex Ante and Ex Post Estimates

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Participant Segment** | **Control Strategy** | **Weather Year** | **Day / Type** | **Average Hourly Reference Load** | **Average Hourly Observed Load** | **Average Hourly Impact** | **Percent Load Reduction** | **Average °F** |
| **PTR/SCTD** |  |  | **Typical Event Day** | 1.96 | 1.53 | 0.44 | 22.2% | 88.35 |
| **1-In-2** | **Monthly System Peak Day** | 1.54 | 1.22 | 0.32 | 20.7% | 82.10 |
| **Typical Event Day** | 1.51 | 1.20 | 0.31 | 20.5% | 81.58 |
| **Ex Post** | **Ex Post Average Event Day** | 2.29 | 1.85 | 0.44 | 19.2% | 92.49 |
| **ALL** | **1-In-10** | **Monthly System Peak Day** | 2.02 | 1.51 | 0.51 | 25.2% | 88.30 |
| **Typical Event Day** | 2.02 | 1.51 | 0.51 | 25.3% | 88.28 |
| **1-In-2** | **Monthly System Peak Day** | 1.59 | 1.21 | 0.38 | 23.6% | 82.07 |
| **Typical Event Day** | 1.55 | 1.19 | 0.36 | 23.4% | 81.54 |
| **Ex Post** | **Ex Post Average Event Day** | 2.35 | 1.83 | 0.52 | 22.0% | 92.40 |
| **SCTD Only** | **4 Degree Setback** | **1-In-10** | **Monthly System Peak Day** | 2.09 | 1.74 | 0.35 | 16.9% | 88.39 |
| **Typical Event Day** | 2.09 | 1.73 | 0.35 | 17.0% | 88.39 |
| **1-In-2** | **Monthly System Peak Day** | 1.65 | 1.39 | 0.26 | 15.8% | 82.12 |
| **Typical Event Day** | 1.62 | 1.36 | 0.25 | 15.6% | 81.60 |
| **Ex Post** | **Ex Post Average Event Day** | 2.42 | 2.08 | 0.34 | 14.0% | 92.38 |
| **50% Cycle** | **1-In-10** | **Monthly System Peak Day** | 1.98 | 1.75 | 0.24 | 12.0% | 88.41 |
| **Typical Event Day** | 1.98 | 1.74 | 0.24 | 12.1% | 88.43 |
| **1-In-2** | **Monthly System Peak Day** | 1.56 | 1.39 | 0.18 | 11.2% | 82.13 |
| **Typical Event Day** | 1.53 | 1.36 | 0.17 | 11.1% | 81.62 |
| **Ex Post** | **Ex Post Average Event Day** | 2.29 | 2.08 | 0.20 | 8.9% | 92.27 |
| **ALL** | **1-In-10** | **Monthly System Peak Day** | 2.05 | 1.74 | 0.30 | 14.8% | 88.40 |
| **Typical Event Day** | 2.04 | 1.74 | 0.30 | 14.9% | 88.42 |
| **1-In-2** | **Monthly System Peak Day** | 1.61 | 1.39 | 0.22 | 13.9% | 82.13 |
| **Typical Event Day** | 1.58 | 1.36 | 0.22 | 13.7% | 81.62 |
| **Ex Post** | **Ex Post Average Event Day** | 2.36 | 2.08 | 0.28 | 11.9% | 92.34 |

# Permanent Load Shifting

## PLS Program Overview

The PLS program provides a one-time incentive payment ($875/kW) to customers who install qualifying PLS technology on chilled water cooling units (which differ substantially from typical central air conditioning units). Incentives will be determined based on the designed peak load shift capability of the system and the installation must undergo a feasibility study by a qualified engineer. The load shift is typically accomplished completely through substituting overnight chiller load for daytime chiller load. All customers are eligible for the program, including residential, commercial, industrial, agricultural, direct access and Community Choice Aggregation customers.

In order to qualify for the PLS program incentive payment, customers must go through the program application and verification process, which includes all of the stages that are required for customers to apply for, and receive a verified incentive amount. These stages are:

1. Customer submits application
2. IOU approves application and sets aside incentive funds
3. Customer submits feasibility study
4. IOU reviews feasibility study
5. IOU conducts pre-installation inspection
6. IOU and customer sign agreement
7. Customer installs PLS system
8. IOU conducts post-installation inspection
9. Customer receives PLS program incentive

After a customer submits an application and the utility approves the application, customers participating in the program must provide, in advance of installation, an engineering feasibility study. This study will include an estimated cooling profile. Energy models will be used to determine a customer's cooling load profile over a year (8,760 hours). To accomplish this, building simulation models will be used to determine hourly cooling needs over the course of a year, based on building specifications, regional temperatures, occupancy and other inputs. Both retrofit and new construction customers will be subjected to the energy modeling process, unless utility approved cooling usage data is available.

The total incentive amount will be determined using a customer’s peak load shift on their maximum cooling demand day (based on the on-peak hours). A conversion factor will be used to convert the cooling load shift tons to electricity load shift (kW). This methodology will be used for both full and partial storage systems. The incentive levels for the program are $875/kW for all IOUs.

The incentive payments are intended to offset the cost of installation and thereby make the system more attractive financially. Under the program rules, the incentive cannot exceed 50% of the installation cost for a given customer, and the incentive for a given site cannot exceed $1.5M. Customers’ incentives will be determined as the least of (1) the incentive reservation amount calculated from the system design, (2) 50% of the actual final installed project cost or (3) $1.5M. In addition, customers will be required to be on a time-of-use (TOU) rate for the first five years after installation.

Customers are required to run the PLS system during all weekday peak periods during summer months (May1 –October 31) from 11am through 6pm. PLS program participants may also shift load during non-summer months, in case cooling is needed during those months. For process cooling installations, cooling may be needed year round.

## PLS Ex-Ante Evaluation Methodology

The PLS program evaluation used two different methodologies for estimating ex-ante load impacts for unidentified projects and identified projects.

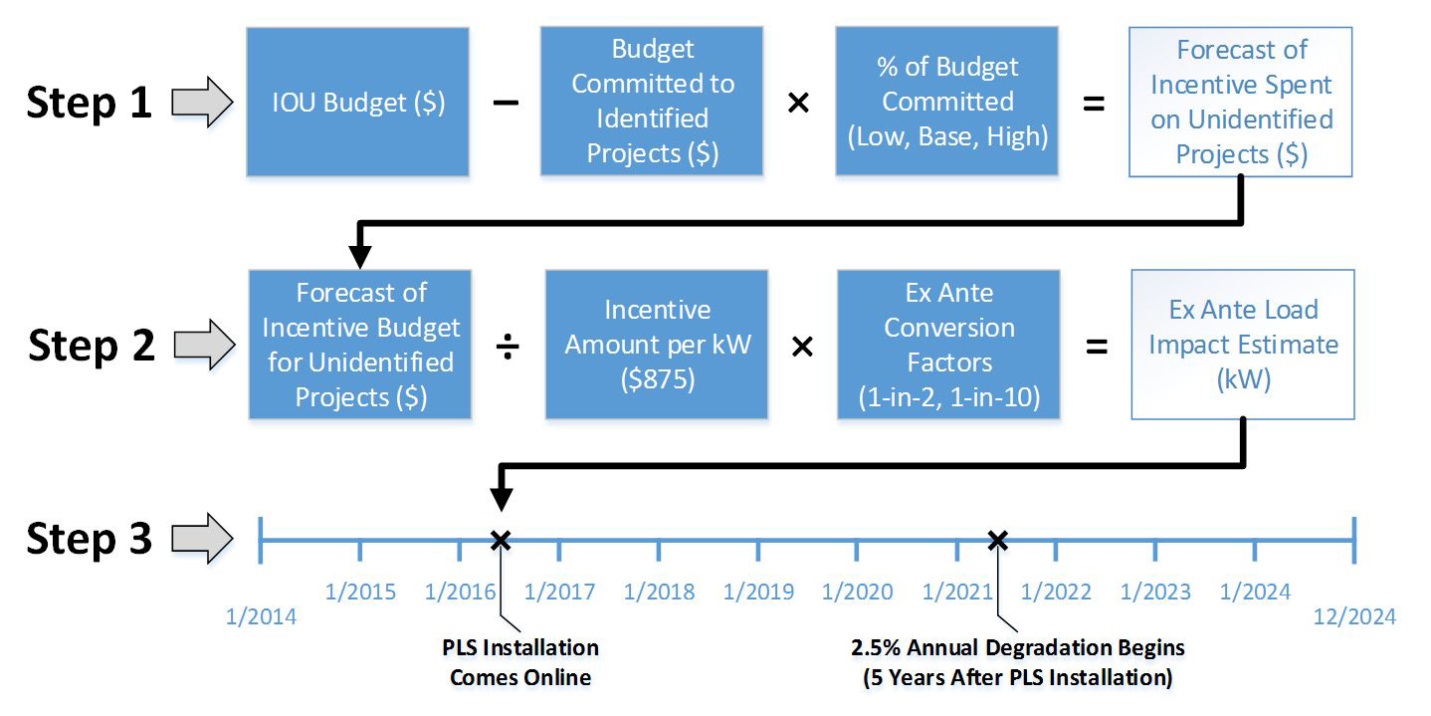
*Unidentified projects:* In addition to customers who have already submitted application it is expected that new customer will apply as well (unidentified projects). Load impacts for unidentified projects are based on assumptions developed with the utility PLS program managers and EM&V staff. The main uncertainty is the number and size of projects that will be included in the program, a range of scenarios was generated for each IOU in order to capture the uncertainty related to market adoption of PLS technologies.

Figure 8-1 summarizes the methodology for estimating ex-ante load impacts for unidentified PLS projects. The three steps for estimating ex-ante load impacts for unidentified projects are:

* **Step 1** involves forecasting the available amount of incentive dollars that will be spent on unidentified projects for each IOU. The first key input for this calculation was the total PLS incentive budget for each IOU. The budget that has been awarded to operational projects or committed to identified projects was subtracted from the total incentive budget amount. Then, the remaining budget for unidentified projects was multiplied by the percentage of each IOU’s budget that will be committed to projects by the end of 2016, under the low, base case and high scenarios. This produced the forecast of incentives available to be spent on unidentified projects.
* **Step 2** converts the incentive dollar forecast into the ex ante load impact estimates. To do this, the forecast of incentive dollars spent on unidentified projects was divided by the incentive amount per kW load shift ($875/kW). This kW load shift amount represents the peak load shift that can be expected under hot, maximum cooling load, weather conditions. The kW load shift was multiplied by the ex ante conversion factors, which converted the load shift under the incentive payment, maximum cooling load and weather conditions to the ex ante load impact estimates for monthly system peak days and average weekdays under 1-in-2 year and 1-in-10 year weather conditions (as per the California DR Load Impact Protocols). The conversion factors were re-estimated for the PY2014 evaluation based on updated building simulation models and newly developed 1-in-2 and 1-in-10 year weather data that addressed the new requirement for reporting results for the CAISO system peak in addition to the IOU system peak.

**Step 3** forecasts when each PLS-TES installation is expected to come online based on slightly different assumptions for each utility (described below). The time between when an application is received and when the installation and verification are completed varies from 8 to 24 months, so projects are not expected to come online until 2016 or later. Over time, the load shifting capacity of the PLS-TES technologies is expected to degrade as the system ages. The forecasts assume that five years after each forecasted PLS-TES installation, the ex ante impacts begin to degrade at a rate of 2.5% per year. This assumption was made in consultation with program managers and it is consistent with last year’s evaluation.

Figure 8-1: Methodology for Estimating Ex-ante Load Impacts of Unidentified PLS Projects



The ex-ante conversion factors were used to convert the load shift under the incentive payment, maximum cooling load and weather conditions to the load shift that can be expected under the various ex-ante temperature scenarios. The ex-ante temperature scenarios include the monthly system peak days and average weekdays under 1-in-2 year and 1-in-10 year weather conditions for the utility specific and CAISO peak. Essentially, the conversion factors facilitate the estimation of the PLS-TES load impacts under a variety of different weather conditions with ease and efficiency. The analysis shows that relative usage values across different weather conditions are basically insensitive to building characteristics, and the ratio for a given ex-ante condition hardly changes as the building characteristics vary substantially. This relationship is a critical factor in the evaluation, and the current conversion factor approach would need to be modified if this weren’t the case.

It is important to note that these conversion factors were developed with building simulation models of space cooling installations. Some of the applications that have been received thus far also include process cooling installations, which have load profiles that frequently differ from the typical space cooling profile. Unfortunately, the process cooling installations do not make good candidates for generalized modeling because they are highly customized by industry and location; in addition, while space cooling loads exhibit significant seasonality due to temperature variation, process cooling loads may vary seasonally by temperature and changes in the underlying production process. The weather sensitivity of the currently modeled process cooling applications was analyzed, and the range of sensitivity in terms of the percentage difference in cooling load between 1-in-2 and 1-in-10 monthly peak days exhibit similar upper and lower limits to commercial AC cycling programs. For the sake of simplicity, lack of generalizability of the process cooling installations and similarity in weather sensitivity ranges, space cooling building simulation models were used to develop the conversion factors for both space cooling and process cooling installations.

The forecast of incentive dollars spent on unidentified projects was used to estimate PLS program enrollment, which is defined as the number of PLS-TES installations that have come online. Before a project comes online, customers must go through the application and verification process, during which some customers may drop off. Therefore, customers are not defined as enrolled until their PLS-TES installation has come online. Nonetheless, for each IOU, the applications that have been received were used to inform assumptions about the following:

* Peak load shift of typical unidentified projects;
* Number of projects of each size; and

Expected project installation and verification timeline (the time between when an application is received and when the installation and verification are completed).

These assumptions are IOU-specific and were informed by the current applications for identified projects. The PY2015 evaluation refined these assumptions based on the most recent information on budget, program enrollment, the current status of identified projects and the recently revised and adopted Statewide PLS Program Handbook (June 2015).

Finally, because local weather conditions influence the load shift that is actually experienced, the ex-ante load impacts are dependent on the specific geographic region in which an installation is located. As such, it was necessary to allocate the unidentified projects to LCAs within each utility’s service area. SDG&E has only a single LCA, so no population weighting was necessary. Considering that the utilities have received applications from customers that are located in LCAs that are not usually associated with having high cooling load, the expectation regarding where these PLS-TES installations will be located is unclear. Essentially, with process cooling being eligible for PLS program incentives, the program is viable in many different climates, as the current applications have shown.

*Identified projects:* Identified projects include those for which customers have completed an application or a feasibility study. Applications are submitted by potential PLS participants to initiate their enrollment in the program. Each application includes an initial estimate of the proposed PLS-TES installation’s load shifting capacity. SDG&E decided to use building simulation modeling, the ex-ante conversion factors were used to convert the expected load shift from the application/feasibility study to ex-ante weather conditions. This methodology is nearly identical to Step 2 and Step 3 in the methodology used for unidentified projects discussed in Section 8.2, except that the incentive amount was taken from the latest available information for that project (the application or feasibility study). In addition, considering that the location and installation date were provided in the application for identified projects, the forecast for SDG&E identified projects incorporates this information by having the project come online on the expected installation date and by assigning the ex-ante load impacts for that project to the customer’s LCA.

## Estimating Ex-Ante Weather Conditions

Table 8-1 shows the values for each weather scenario, weather year and month for a variable equal to the average temperature from midnight to 5 PM (referred to as mean17) for each day type.

Table 8-1:  SDG&E Enrollment Weighted Ex-Ante Weather Values (mean17)

| Day Type | | SDG&E Based Weather | | CAISO Based Weather | |
| --- | --- | --- | --- | --- | --- |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| **Typical Event Day** | | **72.5** | **77.3** | **73.1** | **75.8** |
| **Peak Day** | 67.6 | 75.8 | 64.4 | 72.7 | 72.7 |
| 68.1 | 73.1 | 68.7 | 72.9 | 72.9 |
| 71.8 | 77.8 | 71.5 | 73.5 | 73.5 |
| 74.9 | 78.5 | 75.9 | 76.4 | 76.4 |
| 75.0 | 80.0 | 76.2 | 80.5 | 80.5 |
| 70.8 | 75.9 | 68.3 | 74.7 | 74.7 |
| **Average Weekday** | 62.3 | 66.2 | 63.0 | 62.3 | 62.3 |
| 65.2 | 69.3 | 64.1 | 67.2 | 67.2 |
| 68.7 | 70.4 | 69.3 | 69.2 | 69.2 |
| 70.0 | 72.8 | 70.0 | 73.7 | 73.7 |
| 68.1 | 71.4 | 69.6 | 71.4 | 71.4 |
| 65.2 | 67.7 | 65.4 | 67.7 | 67.7 |

## PLS Ex-Ante Load Impact Estimates

Table 8-2 provides the ex ante load impact estimates for 2016–2026 monthly system peak days in May through October for SDG&E-specific and CAISO 1-in-2 and 1-in-10 year weather conditions for the base scenario. SDG&E’s service territory only has one LCA so the results are not divided geographically. In the base scenario, six SDG&E identified projects come online in 2016 and two additional unidentified project comes online in 2017 to reach the steady state enrollment under the current budget scenario at eight installations producing 4.3 MW of load reduction in 2018. Table 8-2 also shows the expected trajectory of load impacts through 2026. As a result of the assumed 2.5% annual degradation in load impacts after year five of each installation, the aggregate load reduction under August 1-in-10 weather conditions decreases from around 4.3 MW in 2018 to 3.7 MW in 2026.

The difference between utility specific and CAISO peaks tend to vary by month. Impacts range from the CAISO-specific, September 1-in-2 monthly peak day in 2018 being 17% greater than the utility specific comparable peak at 3.5 MW and 4.2 MW respectively; to the utility specific July 1-in-10 monthly peak day in 2018 being 24% greater than the CAISO specific comparable peak at 4.3 MW and 3.5 MW respectively. Year over year, the difference between the utility specific peak and the CAISO peak appears to remain fairly constant. For example, the utility specific August 1-in-10 monthly peak load impact is typically around 4% higher than the comparable CAISO specific impact.

Table 8‑2: SDG&E Ex Ante Load Impact Estimates (1 to 6 PM)   
on Monthly Peak Days for May-October 2016-2026 (kW) – Base Scenario

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Peak Type** | **Forecast Year** | **May** | | **June** | | **July** | | **August** | | **September** | | **October** | |
| **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** |
| Utility Specific | 2016 | 909 | 1,037 | 1,408 | 1,523 | 1,402 | 1,784 | 1,772 | 1,960 | 1,684 | 2,092 | 1,795 | 1,832 |
| 2017 | 3,116 | 3,554 | 3,237 | 3,503 | 3,225 | 4,103 | 3,542 | 3,918 | 3,367 | 4,181 | 3,588 | 3,662 |
| 2018 | 3,251 | 3,707 | 3,377 | 3,654 | 3,364 | 4,280 | 3,695 | 4,087 | 3,512 | 4,362 | 3,742 | 3,820 |
| 2019 | 3,251 | 3,707 | 3,377 | 3,654 | 3,364 | 4,280 | 3,695 | 4,087 | 3,512 | 4,362 | 3,742 | 3,820 |
| 2020 | 3,251 | 3,707 | 3,377 | 3,654 | 3,364 | 4,280 | 3,695 | 4,087 | 3,512 | 4,362 | 3,742 | 3,820 |
| 2021 | 3,173 | 3,618 | 3,296 | 3,566 | 3,284 | 4,176 | 3,606 | 3,989 | 3,428 | 4,257 | 3,653 | 3,728 |
| 2022 | 3,093 | 3,527 | 3,213 | 3,477 | 3,203 | 4,071 | 3,515 | 3,889 | 3,343 | 4,149 | 3,562 | 3,635 |
| 2023 | 3,016 | 3,439 | 3,133 | 3,390 | 3,124 | 3,968 | 3,426 | 3,791 | 3,259 | 4,045 | 3,473 | 3,544 |
| 2024 | 2,941 | 3,353 | 3,054 | 3,305 | 3,046 | 3,868 | 3,340 | 3,696 | 3,178 | 3,942 | 3,387 | 3,456 |
| 2025 | 2,867 | 3,269 | 2,978 | 3,223 | 2,971 | 3,770 | 3,256 | 3,604 | 3,098 | 3,843 | 3,303 | 3,370 |
| 2026 | 2,795 | 3,187 | 2,903 | 3,142 | 2,897 | 3,674 | 3,174 | 3,514 | 3,021 | 3,746 | 3,220 | 3,286 |
| CAISO Specific | 2016 | 796 | 1,079 | 1,319 | 1,551 | 1,506 | 1,441 | 1,813 | 1,889 | 2,026 | 2,066 | 1,629 | 1,828 |
| 2017 | 2,729 | 3,699 | 3,033 | 3,568 | 3,464 | 3,314 | 3,624 | 3,777 | 4,051 | 4,130 | 3,257 | 3,653 |
| 2018 | 2,847 | 3,858 | 3,164 | 3,722 | 3,614 | 3,457 | 3,780 | 3,940 | 4,225 | 4,309 | 3,397 | 3,811 |
| 2019 | 2,847 | 3,858 | 3,164 | 3,722 | 3,614 | 3,457 | 3,780 | 3,940 | 4,225 | 4,309 | 3,397 | 3,811 |
| 2020 | 2,847 | 3,858 | 3,164 | 3,722 | 3,614 | 3,457 | 3,780 | 3,940 | 4,225 | 4,309 | 3,397 | 3,811 |
| 2021 | 2,779 | 3,766 | 3,088 | 3,632 | 3,528 | 3,375 | 3,690 | 3,845 | 4,123 | 4,203 | 3,317 | 3,719 |
| 2022 | 2,709 | 3,671 | 3,011 | 3,541 | 3,440 | 3,291 | 3,597 | 3,748 | 4,019 | 4,096 | 3,234 | 3,625 |
| 2023 | 2,641 | 3,580 | 2,936 | 3,452 | 3,355 | 3,209 | 3,507 | 3,654 | 3,918 | 3,992 | 3,154 | 3,533 |
| 2024 | 2,574 | 3,490 | 2,863 | 3,366 | 3,272 | 3,129 | 3,420 | 3,563 | 3,819 | 3,890 | 3,076 | 3,444 |
| 2025 | 2,510 | 3,403 | 2,791 | 3,281 | 3,191 | 3,051 | 3,334 | 3,473 | 3,723 | 3,790 | 2,999 | 3,357 |
| 2026 | 2,446 | 3,318 | 2,722 | 3,199 | 3,112 | 2,975 | 3,251 | 3,386 | 3,629 | 3,693 | 2,925 | 3,272 |

# SPP Rates

## Small Commercial SPP Rates Overview

This section documents the program year 2015 (PY 2015) load impacts for San Diego Gas and Electric’s (SDG&E) time varying pricing tariffs for small commercial and agricultural customers, including:

* Time-of-use for small commercial customers (TOU-A);
* Time-of-use with a critical peak pricing component for small commercial customers (TOU-A-P);
* Time-of-use for agricultural customers (TOU-PA); and

Critical peak pricing for agricultural customers (TOU-PA-P).

Collectively these rates are referred to as time varying rates. With TOU rates (TOU-A, TOU-PA), prices vary according to a preset schedule by season, weekday/weekend and hour of day. With TOU-CPP rates (TOU-A-P and TOU-PA-P), prices also vary according to a preset schedule but customers also face much larger price signals during critical periods, or events, and in exchange get a discount during all other hours. Customers are notified of critical peak events a day in advance.

Prior to the full-scale implementation of time-varying rates to all non-residential customers, SDG&E offered versions of the SPP rates to a subset of small commercial customers beginning in the summer of 2014. Marketing of SPP rates to small commercial customers was not random, but rather targeted customers who were most likely to benefit from being on one of the two SPP rates and customers with account representatives. Given this marketing strategy, the subset of customers who enrolled on the rates consisted of structural winners who self-selected and are not representative of the entire SDG&E small commercial customer population. This lack of customer diversity further limits the representativeness of the sample to the broader SDG&E population.

## Residential SPP Rates Overview

SDG&E current has a voluntary residential CPP rate (TOU-DR-P) and a new voluntary residential TOU rate (TOU-DR). SDG&E is not providing an ex-ante forecast for these rates at this time due to the large amount of uncertainty due to SDG&E pending GRC phase II application filed in December of 2016. In the GRC phase II application SDG&E proposed to change the on-peak time of use period for all customer classes from 11 a.m.-6p.m. to 4 p.m. – 9p.m and a residential opt-in TOU pilot is currently underway to evaluate what type of load impacts TOU customers provide at this time of day. In addition SDG&E proposed to terminate its PTR program in its GRC phase II filing and to transition PTR customer to the new TOU-DR-P rate available so providing a forecast for both PTR and TOU-DR-P might overstate the results.

## SDG&E’s Implementation of Time Varying Rates

Before all customers can transition over to time varying rates in the fall of 2015, SDG&E made the rates available to a selected group of small commercial customers on an opt-in basis before the summer of 2014. Customer eligibility for the opt-in rates was determined based on billing analysis and marketing focused on a group of customers who had account representatives and/or were expected to save money compared to their current flat rate.[[21]](#footnote-21) Of the customers who were marketed to, approximately 2,600 enrolled in either the TOU or TOU-CPP rate by the end of 2015, with a roughly even split between the two rates.

This report contains an impact analysis of the new rates on these self-selected customers, including impact estimates for summer weekdays when the TOU rate was in effect as well as the four CPP events that were called during the summer (August 28th, and September 9th, 10th and 11th). Customers enrolled in time varying prices during the summer of 2015 were not representative of the broader small commercial and agricultural population. However, this early, voluntary phase was useful for testing enrollment, dispatch, and communication mechanisms, helping identify improvements and refinements for the much larger implementation of default time varying rates.

Starting in November 2015, all small commercial accounts are transitioning over a six month period to a default CPP rate with an underlying TOU structure (TOU-CPP). Customers can opt-out to a TOU rate without a critical peak pricing component (TOU-A). Starting in 2016, flat rates will no longer be available for small commercial and agricultural customers.

Table 9-1 summarizes these enrollment policies and the dates of availability for each customer class. The transition from flat to time varying prices along with the accompanying communications to educate customers about when and how to reduce or shift electricity is considered the primary intervention (or treatment).

**Table 9-1: SPP Rates and Availability**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Customer Segment | Rate | Enrollment Policy | | **Current Enrollment** |
| **February 1, 2014** | **November 2015** |
| Small Commercial\* | TOU | Opt in from non-time-varying rate | Default | 1,141 |
| TOU-CPP | May opt out of TOU-CPP and on to TOU | 1,468 |

\*Note: Starting in November 2015, flat rates will no longer be available for small commercial and agricultural customers.

## Small Commercial SPP Ex-Post Evaluation Design and Methodology

To estimate the impacts of SPP on the voluntary opt-in subset of customers who enrolled in TOU and TOU-CPP rates, an applicable control group was first selected from customers who remained on flat rate tariffs via statistical matching. Second, in order to remove any preexisting differences between the matched control group, impacts will be estimated using a difference-in-differences methodology. This section provides a detailed description of each of these two steps.

### Statistical Matching

The matched control is developed prior to difference-in-differences calculation. It helps ensure the control group is as similar as possible to the group on time varying rates, minimizes the role of the correction for pre-existing differences, and improves the accuracy of the results. By definition, customers who self-select into a program are different than the general population. Propensity score matching explicitly models selection and helps identify a control group that behaved like the participant group when both sets of customers were on flat rates. The main difference is that one group transitioned to time varying rates while the other group remained on flat rates. The control group will be selected by testing different propensity models using out-of-sample testing. The propensity models selected will the one that minimizes the differences in hourly loads (8760) between the treatment and control group during the pre-treatment period.

### Difference in Differences

After identifying matched control groups for each treatment cohort (TOU and TOU-CPP), impact estimates were obtained using difference-in-differences. This approach uses comparisons of the control and treatment groups both before and after implementation of the rate to identify the load impacts.

Using difference-in-differences means that the matched control group does not need to perfectly match the treatment group in the pre-treatment period. This is because any differences that may be due to unobservable factors that could not be included in the matching model will be netted out by the differencing. This feature, however, is not a cure-all and therefore it is still desirable for pre-treatment consumption for the treatment and matched control groups to be as similar as possible.

Difference-in-differences estimation can be implemented using either simple means or a panel regression with fixed effects and time effects. For robustness, both methods were used in this evaluation, but the estimates from the regression model are reported due to their increased precision. The increased precision is achieved by including variables that explain energy use, such as temperature and day-of-week effects, which filter background noise (variation) and allow the signal (the response to TOU rates) to be more easily detected. Separate regression equations were estimated for each hour to produce load impact estimates for all hours of the day. The dependent variable in the regression equation is hourly electricity use and only non-holiday weekdays were included in the analysis. The full panel model specification is presented as Equation 1:

| Variable | Definition |
| --- | --- |
| *i, t* | Indicate observations for each individual (i) and date (t). |
|  | The model constant. |
|  | The change in electricity use due to the treatment. This change is only experienced by the treatment group after TOU is implemented. The parameter represents the difference-in-differences. |
|  | The difference pre and post TOU implementation period unrelated to treatment. |
|  | Change in electricity use due to weather (Avg. temperature during first 17 hours of  the day). |
|  | Change in electricity use due to month. |
|  | Customer fixed effects, which control for unobserved factors that are time invariant and unique to each customer. They do not control for fixed characteristics such as air conditioning that interact with time varying factors like weather. |
|  | The idiosyncratic (white-noise) error for each individual customer and time period. |
|  | A binary indicator of whether or not the customer is part of the treatment or control group. |
|  | A binary indicator of whether the time period occurs before (0) or after (1) implementation of TOU. |
|  | Average temperature during first 17 hours of the day. |
|  | Set of dummy variables for each summer month. |

## Small Commercial SPP Rates Ex-Post Load Impact Estimates

This section present the results of the ex-post impact evaluation for each SPP (TOU/TOU-CPP) rate along with their interpretations.

### TOU Results

Estimated ex-post impacts that were not statistically significant for the TOU rate.

## TOU-CPP Results

Due to the nature of the TOU-CPP rate, there are two separate analyses to be considered: one for non-event weekdays and a second for event days. The non-event day analysis is identical to the TOU analysis since TOU and TOU-CPP rates are equivalent on those days. For event days, several modifications to the analysis must be made. The simplest of these is that the post-treatment days of interest for the TOU-CPP rate are each of the four CPP event days called during the summer of 2015 (August 28th, September 9th, 10th and 11th). Because CPP events are typically called on days that are particularly hot, it is also important to identify “event-like” days in the pre-treatment period and remove all other days in the pre-treatment period from the analysis dataset. These proxy days were chosen from the pre-treatment period weekdays that had both high system load and high average temperature.

Results for the TOU-CPP customers on CPP days was significant for the event hours on average, however individual days failed to meet significance criteria. For the non-event days, results were quite similar to those of the TOU customer population, with few significant results which were likely due to random chance.

### Overall Event Day Impacts

Events were called on August 28th, September 9th, 10th and 11th from 11am to 6pm. During this time, treatment customers reduced their use by 7.2% or 0.2MW across the 1468 accounts that were enrolled on the CPP rate during those events. The remainder of the event day failed to deliver significant, or even nonzero, impacts.

## Small Commercial SPP Ex-Ante Evaluation Methodology

This section provides an overview of small commercial ex-ante estimates. Results for both SDG&E and CAISO 1-in-2 and 1-in-10 weather forecasts are provided by industry. The enrollment forecast and reference loads are explained in the subsequent sections.

### Enrollment Forecast

SDG&E provided an enrollment forecast for monthly enrollment in both TOU and TOU CPP rates starting in January of 2016. Customers began to be defaulted on to the TOU CPP rate starting in November of 2015, with the option of opting out and on to the TOU-only rate.

Table 9-2 shows the overall growth of small commercial and agricultural customers over time, combined with a decreasing TOU-CPP yield which leads to a growing number of customers on the TOU-only rate over time.

Table 9-2: Enrollment Estimates by Rate Type for August of Ex-Ante Years

|  |  |  |  |
| --- | --- | --- | --- |
| **Year** | **TOU-CPP** | **TOU** | **All** |
| 2016 | 106,274 | 9,844 | 116,118 |
| 2017 | 95,105 | 21,284 | 116,389 |
| 2018 | 89,520 | 26,979 | 116,499 |
| 2019 | 89,520 | 27,106 | 116,627 |
| 2020 | 89,520 | 27,215 | 116,735 |
| 2021 | 89,520 | 27,318 | 116,839 |
| 2022 | 89,520 | 27,318 | 116,839 |
| 2023 | 89,520 | 27,318 | 116,839 |
| 2024 | 89,520 | 27,318 | 116,839 |
| 2025 | 89,520 | 27,318 | 116,839 |
| 2026 | 89,520 | 27,318 | 116,839 |

### Reference Loads

Reference loads provide a baseline level of consumption for customers representing what their electricity usage would be in the future if they did not switch to an SPP rate, but rather remained on their current rate. Reference loads can be compared to the predicted loads for customers after they transition to SPP rates to assess the effect of the new rates.

Since nearly all small commercial customers in SDG&E’s service territory are currently on a non-time-varying rate, there is ample data that can be used to model reference loads. The best approach for this modeling (in the absence of holding back a control group) is to develop a regression model that predicts electricity consumption as a function of weather conditions, month, day of week, hour of day, and other variables that influence usage. To develop the best possible model, various specifications were tested and the one that most accurately predicted loads during an out-of-sample test on 10% of the customers was selected as the final model. This model is shown as Equation 2:

|  |  |
| --- | --- |
|  |  |
| Variable | Definition |
| *h, i, d* | Indicate observations for each hour (h), industry (i) and day (d). |
|  | The model constant. |
|  | Cooling degree days on day d, defined as max(0, Avg. daily temp – 60). |
|  | A binary indicator of whether the day of the observation is a weekday (0=weekend, 1=weekday). |
|  | Set of dummy variables for each month of the year. |
|  | Error term (assumed to be mean zero and independent of all other regressors). |

The reference load model was estimated separately for each small commercial industry type for each hour of the day and includes terms for a weekday dummy variable interacted with cooling degree days, the same weekday dummy interacted with cooling degree days squared, the weekday dummy by itself, and a set of dummy variables for the months of the year. This specification captures changes in weather conditions as well as seasonal variation in electricity usage and was used to estimate reference loads for every combination of industry, day type (weekday or weekend), month, and set of weather conditions. Estimated reference loads for the average small commercial customer throughout the year are presented in Table 9-3.

The values in the table represent average peak period load during the peak period for monthly peak days under each set of weather conditions. The highest reference loads during the peak period for this group of customers occur in September for each of the weather scenarios, with the exception of the CAISO 1-in-2 scenario, which peaks in August. During the summer months, the CAISO and SDG&E based reference loads (and underlying weather) are quite similar under 1-in-2 year conditions. For 1-in-10 year conditions, the SDG&E based weather conditions are typically a bit higher than the CAISO based conditions.

**Table 9-3: Estimated Peak Period Reference Loads for Small**

Commercial and Agricultural Customers Under Ex-Ante Weather Conditions

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Month | Reference Loads (kW) | | | |
| CAISO | | SDG&E | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| January | 2.05 | 2.05 | 2.05 | 2.05 |
| February | 2.03 | 2.03 | 2.03 | 2.03 |
| March | 2.00 | 2.13 | 2.00 | 2.09 |
| April | 1.97 | 2.22 | 2.01 | 2.29 |
| May | 2.48 | 2.95 | 2.64 | 3.08 |
| June | 2.84 | 3.12 | 2.83 | 3.13 |
| July | 3.07 | 3.18 | 3.08 | 3.42 |
| August | 3.47 | 3.51 | 3.40 | 3.66 |
| September | 3.46 | 3.77 | 3.42 | 3.74 |
| October | 3.09 | 3.41 | 3.20 | 3.53 |
| November | 2.10 | 2.25 | 2.12 | 2.32 |
| December | 2.05 | 2.05 | 2.05 | 2.05 |

## Small Commercial SPP Rates Ex-Ante Load Impact Estimates

This section presents the results of the ex-ante impact evaluation and the aggregate forecast for the small commercial customers that are on the TOU and TOU-CPP rates.

### TOU Ex-Ante Load Impact Estimates

Aggregate impacts for each month of the year are presented in Table 9-4. The impacts range from a low of about 9.7 MW in May to a high of almost 16 MW in November. It should be noted that impacts are approximately 30–40% larger in the winter compared to the summer, which is a direct consequence of basing the ex-ante estimates on the results from PG&E.

**Table 9-4: Aggregate Ex-Ante TOU Load Impacts for Small Commercial Customers on   
Monthly System Peak Non-Event Days**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Month | Load Impact (MW) | | | |
| CAISO | | SDG&E | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| January | 14.20 | 14.20 | 14.20 | 14.20 |
| February | 14.04 | 14.04 | 14.04 | 14.04 |
| March | 13.81 | 14.49 | 13.81 | 14.26 |
| April | 13.40 | 14.79 | 13.61 | 15.18 |
| May | 9.85 | 11.42 | 10.38 | 11.85 |
| June | 11.26 | 12.21 | 11.26 | 12.24 |
| July | 12.21 | 12.59 | 12.25 | 13.42 |
| August | 13.79 | 13.93 | 13.54 | 14.44 |
| September | 13.66 | 14.73 | 13.50 | 14.61 |
| October | 12.50 | 13.59 | 12.89 | 13.99 |
| November | 14.44 | 15.23 | 14.55 | 15.68 |
| December | 14.20 | 14.20 | 14.20 | 14.20 |

The forecasted enrollment provided by SDG&E shows an increase in enrollment due to natural account growth over time. As mentioned in the introduction, customers will be defaulted on to a TOU-CPP rate starting in November 2015, with the option to opt out of the CPP component on to a TOU-only rate. Table 9-5 provides aggregate impacts for each August Monthly System Peak Non-Event Day in the forecast according to the SDG&E 1-in-2 Weather Forecast.

Table 9-5: Aggregate Ex-Ante TOU Load Impacts for Small Commercial Customers on   
August Monthly Peak Days

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Year** | **2016** | **2017** | **2018** | **2019** | **2020** | **2021-2026** |
| Aggregate Reference Load (MW) | 395.29 | 396.21 | 396.58 | 397.02 | 397.39 | 397.74 |
| Aggregate Impact (MW) | 13.54 | 13.58 | 13.59 | 13.60 | 13.62 | 13.63 |

### TOU-CPP Ex-Ante Load Impact Estimates

Results for the incremental impact of a CPP rate on event days was estimated from PG&E’s default small commercial program starting in 2015. Estimates of impacts were small and failed to meet significance thresholds at conventional levels. Therefore, the results presented here should be interpreted with caution.

Aggregate impacts for each month of the year are presented in Table 9-6. The impacts range from a low of about 10.4 MW in May to a high of almost 16 MW in September. It should be noted that impacts are approximately 30–40% larger in the winter compared to the summer, which is a direct consequence of basing the ex-ante estimates on the results from PG&E.

Table 9-6: Aggregate Ex-Ante TOU Load Impacts for Small Commercial Customers on   
Monthly System Peak Event Days

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Month | Load Impact (MW) | | | |
| CAISO | | SDG&E | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| January | 13.40 | 13.40 | 13.40 | 13.40 |
| February | 13.24 | 13.24 | 13.24 | 13.24 |
| March | 13.02 | 13.68 | 13.02 | 13.46 |
| April | 12.65 | 13.98 | 12.85 | 14.35 |
| May | 10.36 | 12.05 | 10.93 | 12.52 |
| June | 11.85 | 12.87 | 11.84 | 12.90 |
| July | 12.84 | 13.25 | 12.87 | 14.13 |
| August | 14.50 | 14.65 | 14.24 | 15.20 |
| September | 14.38 | 15.52 | 14.21 | 15.39 |
| October | 13.11 | 14.29 | 13.53 | 14.72 |
| November | 13.63 | 14.39 | 13.74 | 14.82 |
| December | 13.40 | 13.40 | 13.40 | 13.40 |

Enrollment in the TOU-CPP rates is forecast to decrease over time. This is because SDG&E forecasts a larger fraction of customers switching to TOU-only rates over time and away from the TOU-CPP rate. Despite a growing population, enrollment will decrease over time, flattening out after 2019. Table 9-7 provides aggregate impacts for each August Monthly System Peak Non-Event Day in the forecast according to the SDG&E 1-in-2 Weather Forecast.

Table 9-7: Aggregate Ex-Ante TOU-CPP Load Impacts for Small Commercial

Customers on August Monthly Peak Days

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Year** | **2016** | **2017** | **2018** | **2019-2026** |
| Aggregate Reference Load (MW) | 361.77 | 323.75 | 304.74 | 304.74 |
| Aggregate Impact (MW) | 14.24 | 12.74 | 12.00 | 2.00 |

# Commercial Thermostats

## Commercial Thermostats Overview

SDG&E’s commercial thermostat program provides commercial customers with programmable communicating thermostats (PCTs). On event days, customers are subject to two different AC cycling strategies—50% cycling and a 4-degree temperature setback. Customers receive the PCTs for free, but do not currently receive an incentive payment, and are able to override the signal or opt out of DR events. More than half of these customers will be defaulted onto Critical Peak Pricing (CPP) by April of 2016. In 2015, the thermostats were activated on residential Peak Time Rebate (PTR) event days.

As of February 2016, over 12,000 PCTs have been rolled out to roughly 2,500 customers. Enrollment has grown substantially since summer 2014, but remained relatively constant since summer 2015. A few participants are considered residential customers in SDG&E’s records, even though these customers are part of a commercial DR program. These residential premises are located in commercially-managed facilities. This small, unique group accounts for roughly 10% of the thermostats in the program. These customers have been segmented for a separate analysis accordingly.

## Commercial Thermostats Ex-Post Evaluation Methodology and Validation

The fundamental problem for estimating load impacts is developing an estimate of the reference load. The reference load is an estimate of what load would have been in the absence of the thermostat control that is in effect for participants. For this evaluation, the focus is on what load would have been on days in which thermostat control was dispatched. The methods used in the commercial thermostat program evaluation rely on the selection of a control group using statistical matching and individual customer regressions.

### Matched Control Group Methodology – Commercial

The primary source of reference loads, and hence impact estimates, is a number of matched control groups. These control groups are assembled from among the non-participant population. The methods used to assemble the groups are designed to ensure that the control group load on event days is an accurate estimate of what load would have been among participants on event days had they not participated.

The fundamental idea behind the matching process is to find customers who were not subject to events that have similar characteristics to those who were subject to events. The control group was selected using a propensity score match to find customers who had demand patterns most similar to participants. In this procedure, a probit model is used to estimate a score for each customer based on a set of observable variables that are assumed to affect the decision to participate in the commercial thermostat program. A probit model is a regression model designed to estimate probabilities—in this case, the probability that a customer would choose to participate.

Once the control group was matched and validated, load impacts were estimated using a triple differences methodology, which combines a difference-in-differences regression and a same-day (weather sensitivity) adjustment[[22]](#footnote-22). This methodology calculates the estimated impacts as the difference in average loads between participants and control customers on event days minus the difference between the two groups on hot, non-event days and then adjusts for differences in weather sensitivity within the treatment and control groups. This calculation controls for residual differences in load between the groups that are not eliminated through the matching process, thus reducing bias. Equation 10‑1 summarizes the triple differences calculation and Table 10-1 provides the definitions for variables in the equation[[23]](#footnote-23).

Equation 10‑1: Specification of Triple Differences Regression

Table 10‑1: Variables Used for Triple Differences Calculation

| Variable | Description |
| --- | --- |
| *kW* | Average demand |
| *treat* | Indicates whether a customer is a participant (treat=1) or a control group member (treat =0) |
| *eday* | Indicates whether a given day was an event (eday=1) or not (eday=0) |
| *eperiod* | Indicates whether a given hour was an event hour (eperiod=1) or not (eperiod=0) |
| *customer* | A set of indicator variables that equal one if cust=i |
| *hour* | A set of indicator variables that equal one if hr=h |
| *day* | A set of indicator variables that equal one if date=t |
| *a* | Estimated effect of the treatment |
| *b, c, d* | Estimated fixed effects |
| *e, f, g* | Estimated parameters |
| *i* | Indexes customers |
| *t* | Indexes the days |
| *h* | Indexes hours |

### Individual Customer Regression Methodology – Residential

For the small group of customers that are considered residential premises in SDG&E’s records, even though they are located on commercially-managed properties, individual customer regressions were used to estimate load impacts. It would have been time-consuming and very difficult (if not impossible) to find an appropriate control group for this small, unique group that accounts for less than 10% of the thermostats in the program, so this within-subjects approach was used instead. The regression model used is specified in Equation 10-2, and the variable definitions are provided in Table 10-2. The customers for whom we used the individual customer regression methodology are very difficult to accurately model because data on when the units are and are not occupied is not available. We validated many models using the same hot non-event days we used to construct the matched control groups, and chose this as the best performing model.

Equation 10‑2: Model Specification for Individual Customer Regressions

Table 10‑2: Variables Used for Individual Customer Regressions

| Variable | Description |
| --- | --- |
| *A* | a is an estimated constant |
| *b, c, and d* | b, c, and d are estimated parameters |
| *mean17* | The mean temperature from midnight until 5 PM |
|  | The error term |

## Commercial Thermostat Ex-Post Load Impact Estimates

SDG&E called four events during summer 2015 during which 1,243 commercial customers and 1,079 commercially managed residential units were enrolled.

### Ex-Post Load Impact Estimates – Commercial

Table 10-3 summarizes the average load reduction for each event day provided by commercial customers across the four-hour event window from 2 to 6 PM. As shown, the average percent reduction ranged from a low of 4% on August 28 to a high of 8% on September 11. An average reduction of 6% was obtained across the four event days. The average load reduction per thermostat ranged from a low of 0.16 kW to a high of 0.33 kW. Aggregate load reductions ranged from 1.8 MW to 3.7 MW. Aggregate load reductions for the four events averaged 3.1 MW per event. Aggregate load reductions for the four events averaged 3.1 MW per event. The average per-thermostat and per-customer load reductions are slightly higher than the estimates calculated for the 2014 program year, which were 0.22 kW and 2.0 kW, respectively. The aggregate impacts also increased, largely as a function of the much greater number of participants.

Table 10‑3: 2015 Commercial Thermostat Ex-Post Load Impact Estimates (2 to 6 PM)

by Event Day (kW per Customer, Aggregate MW, and kW per Thermostat)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **Enrolled Participants** | **Total Number of Thermostats** | **Avg. Reference Load (kW)** | **Avg. Load Reduction (kW)** | **Percent Load Reduction (%)** | **Aggregate Load Reduction (MW)** | **Avg. Thermostat Impact (kW)** | **Mean17 (°F)** |
| Aug 28, 2015 | 1,243 | 11,292 | 37.1 | 1.4 | 3.8% | 1.8 | 0.16 | 82.2 |
| Sep 9, 2015 | 1,243 | 11,292 | 40.9 | 2.5 | 6.2% | 3.1 | 0.28 | 86.5 |
| Sep 10, 2015 | 1,243 | 11,292 | 41.4 | 3.0 | 7.2% | 3.7 | 0.33 | 85.2 |
| Sep 11, 2015 | 1,243 | 11,292 | 39.2 | 3.0 | 7.7% | 3.7 | 0.33 | 82.6 |
| **Average Event** | **1,243** | **11,292** | **39.7** | **2.5** | **6.3%** | **3.1** | **0.27** | **84.1** |

### Ex-Post Load Impact Estimates – Residential

Figure 10-1 shows the hourly load impacts for the average residential customer across the four event days. The number of enrolled customers, 1,079, is the average number of enrolled commercial customers across the four event days. The average impact per customer for all events across the four hour event window was 0.11 kW, or 7.9% of the reference load.

Figure 10‑1: Load Impact (kW) per Hour for the Average 2014 Event Day   
(Average Residential Participant)



## Commercial Thermostat Ex-Ante Evaluation Methodology

Ex ante impacts are intended to represent what the commercial thermostat program can deliver under a standardized set of weather and event conditions given changes in enrollment over the forecast horizon. The weather used for ex-ante load impact estimation is meant to reflect conditions on high demand days when there is a high likelihood that events will be called under normal (1-in-2 year) and extreme (1-in-10 year) weather.

At a high level, ex-ante impact estimates were developed using the following process:

* Ex post estimates were developed using the matching methodology described in Section 10.2, with the key output being the 2015 average event day per-thermostat impact (0.27 kW);
* Second, regression models were estimated that relate hourly usage to weather for customers that are currently enrolled in the commercial thermostat program. This model was fit using one data point for each customer segment, hour and day;
* A regression model was estimated that related the ex-post impacts for 50% cycling customers in the Summer Saver program to average temperatures from midnight to 5 PM (referred to as *mean17*) on the event day. Ex ante weather conditions were used as input to the regression model to predict Summer Saver impacts for each hour for monthly system peak days and for the typical event day; and
* The ratio of impact to weather observed in the Summer Saver program was applied to the 2015 average event day per-thermostat impact for the commercial thermostat program (from Step 1).

The final model specifications used for the reference loads and Summer Saver impact-temperature relationship are shown below. The impact model matches the model used in the Summer Saver evaluation to maintain consistency.

Equation 10‑3: Reference Load Ex-Ante Regression Model Specification

Table 10‑5: Description of Ex-Ante Reference Load Regression Variables

|  |  |
| --- | --- |
| Variable | Description |
| *kW* | Per customer ex-post reference load for each event day |
| *a* | Estimated constant |
| *b and c* | Estimated parameters describing the relationship between temperature and demand |
| *d* | Estimated parameters describing the average difference in load for that weekday from Monday |
| *m* | Estimated parameters describing the average difference in load for that month from January |
| *mean17* | Average temperature from midnight to 5 PM |
| *mean172* | Average temperature from midnight to 5 PM, squared |
| *DOW* | Dummy variable for each weekday (Monday not included) |
| *Month* | Dummy variable for each month (January not included) |
| *Ɛ* | The error term, assumed to be a mean zero and uncorrelated with any of the independent variables |
| *d* | Indexes event days within a given segment |
| *day* | Indexes weekday |
| *month* | Indexes month |

Equation 10‑4: Summer Saver Load Impact Ex-Ante Regression Model Specification

Table 10‑6: Description of Ex-Ante Reference Load Regression Variables

|  |  |
| --- | --- |
| Variable | Description |
| *impact* | Per customer ex-post load impact (kW) for each event day |
| *a* | Estimated constant |
| *b* | Estimated parameter describing the relationship between temperature and demand |
| *mean17* | Average temperature from midnight to 5 PM |
| *Ɛ* | The error term, assumed to be a mean zero and uncorrelated with any of the independent variables |

As a validation of the ex-ante impact model,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Date | Ex-Post Impact (kW) | Ex-Ante Impact (kW) | Difference (kW) | Mean17 |
|
| Aug 28, 2015 | 1.5 | 2.2 | 0.7 | 82.2 |
| Sept 9, 2015 | 2.3 | 2.6 | 0.4 | 86.5 |
| Sept 10, 2015 | 3.0 | 2.5 | -0.5 | 85.2 |
| Sept 11, 2015 | 2.8 | 2.2 | -0.5 | 82.6 |

Table 10-7 shows the results of the ex-ante impact modeling for the four event days at hour ending 4 PM, as compared to the estimates in the ex-post analysis. The ex-post impacts estimated in the 2014 and 2015 analyses do not show an obvious relationship with weather. Since, in general, higher impacts on hotter days are expected, and that is consistent with the findings in the Summer Saver analysis, the impacts for September 10 and 11 are underestimated with the ex-ante methodology.

Table 10‑7: Ex-Post and Ex-Ante Impact Validation for Event Days at Hour Ending 4 PM

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Date | Ex-Post Impact (kW) | Ex-Ante Impact (kW) | Difference (kW) | Mean17 |
|
| Aug 28, 2015 | 1.5 | 2.2 | 0.7 | 82.2 |
| Sept 9, 2015 | 2.3 | 2.6 | 0.4 | 86.5 |
| Sept 10, 2015 | 3.0 | 2.5 | -0.5 | 85.2 |
| Sept 11, 2015 | 2.8 | 2.2 | -0.5 | 82.6 |

### Commercial Thermostat Estimating Ex-Ante Weather Conditions

The CPUC Load Impact Protocols[[24]](#footnote-24) require that ex-ante load impacts be estimated assuming weather conditions associated with both normal and extreme utility operating conditions. Normal conditions are defined as those that would be expected to occur once every 2 years (1-in-2 conditions) and extreme conditions are those that would be expected to occur once every 10 years (1-in-10 conditions). Since 2008, the IOUs have based the ex-ante weather conditions on system operating conditions specific to each individual utility. However, ex-ante weather conditions could alternatively reflect 1-in-2 and 1-in-10 year operating conditions for the California Independent System Operator (CAISO) rather than the operating conditions for each IOU. While the protocols are silent on this issue, a letter from the CPUC Energy Division to the IOUs dated October 21, 2014 directed the utilities to provide impact estimates under two sets of operating conditions starting with the April 1, 2015 filings: one reflecting operating conditions for each IOU and one reflecting operating conditions for the CAISO system.

In order to meet this new requirement, California’s IOUs contracted with Nexant to develop ex-ante weather conditions based on the peaking conditions for each utility and for the CAISO system. The previous ex-ante weather conditions for each utility were developed in 2009 and were updated this year along with the development of the new CAISO based conditions. Both sets of estimates used a common methodology, which is documented in a report delivered to the IOUs.[[25]](#footnote-25)

Table 10-8 shows the value for mean17 for the typical event day and the monthly system peak day under the four sets of weather for which load impacts are estimated. As seen, there are small differences in weather conditions based on SDG&E peak conditions and CAISO peak conditions, for normal and extreme weather. The CAISO-based conditions on the typical event day are slightly higher in a 1-in-2 weather year and lower in a 1-in-10 weather year.

**Table 10‑8: Ex-Ante Weather Values (*mean17*, °F)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Day Type | SDG&E Based Weather (°F) | | CAISO Based Weather (°F) | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| Typical Event Day | 72.4 | 77.2 | 73.0 | 75.7 |
| January Peak Day | 52.6 | 49.1 | 52.4 | 47.5 |
| February Peak Day | 53.9 | 54.2 | 55.0 | 55.2 |
| March Peak Day | 56.4 | 64.8 | 55.0 | 66.6 |
| April Peak Day | 65.6 | 74.3 | 64.2 | 73.9 |
| May Peak Day | 67.6 | 75.7 | 64.4 | 72.7 |
| June Peak Day | 68.1 | 73.0 | 68.6 | 72.8 |
| July Peak Day | 71.7 | 77.7 | 71.5 | 73.5 |
| August Peak Day | 74.9 | 78.4 | 75.8 | 76.4 |
| September Peak Day | 74.9 | 79.8 | 76.1 | 80.3 |
| October Peak Day | 70.7 | 75.8 | 68.3 | 74.6 |
| November Peak Day | 64.1 | 72.5 | 63.0 | 69.6 |
| December Peak Day | 55.5 | 51.1 | 56.9 | 51.1 |

### Commercial Thermostat Ex-Ante Load Impact Estimates

Aggregate ex-ante estimates combine these average estimates with projections of program enrollment provided by SDG&E. Per-thermostat ex-ante estimates also combine the average customer estimates with projections of the average number of thermostats, which is expected to remain around 9 thermostats per customer. Currently, there are nearly 2,526 customers enrolled. This number is expected to increase to 2,689 customers in August 2016, 2,891 customers in August 2017, and remain constant at 2,951 from 2018 through 2026.

Table 10-9 summarizes the 2018-2026 ex-ante load impact estimates by weather year and day type. The third and sixth columns in the table show the average hourly ex-ante load impact per thermostat (kW) over the event period from 1 to 6 PM for each type of weather, followed by the per-customer impact (kW) and the aggregate impact (MW). The first set of rows corresponds to 1-in-2 year weather conditions while the second set covers 1-in-10 year weather conditions. The highest impacts consistently occur on September peak days under both SDG&E and CAISO weather conditions, with aggregate impacts of 4.1 MW in a 1-in-10 year and around 3.0 MW in a 1-in-2 year.

Table 10‑9: 2018-2026 Ex-Ante Load Impact Estimates by Weather Year and Day Type   
(kW per Customer, Aggregate MW, and kW per Thermostat)

| Weather Year | Day Type | SDG&E Mean Hourly Impacts (2-6 PM) | | | CAISO Mean Hourly Impacts (2-6 PM) | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Per Thermostat | Per Customer | Aggregate | Per Thermostat | Per Customer | Aggregate |
| (kW) | (kW) | (MW) | (kW) | (kW) | (MW) |
| 1-in-2 | Typical Event Day | 0.15 | 0.8 | 2.4 | 0.15 | 0.9 | 2.6 |
| January Monthly Peak | 0.00 | 0.0 | 0.0 | 0.00 | 0.0 | 0.0 |
| February Monthly Peak | 0.00 | 0.0 | 0.0 | 0.00 | 0.0 | 0.0 |
| March Monthly Peak | 0.00 | 0.0 | 0.0 | 0.00 | 0.0 | 0.0 |
| April Monthly Peak | 0.06 | 0.3 | 1.0 | 0.04 | 0.2 | 0.7 |
| May Monthly Peak | 0.09 | 0.5 | 1.5 | 0.05 | 0.3 | 0.8 |
| June Monthly Peak | 0.09 | 0.5 | 1.5 | 0.10 | 0.6 | 1.7 |
| July Monthly Peak | 0.14 | 0.8 | 2.3 | 0.13 | 0.8 | 2.2 |
| August Monthly Peak | 0.18 | 1.0 | 2.9 | 0.19 | 1.1 | 3.2 |
| September Monthly Peak | 0.18 | 1.0 | 3.0 | 0.19 | 1.1 | 3.2 |
| October Monthly Peak | 0.13 | 0.7 | 2.1 | 0.09 | 0.5 | 1.6 |
| November Monthly Peak | 0.04 | 0.2 | 0.7 | 0.03 | 0.2 | 0.5 |
| December Monthly Peak | 0.00 | 0.0 | 0.0 | 0.00 | 0.0 | 0.0 |
| 1-in-10 | Typical Event Day | 0.21 | 1.2 | 3.5 | 0.19 | 1.1 | 3.2 |
| January Monthly Peak | 0.00 | 0.0 | 0.0 | 0.00 | 0.0 | 0.0 |
| February Monthly Peak | 0.00 | 0.0 | 0.0 | 0.00 | 0.0 | 0.0 |
| March Monthly Peak | 0.05 | 0.3 | 0.8 | 0.07 | 0.4 | 1.2 |
| April Monthly Peak | 0.17 | 1.0 | 2.8 | 0.16 | 0.9 | 2.7 |
| May Monthly Peak | 0.19 | 1.1 | 3.1 | 0.15 | 0.9 | 2.5 |
| June Monthly Peak | 0.15 | 0.9 | 2.6 | 0.15 | 0.9 | 2.5 |
| July Monthly Peak | 0.21 | 1.2 | 3.6 | 0.16 | 0.9 | 2.7 |
| August Monthly Peak | 0.22 | 1.3 | 3.7 | 0.20 | 1.1 | 3.3 |
| September Monthly Peak | 0.24 | 1.4 | 4.1 | 0.25 | 1.4 | 4.1 |
| October Monthly Peak | 0.19 | 1.1 | 3.2 | 0.17 | 1.0 | 2.9 |
| November Monthly Peak | 0.15 | 0.8 | 2.4 | 0.11 | 0.6 | 1.8 |
| December Monthly Peak | 0.00 | 0.0 | 0.0 | 0.00 | 0.0 | 0.0 |

## Commercial Thermostat Comparison between Ex-Post and Ex-Ante Estimates

The ex-post estimates presented in Section 10.3 and the ex-ante estimates presented above differ for a number of reasons, including differences in weather, enrollment, and estimation methodology. This section discusses the impact of each of these factors on the difference between ex-post and ex-ante impact estimates.

Table 10-10 summarizes the key factors that lead to differences between ex-post and ex-ante estimates for the commercial thermostat program and the expected influence that these factors have on the relationship between ex-post and ex-ante impacts. Given that the load impacts are quite sensitive to variation in weather, even small changes in mean17 between ex-post actual and ex-ante weather conditions can produce relatively large differences in load impacts. Changes in enrollment between the values used for ex-post estimation and the 2016 enrollment values are expected to increase the aggregate impacts by roughly 6% given the continued projected growth of the program.

Table 10‑10: Summary of Factors Underlying Differences Between Ex-Post and Ex-Ante Impacts   
for the Commercial Thermostat Program for the Ex-Ante Typical Event Day

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex-Post | Ex-Ante | Expected Impact |
| Weather | 82 < event day mean17 < 86  Average event day mean17 = 84 | Mean17 for 1-in-2 typical event day = 73.8 and 74.6 for SDG&E and CAISO weather, respectively | Ex ante estimates are highly sensitive to variation in mean17 – ex-ante weather is cooler than the observed weather for 2015, so ex-ante should generally be lower than ex-post, all else equal |
| Mean17 for 1-in-10 typical event day = 79.9 and 78.0 for PG&E and CAISO weather, respectively |
| Enrollment | Enrollment increased by many multiples between 2014 and 2015 events | Enrollment is forecast to steadily increase until 2018, at which point the program will remain stable at 117% of 2015 enrollment. | Ex ante estimates will increase to be roughly 17% than greater than ex-post |
| Methodology | Impacts are largely based on matched control groups and adjustments based on differences in pre-event hours and weather sensitivity | Regression of ex-post reference loads against mean17 for each hour and a weather-based adjustment estimated from Summer Saver weather-sensitivity | Impacts will vary differently with weather, given that Summer Saver is a larger, more established program that shows a strong relationship between weather and impacts, whereas the commercial thermostat temperature-impact relationship has few data points (eight event days over two years) |

Table 10-11 shows how aggregate load impacts change as a result of differences in the factors underlying ex-post and ex-ante estimates. The third column reproduces the ex-post values from Table 10-3. The next column grosses these estimates up by the difference in ex-post and ex-ante enrollment in August 2016. As expected, this produces a small increase in the impacts. The next column shows what the ex-ante model would produce using the same 2016 August enrollment figures, the ex-post event window (2-6 PM), and the ex-post weather conditions for each event day. As discussed above, the ex-ante model over predicts for the August day and under predicts for the last two September days. This is due to the unexpected high impact on the relatively cool September days, and the relatively limited number of events available to determine whether the observed trend of higher impacts on cooler day was spurious, or was due to a real trend. The final four columns show how aggregate load reductions vary with the different ex-ante weather scenarios for the average hour between 2 PM and 6 PM. The SDG&E 1-in-10 conditions are most similar to the 2015 SDG&E ex-post weather conditions on average across all event days, although for any given ex-post day, the weather conditions can differ significantly. Notably, even the coldest event, August 28, is considerably warmer that the SDG&E 1-in-10 weather with a *mean17* of 77.2. Using the SDG&E 1-in-10 year conditions therefore decreases the average impacts by about 23% compared with ex-post weather.

Table 10‑11 Differences in Ex-Post and Ex-Ante Impacts Due to Key Factors

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Date | Mean17 | Ex-Post Impact | Ex-Post Impact with August 2016 Ex-Ante Enrollment | Ex-Ante Model Ex-Post Weather and Event Window | CAISO 1-in-2 | SDG&E 1-in-2 | CAISO  1-in-10 | SDG&E 1-in-10 |
| (°F) | (MW) | (MW) | (MW) | (MW) | (MW) | (MW) | (MW) |
| 8/28/2015 | 82.2 | 1.8 | 2.1 | 3.4 | 2.0 | 1.9 | 2.4 | 2.7 |
| 9/9/2015 | 86.5 | 3.1 | 3.7 | 4.0 |
| 9/10/2015 | 85.2 | 3.7 | 4.4 | 3.8 |
| 9/11/2015 | 82.6 | 3.7 | 4.5 | 3.4 |
| Average | 84.1 | 3.1 | 3.7 | 3.7 |

1. For more information on the model out-of-sample tests and MAPE results see Section 6, Model Validity. [↑](#footnote-ref-1)
2. It is important to note that approximately 70 accounts under a single aggregator were removed from the analysis beginning in August of 2015 due to the fact that they changed their nomination to 0 MW for the remainder of the year. [↑](#footnote-ref-2)
3. [↑](#footnote-ref-3)
4. Though the ex-ante impacts are labeled as an August peak day, the ex-ante results are identical for each monthly system peak day, May through October, because of the way the SDG&E ex-ante impacts were modeled. [↑](#footnote-ref-4)
5. The 1-in-2 and 1-in-10 ex-ante impacts are equal for the 1-in-2 and 1-in-10 weather conditions, because of the SDG&E ex-ante modeling approach. [↑](#footnote-ref-5)
6. For the CBP DA product, approximately 70 accounts under a single aggregator were removed from the ex-post analysis beginning in August of 2015 due to the fact that they changed their nomination to 0 MW. Therefore, we have used the hottest event day (June 30) prior to the removal of these accounts to have a more direct comparison with the ex-ante enrollment and weather forecast. [↑](#footnote-ref-6)
7. The 2014 ex-post results for the CBP DO product were not available in the previous year’s load impact tables, so we have used the average event day results as a proxy. [↑](#footnote-ref-7)
8. In practice, this term is absorbed by the time effects, but it is useful for representing the model logic. [↑](#footnote-ref-8)
9. For ex-ante estimation, SDG&E split its existing default CPP population into medium and large customers. In contrast, ex-post impacts were reported for all default CPP customers. [↑](#footnote-ref-9)
10. Previously SDG&E offered a BIP option B which required that participating customer be notified at least three hours before the event but SDG&E discontinued this option in 2012. [↑](#footnote-ref-10)
11. Including weekends and holidays would require the addition of variables to capture the fact that load levels and patterns on weekends and holidays can differ greatly from those of non-holiday weekdays. Because event days did not occur on weekends or holidays, the exclusion of these data does not affect the model’s ability to estimate *ex-post* load impacts. [↑](#footnote-ref-11)
12. The summer pricing season is June through September for SCE, May through September for SDG&E, and May through October for PG&E. [↑](#footnote-ref-12)
13. In particular, where CDH60 and CDH60\_MA24, the 24-hour moving average of CDH60, are used together for summer *ex-post* regressions, only CDH60 is used for the *ex-ante* models. Similarly, where CDH60\_MA3, the three-hour moving average, is used for *ex-post* regressions, CDH60 is used for the *ex-ante* analysis. See Appendix A for weather variable details. [↑](#footnote-ref-13)
14. A modified regression model is used for SDG&E to better control for large differences in load profiles across months for the few relevant customers, as in the *ex-post* analysis. See Section 3.2.1 above for details. [↑](#footnote-ref-14)
15. It is not possible to calculate an achievement rate for customers with reference loads below their FSLs throughout an event period—the event effectively has no impact on them. [↑](#footnote-ref-15)
16. Event day, pre-event demand is not typically included in propensity score models for calculating event impacts, but it was included here because almost no (less than 15) nonresidential Summer Saver participants are notified of events in advance and so should have no effect of being treated until the event occurs. [↑](#footnote-ref-16)
17. Mean 17 is the average temperature from midnight to 5 p.m. [↑](#footnote-ref-17)
18. Data for the year 2010 was excluded from the reference load estimation process because the evaluation was based on end-use, rather than whole-premise, interval data. [↑](#footnote-ref-18)
19. For hot days, twelve non-event days in 2014 were selected with the highest average peak temperatures across the different weather stations used for the analysis. The dates with these peak temperatures were the 29th and 30th of April, 1st, 2nd, 13th, and 16th of May, 8th of September, 2nd, 3rd, 6th, and 7th of October, and the 5th of November, 2014. Load profiles by season were also compared to confirm that the groups were sufficiently similar. [↑](#footnote-ref-19)
20. A cooling degree hour is equal to 0 when the temperature is less than 65 and equal to the temperature minus 65 when the temperature is greater than 65 [↑](#footnote-ref-20)
21. Such customers are sometimes called “structural winners” because the pattern of their existing load shapes would result in monthly bill savings in the absence of any behavioral response to the rate. [↑](#footnote-ref-21)
22. For more on the triple differences regression methodology, see Imbens and Wooldridge (2009), “Recent Developments in the Econometrics of Program Evaluation” and Chetty et. al. (2009), “Salience and Taxation: Theory and Evidence.” [↑](#footnote-ref-22)
23. A standard difference-in-differences model is used to estimate impacts before 10 AM and after 7 PM. The data used in the triple differences model is restricted to hours ending at 10 AM through 2 PM as well as each event hour for which an impact is being estimated. [↑](#footnote-ref-23)
24. See CPUC Rulemaking (R.) 07-01-041 Decision (D.) 08-04-050, “Adopting Protocols for Estimating Demand Response Load Impacts” and Attachment A, “Protocols.” [↑](#footnote-ref-24)
25. See *Statewide Demand Response Ex-Ante Weather Conditions*. Nexant, Inc. January 30, 2015. [↑](#footnote-ref-25)