Executive Summary of the 2016 SDG&E Measurement and Evaluation Load Impact Reports

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SDGE

A Sempra Energy utility℠

Contents

1 SDG&E's 2016 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, Commercial Thermostats Program, and Voluntary Residential CPP. This report includes a summary of the ex ante forecasts for these demand response activities. The summary ex ante tables that include the 11-year forecast (from 2017 through 2027) 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. SDGE Ex Ante Tables. Ex ante estimates for 2016 are also provided for comparison purposes.

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.

2 Summary of SDG&E's Capacity Bidding Program Report

2.1 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. The Utility may call an event: i) Whenever the Utility's electric system supply portfolio reaches a resource dispatch equivalence of 19,000 Btu/kWh heat rate, or as Utility system conditions warrant. ii) Whenever the California Independent System Operator has issued an alert or warning notice, the California Independent System Operator shall be entitled to request that the utility, at its discretion, call a program event pursuant to this Schedule.

2.2 CBP Ex post Evaluation Methodology

The program year 2016 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 2016 program year.
2. To provide these estimates by various segments, i.e., IOU, program, Local Capacity Area (LCA),[1] industry group, Automated Demand Response (AutoDR) and TA&TI participation, and notification type.
3. To estimate the distribution of load impacts by customer segment for the average event.

AEG used customer-specific regressions to estimate the load impact for each customer on each event day. Customer-specific regressions offered the most flexible, consistent, and appropriate solution for several reasons:

- The individual customer impacts can simply be added together to estimate impacts at any level including, but not limited to, utility, program, aggregator, LCA, NAICS, or notification type.
- They can be easily used to control for variation in load due to weather conditions, geography, and time-related variables (day of week, month, hour, etc.).
- Because impacts are estimated for each customer separately, they also control for unobservable customer-specific effects that are more difficult to account for in aggregate regression models.

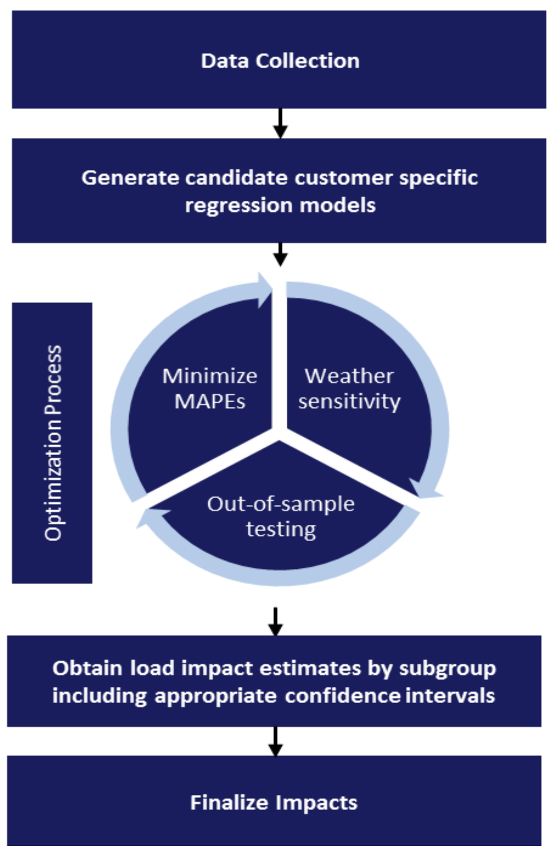
[1] SDG&E has one LCA which comprises its entire service territory

- Commercial and industrial customers often vary significantly from one another in load shape, weather response, and overall size. Customer-specific regressions allow us to capture differences between customers; therefore, they are better able to model changes in energy usage than an aggregated model.
- Because the events are called only on isolated days over the course of the program year, and on all other days the participants and non-participants face similar TOU rates, the data conforms nicely to what researchers often call a repeated-measures design. This simply means that all participants are subjected to the treatment at the same time, repeatedly over the course of the study. In this case, the control can be defined as an absence of the treatment, or the non-event days.[2]

It is not practical to develop models individually for more than 5,000 participants. Therefore 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. The subsections that follow describe the process in more detail.

Figure 2-1 Ex post Analysis Approach



[2] Because of high event frequency for some of the programs, we used up to three years of data to ensure that enough similar non-event days were available for the estimation of the reference load.

2.2.1 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
$Weather_{i,d}$	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
$Month_{i,d}$	A series of indicator variables for each month
$DayOfWeek_{i,d}$	A series of indicator variables for each day of the week
$Year_{i,d}$	An indicator for the year 2016[3]
$OtherEvt_{i,d}$	Equals one on event days of other demand response programs in which the customer is enrolled
$MornLoad_{i,d}$	The average of each day's load in hours 5 a.m. through 10 a.m.
	Impact Variables
$P_{i,d}$	An indicator variable for aggregator program event days
$P * Month_{i,d}$	An indicator variable for aggregator program event days interacted with the month
$P * Year_{i,d}$	An indicator variable for aggregator program event days interacted with the year 2016
$P*NonTypEvent_{i,d}$	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 since much of the day-to-day variation in load is captured by weather terms.
- Non-weather sensitive models include the morning load adjustment and calendar effects.

2.2.2 Optimization Process

[3] Because a large number of events were called in 2016, which was also a relatively mild year, we included data from 2014 and 2015 to ensure that we would have enough event-like days. Therefore, we also included a "year" indictor variable in the models.

After developing a set of candidate models, a single "best" model was selected for each customer. 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.

Below are examples of two final models, one for a weather sensitive customer and one for a non-weather sensitive customer. For both types of models, the model specification is identical for each hour of the day.

Simple weather sensitive example:

$$kwh_{i,d} = \alpha_{i,d} + Month_{i,d} + Weather_{i,d} + P_{i,d} + (P_{i,d} * Weather_{i,d}) + \varepsilon_{it} \quad (2.1)$$

where:

$kwh_{i,d}$ is the customer's consumption in hour i, on day d.

$\alpha_{i,d}$ is the intercept.

$\varepsilon_{i,d}$ is the error for participant in hour i on day d.

and, all other terms are defined in

above.

Simple non-weather sensitive example:

$$kwh_{i,d} = \alpha_{i,d} + MornLoad_{i,d} + DayofWeek_{i,d} + P_{i,d} + \varepsilon_{it} \quad (2.2)$$

where:

$kwh_{i,d}$ is the customer's consumption in hour i, on day d.

$\alpha_{i,d}$ is the intercept.

$\varepsilon_{i,d}$ is the error for participant in hour i on day d.

and, all other terms are defined in

above.

After the "best" model was selected for each customer, AEG calculated the customer-specific impact as follows:

- AEG obtained the actual and predicted load on each hour and day based on the best model specification for each customer.
- AEG used the estimated coefficients and the baseline portion of the model to predict what this customer would have used on each day and hour if there had been no events. We call this prediction the reference load.

- AEG 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.
- In order to show the actual observed load (and avoid confusion associated with the predicted load) we re-estimated the reference load as the sum of the observed load and the load impact.

2.2.3 Obtain Load Impacts and Confidence Intervals by Subgroup

Because we 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. In some cases AEG needed to apply average per-customer impacts as a proxy for the "actual" impacts realized by one or more customers on a given event day because part of their data was invalid and, therefore, omitted during the data validation process. In these cases, we determined the aggregate impact for a particular grouping based on the per-customer average of the customers with valid data in the grouping and the total nominated accounts associated with that grouping for the given event.

It is important to note that the per-customer average may be different depending on the group or subgroup because of the different types and sizes of customers in the grouping. Therefore, during events where average per-customer data was used as a proxy for one or more customers, the sum of the individual subgroup totals for the event may not exactly add up to the total for the larger groupings or populations of customers. Consider the following hypothetical example:

- Subgroup #1 in Product A:
  - ✓ 24 nominated customers
  - ✓ 23 with sufficient valid data to estimate impacts
  - ✓ Aggregate impact for 23 customers = 2,300 kW
  - ✓ Average per-customer impact for the subgroup would be calculated with the aggregated data for the 23 customers: 2,300 kW / 23 customers = 100 kW per customer
  - ✓ Aggregate impact for all 24 nominated customers: 100 kW/customer x 24 customers = 2,400 kW

- Subgroup #2 in Product A:
  - ✓ 76 nominated customers, all with sufficient valid data to estimate impacts
  - ✓ Aggregate impact for 76 customers: 6,460 kW
  - ✓ Average per-customer impact: 6,460 kW / 76 customers = 85 kW per customer

- Total for Product A:
  - ✓ 100 nominated customers

- ✓ 99 with sufficient valid data to estimate impacts
- ✓ Aggregate impact for 99 customers = 2,300 kW + 6,460 kW = 8,760 kW
- ✓ Average per-customer impact for the subgroup would be calculated with the aggregated data for the 99 customers: 8,760 kW / 99 customers = 88.48 kW per customer
- ✓ Aggregate for all 100 nominated customers: 88.48 kW/customer x 100 customers = 8,848 kW

- Sum of Subgroup #1 plus Subgroup #2 = 2,400 kW + 6,460 kW= 8,860 kW, which does not equal the Total for Product A of 8,848 kW.

2.3 CBP Ex post Load Impact Estimates

Table 2-2 below presents a summary of the 2016 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 7 event days over the course of the program year, while DA participants experienced 14 events. Typical events were those called during hours-ending 16-19.

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	124	60	67
6/20/2016	Monday	16-19	138	61	-
7/20/2016	Wednesday	16-19	120	60	67
7/21/2016	Thursday	16-19	120	60	67
7/22/2016	Friday	16-19	120	60	67
7/26/2016	Tuesday	16-19	-	-	67
7/27/2016	Wednesday	16-19	-	-	67
7/28/2016	Thursday	16-19	-	-	67
7/29/2016	Friday	16-19	-	-	67
8/15/2016	Monday	16-19	126	60	-
8/16/2016	Tuesday	16-19	-	-	67
8/17/2016	Wednesday	16-19	-	-	67
8/18/2016	Thursday	16-19	-	-	67
8/19/2016	Friday	16-19	-	-	67
9/26/2016	Monday	16-19	124	60	68
9/27/2016	Tuesday	16-19	124	60	68
10/20/2016	Thursday	16-19	-	-	68

Table 2-3 and table 2-4 show the average event-hour impacts for the CBP DO product and the DA 1-4 hour product. Impacts are included for each event, both at the average per-customer level and in aggregate. The tables include results for the average event day.

Table 2-3: SDG&E CBP Day-Of Product (1-4 Hour and 2-6 Hour Products Combined): Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW) Reference Load	Per Customer Impact (kW) Impact	Aggregate Impact (MW) Reference Load	Aggregate Impact (MW) Impact	% Impact	Temp (˚F)
Avg. Event	184	3.9	197.9	26.1	36.4	4.8	13%	84
6/20/2016	199	3.6	193.4	19.3	38.5	3.8	10%	80
7/20/2016	180	3.6	183.1	19.5	33.0	3.5	11%	80
7/21/2016	180	3.6	187.1	19.7	33.7	3.5	11%	82
7/22/2016	180	3.6	194.4	19.8	35.0	3.6	10%	84
8/15/2016	186	4.5	211.5	23.1	39.3	4.3	11%	83
9/26/2016	184	4.3	211.1	41.3	38.8	7.6	20%	97
9/27/2016	184	4.3	200.7	39.5	36.9	7.3	20%	83

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

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW) Reference Load	Per Customer Impact (kW) Impact	Aggregate Impact (MW) Reference Load	Aggregate Impact (MW) Impact	% Impact	Temp (˚F)
Avg. Event	67	4.0	235.2	19.4	15.8	1.3	8%	79
7/20/2016	67	0.5	205.8	3.9	13.8	0.3	2%	79
7/21/2016	67	0.5	218.0	10.5	14.6	0.7	5%	80
7/22/2016	67	0.5	212.4	11.0	14.2	0.7	5%	81
7/26/2016	67	0.5	214.1	10.4	14.3	0.7	5%	76
7/27/2016	67	0.5	211.3	10.3	14.2	0.7	5%	77
7/28/2016	67	0.5	208.7	10.2	14.0	0.7	5%	77
7/29/2016	67	0.5	197.1	3.8	13.2	0.3	2%	72
8/16/2016	67	7.8	247.3	35.4	16.6	2.4	14%	78
8/17/2016	67	7.8	266.9	6.9	17.9	0.5	3%	77
8/18/2016	67	7.8	242.3	35.7	16.2	2.4	15%	74
8/19/2016	67	7.8	227.4	35.7	15.2	2.4	16%	75
9/26/2016	68	7.8	297.6	52.5	20.2	3.6	18%	97
9/27/2016	68	7.8	283.4	51.0	19.3	3.5	18%	81
10/20/2016	68	5.7	263.6	0.5	17.9	0.0	0%	88

2.4 CBP Ex ante Evaluation Methodology

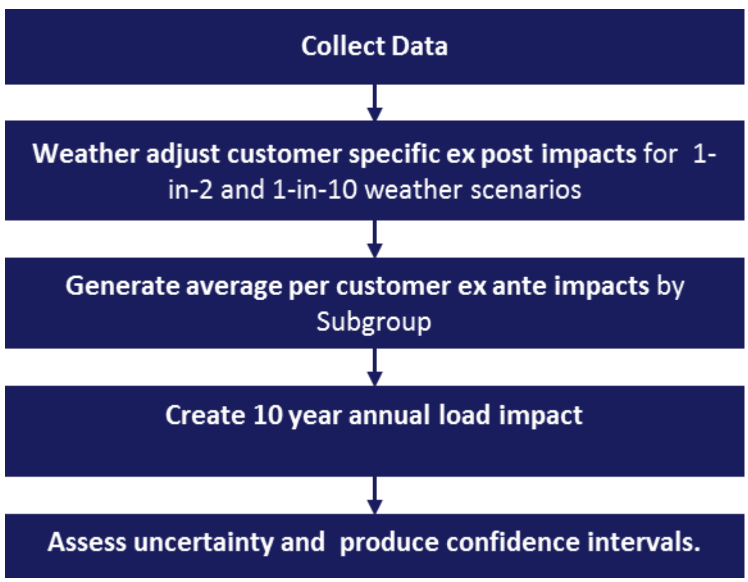
The main goal of the ex ante analysis is to produce an annual 11-year forecast of the load impacts expected from the CBP program.

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

- AEG first provided the IOUs with the appropriate weather-adjusted, per-customer impacts for each subgroup.
- The IOUs used the per-customer impacts, along with contractual MW agreements and adjustments based on historical load reduction performance and/or the latest development of the program, to determine the enrollment forecasts.
- AEG then used the enrollment forecasts and the per-customer ex ante impacts to develop the 11-year annual load impact forecasts for the participant populations and subgroups.

Figure 2-2Figure 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 11 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 peak day 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:

- For each customer, AEG began with the coefficients estimated in the customer-specific regression models developed for the ex post analysis.
- Then, AEG replaced the actual weather, from the program year, with the 1 in 2 and 1 in 10 weather data, based on the actual calendars for each year, to predict a customer's load for each of these scenarios on each day assuming no events are called. The result is a weather-adjusted monthly peak day reference load for each customer for each weather year.
- Next, AEG predicted the weather-adjusted event day load by again applying the coefficients from the ex post models to both the 1 in 2 and 1 in 10 weather data; however, this time we assumed that events were called on each monthly peak day by changing the event-indicator variables from zero to one. We also assumed that all events occurred during the Resource Adequacy window, which is between hour-ending 14 and hour-ending 18. As part of the ex ante forecast development for SDG&E, we applied the impacts predicted under August weather conditions to each month so that the per-customer impacts would not vary by month in a given forecast year. 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. Aggregators target delivery at the nominated level, with little incentive to deliberately over-deliver the load reduction even under extreme weather.
- AEG then calculated the load impact for each of the participants by subtracting the weather-adjusted event-day load from the weather-adjusted reference load.

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 is a capacity-payment program, SDGE allocate the full load impacts from the dual participants of CBP and other energy-payment programs to CBP. Therefore, the CBP impacts for dual participants do not require adjustments.

2.4.3 Creation of 11-Year Annual Load Impact Forecasts

AEG provided the IOUs with the per-customer average ex ante impacts by year and subgroup. SDGE used the per-customer impacts—along with contractual MW adjusted by historical performance relative to the aggregator's MW nomination and/or anticipated program changes—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 11 years.

2.5 CBP Ex ante Load Impact Estimates

For the CBP DA and DO products, the enrollment forecast assumes the customer enrollment will increase by 3% per year starting in 2019 through 2022 due to the CBP program improvements proposed by SDG&E in the application for 2018-2022. In addition, SDG&E forecasts that the customer enrollment in the CBP DO program will increase by another 7% per year starting in 2019 through 2022 due to growth in the Technical Incentives (TI) program. Therefore, total DO enrollment is expected to increase by 10% per year (3% + 7%) starting in 2019 through 2022, due to program improvements and growth in TI. The enrollment forecasts for the DA and DO products after 2022 and through 2027 show a flat trend at the 2022 values.

The ex ante load impact forecast follows the 2017-2027 enrollment forecast trends 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: SDG&E CBP: Average Event-Hour Ex ante Impacts for an August Peak Day, 2017 summarizes the average event-hour load impact forecasts for the DA and DO products on an August peak day in 2017.[4] 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.

Table 2-6: SDG&E CBP: Average Event-Hour Ex ante Impacts for an August Peak Day, 2017

		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	70	13.0	12.1	13.0	13.0	0.91	0.84	0.91	0.91
Total DO	199	25.5	25.3	25.5	25.3	5.07	5.03	5.07	5.04

2.6 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.

2.6.1 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 five 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.

[4] Though labeled as an August peak day in 2017, the results in would be identical for each month, May through October, in the 2017 forecast.

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

	Ex post Year	Accounts	Per Customer (kW) Reference Load	Per Customer (kW) Load Impact	Aggregate (MW) Reference Load	Aggregate (MW) Load Impact	% Impact	Event Temp (˚F)
DA	2012	78	320.3	81.6	25.0	6.4	25%	83
DA	2013	142	304.8	75.9	43.2	10.8	25%	88
DA	2014	163	247.0	60.6	40.4	9.9	25%	87
DA	2015	122	148.0	64.1	18.1	7.8	43%	80
DA	2016	67	235.2	19.4	15.8	1.3	8%	79
DO	2012	321	229.7	30.5	73.7	9.8	13%	86
DO	2013	260	234.5	40.2	61.1	10.5	17%	87
DO	2014	237	228.5	37.0	54.1	8.8	16%	87
DO	2015	223	208.4	25.6	46.4	5.7	12%	82
DO	2016	184	197.9	26.1	36.4	4.8	13%	84

2.6.2 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.5 In addition, the ex ante results reflect the utility peak 1 in 2 weather scenario.

Table 2-8: SDG&E CBP: Previous and Current Ex ante and Ex post, August Peak Day

	Model	Year	Day	Accts	Per Customer (kW) Ref. Load	Per Customer (kW) Impact	Aggregate (MW) Ref. Load	Aggregate (MW) Impact	% Impact	Event Temp (˚F)
DA	Current	Ex post 2016	Aug 16	67	247.3	35.4	16.6	2.4	14%	78
DA	Current	Ex ante 2017	Aug Peak	70	261.4	13.0	18.3	0.9	5%	83
DA	Previous	Ex post 2015	Jun 30	131	205.7	65.1	27.0	8.5	32%	81
DA	Previous	Ex ante 2016	Aug Peak	122	213.5	62.9	26.0	7.7	30%	81
DA	Previous	Ex ante 2017	Aug Peak	122	213.5	62.9	26.0	7.7	30%	81
DO	Current	Ex post 2016	Aug 15	186	211.5	23.1	39.3	4.3	11%	83
DO	Current	Ex ante 2017	Aug Peak	199	184.0	25.5	36.6	5.1	14%	85
DO	Previous	Ex post 2015	Aug 26	216	214.2	25.9	46.3	5.6	12%	84
DO	Previous	Ex ante 2016	Aug Peak	220	187.0	20.7	41.2	4.6	11%	81
DO	Previous	Ex ante 2017	Aug Peak	220	187.0	20.7	41.2	4.6	11%	81

[5] 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.

Table 2-8: shows the following trends for the CBP DA and DO products:

- ***Current Ex post Compared with Previous Ex ante:*** For DA, the current ex post results show lower aggregate impacts than the previous ex ante projections for PY2016 due to lower per customer impacts and lower enrollment. For DO, the current ex post results show comparable aggregate impacts to the previous ex ante projections for PY2016.

- ***Current Ex ante Compared with Previous Ex ante:*** The current ex ante analysis for DA projects lower impacts in PY2017 than did the previous ex ante analysis due to lower expected per customer impacts and lower enrollment. The current PY2017 ex ante estimates for DO are similar to previous ex ante impacts for PY2017.

- ***Current Ex ante Compared with Current Ex post:*** For DA, the current ex ante estimates for PY2017 show lower aggregate impacts than the current ex post estimates for PY2016 due to lower per customer impacts. For DO, the current ex ante estimates for PY2017 show fairly comparable aggregate impacts to the current ex post estimates for PY2016.

3 Summary of SDG&E's Critical Peak Pricing Default Report

3.1 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).

Large C&I customers were defaulted onto CPP, starting in 2008. SDG&E began to default its Small and Medium Business (SMB) customers between November 2015 and April 2016. By April of 2016 over 140,000 SMB customers were defaulted onto CPP. This report covers SDG&E's medium and large customers which are customers 20 kW and larger. A separate CPP study was conducted for SDG&E's small business and agricultural customers.[6]

In 2009, the California Public Utilities Commission (CPUC) issued rate design guidance for dynamic pricing tariffs such as CPP (CPUC decision (D.) 10-02-032). The decision standardized several key elements of dynamic pricing rate design for California IOUs:

- The default tariff for large and medium C&I customers must be a dynamic pricing tariff;[7]
- Default rates must include a high price during peak periods on a limited number of critical event days and TOU rates on nonevent days;
- The opt-out tariff for all nonresidential default customers should be a time varying rate—in other words, there should no longer be a flat rate option for nonresidential customers once the default schedule is completed;
- The critical peak price should represent the cost of capacity required to meet peak energy needs plus the marginal cost of energy—in essence, all capacity value should be allocated to peak period hours on critical event days; and
- Utilities should offer first year bill protection to customers defaulted onto dynamic rates.

The decision also served to standardize other aspects of rate design affecting nonresidential customers, including components of the default process and a schedule for each utility's implementation of dynamic pricing across all customer classes.

SDG&E has developed CPP tariffs that adhere to the principles and direction provided by D.10-02-032 described below:

- SDG&E was the first to default customers onto a CPP tariff, on May 1, 2008.
- SDG&E defaulted customers whose maximum demand exceeded 200 kW for the prior 12 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.

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[6] See Section 9 for SPP Rates.

[7] Customers with loads of 200kW or greater were defaulted onto CPP. SDG&E considers its medium sized customers to be >20 kW and less than 500 kW. Therefore some medium customers were included in the 2008 CPP default rollout.

- For SDG&E, both the CPP event period hours and TOU summer peak period hours are from 11 AM to 6 PM. Off-peak prices apply on the weekends at all three IOUs, unless a CPP event is called on a weekday;
- SDG&E can call CPP events throughout the calendar year and on any day of the week.
- SDG&E notify customers by 3 PM the day before.
- SDG&E offers customers the ability to hedge part or all of their demand against higher CPP prices, a feature known as a capacity reservation level (CRL).
- SDG&E 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). The bill comparison is sent to customers at the end of their first year on the rate. If the bill comparison shows that the customer paid more under CPP than they would have if they were subject to the OAT, then the customer's account is credited the difference.

SDG&E triggers CPP event days using their own protocols, which depend on forecasted conditions for their individual transmission and distribution system. Due to the climatic diversity in California, system load patterns across utilities are not always coincident, particularly between Northern and Southern California. SDG&E system peak occurred on September 26, 2016. Another key difference in ex post results is event duration. SDG&E uses a longer event window, 11 AM to 6 PM.

Table 3-1 provides examples of the default CPP and opt-out TOU rates at each utility. There are a number of different CPP rates at each utility, which vary with customer size and service voltage level. These various CPP rates also change over time due to periodic rate changes. SDG&E defines summer as May through September.

Table 3-1: Example Summer Default CPP Rates at SDG&E[8]

Season	TOU/CPP Component	Type of Charge/Credit	Period	Rate SDG&E AL-TOU
Summer	TOU Component	Energy Charges (per kWh)	On-peak	$0.13
			Semi-peak	$0.12
			Off-peak	$0.09
		Demand Charges (per kW)	On-peak	$21.13
			Semi-peak	$0.00
			Maximum	$24.51
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.28
			On-peak	$0.13
			Semi-peak	$0.12
			Off-peak	$0.09
		Demand Charges (per kW)	On-peak	$10.25
			Semi-peak	$0.00
			Maximum	$24.51
		Capacity Reservation Charge (per kW per month)	Summer	$6.14

[8] Tables 3-1 and 3-2 do not include all CPP rates at each utility, and the rates shown are presented for illustrative purposes only. Rates may vary over the course of the program year, by customer size and service voltage level. The rates shown are for customers at the secondary service voltage level. AL-TOU applies to all SDG&E customers whose monthly maximum demand equals, exceeds, or is expected to equal or exceed 20 kW. This example the SDG&E rate was effective March 1, 2017.

Table 3-2: Example Winter Default CPP Rates at SDG&E

Season	TOU/CPP Component	Type of Charge/Credit	Period	Rate SDG&E AL-TOU
Winter	TOU Component	Energy Charges (per kWh)	On-peak	$0.12
			Semi-peak	$0.10
			Off-peak	$0.08
		Demand Charges (per kW)	On-peak	$7.57
			Semi-peak	$0.00
			Maximum	$24.51
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.28
			On-peak	$0.12
			Semi-peak	$0.10
			Off-peak	$0.08
		Demand Charges (per kW)	On-peak	$7.57
			Semi-peak	$0.00
			Maximum	$24.51
		Capacity Reservation Charge (per kW per month)	Winter	$6.14

3.2 CPP-D Ex post Evaluation Methodology

Ex post evaluation is designed to estimate demand reductions on event days when higher CPP prices are in effect. Ex post impacts reflect the enrollment mix, weather, dispatch strategy and program rules in effect at the time of each event and, as a result, may not reflect the full demand reduction capability of a resource.

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. Reference loads can be estimated using pre-enrollment data, by observing differences in behavior during event and nonevent days (i.e., a within-subjects design), by using an external control group (a between-subjects design) or through a combination of the above. Load impacts are estimated for 2016 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 nonevent day data. However, for CPP customers for which a similar control customer is unavailable, we estimate customer specific regressions—that is, Nexant relied exclusively on each customer's electricity usage patterns on nonevent days to estimate reference load for event days. Nexant employed a rigorous approach to selecting an appropriate matching model that provides accurate matched control group counterparts for as many CPP customers as possible. Multiple models and their associated control groups were assessed in a cross-validation process that quantifies how well a control group predicts load on hot event-like days (proxy days) that were not used to match (an out-of-sample test). This approach was used to select among a set of carefully chosen models.

3.2.1 Proxy Day Selection

Proxy event days are selected by matching historical events to nonevent days based on system loads, temperature conditions, month, and day of week.[9]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 nonevent days. However, comparable nonevent days are not available for some of the days with the most extreme weather.

3.2.2 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. The model specification affects both the quality of the match and the number of participants matched given some threshold for the acceptable quality of a match. In the 2016 evaluation, model selection was conducted in a rigorous and quantitative fashion in order to achieve an accurate match for as many CPP customers as possible.

The 2014 evaluation improved on this approach, and the same methodology was applied for 2015 and 2016, using a more quantitative model selection process that employs a method called leave one out cross validation (LOOCV) over a single set of proxy days. That set of days is selected to be as similar to event days as possible. LOOCV is outlined below:

1. For each of the m candidate models, conduct LOOCV over proxy days:

   For each of the n proxy days:

   i. Develop explanatory variables using data from all proxy days except the nth;
   ii. Fit mth model using explanatory variables and select its associate control group;
   iii. Record load of control group and treatment group individuals on the nth proxy day not used to fit the model; and
   iv. Record number of treatment customers without a match.

[9] For SDG&E, the temperatures were from the Miramar weather station, which is used to assess when to dispatch events.

2. Compute metrics to measure bias and goodness-of-fit of a control group match.

3. Retain models that match at least 75% of treatment customers.

Note that we only retained models that provided matches for over 75% of CPP customers. This was done in order to estimate impacts using difference-in-differences with a matched control group for the vast majority of customers. As noted above, we evaluate the quality of a control group based on the bias and precision of its match with treatment group load on excluded days. Table 3-3 shows the metrics computed in step 2. All metrics were computed over the relevant CPP event hours for each IOU, as that was the principal period over which we had to estimate load impacts. To select a model on the basis of its performance over the entire day, would risk sacrificing precision during event hours for an increase in precision during non-event hours, which is an inefficient trade-off given that load impacts during event hours are of primary interest. We note that while models were evaluated on their performance during event hours, the majority of the models tested incorporate some measure of load in non-event hours. This means that if matching on non-event hour load helps improve the match during event hours, then those models will be featured if they outperform models that do not match on non-event hours.

Table 3-3: Control Group Accuracy Statistics

Statistic Type	Statistic Level	Statistic	Formula	Description	Typical Values
Bias	Program	Average Percent Error	$\frac{\sum \hat{y}_{i,t}}{\sum y_{i,t}} - 1$	Sums up baseline and actual value for individual customers and proxy days for the entire program; calculates error statistics from these values.	Expressed in percentage terms. Can be positive or negative. The closer to zero, the better.
Bias	Program	SD(APE)	$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(APE_t - \overline{APE})^2}$	Measures the average deviation in average percent error on individual proxy days.	Expressed in percentage terms. Can only be positive. The smaller the number, the better.
Goodness-of-fit	Program	Absolute Sum of Errors	$\sum \lvert \hat{y}_{i,t} - y_{i,t} \rvert$	Sums up absolute errors for individual customers and proxy days.	Expressed in kWh terms. Can only be positive. The smaller the number, the better.

3.2.3 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. 99% 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 large C&I treatment and control customers on the average proxy event day, and Figure 3-2 shows the same for small and medium treatment and control customers at SDG&E. The loads match closely, particularly during event hours. As explained in the next section, even these small differences are largely controlled for using the difference-in-differences methodology.

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

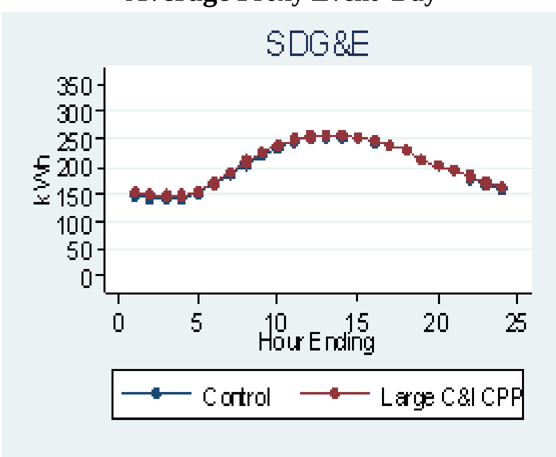
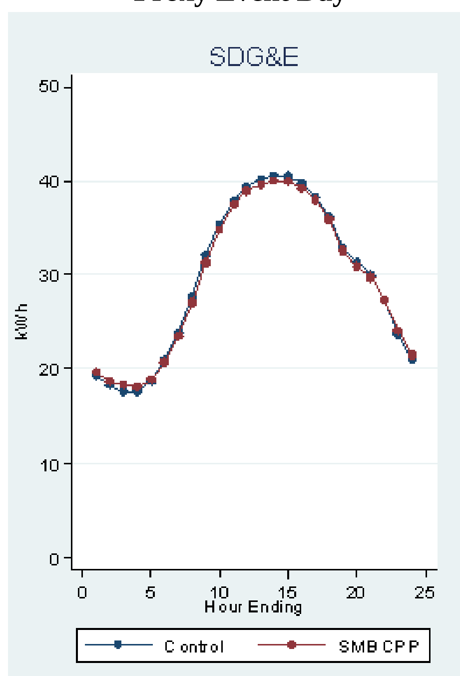


Figure 3-2: Comparison of Matched SMB Treatment and Control Group Load on Average Proxy Event Day



3.2.4 Difference-in-difference

Using the matched control groups, 2016 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).

3.2.5 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 for which an adequate control group match could not be found.[10]

For each customer, Nexant:

- Analyzed hot weekdays from 2016. To the extent possible, the regressions for each customer excluded cooler days, which typically do not provide much information about behavior under event conditions. For example, if the lowest event day maximum temperature a customer experienced was 100°F, only days that exceed 85% of 100°F (or 85°F) were included.
- Estimated 10 different regression models and used them to predict out-of-sample for event-like days where, in fact, CPP events were not called. This allowed us to identify the regression model that produced the most accurate results for each customer. The 10 models vary in how weather variables were defined, if at all, and in the inclusion of monthly or seasonal variables.
- Selected the most accurate model specification and used it to estimate demand reductions during actual event days.

3.3 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 one CPP event in 2016, on Monday, September 26. On this date, there were 12,536 accounts enrolled on SDG&E's tariff in 2016. Enrollment of large customers grew from 826 in 2015 to 1,299 in 2016; an increase of 57%. There were 381 existing medium customers enrolled in the statewide CPP in 2015. All customers on A6, AY, AL and AD rates are considered medium and large customers, and are reported under in the statewide CPP report and load impact tables. All other nonresidential customers are considered small commercial customers and are reported in the small commercial TOU and TOU-CPP report and load impact

[10] At SDG&E, individual customer regressions were performed for 90 customers. These customers tended to be in the 1st usage quintile.

tables. Table 3-4 shows the counts of customers on each rate and each size segment on the event day. The participant-weighted average temperature[11] during the event period was 97.6°F.

Table 3-4: Customer Size Designations

Reporting Group	Reporting Group Description	Customer Size	Annual Max Demand	Count 2016	Count 2015
Statewide CPP	Customers on A6, AY, AL and AD rates enrolled in CPP by the event day	Large	> 200kW	1,299	826
		Medium	20 - 199kW	11,237	381
		All	All	12,536	1,207

Table 3-5 shows the ex post load impact estimates by customer size for the only event day in 2016. The participant-weighted average temperature during the event period was 97.6°F. Percent impacts ranged from 2.1% for 11,237 medium customers to 3.4% for large customers. Average impacts ranged from 0.8kW to 9.6kW and aggregate impacts across events ranged from 9.3 MW to 12.4 MW. For the whole program on the event day, the average participant reduced peak period load by 2.6%, or 1.7 kW. In aggregate, SDG&E's CPP customers reduced load by 21.7 MW in aggregate.

Table 3-5: Default CPP Ex Post Load Impact Estimates on the 2016 SDG&E CPP Event (11 AM to 6 PM)

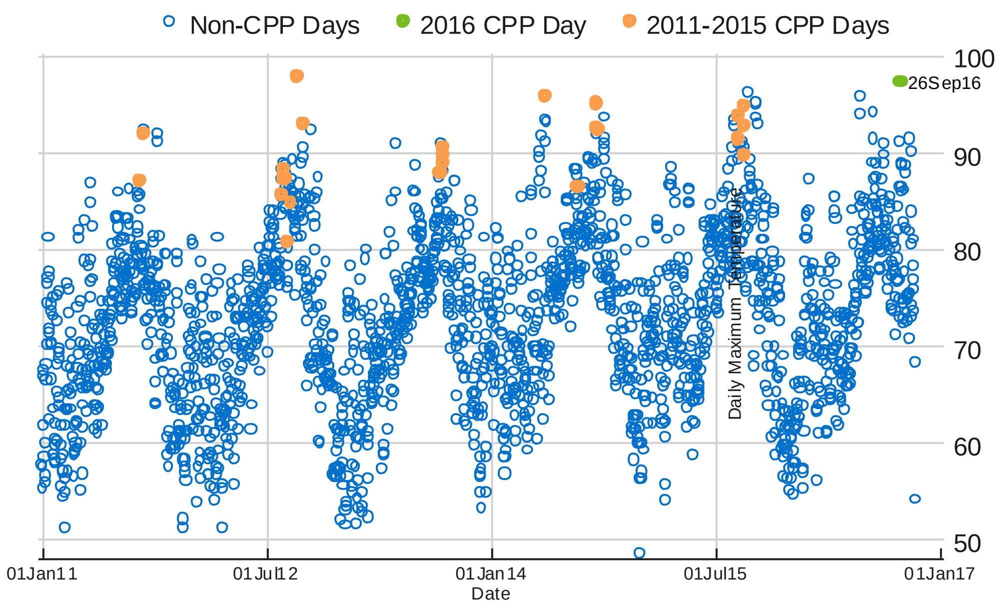
Event Date	Customer Size	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp.	Daily Maximum Temp.
			(kW)	(kW)	(kW)	(MW)	%	°F	°F
9/26/2016	Large	1,299	283.4	273.8	9.6	12.4	3.4%	97.8	99.7
	Medium	11,237	41.0	40.1	0.8	9.3	2.1%	97.5	99.6
Avg. Event		**12,536**	**65.7**	**63.9**	**1.7**	**21.7**	**2.6%**	**97.6**	**99.6**

As only one event was called across the whole territory during the summer of 2016, very few conclusions can be reached about the impacts of the CPP event on all customer groups. The 2016 event day, on Monday, September 26th, was highly unusual in several regards and the results of the impact analysis should be interpreted with caution. Figure 3-3 shows the participant-weighted daily maximum temperature for SDG&E's territory over the last five years. Orange data points represent past CPP days, while the green data point represents this year's CPP event. With a daily maximum temperature of over 99F, it is the hottest CPP event day since 2012. With such hot weather, customers with temperature-sensitive loads may not have been able to respond to the event. The CPP event was also called on a Monday, the first time since 2014 that this

[11] Participant-weighted average temperature is the average temperature during the event hours for all customers participating in the CPP event.

happened. Of concern is that customers may not have received notification in time to respond to a Monday morning event. Roughly 7,200 customers were notified that an event was scheduled to take place, out of roughly 12,500 medium and large CPP customers. This lack of notification was another likely contributor to the lower than usual impacts observed during this year.

Figure 3-3: Daily Maximum Temperature Trends for SDG&E CPP Events



3.4 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.[12]

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) and by utility. For large customers, the ex ante estimation process began by re-estimating ex post load impacts for persistent customers with data for all events in 2015 and 2016, using the same estimation model. Estimates may be sensitive to modeling variation and customer churn, so this re-estimation is necessary to derive impacts that can be used to reliably model a relationship with temperature. Furthermore, both 2015 and 2016 events are needed to provide enough data points.

[12] SDG&E updated its 1 in 2 and 1 in 10 weather conditions to be used for all weather sensitive programs (see Table 10-7 for details).

As SDG&E defaulted a large number of new customers on to the CPP program in 2016, these newly defaulted customers were not expected to behave in the same way that long-term CPP customers did. To account for this, persistent large customers were modeled using two years of ex post data in the manner described above, however new large customers and medium customers were estimated using only one year of ex post data. Although there were a small number of persistent medium customers in SDG&E's territory, they were a relatively small portion of the total medium population (less than 400 out of 11,237) so any persistent impact would not be appreciably different once averaged in to the full new customer population. Roughly 11,000 medium customers at SDG&E were defaulted by the spring of 2016.

Nexant then modeled reference loads for 1 in 2 and 1 in 10 weather conditions. Reference loads are estimated separately for the large and 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 medium C&I customer class, hourly load for a representative sample of medium C&I customers is modeled by LCA as a function of temperature and month.[13] 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 2015 and 2016 for large persistent customers for SDG&E 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.

3.5 CPP-D Ex ante Load Impacts Estimates

This section presents ex ante load impact estimates for SDG&E's nonresidential CPP tariff. 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 2015 and 2016 when possible. As the vast majority of customers on CPP rates in SDG&E's territory in 2016 are newly defaulted, there is little historical data on which to base their ex ante load impacts. For customers persistent across two years of CPP events, both years were used to estimate the relationship between weather and percent load impacts. All new customers relied on load impacts modeled only by the 2016 event. For large persistent customers, six 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.

[13] Considering that SDG&E only has one LCA, load is modeled by industry instead, to facilitate applying industry specific cross price elasticities to estimate percent reductions.

This section presents the ex ante load impact projections separately for medium and large customers projected to receive service under SDG&E's default CPP tariff. Load reduction capability is summarized for each segment under annual system peak day conditions for a 1 in 2 and a 1 in 10 weather year for selected years (e.g., 2017, 2018 and 2027). The estimates presented here are at the program level and do not account for dual enrollment of CPP participants in other DR programs.

In addition to reflecting ex ante weather conditions and a standard event window, ex ante load impacts take into account both utility enrollment forecasts and changes to the design of default CPP ordered or approved by the CPUC. This section details how weather, enrollment and program changes affect any differences between ex post and ex ante impacts. A substantive change is scheduled for SDG&E in the 2017–2027 forecast horizon: SDG&E defaulted medium C&I customers onto CPP rates by April 2016. These customers can elect to opt out to TOU rates if they do not wish to take a CPP rate.

3.5.1 Large C&I Ex ante Impacts

The ex ante impact estimates for SDG&E are based on ex post load impacts of CPP events that occurred in 2015 and 2016 when possible. As the vast majority of customers on CPP rates in SDG&E's territory in 2016 are newly defaulted, there is little historical data on which to base their ex ante load impacts. For customers persistent across two years of CPP events, both years were used to estimate the relationship between weather and percent load impacts. All new customers relied on load impacts modeled only by the 2016 event. For large persistent customers, six 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.

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 2016 (and 2015 when applicable for large persistent customers) to estimate model coefficients. By removing variation in the customer mix from the analysis, we are better able to identify the underlying relationship between temperature and percent impacts. The steps involved in the analysis are as follows. For new large customers as well as the medium and small customers who were overwhelmingly new customers, one year of data was used instead of two.

1. Identify persistent customers from 2015 and 2016;
2. Re-run 2015 and 2016 ex post analysis for just persistent customers to yield persistent customer ex post impacts;
3. Model persistent customer ex post impacts as a function of weather;
4. Apply percent impacts model to ex ante weather conditions;

5. Identify large ex post customers enrolled at the end of the summer in 2016 who are also in the large demand category and have a full panel of data for 2016, and model their reference load as a function of temperature;
6. Apply reference load model to ex ante weather conditions;
7. Combine percent impacts and reference load for each set of ex ante conditions to get kW impacts for the average customer;
8. Multiply average customer impacts by ex ante enrollment.

Table 3-6 shows SDG&E's enrollment projections for large C&I CPP customers through 2027. Overall, 1,299 large customers were enrolled in default CPP in 2016 on the September 26th event day. 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 3-6: SDG&E Enrollment Projections for Large CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2017	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425
2018	1437	1437	1437	1437	1437	1437	1437	1437	1437	1437	1437	1437
2019	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461
2020	1481	1481	1481	1481	1481	1481	1481	1481	1481	1481	1481	1481
2021	1498	1498	1498	1498	1498	1498	1498	1498	1498	1498	1498	1498
2022	1517	1517	1517	1517	1517	1517	1517	1517	1517	1517	1517	1517
2023	1536	1536	1536	1536	1536	1536	1536	1536	1536	1536	1536	1536
2024	1556	1556	1556	1556	1556	1556	1556	1556	1556	1556	1556	1556
2025	1577	1577	1577	1577	1577	1577	1577	1577	1577	1577	1577	1577
2026	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598
2027	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620

3.5.1.1 Monthly System Peak Day Impacts

Table 3-7 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 33 MW to 38 MW between 2017 and 2027. Impacts based on 1 in 10 year SDG&E weather conditions are slightly higher than the 1 in 2 scenarios due to higher reference loads modeled under more extreme weather scenarios.. 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 and 1 in 10 weather scenarios are slightly higher than their SDG&E-specific counterparts. 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 3-7: 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 (MW 1–6 PM)	Aggregate Estimated Load w/ DR (MW 1–6 PM)	Aggregate Load Impact (MW 1–6 PM)	% Load Reduction (%)	Weighted Temp.[14] (°F)
SDG&E	1 in 10	2017	1425	406.7	373.3	33.4	8.2%	85.9
		2018	1437	409.6	376.2	33.4	8.1%	85.9
		2027	1620	457.7	419.6	38.1	8.3%	85.9
	1 in 2	2017	1425	403.9	370.4	33.5	8.3%	80.8
		2018	1437	406.8	373.3	33.5	8.2%	80.8
		2027	1620	454.6	416.4	38.2	8.4%	80.8
CAISO	1 in 10	2017	1425	395.2	361.6	33.6	8.5%	83.0
		2018	1437	398.0	364.4	33.6	8.4%	83.0
		2027	1620	444.9	406.5	38.4	8.6%	83.0
	1 in 2	2017	1425	392.6	358.9	33.7	8.6%	82.7
		2018	1437	395.4	361.7	33.7	8.5%	82.7
		2027	1620	442.0	403.5	38.5	8.7%	82.7

3.5.1.2 Comparison of 2015 and 2016 Ex ante Estimates

Table 3-8 compares the ex ante estimates produced for the 2015 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. Increases in both the number of forecasted enrolled customers and reference loads drove higher aggregate impact estimates in 2016 compared to 2015. Enrollment is up by approximately 10% compared to 2015, while reference loads increased by approximately 20% for the 2017 forecast year. While the percent impacts for large customers are roughly the same in both forecasts, the differences in reference loads and enrollments result in impacts that are roughly 30% higher in the 2016 ex ante analysis compared to 2015.

[14] Refers to the average temperature that a customer would experience under the respective weather conditions in ex ante.

Table 3-8: Comparison of Ex ante Estimates to Prior Year Estimates

Weather Year	Year	Accounts		Reference Loads (MW)		Percent Reductions		Aggregate Impacts (MW)	
		2015 Estimates	2016 Estimates	2015 Estimates	2016 Estimates	2015 Estimates	2016 Estimates	2015 Estimates	2016 Estimates
1 in 10	2017	1,282	1,425	237.6	285.4	8.3%	8.2%	25.3	33.4
	2018	1,295	1,437	237.6	285.0	8.3%	8.1%	25.5	33.4
	2026	1,419	1,598	237.5	282.8	8.3%	8.3%	27.9	37.6
1 in 2	2017	1,282	1,425	225.7	283.4	7.7%	8.3%	22.3	33.5
	2018	1,295	1,437	225.7	283.1	7.7%	8.2%	22.5	33.5
	2026	1,419	1,598	225.6	280.9	7.7%	8.4%	24.6	37.7

3.5.1.3 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 3-9 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 lower than the ex post values when based on SDG&E ex ante weather and also lower than the averaged persistent and large new 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 as well as the negative relationship between temperature and load due to the inclusion of the 2016 event day. Changes in enrollment between the values used for ex post estimation and the 2016 enrollment values increase impact estimates by about 10%.

Table 3-9: Summary of Factors Underlying Differences between Ex Post and Ex Ante Impacts for the Large CPP

Customers for the Ex Ante Typical Event Day

Factor	Ex post	Ex ante	Expected Impact
Weather	Default CPP customers: Average event day mean17 = 82.1	Program specific mean17 for 1 in 2 typical event day = 74.4 and 73.0 for SDG&E and CAISO weather, respectively Program specific mean17 for 1 in 10 typical event day = 78.6 and 75.7 for SDG&E and CAISO weather, respectively	Ex ante estimates are sensitive to variation in mean17 – impacts will be higher based on both SDG&E weather and CAISO weather
Enrollment	One event was called, no enrollment trend is observed	2016 enrollment is forecast to be about 10% higher	Ex ante estimates will be about 10% higher than ex post
Methodology	2016 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 and one year for new larger 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 weaker temperature relationship than those for all customers. Impacts will be lower at higher temperatures. New large customers exhibit the expected positive correlation between load and temperature, which explains the overall increase in reference load compared to 2015.

Table 3-10 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 2016 ex post impacts and the projected enrollment for August of 2017 to produce a scaled-up ex post impact estimate, which is slightly larger due to the increased large customer enrollment. The next column shows what the ex ante model would produce using the same August 2017 enrollment figures and the ex post weather conditions for each event day. It is important to note that the 2016 event day mean17 was only 82.1F, which represents a warm day, but does not capture the extreme late-afternoon temperatures that drove the high maximum temperature. Any impacts are calculated on the basis of the relationship between mean17 and percent impacts, which does not capture the extreme heat on the 2016 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. One-in-ten weather scenarios show smaller impacts overall compared to one-in-two due to the slightly negative relationship between mean17 and load over the large customers attributable to the low performance in the 2016 event.

Table 3-10: 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)
9/26/2016	82.1	12.4	13.7	16.5	20.7	21.3	18.2	16.8
Avg.	82.1	12.4	13.7	16.5				

3.6 Medium C&I Ex ante Impacts

The steps involved in the analysis are as follows. Model persistent customer ex post impacts as a function of weather:

1. Apply percent impacts model to ex ante weather conditions;
2. Identify medium and small ex post customers enrolled at the end of the summer in 2016 who have a full panel of data for 2016, and model their reference load as a function of temperature;
3. Apply reference load model to ex ante weather conditions;
4. Combine percent impacts and reference load for each set of ex ante conditions to get kW impacts for the average customer;
5. Multiply average customer impacts by ex ante enrollment.

Table 3-11 shows SDG&E's enrollment projections for medium and small CPP customers through 2027. Overall, 11,237 medium were enrolled in default CPP in 2015. The forecasted year-to-year change in enrollment is a gradual decrease which represents the rate of customer opt out of the CPP tariff.

Table 3-11: 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.
2017	11,320	11,320	11,320	11,320	11,320	11,320	11,320	11,320	11,320	11,320	11,320	11,320
2018	11,221	11,221	11,221	11,221	11,221	11,221	11,221	11,221	11,221	11,221	11,221	11,221
2019	11,075	11,075	11,075	11,075	11,075	11,075	11,075	11,075	11,075	11,075	11,075	11,075
2020	10,884	10,884	10,884	10,884	10,884	10,884	10,884	10,884	10,884	10,884	10,884	10,884
2021	10,649	10,649	10,649	10,649	10,649	10,649	10,649	10,649	10,649	10,649	10,649	10,649
2022	10,374	10,374	10,374	10,374	10,374	10,374	10,374	10,374	10,374	10,374	10,374	10,374
2023	10,063	10,063	10,063	10,063	10,063	10,063	10,063	10,063	10,063	10,063	10,063	10,063
2024	9,718	9,718	9,718	9,718	9,718	9,718	9,718	9,718	9,718	9,718	9,718	9,718
2025	9,344	9,344	9,344	9,344	9,344	9,344	9,344	9,344	9,344	9,344	9,344	9,344
2026	8,945	8,945	8,945	8,945	8,945	8,945	8,945	8,945	8,945	8,945	8,945	8,945
2027	8,526	8,526	8,526	8,526	8,526	8,526	8,526	8,526	8,526	8,526	8,526	8,526

3.6.1 Monthly System Peak Day Impacts

Table 3-12 summarizes the aggregate load impact estimates for medium and small 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. Note that there are roughly 230 small customers with a maximum annual demand of less than 20kW that are nevertheless on medium customer tariffs. Since their percentage of the total number of medium customers is so small (230 out of more than 11,000) they were not estimated separately and are reported here under the medium customer grouping.

Looking first at the aggregate load impacts based on SDG&E-specific, 1 in 2 year weather conditions, load reductions will decline from roughly 2.9 MW to 2.2 MW between 2017 and 2027. Impacts based on 1 in 10 year SDG&E weather conditions equal roughly 3.0 MW in 2017 and will decline to 2.2 MW by 2027. These estimates equal roughly 0.7% of the aggregate reference load for medium and small customers and decline over time as the number of enrolled medium and small customers decrease. Impact estimates based on CAISO-specific, 1 in 2 and 1 in 10 scenarios are slightly smaller than the SDG&E specific scenarios. 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 3-12: 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 (MW 11 AM–6 PM)	Aggregate Estimated Load w/ DR (MW 11 AM–6 PM)	Aggregate Load Impact (MW 11 AM–6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
SDG&E	1 in 10	2017	11,320	449.5	446.5	3.0	0.7%	86.3
		2018	11,221	445.6	442.6	2.9	0.7%	86.3
		2027	8,526	338.5	336.3	2.2	0.7%	86.3
	1 in 2	2017	11,320	445.2	442.3	2.9	0.7%	81.0
		2018	11,221	441.4	438.5	2.9	0.7%	81.0
		2027	8,526	335.4	333.2	2.2	0.7%	81.0
CAISO	1 in 10	2017	11,320	433.4	430.5	2.8	0.7%	83.5
		2018	11,221	429.6	426.8	2.8	0.7%	83.5
		2027	8,526	326.4	324.3	2.1	0.7%	83.5
	1 in 2	2017	11,320	429.7	426.9	2.8	0.7%	83.2
		2018	11,221	425.9	423.2	2.8	0.7%	83.2
		2027	8,526	323.7	321.5	2.1	0.7%	83.2

3.6.2 Relationship between Ex Post and Ex Ante Estimates

Table 3-13 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 2016 season, which drove reference loads down.

Table 3-13: Summary of Factors Underlying Differences between Ex Post and Ex Ante Impacts for the Medium

CPP Customers for the Ex Ante Typical Event Day

Factor	Ex Post	Ex Ante	Expected Impact
Weather	Default CPP customers: Average event day mean17 = 81.7	Program specific mean17 for 1 in 2 typical event day = 72.4 and 73.1 for SDG&E and CAISO weather, respectively Program specific mean17 for 1 in 10 typical event day = 77.4 and 75.9 for SDG&E and CAISO weather, respectively	Ex ante impact estimates are not sensitive to mean17 as we only have one data point for these customers' response to temperature.
Enrollment	Only one event for these customers – there cannot be any trend in enrollment	2017 enrollment is forecast to be about 3% higher	Ex ante estimates will be about 3% higher than ex post
Methodology	2016 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 one 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	Reference loads decrease as ex ante weather is cooler than the event day, driving lower impacts

Table 3-14 shows how aggregate load impacts change for medium and small CPP customers as a result of differences in the factors underlying ex post and ex ante estimates. The third column uses the 2016 ex post impacts shown in Table 8-1 and the projected enrollment for August of 2017 to produce a scaled-up ex post impact estimate, which is slightly higher than the average ex post impact due to increased enrollment. 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 2016 SDG&E ex post weather conditions, although the impacts are still lower than the ex post event day.

Table 3-14: Differences in Medium CPP Ex Post and Ex Ante Impacts Due to Key Factors

<table>
<tr><th rowspan="2">Date</th><th>Mean 17</th><th>Ex Post Impact</th><th>Ex Post Impact with Ex Ante Enrollment</th><th>Ex Ante Model Ex Post Weather</th><th>CAISO 1 in 2</th><th>SDG&E 1 in 2</th><th>CAISO 1 in 10</th><th>SDG&E 1 in 10</th></tr>
<tr><th>(F)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th></tr>
<tr><td>9/26/2016</td><td>81.7</td><td>9.3</td><td>9.6</td><td>1.2</td><td rowspan="2">1.1</td><td rowspan="2">1.1</td><td rowspan="2">1.0</td><td rowspan="2">1.0</td></tr>
<tr><td>Avg.</td><td>81.7</td><td>9.3</td><td>9.6</td><td>1.2</td></tr>
</table>

4 Summary of SDG&E’s Base Interruptible Program (BIP) Report

4.1 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 were 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.[15] There were no participants in 2006, three participants in 2007, five

[15] 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.

participants in 2008, 20 in 2009, 19 customers in 2010, 21 customers in 2011, 11 in 2012, seven participants in 2013 and 2014, five participants in 2015, and seven participants in 2016.

4.2 BIP Ex post and Ex ante Evaluation Methodology

This section explains the methodology that was used to develop ex post and ex ante load impact estimates for BIP. It covers the development of regression models and an assessment of their accuracy.

The first step in calculating event day impacts is estimating the reference loads of the customers participating in the program. Reference loads indicate how customers would have behaved in the absence of a DR event. Reference loads are estimated using regression analysis of customer usage on days that are similar to, but not actual, BIP event days. The observed loads are then subtracted from the loads to estimate ex post impacts. In ex ante analysis, historical weather data is used to determine the weather patterns of a typical BIP event day. The same models used in the ex post analysis are then run on these typical BIP event days to determine ex ante reference loads. However, in ex ante analysis, there are no observed loads to compare to the reference loads. In order to estimate ex ante impacts, impacts are calculated as a function of:

- Forecasted load in the absence of a DR event (i.e., the reference load);
- The participant's FSL; and
- Over/under performance relative to the FSL.

The reference loads are estimated using the regression models presented in Figure 4-1. Over/under performance, which is a measure of how well customers perform during BIP events relative to the FSL, is determined for each industry using historical event data. The number of events is too small to be used in a regression to predict the load with DR. Instead, impacts were estimated using average historical performance by industry, relative to FSL.
Several regression models to estimate reference loads were tested. The final regression models used to predict reference loads were chosen based on bias and accuracy metrics. Having low bias and high accuracy across all the industries also factored into the decision. In addition, varying datasets were tested to see if it would be beneficial to include data for both 2015 and 2016 compared to just 2016. The estimated models were based on two years of hourly load data for each customer, using all 24 hours for each individual customer's regression.

4.2.1 Regression Model

The regression model was used to predict the kW load for each hour separately for each participant. The regression models were based on many variables, consisting largely of shape and trend variables (and interaction terms) designed to track variation in load across days of the week and hours of the day. Weather variables were tested and had significant impacts for certain customers. Binary variables representing season were also included to capture the change in load due to seasonal variation. The regression models are as follows:

Figure 4-2: Reference Load Model – SDG&E

$$kW_t = A + \sum_{i=1}^{24} B_i \times Hour_i \times BIP\_Eventday_t + \sum_{i=1}^{24} C_i \times Hour_i \times CPP\_Eventday_t + \sum_{i=1}^{24} D_i \times Hour_i$$

$$\times DBP\_Eventday_t + \sum_{i=1}^{24} E_i \times Hour_i \times \text{morningload} + \sum_{i=1}^{5} F_i \times DOW_t +$$

$$+ \sum_{i=1}^{24} G_i \times Hour_i \times \text{Month} + \sum_{i=1}^{24} H_i \times Hour_i \times \text{Summer} + \sum_{i=1\text{ s}}^{24} I_i \times Hour_i \times \text{Summer}$$

$$\times \text{CDH}_{\text{MA3}} + \sum_{i=1}^{24} J_i \times Hour_i \times \text{Winter } \times \text{CDH60}$$

$$+ \sum_{i=1}^{24} K_i \times Hour_i \times \text{Winter } \times \text{HDH60} + \sum_{i=1}^{24} L_i \times Hour_i \times \text{Winter } \times \text{CDD}$$

$$+ \sum_{i=1}^{24} M_i \times Hour_i \times \text{HDD } + \sum_{h=1}^{24} N_i \times Hour_h$$

Table 4-1: Variable Descriptions

Variable	Description
kW_t	hourly BIP customer load at time t
A	estimated constant term
$B - O$	estimated parameters
CDD_t	cooling degree days (base 60)
CDH_t	cooling degree hours (base 60)
CDH_t	cooling degree hours (base 60) per day
HDH_t	heating degree hours (base 60) per day
$MorningLoad$	average customer load between 12 AM and 9 AM
$OvernightCDH$	total number of cooling degree hours (base 60) between 12am and 10am
$DayType_j$	series of binary variables representing five different day types (Mon., Tues.-Thurs., Fri., Sat., Sun./Holiday)
$Month_j$	series of binary variables for each month
$Hour_i$	series of binary variables for each hour, which is interacted with all of the remaining variables because each has an impact that varies by hour
CDH_{MA3_t}	moving average of 3 prior cooling degree hours (base 60)
$CPP\_Eventday_t$, $BIP\_Eventday_t$ $DBP\_Eventday_t$, $DRC\_Eventday_t$	binary variable representing each program event day if customer is also enrolled in that program
$Summer_t$, $Winter_t$	binary variables that indicate if month is between May and October for each hour
e_t	error term

4.2.2 Model Accuracy and Validity Assessment

A) Out-of-sample Validation

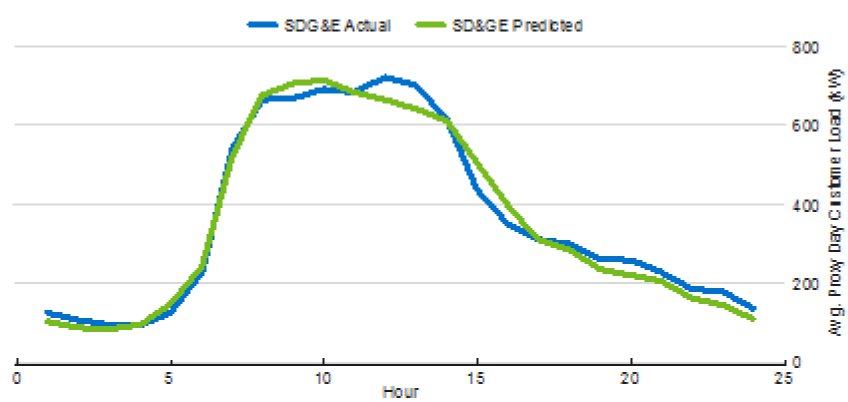
Although regressions were run for each individual customer in the BIP, what matters most is that the reference loads for all customers combined, or for selected groups of customers (e.g., industry types and LCA) are accurate. The regressions are not as accurate at the individual customer level, but when aggregated, overestimates and underestimates generally balance each other out and the resulting aggregate reference load is more accurate. Given that load impacts are calculated as the difference between the reference load and the FSL (after factoring in over/under performance), any error in the estimated reference load would cause an error in the estimated load impact.

Considering that BIP events are usually called on high system load days, it is important that the model predicts accurately on these days. In the first test of model accuracy, a series of out-of-sample validations is conducted. Rather than running the model on all of the available load data, a group of three randomly selected high system load days is withheld from the estimation. Although these three days are not included in the estimating sample, the model is used to predict load on those days. This process is repeated three times so that, in total, out-of-sample predictions of load are generated for the top nine system load days for each customer.

This validation process most closely aligns with what is expected of the model in the ex post and ex ante analyses. In the ex ante analysis, the model is used to simulate the reference load and load with DR under 1 in 2 and 1 in 10 weather year scenarios. The ex post analysis estimates load reductions by predicting what load would have been if an event was not called. In both of these analyses, out-of-sample predictions are generated for scenarios in which actual, unperturbed load data is not available. Therefore, out-of-sample validation using randomly selected high system load days is a logical test to determine which model is most accurate.

Figure 4-3 shows the results of the out-of-sample validation for the average of the top nine system load days for each customer. As seen in the figure, the model accurately predicts load on high system load days even if those days are not included in the estimating sample.

Figure 4-3: Actual vs. Predicted Average Load
Out-of-sample Validation for Top Nine System Load Days[16]



B) Goodness of Fit Measures

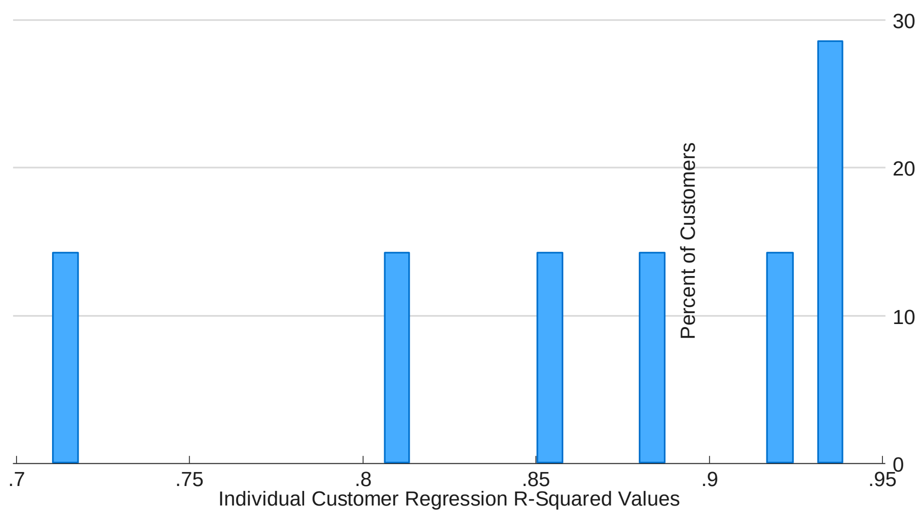
Although regressions were estimated at the individual customer level, from a program standpoint, the focus is less on how the regressions perform for individual customers than it is on how the regressions perform for the average participant and for specific customer segments.

[16] Note that there are two lines for each IOU in the graph, but due to the small error between estimated and actual values, it is difficult to distinguish the two lines. A table of the hourly values for each IOU is provided in Appendix A.

Individual customers exhibit more variation and less consistent energy use patterns than the average participant population. Likewise, the regressions are better at explaining the variation in electricity consumption and load impacts for the average customer (or average customer within a specific segment) than for individual customers. Put differently, it is more difficult to fully explain how a customer from a specific industry behaves on an hourly basis than it is to explain how the average customer in that industry behaves on an hourly basis. Because of this, we present measures of the explained variation, as described by the R-squared goodness-of-fit statistic, for the individual regressions, for specific customer segments and for the average customer overall.

As shown in Figure 4-4, the model has relatively high R-squared values for SDG&E BIP customers. All individual customer regressions have an R-squared value above 0.7.

Figure 4-4: Distribution of R-squared Values from Individual Regressions for SDG&E BIP Customers



In order to estimate the average customer R-squared values for each industry, LCA or the program as a whole, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour. This process produced regression-predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value. The R-squared values for the average participant and for the average customer by segment were estimated using the following formula:[17]

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[17] Technically, the R-squared value needs to be adjusted based on the number of parameters and observations from each regression. Given that the number of observations per regression was typically over 8,000, the effects of the adjustment were anticipated to be minimal. As a result, the unadjusted R-squared value is presented in order to avoid the complication of tracking the number of observations and parameters from each individual regression.

$$R^2 = 1 - \frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - \bar{y})^2}$$

Table 4-2: Variable Descriptions

Variable	Description
y_t	Actual energy use at time t
$\hat{y}_t$	Regression-predicted energy use at time t
$\bar{y}$	Average energy use across all time periods

Table 4-3 summarizes the amount of variation explained by the regression model by industry. SDG&E BIP customers have a higher R-squared of 0.87. Retail stores have the highest aggregate R-squared value 0.94. Table 4-4 summarizes R-squared values.

Table 4-3: Aggregate R-squared Values by Industry

Industry	SDG&E
Agriculture, Mining & Construction	0.84
Manufacturing	0.81
Wholesale, Transport & Other Utilities	–
Retail Stores	0.94
Offices, Hotels, Finance & Services	–
Schools	–
Institutional/Government	–
Other/Unknown	–
All Customers	**0.87**

Table 4-4: Aggregate R-squared Values

Utility	Local Capacity Area	R-squared
SDG&E	San Diego	0.87

C) Over/Under Performance Adjustment

In addition to estimating the reference load for the ex ante load impacts, historical event day behavior was analyzed and incorporated into PG&E, SCE, and SDG&E ex ante results to adjust for over/under performance. For most DR programs, the ex post impacts from previous events are applied to the ex ante estimates. For example, if a customer provided a load reduction of 500 kW on average, the typical event day on an ex ante basis would show a load reduction of roughly 500 kW for that customer. For BIP, similar performance relative to the FSL is expected, not similar reductions. Consider a BIP customer that provided an average load reduction of 500 kW with an average reference load of 800 kW during event hours. Assume that this customer had an FSL of 300 kW and with an average load reduction of 500 kW; this customer fully complied with its FSL obligations. Since this customer fully complied, it is expected that this customer would fully comply in future events. Therefore, if the predicted reference load for a typical event day is 950 kW, an impact of 650 kW would be expected (950 kW – 300 kW FSL). If we applied the same 500 kW reduction from previous events, the estimated load with DR would be 450 kW (950 kW – 500 kW), which would suggest that the customer substantially under-complied relative to its FSL of 300 kW. If a customer did not under-comply in previous events, it is not expected that it would under-comply on an ex ante basis. Therefore, the ex ante impacts are based on the estimated reference load and the FSL after adjusting for over/under performance.

Over/under performance is calculated at the industry level. Therefore, a customer in a given industry is assumed to perform similar to the recent historical performance of customers in its industry. This over/under performance adjustment in the ex ante analysis is necessary simply because there is limited (if any) event history for individual customers. Because very few actual BIP events have been called since 2006 (the exception being annual test events), we only have historical performance data for one to three BIP events for most participants. Furthermore, this analysis does not consider the performance data of customers on interruptible programs that existed prior to BIP.

4.3 BIP Ex post Load Impact Estimates

SDG&E called a BIP event on September 26 that lasted from 1 to 5 PM for all customers. All customers received 30-minute notice of the event. In total, seven customers participated in the event.

The average aggregate load drop from 1 to 5 PM was 1.5 MW. Overall, the load impact represents roughly a 60% reduction relative to the reference load of 2.6 MW. This year, BIP participants at SDG&E reduced load down to their FSL of 1.6MW, providing approximately 151% of the necessary reductions.

Table 4-5 shows the aggregate load impact for all SDG&E BIP participants. The seven event participants span four industry categories, with four or fewer customers within each category. Impacts for specific industries are excluded from this report to protect the confidentiality of the participants' identities.

Table 4-5: Aggregate Load Impact for September 26th2016 SDG&E Event

Customer Category	Number of Customers	Hour Ending	Ref. Load (MW)	Load with DR (MW)	Load Reduction (MW)	Aggregate FSL (MW)	% Load Reduction	Performance (%)
All Customers	7	14	3.2	1.2	2.0	1.6	61.7	120.0
		15	2.7	1.1	1.7	1.6	60.9	144.6
		16	2.4	1.0	1.4	1.6	58.3	166.2
		17	2.0	0.9	1.1	1.6	55.5	260.8
		Avg.	2.6	1.1	1.5	1.6	59.5	151.1

Data from both the 2015 and 2016 BIP events were used in the over/underperformance analysis. No new customers joined or left the program since the 2015 event, so comparison of event performance across these two years will provide stable estimates of the program's ability to deliver ex ante impacts.

4.4 BIP Ex ante Load Impacts Estimates

Table 4-6 shows the aggregate on-peak ex ante load impact estimates for each day type by weather year and forecast year. Aggregate impacts fluctuate throughout the year as a result of the change in peak period timing, but grow steadily due to increased enrollment. Aggregate load impacts for the utility 1 in 10 weather year vary from 0.3 MW in December 2022 to 8.8 MW in April 2022. This variation is due to the fact that BIP participants' electricity usage is higher from 1 to 6 PM than it is from 4 to 9 PM. Additionally, one large customer exhibits seasonal load patterns that are much lower in the winter months, limiting the impacts they can deliver during November and December.

Table 4-6: SDG&E BIP Ex ante Aggregate On-peak Load Impacts (MW) for each Day Type by Weather Year and Forecast Year

Weather Year	Day Type	Peak Period	2017	2018	2019	2020	2021	2022-2027
CAISO 1 in 10	Typical Event Day	1 to 6 PM	0.7	6.1	6.2	6.3	6.4	6.5
	January Peak	4 to 9 PM	0.1	5.8	5.8	5.8	5.9	5.9
	February Peak	4 to 9 PM	0.1	4.0	4.0	4.1	4.1	4.1
	March Peak	4 to 9 PM	0.4	3.0	3.0	3.1	3.1	3.2
	April Peak	1 to 6 PM	1.1	7.2	7.3	7.4	7.5	7.6
	May Peak	1 to 6 PM	1.0	6.8	6.9	7.0	7.1	7.3
	June Peak	1 to 6 PM	0.9	6.6	6.7	6.8	6.9	7.0
	July Peak	1 to 6 PM	0.7	5.3	5.4	5.5	5.6	5.7

	August Peak	1 to 6 PM	0.7	6.2	6.3	6.4	6.4	6.5
	September Peak	1 to 6 PM	0.7	3.4	3.5	3.6	3.7	3.8
	October Peak	1 to 6 PM	0.6	5.4	5.5	5.6	5.7	5.8
	November Peak	4 to 9 PM	0.1	5.3	5.4	5.4	5.4	5.5
	December Peak	4 to 9 PM	0.1	0.5	0.5	0.6	0.6	0.6
CAISO 1 in 2	Typical Event Day	1 to 6 PM	0.7	6.2	6.3	6.4	6.5	6.6
	January Peak	4 to 9 PM	0.1	4.6	4.6	4.6	4.7	4.7
	February Peak	4 to 9 PM	0.1	3.8	3.8	3.9	3.9	3.9
	March Peak	4 to 9 PM	0.3	2.0	2.0	2.1	2.1	2.1
	April Peak	1 to 6 PM	1.0	5.0	5.1	5.2	5.3	5.4
	May Peak	1 to 6 PM	1.1	7.7	7.9	8.0	8.1	8.2
	June Peak	1 to 6 PM	0.9	7.3	7.4	7.5	7.6	7.8
	July Peak	1 to 6 PM	0.7	5.0	5.1	5.2	5.3	5.4
	August Peak	1 to 6 PM	0.7	6.4	6.5	6.6	6.6	6.7
	September Peak	1 to 6 PM	0.7	3.0	3.1	3.2	3.3	3.4
	October Peak	1 to 6 PM	0.7	5.4	5.5	5.6	5.7	5.8
	November Peak	4 to 9 PM	0.1	3.5	3.6	3.6	3.7	3.7
	December Peak	4 to 9 PM	0.1	0.1	0.2	0.2	0.2	0.3
SDG&E 1 in 10	Typical Event Day	1 to 6 PM	0.7	6.0	6.1	6.2	6.3	6.3
	January Peak	4 to 9 PM	0.1	6.6	6.6	6.7	6.7	6.7
	February Peak	4 to 9 PM	0.0	3.5	3.5	3.5	3.6	3.6
	March Peak	4 to 9 PM	0.4	3.8	3.9	3.9	4.0	4.1
	April Peak	1 to 6 PM	1.1	8.3	8.4	8.5	8.7	8.8
	May Peak	1 to 6 PM	1.0	6.4	6.5	6.7	6.8	6.9
	June Peak	1 to 6 PM	0.9	7.1	7.3	7.4	7.5	7.6
	July Peak	1 to 6 PM	0.8	5.2	5.3	5.4	5.5	5.6
	August Peak	1 to 6 PM	0.7	6.0	6.0	6.1	6.2	6.3
	September Peak	1 to 6 PM	0.7	2.6	2.7	2.8	2.9	3.0
	October Peak	1 to 6 PM	0.6	4.3	4.4	4.4	4.5	4.6
	November Peak	4 to 9 PM	0.1	8.0	8.0	8.1	8.1	8.2
	December Peak	4 to 9 PM	0.1	0.2	0.2	0.3	0.3	0.3
SDG&E 1 in 2	Typical Event Day	1 to 6 PM	0.7	6.1	6.2	6.3	6.4	6.5
	January Peak	4 to 9 PM	0.1	3.9	4.0	4.0	4.0	4.1
	February Peak	4 to 9 PM	0.1	3.9	3.9	3.9	4.0	4.0
	March Peak	4 to 9 PM	0.4	1.6	1.6	1.7	1.7	1.8
	April Peak	1 to 6 PM	1.1	6.4	6.5	6.6	6.7	6.8
	May Peak	1 to 6 PM	1.1	6.7	6.8	6.9	7.1	7.2
	June Peak	1 to 6 PM	0.9	7.0	7.1	7.2	7.3	7.4
	July Peak	1 to 6 PM	0.7	5.6	5.7	5.8	5.9	6.0
	August Peak	1 to 6 PM	0.7	6.1	6.2	6.3	6.4	6.5

	September Peak	1 to 6 PM	0.8	2.8	2.9	3.0	3.1	3.2
	October Peak	1 to 6 PM	0.7	5.0	5.1	5.2	5.3	5.4
	November Peak	4 to 9 PM	0.1	5.0	5.1	5.1	5.1	5.2
	December Peak	4 to 9 PM	0.1	0.6	0.6	0.6	0.7	0.7

4.5 BIP Comparison of current Ex post versus Ex ante

BIP Ex ante load impact estimates developed by combining three key pieces of information that can be summarized as follows:

A. Estimate reference load for continuing or new BIP participants under 1 in 2 and 1 in 10 weather conditions for 12 day types (typical peak days for each month of the year). These estimates of reference load under varying weather and month conditions are obtained by using the models developed in the ex post analysis.
B. Obtain the FSLs for all continuing or new BIP participants that will be in effect in 2017. These FSLs may or may not be the same as those in effect during the 2013 test events for continuing customers, since customers have the opportunity to change their FSLs in November every year.
C. Apply historic over/under-performance factors to FSLs. Over/under-performance is estimated for each industry for each IOU. Load impact is derived by deducting the expected performance (the kW level customers are expected to reach during event hours, obtained in Step B above) from the estimated reference load obtained in Step A above.

Before comparing the 2016 ex post load impacts to 2017 ex ante estimates, it is helpful to review ex post load impacts for 2015 and 2016 side by side. Table 4-7 presents two years of BIP ex post load impact estimates for SDG&E. There were two more customers participating in BIP SDG&E in 2016 than there were in 2015. Aggregate impact remained flat at 1.5MW from 2015 to 2016, despite an increase in participants from 5 to 7. Per-customer impacts decreased as reference loads decreased. Percent load reductions improved slightly, but not enough to offset the smaller reference loads. FSL performance greatly improved from 99% of the firm service level to over 150% of the committed reduction. That being said, with such small numbers of customers in the program, the uncertainty around the estimates of reference load are greater than they are for the other two IOUs. BIP performance at SDG&E should be cited in tandem with the sample size and uncertainty.

Table 4-7: Multiyear Comparison of SDG&E BIP Ex Post Load Impacts

Event Date	Number of Customers	Reference Load (kW)	Load Reduction (kW)	Aggregate Load Reduction (MW)	Load Reduction (%)	Performance (%)	Average Event CDH
9/26/2016	7	371.4	221.8	1.5	60	151	28.4
8/28/2015	5	568.8	309.0	1.5	54.3	99	13.5

Table 4-8 shows the ex post and ex ante results from this load impact evaluation side by side. Aggregate ex ante results are smaller than ex post due to the loss of one customer. Impacts for the 1 in 10 utility scenario is slightly higher than the 1 in 2 aggregate impacts as warmer weather drives higher reference loads for these six BIP customers. However, it's important to note that SDG&E's BIP customers have highly variable daily load profiles. During the mid to late afternoon, the average customer reference load drops below the average FSL. This has important implications for winter weather events, where no load relief could be expected as customers are already operating below their FSL.

Table 4-8: Ex Ante Estimates vs. Ex Post Estimates from the 2016 Evaluation

Result Type	Weather Year / Date	Number of Customers	FSL (kW)	Reference Load (kW)	Performance (%)	Aggregate Load Reduction (MW)	Average Event CDH
Ex Ante (2017)	SDG&E 1 in 2, July Monthly Peak	6	204.3	331.1	96	0.7	12.7
Ex Ante (2017)	SDG&E 1 in 10, July Monthly Peak	6	204.3	336.8	95	0.8	18.2
Ex Post (2016)	9/26/2016	7	225.1	371.4	151	1.5	28.4

Figure 4-5 and Table 4-9 present the differences between ex ante load impact estimates from the 2015 and 2016 BIP load impact evaluations. While the 2015 ex ante impact estimates assumed neither load growth nor new customer enrollments, enrollment assumptions drove the considerable change in 2016 ex ante impacts. While one customer dropped off the program between 2016 and 2017, SDG&E expects to enroll a large new customer in 2018, as well as an additional 5 smaller BIP customers between 2018 and 2022. Assumptions about these new customer's FSLs as well as reference loads drove the substantial differences in load impacts for ex ante.

Figure 4-5: Ex Ante Aggregate Impacts for a 1 in 2 Weather Year, August Monthly Peak Day by Evaluation Year and Forecast Year

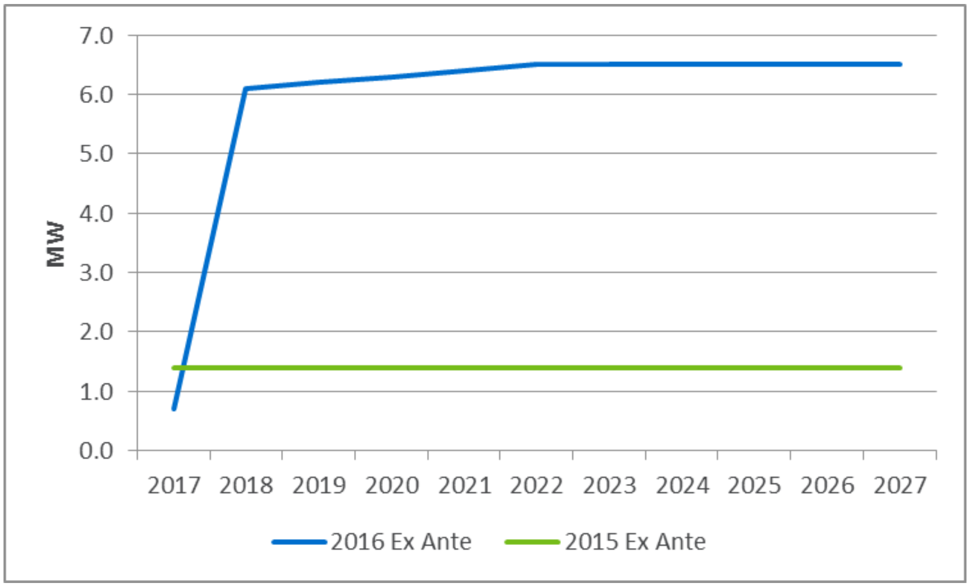


Table 4-9: Ex Ante Utility 1 in 2 Weather Year, August Monthly Peak Day Estimations for Forecast Year 2022 by Evaluation Year

Evaluation Year	Number of Customers	FSL (kW)	Reference Load (kW)	Performance (%)	Aggregate Load Reduction (MW)
2016	12	227.2	803.9	102	6.5
2015	7	281.3	469.5	107	1.4

5 Summary of SDG&E's Demand Bidding Program Report

Both the DBP day-ahead and the DBP day-of programs ended in December of 2016. Therefore there will be no ex ante reports.

6 Summary of the Summer Saver Program

6.1 Summer Saver Program Description

The Summer Saver program is a 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 shows the number of participants for each cycling option for program year 2016.

Table 6-1: Summer Saver Enrollment October 2016

Customer Type	Cycling Option	Enrolled Customers	Enrolled Control Devices	Enrolled Tons
Commercial	30%	1,047	3,052	11,823
	50%	3,522	7,711	29,637
	Total	4,569	10,763	41,460
Residential	50%	12,733	14,862	52,112
	100%	8,167	10,113	36,767
	Total	20,900	24,975	88,879
Grand Total		**25,469**	**35,738**	**130,338**

6.2 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. The primary task in estimating ex ante load impacts—which is often of more practical concern—is to make the best use of historical data on loads and load impacts to predict future program performance. The data and models used to estimate ex post impacts are typically the key inputs to the ex ante analysis.

Two separate approaches were used for estimating the reference loads: a randomized controlled trial (RCT) design and a propensity score matching (PSM) design. Residential customer impacts were estimated using an RCT. The nonresidential customer impacts were estimated with a PSM study. Under the randomized controlled trial, random samples of residential Summer Saver customers were selected for each cycling strategy. During each event, half of the sample did not have their CAC units cycled so that these customers could be used to provide a reference load for those who did have their units cycled. Under the PSM design, a matched control group was selected for most of the nonresidential Summer Saver program participants.[18]

An RCT is an experimental research approach in which 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 had their CAC unit cycled while the remaining customers served as the control group. The group that received the event signal alternated from

[18] A small end-use sample of the nonresidential program population was subject to an RCT (n < 150 in treatment and control) and was excluded from the analysis.

event to event. This design has significant advantages in providing fast, reliable impact estimates if sample sizes are large enough.

Consistent with the methodology used in the 2015 evaluation, a matched control group was selected for the nonresidential program population—whereby one matched nonparticipant was selected for each participant on each event. The entire SDG&E small commercial customer population 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 based on certain characteristics. In this case, those characteristics were typical peak demand on hot nonevent days and demand in the morning and early afternoon prior to the event. This approach minimizes the differences between participants and matched nonparticipants.[19]

Ex post event impacts for each cycling option were estimated for each hour of each event for both RCT and PSM customers by averaging the load of the participants in the group that experienced the event and subtracting it from the average adjusted load of the group that did not receive the event. The adjustment was based on the ratio of usage between the treatment and control groups an hour prior to the event start. For example, if the average usage in the treatment group during the hour preceding an event is 1.2 kW and the average usage in the control group is 1.3 kW, the ratio would equal 0.92 (1.2/1.3=0.92) and the control group load for the entire day would be multiplied by 0.92 to more closely match treatment group load. This adjustment is referred to as a same-day adjustment and is an effective way of accounting for small differences in load that can arise between randomly assigned treatment and control groups.

Hourly impact estimates for the residential and nonresidential Summer Saver population were calculated by taking a weighted average of the impact estimates for each cycling option, with weights determined by the number of tons enrolled on each cycling option. Similar weighting was done to calculate cycle percentage level impacts. For cycle percentage level impacts, weights were determined by the number of tons enrolled in each climate zone. Impacts for the average event day were calculated from treatment and control group load shapes averaged across all five 2016 Summer Saver events.

6.3 Summer Saver Ex post Load Impact Estimates

This section contains the ex post load impact estimates for program year 2016. Residential estimates are provided first, followed by nonresidential estimates.

[19] Event day, pre-event demand is not typically included in propensity score models for calculating event impacts, but it was included here because less than 15 nonresidential Summer Saver participants were notified of events in advance and so they should have no effect of being treated until the event occurred.

6.3.1 Summer Saver Residential Ex post Load Impact Estimates

Five Summer Saver events were called in 2016. Table 6-2 shows the date, day of week, and the start and end time for each event. All residential and nonresidential participants were called for each event, except for the control group customers that were held back for measurement and evaluation purposes. All five Summer Saver events in 2016 lasted for four hours and took place between 3 and 7 PM. Unlike in 2015 when three events took place on weekends, all 2016 events occurred on weekdays.

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

Year	Date	Impact			Mean17 (°F)
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2015	8/13/2015	0.42	0.50	10.52	78
	8/14/2015	0.36	0.43	9.05	79
	8/16/2015	0.70	0.84	17.75	82
	8/26/2015	0.35	0.42	8.95	80
	8/27/2015	0.54	0.64	13.65	82
	8/28/2015	0.59	0.70	14.90	84
	9/9/2015	0.68	0.81	17.22	88
	9/10/2015	0.45	0.54	11.39	86
	9/11/2015	0.51	0.61	13.02	84
	9/20/2015	0.34	0.41	8.71	84
	9/24/2015	0.48	0.58	12.23	78
	9/25/2015	0.40	0.47	10.05	79
	10/9/2015	0.43	0.51	10.84	81
	10/10/2015	0.45	0.54	11.35	88
	10/13/2015	0.30	0.36	7.59	82
	Average*	0.53	0.63	13.34	83
2016	6/20/2016	0.27	0.32	6.20	82
	7/22/2016	0.56	0.67	12.87	80
	8/15/2016	0.45	0.54	10.39	80
	9/26/2016	0.34	0.40	7.69	80
	9/27/2016	0.18	0.21	4.06	84
	Average**	0.36	0.42	8.13	81

* Reflects the average 3–7 PM weekday 2015 Summer Saver event

** Reflects the average 2016 Summer Saver event

6.3.2 Summer Saver Nonresidential Ex post Load Impact Estimates

Table 6-3 presents ex post load impact estimates for nonresidential customers for each 2016 event day and an average event day across the five 2016 Summer Saver events. Table 6-3 also shows the 2015 ex post load impacts for comparison. Nonresidential customers represent nearly 18% of total Summer Saver participants and approximately 32% of enrolled CAC tonnage. Nonresidential aggregate impacts varied from a low of 0.5 MW on September 27 to a high of 1.7 MW on June 20. Nonresidential load impacts experienced their peaks and lows differently than the residential segment. While all of the events in 2016 took place between 3 and 7 PM, the 2015 events help to demonstrate when nonresidential customers experience their peaks. In 2015, the three events with the latest event hours, 4 to 8 PM, show average load impacts of 0.16 kW per premise; the nine events with event hours 3 to 7 PM show an average load impact of 0.31 kW, while the two events with event hours of 2 to 6 PM show the highest load impacts averaging 0.50 kW per premise, even though the temperatures recorded before and during those events are among the coolest across all events. On average, the premise level impact observed in 2016 was 0.28 kW, which took place under slightly cooler temperatures than the average 3 to 7 PM in 2015. While nonresidential load impacts are not very weather sensitive, they do demonstrate sensitivity to whether or not the event includes more or fewer standard business hours. The 2016 impacts are comparable to those observed in 2015, and neither year had average event impacts that were statistically significant at the 90% confidence level. In other words, the confidence interval around each impact includes zero.

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	8/13/2015	0.12	0.28	1.26	77
	8/14/2015	0.08	0.19	0.85	78
	8/16/2015	0.12	0.29	1.32	80
	8/26/2015	0.09	0.21	0.95	79
	8/27/2015	0.12	0.30	1.34	80
	8/28/2015	0.10	0.25	1.12	83
	9/9/2015	0.11	0.26	1.17	87
	9/10/2015	0.15	0.36	1.66	85
	9/11/2015	0.14	0.34	1.56	83
	9/20/2015	0.06	0.14	0.62	83
	9/24/2015	0.23	0.54	2.45	77
	9/25/2015	0.20	0.47	2.12	78
	10/9/2015	0.14	0.34	1.55	80
	10/10/2015	0.15	0.35	1.58	87
	10/13/2015	0.04	0.08	0.38	81
	Average*	0.13	0.30	1.38	82
2016	6/20/2016	0.16	0.39	1.72	80
	7/22/2016	0.16	0.37	1.66	79
	8/15/2016	0.13	0.31	1.38	79
	9/26/2016	0.10	0.24	1.08	81
	9/27/2016	0.04	0.10	0.45	84
	Average**	0.12	0.28	1.26	81

* Reflects the average 3-7 PM weekday 2015 Summer Saver event

** Reflects the average 2016 Summer Saver event

6.4 Summer Saver Ex ante Evaluation Methodology

The methodology for the 2016 evaluation differs from that used in previous years' evaluations in a number of ways. The changes, described below, are driven by declining ex post impacts for both customer segments from 2010 to 2016, lower observed impacts for both customer segments later in the summer (September and October), and anticipated program changes that will significantly alter the composition of the residential Summer Saver population in future years.

Ex ante load impacts were developed 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 2015 and 2016 were used in the estimation database for developing the ex ante model. Unlike in 2015, where ex post events from 2010 to 2014 were included in the ex ante model, the 2016 evaluation restricts the ex post events to only 2015 and 2016 to better reflect the current state of the Summer Saver program. As in the 2015 evaluation, only the hours from 2 to 5 PM were used for the analysis because these hours were common across the greatest number of ex post event days. September 20, 2015 was excluded from the ex ante regression analysis because this was an emergency event that was called between 1:35 to 3:35 PM.

Unlike in previous years' evaluations, the methodology for estimating ex ante impacts in 2016 differs slightly between residential and nonresidential participants. For residential customers, the average load reduction from 2 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 for events taking place in May through August and for events taking place in September and October. Estimating two different models better captures the difference in customer responses to events called earlier in the summer relative to those called towards the end of the summer. This behavioral shift is reflected in the consistently observed differences in the magnitude of impacts from events earlier in the summer, relative to events that occur later in the summer.

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:

$$\mathrm{impact_d} = \mathrm{b_0} + \mathrm{b_1} \cdot \mathrm{mean17_d} + \varepsilon_\mathrm{d}$$

Table 6-4 shows the descriptions of the ex ante regression variables.

Table 6-1: Ex Ante Regression Variables

Variable	Description
$\mathrm{Impact_d}$	Average per ton ex post load impact for each event day from 2 to 5 PM
$\mathrm{b_0}$	Estimated constant
$\mathrm{b_1}$	Estimated parameter coefficient
$\mathrm{mean17_d}$	Average temperature over the 17 hours prior to the start of the event for each event day
ε_d	The error term for each day d

Finally, for residential customers, the ex ante methodology described above was applied twice, once to estimate impacts for 2017, and again to estimate ex ante impacts for 2018 through the end of the forecast horizon. This is done to reflect the changes SDG&E anticipates implementing over the next two program years. In 2017, the bottom 30% of residential users will be dropped from the Summer Saver population, and starting in 2018, residential solar customers will no longer be able to participate in the program, shedding an additional proportion of the residential population.

6.5 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 2017–2027. Unlike in previous program years, enrollment in the Summer Saver program is expected to change substantially in the early years of the forecast horizon, so the tables in this section will show predictions for specific years in the 2017–2027 forecast horizon, based on the assumptions for how the program will change in future years. The most significant changes will occur on the residential side, with the bottom 30% of users being dropped from the program in 2017 and with solar customers no longer allowed to participate starting in 2018.

In 2016 and in recent previous program years, the nonresidential impacts at the end of the summer (September and October) have been substantially smaller than impacts observed in May through August, even under similar and sometimes hotter temperatures. Additionally, nonresidential ex post impacts have been observed to be much less weather sensitive than impacts for residential customers. To better reflect the behavior of nonresidential impacts throughout the summer, the 2016 evaluation will use only the average 2 to 5 PM ex post impacts from May through August and from September through October to generate impacts for the corresponding ex ante months. In other words, the ex ante impacts for nonresidential customers will no longer be weather sensitive.

Tables 6-5 and 6-6 summarize the average and aggregate load impact estimates per premise under SDG&E-specific peaking conditions and CAISO peaking conditions for 2017 and for 2018, respectively. For residential customers, these transitional years reflect the most significant changes to enrollment and population usage characteristics.

Table 6-5: Summer Saver 2017 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 1 in 2	SDGE 1 in 2	CAISO 1 in 10	SDGE 1 in 10	CAISO 1 in 2	SDGE 1 in 2	CAISO 1 in 10	SDGE 1 in 10
Residential	Typical Event Day	0.56	0.60	0.67	0.79	8.4	9.0	10.0	11.8
	May Monthly Peak	0.26	0.43	0.56	0.71	3.9	6.5	8.4	10.7
	June Monthly Peak	0.39	0.35	0.55	0.73	5.9	5.2	8.3	11.0
	July Monthly Peak	0.49	0.56	0.58	0.70	7.4	8.5	8.7	10.5
	August Monthly Peak	0.66	0.73	0.69	0.76	9.9	10.9	10.3	11.4
	September Monthly Peak	0.62	0.63	0.64	0.65	9.2	9.4	9.5	9.7
	October Monthly Peak	0.59	0.60	0.61	0.63	8.7	8.9	9.1	9.4
Non-Residential	Typical Event Day	0.59	0.59	0.59	0.59	2.2	2.2	2.2	2.2
	May Monthly Peak	0.59	0.59	0.59	0.59	2.2	2.2	2.2	2.2
	June Monthly Peak	0.59	0.59	0.59	0.59	2.2	2.2	2.2	2.2
	July Monthly Peak	0.59	0.59	0.59	0.59	2.2	2.2	2.2	2.2
	August Monthly Peak	0.59	0.59	0.59	0.59	2.2	2.2	2.2	2.2
	September Monthly Peak	0.51	0.51	0.51	0.51	1.9	1.9	1.9	1.9
	October Monthly Peak	0.51	0.51	0.51	0.51	1.9	1.9	1.9	1.9

Table 6-6: Summer Saver 2018 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 1 in 2	SDGE 1 in 2	CAISO 1 in 10	SDGE 1 in 10	CAISO 1 in 2	SDGE 1 in 2	CAISO 1 in 10	SDGE 1 in 10
Residential	Typical Event Day	0.57	0.61	0.67	0.77	7.3	7.8	8.6	9.9
	May Monthly Peak	0.31	0.46	0.57	0.70	4.0	5.9	7.4	9.1
	June Monthly Peak	0.43	0.38	0.57	0.72	5.5	5.0	7.3	9.3
	July Monthly Peak	0.51	0.57	0.59	0.69	6.6	7.4	7.6	8.9
	August Monthly Peak	0.66	0.72	0.68	0.75	8.5	9.2	8.7	9.6
	September Monthly Peak	0.59	0.60	0.61	0.63	7.5	7.7	7.8	8.1
	October Monthly Peak	0.54	0.56	0.57	0.61	6.8	7.1	7.3	7.7
Non-Residential	Typical Event Day	0.59	0.59	0.59	0.59	1.9	1.9	1.9	1.9
	May Monthly Peak	0.59	0.59	0.59	0.59	1.9	1.9	1.9	1.9
	June Monthly Peak	0.59	0.59	0.59	0.59	1.9	1.9	1.9	1.9
	July Monthly Peak	0.59	0.59	0.59	0.59	1.9	1.9	1.9	1.9
	August Monthly Peak	0.59	0.59	0.59	0.59	1.9	1.9	1.9	1.9
	September Monthly Peak	0.51	0.51	0.51	0.51	1.6	1.6	1.6	1.6
	October Monthly Peak	0.51	0.51	0.51	0.51	1.6	1.6	1.6	1.6

For a typical event day in a 1 in 2 year, SDG&E-specific weather conditions, the impact per premise is 0.60 kW for residential customers in 2017 and increases slightly to 0.61 kW in 2018. The 1 in 10 year typical event day estimates are 31% and 27% higher in 2017 and 2018, respectively. Under 1 in 2 CAISO peak conditions, the typical event day residential load impact per premise is 0.56 kW in 2017 and 0.57 in 2018. Under CAISO 1 in 10 weather conditions, per premise impacts are 20% and 17% higher in 2017 and 2018, respectively. These large differences between 1 in 2 and 1 in 10 load impacts are driven by the larger differences in mean17, which vary by 5 or 6 degrees across some of the above conditions; a difference of 5 degrees on average over 17 hours represents a very large difference in temperature conditions and air conditioning requirements.

Because nonresidential ex ante estimates are only based off of the average 2 to 5 PM ex post impacts for May through August events and separately for September through October, there is no variation in estimated load impacts between CAISO and SDG&E weather conditions, 1 in 2 and 1 in 10 conditions, or by month. The only difference seen is between May through August months, which have an estimated per premise load impact of 0.59 kW versus September and October, which have a load impact of 0.51 kW.

The aggregate program load reduction potential for residential customers is 9.0 MW for a typical event day under SDG&E-specific 1 in 2 year weather conditions in 2017, and 7.8 MW in 2018. Under SDG&E-specific 1 in 10 year weather conditions, the aggregate impacts for 2017 and 2018 are 11.8 MW and 9.9 MW, respectively. The aggregate impacts under CAISO weather conditions are slightly lower for both weather year types. For nonresidential customers, the aggregate impacts for May through August are 2.2 MW in 2017 and 1.9 MW in 2018. For September and October, the aggregate impacts are 1.9 MW and 1.6 MW for 2017 and 2018, respectively.

6.6 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 6-77 presents an overall comparison of 2016 ex post load impacts and the ex ante load impacts as estimated for 2017. Only the months of June through September are shown for comparison, since there were no events taking place in May or October 2016. It is important to note that the 2017 ex ante impacts reflect the drop of the bottom 30% of residential users, as well as month-to-month enrollment decreases of approximately 1% for both residential and nonresidential customers. Additionally, the 2017 ex ante impacts reflect the new estimation methodology that estimates impacts for May through August separately from September through October.

Table 6-7: Comparison of 2016 Ex Post Load Impacts to 2017 Ex Ante Load Impacts by Month

Month	2016 Ex Post Average Aggregate Impacts* (MW)	2017 Ex Ante Impact** SDG&E 1 in 2 (MW)
June	8.7	7.4
July	14.6	10.6
August	12.2	13.0
September	6.5	11.2

*Average of 2016 events by month

**For RA hours of 1-6 PM

7 Summary of the Opt-in Peak Time Rebate Program (PTR) and Residential Small Customer Technology Deployment (SCTD) Program

7.1 Program Overview

7.1.1 Opt-in PTR Program Description

The PTR 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.

7.1.2 SCTD Program Description

The SCTD program provides demand response enabling technology to residential customers. In 2016 the enabling technology was offered at no cost to qualifying customers through the PTR program. The enabling technology offered in 2016 was the Ecobee Smart Si thermostat (https://www.ecobee.com/faqs/smartsi/). This thermostat is signaled by SDG&E through Wi-Fi through use of an Ecobee utility portal. Two cycling strategies were implemented. The first strategy was a 4-degree thermostat setback and the other was a 50% AC cycling strategy. Customers were randomly assigned to one of the two strategies. Although PTR events were 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 as of May 2014, 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 but their thermostat was curtailed, 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.

7.2 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.

7.2.1 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.

7.2.2 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 three major participant characteristics: PTR participation, SCTD participation, and having Net Energy Metering (NEM). Each of the six possible participant combinations of these characteristics was also stratified by climate zone (coastal and inland). In total, this provided 12 different strata from which to develop control groups:

PTR Participant	Net Energy Metered	SCTD Participant	Climate Zones
✓	✓	×	Inland, Coastal
✓	×	×	Inland, Coastal
✓	✓	✓	Inland, Coastal
✓	×	✓	Inland, Coastal
×	×	✓	Inland, Coastal
×	✓	✓	Inland, Coastal

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.

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 2015 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 and SCTD participants by the stratification detailed above, as well as for the other various participant subgroups, namely 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: seasonal kWh usage, total annual 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, coefficient of variation of annual consumption, usage size category, and dummy variables for Low Income and Summer Saver customers.

The second stage of matching saw the additional inclusion of hourly kWh usage during the event hours for summer hot days[20] and coefficients of variation of kWh usage during event hours.

[20] Twelve non-event days in summer 2016 and September 2015 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 8th, 24th, and 25th of September 2015, 20th of June, 21st, 22nd, 28th of July, 15th of August, 27th, 28th, 29th, and 30th of September 2016. Load profiles by season were also compared to confirm that the groups were sufficiently similar.

7.2.3 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.

7.2.4 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),[21] 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:

$$
\begin{aligned}
kWh_t = \beta_0 &+ \sum_d \beta_1^d \times DOW_d + \sum_m \beta_2^m \times Month_m + \sum_h \beta_3^h \times Hour_h \\
&+ \sum_d \sum_h \beta_4^{h,d} \times Hour_h \times DOW_d + \sum_m \sum_h \beta_5^{h,m} \times Hour_h \times Month_m + \beta_6 \\
&\times CDH65 + \sum_h \beta_7^h \times Hour_h \times CDH65_h + \sum_h \beta_8^h \times Hour_h \times CDH65_h \times Event \\
&+ \sum_h \beta_9^h \times Hour_h \times CDH65_h \times Event \times InactivePart \\
&+ \sum_h \beta_{10}^h \times \mathrm{Hour}_h \times \mathrm{CDH65}_h \times \mathrm{Event} \times \mathrm{ActivePart} + \varepsilon_t
\end{aligned}
$$

Where

kWh_t	Is the kWh in hour t
β_0	Is the intercept
β_1^d	Is the set coefficient for day of week (DOW) d
β_2^m	Is the set of coefficient for month m
β_3^h	Is the set of coefficients for hour h

[21] 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

$\beta_4^{h,d}$	Is the set of coefficients for the interaction of hour h and DOW d
$\beta_5^{h,m}$	Is the set of coefficients for the interaction of hour h and month m
β_6	Is the coefficient for cooling degree hours (CDH)
β_7^h	Is the set of coefficients for CDH interacted with hour h
β_8^h	Is the set of coefficients for the interaction of CDH with event days
β_9^h	Is the set of coefficients for interaction of CDH with hour h and event days for inactive participants
β_{10}^h	Is the set of coefficients for interaction of CDH with hour h and event days for active participants
ε_t	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.

7.2.5 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.

7.3 PTR and SCTD Residential Ex post Load Impact Estimates

In 2016, SDG&E called a total of one PTR event and one SCTD event. The event was on the same day for both programs: September 26th, 2016. Table 7-1 presents the ex post load impacts for PTR participants without any load control (SCTD or Summer Saver). Table 7-2 presents the ex post load impacts for all SCTD participants. Table 7-3 presents the ex post load impacts for PTR participants that are dually enrolled in Summer Saver.

Table 7-1: PTR with No Load Control 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
September 26th, 2016	68,937	1.09	1.01	0.08	8.3%	5.51	98.7

Table 7-1: SCTD Residential 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
September 26th, 2016	9,670	1.79	1.37	0.42	25.1%	4.04	100.5

* Participants excluding Summer Saver load control.

Table 7-3 PTR Dually Enrolled in Summer Saver Ex Post Load Impact Estimates – Average 2016 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	3,915	1.50	1.31	0.19	12.3%	0.73	100.7
Summer Saver – 50% Cycling	1,408	1.70	1.72	-0.03	-1.4%	-0.04	100.9
Summer Saver – 100% Cycling	2,505	1.38	1.08	0.31	22.0%	0.77	100.6

7.4 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 5-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-only enrollments will stay constant and that the SCTD program will continue to grow. By the end of 2017, the PTR program is expected to grow to over 81,000 participants (driven by dual enrollments from SCTD), and the SCTD program is expected to grow to over 15,000 participants. By the end of 2022, the PTR program is forecasted to grow to almost 90,000 participants, while the SCTD program is forecasted to grow to over 30,000 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 2016. 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 Table 7-4.

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**	17%	46%	63%
	50% Cycle	4%	33%	37%
	All	21%	79%	100%
PTR Dually Enrolled in Residential SCTD	**4 Degree Setback**	22%	35%	57%
	50% Cycle	16%	28%	43%
	All	38%	62%	100%
SCTD-Only	**4 Degree Setback**	22%	36%	57%
	50% Cycle	16%	27%	43%
	All	37%	63%	100%

7.5 PTR and SCTD Residential Ex ante Load Impacts

7.5.1 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 2018. 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 0.041 kW during the resource availability hours (1:00pm to 6:00 pm). The average estimated aggregate load reduction under this scenario is 2.87 MW. For a 1 in 10 typical event day, the estimated load reduction is higher, at 0.054 kW. The average estimated aggregate reduction is 3.77 MW. These estimates represent approximately 5.7% and 5.9% of the reference load, respectively for each weather scenario.

Table 7-5: 2018 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	0.23	0.22	0.015	6.3%	1.04	0.21	0.20	0.014	6.4%	0.95
		Jul	0.51	0.49	0.025	5.0%	1.77	0.46	0.44	0.022	4.7%	1.51
		Aug	0.58	0.55	0.032	5.5%	2.22	0.55	0.52	0.030	5.4%	2.07
	Monthly System Peak Day	Jun	0.75	0.70	0.050	6.6%	3.47	0.36	0.33	0.023	6.6%	1.63
		Jul	0.85	0.80	0.049	5.7%	3.39	0.67	0.63	0.036	5.4%	2.51
		Aug	0.87	0.82	0.051	5.8%	3.54	0.82	0.78	0.048	5.8%	3.35
	Typical Event Day	Aug	0.91	0.86	0.054	5.9%	3.77	0.72	0.68	0.041	5.7%	2.87

7.5.2 PTR Dually Enrolled in Summer Saver

As a reminder, the control group for these dually enrolled participants are Summer Saver participants that are not dually enrolled in PTR, and the forecasted impacts are incremental savings over and above those realized from the Summer Saver program. For a 1 in 2 typical event day, the estimated incremental load reduction for the average participant is 0.081 kW during event hours. For a 1 in 10 typical event day, the estimated load reduction is higher, at 0.106 kW. These estimates are higher than the PTR-only group. The average incremental estimated aggregate load reductions are 0.25 MW (11.7%) and 0.32 MW (13.1%), respectively.

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 2018. As a reminder, the control group for these dually enrolled participants are Summer Saver participants that are not dually enrolled in PTR, and the forecasted impacts are incremental savings over and above those realized from the Summer Saver program. For a 1 in 2 typical event day, the estimated incremental load reduction for the average participant is 0.081 kW during event hours. For a 1 in 10 typical event day, the estimated load reduction is higher, at 0.106 kW. These estimates are higher than the PTR-only group. The average incremental estimated aggregate load reductions are 0.25 MW (11.7%) and 0.32 MW (13.1%), 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)
Average Weekday	Jun	0.59	0.56	0.031	5.2%	0.09	0.58	0.55	0.030	5.1%	0.09
	Jul	0.93	0.88	0.051	5.5%	0.15	0.85	0.81	0.042	4.9%	0.13
	Aug	0.98	0.92	0.062	6.3%	0.19	0.95	0.89	0.058	6.2%	0.18
Monthly System Peak Day	Jun	1.20	1.10	0.101	8.4%	0.31	0.72	0.68	0.045	6.3%	0.14
	Jul	1.35	1.25	0.097	7.2%	0.29	1.10	1.03	0.069	6.3%	0.21
	Aug	1.28	1.19	0.097	7.6%	0.29	1.25	1.16	0.093	7.5%	0.28
Typical Event Day	Aug	1.37	1.26	0.106	7.8%	0.32	1.15	1.07	0.081	7.1%	0.25

7.5.3 PTR Dually Enrolled in Residential SCTD

Table 7-7shows 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 2018. For a 1 in 2 typical event day, the estimated load reduction for the average dual PTR-SCTD participant is 0.26 kW during resource availability hours. For a 1 in 10 typical event day, the estimated load reduction is 0.34 kW. The average estimated aggregate load reductions are 2.04 MW (28.7%) and 2.68 MW (29.9%), respectively.

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)
Average Weekday	Jun	0.01	-0.09*	0.096	1053%	0.75	-0.01	-0.10	0.092	-762.3%	0.72
	Jul	0.49	0.33	0.162	32.9%	1.28	0.39	0.25	0.141	36.3%	1.11
	Aug	0.61	0.42	0.195	31.8%	1.56	0.56	0.38	0.183	32.5%	1.46
Monthly System Peak Day	Jun	0.88	0.56	0.323	36.6%	2.53	0.20	0.02	0.189	92.1%	1.48
	Jul	1.06	0.76	0.306	28.8%	2.42	0.74	0.51	0.225	30.6%	1.78
	Aug	1.07	0.76	0.309	28.9%	2.47	1.01	0.72	0.295	29.1%	2.35
Typical Event Day	Aug	1.17	0.83	0.335	28.7%	2.68	0.85	0.60	0.255	29.9%	2.04

*negative numbers are driven by Net Energy Metered customers.

7.5.4 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 2018. For a 1 in 2 typical event day, the estimated load reduction for the average SCTD-only participant is 0.17 kW during the resource availability hours. For a 1 in 10 typical event day, the estimated load reduction is 0.22 kW. The average estimated aggregate load reductions are 1.08 MW (17.5%) and 1.41 MW (17.2%), respectively. As the enrollment in the SCTD programs continues to grow, these aggregate estimates will increase.

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

Day / Type	Month	1 in 10 Average Hourly Reference Load (kWh)	1 in 10 Average Hourly Observed Load (kWh)	1 in 10 Average Hourly Impact (kWh)	1 in 10 Percent Load Reduc-tion	1 in 10 Average Total Hourly Impact (MWh)	1 in 2 Average Hourly Reference Load (kWh)	1 in 2 Average Hourly Observed Load (kWh)	1 in 2 Average Hourly Impact (kWh)	1 in 2 Percent Load Reduc-tion	1 in 2 Average Total Hourly Impact (MWh)
Average Weekday	Jun	0.11	0.05	0.059	52.2%	0.38	0.09	0.04	0.056	61.1%	0.36
	Jul	0.61	0.50	0.105	17.4%	0.68	0.51	0.42	0.090	17.8%	0.58
	Aug	0.71	0.58	0.128	18.0%	0.84	0.66	0.54	0.120	18.1%	0.78
Monthly System Peak Day	Jun	0.97	0.76	0.207	21.4%	1.33	0.30	0.21	0.090	29.6%	0.58
	Jul	1.17	0.97	0.198	17.0%	1.29	0.85	0.70	0.145	17.1%	0.94
	Aug	1.16	0.96	0.199	17.2%	1.30	1.10	0.91	0.190	17.2%	1.24
Typical Event Day	Aug	1.25	1.04	0.216	17.2%	1.41	0.94	0.78	0.165	17.5%	1.08

7.5.5 Comparison of 2016 and 2015 Ex Ante Estimates

Table 7-9Table 7- shows the comparisons between the ex ante estimates in the current evaluation and those reported in the previous evaluation for the forecast year 2018. The current ex ante impact estimates are the same for the PTR-only group – both the current and previous estimates are 0.04 kW for a 1 in 2 event day and 0.05 kW for a 1 in 10 event day. The percentage load reductions are higher in the current estimates, from approximately 4% in the previous analysis to approximately 6% in the current analysis for a 1 in 10 year.

The estimates for the group dually enrolled in Summer Saver are lower in the current evaluation. The current estimates for incremental Summer Saver impacts are 0.08 kW for a 1 in 2 event day and 0.11 kW for a 1 in 10 event day, compared to 0.16 kW and 0.23 kW in the previous evaluation. The percentage load reductions are also lower in the current estimates, from approximately 13% in the previous analysis to approximately 8% in the current analysis for a 1 in 10 year. The current ex ante event day estimates for the incremental PTR effects on dually enrolled Summer Saver participants are still higher than the PTR-only group.

Table 7-9: Comparison of 2015 and 2014 Ex Ante Estimates – Forecast Year 2018, 1 P.M to 6 P.M.

			Current				Previous			
Participant Segment	Weather Year	Day / Type	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	1.28	1.19	0.10	7.6%	1.77	1.54	0.23	13.1%
		Typical Event Day	1.37	1.26	0.11	7.8%	1.79	1.55	0.23	13.1%
	1 in 2	Monthly System Peak Day	1.25	1.16	0.09	7.5%	1.42	1.26	0.17	11.7%
		Typical Event Day	1.15	1.07	0.08	7.1%	1.41	1.24	0.16	11.7%
PTR/SS	1 in 10	Monthly System Peak Day	1.07	0.76	0.31	28.9%	2.02	1.51	0.51	25.2%
		Typical Event Day	1.17	0.83	0.33	28.7%	2.02	1.51	0.51	25.3%
	1 in 2	Monthly System Peak Day	1.01	0.72	0.29	29.1%	1.59	1.21	0.38	23.6%
		Typical Event Day	0.85	0.60	0.25	29.9%	1.55	1.19	0.36	23.4%
PTR/SCTD	1 in 10	Monthly System Peak Day	1.16	0.96	0.20	17.2%	2.05	1.74	0.30	14.8%
		Typical Event Day	1.25	1.04	0.22	17.2%	2.04	1.74	0.30	14.9%
	1 in 2	Monthly System Peak Day	1.10	0.91	0.19	17.2%	1.61	1.39	0.22	13.9%
		Typical Event Day	0.94	0.78	0.17	17.5%	1.58	1.36	0.22	13.7%
SCTD Only	1 in 10	Monthly System Peak Day	1.28	1.19	0.10	7.6%	1.77	1.54	0.23	13.1%
		Typical Event Day	1.37	1.26	0.11	7.8%	1.79	1.55	0.23	13.1%
	1 in 2	Monthly System Peak Day	1.25	1.16	0.09	7.5%	1.42	1.26	0.17	11.7%
		Typical Event Day	1.15	1.07	0.08	7.1%	1.41	1.24	0.16	11.7%

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 0.36 kW on 1 in 2 event days and 0.51 kW on 1 in 10 event days. The current analysis projects 0.25 kW on 1 in 2 event days and 0.33 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 23.4%, while the current estimates are

29.9%. For the SCTD-only participants, the current forecasts are lower in absolute impacts, but higher in terms of percentage impacts. The previous analysis found estimates of 0.22 kW (13.7%) on 1 in 2 event days and 0.30 kW (14.9%) on 1 in 10 event days. The current analysis projects 0.17 kW (17.5%) on 1 in 2 event days and 0.22 kW (17.2%) on 1 in 10 event days.

7.6 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 for the 2016 event was extremely hot, and thus the results are higher than those associated with 1 in 10 weather conditions.

For the overall PTR-only group, the ex post results show an average event hour load reduction of 0.08 kW, while the 1 in 10 ex ante estimates show average event hour load reductions of 0.05 kW, both around 6% of the reference load. The predicted 1 in 10 average event hour load reductions for the overall PTR-Summer Saver dually enrolled group (0.11 kW, or 7.8%) are similar, but slightly lower than the ex post impacts (0.15 kW, or 10.3%). The same relationship exists for the 100% cycling sub-group. Since the 50% cycling sub-group had minimal ex post impacts, this is reflected in its ex ante estimate. For the dually enrolled PTR-SCTD group, the ex post and 1 in 10 ex ante estimates are essentially identical in terms of percentage impacts, at 28.2% and 28.7%, respectively. The absolute ex post impacts are higher, at 0.43 kW, compared to the 1 in 10 ex ante estimate of 0.33 kW. The estimates for the load control sub-groups are also similar. The 4 degree setback group's 1 in 10 ex ante estimate is 0.10 kW lower (both approximately 30% reduction) than the ex post estimate, while the 50% cycling group's is 0.12 kW lower (31% and 32%, respectively). The SCTD-only ex post estimates are more similar to the 1 in 10 ex ante estimates. The overall event hour load reduction estimate is 0.25 kW (14.7%) for the ex post and 0.22 kW (17.2%) for the 1 in 10 ex ante. The 50% cycling sub-group has averages of 0.25 kW (14.7%) for ex post and 0.22 (17.6%) for the 1 in 10 ex ante estimate. The 4 degree setback has an ex post estimate of 0.35 kW (21.3%), compared to the ex ante average of 0.29 (21.8%) 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	0.87	0.82	0.05	5.8%	86.60
			Typical Event Day	0.91	0.86	0.05	5.9%	87.90
		1 in 2	Monthly System Peak Day	0.82	0.78	0.05	5.8%	85.43
			Typical Event Day	0.72	0.68	0.04	5.7%	82.46
		Ex Post	Ex Post Average Event Day	1.25	1.17	0.08	6.4%	99.33
PTR/SS	100	1 in 10	Monthly System Peak Day	1.17	1.02	0.15	12.9%	88.03
			Typical Event Day	1.24	1.08	0.16	13.2%	90.24
		1 in 2	Monthly System Peak Day	1.14	1.00	0.14	12.6%	87.10
			Typical Event Day	1.05	0.93	0.13	11.9%	84.33
		Ex Post	Ex Post Average Event Day	1.34	1.10	0.23	17.5%	100.28
	50	1 in 10	Monthly System Peak Day	1.47	1.47	0.00	0.0%	88.87
			Typical Event Day	1.59	1.59	0.00	0.1%	91.60
		1 in 2	Monthly System Peak Day	1.44	1.44	0.00	0.0%	88.07
			Typical Event Day	1.32	1.32	0.00	0.1%	85.41
		Ex Post	Ex Post Average Event Day	1.63	1.63	0.00	0.0%	100.60
	ALL	1 in 10	Monthly System Peak Day	1.28	1.19	0.10	7.6%	88.34
			Typical Event Day	1.37	1.26	0.11	7.8%	90.74
		1 in 2	Monthly System Peak Day	1.25	1.16	0.09	7.5%	87.46
			Typical Event Day	1.15	1.07	0.08	7.1%	84.73
		Ex Post	Ex Post Average Event Day	1.45	1.30	0.15	10.3%	100.40
PTR/SCTD	4 Degree Setback	1 in 10	Monthly System Peak Day	1.09	0.76	0.33	30.6%	87.39
			Typical Event Day	1.18	0.82	0.36	30.5%	89.19
		1 in 2	Monthly System Peak Day	1.03	0.71	0.32	30.9%	86.35
			Typical Event Day	0.86	0.59	0.27	31.7%	83.49
		Ex Post	Ex Post Average Event Day	1.53	1.08	0.46	29.8%	99.94
	50% Cycle	1 in 10	Monthly System Peak Day	1.11	0.76	0.34	30.9%	87.56

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	1.21	0.84	0.37	30.7%	89.46
		1 in 2	Monthly System Peak Day	1.05	0.72	0.33	31.1%	86.55
			Typical Event Day	0.88	0.60	0.28	31.9%	83.71
		Ex Post	Ex Post Average Event Day	1.50	1.01	0.49	32.4%	100.03
	ALL	1 in 10	Monthly System Peak Day	1.07	0.76	0.31	28.9%	87.46
			Typical Event Day	1.17	0.83	0.33	28.7%	89.31
		1 in 2	Monthly System Peak Day	1.01	0.72	0.29	29.1%	86.44
			Typical Event Day	0.85	0.60	0.25	29.9%	83.59
		Ex Post	Ex Post Average Event Day	1.51	1.09	0.43	28.2%	99.95
SCTD Only	4 Degree Setback	1 in 10	Monthly System Peak Day	1.22	0.95	0.27	21.8%	87.46
			Typical Event Day	1.32	1.03	0.29	21.8%	89.30
		1 in 2	Monthly System Peak Day	1.16	0.90	0.25	21.9%	86.43
			Typical Event Day	0.99	0.77	0.22	22.2%	83.58
		Ex Post	Ex Post Average Event Day	1.65	1.30	0.35	21.3%	99.96
	50% Cycle	1 in 10	Monthly System Peak Day	1.16	0.96	0.20	17.5%	87.52
			Typical Event Day	1.26	1.04	0.22	17.6%	89.40
		1 in 2	Monthly System Peak Day	1.11	0.91	0.19	17.6%	86.50
			Typical Event Day	0.95	0.78	0.17	17.7%	83.66
		Ex Post	Ex Post Average Event Day	1.72	1.47	0.25	14.7%	99.96
	ALL	1 in 10	Monthly System Peak Day	1.16	0.96	0.20	17.2%	87.49
			Typical Event Day	1.25	1.04	0.22	17.2%	89.34
		1 in 2	Monthly System Peak Day	1.10	0.91	0.19	17.2%	86.46
			Typical Event Day	0.94	0.78	0.17	17.5%	83.62
		Ex Post	Ex Post Average Event Day	1.71	1.46	0.25	14.7%	99.92

8 Summary of the Permanent Load Shifting (PLS) Program

8.1 PLS Program Overview

The PLS program provides a one-time incentive payment ($875/kW) to customers who install qualifying PLS-Thermal Energy Storage (TES) technology on typical central air conditioning units or process cooling equipment. Incentives are determined based on the designed load shift capability of the system and the project must undergo a feasibility study prepared by a licensed engineer. The load shift is typically accomplished through shifting of daytime chiller load to overnight hours. All electric customers on time-of-use electricity rates are eligible for the program, including residential, commercial, industrial, agricultural, direct access, and Community Choice Aggregation customers.

To qualify for the PLS program incentive payment, customers must go through the program application, approval 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 complete application;
2. Customer submits feasibility study;
3. IOU reviews feasibility study prior to approval;
4. IOU conducts pre-installation inspection, including pre-installation M&V, and, if customer passes, approves application and sets aside incentive funds;
5. IOU and customer sign agreement (SCE only);
6. Customer submits project design;
7. Customer installs PLS-TES system;
8. Customer submits Commissioning Report;
9. IOU reviews commissioning report and conducts post-installation inspection, tests, cost, and any other verifications; and
10. Customer receives final PLS technology incentive.

After submitting an application, participating customers must provide, in advance of installation, a feasibility study prepared by a licensed engineer. This study must include an estimated cooling profile for each hour for a year based on building simulation models and input about building specifications, regional temperatures, occupancy, and other inputs. Both retrofit and new construction customers are subject to the energy modeling process unless utility approved cooling usage data is available.

The total incentive amount is determined using a customer's load shift on their maximum cooling demand day—based on the on-peak hours. A conversion factor[22] is used to convert the cooling load shift tons to electricity load shift (kW) for both full and partial storage systems. The incentive levels for the program are $875/kW-shifted for all IOUs.

The incentive payments are intended to offset a portion of the cost of installation, thereby making the system more attractive financially. Under the program rules, the incentive is the lesser of (1) the incentive reservation amount calculated from the approved feasibility study and

[22] A conversion factor will be used to convert the cooling load shift (tons) to electricity load shift (kW) capacity. This calculation method is applied for both full and partial storage systems. A conversion factor of 0.7 kW/ton will be applied to water-cooled chillers and 1.2 kW/ton will be applied to air-cooled chillers.

post-installation approval; (2) 50% of the actual final installed project cost; or (3) $1.5 million. In addition, customers are required to be on a time-of-use electric rate and provide trend data to the IOU's about their TES system for the first five years after installation. In the participation component of the program, customers are required to run their TES system on summer weekdays for five years after installation, thereby realizing electric bill savings, and submit monitored system data to the IOU. The systems are expected to have a lifetime of about 20 years.

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.

8.2 PLS Ex post Evaluation Methodology

For program year 2016, there was one SDG&E customer that was completed and paid out. However, the data was not provided within the time needed for it to be incorporated into this report.

8.3 PLS Ex ante Evaluation Methodology

The PLS program evaluation forecasts load impacts for three different types of projects:

- **Operational** - customers with installed and operational PLS systems;
- **Identified** - those for which customers have completed an application or feasibility study; and
- **Unidentified** - applications that are expected to be submitted during the current funding cycle.

8.3.1 Operational Projects

There were two similar methods used for ex ante estimation for operational sites, depending on whether ex post estimation used premise level meter data or operational data.

- *Ex poste based on premise level data*. The methodology for ex ante estimation for the operational site using premise level data is based off the ex post estimation, but contains three extra modeling steps—developing a model to estimate the relationship between temperature and the ex post load shift, predict the reference load under ex ante conditions using the same model used for ex post, and predict the ex ante load impacts based on the ex ante weather conditions—all as functions of outdoor air temperature and time.

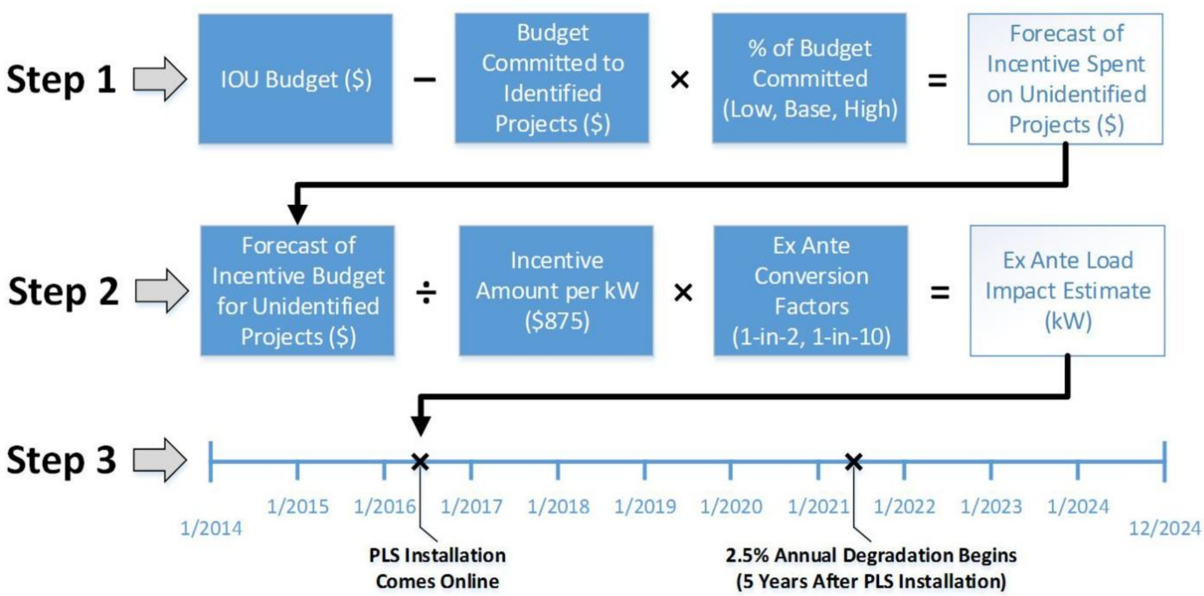
- *Ex post based on operational data*. The methodology for ex ante estimation for the operational site using operational data is based off the ex post estimation, but contains two extra modeling steps— developing a model for cooling tons and developing a model for post-installation cooling system usage—both as functions of outdoor air temperature and time. These models need to be developed because neither cooling tons nor is post-installation usage observable under ex ante conditions.

8.3.2 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 three stage methodology for estimating ex ante load impacts for unidentified PLS projects:

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



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 identify 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 the 2017 bridge year and the end of 2022,

respectively, under the low, base case, and high scenarios. [23] 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[24] that can be expected under hot, maximum cooling load, weather conditions. The kW load shift was multiplied by the ex ante conversion factors,[25] 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 2017 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.[26] This assumption was made in consultation with program managers and it is consistent with last year's evaluation.

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

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[23] The percent budget commitment does not necessarily reflect the amount that will ultimately be spent, since some projects may drop from the PLS program prior to installation—for instance, if the feasibility study indicates that the project would not be cost-effective for the customer. To account for this, the forecast assumes a drop off rate between projects committed and projects actually installed. In the PY2015 evaluation, the assumed drop off rate was 10%.

[24] This peak load shift value is the amount of demand shifting that each utility expects to pay incentives for. This means that these are expected output from the model used in the engineering feasibility study for each site. Although we do not know with certainty what conditions the engineers performing the study used to represent peak yearly conditions, the new building simulation models were calibrated such that the 1 in 10 peak day conditions for the hottest month in each LCA represented the maximum cooling load conditions. Because the models creating the conversion factors used the weather from the hottest 1 in 10 peak day to set the maximum cooling load, and consequently the maximum peak load shift, the hottest 1 in 10 peak weather day can also be used as a proxy for weather conditions under which the incentive would be calculated.

[25] The ex ante conversion factors are described in detail on the following page. In summary: 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.

[26] This estimate of 2.5% degradation was developed as a mutually agreed upon value by the IOUs based on past experience in energy efficiency program implementation. The operational data being collected and evaluation will help to refine this estimate in the future.

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 methodology for developing the conversion factors is described in Appendix A. In the appendix, Nexant provides evidence that it is not necessary to know the specific building characteristics, and that conversion factors may be used for this evaluation. The analysis shows that relative usage values across different weather conditions are basically insensitive to building characteristics, likely due to building codes that establish standard materials for window insulation and other weatherization factors, and that the ratio for a given ex ante condition hardly changes even 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. For example, agricultural customer process cooling loads tend to follow the harvest schedule in addition to being temperature sensitive. 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 applied to 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. Section 5 provides a summary of the assumptions for the PY2016 evaluation, which refines the assumptions used in the PY2015 evaluation based on the most recent information on budget, program enrollment, and the current status of identified projects.

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. Without any information on where these projects will actually be located, the aggregate peak load shift was allocated to each LCA in proportion to the distribution of C&I customers with annual maximum demand greater than 200 kW for PG&E and 1 MW for SCE located in each LCA. The 200 kW and 1 MW thresholds were determined based on the existing pool of applications. 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.

8.3.3 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 8.3.2, 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.

8.4 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		73.1	79.0	72.3	75.7
Peak Day	May	78.1	64.7	72.2	72.7
	June	77.8	71.2	73.6	72.9
	July	78.7	70.9	75.4	73.5
	August	78.7	73.5	76.0	76.4
	September	80.7	73.6	77.6	80.5
	October	76.3	68.0	72.6	74.7
Average Weekday	May	65.7	62.1	61.4	62.3
	June	67.3	63.5	65.6	67.2
	July	69.2	70.5	68.2	69.2
	August	70.3	67.6	69.5	73.7
	September	70.4	67.8	69.8	71.4
	October	66.0	63.1	65.5	67.7

8.5 PLS Ex ante Load Impact Estimates

Table 8-2 provides the ex ante load impact estimates for 2017–2027 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. 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 19% greater than the utility specific comparable peak at 2.3 MW and 2.0 MW, respectively, to the utility specific July 1 in 10 monthly peak day in 2018 being 23% greater than the CAISO specific comparable peak at 2.4 MW and 1.9 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 September 1 in 10 monthly peak load impact is typically around 1.4% 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 2017-2027 (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	2017	1,573	1,798	1,632	1,773	1,654	2,081	1,805	1,996	1,733	2,133	1,828	1,873
	2018	1,786	2,041	1,853	2,012	1,874	2,361	2,047	2,263	1,963	2,418	2,073	2,123
	2019	2,148	2,454	2,229	2,419	2,249	2,838	2,459	2,718	2,354	2,904	2,490	2,549
	2020	2,494	2,848	2,588	2,808	2,607	3,293	2,852	3,153	2,727	3,368	2,888	2,955
	2021	2,917	3,330	3,028	3,283	3,044	3,849	3,332	3,685	3,184	3,935	3,374	3,452
	2022	3,307	3,776	3,433	3,722	3,450	4,364	3,777	4,177	3,608	4,460	3,825	3,912
	2023	3,693	4,217	3,834	4,157	3,851	4,873	4,217	4,664	4,026	4,979	4,270	4,367
	2024	3,841	4,386	3,987	4,323	4,006	5,067	4,385	4,850	4,187	5,178	4,440	4,541
	2025	3,789	4,327	3,932	4,264	3,953	4,998	4,326	4,786	4,132	5,108	4,380	4,481
	2026	3,727	4,257	3,868	4,196	3,891	4,917	4,257	4,709	4,067	5,026	4,310	4,410
	2027	3,657	4,177	3,795	4,117	3,820	4,824	4,177	4,622	3,992	4,932	4,229	4,328
CAISO Specific	2017	1,380	1,860	1,531	1,801	1,765	1,697	1,852	1,925	2,059	2,103	1,660	1,859
	2018	1,566	2,113	1,739	2,044	2,001	1,923	2,099	2,183	2,335	2,385	1,882	2,109
	2019	1,883	2,543	2,091	2,459	2,404	2,309	2,520	2,622	2,806	2,865	2,260	2,533
	2020	2,186	2,953	2,428	2,855	2,788	2,676	2,923	3,041	3,255	3,323	2,622	2,939
	2021	2,556	3,455	2,839	3,339	3,258	3,126	3,414	3,553	3,805	3,883	3,064	3,434
	2022	2,898	3,919	3,220	3,786	3,694	3,543	3,870	4,027	4,313	4,402	3,472	3,893
	2023	3,236	4,377	3,596	4,229	4,124	3,955	4,320	4,496	4,815	4,914	3,876	4,346
	2024	3,365	4,552	3,739	4,397	4,289	4,113	4,492	4,676	5,007	5,109	4,031	4,519
	2025	3,319	4,490	3,689	4,338	4,232	4,059	4,433	4,613	4,939	5,040	3,977	4,458
	2026	3,265	4,417	3,629	4,267	4,165	3,995	4,362	4,540	4,859	4,958	3,913	4,386
	2027	3,203	4,333	3,561	4,187	4,088	3,922	4,281	4,455	4,768	4,864	3,840	4,303

9 Summary of the SPP (Small CPP & TOU Rates)

9.1 SPP (Small CPP & TOU Rates) Overview

This section documents the program year 2016 (PY 2016) 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.

9.1.1 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.[27] 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.

[27] 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.

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 (Dec. 2016)
		February 1, 2014	November 2015	
Small Commercial*	TOU	Opt in from non-time-varying rate	Default	6,639
	TOU-CPP		May opt out of TOU-CPP and on to TOU	114,239

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

9.1.2 Small CPP Event Notification

A limited number, roughly 25%, of small commercial CPP customers received notification in advance of the CPP event. Notification is essential for establishing response to an event-based program, as customers are not likely to modify behavior without knowing that an event is scheduled to take place. Structural challenges as well as the peculiarity of the event day hampered notification efforts in the following ways:

- Customer-specific notification for CPP was done on an opt-in basis, rather than as default. Customers who were defaulted on to the CPP rate had to sign up to receive notification prior to an event.
- Active CPP events are shown on SDG&E’s website for customers who may not have received email or SMS notification. News media also alerted all customers in SDG&E’s territory to the extreme heat on the event day; however this was not specifically targeted at CPP customers.
- Timing of CPP event notification must be considered. Customers were notified between 8:00 and 10:00 pm on the Sunday night before the Monday morning event.
- Improving efforts to communicate CPP event will likely lead to greater ability to detect meaningful impacts.

9.2 SPP Ex Post Evaluation Methodology

To estimate load impacts, it is necessary to estimate what energy consumption would have been in the absence of TOU and CPP-TOU rates—the counterfactual or reference load. To infer that TOU prices changed electricity use patterns, one must be able to systematically eliminate plausible alternative explanations for differences in electricity use patterns, including random chance.

In general, an estimate of the effect of the TOU rate implementation can be accomplished in two ways; either by comparing the pre- and post-period usage of customers who were defaulted on to the rate, known as a within-subjects estimate, or comparing usage of the defaulted customers to a group of customers who are not subject to treatment, or a control group method. A within-subjects analysis was selected due to the lack of a viable control group for TOU customers. The within-subjects method has significant practical limitations; namely that during the time between the pre and post periods, other changes could occur in those businesses that would affect their demand. These changes are likely to be unknown to the evaluator, such as change in the businesses' operating hours, and therefore could be misattributed to the effect of the TOU rate. Another way to put it, is that models that rely on pre-post models assume that, on average, the only difference between the pre and post period is the change in rates and variables included in the model (e.g., weather). With customer data from 2013 through 2016, there are likely to be material differences in electricity demand profiles within a single customer over that time period.

9.2.1 SPP Ex Post Evaluation Methodology for Small CPP Events

For event-based impact estimation, it is common to rely on the use of a control group to observe the counterfactual load. While there was a group of base TOU customers not on the CPP rate during the CPP event, the group was small and not randomly assigned. Without random assignment there may be differences between the treatment group and the opt-out group that could limit the similarity in behavior between the treatment group and opt-out customers. This, in turn, prevents the opt-out group from acting as a true counterfactual. Instead, regression analysis to model the relationship between weather and demand on non-event days in order to establish what customer energy use patterns would have been absent curtailments on event days was used. This approach works because the intervention is introduced on some days and not on others, making it possible to observe loads patterns with and without the program treatment. This enables the evaluator to assess whether the outcome – electricity use – rises or falls with the presence or absence of CPP. This approach hinges on having comparable non-CPP days. When all of the hottest days are CPP days, the counterfactual is based on extrapolating trends beyond the range of non-event temperatures, producing less accurate and less reliable impact estimates for the hottest days. While the September 26th CPP day was the hottest day of the summer, as well as the SDG&E system peak day, there were several other hot non-event days that were available to act as proxy days.

The process for model selection relied on out-of-sample placebo tests. 10 distinct model specifications were defined and each of the 10 models were run using non-event data. The regression model is used to predict electricity use on a placebo event day – an out-of-sample prediction. The process was repeated for multiple placebo event days and recorded the actual and predicted loads for each day. The out-of-sample predictions are compared to actual electricity use observed on that day, which is used to calculate metrics for bias and precision. The best model is identified by first narrowing the candidate models to the three with least bias and then selecting the model with the highest precision. Finally, the best performing model is used to estimate the counterfactual for actual event days.

9.2.2 SPP Ex Post Evaluation Methodology for TOU Rates

Because the TOU transition waves were done in non-random customer groupings, there was reason to believe that each wave would have varying observable and unobservable characteristics that would affect their response to the new rate structure. As no viable control group was available within the SDG&E small commercial population to provide an estimate of the counterfactual demand after the transition to TOU rates, several alternate methods were considered to estimate the impact of the transition to time-varying rates, and determined that the best available approach was to use a within-subjects methodology, where pre-transition usage data was used to estimate the post-transition period, normalized by weather and day variables. This method is straightforward, requiring standard evaluation data and well-established methods. However, this approach involves an inherent risk of bias as it assumes that nothing within each customer's business changed over three years of pre and post period data, except weather and the implementation of TOU rates. Additionally, there is a risk that small impacts may be lost in the noise, where variability within each of the pre and post periods eclipses the effect of the TOU rates.

To estimate load impacts, it is necessary to estimate what energy consumption would have been in the absence of TOU and CPP-TOU rates—the counterfactual or reference load. The key challenge of evaluation is attribution. Did the introduction of TOU and CPP-TOU rates cause a decrease in electricity consumption during peak periods when prices were higher or can the differences in peak period electricity use be explained by other factors? To infer that TOU prices changed electricity use patterns, one must be able to systematically eliminate plausible alternative explanations for differences in electricity use patterns, including random chance.

While control group (or nonparticipant group) methods for evaluating the effect of a TOU rate are preferred, the significant challenge is finding good quality control group that is representative of what the treatment customers would have done in the absence of the TOU implementation. The representative nature of the control group is critical, since that assumption implies that any unobserved changes happening in the treatment group are likely to be happening in the control group as well, reducing the chance that a change is misattributed to treatment. SDG&E did not withhold a random subset of customers from the implementation of default TOU rates during the 2015-2016 transition, meaning that any remaining customers on the flat rate are likely to be different in behavior from the treatment customers in significant ways.

As an alternative method for evaluating the impacts of TOU rates on SDG&E's SMB customer population to mitigate the issues raised above, a within-subjects approach was chosen. This approach aggregated the interval data of all customers who transitioned to the TOU rate between October 2015 and May 2016 and performed a regression analysis to identify differences in the pre and post period usage. Aggregating the interval data has the advantage of reducing random noise at the individual customer's usage level, making it easier to distinguish small impacts from random fluctuations.

9.3 Small CPP Ex Post Load Impact Estimates

9.3.1 Small Commercial CPP Estimates

Only data for customers who have transitioned to the TOU-CPP rate by May 1, 2016 are analyzed for the ex post load impact (customers who opted on to the TOU-only rate are excluded). The analysis showed that almost zero CPP load impacts were achieved for the average customer. One factor driving the low CPP impacts is poor event notification. Only 25% of customers were notified of the CPP event.

CPP impacts for a variety of customer segments are analyzed. Table 9.1 presents average CPP load impacts and percent impacts for several different cohorts within seven categories:

- Customer deciles based on average pre-treatment annual kwh
- Coastal region, determined by climate zone (i.e. coastal vs. inland)
- Enrollment cohorts, subset by the 3-month period in which the customer opted in or was defaulted.
- Industry / sector
- Daily load shape
- Whether the customer received notification for the CPP event
- Dual enrollment in other demand response programs.

As a whole, even within each category, individual groups showed little or no impacts, with a few groups showing negative impacts (increased demand).

Table 9-1 shows CPP load impacts that were achieved by four distinct customer subcategories (highlighted in green). Of particular note are customers dually enrolled in Commercial Thermostats, where demand response is enabled by the provision of a programmable communicating thermostat. These customers showed significant impacts while the devices were set to respond to the event. Customers enrolled between January and March 2015 as well as those who enrolled between July and September 2015 also showed statistically significant impacts. These customers were part of the opt-in pilot rather than defaulted, suggesting that opt-in customers were more likely to respond to an event than customers who were defaulted. Opt in customers were also more likely to have notification methods in place, meaning they were more likely to be aware of the event than the rest of the CPP population.

Table 9-1 Average Customer Small CPP Load Impacts and Percent Impacts

Category	Load w/o DR	Impact	Std. Error	%Impact	Avg. Event Temp
All	4.00	0.00	0.08	0.01%	97.44
Bins Ann kWh	**4.00**	- **0.01**	**0.08**	- **0.98%**	**97.44**
Decile 1	0.04	0.00	0.00	-5.11%	97.21
Decile 2	0.31	-0.01	0.01	-3.21%	97.21
Decile 3	0.78	-0.01	0.02	-1.15%	97.41
Decile 4	1.29	-0.01	0.03	-0.80%	97.45
Decile 5	2.00	0.00	0.05	-0.23%	97.48
Decile 6	2.86	0.01	0.07	0.35%	97.46
Decile 7	3.94	0.02	0.09	0.44%	97.51
Decile 8	5.52	0.02	0.12	0.32%	97.50
Decile 9	7.86	0.05	0.14	0.70%	97.57
Decile 10	15.40	-0.18	0.27	-1.14%	97.59
Coastal	**3.95**	**-0.03**	**0.08**	**-0.89%**	**97.20**
Coastal	3.78	-0.17	0.08	-4.43%	96.20
Inland	4.12	0.11	0.08	2.64%	98.21
Enrollment Cohort	**21.51**	**-2.39**	**1.94**	**-4.27%**	**97.46**
AMJ15	4.55	-0.07	0.19	-1.59%	97.22
AMJ16	4.39	-0.02	0.08	-0.32%	97.03
JAS15	5.63	-0.44	0.15	-7.68%	97.10
JFM15	2.22	-0.21	0.08	-9.31%	97.83
JFM16	3.98	0.03	0.08	0.84%	97.58
OND15	2.97	-0.03	0.05	-1.14%	97.32
Prior to 2015	1.86	-0.06	0.04	-3.34%	97.71
Industry	**4.51**	**-0.06**	**0.11**	**-1.21%**	**97.42**

Agriculture, Mining & Construction	3.28	-0.15	0.08	-4.63%	97.11
Manufacturing	5.83	-0.08	0.11	-1.36%	97.92
Offices, Hotels, Finance, Services	4.42	0.04	0.08	1.03%	97.57
Other or Unknown	2.12	0.00	0.05	-0.11%	97.25
Retail Stores	5.34	0.00	0.10	0.10%	97.48
Schools	4.99	0.14	0.13	2.89%	97.22
Wholesale, Transport & Other Utilities	5.58	-0.36	0.22	-6.42%	97.35
Load Shape	**3.09**	**-0.02**	**0.07**	**-3.90%**	**97.45**
Afternoon Peak	5.20	0.04	0.13	0.85%	97.47
Early Peak	4.83	0.04	0.10	0.82%	97.64
Nearly Flat	3.90	-0.03	0.06	-0.71%	97.30
Night Load	0.99	-0.09	0.04	-9.17%	97.20
U-Shaped	0.53	-0.06	0.03	-11.26%	97.63
Notification	**46.14**	**-6.35**	**4.01**	**-6.34%**	**97.66**
Not Notified	3.90	0.02	0.07	0.54%	97.44
Notified	88.39	-12.72	7.94	-13.22%	97.88
Other DR	**4.91**	**-0.10**	**0.14**	**-0.43%**	**97.66**
CBP	2.23	0.09	0.18	4.01%	98.53
None	3.91	0.01	0.07	0.15%	97.45
Commercial Thermostats	8.14	-0.46	0.19	-5.52%	97.51
SS	5.37	-0.02	0.13	-0.36%	97.14

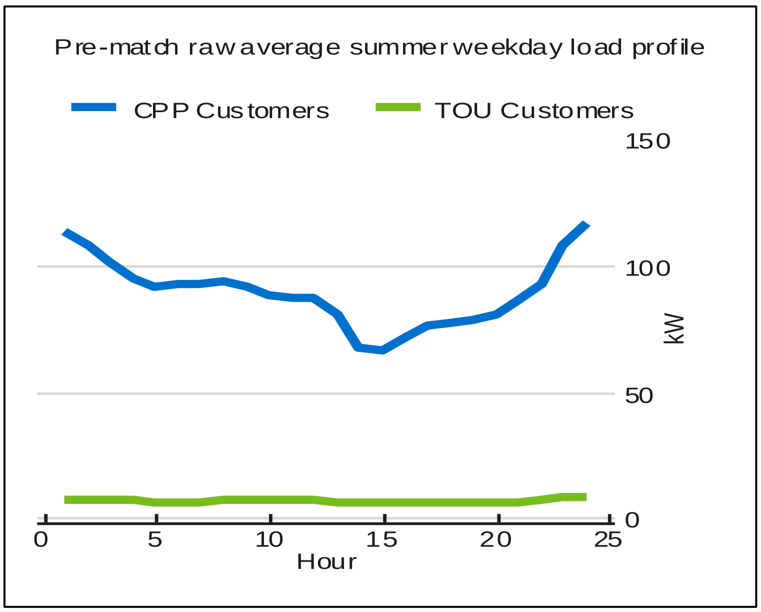
9.3.2 Agricultural CPP Ex Post Estimates

Agricultural customers were exposed to a slightly different treatment than SDG&E's small commercial customers during this transition to TOU and CPP rates. Customers on PA rates were transitioned over the same period of time as the small commercial customers; however they were defaulted on to a TOU rate without a CPP component. Agricultural customers then had the option to enroll voluntarily in the CPP rate. The impact of experiencing the CPP event is expected to be slightly different for the agricultural customers due to fact that they opted in to the program. These customers are more likely to understand the rate and how to reduce load on the event days.

However, opt-in programs often have much lower levels of enrollment than default programs, where entire populations are switched on to an event based program like the small commercial CPP rate. Agricultural customers may choose to opt in based on their ability to respond, their aversion to increased event-day prices, or because they are structural winners – that is they already reduce load during normal peak hours and do not need to shift behavior to avoid penalties.

On the 2016 event day, 141 agricultural customers were enrolled in CPP out of approximately 3,800 total agricultural customers. Shown below in Figure 9-1 is the average load profile of agricultural customers on the average summer weekday. The customers that opt in to the CPP program have significantly higher average daily usage as well as a U-shaped load, with much higher consumption during the early morning and late evening than during peak hours in the middle of the day. This supports the theory that agricultural customers who opt in to CPP are structural winners; that is, they are already reducing usage in the expected time without the incentive of the rate to make them shift consumption.

Figure 9-1 Average Agricultural CPP and TOU Load Shapes



9.4 TOU Ex post Load Impact Estimates

9.4.1 Small Commercial TOU Ex Post Estimates

Table 9-2 summarizes the impacts due to SDG&E's implementation of mandatory TOU rates for each rate period. It presents the average reduction by season, day type and rate period for small commercial customers. With DR, however, the reductions attained during peaking conditions rather than on the average weekday are often of more interest.

Rate blocks were split according to summer and winter seasons, weekday or weekend day type, and the time-varying rate category: on peak, semi-peak (or shoulder peak time), and off peak. Table 9-2 gives the schedule of rate categories for each season. Note that holidays follow a weekend schedule, regardless of season.

Table 9-2 TOU Rate Schedule

Season	Day Type	Rate Block	Time
Winter	Weekend	Off Peak	All Day
	Weekday	Off Peak	10pm-6am
		Semi Peak	6am-5pm 8pm-10pm
		On Peak	5pm-8pm
Summer	Weekend	Off Peak	All Day
	Weekday	Off Peak	10pm-6am
		Semi Peak	6am-11am 6pm-10pm
		On Peak	11am-6pm

Ten false transition dates were chosen from the summer of 2015. Note that customers who had already opted in to the TOU rate were excluded from these results as they had transitioned by the time of the false experiments. These results demonstrate both the range of variability in the underlying data as well as the true results for the TOU transition; with a range of impacts +/-10% from a mean of roughly 0. This corresponds to impacts in the +/-0.2 to 0.4kW range. False experiment results ranged in confidence bands between +/- 5% for weekday results and +/-10% for weekend results. This implies that any impacts associated with the TOU transition that resulted in load impacts smaller than 5-10% would not be able to be detected.

The only significant impact was a reduction in the demand associated with weekday off peak usage. This indicates that customers were using less energy during weekday evenings, when energy prices are at their lowest. Contrary to the expected economic theory, which suggests that customers would shift usage to relatively lower-cost periods such as off-peak periods resulting in increased use, customers did the opposite.

9.4.2 Agricultural TOU Ex Post Estimates

Approximately 3,800 agricultural customers were defaulted on to a TOU rate during period of November 2015 through April 2016. Similar to the small commercial customers, no control group was able to be withheld from the rate transition. As a result of this, there were no agricultural customers remaining on a flat rate to form a basis of comparison during the post-transition summer. This in turn makes assigning any causal relationship between the implementation of TOU rates and subsequent rate changes extremely challenging.

To assess the degree to which agricultural customers began to shift their load in response to TOU price signals, the change in daily load consumption per rate block are first accessed. The rate blocks for agricultural customers are the same as those for the small commercial customers, summarized in Table 9-3. If load shifting is occurring, the percentage of daily consumption in each rate block would change from the pre-transition period to the post-transition period. Table 9-3 shows the result of this analysis. Consumption across periods did not shift substantially; off peak consumption stayed the same, and a slight increase in semi-peak consumption during weekdays was offset by a slight decrease in weekday on-peak consumption. These shifts, however, are too small to be distinguishable from noise.

Table 9-3 Agricultural Customer Consumption Shares by Summer Rate Block

Weekday	Rate Block	Avg kW Pre	Avg kW Post	Share Pre	Share Post
Weekend	Off Peak	3.0	2.6	100.0%	100.0%
Weekday	Off Peak	3.3	2.8	31.3%	31.3%
	Semi Peak	3.6	3.1	34.3%	34.8%
	On Peak	3.6	3.1	34.4%	33.9%

9.5 SPP Ex Ante Load Impact Estimates

Because the evaluation did not produce any significant ex post impacts for either the CPP or TOU components of the small commercial or agricultural rate transition, ex ante impacts were not estimated. As discussed above, while there are some customer segments that produced significant impacts, no significant impacts were observed overall.

10 Summary of the Commercial Thermostats Program

10.1 Commercial Thermostats Overview

SDG&E's commercial thermostats 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 were defaulted onto Critical Peak Pricing (CPP) in April of 2016 and were called to reduce loads on the CPP event day in September 2016.

Currently, there are approximately 2,608 customers enrolled with a total of 13,735 thermostats. This number is expected to increase to 17,350 thermostats in August 2017, then decline slowly to approximately 14,500 thermostats by 2022 after which enrollment stabilizes at 14,200 for the remainder of the forecast period.

10.2 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.

10.2.1 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.[28] 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

[28] 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."

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.[29]

Equation 10-1: Specification of Triple Differences Regression

$$kW_{i,t,h} = a * treat_i * eday_t * eperiod_h + \sum_{cust=1}^{customers} b_{cust} * customer_{cust\ i} + \sum_{hr=1}^{hours} c_{hr} * hour_{hr\ h}$$
$$+ \sum_{date=1}^{days} d_{date} * day_{date\ t} + e * eday_t * eperiod_h + f * treat_i * eperiod_h$$
$$+ g * treat_i * eday_t + u_{ith}$$

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

[29] 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.

10.2.2 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

$$kwh_{it} = a + b * mean17_{i,t} + c * mean17_{i,t}^2 + e_{i,t}$$

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
ε	The error term

10.3 Commercial Thermostats Ex post Load Impact Estimates

SDG&E called one CPP event during summer 2016 during which 1,724 commercial customers and 884 commercially managed residential units were enrolled.

10.3.1 Ex post Load Impact Estimates – Commercial

Table 10-3 summarizes the average load reduction for the event day provided by commercial customers across the four-hour event window from 2 to 6 PM. As shown, the average percent reduction was approximately 7%. The average load reduction was 2.2kW per customer, while aggregate load reductions were approximately 3.8MW. With an average of 7.4 thermostats per customer, the per-thermostat impact is approximately 0.3kW.

Table 10-3: 2016 Commercial Thermostat Ex post Load Impact Estimates (2 to 6 PM)

On the 2016 Event Day, Commercial Customers

(kW per Customer, Aggregate MW, and kW per Thermostat)

Segment	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)	Mean 17 (°F)
Commercial	1,724	12,829	31.49	2.20	7.0%	3.80	0.30	81.43

10.3.2 Ex post Load Impact Estimates – Residential

Table 10-4 shows the average event-window impact on the event day. The average impact per customer for the 884 customers enrolled across the four hour event window was a statistically significant 0.47 kW, or 45% of the reference load.

Table 10-4: 2016 Commercial Thermostat Ex post Load Impact Estimates (2 to 6 PM)

On the 2016 Event Day, Residential Customers

(kW per Customer, Aggregate MW, and kW per Thermostat)

Segment	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)	Mean 17 (°F)
Residential	884	905	1.05	0.47	44.6%	0.41	0.46	81.82

10.4 Commercial Thermostats 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:

1. Ex post estimates were developed using the matching methodology described in Section 10.2, with the key output being the 2016 average event day per-thermostat impact;
2. 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;

3. Impacts were calibrated using the ratio of ex post cooling degree days to ex ante weather condition cooling degree days. This approach is used to capture the fact that cooling loads are sensitive to the weather conditions and as such, the expected load relief from this program will be substantially different during a hot day in September rather than a mild day in April.

The final model specifications used for the reference loads and impact-temperature relationship are shown below in Equation 10-3 and Table 10-5.

Equation 10-3: Reference Load Ex ante Regression Model Specification

$$kW_t = a + b \cdot mean17_t + c \cdot mean17_t^2 + \sum_{day=Tuesday}^{Friday} d_{day} \cdot DOW_{t,day} + \sum_{month=February}^{December} m_{month} \cdot Month_{t,month} + \varepsilon_t$$

Table 10-4: 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
$mean17^2$	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)
ε	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

As a validation of the ex ante impact model, Table 10-6 shows the results of the ex ante impact modeling for the 2016 event day at hour ending 4 PM, as compared to the estimates in the ex post analysis. Since, in general, higher impacts on hotter days are expected, the ex ante impacts are slightly smaller than ex post as the predicted event day is cooler, therefore having smaller reference loads as well as impacts.

Table 10-6: Ex Post and Ex Ante Impact Validation for Event Days at Hour Ending 4 PM

Day Type	Thermostats per Customer	Mean17	Enrolled	Per Customer Impact (kW)
Ex Post Event Day	7.4	81.4	1724	2.0
Ex Ante September Peak Day	7.4	78.7	2136	1.6

10.4.1 Commercial Thermostats Estimating Ex ante Weather Conditions

The CPUC Load Impact Protocols[30] 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.[31] While the CAISO weather scenario remains the same as the 2015 ex ante scenario, the

[30] See CPUC Rulemaking (R.) 07-01-041 Decision (D.) 08-04-050, "Adopting Protocols for Estimating Demand Response Load Impacts" and Attachment A, "Protocols."
[31] See *Statewide Demand Response Ex ante Weather Conditions*. Nexant, Inc. January 30, 2015.

SDG&E ex ante weather conditions were updated to reflect the weather conditions corresponding to the top system load days from 2007 to 2016.

Table 10-7 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 10-7: 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	74.3	78.3	72.9	75.5
January Peak Day	53.9	45.8	52.6	47.7
February Peak Day	54.2	53.7	55.2	55.4
March Peak Day	58.1	71.2	55.3	66.7
April Peak Day	68.0	76.5	64.1	73.7
May Peak Day	70.0	77.7	64.2	72.4
June Peak Day	67.8	75.9	68.5	72.7
July Peak Day	73.7	75.1	71.4	73.3
August Peak Day	77.9	78.4	75.6	76.1
September Peak Day	74.3	78.3	72.9	75.5
October Peak Day	53.9	45.8	52.6	47.7
November Peak Day	54.2	53.7	55.2	55.4
December Peak Day	58.1	71.2	55.3	66.7

10.4.2 Commercial Thermostats Ex ante Load Impact Estimates

Section 10.4 summarized the methodology used to develop ex ante impact estimates for the average customer, under ex ante weather conditions. 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 7 thermostats per customer.

Table 10-8 summarizes the 2017 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 5.4MW and 7MW in a 1 in 10 year and roughly 3.9 to 4.6 MW in a 1 in 2 year.

Table 10-8: 2017 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	0.20	0.95	3.43	0.17	0.84	3.01
	January Monthly Peak	0.00	0.00	0.00	0.00	0.00	0.00
	February Monthly Peak	0.00	0.00	0.00	0.00	0.00	0.00
	March Monthly Peak	0.00	0.00	0.00	0.00	0.00	0.00
	April Monthly Peak	0.09	0.43	1.54	0.04	0.19	0.69
	May Monthly Peak	0.11	0.55	2.00	0.04	0.18	0.65
	June Monthly Peak	0.08	0.40	1.46	0.09	0.44	1.58
	July Monthly Peak	0.17	0.81	2.91	0.14	0.68	2.45
	August Monthly Peak	0.27	1.29	4.63	0.22	1.07	3.86
	September Monthly Peak	0.27	1.28	4.60	0.22	1.07	3.86
	October Monthly Peak	0.14	0.69	2.48	0.11	0.51	1.83
	November Monthly Peak	0.11	0.51	1.81	0.03	0.14	0.51
	December Monthly Peak	0.00	0.00	0.00	0.00	0.00	0.00

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 10	Typical Event Day	0.29	1.37	4.95	0.23	1.08	3.91
	January Monthly Peak	0.00	0.00	0.00	0.00	0.00	0.00
	February Monthly Peak	0.00	0.00	0.00	0.00	0.00	0.00
	March Monthly Peak	0.13	0.64	2.22	0.07	0.34	1.18
	April Monthly Peak	0.22	1.04	3.71	0.16	0.77	2.72
	May Monthly Peak	0.23	1.11	4.01	0.16	0.75	2.72
	June Monthly Peak	0.22	1.05	3.82	0.16	0.77	2.79
	July Monthly Peak	0.20	0.97	3.50	0.17	0.82	2.97
	August Monthly Peak	0.28	1.37	4.93	0.23	1.12	4.06
	September Monthly Peak	0.41	1.97	7.07	0.31	1.49	5.35
	October Monthly Peak	0.31	1.51	5.42	0.20	0.97	3.48
	November Monthly Peak	0.27	1.29	4.63	0.10	0.49	1.77
	December Monthly Peak	0.00	0.00	0.00	0.00	0.00	0.00

10.5 Commercial Thermostats 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 10-9 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.

Table 10-9: 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	Average event day mean17 = 81.4	Mean17 for 1 in 2 typical event day = 74.3 and 72.9 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 2016, so ex ante should generally be lower than ex post, all else equal
		Mean17 for 1 in 10 typical event day = 78.3 and 75.5 for PG&E and CAISO	
Enrollment	Only one event in 2016, cannot establish a trend	Enrollment is forecast to grow to about 17,500 thermostats through 2017, after which the program will decrease to a steady state of 14,200 thermostats by 2022	Ex ante estimates will increase as the number of thermostats enrolled increases, then decrease to a steady state
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 depending on what the ultimate relationship between weather and impacts these customers demonstrate. The commercial thermostat temperature-impact relationship has few data points to estimate such a relationship.

Table 10-10 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 5. The next column grosses these estimates up by the difference in ex post and ex ante enrollment in August 2017. 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. The substantial increase in the fourth column (ex ante model using ex post weather) is due to the extreme heat of the 2016 event day compared to the September monthly peak ex ante weather conditions. 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.

Table 10-10 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)
9/26/2016	81.4	3.8	4.7	5.3	3.2	3.9	4.5	5.9

11 Summary of the Voluntary Residential CPP Rate

11.1 Voluntary Residential CPP Rate Overview

This section documents the program year 2016 (PY 2016) load impacts for SDG&E's time varying pricing tariffs for residential customers, including:

a. Voluntary CPP-TOU residential customers (non-event) (TOU-DR)
b. Voluntary CPP-TOU residential customers (event) (TOU-DR-P)

These are collectively referred to as the residential smart pricing project (SPP) rates. The SPP rates became active in February of 2015. The current TOU periods for the residential SPP rates are:

Summer (May 1- Oct 31)
On-Peak 11 a.m. – 6 p.m. weekdays, excluding holidays
Semi-Peak 6 a.m. – 11 a.m. and 6 p.m. – 10 p.m. weekdays, excluding holidays
Off-Peak 10 p.m. – 6 a.m. weekdays, and all hours on weekends & holidays
CPP: 11a.m.-6p.m. all days.

Winter (Nov 1 – April 30)
On-Peak 5 p.m. – 8 p.m. weekdays, excluding holidays
Semi-Peak 6 a.m. – 5 p.m and 8 p.m. – 10 p.m. weekdays, excluding holidays
Off-Peak 10 p.m. – 6 a.m. weekdays, and all hours on weekends & holidays
CPP: 11a.m.-6p.m. all days.

Critical Peak Pricing (CPP) events are called in conjunction with SDG&E's Reduce Your Use (RYU) program. Up to 18 RYU events can be triggered per year, on any day of the week, at any time during the year. A CPP event period adder of $1.16/kWh applies on event days. In return, enrollees receive credits on their electric commodity cost during all TOU pricing periods on non-RYU event days. Participants are generally notified of events by 3 p.m. on the business day prior to the event, and several notification options are available, including email and text. For the first full season following their enrollment, CPP participants are eligible for *bill protection*, which guarantees that their bill will be no larger than what it would have been under their otherwise applicable tariff.

11.2 Voluntary Residential CPP Rate Ex Post Evaluation Methodology

The *ex post* load impact evaluations for the TOU-DR (TOU henceforth) and TOU-DR-P (CPP henceforth) rates apply difference-in-differences methods that involve selecting quasi-experimental matched control groups and then comparing the usage of treatment and control group customers on relevant days or time periods, where the comparisons are then adjusted by their usage differences on pre-treatment or non-event days. The control groups were selected by matching each treatment customer to one of an initial sample of eligible non-treatment customers in relevant population segments (*e.g.*, climate zone, CARE status, and enrollment in RYU), based on the closest match of load profiles. This difference-in-differences approach with matched control groups is available for this study since both rates are new, meaning that customers' pre-treatment data are recent, and hourly interval load data are available for all of SDG&E's customers.

11.2.1 Ex post models for estimating CPP load impacts

The load impact estimation model for CPP accounts for customer-specific and date-specific fixed effects (which include weather and day-type factors) and effectively estimates the CPP load impact as the difference between CPP and control-group customer loads on event days, controlling for the aforementioned fixed effects. This can be described as a difference-in-differences estimate (the difference between treatment and control group usage on event days, adjusted for differences on non-event days). The primary customer-level fixed-effects regression model used in the analysis is shown below, where the equation is estimated separately for each of the 24 hours. This model in general produces load impact estimates for each hour of every event, though only one event was called in 2016:

$$kW_{c,d} = \beta_0 + \Sigma_{Evts(i)} (\beta_{1,i} \text{ x } CPP_{c,d} \text{ x } Evt_{i,d}) + \beta_2 \text{ x } \mathrm{CPP}_{c,d} + \Sigma_{Cust} (\beta_{3,Cust} \text{ x } C_c) + \Sigma_{day} (\beta_{4,day} \text{ x } D_{day,d}) + \beta_5 \text{ x } SS\_Evt_{c,d} + \beta_6 \text{ x } SCTD\_Evt_{c,d} + \varepsilon_{c,d}$$

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

Symbol	Description
$kW_{c,d}$	Load in a particular hour for customer *c* on day *d*
$CPP_{c,d}$	Variable indicating whether customer *c* is a CPP (1) or Control (0) customer on day *d*
$Evt_{i,d}$	Variable indicating that day *d* is the i^{th} event day (1=i^{th} event, 0 if not)
$SCTD\_Evt_{c,d}$	Variable indicating that day *d* is a *SCTD* event day (1= event, 0 if not) for customer *c*
$SS\_Evt_{c,d}$	Variable indicating that day *d* is *a Summer Saver* event day (1=event, 0 if not) for customer *c*
β_0	Estimated constant coefficient
$\beta_{1,d}$	Estimated load impact for event *d*
β_2	Estimated TOU response
$\beta_{3,Cust}$ and $\beta_{4,day}$	Customer and day fixed-effects
$\beta_{5,d}$	Estimated average *SCTD* load impact for event *d*
$\beta_{6,d}$	Estimated average *Summer Saver* load impact for event *d*
C_c	Variable indicating that the observation is for customer *c*
$D_{day,d}$	Date indicator variable (1 = date *d* equals date *day*)
$\varepsilon_{c,d}$	Error term

Since only one event was called, we can produce estimates of load impacts for the average event by customer type (e.g., Climate zone and CARE status) simply by estimating separate models for each type and reporting the estimated impacts.

11.2.2 Ex post models for estimating TOU load impacts

To obtain TOU load impacts (for both the TOU-only and CPP customers), we estimate a distinct model for each required result. For example, to get the average TOU load impacts on August non-holiday weekdays, we estimate a model that includes only days of that day type.[32] In this case, we simplify the model to include customer and day fixed effects, plus a variable to estimate the load impact (i.e., the coefficient β 1). Separate models are estimated by hour, month, day-type (i.e., average weekday versus peak month day), applicable customer groups (e.g., climate zone and CARE status), where the customer-level fixed-effects models are of the following form:[33]

$$kW_{c,d} = \beta_0 + \beta_1 \text{ x } (TOU_c \text{ x } Post_d) + \Sigma_{Cust} (\beta_{2,Cust} \text{ x } C_c) + \Sigma_{days} (\beta_{3,day} \text{ x } D_{day}) + \beta_4 \text{ x } Evt_{c,d} + \beta_5 \text{ x } SS\_Evt_{c,d} + \beta_6 \text{ x } SCTD\_Evt_{c,d} + \varepsilon_{c,d}$$

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

[32] In cases where insufficient numbers of observations were available, we modified the approach by combining day-types. For example, for TOU-only customers, we combined observations for all summer weekdays to estimate a constant summer percentage load impact. Day-type specific reference load is calculated as the day-type observed load divided by one minus the percentage load impact (*i.e.,* Ref=Obs/(1-PctLI)). We can then apply the estimated percentage load impact to reference loads for the average weekday for each month to obtain monthly load impact *levels*.

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

Symbol	Description
$kW_{c,d}$	Load in a particular hour for customer *c* on day *d*
TOU_c	Variable indicating whether customer *c* is a TOU or CPP (1) or Control (0) customer
$Evt_{c,d}$	Variable indicating whether day *d* is an event day for customer *c* [34]
$Post_d$	Variable indicating that day *d* is in the post-enrollment period
$SCTD\_Evt_{c,d}$	Variable indicating that day *d* is a *SCTD* event day (1= event, 0 if not) for customer *c*
$SS\_Evt_{c,d}$	Variable indicating that day *d* is *a* Summer Saver event day (1=event, 0 if not) for customer *c*
β_0	Estimated constant coefficient
β_1	Estimate of TOU load impact
$\beta_{2,Cust}$ and $\beta_{3,day}$	Estimated customer and day fixed effects
β_4	Estimate of average event-day load impact
β_5 and β_6	Estimated average *SCTD* and SS event event-day load impacts
C_c	Variable indicating that the observation is associated with customer *c*
D_{day}	Variable indicating that the observation is for day *d*
$\varepsilon_{c,d}$	Error term

11.2.3 Control Group Matching

The matching process differed for customers on the two rates. Since the TOU/CPP (TOU-DR-P) customers experienced TOU rates on all non-event days, and the CPP rate on event days, we treat those customers as CPP customers when evaluating CPP load impacts, and as TOU customers when evaluating TOU impacts. For analyzing CPP impacts, the TOU/CPP customers were matched to potential control group customers using loads on selected event-like non-event days (*e.g.*, days with temperatures most like those on the event day) in 2016.[35]

For analyzing TOU impacts, for both TOU/CPP and TOU-only customers, the treatment customers were matched on the basis of loads in the pre-treatment period (November 2014 through September 2015). The TOU customers were matched separately by season, based on two pairs of hourly loads for each season – one for all weekdays, and one for a subset of the hottest (or coldest) weekdays. Matching for the *winter* season used data for November 2014 through April 2015, while that for the *summer* season used data for May through September of 2015.

Matching was based on Euclidean distance minimization between treatment and potential control group customer loads. This approach minimizes the difference between a standardized usage metric of the treatment and potential control group customers. In this case, the standardized metric combines the 48 hourly load difference statistics for the two average

[34] For CPP customers, the *Evt* variable indicates that a day is a CPP event day. For TOU customers who are also enrolled to receive RYU alerts, that variable indicates that a day is a PTR/RYU event day.
[35] The event-like non-event days in 2016 were 7/20, 7/21, 7/26, 7/27, 7/28, 8/16, 8/17, 9/28, 9/29, and 9/30.

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

11.2.4 Validity assessment

Because a control-group approach is employed, the validity assessment focuses on comparisons of treatment and control-group loads for selected event-like non-event days (for CPP) or pre-treatment loads (TOU). We also report statistics such as the relative root mean square error and mean percent error, which provide formal estimates of the percent differences between treatment and control group loads.

11.3 Voluntary Residential CPP Rate & TOU Ex post Load Impacts

This section summarizes the findings from the ex post load impact evaluation analysis of the CPP portion of the TOU-DR-P rate. For CPP, the primary load impact results include average estimated event-hour load impacts (i.e., the average of the hourly load impacts estimated for the seven-hour event window from 11 a.m. to 6 p.m.), in aggregate and per-customer, for the single event day on September 26, 2016. Results of the analysis of the TOU portion of the rate (i.e., peak load impacts on non-event days) are presented in Section 11.3.2, along with results for the TOU rate.

11.3.1 Voluntary Residential CPP Rate Ex post Load Impact Estimates

For the CPP event called on September 26, 2016, average event-hour reference loads[36] and load impacts, at an aggregate and per-customer basis are calculated.

Table 11-1 summarizes reference load and load impact results for CPP customers, by climate zone. The first two columns show the climate zone and numbers of enrolled customers. The next two columns show aggregate estimated reference loads and load impacts for the average event hour, in MW. The next two columns show the same variables for the average customer, in units

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

of kW. The last two columns show the load impacts as a percentage of the reference loads and the average temperature during the event window.

Table 11-1: Average CPP Event-Hour Load Impacts – *September 26 Event*

Climate Zone	Enrolled	Aggregate		Per-Customer		% Load Impact	Ave. Event Temp.
		Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)		
Coastal	1,773	1.91	0.30	1.08	0.17	16%	98
Inland	1,290	1.62	0.15	1.25	0.11	9%	102
All	3,063	3.51	0.44	1.15	0.14	13%	99

Program enrollment was 3,063 customers, skewed somewhat toward the Coastal climate zone.[37] The aggregate reference load was 3.51 MW. Per-customer load impacts averaged 0.17 kW for customers in the Coastal climate zone, representing 16 percent of their reference load, and 0.11 kW, or 9 percent, for the Inland climate zone. Average event-window temperatures were somewhat cooler in the Coastal zone, at 98 degrees, than the 99-degree temperature for the Inland zone. The substantially greater responsiveness of the Coastal customers is somewhat surprising, with no obvious explanation.

11.3.2 TOU Ex post Load Impact Estimates

This sub-section shows load impact results for those customers enrolled in the TOU (TOU-DR) rate. Table 11-2 summarizes the average reference loads and load impacts for the TOU peak period (*i.e.*, 11 a.m. to 6 p.m. for May through October, and 5 to 8 p.m. for November through April), for the average weekday *by month*, on an aggregate and per-customer basis. The months are shown starting with the first month included in the analysis (October 2015).[38] Enrollment continued throughout the period, with the numbers of enrolled customers rising from 204 in October 2015 to 819 in September 2016.[39] Percentage load impacts were essentially the same for the summer and winter months due to the estimation method that combined data for all months in the relevant season, and constrained the estimated percentage peak load impact to be the same across months.

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[37] This enrollment number differs from the number of customers that were used in the regression models, for whom all required data were available (*e.g.*, all selected event-like days, as well as the event day). SDG&E reported that enrollment reached nearly 3,150 by the end of September.

[38] Winter month (Nov. 2015-Apr. 2016) are shaded in blue. Due to the relatively small enrollment numbers and therefore aggregate load levels, the aggregate loads are shown in units of kWh per hour, or kW.

[39] As for CPP, the enrollment numbers in the tables differ from the number of customers used in the regression models, which is a subset of customers that have all the required data for conducting the *ex post* load impact analysis; SDG&E reported that enrollment in TOU-DR reached 824 in late September.

Table 11-2: TOU Peak Load Impacts for TOU Customers – *Average Weekday by Month*

Month	Climate Zone	Enrolled	Aggregate		Per-Customer		% Peak Load Impact	Ave. Peak Temp.
			Peak Ref. Load (kW)	Peak Load Impact (kW)	Peak Ref. Load (kW)	Peak Load Impact (kW)		
Oct-15	All	204	144	7.7	0.71	0.038	5.4%	79
Nov-15	All	254	276	12.0	1.09	0.047	4.3%	64
Dec-15	All	296	366	16.1	1.24	0.055	4.4%	59
Jan-16	All	328	365	16.0	1.11	0.049	4.4%	60
Feb-16	All	411	412	17.5	1.00	0.042	4.2%	66
Mar-16	All	468	409	17.1	0.87	0.037	4.2%	63
Apr-16	All	510	430	18.3	0.84	0.036	4.3%	67
May-16	All	549	330	17.5	0.60	0.032	5.3%	68
Jun-16	All	599	498	26.7	0.83	0.045	5.3%	74
Jul-16	All	670	722	39.0	1.08	0.058	5.4%	77
Aug-16	All	745	792	42.8	1.06	0.057	5.4%	78
Sep-16	All	819	715	38.4	0.87	0.047	5.4%	78

Table 11-3 shows results by season and climate zone. Because of relatively low enrollment in October 2015 and the discontinuity between that month and the summer of 2016, the results for the summer season include only May through September of 2016. Summer peak load impacts were similar in percentage terms for the two climate zones. However, winter percentage peak load impacts were larger in the Coastal zone (5.3%) than in the Inland zone (3.3%). It also shows the effect of TOU on average *daily* usage by month. TOU customers changed their energy consumption by small amounts in each month of the year, with some increases and some reductions. The overall change was an average annual *reduction* of less than 0.1 percent.

Table 11-3: TOU Peak Load Impacts for TOU Customers – *Average Weekday by Season & Climate Zone*

Season	Climate Zone	Enrolled (Average)	Aggregate		Per-Customer		% Peak Load Impact	Ave. Peak Temp.
			Peak Ref. Load (kW)	Peak Load Impact (kW)	Peak Ref. Load (kW)	Peak Load Impact (kW)		
Summer	Coastal	382	318	17.4	0.80	0.044	5.5%	73
	Inland	294	313	17.8	1.04	0.059	5.7%	78
	All	676	630	35.1	0.90	0.050	5.6%	75
Winter	Coastal	213	201	10.7	0.90	0.048	5.3%	65
	Inland	165	184	6.1	1.09	0.036	3.3%	63
	All	378	384	16.7	0.99	0.043	4.4%	64

11.3.3 SCTD Load Impacts

This section compares the Voluntary Residential CPP load impact estimates for customers that were dually enrolled in CPP and the Small Customer Technology Deployment ("SCTD") program during 2016. Customers enrolled in SCTD had one event called on September 26. The event hours are 2 to 6 p.m., shorter than the CPP event window of 11 a.m. to 6 p.m.

Table 11-4 summarizes reference loads and load impacts for all CPP customers along with customers dually enrolled in CPP and SCTD, during the CPP event-hour window. Program enrollment in CPP and SCTD was 130 customers, a small proportion of the 3,062 customers enrolled in CPP. The average per-customer peak-hour reference load and load impact estimate is larger for dually enrolled customers. Nevertheless, the percentage load impact also remains larger, at 16.3 versus 12.6 percent.

Table 11-4: Comparison of Average CPP Event-Hour Load Impacts for Customers Dually Enrolled in SCTD and CPP – *September 26, 2016 Event*

Group	Enrolled	Aggregate		Per-Customer		% Peak Load Impact	Ave. Peak Temp.
		Peak Ref. Load (kW)	Peak Load Impact (kW)	Peak Ref. Load (kW)	Peak Load Impact (kW)		
ALL CPP	3,063	3,511	442.7	1.15	0.14	13%	99
CPP+SCTD	130	175	28.5	1.35	0.22	16%	100

11.4 Ex ante Load Impacts

Ex ante load impacts represent forecasts of load impacts that are expected to occur when program events are called in future years (CPP), or in TOU peak periods (TOU), under standardized weather conditions. Since SDG&E called only one RYU/CPP event in 2016, we have only that event on which to base forecasts going forward. As a result, load impacts for different weather scenarios were developed by applying the estimated percentage load impact from the *ex post* analysis to weather-sensitive reference loads. Those were developed using regression models similar to those used in the *ex post* analysis, and then simulating loads under the four alternative weather scenarios.

An issue in producing the *ex ante* load impact forecasts for CPP is that the Protocols call for estimating load impacts for the Resource Adequacy (RA) hours of 1 to 6 p.m. during summer months, and 4 to 9 p.m. in winter months, while the CPP events are called during the program hours of 11 a.m. to 6 p.m. year-round. Therefore, load impacts using the event hours that are indicated by the tariff are simulated first, then the load impacts across the RA window are summarized as required.

Table 11-5 shows the monthly pattern of aggregate ex ante load impacts averaged over the RA window for the system peak day of that month in 2017 for SDG&E's 1 in 2 and 1 in 10, and similarly, for CAISO's 1 in 2 and 1 in 10. Load impacts are greatest in the summer months, reaching a maximum in August.

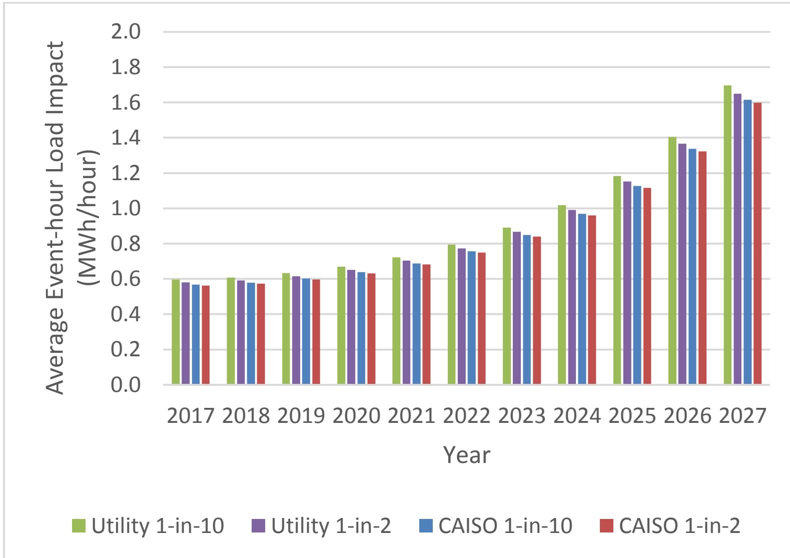
Table 11-5: Aggregate CPP Load Impacts (MW), by Month – 2017

	Load Impact (MW)			
	SDGE		CAISO	
Month	1 in 2	1 in 10	1 in 2	1 in 10
Jan	0.40	0.43	0.40	0.43
Feb	0.38	0.44	0.37	0.34
Mar	0.32	0.32	0.34	0.30
Apr	0.56	0.60	0.53	0.58
May	0.63	0.76	0.42	0.64
Jun	0.57	0.77	0.56	0.71
Jul	0.76	0.84	0.75	0.75
Aug	0.82	0.85	0.80	0.81
Sep	0.79	0.86	0.72	0.79
Oct	0.62	0.78	0.49	0.59
Nov	0.36	0.40	0.33	0.36
Dec	0.45	0.47	0.41	0.46

Figure 11-1 illustrates the growth in forecast CPP load impacts, and the relatively minor differences between the aggregate *ex ante* load impacts for the alternative weather scenarios over the forecast period.[40]

[40] The relatively minor differences are due in part to the assumed constant percentage load impact, due to the occurrence of only one event in 2016. As experience is gained from additional events, the load impacts will likely be found to be weather sensitive.

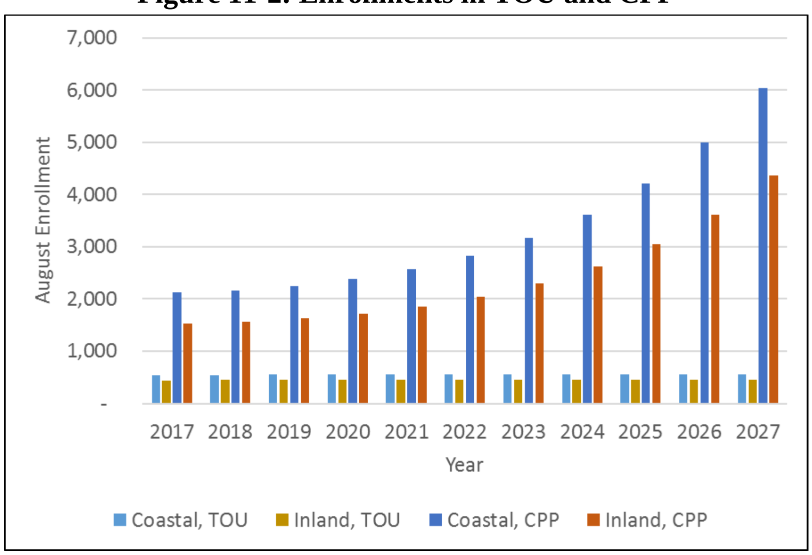
Figure 11-1: Aggregate CPP Load Impacts (MW), by Year and Weather Scenario – (*SDG&E 1 in 2 Peak Day, RA Window*)



11.4.1 Voluntary Residential CPP Enrollment Forecast

Figure 11-2 shows SDG&E's enrollment forecasts for the TOU and CPP rates. Enrollment is anticipated to be essentially flat for TOU after 2019, while enrollment in CPP is forecasted to nearly triple by the end of the forecast period. Enrollment is expected to be somewhat greater in the Coastal climate zone than in the Inland for both rates.

Figure 11-2: Enrollments in TOU and CPP



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