Executive Summary of the 2018 SDG&E Measurement and Evaluation Load Impact Reports

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A Sempra Energy utility℠

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1 Background

San Diego Gas & Electric (SDG&E) presents this Executive Summary for its Demand Response (DR) activities for program year 2018 in accordance with (D.) 08-4-050. In Decision (D.) 08-04-050 the California Public Utility Commission (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 their DR activities in accordance with the load impact protocols[1] and to file the load impact reports by April 1st each year. The load impact protocols require the preparation of a voluminous number 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 Commission. 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 and to provide the Commission's Energy Division (ED). The 2010 decision also directed the utilities to file an executive summary of the load impact reports.

This Executive Summary provides all relevant information regarding the load impact evaluations. Program descriptions, program options, *ex post* load impact methodology, program year 2018 event results, updated weather, *ex ante* methodology and *ex ante* load impacts. Much of the information presented in the executive summary are excerpts taken from the individual load impact reports.

In 2016 and 2017 SDG&E filed two separate applications that would affect SDG&E's future DR activities: The General Rate Case Phase 2 (GRCP2) application and the 2018-2022 DR application. Both applications received decisions during the second half of 2017, that had the following impacts on SDG&E's demand response activities:

SDG&E's GRCP2 application proposed to -

- change the trigger for its day ahead dynamic rates;
- align the day ahead triggers;
- change SDG&E's Time-Of-Use periods;
- move the month of May into the winter season;
- change the hours during which Critical Peak Pricing (CPP) events could be called from the period 11am-6pm to the period 2pm-6pm;
- sunset SDG&E's Peak Time Rebate (PTR) program at the end of 2018.

[1] On April 24, 2008 D.08-04-050 adopted the protocols used in estimation of demand response load impacts.

In August 2017 D.17-08-030 provided GRCP2 approval and directed SDG&E to file an advice letter by December 1, 2017 for implementation of these changes for the 2018 calendar year. Since TOU period definitions changed for all SDG&E's TOU customers, load Impact studies that estimated dynamic rate reductions also attempted to estimate load impacts associated with the change in TOU periods.

The second filing made on January 17, 2017 was the 2018-2022 Demand Response Program Application. In this application SDG&E proposed several modifications to its existing DR programs and proposed two new DR pilots. Among those modifications were requests to improve the Capacity Bidding Program (CBP) by reducing the number of products offered and simplifying the program. On December 13, 2017 the CPUC issued D.17-12-003 that provided approval of SDG&E's DR program application and among other things directed the Permanent Load Shifting (PLS) program to be suspended after 2018. Additionally, SDG&E was directed to file Advice Letters for the modifications to its CBP program.

These recent decisions impact SDG&E's DR activities going forward, as PLS and PTR will be discontinued at the end of 2018. For that reason, there are no *ex ante* load impacts for after 2018 for PTR and PLS. SDG&E is currently rolling out Default TOU to its residential customers in 2019. In December 2018, D.18-12-004, authorized SDG&E to move forward with defaulting all eligible residential customers onto to TOU, therefore SDG&E's 2018 Residential Default TOU pilot does not contain an ex ante estimates for future years in this filing. SDG&E plans to estimate ex ante load impacts in its 2019 Residential Default TOU study.

This report contains a summary of the *ex post* and *ex ante* load impacts of the SDG&E's Demand Response activities and includes the following programs and dynamic rates:

1. Capacity Bidding Program (CBP)
2. Critical Peak Pricing Default (CPP-D)
3. Base Interruptible Program (BIP)
4. AC Saver Day Of
5. Peak Time Rebate (PTR) and AC Saver Day Ahead Residential
6. AC Saver Day Ahead Commercial
7. Default Small Commercial CPP and TOU
8. Voluntary Residential CPP and TOU
9. Default Residential TOU Pilot

Ex ante forecasts for SDG&E's demand response activities are provided in Appendix A. Starting in program year 2014, SDG&E was directed to include weather scenarios for load impacts that were coincident with the CAISO system peak.[2]

CPUC decision on D.18-06-030 Adopting Local Capacity Obligations for 2019 and Refining the Resource Adequacy Program. Specifically Ordering Paragraphs 13 and 14 states:

> 13. The resource adequacy measurement hours are modified to HE17-HE21 (4:00 p.m. – 9:00 p.m.) for each month of the year beginning in 2019.
>
> 14. Combined storage and demand response projects are eligible to participate in the Resource Adequacy program.

Therefore, all *ex ante* load impact summaries are averaged over the current Resource Adequacy (RA) hours of 4pm to 9pm for all programs and/or dynamic rates. It should also be noted that ex post weather conditions are typically not the same as the 1 in 2, or 1 in 10 weather scenarios used in the ex ante tables. In other words, the actual monthly peak could be 1 in 4 or 1in 7 weather condition and therefore will not match up the forecasts required in this filing.

Located in Appendix A, the ex ante tables contain both SDG&E and CAISO load impacts. The tables include the following:

- 1 in 2 weather scenario for individual programs
- 1 in 2 weather scenario for the portfolio,
- 1 in 10 weather scenario for individual programs, and
- 1 in 10 weather scenario for the portfolio

Table 1-1 presents the Program Year (PY) 2018 ex post estimates for:

- The Average Event Day Load Impact (MW): Represents the average across all SDG&E events, and
- The Load Impacts (MW) for SDG&E's Peak Day (August 9th, 2019)

Table 1-2 shows the Program Year (PY) 2018 Ex ante estimates for the year of 2019 (SDG&E August peak month in 2018).

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[2] . In October of 2014 SDG&E received a letter from the Director the CPUC's Energy Division. The letter informed the IOUs that they needed to include ex ante forecasts that are to be used for RA should be with respect to the CAISO's system peak.

Table 1-1: Program Year (PY) 2018 Ex post estimates

Program Name	# of Customers on Average Event Day	Event Window Average Event Day	Average Event Day Load Impact (MW)	Event Window Peak Day (8/9)	SDGE Peak Day Load Impact in MW (August 9th, 2018)
BIP	3	HE13-HE16	1.10	HE13-HE16	1.10
AC Saver Day Ahead Residential	10,007	HE17-21	1.70	HE19-HE20	2.04
AC Saver Day Of Commercial	4,434	HE19-HE20	0.53	HE19-HE20	0.91
AC Saver Day Of Residential	9,716	HE19-HE20	2.40	HE19-HE20	3.21
CBP DA (Including products 11am-7pm)	25	HE19	0.13	HE18-HE19	0.12
CBP DA (Including products 1pm-9pm)	2	HE19	0.06	HE18-HE21	0.15
CBP DO (Including products 11am-7pm)	97	HE19	0.74	HE18-HE19	0.66
CBP DO (Including products 1pm-9pm)	89	HE19	2.72	HE18-HE21	2.44
CPPD Large (Excluding TD)	1,211	HE15-HE18	6.90	HE15-HE18	5.10
CPPD Medium (Excluding TD)	12,854	HE15-HE18	1.90	HE15-HE18	2.30
Default Small Commercial TOU and CPP Rates (Excluding TD)	111,149	HE15-HE18	2.72	HE15-HE18	7.10
AC Saver Day Ahead Commercial (including Quasi-Residential)	1,559	HE19-HE20	0.74	HE19-HE20	0.96
Peak Time Rebate (PTR) with no TD or AC Saver DO	70,175	HE15-HE18	2.20	HE15-HE18	2.11
TOU Load Impact for All Grandfathered Customers**	430	HE12-HE18	0.02	HE12-HE18	0.00
TOU Load Impact for All Non-Grandfathered Customers**	7,488	HE17-HE21	0.79	HE17-HE21	1.19
Technology Deployment (TD) on Small Commercial CPP plus CPP (Large and Medium)	1,776	HE15-HE18	2.37	HE15-HE18	2.37
Voluntary Residential grandfathered CPP customers on Technology Deployment (TD)	3	HE15-HE18	0.00	HE15-HE18	0.01
Voluntary Residential CPP customers on Technology Deployment (TD)	596	HE15-HE18	0.35	HE15-HE18	0.39
Voluntary Residential CPP excluding Technology Deployment (TD) customers	6,201	HE15-HE18	1.16	HE15-HE18	1.43
Voluntary Residential grandfathered CPP excluding Technology Deployment (TD) customers	423	HE15-HE18	0.11	HE15-HE18	0.14
Total	**238,238**		**28.64**		**33.73**

*HE means hour ending

**The average Event Day Load Impact for TOU Load Impact for All Non-Grandfathered Customers and TOU Load Impact for All Non-Grandfathered Customers was based on August average weekday.

***The SDG&E Peak Day Load Impact for TOU Load Impact for All Non-Grandfathered Customers and TOU Load Impact for All Non-Grandfathered Customers was based on August system peak.

Table 1-2: Program Year (PY) 2018 Ex ante estimates* based on 1 in 2 SDG&E weather scenarios for the year of 2019 (SDG&E August peak month in 2018)

Program	Forecasted Customers in August 2019	Ex ante estimates for the month of August 2019 (MW)
BIP	6	0.86
AC Saver Day Ahead Commercial (including Quasi-Residential)	1,563	1.09
AC Saver Day Ahead Residential	17,202	3.07
AC Saver Day Of Commercial	4,288	1.06
AC Saver Day Of Residential	9,182	3.56
CBP DA (Including products 11am-7pm)	61	0.11
CBP DA (Including products 1pm-9pm)	4	0.07
CBP DO with TATI (Including products 11am-7pm)	100	0.76
CBP DO with TATI (Including products 1pm-9pm)	92	1.90
CPPD Large (Excluding TD)	1,391	4.15
CPPD Medium (Excluding TD)	12,055	-0.66
Default Small Commercial TOU and CPP Rates (Excluding TD)	107,605	2.07
TOU Load Impact for All Grandfathered Customers	418	0.01
TOU Load Impact for All Non-Grandfathered Customers	12,305	2.13
Technology Deployment (TD) on Small Commercial CPP plus CPP (Large and Medium)	1,867	0.49
Voluntary Residential grandfathered CPP customers on Technology Deployment (TD)	3	0.00
Voluntary Residential CPP customers on Technology Deployment (TD)	743	0.03
Voluntary Residential CPP excluding Technology Deployment (TD) customers	7,825	0.60
Voluntary Residential grandfathered CPP excluding Technology Deployment (TD) customers	415	0.02
Total	177,124	21.32

* Some of the Ex Ante estimates are noticeably lower this year (2019) due to the change in the RA window, moving later in the day from 1pm-6pm to 4pm-9pm.

** The table does not include ex post estimates for PTR as it ended on 12/31/18

2 Summary of SDG&E's Capacity Bidding Program (CBP) Report[3]

2.1 CBP Program Description

Effective December 1, 2017, SDG&E made changes to their TOU periods, redefining the on-peak period to be 4 PM to 9 PM for all days and seasons and moving the month of May into the winter season. As of PY2018, SDG&E reduced its number of CBP products from nine to four. There were two Day Ahead (DA) 2-4 hour duration products, one with operating hours of 11 AM - 7 PM and the other with operating hours of 1 PM - 9 PM. Similarly, there were two Day Of (DO) 2-4 hour duration products, one with operating hours of 11 AM - 7 PM and the other with operating hours of 1 PM - 9 PM. SDG&E CBP events may be called Monday through Friday, excluding holidays, during May[4] through October. Effective July 1, 2018, the following changes were made to the CBP program triggers:

- **Day-Ahead Product:** The Utility may call an Event whenever the day ahead market price is equal to or greater than $75/MWh or as utility system conditions warrant. Day-ahead market price is defined as California Independent System Operator (CAISO) DLAP or applicable pnode SDGE-APND day-ahead market locational marginal price (DAM LMP).
- **Day-Of Product:** The Utility may call an Event whenever the forecasted real time price is equal to or greater than $95/MWh Day-Of 11 a.m. to 7 p.m.; $110/MWh Day-Of 1 p.m. to 9 p.m. or as Utility system conditions warrant. Real time price is defined as the CAISO DLAP or applicable pnode_SDGE-APND average hourly real time market locational marginal price (LMP).

The Commission approved several CBP changes requested by SDG&E. As a result, SDG&E is reducing its number of CBP products from nine to four beginning in 2018. There were two DA 2-4 hour products, one with the hours of 11 AM - 7 PM and the other with the hours of 1 PM - 9 PM. Similarly, there will be two DO 2-4 hour products, one with the hours of 11 AM - 7 PM and the other with the hours of 1 PM - 9 PM. Table 2-1 and Table 2-2 compare the 2017 and 2018 CBP products for SDG&E.

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[3] The 2018 CBP statewide load impact study was conducted by Applied Energy Group. This section of the Executive Summary contains excerpts from the following evaluation: Parameter, K. AEG. (2019). "2018 Statewide Load Impact Evaluation of California Aggregator Demand Response Programs: *Ex post and Ex ante Load Impacts*"

[4] Even though SDG&E redefined the month of May to be a Winter Month, most if not all DR resources are available in May each year.

Table 2-1 PY2018 CBP product types:

Day-Ahead Products	Hours	Minimum Duration per Event	Maximum Duration per Event	Maximum Cumulative Event Duration Per Operational Month	Maximum Events Per Day
2 to 4 hours	11am to 7pm	2 hours	4 hours	24	1
2 to 4 hours	1pm to 9pm	2 hours	4 hours	24	1

Day-Of Products	Hours	Minimum Duration per Event	Maximum Duration per Event	Maximum Cumulative Event Duration Per Operational Month	Maximum Events Per Day
2 to 4 hours	11am to 7pm	2 hours	4 hours	24	1
2 to 4 hours	1pm to 9pm	2 hours	4 hours	24	1

Table 2.2 PY2017 CBP Products

Product / Notification Time	Event Duration Limit	Hours	Triggers
Day-Ahead / by 3 PM day prior to event	1-4 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $75/MWh
Day-Ahead / by 3 PM day prior to event	2-6 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $75/MWh
Day-Ahead / by 3 PM day prior to event	4-8 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $75/MWh
Day-Of – 30 min.	1-4 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of – 30 min.	2-6 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of – 30 min.	4-8 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of / two hours prior to event	1-4 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of / two hours prior to event	2-6 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of / two hours prior to event	4-8 hours	11 AM – 7 PM	15,000 Btu/kWh heat rate AND $140/MWh

2.2 CBP Ex post Evaluation Methodology

The PY2018 *ex post* analysis was designed specifically to meet each of the following goals:

- To develop hourly and daily load impact estimates for each event in the 2018 program year.

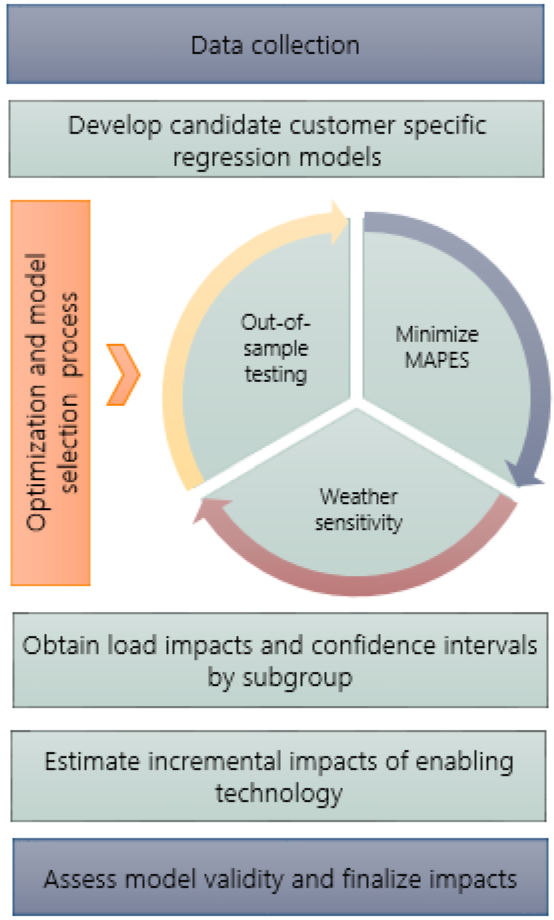
- To provide these estimates by various segments: IOU, program, LCA, industry group, Automated Demand Response (Auto DR) and Technology TA & Technology Incentives (TI) participation, and notification type.
- To estimate the distribution of load impacts by customer segment for the average event.

The consultant Applied Energy Group (AEG) used customer-specific regressions to estimate the load impact for each customer on each event day. Given the goals of the project and the potential differences across service territories, 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, Local Capacity Area (LCA), North American Industry Classification System (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.
- 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.

It is not practical to develop models individually for thousands of 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



2.2.1 Develop Candidate Customer-Specific Regression Models

Table 2-3 presents the different explanatory variables used to create candidate models for the CBP.

Table 2-3: 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
$OtherEvt_{i,d}$	Equals one on event days of other demand response programs in which the customer is enrolled
$\text{EarlyMornLoad}_{\text{i,d}}$	The average of each day's load in hours 12 AM through 4 AM
$\text{MornLoad}_{\text{i,d}}$	The average of each day's load in hours 4 AM through 10 AM
$\text{EveLoad}_{\text{i,d}}$	The average of each day's load in hours 9 PM through 12 AM
	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*EventHouri,d	An indicator variable for aggregator program event days interacted with an indicator for the hour the event is called

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:

- Weather-sensitive models that include weather effects and calendar effects. These models are less likely to require a load adjustment since much of the day-to-day variation in load is captured by weather terms.
- Non-weather sensitive models include the load adjustment and calendar effects.

2.2.2 Optimization Process

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:

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

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:

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

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. This is the prediction of 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.
- To show the actual observed load (and avoid confusion associated with the predicted load) AEG 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 impacts are estimated 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.

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 2-4 presents a summary of the 2018 events for SDG&E's CBP program by product. Over the course of the program year, the DO product participants experienced only three event days, while the DA product participants experienced a total of 26 events. Events were called with various event windows. The average event day is defined as the average of all events called in PY2018 regardless of event window. Impacts are presented for the average event day on the common event hour, HE-19, which is the hour when all event windows overlap.

Table 2-4: Number of Accounts nominated by event – *SDG&E CBP*

Date	Day of Week	Event Hours (HE)	# Accounts DA 11-7 Hour	# Accounts DA 1-9 Hour	# Accounts DO 11-7 Hour	# Accounts DO 1-9 Hour
Avg. Event	-	19	25	2	97	89
Jul 6, 2018	Friday	16-19	65	1	-	-
Jul 10, 2018	Tuesday	16-19	65	-	-	-
Jul 11, 2018	Wednesday	18-19	65	-	-	-
Jul 12, 2018	Thursday	18-19, 19-20	65	1	-	-
Jul 16, 2018	Monday	17-19	65	-	-	-
Jul 18, 2018	Wednesday	18-19, 18-21	65	1	-	-
Jul 20, 2018	Friday	19-20	-	1	-	-
Jul 23, 2018	Monday	17-19	65	-	-	-
Jul 24, 2018	Tuesday	18-19, 19-20	65	1	-	-
Jul 25, 2018	Wednesday	18-19, 19-20	65	1	-	-
Aug 1, 2018	Wednesday	18-19, 19-20	2	1	-	-
Aug 6, 2018	Monday	18-19, 18-20, 18-21	2	1	97	89
Aug 7, 2018	Tuesday	16-19, 18-21	2	1	97	89
Aug 8, 2018	Wednesday	16-19, 18-21	2	1	-	-
Aug 9, 2018	Thursday	18-19, 18-21	2	1	97	89
Oct 1, 2018	Monday	16-19	2	-	-	-
Oct 18, 2018	Thursday	18-19	2	-	-	-
Oct 19, 2018	Friday	18-19	2	-	-	-
Oct 22, 2018	Monday	18-19	2	-	-	-
Oct 23, 2018	Tuesday	18-19, 19-20	2	4	-	-
Oct 24, 2018	Wednesday	18-19, 19-20	2	4	-	-
Oct 25, 2018	Thursday	18-19, 19-20	2	4	-	-
Oct 26, 2018	Friday	18-19, 18-20	2	4	-	-

Table 2-4: Number of Accounts nominated by event – *SDG&E CBP (Continued)*

Date	Day of Week	Event Hours (HE)	# Accounts DA 11-7 Hour	# Accounts DA 1-9 Hour	# Accounts DO 11-7 Hour	# Accounts DO 1-9 Hour
Oct 29, 2018	Monday	18-19, 19-20	2	4	-	-
Oct 30, 2018	Tuesday	18-19, 19-20	2	4	-	-
Oct 31, 2018	Wednesday	18-19, 19-20	2	4	-	-

Table 2-5 through table 2-8 show the average event-hour impacts for the four CBP products. 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 2-5: SDG&E CBP Day Ahead 11 AM to 7 PM Product: Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Avg. Event	25	0.2	159.6	5.1	3.9	0.1	3%	75
Jul 6, 2018	65	0.4	245.0	16.8	15.9	1.1	7%	95
Jul 10, 2018	65	0.4	255.5	16.8	16.6	1.1	7%	82
Jul 11, 2018	65	0.4	217.5	5.5	14.1	0.4	3%	79
Jul 12, 2018	65	0.4	216.1	5.5	14.0	0.4	3%	77
Jul 16, 2018	65	0.4	231.4	7.9	15.0	0.5	3%	77
Jul 18, 2018	65	0.4	197.5	5.5	12.8	0.4	3%	75
Jul 23, 2018	65	0.4	261.3	7.9	17.0	0.5	3%	85
Jul 24, 2018	65	0.4	229.1	5.5	14.9	0.4	2%	82
Jul 25, 2018	65	0.4	219.3	5.5	14.3	0.4	2%	80
Aug 1, 2018	2	0.2	63.2	62.4	0.1	0.1	99%	86
Aug 6, 2018	2	0.2	63.3	62.4	0.1	0.1	99%	96
Aug 7, 2018	2	0.2	75.4	74.5	0.2	0.1	99%	96
Aug 8, 2018	2	0.2	75.5	74.5	0.2	0.1	99%	88
Aug 9, 2018	2	0.2	63.3	62.4	0.1	0.1	99%	81
Oct 1, 2018	2	0.1	75.0	74.5	0.1	0.1	99%	72
Oct 18, 2018	2	0.1	62.9	62.4	0.1	0.1	99%	68
Oct 19, 2018	2	0.1	62.9	62.4	0.1	0.1	99%	69
Oct 22, 2018	2	0.1	62.9	62.4	0.1	0.1	99%	64
Oct 23, 2018	2	0.1	62.9	62.4	0.1	0.1	99%	70

Table 2-5: SDG&E CBP Day Ahead 11 AM to 7 PM Product: Impacts by Event (Continued)

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Oct 24, 2018	2	0.1	63.0	62.4	0.1	0.1	99%	72
Oct 25, 2018	2	0.1	63.0	62.4	0.1	0.1	99%	74
Oct 26, 2018	2	0.1	62.9	62.4	0.1	0.1	99%	76
Oct 29, 2018	2	0.1	62.9	62.4	0.1	0.1	99%	69
Oct 30, 2018	2	0.1	62.9	62.4	0.1	0.1	99%	63
Oct 31, 2018	2	0.1	62.8	62.4	0.1	0.1	99%	63

Table 2-6: SDG&E CBP Day Ahead 1 PM to 9 PM Product: Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Avg. Event	2	0.0	1,013.3	28.1	2.2	**0.1**	3%	74
Jul 6, 2018	1	0.0	2,683.9	137.9	2.7	0.1	5%	95
Jul 12, 2018	1	0.0	2,087.6	17.6	2.1	<0.1	1%	73
Jul 18, 2018	1	0.0	1,932.5	146.5	1.9	0.1	8%	70
Jul 20, 2018	1	0.0	1,809.6	17.6	1.8	<0.1	1%	73
Jul 24, 2018	1	0.0	2,093.6	17.6	2.1	<0.1	1%	76
Jul 25, 2018	1	0.0	1,929.6	17.6	1.9	<0.1	1%	73
Aug 1, 2018	1	0.0	2,227.6	17.6	2.2	<0.1	1%	80
Aug 6, 2018	1	0.0	2,309.8	97.8	2.3	0.1	4%	83
Aug 7, 2018	1	0.0	2,352.5	146.5	2.4	0.1	6%	81
Aug 8, 2018	1	0.0	2,227.5	146.5	2.2	0.1	7%	85
Aug 9, 2018	1	0.0	2,516.5	146.5	2.5	0.1	6%	85
Oct 23, 2018	4	0.1	503.7	12.0	2.0	<0.1	2%	66
Oct 24, 2018	4	0.1	504.2	12.0	2.0	<0.1	2%	66
Oct 25, 2018	4	0.1	515.7	12.0	2.1	<0.1	2%	67
Oct 26, 2018	4	0.1	554.7	32.1	2.2	0.1	6%	70
Oct 29, 2018	4	0.1	502.6	12.0	2.0	<0.1	2%	64
Oct 30, 2018	4	0.1	480.5	12.0	1.9	<0.1	2%	65
Oct 31, 2018	4	0.1	465.5	12.0	1.9	<0.1	3%	67

Table 2-7: SDG&E CBP Day Of 11 AM to 7 PM: Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Avg. Event	97	1.4	112.2	7.6	10.9	0.7	7%	85
Aug 6, 2018	97	1.4	111.3	6.8	10.8	0.7	6%	85
Aug 7, 2018	97	1.4	113.7	8.6	11.0	0.8	8%	89
Aug 9, 2018	97	1.4	114.1	6.8	11.1	0.7	6%	87

Table 2-8: SDG&E CBP Day Of 1 PM to 9 PM: Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Avg. Event	89	2.6	159.4	30.6	14.2	2.7	19%	83
Aug 6, 2018	89	2.6	156.2	27.4	13.9	2.4	18%	81
Aug 7, 2018	89	2.6	155.6	27.4	13.8	2.4	18%	82
Aug 9, 2018	89	2.6	160.3	27.4	14.3	2.4	17%	84

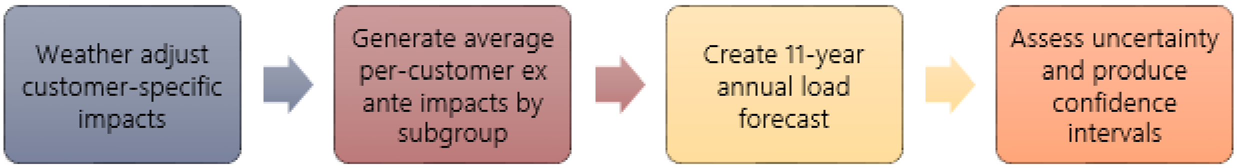
2.4 CBP Ex ante Evaluation Methodology

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. The Forecast is produced for 1 in 2, and 1 in 10 peak weather-condition for each month. 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 2-2 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 produced a set of impacts under each of the different weather scenarios (monthly peak day and typical event day for 1-in-2 weather year and 1-in-10 weather year for each of the three IOUs and CAISO). It is important to note that the CBP impacts are inherently nomination-driven, not weather-responsive. The customer-specific regression models estimated flat per-customer average impacts across the weather scenarios, but the percent impacts vary. To do this, the following steps were completed:

- 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 to predict a customer's load for each of these scenarios assuming no events are called. The result will be a weather-adjusted reference load for each customer for each weather scenario required.

- Next, AEG determined the most prevalent event hour called for each customer. This was most often HE19 for all three IOUs, with HE18 and HE20 for select customers. Using the regression model of the selected hour, AEG estimated the non-weather dependent load impact using a linear combination of the coefficients of the impact variables.

- AEG applied this load impact estimate to all hours of the Resource Adequacy window, which is HE17 through HE21 year-round as of PY2019.

- Finally, AEG calculated the predicted load for each scenario by adding the estimated load impact to 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 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, AEG also worked with the IOUs to determine the best way to account for participation between notification types to ensure that they are not double-counted in the per-customer averages.

Since CBP is a capacity-payment program, the IOUs allocate to CBP the full load impacts from CBP participants dually-enrolled in other DR or energy-payment programs. The CBP impacts do not require adjustments to account for dual-participation in other programs.

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. SDG&E 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 1% 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 4% per year 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 2029 show a flat trend at the 2022 values.

The ex ante load impact forecast follows the 2019-2029 enrollment forecast trends for the DA and DO products. In addition, the impacts are also estimated to remain constant during the months of May through October.

Table 2-9 summarizes the average event-hour load impact forecasts for the DA and DO products on an August peak day in 2019. The table includes the per-customer average impacts, aggregate impacts, and corresponding percent impacts under the 1-in-2 and 1-in-10 weather scenarios and for the utility peak and the CAISO peak.

Table 2-9: SDG&E CBP: Average Event-Hour *Ex ante* Impacts for an August Peak Day, 2019

Notice	# of Accts	Per Customer Impact (kW)	Aggregate Impact (MW)	Percent Impact (%)			
				Utility Peak		CAISO Peak	
				1-in-2	1-in-10	1-in-2	1-in-10
Total Day Ahead	65	2.8	0.2	1.2%	1.2%	1.2%	1.2%
Total Day Of	191	13.9	2.7	10.8%	10.5%	10.7%	10.7%

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 2-10 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.

Table 2-10: SDG&E CBP: Previous and Current *Ex post,* Average Event Day

Notice	Ex post Year	# of Accts	Per Customer Impact (kW)		Aggregate Impact (MW)			
			Reference Load	Impact	Reference Load	Impact	% Impact	Temp (˚F)
Day Ahead	2017	68	241.1	9.9	16.4	0.7	4%	77
	2018	27	228.5	6.9	6.1	0.2	3%	75
Day Of	2017	174	144.3	18.4	25.1	3.2	13%	85
	2018	186	134.8	18.6	25.1	3.5	14%	84

2.6.2 Previous and Current *Ex ante* and *Ex post*

Table 2-11: 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] For DA current ex post, a July event day was selected because July participation is the most representative of the DA PY2018 participant population. In addition, the ex ante results reflect the utility peak 1-in-2 weather scenario.

Table 2-11: SDG&E CBP: Previous and Current *Ex ante* and *Ex post*, August Peak Day

	YYr	Mo del	Day	# of Accts	Per Customer Impact (kW)		Aggregate Impact (MW)			
					Ref. Load	Impact	Ref. Load	Impact	% Impact	Temp (˚F)
Day Ahead	2018	Previous Ex ante	Aug Peak	69	248.9	9.8	17.2	0.7	4%	80
		Current Ex post	Jul 18th[6]	66	185.9	3.7	12.3	0.2	2%	75
	2019	Previous Ex ante	Aug Peak	71	248.9	9.8	17.7	0.7	4%	80
		Current Ex ante	Aug Peak	65	227.2	2.8	14.7	0.2	1%	84
Day Or	2018	Previous Ex ante	Aug Peak	171	141.3	18.5	24.2	3.2	13%	84
		Current Ex post	Avg Event	186	134.8	18.6	25.1	3.5	14%	84
	2019	Previous Ex ante	Aug Peak	183	141.3	18.5	25.9	3.4	13%	84
		Current Ex ante	Aug Peak	191	129.0	13.9	24.7	2.7	11%	83

Table 2-11: shows the following trends for the CBP DA and DO products:

- **Current Ex post vs. Previous Ex post***:* For DA, there is a decrease in enrollment in PY2018. Note that Table 2-11shows the participant counts of an average event day. This decrease in participation, on average, is due to very low nominations in the months of August and October (3 and 4 participants, respectively) compared to 66 participants nominated in July. As a result, we see lower aggregate impacts in PY2018 (0.2 MW) compared to PY2017 (0.7 MW). For DO, we see very similar per-

[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.

[6] PG&E CBP Day Of received the highest participation in the month of July. The July 18, 2018 event had the most comparable aggregate impacts to an average event day.

customer impacts between PY2017 and PY2018 and a small increase in enrollment, resulting in higher aggregate impacts in PY2018 (3.5 MW) compared to PY2017 (3.2 MW).

- ***Current Ex post Compared with Previous Ex ante:*** For DO, the actual PY2018 per-customer impacts are very close to previously projected estimates. In PY2018, SDG&E's DO program enrolled more customers (186 participants) than projected (171 participants), resulting in higher aggregate impacts in PY2018. For DA, comparing the previous ex ante estimates to the July 18th event, the aggregate and per-customer impacts are considerably lower in PY2018 despite having comparable enrollment. This is likely due to more events being called later in the day (between 5 PM – 7 PM). With the majority of PY2018 DA participants being offices/hotels/financial services, which likely do not have load to curtail during these hours, we are seeing much lower impacts for the DA program.

- ***Current Ex ante Compared with Previous Ex ante:*** The current ex ante estimates for have been updated according to what was achieved in PY2018. DA enrollment projections decreased while DO enrollment projections increased. Since we saw a significant drop in PY2018 ex post per-customer impacts, the current PY2019 aggregate ex ante impacts for DA (0.2 MW) are lower to previous ex ante impacts for PY2019 (0.7 MW). For DO, the current PY2019 ex ante estimates were updated to reflect how events were called and how participants responded in PY2018. The RA window is between 4 PM – 9 PM, while DO events were called between 5 PM – 7 PM and 5 PM – 9 PM. In the current PY2018 estimates, we assume a very low pre-cooling effect from 4 PM – 5 PM, resulting in lower average event-hour impacts. This gives us lower projected impacts in 2018 (2.7 MW) than did the previous ex ante analysis (3.4 MW).

- ***Current Ex ante Compared with Current Ex post:*** For DA, the current ex ante estimates for PY2019 show comparable aggregate impacts (0.2 MW) to the current ex post estimates for PY2018 (0.2 MW). For DO, the current ex ante estimates for PY2019 (2.7 MW) show lower aggregate impacts to the current ex post estimates for PY2018 (3.5 MW) due to lower expected per-customer impacts.

3 Summary of SDG&E's Critical Peak Pricing Default Report[7]

3.1 CPP Rate Description

Critical Peak Pricing Default (CPP-D) is a commodity tariff for bundled customers that provides an opportunity to manage electric costs by either reducing load during high cost pricing periods or shifting load from high cost pricing periods to lower cost pricing periods. Except as set forth below, this schedule is the default commodity rate for customers currently receiving bundled utility service on a commercial/industrial rate schedule for customers whose Maximum Monthly Demand is equal to or exceeds or is expected to equal or exceed 20 kW for twelve consecutive months (e.g. schedule AL-TOU) and whose facility is equipped with the appropriate electric metering. This Schedule is optionally available to a customer taking service under Schedules A-TOU, OL-TOU, AL-TOU, AY-TOU, or DG-R and whose demand is below 20 kW for three consecutive months. This Schedule is also optionally available to Expanded California Alternate Rates for Energy (CARE) customers. Customers taking service under this Schedule will continue to be subject to the terms and provisions of their otherwise applicable Utility Distribution Company tariff. Pursuant to the specific requirements set forth below, customers can opt-out from receiving service under this schedule and receive service under a different applicable commodity rate. This Schedule is not applicable to Direct Access (DA) or Community Choice Aggregation (CCA) customers.

The ex ante forecast of the small commercial CPP load impacts will be included in a separate evaluation.

[7] The CPP statewide load impact evaluation was conducted by Applied Energy Group. This section of the Executive Summary contains excerpts from the following evaluation: 2018 Statewide Load Impact Evaluation of California Non-Residential Critical Peak Pricing Programs, Ex-Post and Ex ante Load Impacts, March 18th, 2019

a) New TOU Time Periods

All time periods listed are applicable to local time. The definition of time will be based upon the date service is rendered.

CPP Event Days

CPP Event Period 2:00 p.m. – 6:00 p.m. Any day of the Week, Year-Round

Non-CPP Event Days

TOU Period – Weekdays	Summer	Winter
On-Peak	4:00 p.m. – 9:00 p.m.	4:00 p.m. – 9:00 p.m.
Off-Peak	6:00 a.m. – 4:00 p.m.; 9:00 p.m. – midnight	6:00 a.m. – 4:00 p.m. Excluding 10:00 a.m.–2:00 p.m.in March and April; 9:00 p.m. - midnight
Super-Off-Peak	Midnight – 6:00 a.m.	Midnight – 6:00 a.m. 10:00 a.m. – 2:00 p.m. in March and April

TOU Period – Weekends and Holidays	Summer	Winter
On-Peak	4:00 p.m. – 9:00 p.m.	4:00 p.m. – 9:00 p.m.
Off-Peak	2:00 p.m. – 4:00 p.m.; 9:00 p.m. – midnight	2:00 p.m. – 4:00 p.m. 9:00 p.m. - midnight
Super-Off-Peak	Midnight – 2:00 p.m.	Midnight – 2:00 p.m.

Seasons:

Summer June 1 – October 31

Winter November 1 – May 31

For the periods during CPP Event Days, customers will pay the CPP Event Day Adder and the corresponding energy charges for the time period.

b) CPP Events and Triggers

A maximum of eighteen (18) CPP Events can be triggered on any day of the week, year-round. CPP Events shall be effective from 2:00 p.m. – 6:00 p.m. A CPP Event may be triggered if the day-ahead system load forecast for the potential event day is greater than 4,000 MW. Events may also be triggered in response to high forecasted temperatures, extreme conditions, and emergencies. 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. Events may be triggered for testing/evaluation purposed. If two CPP events are cancelled, the two cancelled CPP Events will be credited as one (1) CPP event towards the maximum number CPP Events that can be called during the year.

c) Grand Fathered Time Periods for TOU

TOU Period Grandfathering: Pursuant to D.17-01-006, TOU Period Grandfathering permits certain eligible behind-the-meter solar customers to continue billing under grandfathered TOU period definitions for a specific period of time after new TOU Periods are implemented.

TOU Period Grandfathering Eligible Customer Generator (Non-Residential): a non-residential customer with an on-site solar system, who opts into a TOU tariff prior to July 31, 2017. The customer must have: (1) filed an initial interconnection application by January 31, 2017 and (2) achieved completion of the interconnection application, including final building inspection by July 31, 2017. The on-site solar system must be designed to offset at least 15% of the customer's current annual load. For schools, defined here to include all accounts held by public school districts serving students in kindergarten through grade 12 and county offices of education, the non-residential account must have: (1) filed an initial interconnection application by March 31, 2017 and (2) achieved completion of the interconnection application, including final building inspection by August 31, 2018.

TOU Period Grandfathering Term (Non-Residential): Upon SDG&E's implementation of updated TOU periods adopted in D.17-08-030 on August 24, 2017, TOU Grandfathering Eligible Customer Generators will continue to be billed under prior existing TOU periods and resulting rates for the remainder of their applicable TOU Grandfathering Term, which begins upon issuance of a permission to operate customer's on-site solar system and continues for 10 years. In no event shall the duration a customer's grandfathering term extend beyond July 31, 2027 (December 31, 2027 for schools). Upon expiration of a customer's TOU period Grandfathering Term, the customer will be billed using his otherwise applicable TOU periods and associated rates beginning with the customer's next billing cycle.

TOU Period Grandfathering Rates: Customers receiving service under this schedule shall be provided with Bill Protection for the first twelve months of service from the default date.

TOU Grandfathering Time Periods

All time periods listed are applicable to local time. The definition of time will be based upon the date service is rendered.

CPP Event Days

CPP Event Period	2 p.m. – 6 p.m. any day of the week, year-round

Non-CPP Event Days

Summer (June 1- Oct 31)

On-Peak	11 a.m. – 6 p.m. Weekdays
Semi-Peak	6 a.m. – 11 a.m. Weekdays
	6 p.m. – 10 p.m. Weekdays
Off-Peak	10 p.m. – 6 a.m. Weekdays
	Plus Weekends & Holidays

Winter (Nov 1 – May 31)

On-Peak	5 p.m. – 8 p.m. Weekdays
Semi-Peak	6 a.m. – 5 p.m. Weekdays
	8 p.m. – 10 p.m. Weekdays
Off-Peak	10 p.m. – 6 a.m. Weekdays
	Plus Weekends & Holidays

For the periods during CPP Event Days, customers will pay the CPP Event Day Adder and the corresponding energy charges for the time-period.

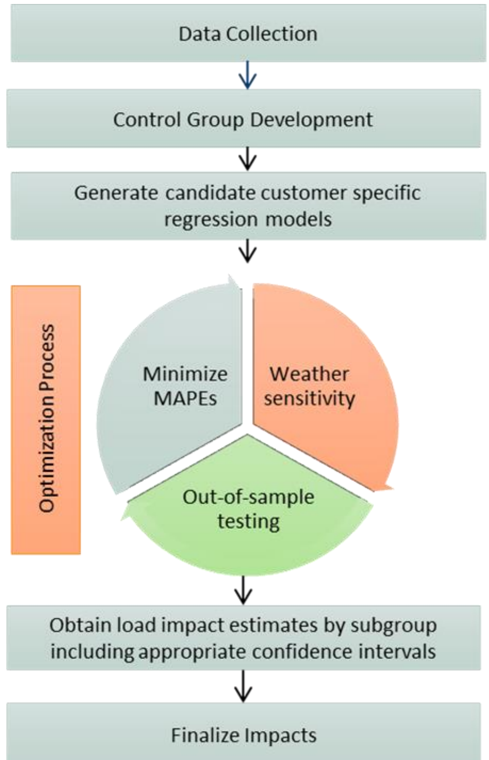
3.2 CPP-D Ex post Evaluation Methodology

AEG's approach to the ex post analysis is described at a high level below and summarized in Figure 3-1.

- For subgroups where it was feasible, AEG developed a matched control group. For subgroups where it was not feasible, AEG employed a within subjects' design leveraging event-like days in 2018. Figure 3-1 presents the methodology used to estimate impacts for each subgroup.
- Then, AEG estimated subgroup level models for each IOU, size, and industry. In some cases, separate models were estimated for those who were notified of event and those who were not notified of events. All subgroup level models were ultimately selected using our optimization process.

Finally, AEG estimated the ex post impact for each customer so that they could be aggregated easily into the various reporting subgroups required for the analysis.

Figure 3-1 Ex post Analysis Approach



3.2.1 Data Collection

To address each of the load impact objectives, AEG collected the following types of data:

- Customer information for the CPP customers and potential control-group customers (e.g., industry group, weather station, LCA, size group);
- Billing-based interval load data on event days and event-like non-event days (i.e., hourly loads for each treatment and potential control group customers);
- Weather data (i.e., hourly temperatures and other variables for the relevant time period, by weather station);
- Program event data (i.e., dates and hours of CPP events and any programs in which CPP customers are dually enrolled).

3.2.2 Event-like Days Selection

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

The event-like days included 5 to 15 days which are comparable to called event days in weather, day of the week, and month of the year. A Euclidean distance metric (similar to what is described below) to select days that are as similar as possible to actual event days using multiple weather-based criteria.[8]

3.2.3 Matched Control Group Development

To create the matched control groups, a Stratified Euclidean Distance Matching (SEDM) technique was used. The basic steps were as follows:

Step 1 is to define both the participant and non-participant populations and the treatment and pre-treatment periods for each participant. Once the participant and non-participant populations are identified, both populations can be assigned to strata or filters that are categorical in nature. For CPP participants, size and industry type are key filters. This ensured that customers with similar usage characteristics were matched to one another, capturing some of the unobservable attributes that affect the way customers use energy.

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

- The average demand on event-like days during the typical event window;
- The maximum demand on event-like days;
- And the average demand on event-like days during the hours outside the typical event window.

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

$$ED = \sqrt{w_1(avgevnt_{Ti} - avgevnt_{Ci})^2 + w_2(peak_{Ti} - peak_{Ci})^2 + w_3(avgnonevnt_{Ti} - avgnonevnt_{Ci})^2}$$

[8] SDG&E did were not a suitable number of event-like days in 2018. Therefore, the ultimate pool of non-event days included data from 2017 in order to achieve an appropriate event-like day match.

After calculating the distance metric within each group for each possible combination of participant and control customer, the control customer with the smallest distance is matched to each participant without replacement. The closest matches are selected for each of the participants, creating a one-to-one match of control customers to participants.

3.2.4 Develop Candidate Regression Models

Given the evaluation timeline, it would be difficult to develop models individually for the 64 industry and size subgroups across the three IOUs. Therefore, a set of candidate models are developed which were fit to all subgroups and utilized an algorithm developed in previous Statewide DR evaluations to select the best model for each subgroup.

The regression models can be thought of as being made up of building blocks, which are in turn made up of one or more explanatory variables. These different sets of variables can be combined in different ways to represent different types of customers. The blocks can be generally categorized into either “baseline” variables, or “impact” variables and could be made up of a single variable (e.g., cooling degree hours, CDH), or a group of variables (e.g., days of the week). The baseline portion of the model explains variation in usage unrelated to demand response events, while the impact portion explains the variation in usage related to a DR event.[9]

The candidate models fit into two basic categories:

- Weather sensitive models which include weather effects and calendar effects.
- Non-weather sensitive models that include the morning load adjustment and calendar effects.

Table 3-11 below presents the listing of the different variables and variable combinations that were used to develop the candidate models.

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

Table 3-1 Variables Included in Candidate Regression Models

Type of Variable	Variable	Description
Dependent	$kWh_{i,t}$	Hourly consumption for customer *i* in hour/day *t*
Baseline Fixed effect	α_i	Indicator variable for each customer *i*
Baseline Calendar	Day of Week $_t$	Indicator variable for each day of the week
Baseline Calendar	Weekday $_t$	Indicator variable taking on the value of 1 for each weekday and 0 for weekends and holidays
Baseline Calendar	Month of Year t	Indicator variable for each month of the year
Baseline Weather	$CDH_{i,t}$	Cooling degree hours (base 65) for customer *i* in hour/day *t*
Baseline Weather	Meantemp $_{i,t}$	Mean temperature for customer *i* on day *t*
Baseline Adjustment	Morning Load $_{i,t}$	Average of hours 5-10 for customer *i* on day *t*
Baseline Adjustment	Late morning load $_{i,t}$	Average of hours 7-12 for customer *i* on day *t*
Impact	Event $_{i,t}$	Indicator that takes on a value of 1 if customer *i* participated in event *t*
Impact Interaction	(Event * Notification) $_{i,t}$	Interaction between event and notification that takes on a value of 1 if customer *i* was notified of event *t*
Impact Interaction	(Event * CDH) $_{i,t}$	Interaction between event and CDH for customer *i* on event *t*
Impact Interaction	(Event * month) $_{i,t}$	Interaction between event and month for customer *i* on event *t*

Various combinations of the variables above resulted in 24 potential candidate models. Appendix B of the CPP report[10] contains a list of the 24 potential models, and the final models chosen for each subgroup by IOU.

3.2.5 Optimization and Model Selection Process

Our optimization process incorporates the validation of the subgroup regression models. The subgroup models are designed to:

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

To meet these two specific goals, our optimization process includes an analysis of both the in-sample and out-of-sample MAPE and the MPE for each of the candidate regression models for each subgroup. Out-of-sample tests were used to show how well each of the candidate models could predict a participant's load on non-event days that were as similar as possible to

[10] See Appendix B of the 2018 Statewide Load Impact Evaluation for California Non-Residential Critical Peak Pricing Programs,

actual event days; this test gives us an estimate of how well each model could predict the reference load. In-sample tests are used to show how well each model performs on the actual event days; therefore, it helps to understand how well the model is able to match the actual load. The optimization procedure has several steps, which are described below:

- First, out-of-sample event-like days were identified as described above.
- After identifying the event-like days, those days are removed from the analysis dataset and the candidate models are fit to the remaining data.
- Next, the results of the candidate models are used to predict the usage on the out-of-sample days. The error and bias in the reference load is assessed by calculating the MAPE and MPE between the actual usage and the predicted usage on the out-of-sample days.
- Finally, the actual and predicted loads are compared on the event days from the given program year. The MAPE and MPE is calculated on these days to assess the error and bias in the predicted load.

The final step of the process is to select the candidate model with the minimum weighted MAPE and MPE for each subgroup. This model then becomes the final model specification. The steps are described in more detail in the model validity subsection below.

3.2.6 Obtain Load Impacts and Confidence Intervals by Segment

The following example illustrates the process of estimating the impacts from the final model for a single subgroup. There were ultimately 64 subgroups in the actual analysis, each with their own final model specification determined by the optimization process[11] Nevertheless, the process will be the same in each case.

It is assumed that the subgroup is weather sensitive and that the final model specification includes calendar and weather effects in the baseline portion of the model. In this simple example below, α_t, δ_t, and CDH_t, make up the baseline blocks of the model, and explain variation in kwh_t unrelated to demand response events. The remaining variables, $EVNT$, and the interaction term $(\alpha_t * EVNT)$ are the impact blocks and explain the variation in kwh_t related to a DR event.[12] An hourly model like equation (1) below can be equivalently estimated as one model with hourly dummy variables, or as 24 separate hourly models.

$$kwh_{it} = \beta_0 + \alpha_t + \delta_t + CDH_t + EVNT + (\alpha_t * EVNT) + \varepsilon_{it} \quad (1)$$

Where:

[11] See Appendix A of the 2018 Statewide Load Impact Evaluation of California Non-Residential Critical Peak Pricing Program

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

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

β_0 is the intercept

α_t is a vector of segment indicators, i.e. AutoDR, LCA, etc.

δ_t is a vector of calendar variables, i.e. month, year, and day or week

CDH_t represents the cooling degree hours for hour t

$EVNT$ is a dummy variable indicating that hour t was on a CPP or PDP event day

$(\alpha_t * EVNT)$ is an interaction between the event indicator and the segment indicator variables

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

This type of time-series model is likely to have auto-correlated errors which will be handled either directly through modeling the appropriate autoregressive process or more simply by using the Newey-West error correction.

The model above is used to estimate the load impacts as follows:

- First, the actual and predicted load is obtained for each participant on each hour and day based on the specification defined in equation (1).
- Next, the estimated coefficients are used and the baseline portion of the model to predict what this participant would have used on each day and hour, if there had been no events. This prediction is called the reference load.
- AEG calculated the difference between the reference load (the estimate based on the baseline blocks) and the predicted load (the estimate based on the baseline + impact blocks) on each event day. This difference represents our estimated load impact for each participant.

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

3.2.7 Assess model validity and finalize impacts

It was selected and validated the subgroup regression models during our optimization process. The first aspect of our process includes assessing the accuracy of the model for the in-sample period, meaning that AEG assessed the ability of the models to predict the actual load on each event day. The second aspect of our validation approach includes out-of-sample testing using a set of event-like days. This process allows us to assess the ability of the models to accurately predict the reference load.

To select similar non-event days, a Euclidean Distance matching approach was used. Euclidean distance is a simple and highly effective way of creating matched pairs. Three different Euclidean distance metrics were used to select similar non-event days: (1) daily maximum temperature; (2) average daily and daily maximum temperatures; and (3) average daily temperature. The Euclidean distance metrics used can be calculated by Equation 2 through 5 below.

$$ED_1 = \sqrt{(MaxTemp_{event} - MaxTemp_{non-event})^2} \tag{2}$$

$$ED_2 = \sqrt{(MeanTemp_{event} - MeanTemp_{non-event})^2 + (MaxTemp_{event} - MaxTemp_{non-event})^2} \tag{3}$$

$$ED_3 = \sqrt{(MeanTemp_{event} - MeanTemp_{non-event})^2} \tag{4}$$

Next, AEG estimated the MAPE and MPE, for the event window, for each customer, and for each candidate model, both for the in-sample period and for the out-of-sample period. This results in thousands of in-sample and out-of-sample tests. Recall that the goal of the tests is to find the best model for each subgroup in terms of its ability to predict the reference load and the actual load for each customer. Therefore, the tests were collasped into a single metric, which can be calculated for each subgroup and each candidate model.

The metric is defined in Equation 5 below:

$$\boldsymbol{metric_{ic}} = (0.5 * EvntMAPE) + (0.5 * EvntlikeMAPE) \tag{5}$$

Once AEG computed a single metric for each subgroup and candidate model combination, the best model for each customer was selected by choosing the model specification with the smallest overall metric.

3.2.8 Additional TOU Ex Post Analysis due to new Time of Use Periods

SDG&E expressed interest in an analysis to estimate the changes in TOU periods and season. As of December 2017, SDG&E implemented new TOU periods for all its customers and moved the month of May into the Winter season. To estimate the impact of these changes, a pre-post analysis like the approach described above is used with the following key changes:

- The analysis period will be December 1, 2016 through November 30, 2018, wherein December 1, 2016 through November 30, 2017 is the pre-treatment period and December 1, 2017 through November 20, 2018 is the post-treatment period;

- The hourly regression models rare estimated on aggregated daily data. C&I usage tends to be highly variable at the customer-level and aggregation minimizes that variation. AEG has had much success in estimating 8760 TOU C&I impacts on aggregated daily data. The final subgrouping used in the main ex post analysis is followed or a very simple program-level aggregation is used for the large customers and medium customers. The in-sample and out-of-sample tests will be performed on average day types instead of event days and event-like days. Average day types will likely include summer weekdays, summer weekends/holidays, winter weekdays, winter weekends/holidays, and CPP event days.

3.3 CPP-D Ex post Load Impacts Estimates

This section documents the findings from the *ex post* load impact analysis for SDG&E. The primary load impact results include estimates of average event-hour load impacts, in aggregate and per-customer, for the typical event day as well as for each individual event. Results for all hours for the typical event day are also illustrated in figures and presented in data tables.

3.3.1 CPP Large Customers

This section summarizes results for all large SDG&E customers, defined as customers with maximum demand over 200 kW. The presented results include: the average event-hour load impact by event day and the hourly load impact for the average event day.

Figure 3-2 presents the average event-hour ex post load impacts for each individual event day for all of SDG&E's large CPP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 80 percent confidence intervals around these estimates (i.e., the 10th and 90th percentile scenarios from the uncertainty-adjusted load impacts). The orange line represents the average temperatures experienced by the participants during the event hours.

These results indicate that large customers had statistically significant load reductions on each of the six event days, ranging from 5.1 MW to 8.8 MW. The load impact averaged 6.9 MW, with half of the event days (3 days) having a load impact above 8 MW.

Figure 3-2: SDG&E Large all Participants: Average Event-Hour Impacts by Event

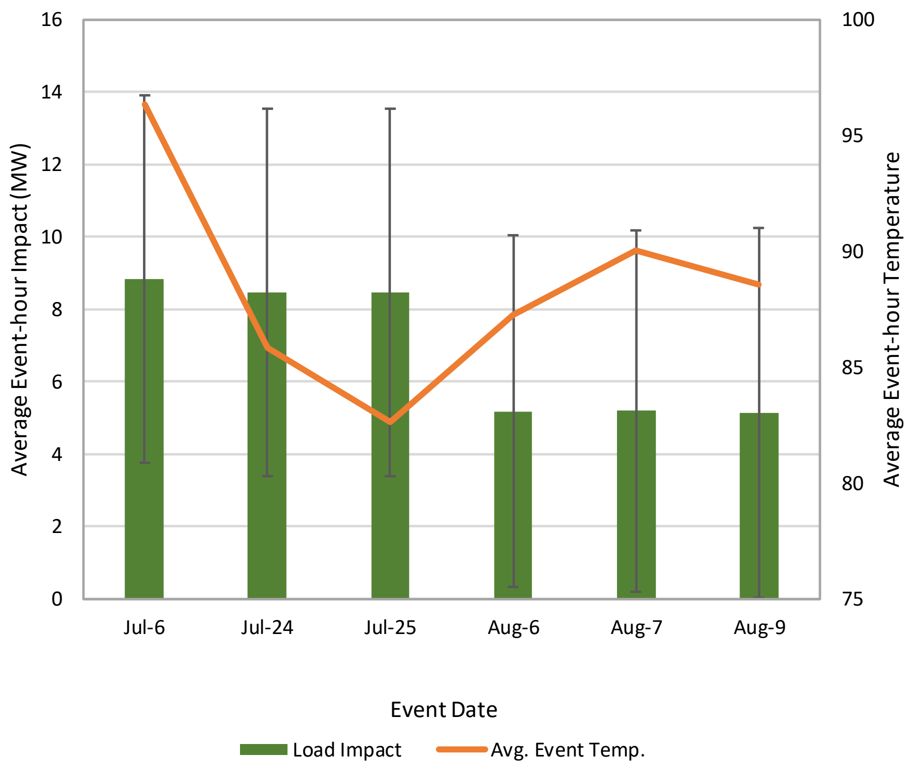


Table 3-2 summarizes the event-hour impacts on each event, including the number of participants enrolled during each event, the aggregate and per customer reference load and load impacts, the percent impact, and the average temperature. Load impacts as a percent of the reference load were 2.0% on average across the six events. The enrollment remained stable over the six events, averaging 1,211 participants

Table 3-2: Average Event-Hour Load Impacts by Event, *SDG&E Large*

Event Date	# Enrolled	Aggregate (MWh/hour)		Per-Customer (kWh/hour)		% Load Impact	Ave. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
7/6/2018	1,207	335.1	8.8	277.6	7.3	2.6%	96.4
7/24/2018	1,209	352.1	8.5	291.2	7.0	2.4%	85.9
7/25/2018	1,209	340.	8.5	281.5	7.0	2.5%	82.6
8/6/2018	1,213	350.6	5.2	289.0	4.3	1.5%	87.2
8/7/2018	1,213	350.9	5.2	289.3	4.3	1.5%	90.0
8/9/2018	1,213	359.6	5.1	296.5	4.2	1.4%	88.5
Typical Event Day	**1,211**	**348.1**	**6.9**	**287.5**	**5.7**	**2.0%**	**88.5**

3.3.2 CPP Medium Customers

This section summarizes results for all medium SDG&E program participants, defined as customers with maximum demand less than 200 kW.

Figure 3- presents the average event-hour ex post load impacts for each individual event day for all of SDG&E's medium CPP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 80 percent confidence intervals around these estimates (i.e., the 10th and 90th percentile scenarios from the uncertainty-adjusted load impacts). The orange line represents the average temperatures experienced by the participants during the event hours.

These results indicate that medium CPP participants had statistically significant load impacts on four of the six event days (ranging from -1.9 to 6.6 MW). One day showed an insignificant impact, and one day showed a statistically significant load increase.

Figure 3-3 SDG&E Medium all Participants: Average Event-Hour Impacts by Event

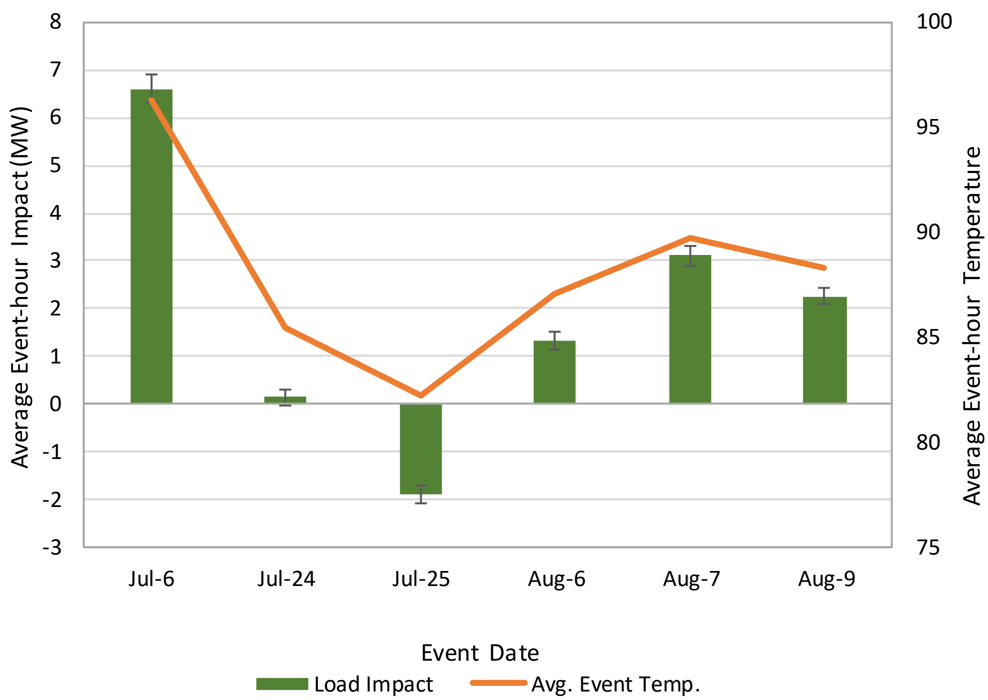


Table 3- summarizes the event-hour impacts on each event, including the number of participants enrolled during each event, the aggregate and per customer reference load and load impacts, the percent impact, and the average temperature.

Table 3-3 SDG&E Medium all Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MWh/hour)		Per-Customer (kWh/hour)		% Load Impact	Ave. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
7/6/2018	12,800	437.1	6.6	34.1	0.5	0.0%	82.2
7/24/2018	12,832	435.6	0.1	33.9	0.0	-0.5%	87.0
7/25/2018	12,834	420.3	(1.9)	32.7	(0.1)	0.3%	89.7
8/6/2018	12,880	437.0	1.3	33.9	0.1	0.7%	88.3
8/7/2018	12,882	446.3	3.1	34.6	0.2	0.5%	**88.2**
8/9/2018	12,896	448.9	2.3	34.8	0.2	0.4%	96.3
Typical Event Day	**12,854**	**437.5**	**1.9**	**34.0**	**0.2**	**0.0%**	85.5

3.4 Analysis of New TOU period Load Impacts

As of December 2017, SDG&E implemented new TOU periods for all its customers and moved the month of May into the Winter season. To estimate the impact of these changes, a simple regression analysis was performed and examined changes in consumption in each hour from the previous TOU periods to the current TOU periods. The changes were as follows:

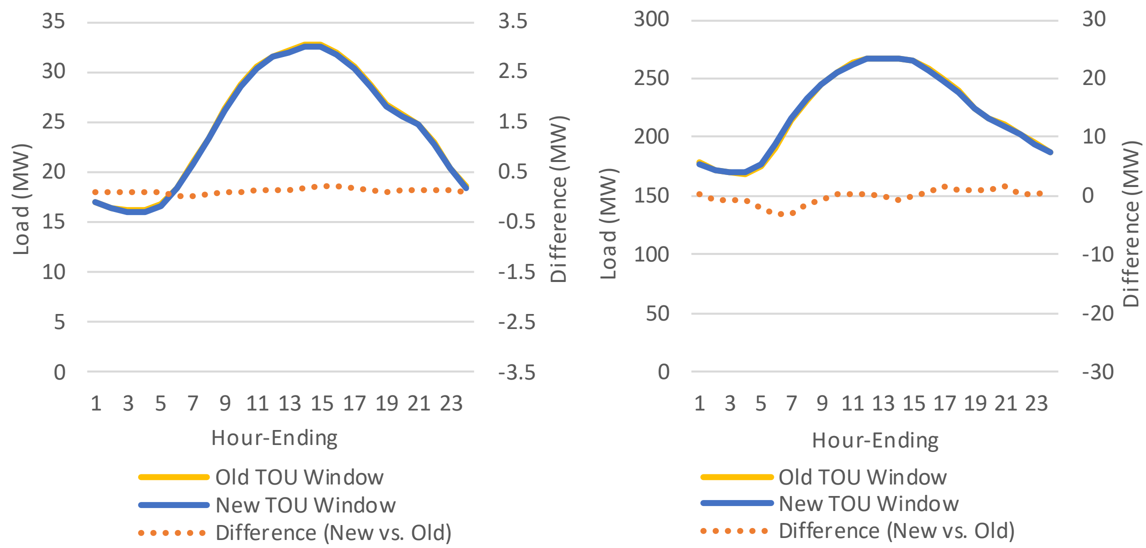
- The underlying TOU period (on event and non-event days) moved from 11 am – 6 pm to 4 – 9 pm.
- The CPP event window moved from 11 am – 6 pm to 2 – 6 pm.

AEG looked for changes in consumption on both non-event days and on event days in both the large and medium segments.

The analysis of non-event days ***did not show*** any material changes in consumption resulting from the changes in the TOU window. In

Figure below shows the model's prediction of 2018 average non-event day consumption under the new TOU window (in blue) vs. the old TOU window (in yellow). The orange dotted line represents the difference between the two. While some of the differences were statistically significant, the closeness of the overall load shapes, and the lack of meaningful pattern in the differences suggests that, on average, neither small nor large customers have changed their consumption patterns in response to the TOU window change.

Figure 3-4 Changes in Consumption Medium and Large Customers: New vs. Old TOU Window



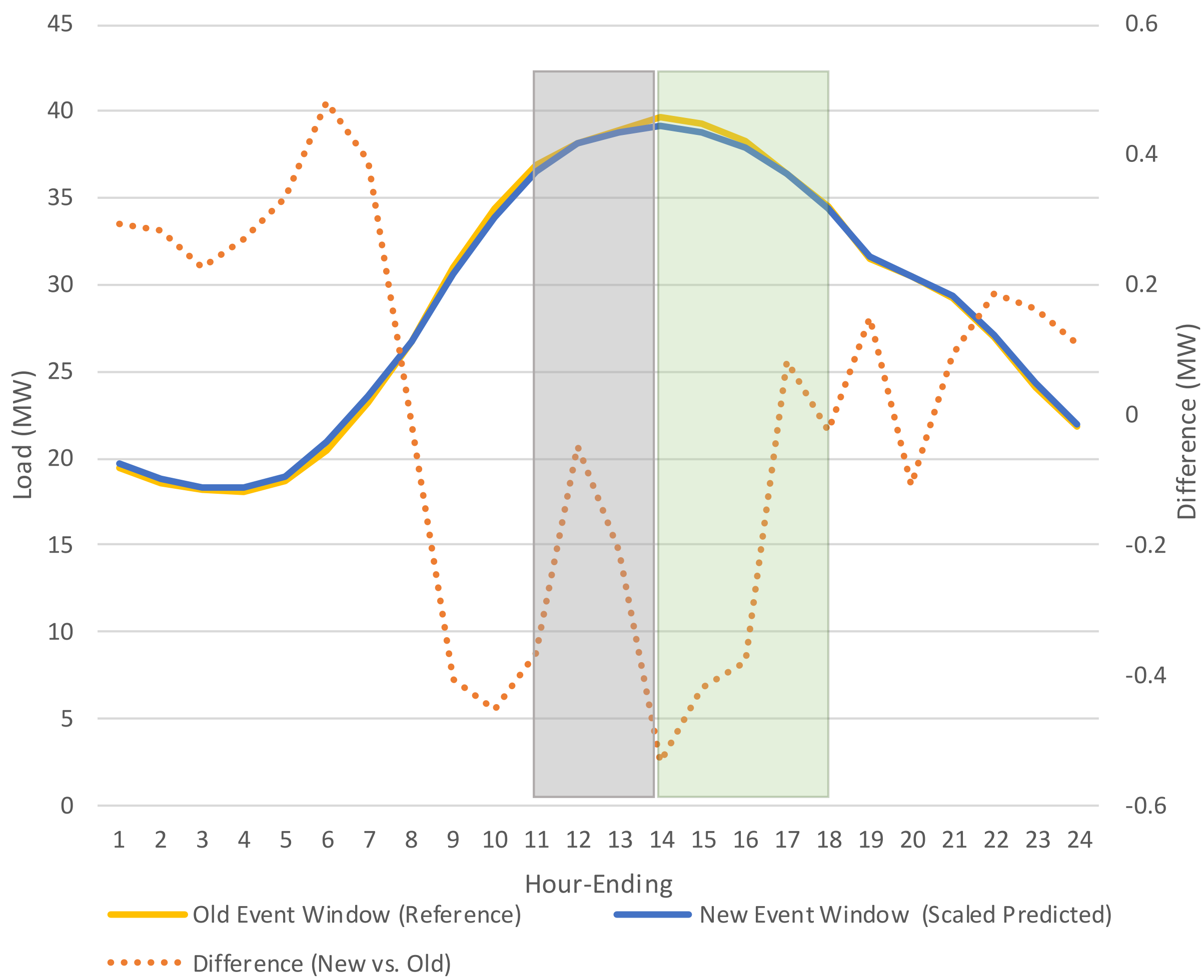
The analysis of event days did suggest that customers are responding to the new CPP event window. In Figure below the model's prediction of 2018 average event day consumption under the new event window is shown (in blue) vs. the old event window (in yellow) for SDG&E's large customers. The orange dotted line represents the difference between the two. In addition, two shaded areas were included. The grey shaded area represents the period that used to be part of the event window (11 am – 2 pm) in 2017. The green shaded area represents the period covered by the new event window (2 – 6 pm). The figure exhibits the following trends:

- The model shows that customers use less under the new event window in the mid-morning hours (which would have immediately preceded the old event window). This is likely because any shifting that customers were doing prior to an event (under the old window) is no longer needed at that time under the new window.
- Customers also appear to be using more during in the grey shaded area under the new vs. old event window. This increase in usage is expected since the grey shaded period is no longer part of the event.
- In the green shaded area, customers are using less, on average, than they did under the old event window between 4 and 5 pm, however they are using slightly more by 6 pm. Again, this for the most part, matches with how one would expect customers to respond to the new window.

It is important to note, that while there is evidence of changes in consumption in response to the new event window, the changes are likely smaller than one might expect under the assumption that all large customers fully understood the change and adjusted their response accordingly. It may be that some customers changed their behavior, while others did not.

SDG&E's medium CPP customers results were similar to those seen in the large customers, however they are smaller in magnitude and had fewer significant point estimates. Especially for the medium customers, it is important to note, that while evidence of changes in consumption in response to the new event window are seen, the changes are smaller than one might expect and it is very likely that some customers changed their behavior, while many others did not.

Figure 3-5: Changes in Consumption Large Customers: New vs. Old Event Window

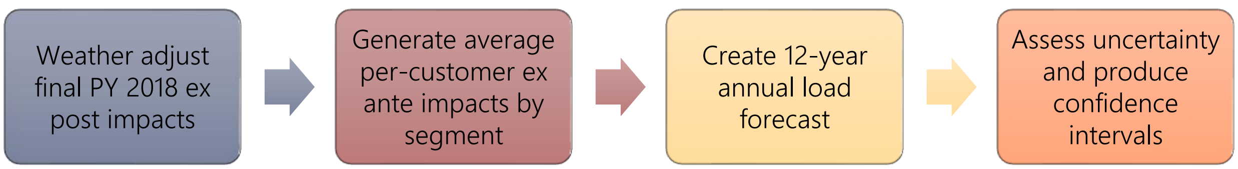


3.5 CPP-D Ex ante Evaluation Methodology

The main goal of the ex ante analysis is to produce an annual twelve-year forecast of the load impacts expected from the CPP programs. Separate forecasts are to be produced for each busbar and bundled v. direct access (as applicable). It was produced a set of impacts under each of the different weather scenarios required: monthly peak day and typical event day for 1-in-2 weather year and 1-in-10 weather year for each of the SDG&E and the CAISO scenarios. A portfolio forecast that excludes the forecasted load impacts of dually-enrolled customers will also be provided. An annual twelve-year forecast will be produced for each of the following:

- SDG&E large customers (≥ 200 kW) and medium customers (20 kW ≤ x < 200 kW).

The approach achieves this goal by first determining the appropriate weather-adjusted, per-customer impact for each of the segments of interest, and then multiplying that impact by the number of participants for each year specified by the enrollment forecast. First, AEG describes the various steps involved in implementing this approach in detail. Then uncertainty in the forecast and the calculation of confidence intervals are addressed. The figure below provides an overview of the ex ante analysis approach.



In the subsections that follow the analysis steps are described in more detail.

3.5.1 Weather-Adjusted Impacts

The first step in the ex ante analysis was to use the ex post regression models to predict weather-adjusted impacts for each segment of interest. This will produce a set of impacts under each of the required weather scenarios. To do this, the following steps are carried out:

- For each program, AEG began with the coefficients estimated in the subgroup 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 to predict a customer's load for each of these scenarios assuming no events are called. The result was a weather-adjusted reference load for each customer for each weather scenario required.
- 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 it was assumed that events were called by changing the event indicator variables from zero to one.
- The load impact for each customer were calculated by subtracting the weather-adjusted event-day load from the weather-adjusted reference load.

3.5.2 Generation of Per-Customer Average Impacts by Segment

Once weather-adjusted impacts were predicted for each customer, for each of the desired weather scenarios, it became a relatively simple exercise to average the individual impacts and generate per-customer average impacts by segment of interest.

3.5.3 Creation of 12-Year Annual Load Impact Forecasts

The next step in the analysis will be to use the set of per-customer average impacts to create an annual forecast of load impacts over the next 12 years. The approach for each utility is described below:

- The 2018 ex post impacts weather adjusted per customer subgroup level impacts were multiplied by the number of customers in each IOU's enrollment forecast by month and year to develop the 12-year load forecast

3.6 CPP-D Ex ante Load Impacts Estimates

This section presents the ex ante results, which include the load impact forecasts for the 1-in-2 and 1-in-10 weather conditions for SDG&E. A summary of the enrollment forecast, and load impacts is provided, followed by a discussion of the relationship between ex post and ex ante estimates.

One of the key changes for the 2019 - 2029 ex ante forecast is that the resource adequacy (RA) window is now 4-9 pm instead of 1-6 pm. SDG&E's event windows will remain unchanged, which means that the PDP and CPP programs are only available during the first two hours of the new RA window while all other hours are non-event hours. This results in significantly lower (and sometimes even negative) impacts within the RA window which has not been seen in previous evaluations.

3.6.1 Large and Medium C&I *Ex ante* Impacts

Enrollment and Load Impact Summary

Table 3-4 summarizes the average event-hour load impact forecasts for non-residential CPP participants on a typical event day in 2019. 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. As noted above, because of the differences between the actual program availability, 2-6 p.m. and the RA window 4-9 p.m. the ex ante impacts for CPP are very small and can be either positive or negative.

Table 3-4 SDG&E Typical Event Enrollment and Impacts by Size: 2019

Size	# of Accts	Aggregate Impact (MW)				Per-Customer Impact (kW)			
		Utility Peak		CAISO Peak		Utility Peak		CAISO Peak	
		1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Large	1,471	4.5	4.4	4.5	4.4	3.0	3.0	3.0	3.0
Medium	12,603	(1.2)	0.3	(1.5)	(0.6)	(0.1)	0.0	(0.1)	(0.0)
Total CPP	**14,074**	**3.3**	**4.6**	**2.9**	**3.8**	**0.2**	**0.3**	**0.2**	**0.3**

The enrollment forecast is presented and the ex ante impact forecast side-by-side. The enrollment forecast shows a steady increase in participants from about 1,470 in 2019 to just over 1,800 in 2029. Additional participation comes mainly from population growth. Similarly, the ex ante MW forecast steadily increases from around 0.6 MW in 2019 to 0.7 MW by 2029.

Figure 3-6: SDG&E Large Enrollment and Impact Forecast SDG&E 1-in-2: 2019 - 2029

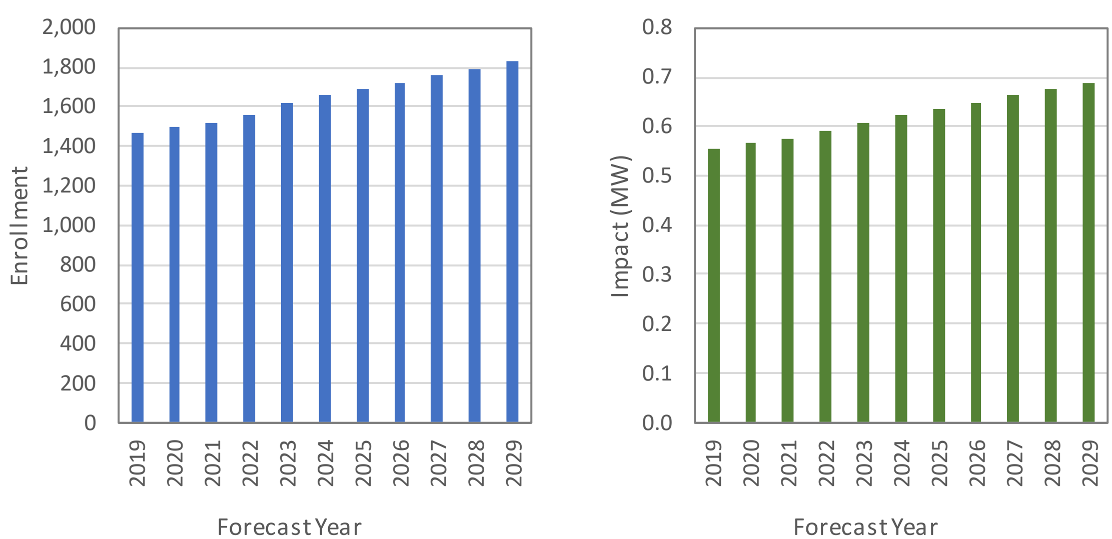
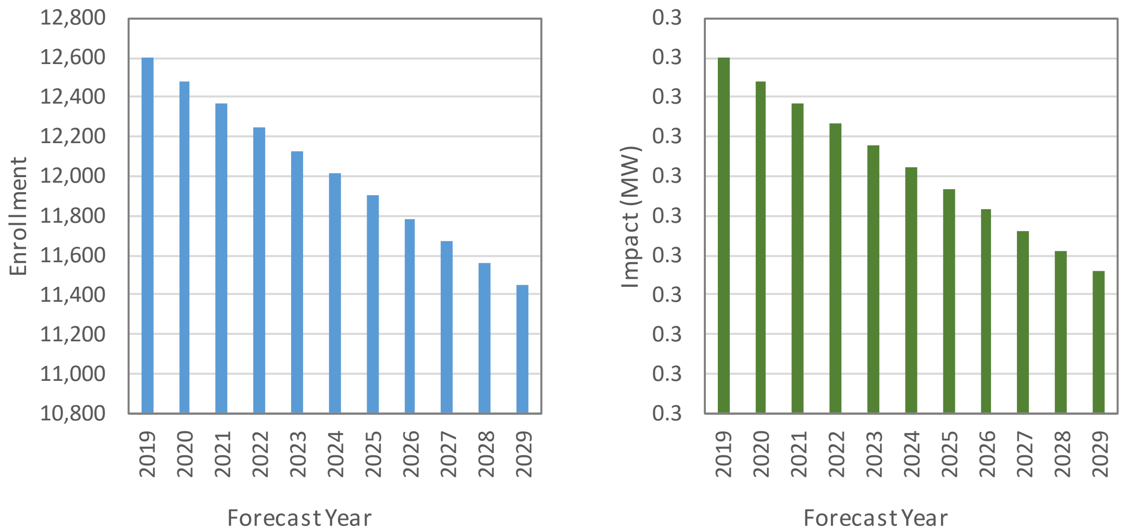


Figure 3-7 SDG&E Medium Enrollment and Impact Forecast SDG&E 1-in-10: 2019 - 2029



3.7 CPP Large & Medium- Relationship between *Ex post* and *Ex ante* Estimates

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

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

The term "current" refers to the present study, which includes ex post and ex ante results for PY2018. The term "previous" refers to findings in reports for PY2017.

Previous vs. Current Ex post

Table summarizes the non-residential CPP average event-hour ex post load impact results for the past two years on an average event day. The table includes the number of participating accounts, the average event-hour reference loads, and average event temperature by size groups. Both per-customer and aggregate results are presented.

Table 3-5 SDG&E Non-Residential CPP: Previous and Current Ex post, Average Event Day

	Ex post Year	# of Accts	Aggregate (MW)		Per-Customer (kW)		% Impact	Event Temp (˚F)
			Reference Load	Load Impact	Reference Load	Load Impact		
Large	2017	1,281	414.8	18.0	323.8	14.1	4.3%	91.9
	2018	1,211	348.1	6.9	287.5	5.7	2.0%	88.5
Medium	2017	11,808	455	1.0	38.5	0.1	0.2%	91.4
	2018	12,854	437.5	1.9	34.0	0.2	0.4%	88.2

In the large group, enrollment fell slightly, as did both per customer and total overall reference load. Per customer reference loads fell by more nearly 50 kW and overall reference load fell in excess of 50 MW. This resulted in a corresponding drop in impacts from 18 to 6.9 MW which suggests that several large, but high responding, customers may have left the program in 2018. In addition, the change in the event window resulted in reductions in impacts in several industries, particularly manufacturing, for which impacts were larger during mid-day hours and smaller during afternoon hours.

In the medium group, enrollment increased slightly while both aggregate and per customer reference loads fell. Impacts, conversely, increased slightly from 0.2% to 0.4%.

Previous versus current ex ante

Table compares the current year's analysis with the previous year's analysis of non-residential CPP ex post and ex ante average event-hour impacts. The ex post results represent events on typical event days and ex ante results represent events on monthly system peak days in August. In addition, the ex ante results reflect the utility peak 1-in-2 weather scenario.

Table 3-6 SDG&E Non-Residential CPP: Previous and Current Ex ante and Ex post

	Model	Year	# of Accts	Aggregate (MW) Ref. Load	Aggregate (MW) Impact	Per-Customer (kW) Ref. Load	Per-Customer (kW) Impact	% Impact	Event Temp (˚F)
LARGE	Previous	Ex post 2017	1,281	414.8	18.0	323.8	14.1	4.3%	91.9
		Ex ante 2018	1,300	396.6	14.4	302.2	11.1	4.3%	86.2
	Current	Ex post 2018	1,211	348.1	6.9	287.5	5.7	2.0%	88.5
		Ex ante 2019	1,471	378.5	4.4	257.3	3.0	1.2%	82.5
MEDIUM	Previous	Ex post 2017	11,808	455.0	1.0	38.5	0.1	0.2%	91.4
		Ex ante 2018	11,982	439.9	0.9	36.7	0.1	0.2%	86.1
	Current	Ex post 2018	12,854	437.5	1.9	34.0	0.2	0.4%	88.2
		Ex ante 2019	12,603	372.1	(0.7)	29.6	(0.1)	0.0%	82.3

Table shows the following trends for the non-residential CPP on an August peak day:

- **Current Ex post Compared with Previous Ex ante:** The aggregate ex post impacts for large customers were lower in PY2018 (6.9 MW) than projected to be in the previous ex ante forecast (14.4 MW) due to lower than forecasted enrollment, lower reference loads, and lower impacts. Again, this may suggest that several large, but high responding, customers may have left the program in 2018.
- **Current Ex ante Compared with Previous Ex ante**: Comparing to previous ex ante analysis, the current ex ante analysis forecasts a significant decrease in impacts, however most of this decrease is related to the fact that the CPP program is only available to be called during the first two hours of the RA window, while remaining hours are directly after an event when customers might be increasing their loads.
- **Current Ex ante Compared with Current Ex post:** Again, as the current ex ante is compared to the current ex post, one can see that the impacts are significantly lower even with relatively stable enrollment because the event window does not align with the RA window.

4 Summary of SDG&E's Base Interruptible Program (BIP) Report[13]

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 Firm Service Level (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 20 minutes before the event. Monthly incentive payments are $12 per kW during May through October and $2 per kW during all other months. Currently, the monthly incentive payments are $10.80 per kW during May through October and $1.80 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 historically low, consistent with the California Public Utilities Commission ("Commission" or "CPUC") direction to focus marketing efforts on price responsive programs.[14] There were no participants in 2006, three participants in 2007, five participants in 2008, 20 in 2009, 19 customers in 2010, 21 customers in 2011, 11 in 2012, seven participants in 2013 and 2014, five participants in 2015, seven participants in 2016, six in 2017, and three in 2018.

4.2 BIP Ex post Evaluation Methodology

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

- Seasonal and hourly time patterns (e.g., year, month, day-of-week, and hour, plus various hour/day-type interactions);
- Weather, including hour-specific weather coefficients;

---

[13] The BIP statewide load impact evaluation was conducted by Christensen Associates. This section of the Executive Summary contains excerpts from the following evaluation: Hansen, D. & Clark, M., Armstrong, D., Christensen Associates (2019). "2018 Load Impact Evaluation of California Statewide Base Interruptible Programs (BIP) for Non-Residential Customers: *Ex post and Ex ante Report*"

[14] 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.

- Event variables. A series of dummy variables was included to account for each hour of each event day, allowing us to estimate the load impacts for all hours across the event days.

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

A variety of weather variables were tested in an attempt to determine which set best explains usage on event-like non-event days. Each customer was first classified according to whether it is weather-sensitive. AEG selected specifications by customer group, defined by industry group and weather sensitivity (i.e., sixteen groups, with eight industry groups for each of the non-weather-sensitive customers and weather-sensitive customers).

4.2.1 Regression Model

The following is a general form of the model that was separately estimated for each enrolled BIP customer. Table 4-1 below describes the terms included in this equation for the observed demand in a given hour *h* and date *d*:

$$
\begin{aligned}
Q_t \;=\; & \sum_{i=1}^{24}(b_i^h \times h_{i,t}) + \sum_{Evt=1}^{E}\sum_{i=1}^{24}(b_{i,Evt}^{BIP} \times h_{i,t} \times BIP_t) + \sum_{DR}\sum_{i=1}^{24}(b_i^{DR} \times h_{i,t} \times OtherEvt_{i,t}^{DR}) \\
& + \sum_{i=1}^{24}(b_i^{Weather} \times h_{i,t} \times Weather_t) + \sum_{i=1}^{24}(b_i^{MornLoad} \times h_{i,t} \times MornLoad_{i,t}) \\
& + \sum_{j=2}^{5}(b_j^{DTYPE} \times DTYPE_{j,t}) + \sum_{i=2}^{24}(b_i^{MON} \times h_{i,t} \times MON_t) + \sum_{i=2}^{24}(b_i^{FRI} \times h_{i,t} \times FRI_t) \\
& + \sum_{i=6}^{10}(b_i^{MONTH} \times MONTH_{i,t}) + \sum_{i=2}^{24}(b_i^{SUMMER} \times h_{i,t} \times SUMMER_t) + e_t
\end{aligned}
$$

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

Variable Name	Variable Description
Q_t	the demand in hour t for a BIP customer
The various b's	the estimated parameters
$h_{i,t}$	an indicator variable for hour i, equal to one when t corresponds to hour i of a given day
BIP_t	an indicator variable for program event days
E	the number of program event days that occurred during the program year
$OtherEvt_{i,t}^{DR}$	an indicator variable for event day *DR* of other demand response programs in which the customer is enrolled (e.g. *DR* = CPP Event 1, CPP Event 2, ...)
$Weather_t$	the weather variables selected using our model screening process
$MornLoad_t$	a variable equal to the average of the day's load in hours 1 through 10 (may be excluded via model screening)
$DTYPE_{j,t}$	a series of indicator variables for each day of the week
MON_t, FRI_t,	indicator variables for Monday and Friday
$MONTH_{j,t}$	a series of indicator variables for each month (model screening may include separate hourly profiles by month)
$SUMMER_t$	an indicator variable for the summer pricing season[15]
e_t	the error term

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

The model allows for the hourly load profile to differ by time periods, which can vary across specifications selected for each customer group. The time-based patterns reflect day of week, with separate profiles for Monday, Tuesday through Thursday, and Friday; month of year; and pricing season (i.e., summer versus winter), to account for potential customer load changes in response to seasonal changes in rates.

[15] The summer pricing season is June through September for SCE, June through October for SDG&E, and May through October for PG&E.

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

A parallel set of winter models was estimated for each customer, which were used to simulate *ex ante* reference loads for those months. The structure matches the model described above, with the appropriate month indicators substituted in. A separate model selection process was conducted for the winter models.

4.2.2 Development of Uncertainty-Adjusted Load Impacts

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. In the case of *ex post* load impacts, the parameters that constitute the load impact estimates are not estimated with certainty. The uncertainty-adjusted load impacts are based on the variances associated with the estimated load impact coefficients.

Specifically, the variances of the estimated load impacts were added across the customers who are called during the event in question. These aggregations were performed at either the program level, by industry group, or by LCA, as appropriate. The uncertainty-adjusted scenarios were then simulated under the assumption that each hour's load impact is normally distributed with the mean equal to the sum of the estimated load impacts and the standard deviation equal to the square root of the sum of the variances of the errors around the estimates of the load impacts. Results for the 10th, 30th, 70th, and 90th percentile scenarios are generated from these distributions.

In order to develop the uncertainty-adjusted load impacts associated with the average event hour (i.e., the bottom rows in the tables produced by the *ex post* table generator), an additional set of customer-specific regression models were estimated in which each event day's average event-hour load impact is estimated using a single variable (rather than the hour-specific variables used in the primary model described above). The standard error associated with these event-specific coefficients serves as the basis of the average event-hour uncertainty-adjusted load impacts for each *ex post* event day. The standard errors are used to develop the uncertainty-adjusted scenarios in the same manner as the hour-specific standard errors in the primary model.

4.3 BIP Ex post Load Impact Estimates

Average event-hour reference loads and load impacts for SDG&E single event (August 9, 2018) are summarized in Table 4-2. The average load impact over the four-hour event was 1.1MW

Table 4-2: Average Event-hour Load Impacts, *SDG&E*

Event	Date	Day of Week	Estimated Reference Load (MW)	Observed Load (MW)	Estimated Load Impact (MW)	% LI
1	8/09/2018	Thursday	1.6	0.4	1.1	73.2%

Table 4-3 compares the average observed load to the FSL on the event day. The observed load was below the FSL throughout the event.

Table 4-3: Average Event-hour Observed Loads and FSLs, *SDG&E*

Event	Date	Day of Week	Observed Load (MW)	Firm Service Level (MW)	Estimated LI / LI at FSL
1	8/09/2018	Thursday	0.42	0.34	93.7%

4.4 BIP Ex ante Evaluation Methodology

The DR Load Impact Evaluation Protocols require that hourly load impact forecasts for event-based DR resources must be reported at the program level and by LCA for the following scenarios:

- For a typical event day in each year; and
- For the monthly system peak load day in each month for which the resource is available;

under both:

- 1-in-2 weather conditions for both utility-specific and CAISO-coincident load conditions, and
- 1-in-10 weather conditions for both utility-specific and CAISO-coincident load conditions;

at both:

- the program level (i.e., in which only the program in question is called), and
- the portfolio level (i.e., in which all demand response programs are called).

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

1. Define data sources;
2. Estimate *ex ante* regressions and simulate reference loads by service account and scenario;
3. Calculate historical FSL achievement rates from *ex post* results;

4. Apply achievement rates to the reference loads; and
5. Scale the reference loads using enrollment forecasts.

Each of these steps is described below.

1. *Define data sources*

The reference loads are developed using data for customers enrolled in BIP at the start of the 2019 program year. The load impacts are developed using the historical FSL achievement rates of customers remaining enrolled at the start of the 2019 program year, based on their estimated *ex post* load impacts during program year 2018.

For each service account, the appropriate size group and LCA were determined. Although BIP customers may be dually enrolled in some other DR programs, the BIP obligation takes precedence on event days, so program-specific scenarios (in which each DR program is assumed to be called in isolation) are identical to portfolio-level scenarios (in which all DR programs are assumed to have been called) for this program.

2. *Simulate reference loads*

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

For the summer months, the re-estimated regression equations were similar in design to the *ex post* load impact equations, differing in two ways. First, the *ex ante* models excluded the morning-usage variables. While these variables are useful for improving accuracy in estimating *ex post* load impacts for particular events, they complicate the use of the equations in *ex ante* simulation. That is, they would require a separate simulation of the level of the morning load. The second difference between the *ex post* and *ex ante* models is that the *ex ante* models do not use weather variables using information from prior days.[16] The primary reason for this is that the *ex ante* weather days were not selected based on weather from the prior day, restricting the use of lagged weather variables to construct the *ex ante* scenarios.

Because BIP events may be called in any month of the year, separate regression models were estimated to allow for simulated winter reference loads. The winter model is shown below. This model is estimated separately from the summer *ex ante* model. It only differs from the summer

[16] In particular, where CDH60 and CDH60_MA24, the 24-hour moving average of CDH60, are used together for summer *ex post* regressions, only CDH60 is used for the *ex ante* models. Similarly, where CDH60_MA3, the three-hour moving average, is used for *ex post* regressions, CDH60 is used for the *ex ante* analysis. See Appendix A for weather variable details.

model in two ways: it includes different weather variables; and the month dummies relate to a different set of months. Table 4-4 describes the terms included in the equation.

$$\begin{aligned} Q_t = & \sum_{i=1}^{24}(b_i^h \times h_{i,t}) + \sum_{Evt=1}^{E}\sum_{i=1}^{24}(b_{i,Evt}^{BIP} \times h_{i,t} \times BIP_t) + \sum_{DR}\sum_{i=1}^{24}(b_i^{DR} \times h_{i,t} \times OtherEvt_{i,t}^{DR}) \\ & + \sum_{i=1}^{24}(b_i^{Weather} \times h_{i,t} \times Weather_t) + \sum_{j=2}^{5}(b_j^{DTYPE} \times DTYPE_{j,t}) \\ & + \sum_{i=2}^{24}(b_i^{MON} \times h_{i,t} \times MON_t) + \sum_{i=2}^{24}(b_i^{FRI} \times h_{i,t} \times FRI_t) \\ & + \sum_{j=2-4,11-12}(b_j^{MONTH} \times MONTH_{j,t}) + e_t \end{aligned}$$

Table 4-4: Descriptions of Terms included in the *Ex ante* Regression Equation

Variable Name	Variable Description
Q_t	the demand in hour t for a customer enrolled in BIP prior to the last event date
The various b's	the estimated parameters
$h_{i,t}$	an indicator variable for hour i, equal to one when t corresponds to hour i of a given day
BIP_t	an indicator variable for program event days
E	the number of program event days that occurred during the program year
$OtherEvt_{i,t}^{DR}$	an indicator variable for event day DR of other demand response programs in which the customer is enrolled (e.g. DR = CPP Event 1, CPP Event 2, ...)
$Weather_t$	the weather variables selected using our model screening process
$DTYPE_{j,t}$	a series of indicator variables for each day of the week
MON_t, FRI_t,	indicator variables for Monday and Friday
$MONTH_{j,t}$	a series of indicator variables for each month
e_t	the error term

Similar to the *ex post* analysis, a variety of weather variables were tested and included in the above regression equation to determine the best specification for explaining usage on event-like non-event days. Each specification is tested separately by customer group, defined by industry group and weather sensitivity. Once these models were estimated, 24-hour load profiles were simulated for each required scenario. The typical event day was assumed to occur in August. In 2014, two sets of 1-in-2 and 1-in-10 weather years were introduced in the load impact analyses. The sets are differentiated according to whether they correspond to utility-specific conditions or CAISO-coincident conditions. The weather conditions used in prior evaluations corresponded to the utility-specific scenarios.

3. Calculate forecast load impacts

Each service account's FSL achievement rate is defined as the estimated load impact divided by the difference between the reference load and the FSL. A result of 100 percent implies that the customer dropped its load exactly to its FSL. Values greater than 100 percent imply event-day loads lower than the FSL, and values less than 100 percent imply event-day loads higher than the FSL.[17]

The achievement rates are based on the estimates for the most recent observed event day. In consultation with the utilities, it was determined that using a longer time period (e.g., three years of *ex post* load impacts) was not appropriate for this program. Specifically, as customers experience events, they are re-tested if they fail to meet their obligation (i.e., reduce load to the FSL). If they continue to fail, their FSL is increased to the point at which the customer is expected to be able to comply. Therefore, the most recent load impact estimates should provide a good indication of customer performance going forward. In addition, some program design changes make older load impacts less relevant as predictors of future performance. For example, an increased excess energy charge for non-compliance (and a higher excess energy charge for failing to comply during re-test events) may make more recent performance rates higher than performance rates in the more distant past.

From these customer-level forecasts of reference loads and load impacts, results are formed for any given sub-group of customers (e.g., customers over 200 kW in size in the Greater Bay Area), by summing the reference loads and load impacts across the relevant customers.

Because the forecast event window (4:00 to 9:00 p.m. in all other months) differs from the historical event window (which can vary across utilities and event days), an adjustment was made to the historical load impacts for use in the *ex ante* study. Load impacts are assumed to be zero until the hour prior to the beginning of the event, at which time the customer's historical FSL performance rate is applied to the forecast window to best represent the pattern of customer response given the limitations of the observed events. Forecast load impacts are developed through the end of the event day because customers load reductions often persist well after the end of the event hours.

The uncertainty-adjusted load impacts (i.e., the 10th, 30th, 50th, 70th, and 90th percentile scenarios of load impacts) are based on the standard errors associated with the estimated load impacts from the event day used to determine the customer's event-day achievement rate, scaled to account for the difference between observed and forecast enrollments. The square of these standard errors (i.e., the variance) is added across customers within each required subgroup. Each uncertainty-adjusted scenario is then calculated under the assumption that the load impacts

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[17] It is not possible to calculate an achievement rate for customers with reference loads below their FSLs throughout an event period—the event effectively has no effect on them.

are normally distributed with a mean equal to the total estimated load impact and a variance based on the standard errors in the estimated load impacts. The uncertainty-adjusted load impacts for the average event hour are based on the same event-hour standard errors used in the *ex post* study.

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

In this step, the customer-specific FSL achievement rates are applied to the reference loads for each scenario to produce all of the required estimated event-day loads and load impacts. For customers for which an achievement rate cannot be calculated, either because their reference loads were below their FSLs, the average achievement rate among all customers is used. The FSL achievement rate is assumed to be 100% for newly enrolled customers, as well as for customers that change their FSL in the beginning of 2019.

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

SDG&E forecasts BIP enrollments to increase to five customers by the end of 2018 and is forecasted to increase by one in each year until 2022, at which time enrollment is forecast to remain constant at nine service accounts through 2029.

4.5 BIP Ex ante Load Impacts Estimates

Figure 4-1 shows the load impact forecast for an August 2019 event day in a utility-specific 1-in-2 weather year. The average hourly load impact from 4:00 to 9:00 p.m. is forecast to be 0.86 MW, which represents 65 percent of the enrolled reference load. The average event-hour program load of 0.46 MW is lower than the program-level FSL of 0.48 MW. Customers over-perform throughout all event hours, consistent with our *ex post* estimates for the August 9, 2018 event day that serves as the basis for the *ex ante* load impacts.

Figure 4-1: SDG&E Hourly Event Day Load Impacts for the August 2019 Event Day in a Utility-Specific 1-in-2 Weather Year

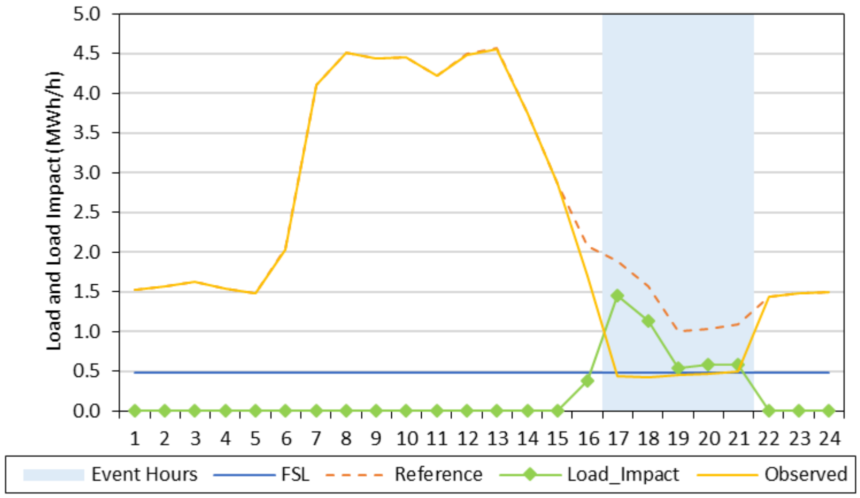
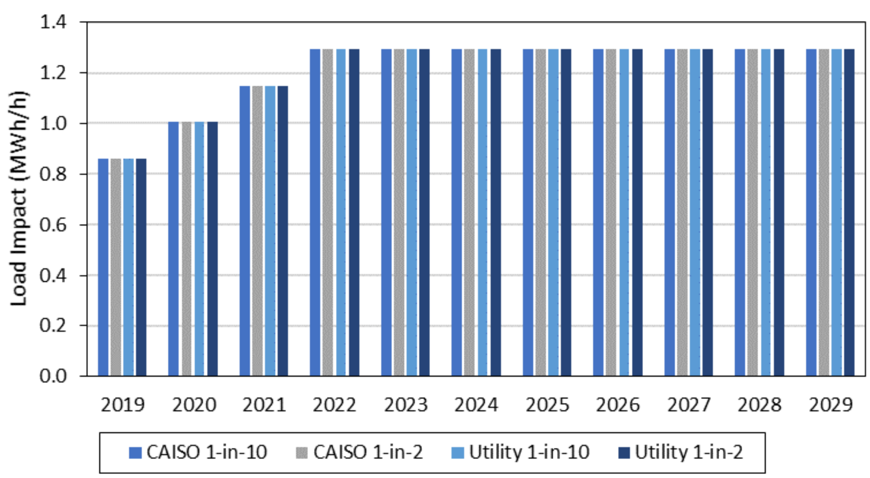


Figure 4-2 illustrates 2019 to 2029 August load impact for each forecast scenario, differentiated by 1-in-2 versus 1-in-10 weather conditions under both utility-specific and CAISO-coincident peak conditions. The enrollment forecast slightly increases until 2022 and then remains constant. These load impacts are consistent with the increases in enrollments and the load impacts found in the *ex post* analysis. The load impacts are equivalent for each weather scenario because each customer was classified as not weather sensitive.

Figure 4-2: Average August *Ex ante* Load Impacts by Scenario, 2019-2029, *SDG&E*



4.6 BIP Comparison of current Ex post versus Ex ante

4.6.1 Previous versus current *Ex post*

Table 4-5 compares ex post load impacts between PY2017 and PY2018. The PY2017 load impacts are based on the August 31, 2017 event with event hours-ending 12 through 15, while the PY2018 load impacts are based on the single August 9, 2018 event with event hours-ending 13 through 16. Thus, the event length is the same, but the 2018 event is shifted one-hour later. Enrollment has dropped from six to three customers. While the difference in enrollment numbers reduces aggregate loads and load impacts, the customers that de-enrolled from the program were relatively small. A greater cause of the difference is that the PY2018 later event hour corresponds to a period of lower references loads and consequently lower load impacts. Specifically, enrolled customers operate at or near their FSLs beginning around HE15.

Table 4-5: Comparison of *Ex post* Impacts in PY2017 and PY2018, *SDG&E*

Level	Outcome	Ex post PY2017	Ex post PY2018
Total	# SAIDs	6	3
	Reference (MWh/h)	3.6	1.6
	Load Impact (MWh/h)	2.5	1.1
Per SAID	Reference (kWh/h)	596.5	517.9
	Load Impact (kWh/h)	423.8	378.9
	% Load Impact	71.1%	73.2%

4.6.2 Previous versus current *Ex ante*

In this sub-section, the *ex ante* forecast prepared is compared following PY2016 (the “previous study”) to the *ex ante* forecast contained in this study (the “current study”). Table 4-6 presents this comparison for the ex ante forecasts of the utility-specific 1-in-2 August typical event day. Reference loads and load impacts are significantly lower in the current study. The RA window is from 1 to 6 p.m. in the previous study and 4 to 9 p.m. in the current study. The later RA window occurs when most customers are already operating at or near their FSL, resulting in zero load impacts for these customers.

Table 4-6: Comparison of *Ex ante* Impacts from PY2017 and PY2018 Studies, *SDG&E*

Level	Outcome	*Ex ante* 2019 Typical Event Day, *Previous Study*	*Ex ante* 2019 Typical Event Day, *Current Study*
Total	# SAIDs	8	6
	Reference (MWh/h)	2.7	1.3
	Load Impact (MWh/h)	1.4	0.9
	FSL (MWh/h)	1.6	0.5
Per SAID	Reference (kWh/h)	340.7	219.6
	Load Impact (kWh/h)	178.8	143.6
	% Load Impact	52.5%	65.4%

4.6.3 Previous Ex ante versus current *Ex post*

Table 4-7 compares the ex ante forecast prepared following PY2017 to the PY2018 ex post load impact estimates contained in this report for the August 9, 2018 event day. The ex ante load impacts are based on the typical event day in a utility-specific 1-in-2 weather year. The average per-customer reference load and load impact increased because of the de-enrollment of small customers. The earlier event hours in the ex post analysis (HE 13-16 vs HE 14-18) also contributes to larger per-customer load impacts because customers still enrolled have larger loads during this period. The aggregate load impact is similar even with the reduction of four customers.

Table 4-7: Comparison of Previous *Ex ante* and Current *Ex post* Impacts, *SDG&E*

Level	Outcome	*Ex ante* 2018 Typical Event Day, Previous Study	*Ex post PY2018*
Total	# Customers	7	3
	Reference (MW)	2.4	1.6
	Load Impact (MW)	1.3	1.1
Per SAID	Reference (kW)	340.7	517.9
	Load Impact (kW)	178.8	378.9
	% Load Impact	52.5%	73.2%

4.6.4 Current *ex post* versus current *ex ante*

Table 4-8 shows a comparison of *ex post* and *ex ante* load impacts. Enrollment increases, but the aggregate load impact is nonetheless forecast to be lower in the forecast period. The decreased reference loads and load impacts is caused by the RA window of 4 to 9 p.m. corresponding to a period when most of the customers are already operating at or near their FSLs. The ex ante forecast is based on the ex post FSL achievement (i.e., observed loads) relative to the FSL during event hours. In terms of achievement relative to the FSL, the ex post and ex ante load impacts for the three continuing customers match by design. However, the forecast reference loads may differ from the ex post event-hour reference loads for various reasons. For instance, forecast reference loads are lower partly due to a difference in event windows, as the historical event was earlier than the ex ante event window (hours-ending 13 to 16 vs. 17 to 21, respectively). The later ex ante window includes hours with relatively low loads, which reduces the load impact because the FSL does not change across hours.

Table 4-8: Comparison of Current *Ex post* and Current *Ex ante* Impacts, *SDG&E*

Level	Outcome	*Ex post* PY2018	*Ex ante* 2019 Typical Event Day, Current Study
Total	# Customers	3	6
	Reference (MWh/h)	1.6	1.3
	Load Impact (MWh/h)	1.1	0.9
	FSL (MWh/h)	0.3	0.5
Per SAID	Reference (kWh/h)	517.9	219.6
	Load Impact (kWh/h)	378.9	143.6
	% Load Impact	73.2%	65.4%

Table 4-9 below describes the factors that differ between the *ex post* and *ex ante* load impacts for SDG&E.

Table 4-9: SDG&E BIP *Ex post* versus *Ex ante* Factors, Typical Event Day

Factor	Ex post	Ex ante	Expected Impact
Weather	95 degrees Fahrenheit during HE 13 to 16 on the August 9th event day	82.7 degrees Fahrenheit during HE 17 to 21 on utility-specific 1-in-2 typical event day	Program load is not very weather sensitive, so a small effect.
Event window	HE 13 to 16	HE 17 to 21.	Reference loads are substantially lower during 4 to 9 p.m., dragging down the average ex ante reference loads and load impacts relative to ex post.
% of resource dispatched	All	All	None
Enrollment	3 service accounts	6 service accounts	Increase aggregate reference load and load impact. No increase in per-customer reference load or load impacts because results are scaled by enrollments.
Methodology	Customer-specific regressions using own within-subject analysis.	Reference loads are simulated from customer-specific regressions.	Possible difference between simulated ex ante and estimated ex post reference loads. In this case, however, the aggregate differences are minimal.

5 Summary of the AC Saver Day Of Program[18]

5.1 AC Saver Day Of Program Description

San Diego Gas and Electric Company's (SDG&E) AC Saver Day Of program is a demand response resource based on central air conditioner (CAC) load control that is implemented through an agreement between SDG&E and Comverge, Inc.[19] This report provides 2018 ex post load impact estimates and ex ante load impact estimates for an 11-year forecast horizon (2019–

[18] The AC Saver Day Of Load Impact Evaluation was conducted by Nexant Inc. This section of the Executive Summary contains excerpts from the following evaluation: Potter, C. & Gottlieb, R., Nexant, Inc. (2019). "AC Saver Day Of 2018 Load Impact Program Evaluation".

[19] AC Saver Day Of was previously marketed to SDG&E customers as the Summer Saver program. The program name changed to AC Saver Day Of in 2018.

2029) as required by the California Public Utilities Commission (CPUC) Load Impact Protocols[20].

The AC Saver Day Of program is classified as a day-of demand response program and is available to both residential and commercial customers, where eligible commercial customers are subject to a demand limit; only those commercial customers with average monthly peak demand up to a maximum of 100 kW over a 12-month period may participate. AC Saver Day Of events may only be called during the months of April through October. Under the current program, load control events may not run for more than 4.5 hours. Participants' air conditioners cannot be cycled for more than 4.5 hours in any event day and events cannot be triggered for more than 80 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 commercial customers alike.

Relatively new to the program design is the current program event triggering mechanism. Previously, an event was triggered by system conditions, specifically when day-ahead forecasted system load reaches 4,000 MW. Under program design changes that took place in 2017, event triggers vary by month. During the months of July, August, or September, an AC Saver Day Of event can be triggered by any of the following criteria:

- Generator heat rates reaching or exceeding 19,000 Btu[21] /kWh;
- Imminent statewide or local emergencies, extreme conditions, and/or local distribution needs; or
- Upon the award of a bid into the California Independent System Operator (CAISO) wholesale market.

AC Saver Day Of events may be called between noon and 9 PM, and each event may last 1 to 4.5 hours in duration. Prior to 2017, an AC Saver Day Of event could be called between noon and 8 PM, and each event could last 2 to 4 hours.

There are two enrollment options for both residential and commercial 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 $10.35 per ton per year of CAC capacity and the 100% cycling option pays $27 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:

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[20]See CPUC Rulemaking 07-01-041 Decision (D.) 08-04-050, "Adopting Protocols for Estimating Demand Response Load Impacts" and Attachment A, "Protocols."

[21] British thermal unit, defined as the amount of heat required to raise the temperature of one pound of water by one degree Fahrenheit.

- $41.40 for 50% cycling; or
- $108 for 100% cycling.

Commercial customers have the option of choosing 30% or 50% cycling. The incentive payment for 30% cycling is $4.50 per ton per year and $7.50 per ton per year for the 50% cycling option. A commercial customer with five tons of air conditioning would be paid the following in the form of an annual credit on their SDG&E bill:

- $22.50 for 30% cycling; or
- $37.50 for 50% cycling.

Enrollment in the AC Saver Day Of program as of October 2018 is summarized in Table 5-1. Total enrollment—as measured by number of customers, number of devices, and CAC capacity (measured in tons)—has decreased since 2017 due to the program change to drop residential program participants with a net energy metering (NEM) agreement with SDG&E. As of October 2018, there were 15,475 customers enrolled in the program, which in aggregate represents 83,124 tons of CAC capacity. This represents about a 24% decrease in enrolled customers and in enrolled tons relative to 2017. For the 2018 program year, residential customers represented approximately 71% of AC Saver Day Of participants and accounted for about 53% of the program's total cooling tons. About 65% of residential customers selected the 50% cycling option and approximately 21% of commercial customers chose the 30% cycling option, which represent the lower of the two cycling strategies offered to those customer segments. After holding steady around 50% for many years, the percentage of residential customers taking the 100% cycling option has steadily declined—from 46% in 2014 to 37% in 2017 and to 35% in 2018. The reverse trend has been observed among commercial customers selecting the 50% option, from 60% in 2010 to 79% in 2017, and holding at 79% in 2018.

Table 5-1: AC Saver Day Of Enrollment - October 2018

Customer Type	Cycling Option	Enrolled Customers	Enrolled Control Devices	Enrolled Tons
Commercial	30%	936	2,702	10,336
	50%	3,498	7,547	28,377
	Total	4,434	10,249	38,714
Residential	50%	7,160	8,123	27,999
	100%	3,881	4,615	16,411
	Total	11,041	12,738	44,410
Grand Total		15,475	22,987	83,124

5.2 AC Saver Day Of Ex post Evaluation Methodology

The primary task in developing ex post load impacts is to estimate 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 distinct approaches were used for estimating the reference loads: a randomized controlled trial (RCT) design and a statistical matching design. Residential customer impacts were estimated using an RCT. The commercial customer impacts were estimated with a matching study. Under the randomized controlled trial, random samples of residential AC Saver Day Of 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 matching design, a matched control was selected for nearly all of the commercial AC Saver Day Of program participants.

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 3,200 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 event to event. This design has significant advantages in providing fast, reliable impact estimates if sample sizes are large enough.

Consistent with the methodology since the 2015 AC Saver Day Of evaluation, a matched control group was selected for the commercial program population—whereby one nonparticipant was selected as a match for each participant on each event. The entire SDG&E small and medium business (SMB) 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 a dissimilarity statistic described in Equation 5-1. The dissimilarity statistic measures how similar each candidate for a match is to any given participant customer based on how well (or not) their energy usage characteristics match those of the participant on both the event day and other hot non-event days in 2018, called proxy days. Details surrounding the selection of 2018 proxy days are presented, including a list of the 2018 proxy days, are provided in Appendix A of the PY18 AC Saver Day Of Load Impact Report. The characteristics used in the dissimilarity statistic are:

- Average demand during the hours 6 to 8 PM on the average proxy day;
- Average demand from midnight to 10 AM on the event day; and

- Average demand from 10 AM to the start of the event for each event day.

Equation 5-1: Dissimilarity Statistic for Commercial Matching

$$Dissimilarity_i = (PeakProxy_i - PeakProxy_1)^2 + (EventMorn_i - EventMorn_1)^2 + (EventMidday_i - EventMidday_1)^2$$

Variable	Definition
$PeakProxy$	Average demand across the 2018 proxy days during the hours of 6 to 8 PM
$EventMorn$	Average demand on the event day from midnight to 10 AM
$EventMidday$	Average demand on the event day from 10 AM to 3 PM to the start of the event
1	Commercial AC Saver Day Of participant to be matched
i	Indexes the pool of control customers

This dissimilarity statistic used was chosen as the optimal metric for matching among four alternately specified metrics and following an out-of-sample testing exercise with many propensity score matching models that suggested an alternative approach may perform better. The best metric was chosen based on pre-treatment balance measures.

Matches were chosen such that only customers in the same industry and climate zone would be matched to one another. Likewise, NEM customers were only matched to other NEM customers. This approach minimizes the differences between participants and matched nonparticipants while allowing for good subgroup estimates.

The matching process simply proceeds, one AC Saver Day Of participant at a time, by selecting the non-participant with the same industry and NEM status and with the smallest dissimilarity statistic. A single non-participant may be selected more than once as a matched control customer.

Ex post event impacts were estimated for a broad collection of program segments including customer class, cycling strategy, NEM status, climate zone, industry, size, and status of dual-enrollment in other pricing and demand response programs at SDG&E.

Within each of these program segments, load impacts were estimated for each hour of each event day for both RCT and matching customers using two approaches.

First, the difference between the average demand for those customers who were cycled (the treatment group) and those who were not (the control group) was calculated. This is referred to as the difference in average hourly load as the "unadjusted" load impact.

However, since randomization and matching both can leave some residual differences between the treatment and control groups that is not due to the CAC cycling, Nexant also estimated the "adjusted" load impact that takes into account the small differences between the treatment and control group usage and thereby improves the accuracy and precision of the estimate. This adjusted estimate of load impacts is determined by a lagged dependent variable (LDV) regression model.

The regression, described in Equation 5-2, essentially uses variation among the group that was not cycled to figure out the relationship between demand before the event and on proxy days to the demand during the event window and afterward. The regression can then make a prediction for all of the cycled customers based on that simple model. This is very similar to how a ratio adjustment works. A ratio adjustment multiplies event window demand for the control group by the difference the cycled and control demand prior to the event. An LDV model with one variable does the same thing, but it allows the adjustment to account for differences between the cycled and control group on proxy days as well.[22]

Equation 5-2: LDV Model for Estimating Impacts

$$Demand_i = a + t * Cycled_i + b * Proxy_i + c * ProxyWindow_i + d * ProxyEve_i + e * EventMorn1_i \\ + f * EventMorn2_i + g * EventMorn3_i + h * PreEvent_i + u_i$$

[22] Such an LDV model would be specified as

$$Demand_i = a_2 + t_2 * Cycled_i + h_2 * PreEvent_i + u_i$$

Variable	Definition
$Demand$	Average demand in the event hour being studied
$Cycled$	An indicator for whether customer i was cycled
$Proxy$	Average demand in the hour being studied on the average proxy day
$ProxyWindow$	Average demand in the event window on the average proxy day
$ProxyEve$	Average demand after the event window on the average proxy day
$EventMorn1$	Average demand from midnight to 7 AM on the event day
$EventMorn2$	Average demand from 7 AM to 10 AM on the event day
$EventMorn3$	Average demand from 10 AM to four hours before the event on the event day
$PreEvent$	Average demand during the four hours before the event
i	Customer index
t	Estimated impact
$a - h$	Estimated regression coefficients
u	Error term

For estimating treatment effects, as what was done in this setting, the adjustments from the LDV only change the estimate of the treatment effect if the group that was cycled is different from the group that was not cycled on proxy days or in the hours leading up to the event. These differences should be relatively small for most of the important treatment effect estimates since the matching and RCT performed well. When that is true, the treatment effect estimates with and without the adjustment will look similar, but the confidence intervals will be much smaller for the adjusted version because the LDV model uses the data more efficiently.

Hourly impact estimates for the residential AC Saver Day Of 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, and climate zone within cycling option.

5.3 AC Saver Day Of Ex post Load Impact Estimates

5.3.1 AC Saver Day Of Residential *Ex post* Load Impact Estimates

A total of 18 AC Saver Day Of events were called in 2018 including two EM&V early afternoon test events. Table 5-2 presents ex post load impacts for the residential program segment for program years 2018 and 2017, for comparison. The 2018 ex post load impacts do not include load impact estimates for the two EM&V early afternoon events since the event windows on those days occur outside of the new RA hours.

Aggregate residential load impacts ranged from a low of -0.07 MW on September 27, 2018 to a high of 5.71 MW on July 6, 2018. This low result on September 27th is explained in part by a temperature metric that captures overnight heat buildup – the average temperature from midnight to 5 PM, denoted “mean17” – which was only 69.9 °F on that day. Such a low temperature earlier in the day indicates that cooling loads during the event window would likely be minimal. The two other event days with mean17’s below 70 °F, June 6th and September 26th, showed similarly low load impacts of 0.54 MW and 0.11 MW, respectively. Conversely, the mean17 on July 6th was 81.8 °F, and the mean17 on the day with the second-highest load impact of 3.45 MW, August 7th, was 79.4 °F. All 2018 AC Saver Day-of residential impacts are statistically significant at the 90% confidence level with the exceptions of the two September events.

“Average Event Day” load impacts are calculated using only events with the same event duration and time of day. This is done because load impacts for the direct load control of residential CAC units are highly sensitive to the hour in which the event was dispatched, so events with different event times cannot be directly compared. In this case, the average event day load impacts are calculated using the events on July 12, 16, 19, 20, 24, 25, 30, and 31, August 6, 7, and 9, and September 26. All twelve of these events were dispatched from 6 to 8 PM. Note that load impacts for these event days reflect a wide variety of temperature conditions. The twelve 2018 AC Saver Day Of events included in the Average Event Day estimate yield an aggregate load reduction of 2.40 MW.

The Average Event Day load impacts per premise in 2017 and 2018 were 0.42 kW and 0.25 kW, respectively. These averages were calculated using events with similarly timed event windows (4-8 PM in 2017 and 6-8PM in 2018), but with hotter average mean17 temperatures in 2017 (80 °F) than in 2018 (77 °F), and hotter average event window temperatures in 2017 (89 °F) then in 2018 (81 °F). Besides the large temperature difference, one key driver of the difference in aggregate ex post load impacts between 2017 and 2018 is the number of residential customers enrolled in the program: while 2017 saw 13,826 average participants per event, 2018 saw only 9,716. These drop-in customers are due in part to normal attrition and due to the removal of residential customers with NEM from the participant list.

Table 5-2: AC Saver Day Of Residential *Ex post* Load Impact Estimates

Year	Date	Impact			Mean17 (°F)
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2017	8/1/2017	0.31	0.37	5.72	76
	8/2/2017	0.19	0.23	3.12	78
	8/3/2017	0.32	0.39	5.33	80
	8/28/2017	0.31	0.36	5.04	76
	8/31/2017	0.43	0.51	7.02	82
	9/1/2017	0.50	0.59	8.18	84
	Average*	**0.35**	**0.42**	**5.74**	**80**
2018	6/12/2018	0.05	0.06	0.62	69
	7/6/2018	0.57	0.66	6.62	82
	7/12/2018	0.16	0.19	1.83	76
	7/16/2018	0.11	0.13	1.27	73
	7/17/2018	0.10	0.11	1.09	74
	7/19/2018	0.09	0.10	1.01	74
	7/20/2018	0.11	0.13	1.24	73
	7/24/2018	0.33	0.38	3.73	80
	7/25/2018	0.23	0.27	2.63	77
	7/30/2018	0.30	0.35	3.39	79
	7/31/2018	0.24	0.27	2.66	79
	8/6/2018	0.33	0.38	3.70	77
	8/7/2018	0.35	0.41	3.97	79
	8/9/2018	0.29	0.33	3.21	83
	9/26/2018	0.01	0.01	0.09	68
	9/27/2018	-0.01	-0.01	-0.08	70
	Average**	0.21	0.25	2.40	77
* Reflects the average 2017 AC Saver Day Of event (all 4-8PM weekday events)					
** Reflects the average 6-8 PM 2018 AC Saver Day Of event					

5.3.2 AC Saver Day Of Commercial *Ex post* Load Impact Estimates

Table 5-3 presents the ex post load impact estimates for commercial customers for each 2018 event day (excluding the two EM&V early afternoon event days) and the Average Event Day. Here again, the Average Event Day load impacts are calculated using July 12, 16, 19, 20, 24, 25, 30, and 31, August 6, 7, and 9, and September 26. All twelve of these events were dispatched from 6 to 8 PM. Several 2017 ex post load impacts are shown for comparison. The commercial segment of AC Saver Day Of is smaller than the residential segment: commercial customers represent about 29% of the total AC Saver Day Of participants and about 47% of the enrolled CAC tonnage. In addition to the lower number of enrolled commercial customers and cooling tons, the per premise load impacts for commercial customers are smaller than those for residential customers. This is due in part to the fact that enrolled commercial CAC units are cycled less than the residential CAC units – commercial units have options of 30% or 50%, versus residential unit options of 50% or 100%. Additionally, commercial load impacts are lower than residential impacts due to the timing of the AC Saver Day Of events, which in 2018 predominantly occur when per premise load is ramping down towards the commercial daily minimum usage that occurs in the evening and overnight hours, as opposed to during the residential daily maximum usage that occurs at the same time.

Commercial aggregate impacts vary from a low of 0.11 MW (not statistically significant) on July 20 to a high of 1.48 MW on July 6. The peak for commercial load impact occurs on the same day as the residential segment, which is expected given the high temperature that day.

The 2018 commercial per premise impacts are approximately half of those observed in 2017, as is also the case in the residential section. The Average Event Day load impact in 2017 (when events were called from 4-8 PM) was 0.21 kW per premise, and the Average Event Day load impact was 0.12 kW in 2018 (when events were called from 6-8 PM). This, again, is likely due in part to the higher temperatures experienced in 2017 relative to 2018. In the case of the commercial impacts, all per premise impacts below 0.10 kW are not statistically significant.

Table 5-3: AC Saver Day Of Commercial *Ex post* Load Impact Estimates

Year	Date	Impact			Mean17 (°F)
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2017	8/1/2017	0.08	0.19	0.83	80
	8/2/2017	0.09	0.20	0.90	83
	8/3/2017	0.16	0.37	1.65	81
	8/28/2017	0.10	0.24	1.06	81
	8/31/2017	0.11	0.26	1.15	85
	9/1/2017	0.06	0.15	0.66	90
	Average*	**0.09**	**0.21**	**0.93**	**84**
2018	6/12/2018	0.06	0.14	0.61	69
	7/6/2018	0.14	0.33	1.48	81
	7/12/2018	0.03	0.06	0.27	75
	7/16/2018	0.02	0.05	0.21	72
	7/17/2018	0.02	0.05	0.24	74
	7/19/2018	0.07	0.17	0.74	74
	7/20/2018	0.01	0.02	0.11	73

Table 5-3: AC Saver Day Of Commercial *Ex post* Load Impact Estimates (Continued)

Year	Date	Impact			Mean17 (°F)
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2018	7/24/2018	0.04	0.11	0.47	79
	7/25/2018	0.08	0.20	0.87	76
	7/30/2018	0.06	0.13	0.58	79
	7/31/2018	0.04	0.10	0.45	78
	8/6/2018	0.07	0.17	0.76	77
	8/7/2018	0.06	0.13	0.60	79
	8/9/2018	0.09	0.20	0.91	83
	9/26/2018	0.04	0.09	0.42	68
	9/27/2018	0.05	0.11	0.48	69
	Average**	0.05	0.12	0.53	76

* Reflects the average 2017 AC Saver Day Of event (all 4-8 PM weekday events)
** Reflects the average 6-8 PM 2018 AC Saver Day Of event

5.4 AC Saver Day Of Ex ante Evaluation Methodology

Ex ante load impacts were developed using relatively recent ex post load impacts. While reliably estimated load impacts are available going back ten years, the older load impact estimates are not likely to be as relevant as the most recent ones, due to the fact that the program's fleet has been aging over the past ten years without any significant program efforts to refresh older equipment in field. Ex post load impacts from 2017 and 2018 were used as the foundational data for developing the ex ante model that estimates AC Saver Day Of load impacts' weather response.

In 2017 and 2018, the majority of events were called markedly later in the day than in previous years. In estimating ex ante load impacts, a single model was fit that estimates the weather responsiveness of average ex post load impacts. Since events were called so late in the day in 2017, the average load impacts used for 2017 events are defined as the average load impact across the window 6 to 8 PM. The benefit of these selections of the hours included in the averages are that none of the hours included in them are first-hour load impacts (which are usually much lower than impacts later in events and one strives for consistency in what the average represents) and that they result in the greatest amount of data points available for estimating the model. The remainder of this section refers to this set of average load impacts, the 6 to 8 PM average ex post impacts from 2017 and 2018 as the core ex post impacts.

Another important quality of the core ex post load impacts used in estimating ex ante load impacts is that all ex post impacts in the estimation dataset reflect important changes to the program; the drop of the bottom 30% of electricity users that occurred in 2017 and the drop of residential NEM customers in 2018.

The methodology for estimating ex ante impacts in 2018 is the same for residential and commercial participants. The core ex post load impacts are 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 is used to capture the impact of heat buildup leading up to and including the event hours. Per ton load impacts have historically been used in the AC Saver Day Of load impact evaluation 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 regressions only include one explanatory variable; more complicated models were not found to perform better in prior AC Saver Day Of evaluations, owing mostly to the relatively limited dataset of ex post load impacts that is available for ex ante estimation. Equation 5-3 presents the model that was used to predict average ex post impacts as a function of weather. This model is estimated separately by customer class (residential and commercial) and cycling strategy. The estimated parameters from the models are used to predict load impacts under 1-in-2 and 1-in-10-year ex ante weather conditions.

Equation 5-3 *Ex ante* Model for Predicting *Ex post* Load Impacts' Weather Response

$$impact_d = b_0 + b_1 \cdot mean17_\mathrm{d} + \varepsilon_d$$

Variable	Definition
$Impact_d$	Core 2017-2018 *ex post* impact
b_0	Estimated constant
b_1	Estimated parameter coefficient
$mean17_d$	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*

5.5 AC Saver Day Of Ex ante Load Impact Estimates

Table 5-4 summarizes the average and aggregate load impact estimates per premise under SDG&E-specific peaking conditions and CAISO peaking conditions for 2019. The per premise load impacts are highest under both CAISO and SDG&E system September monthly peak conditions for residential and commercial. Similarly, the per premise impacts are lowest for the May monthly peak for all scenarios and customer types, except for SDG&E 1-in-2 weather conditions which are lowest for the June monthly peak.

For a typical event day in a 1-in-2 year under SDG&E-specific weather conditions, the impact per premise is 0.28 kW for residential customers and 0.44 kW under 1-in-10 weather conditions. The hottest weather conditions are expected in the month of September, where under the SDG&E-specific 1-in-2 conditions per premise load impacts peak at 0.48 kW and at 0.57 kW under 1-in-10 conditions. Large differences between 1-in-2 and 1-in-10 load impacts are driven by large 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.

Load impacts for commercial customers follow similar patterns. Under the SDG&E peaking scenarios, typical event day per premise load impacts are 0.21 kW under the 1-in-2 assumption and 0.27 kW under the 1-in-10 assumption. In September, commercial per premise load impacts peak at 0.30 kW under 1-in-2 conditions and 0.33 under 1-in-10 conditions. While the commercial load impacts are very similar to residential impacts, they on the one hand reflect lower cycling strategies and on the other reflect more CAC units enrolled in the program per premise. The net effect is that commercial load impacts are similar, but somewhat lower, than residential. The milder cycling strategies also yield less-sensitive load impacts for commercial participants as compared to residential participants.

The aggregate program load reduction potential for residential customers is 2.6 MW for a typical event day under SDG&E-specific 1-in-2 year weather conditions in 2018 and 0.9 MW for commercial customers. Under SDG&E-specific 1-in-10 year weather conditions, the aggregate impacts for residential and commercial customers are 4.0 MW and 1.2 MW, respectively. The aggregate impacts under CAISO weather conditions are slightly lower for both weather year types.

Table 5-4: AC Saver Day Of 2019 *Ex ante* Load Impact Estimates by CAISO and SDG&E-specific Weather and Day Type

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	0.27	0.28	0.40	0.44	2.5	2.6	3.7	4.0
	May Monthly Peak	0.00	0.07	0.28	0.32	0.0	0.7	2.9	3.4
	June Monthly Peak	0.00	0.00	0.46	0.37	0.0	0.0	4.9	3.9
	July Monthly Peak	0.16	0.26	0.31	0.34	1.5	2.4	2.9	3.2
	August Monthly Peak	0.43	0.39	0.39	0.47	3.9	3.6	3.6	4.3
	September Monthly Peak	0.49	0.48	0.45	0.57	4.4	4.3	4.1	5.2
	October Monthly Peak	0.18	0.26	0.35	0.37	1.6	2.4	3.1	3.4
Commercial	Typical Event Day	0.21	0.21	0.26	0.27	0.9	0.9	1.1	1.2
	May Monthly Peak	0.09	0.13	0.21	0.23	0.4	0.6	0.9	1.0
	June Monthly Peak	0.10	0.10	0.27	0.24	0.4	0.4	1.2	1.0
	July Monthly Peak	0.16	0.20	0.21	0.23	0.7	0.9	0.9	1.0
	August Monthly Peak	0.27	0.25	0.25	0.29	1.1	1.1	1.1	1.2
	September Monthly Peak	0.30	0.30	0.29	0.33	1.3	1.3	1.2	1.4
	October Monthly Peak	0.17	0.20	0.24	0.25	0.7	0.9	1.0	1.1

5.6 Relationship between Ex post and Ex ante Load Impact Estimates

Table 5-5 facilitates a comparison of the ex post load impact estimate for the July 6th event and ex ante estimates for 1-in-2 and 1-in-10 SDG&E weather conditions. This event in particular was selected because its event window of 4 PM to 8 PM lined up with a large number of 2017 events, all of which were used together to create an approximate load shape for the RA window of 4 PM to 9 PM. Because this was the only event in 2018 with an event window of 4 PM to 8 PM, this is the only event that can be directly compared with ex ante results using the method described in this section.

This table demonstrates the four important changes that are made to go from ex post results to ex ante predictions: enrollment numbers, predictions using a weather-dependent model, the event window, and weather. The steps below help explain each of these changes:

1. First, 8.1 MW (Column D) was delivered by AC Saver Day Of on July 6th, 2018, when the heat build-up (as measured by mean17) was 81.4 °F (Column B). This load impact was generated by 14,496 AC Saver Day Of participants (Column C).

2. Given the mean17 observed on this date (Column B), and the observed enrollment numbers (Column C), our ex ante model predicts that one would expect AC Saver Day Of to deliver 5.8 MW of load reduction (Column E). This model is based on a multitude of event days from 2017 and 2018, and because our model is linear, this difference between ex post (Column D) and ex ante (Column E) implies that the load impact observed on July 6th, 2018 was higher than average.

3. The next step is to perform the same ex ante model calculation as in Step 2, but to use the predicted enrollment numbers (Column F) in place of the observed enrollment numbers (Column C). With the total enrollment number changing, there may also be changes in the proportions of residential and commercial customers, and of the enrollments in different cycling options within each customer type, all of which is captured by the model. Using these new enrollment figures, our ex ante model predicts that one would expect AC Saver Day Of to deliver 5.4 MW of load reduction (Column G) on a day with a similar temperature profile as July 6th, 2018 (Column B).

4. Another key difference in going from ex post to ex ante results is that ex ante results are designed to cover the RA window of 4 PM to 9 PM, which is longer than any AC Saver Day Of events. This is resolved by creating an approximate load shape that covers the RA window, which is used to convert the ex ante model output to an ex ante impact. Here, the observed ex post load impact is taken (Column D), then the predicted enrollment numbers from ex ante (Column F) are applied and stretch the hourly impacts to fit the approximate RA window load shape. This gives an adjusted ex post load impact of 6.7 MW (Column H).

5. We may now compare this adjusted ex post impact "apples-to-apples" with ex ante load impacts, since they now use the same enrollment (Column F) and RA window load shape. Our adjusted ex post load impact of 6.7 MW (Column H) occurs at a mean17 value of 81.4 °F (Column B). That temperature is higher than the 1-in-10 mean17 value for a July monthly system peak day of 78.0 °F (Column K); therefore, one expects the adjusted ex post load impact to be larger in magnitude than the 1-in-10 ex ante load impact estimate. Indeed, this is the case – the 1-in-10 ex ante load impact estimate is 4.2 MW (Column L), which is substantially lower than the adjusted ex post load impact of 6.7 MW (Column H).

Table 5-5 Comparison of 2018 *Ex post* Load Impacts to 2019 *Ex ante* Load Impacts

Ex Post	Date and Event Time	A	7/6/2018 4 - 8 PM
	Mean17 (°F)	B	81.4
	Ex Post Enrollment	C	14,496
	Ex Post Estimate (MW)	D	8.1
	Ex Ante Estimate Using 2018 Enrollment (MW)	E	5.8
	Ex Ante Enrollment	F	13,579
	Ex Ante Estimate Using 2019 Enrollment (MW)	G	5.4
	Ex Post Estimate Using 2019 Enrollment and Adjusted to RA Window (MW)	H	6.7
SDG&E 1-in-2	Mean17 (°F)	I	75.6
	Ex Ante Estimate Using 2019 Enrollment and Adjusted to RA Window (MW)	J	3.3
SDG&E 1-in-10	Mean17 (°F)	K	78
	Ex Ante Estimate Using 2019 Enrollment and Adjusted to RA Window (MW)	L	4.2

6 Summary of the Opt-in Peak Time Rebate Program (PTR) and AC Saver Day Ahead Residential Program[23]

6.1 Program Overview

6.1.1 Opt-In Peak Time Rebate Program Overview

The PTR program provides customers with notification on a day-ahead basis that a PTR event will occur on the following day. The PTR program is marketed as Reduce Your Use. In emergency situations, an 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 usage 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.

Table 6-1 summarizes the PTR program enrollment. Slightly more than 83,000 customers had enrolled in the PTR program between May 1st and August 9th, 2018 (the last PTR event day). Roughly two and half percent of these participants were dually enrolled in the AC Saver DO (aka Summer Saver) program and roughly eleven percent of participants enrolled in PTR a DR enabling thermostat (TD on PTR). These TD on PTR participants were eligible for the premium incentive ($1.25/kWh) for reducing energy use through automated DR enabling technologies.

Approximately 60% of PTR participants enrolled for email notification only, with another 14.6% enrolled jointly in email and text notifications. Text message-only notifications account for most of the remaining participants at 17.5%. Only 2.1% of participants received only telephone notifications.

[23] The PTR and AC Saver Day Ahead evaluation was conducted by Itron. This section of the Executive Summary contains excerpts from the following evaluation: ITRON (2019). "2018 Impact Evaluation of San Diego Gas & Electric's Peak Time Rebate and AC Saver Day Ahead Residential Programs: *Ex Post and Ex Ante Report*".

Table 6-1: Summary of PTR Enrollment by Customer Category[1]

Customer Category[2]	Participants	
	N	%
PTR without Enabling Technology	72,507	87.0%
TD on PTR	8,976	10.8%
Dually enrolled in AC Saver DO	1,853	2.2%
Coastal Climate Zone	41,851	50.2%
Inland Climate Zone	41,485	49.8%
Notification Type – Email Only	49,049	58.9%
Notification Type – Text Only	14,563	17.5%
Notification Type – Phone Only	1,723	2.1%
Notification Type – Email & Text	12,202	14.6%
Notification Type – Email & Phone	2,816	3.4%
Notification Type – Text & Phone	715	0.9%
Notification Type – All Three	2,055	2.5%
All PTR Participants	83,336	100%

[1] Active at any point between May1,2018 and August 9, 2018 (the PTR event season)
[2] Participants with unknown Notification Types are not included as a customer category, but are included in participant counts

6.1.2 *Overview of the Residential AC Saver Day Ahead Program*

The residential AC Saver DA program provides demand response through a four-degree setback on a DR enabling thermostats during events. AC Saver DA events last two to four hours and can be called between 12:00 p.m. and 9:00 p.m. In 2018, there were eighteen AC Saver DA events with varying event hours and durations, but generally ran for two hours between 6:00 p.m. and 8:00 p.m. There are two thermostat options for participant in the program, free and Bring Your Own Thermostat (BYOT). In past years, SDG&E offered a free Ecobee Smart Si thermostat to qualifying customers in the previously named SCTD program. Beginning in 2017, SDG&E added a BYOT option to the program. The eligible BYOT thermostats include the Nest Learning Thermostat, the Nest Thermostat E, the Ecobee 3 Thermostat, and the Ecobee 4 Thermostat.

Table 6-2 summarizes the AC Saver DA program enrollment. Slightly more than 11,800 customers were enrolled in the AC Saver Program between May 1st and September 30th, 2018. As seen, participation in the program was roughly equal between inland and costal climate zones.

Approximately two thirds (61%) of program participant were equipped with BYOT thermostats whereas 36% of participants received a free thermostat.

Table 6-2: Summary of AC Saver DA Enrollment by Customer Category[1]

Customer Category[2]	Participants	
	N	%
Coastal Climate Zone	5,942	50%
Inland Climate Zone	5,916	50%
BYOT Thermostat Source[2]	7,291	61%
Free Thermostat Source[2]	4,272	36%
All AC Saver DA Participants	11,858	100%

[1] Active at any point between May1,2018 and September 30, 2018 (AC Saver DA event season)

[2] Participants with unknown thermostat sources are not included as a customer category, but are included in participant counts

6.2 PTR and AC Saver Day Ahead Ex post Evaluation Methodology and Validation

To estimate ex post load impacts for the PTR opt-in and AC Saver DA programs, Itron developed regression-based models 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 matching and ex post estimations are described in detail below.

6.2.1 *Control Group Selection*

Control groups were used to measure impacts from the PTR and AC Saver DA programs. The use of control groups help improve the estimation of reference loads and impacts when obfuscating conditions exist, such as: 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, c) small average impacts relative to the overall size of the average participant load during the events. To develop control groups for this evaluation, Itron used a Stratified Propensity Score Matching (SPSM) method.

6.2.2 *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[24]: PTR participation, thermostat participation, and having Net Energy Metering (NEM). Each of the six possible participant combinations of these characteristics were also stratified by climate zone (coastal and inland). In total, this provided 12 different strata from which to develop control groups.

Table 6-3: Pre-Matching Participant Stratification

Strata	PTR Participant/Rate	Net Energy Metered	Thermostat Participant (Including AC Saver DA and TD on PTR)	Climate Zones
1	✓	✓	×	Inland, Coastal
2	✓	×	×	Inland, Coastal
3	✓	✓	✓	Inland, Coastal
4	✓	×	✓	Inland, Coastal
5	×	✓	✓	Inland, Coastal
6	×	×	✓	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 used the hourly interval data for a random sample of 500,000 non-participant customers. The PSM selected the control group using variables developed from interval data. The matching was performed separately for PTR, TD on PTR participants by the stratification detailed above, as well as for the other various participant subgroups, namely Summer Saver and Low Income.

After experimenting with various combinations, the final set of variables based on interval data for the months of June through October of 2018 were chosen. The logit model for strata 1,2,3, and 4 included hot day[25] morning kWh usage, hot day event hours kWh usage, hot day evening kWh usage, and annual usage size dummy variables (small and medium). Strata 5 and 6 are included also included average monthly weekday usage.

24 Participant characteristics are based on the characteristics at the start of the event season. Some TD on PTR moved from a PTR rate to the AC Saver DA program on September 19, 2018. All TD on PTR participants are included in the PTR Participant and thermostat participant strata. As a result, AC Saver DA and TD on PTR participants are in mutually exclusive strata.

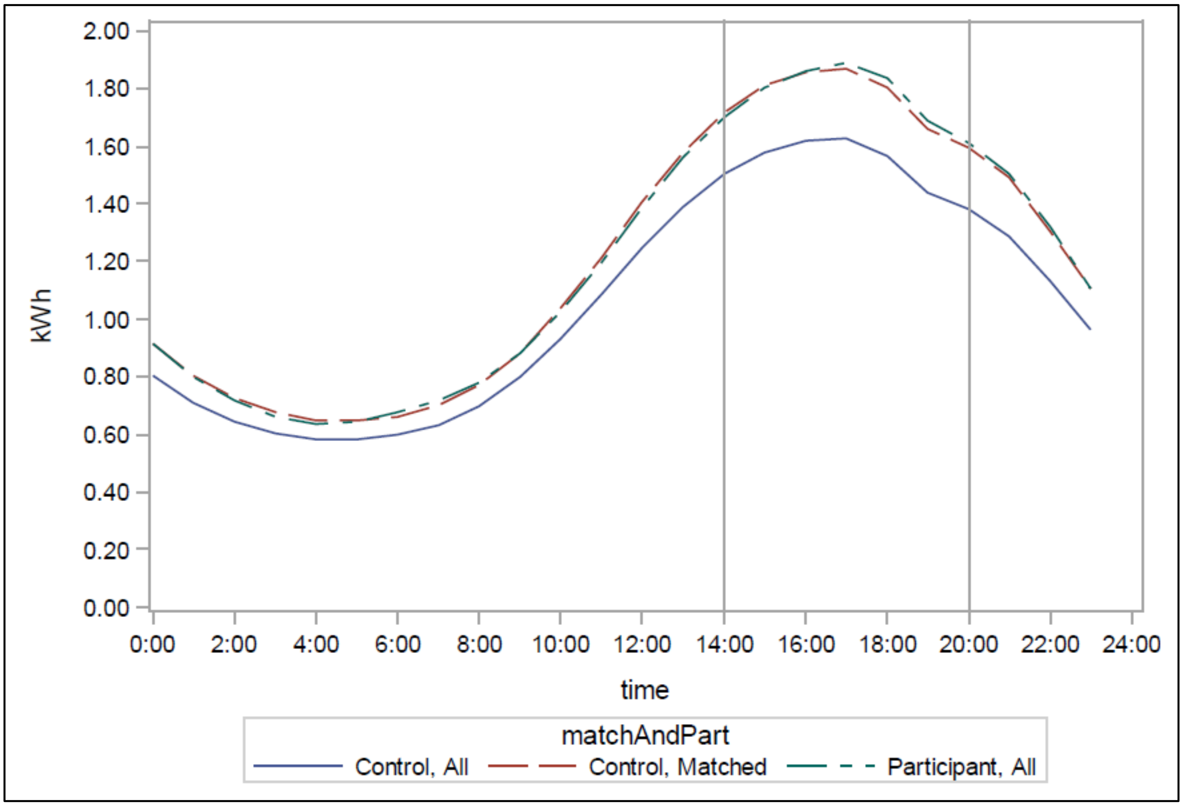
25 For hot days, Itron selected the five non-event days in the summer of 2018 with the highest average peak temperatures across the different weather stations used for the analysis. The dates with these peak temperatures were the 23rd and 27th of July and the 1st, 8th, and 10th of August 2018. Load profiles by season were also compared to confirm that the groups were sufficiently similar.

6.2.3 *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 AC Saver DA 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. The candidate premises selected in the PSM have virtually the same profile as the participants, whereas the load profile for all non-participant premises before matching has substantially lower consumption.

Figure 6-1 shows a comparison of the average hourly load profile on hot days for the participant and control groups for the Inland PTR group before and after the matching. The event window is marked by vertical lines and it is clear that the control and participants line up much more closely after the matching during these key hours. While the t-test results are strong evidence that the PSM method worked well, these visual representations provide further confirmation of its success.

Figure 6-1: Comparison of Hourly Hot Day Load Profiles for Control Group with All and Only Matched PTR Participants



6.2.4 *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 dummy variables for hour, day of the week, month, and event indicators, along with continuous variables for cooling degree hours (CDH65). 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:

$$
\begin{aligned}
kWh_{i,t} = \beta_0 &+ \sum\nolimits_d \beta_1^d \times DOW_t^d + \sum\nolimits_m \beta_2^m \times Month_t^m + \sum\nolimits_h \beta_3^h \times Hour_t^h \\
&+ \sum\nolimits_d \sum\nolimits_h \beta_4^{h,d} \times Hour_t^h \times DOW_t^d + \sum\nolimits_m \sum\nolimits_h \beta_5^{h,m} \times Hour_t^h \times Month_t^m \\
&+ \beta_6 \times CDH65_{i,t} + \sum\nolimits_h \beta_7^h \times Hour_t^h \times CDH65_{i,t} + \sum\nolimits_h \beta_8^h \times Hour_t^h \times Event_t \\
&+ \sum\nolimits_h \beta_9^h \times Hour_t^h \times Event_t \times CDH65_{i,t} \\
&+ \sum\nolimits_h \beta_{11}^h \times Hour_t^h \times Event_t \times InactivePart_{i,t} \\
&+ \sum\nolimits_h \beta_{12}^h \times Hour_t^h \times Event_t \times ActivePart_{i,t} \\
&+ \sum\nolimits_h \beta_{13}^h \times Hour_t^h \times Event_t \times InactivePart_{i,t} \times CDH65_{i,t} \\
&+ \sum\nolimits_h \beta_{14}^h \times Hour_t^h \times Event_t \times ActivePart_{i,t} \times CDH65_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

Where:

$kWh_{i,t}$	Is the kWh in time *t* for site *i*
DOW_t^d	Is the day of week dummy variable series, = 1 if time *t* is day *d*, and = 0 otherwise
$Month_t^m$	Is the month dummy variable series, = 1 if time *t* is month *m*, and = 0 otherwise
$Hour_t^h$	Is the hour dummy variable series, = 1 if time *t* is hour *h*, and = 0 otherwise
$CDH65_{i,t}$	Is the cooling degree hour for site *i* and hour *t*, calculated using 65 degree as base
$Event_t$	= 1 if time *t* is in an event day, and = 0 otherwise
$ActivePart_{i,t}$	= 1 if at time *t*, site *i* is an active participant, and = 0 otherwise
$InactivePart_{i,t}$	= 1 if site *i* participated after time *t*, and = 0 otherwise
β_0	Is the intercept
β_1^d	Is the set coefficients for day of week (DOW) *d*
β_2^m	Is the set of coefficients for month *m*
β_3^h	Is the set of coefficients for hour *h*
$\beta_4^{h,d}$	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), measuring how much more energy a site would consume, on average, if the cooling degree hours go up by one
β_7^h	Is the set of coefficients for CDH interacted with hour *h*, measuring how much more energy a site would consume, on average, if the cooling degree hours go up by one in hour *h*
β_8^h	Is the set of coefficients that measure how much energy the non-participants would consume more during the event days than non-event days, and in hour *h*, on average
β_9^h	Is the set of coefficients that measure how much more energy the non-participants would consume during the event days than non-event days, if cooling degree hour increases by one, and in hour *h*

β_{11}^{h}	Is the set of coefficients that measure how much energy the inactive participants would consume more during the event days than non-event days, and in hour *h*, on average
β_{12}^{h}	Is the set of coefficients that measure how much energy the active participants would consume more during the event days than non-event days, and in hour *h*, on average
β_{13}^{h}	Is the set of coefficients that measure how much more energy the inactive participants would consume during the event days than non-event days, if cooling degree hour increases by one, and in hour *h*
β_{14}^{h}	Is the set of coefficients that measure how much more energy the active participants would consume during the event days than non-event days, if cooling degree hour increases by one, and in hour *h*
$\varepsilon_{i,t}$	Is the error term for site *i* at time *t*

The program impacts were modeled for each hour separately using two variables, 1) the dummy variable that indicates event days, and 2) the interaction of cooling degree hours with event dummy variables. The first one estimates, on average, how much energy a participant would use during an event hour, compared to non-participants. If on average, a participant saved energy during event days, one would then expect a negative coefficient for this variable, or $\beta_{12}^{h}<0$.

The second part estimates how much more energy a participant would consume compared to a non-participant as temperature goes up by one degree. So, if the participants save more when temperature is higher, one would expect a negative coefficient for this term, or $\beta_{14}^{h}<0$. However, if on the other hand, a participant would save less when temperature goes up, one would expect a positive coefficient, or $\beta_{14}^{h}>0$, which would indicate marginally negative savings.

6.2.5 *AC Saver Day Ahead Ex post Methodology*

The model used to estimate savings for the AC Saver DA participants varied from the PTR program. Two key differences exist between the PTR and AC Saver DA models. The first difference is the inclusion of an event hour interaction between specified event hours and AC Saver DA participation to account for varying event hours on event days. And the inclusion of band hours (the hour before and after each event) to account for variation between pre-cooling and snapback during event hours.

Using the population of AC Saver DA participants and its associated matched control group, ex post impacts were using the equation below:

$$
\begin{aligned}
kWh_{i,t} = \beta_0 &+ \sum_d \beta_1^d \times DOW_t^d + \sum_m \beta_2^m \times Month_t^m + \sum_h \beta_3^h \times Hour_t^h \\
&+ \sum_d \sum_h \beta_4^{h,d} \times Hour_t^h \times DOW_t^d + \sum_m \sum_h \beta_5^{h,m} \times Hour_t^h \times Month_t^m \\
&+ \beta_6 \times CDH65_{i,t} + \sum_h \beta_7^h \times Hour_t^h \times CDH65_{i,t} + \sum_h \beta_8^h \times Hour_t^h \times Event_t \\
&+ \sum_h \beta_9^h \times Hour_t^h \times Event_t \times CDH65_{i,t} \\
&+ \sum_h \beta_{11}^h \times Hour_t^h \times Event_t \times InactivePart_{i,t} \\
&+ \sum_h \beta_{12}^h \times Hour_t^h \times Event_t \times ActivePart_{i,t} \\
&+ \sum_h \beta_{13}^h \times Hour_t^h \times Event_t \times InactivePart_{i,t} \times CDH65_{i,t} \\
&+ \sum_h \beta_{14}^h \times Hour_t^h \times Event_t \times ActivePart_{i,t} \times CDH65_{i,t} \\
&+ \sum_h \beta_{15}^h \times Hour_t^h \times BandHour_t \\
&+ \sum_h \beta_{16}^h \times Hour_t^h \times BandHour_t \times CDH65_{i,t} \\
&+ \sum_h \beta_{17}^h \times Hour_t^h \times BandHour_t \times InactivePart_{i,t} \\
&+ \sum_h \beta_{18}^h \times Hour_t^h \times BandHour_t \times ActivePart_{i,t} \\
&+ \sum_h \beta_{19}^h \times Hour_t^h \times BandHour_t \times InactivePart_{i,t} \times CDH65_{i,t} \\
&+ \sum_h \beta_{20}^h \times Hour_t^h \times BandHour_t \times ActivePart_{i,t} \times CDH65_{i,t} \\
&+ \sum_h \beta_{21}^h \times Hour_t^h \times EventHour_t \\
&+ \sum_h \beta_{22}^h \times Hour_t^h \times EventHour_t \times CDH65_{i,t} \\
&+ \sum_h \beta_{23}^h \times Hour_t^h \times EventHour_t \times InactivePart_{i,t} \\
&+ \sum_h \beta_{24}^h \times Hour_t^h \times EventHour_t \times ActivePart_{i,t} \\
&+ \sum_h \beta_{25}^h \times Hour_t^h \times EventHour_t \times InactivePart_{i,t} \times CDH65_{i,t} \\
&+ \sum_h \beta_{26}^h \times Hour_t^h \times EventHour_t \times ActivePart_{i,t} \times CDH65_{i,t}
\end{aligned}
$$

Where:

kWh_t	Is the kWh in hour t
DOW_t^d	Is the day of week dummy variable series, = 1 if time *t* is day *d*, and = 0 otherwise
$Month_t^m$	Is the month dummy variable series, = 1 if time *t* is month *m*, and = 0 otherwise

$Hour_t^h$	Is the hour dummy variable series, = 1 if time *t* is hour *h*, and = 0 otherwise
$CDH65_{i,t}$	Is the cooling degree hour for site *i* and hour *t*, calculated using 65 degrees as base
$Event_t$	= 1 if time *t* is in an event day, and = 0 otherwise
$EventHour_t$	= 1 if time *t* is an event hour, and = 0 otherwise. This term is not included in PTR model, because PTR events were all called during the same time period. So, since the model is effectively estimated by hour, for PTR model, this term is the same as $Event_t$, during the event hours.
$BandHour_t$	= 1 if time *t* is one hour before or after event, and = 0 otherwise. This term is not included in PTR model, and the reason is same as for variable $EventHour_t$. This term is included to capture the possible pre-cooling and snapback effect of the program.
$ActivePart_{i,t}$	= 1 if at time *t*, site *i* is an active participant, and = 0 otherwise
$InactivePart_{i,t}$	= 1 if site *i* participated after time *t*, and = 0 otherwise
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 coefficients for month *m*
β_3^h	Is the set of coefficients for hour *h*
$\beta_4^{h,d}$	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), measuring how much more energy a site would consume, on average, if the cooling degree hours go up by one
β_7^h	Is the set of coefficients for CDH interacted with hour *h*, measuring how much more energy a site would consume, on average, if the cooling degree hours go up by one in hour *h*
β_8^h	Is the set of coefficients that measure how much energy the non-participants would consume more during the event days than non-event days, and in hour *h*, on average
β_9^h	Is the set of coefficients that measure how much more energy the non-participants would consume during the event days than non-event days, if cooling degree hour increases by one, and in hour *h*
β_{11}^h	Is the set of coefficients that measure how much energy the inactive participants would consume more during the event days than non-event days, and in hour *h*, on average
β_{12}^h	Is the set of coefficients that measure how much energy the active participants would consume more during the event days than non-event days, and in hour *h*, on average
β_{13}^h	Is the set of coefficients that measure how much more energy the inactive participants would consume during the event days than non-event days, if cooling degree hour increases by one, and in hour *h*
β_{14}^h	Is the set of coefficients that measure how much more energy the active participants would consume during the event days than non-event days, if cooling degree hour increases by one, and in hour *h*
β_{15}^h	Is the set of coefficients that measure how much energy the non-participants would consume more during the band hours than otherwise, and in hour *h*, on average
β_{16}^h	Is the set of coefficients that measure how much more energy the non-participants would consume during the band hours than otherwise, if cooling degree hour increases by one, and in hour *h*
β_{17}^h	Is the set of coefficients that measure how much energy the inactive participants would consume more during the band hours than otherwise, and in hour *h*, on average
β_{18}^h	Is the set of coefficients that measure how much energy the active participants would consume more during the band hours than otherwise, and in hour *h*, on average
β_{19}^h	Is the set of coefficients that measure how much more energy the inactive participants would consume during the band hours than otherwise, if cooling degree hour increases by one, and in hour *h*
β_{20}^h	Is the set of coefficients that measure how much more energy the active participants would consume during the band hours than otherwise, if cooling degree hour increases by one, and in hour *h*

β_{21}^{h}	Is the set of coefficients that measure how much energy the non-participants would consume more during the event hours than otherwise, and in hour *h*, on average
β_{22}^{h}	Is the set of coefficients that measure how much more energy the non-participants would consume during the event hours than otherwise, if cooling degree hour increases by one, and in hour *h*
β_{23}^{h}	Is the set of coefficients that measure how much energy the inactive participants would consume more during the event hours than otherwise, and in hour *h*, on average
β_{24}^{h}	Is the set of coefficients that measure how much energy the active participants would consume more during the event hours than otherwise, and in hour *h*, on average
β_{25}^{h}	Is the set of coefficients that measure how much more energy the inactive participants would consume during the event hours than otherwise, if cooling degree hour increases by one, and in hour *h*
β_{26}^{h}	Is the set of coefficients that measure how much more energy the active participants would consume during the event hours than otherwise, if cooling degree hour increases by one, and in hour *h*
$\varepsilon_{i,t}$	Is the error term for site *i* at time *t*

The program impacts were modeled for each hour separately using six variables:

1. The dummy variable that indicates event days.
2. The dummy variable that indicates event hours.
3. The dummy variable that indicates band hours.
4. The interaction of cooling degree hours with event day dummy variables.
5. The interaction of cooling degree hours with event hour dummy variables.
6. The interaction of cooling degree hours with band hour dummy variables.

Essentially, this is the same model as the one for PTR program, including one constant term and one interaction term to allow the savings differ by temperature. This model just estimates the event hours and band hours separately than all the other hours. This is because, for PTR program, all the events were called for the same four hours of the day, but for AC Saver Day Ahead program, for different event days, the event hours were different. For example, while most of the events ended at 8 p.m., on July 17th, the event was called until 9 p.m., and was the only event that ended at 9 p.m. Therefore, if PTR model were applied here, the savings during hour 8 p.m. – 9 p.m. on July 17th would be averaged across all 18 days when events were called, and on top of which, hour 8 p.m. – 9 p.m. was the snapback hour for most of the other event days, so the saving from July 17th would be blended with the negative impacts from the snapback effects during the other event days. In this case, both the program effects and the snapback effects would be underestimated.

Another item worth pointing out is the definition of band hours. It includes one hour before and one hour after the event hours. First thing to mention is that this would not mix the pre-cooling effects and the snapback effects, since the pre-cooling band hours include, depending on which event day, hour 15, 16 and 17 (3 – 4 p.m., 4 – 5 p.m. and 5 – 6 p.m.), and snapback band hours include hour 19, 20 and 21 (7 – 8 p.m., 8 – 9 p.m. and 9 – 10 p.m.). Secondly, the model assumes that both pre-cooling effects and snapback effects would take place for only one hour.

This is because, from the past evaluations, it was shown that the pre-cooling, if any, took place only for one hour, and most of the snapback effects were during the first hour after the event.

Therefore, the program impacts during the hours other than event hours or band hours, if any, would be estimated through the variable $Event_t$, and is estimated separately for each hour.

Each set of estimated impacts were grouped by AC Saver DA thermostat source (BYOT or Free) as well as overall.

6.3 PTR and AC Saver Day Ahead Ex post Load Impact Estimates

In 2018, SDG&E called a total of six PTR events and eighteen AC Saver DA events. All PTR events hours occurred from 2 p.m. to 6 p.m., while AC Saver DA event hours varied across event days. AC Saver DA events generally started at 6 pm and went until 8 pm, however specific event times varied across event days. Table4 and Table 6-5 list the PTR and AC Saver DA event Days and hours below.

Table 6-4: List of PTR Event Days and Event Hours

Event Day	Event Start	Event End
July 6th, 2018	2:00pm	6:00pm
July 24th, 2018	2:00pm	6:00pm
July 25th, 2018	2:00pm	6:00pm
August 6th, 2018	2:00pm	6:00pm
August 7th, 2018	2:00pm	6:00pm
August 9th, 2018	2:00pm	6:00pm

Table 6-5: List of AC Saver DA Event Days and Event Hours

Event Day	Event Start	Event End
June 11th, 2018	6:00pm	8:00pm
June 12th, 2018	5:00pm	8:00pm
July 6th, 2018	4:00pm	8:00pm
July 12th, 2018	6:00pm	8:00pm
July 16th, 2018	6:00pm	8:00pm
July 17th, 2018	5:00pm	9:00pm
July 19th, 2018	6:00pm	8:00pm
July 20th, 2018	6:00pm	8:00pm
July 25th, 2018	6:00pm	8:00pm
July 30th, 2018	6:00pm	8:00pm
July 31st, 2018	6:00pm	8:00pm
August 6th, 2018	6:00pm	8:00pm
August 7th, 2018	6:00pm	8:00pm
August 9th, 2018	6:00pm	8:00pm
September 18th, 2018	6:00pm	8:00pm
September 20th, 2018	6:00pm	8:00pm
September 26th, 2018	6:00pm	8:00pm
September 27th, 2018	5:00pm	7:00pm

Table 6-6 through Table 6-8 present a summary of these PTR, TD on PTR and AC Saver DA impact estimates

Table 6-6: PTR Ex Post Load Impact Estimates-By 2018 Event Date (2:00pm to 6:00pm)

Event Dates	Active Participants	Mean Reference Load (kW)	Mean Observed Load (kW)	Mean Impact (kW)	% Load Reduction	Aggregate Load Reduction	Mean °F
July 6th, 2018	80,539	1.55	1.40	0.15	10.4%	12.31	98.9
July 24th, 2018	80,511	1.35	1.25	0.11	8.5%	8.49	90.5
July 25th, 2018	80,758	1.19	1.11	0.09	8.0%	7.04	87.4
August 6th, 2018	80,764	1.24	1.13	0.11	9.9%	8.89	91.3
August 7th, 2018	80,965	1.35	1.23	0.12	9.7%	9.65	92.9
August 9th, 2018	81,253	1.54	1.44	0.10	6.7%	8.16	89.6
Average 2018 Event	80,798	1.37	1.26	0.11	8.8%	9.09	91.8

Table 6-7: PTR Ex Post Load Impact Estimates-By 2018 Event Date (2:00pm to 6:00pm)

Event Dates	Active Participants	Mean Reference Load (kW)	Mean Observed Load (kW)	Mean Impact (kW)	% Load Reduction	Aggregate Load Reduction	Mean °F
July 6th, 2018	8,684	1.84	1.11	0.74	42.9%	6.38	100.0
July 24th, 2018	8,667	1.62	1.06	0.56	38.8%	4.88	91.7
July 24th, 2018	8,685	1.31	0.82	0.50	44.2%	4.33	88.7
August 6th, 2018	8,649	1.46	0.88	0.58	46.2%	4.98	92.4
August 7th, 2018	8,644	1.59	0.98	0.61	43.9%	5.24	93.8
August 9th, 2018	8,654	1.81	1.28	0.53	30.5%	4.55	89.9
Average 2018 Event	8,664	1.61	1.02	0.58	40.3%	5.06	92.7

Table 6-8: AC Saver DA Ex Post Load Impact Estimates by 2018 Event Date

Event Dates	Active Participants	Mean Reference Load (kW)	Mean Observed Load (kW)	Mean Impact (kW)	% Load Reduction	Aggregate Load Reduction	Mean °F
June 11, 2018	9,093	1.06	0.91	0.15	14.2%	1.38	75.7
June 12, 2018*	9,109	1.03	0.87	0.16	15.7%	1.47	75.7
July 6, 2018†	9,401	2.24	1.99	0.25	11.3%	2.36	94.8
July 12, 2018‡	9,500	1.45	1.32	0.13	9.2%	1.28	80.0
July 16, 2018	9,573	1.27	1.12	0.15	11.9%	1.45	75.7
July 17, 2018†	9,588	1.21	1.06	0.15	12.2%	1.42	73.7
July 19, 2018	9,612	1.26	1.10	0.16	12.4%	1.51	76.9
July 20, 2018	9,629	1.35	1.19	0.16	11.8%	1.53	77.2
July 25, 2018	9,734	1.65	1.47	0.18	10.9%	1.76	81.2
July 30, 2018	9,832	1.75	1.56	0.19	10.7%	1.84	82.6
July 31, 2018	9,852	1.63	1.45	0.18	10.9%	1.76	80.8
August 6, 2018	9,959	1.92	1.71	0.21	10.7%	2.05	86.0
August 7, 2018	9,973	1.95	1.74	0.21	10.8%	2.11	86.9
August 9, 2018	10,022	1.88	1.68	0.20	10.8%	2.04	85.8
September 18, 2018	10,174	1.06	0.92	0.14	13.0%	1.40	72.9
September 20, 2018	11,707	0.98	0.86	0.12	12.2%	1.40	69.6
September 26, 2018	11,682	0.99	0.87	0.12	12.6%	1.45	70.5
September 27, 2018	11,679	1.04	0.86	0.18	17.4%	2.12	77.1
2018 Average**	10,007	1.45	1.28	0.17	12.1%	1.70	79.5

* Three-hour event starting at 5:00pm and ending at 8:00pm

† Four-hour event: the July 6th event started at 4:00pm and ended at 8:00pm, the July 17th event started at 5:00pm and ended at 9:00pm

‡One BYOT thermostat vendor signaled participants two hours before the reported event start, effectively making the July12th event a four-hour event for a portion of the population

**2018 Averages represent the average of all event hours

6.4 Ex Ante Methodology and Results

6.4.1 Estimated Ex Ante Load Impacts for the AC Saver Day Ahead Program

Ex ante impacts for the residential AC Saver Day Ahead program were estimated by combining the regression model results from the ex post impacts with two other sources of data. The first data source was a 10-year forecast of enrollment for the program, as well as by thermostat source (free vs. Bring Your Own Thermostat). 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 involved two main steps.

The first step combined the parameters from ex post regression model with the weather scenarios from the various year and day types, to calculate per participant average reference loads, observed loads, and load impacts. The standard errors from the impact variable parameters were used to calculate the uncertainty estimates. It worth pointing out that the 2018 AC Saver program has different event hours for different days, ranging from 4 pm to 9 pm, same as the RA hours for ex ante estimation. However, for 8 pm to 9 pm, there was only one event, and from 4 pm to 5 pm, there were two events for half of the participants, and one for the other half (due to vendor-specific signaling). In all scenarios, the sample is too small to make valid reference. Therefore, in the ex ante estimation, the following adjustments were made:

1. Event hour 16 (4 pm to 5 pm) uses estimation results from hour 17 (5 pm to 6 pm)
2. Event hour 20 (8 pm to 9 pm) uses estimation results from hour 19 (7 pm to 8 pm)

Similarly, for the first hour after event (hour 21), to capture the snapback effect that can be observed from 2018 AC Saver participants' load, ex post estimation results from hour 20 were applied, since 16 out of 18 AC Saver events ended at 8 pm. In addition, to capture the observed pre-cooling effect during AC Saver events, the ex ante estimation applied weighted average of parameters for all the pre-event hours, including hour 15, 16 and 18, using the number of active participants as weights.

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 AC Saver Day Ahead residential program is expected to grow to over 20,000 participants by the end of 2019. By the end of 2022, the program is forecasted to grow to over 40,000 participants. These projections are then expected to remain relatively constant throughout the remainder of the ex ante forecast period.

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 thermostat sources based on the relative shares as of the event days from 2018. 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. The shares used for the allocation of the enrollment forecast are presented in table 6-9.

Table 6-9: Shares for Allocation of Enrollment Forecast

Participant Segment		Coastal	Inland	All	Number of Participants
AC Saver Day Ahead	**BYOT**	37%	27%	64%	5,536
	Free	14%	22%	36%	4,217
	All	51%	49%	100%	10,007*

* AC Saver DA Participants with Unknown thermostat source were excluded from the enrollment shares for ex ante.

6.5 Ex ante Load Impact Results

6.5.1 AC Saver Day Ahead

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Figure2 show the ex ante load impact estimates for the average customer only enrolled in the AC Saver Day Ahead program for the various combinations of day types and weather scenarios for 2019. 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 0.172 kW during the resource availability hours. For a 1-in-10 typical event day, the estimated load reduction is slightly higher, at 0.185 kW. The estimated aggregate load reductions are 2.96 MW (10.5%) and 3.18 MW (9.7%), respectively. As the enrollment in the AC Saver Day Ahead program continues to grow, these aggregate estimates will increase.

For the AC Saver Day Ahead program customers, those who received free thermostats are forecasted to reduce usage by 0.116 kW for the 1-in-2 weather condition, and by 0.112 kW for the 1-in-10 weather condition, which are about 5.6% and 6.8% of the corresponding reference usages, respectively. On the other hand, the BYOT customers are forecasted to reduce usage by 0.226 kW (14.3%), and 0.267 kW (14.5%), respectively. The forecasted program impact for the BYOT group is higher than that for group who received free thermostats.\

Figure 6-2: 2019 Ex ante Hourly Load Profile – AC Saver day ahead Average Customer

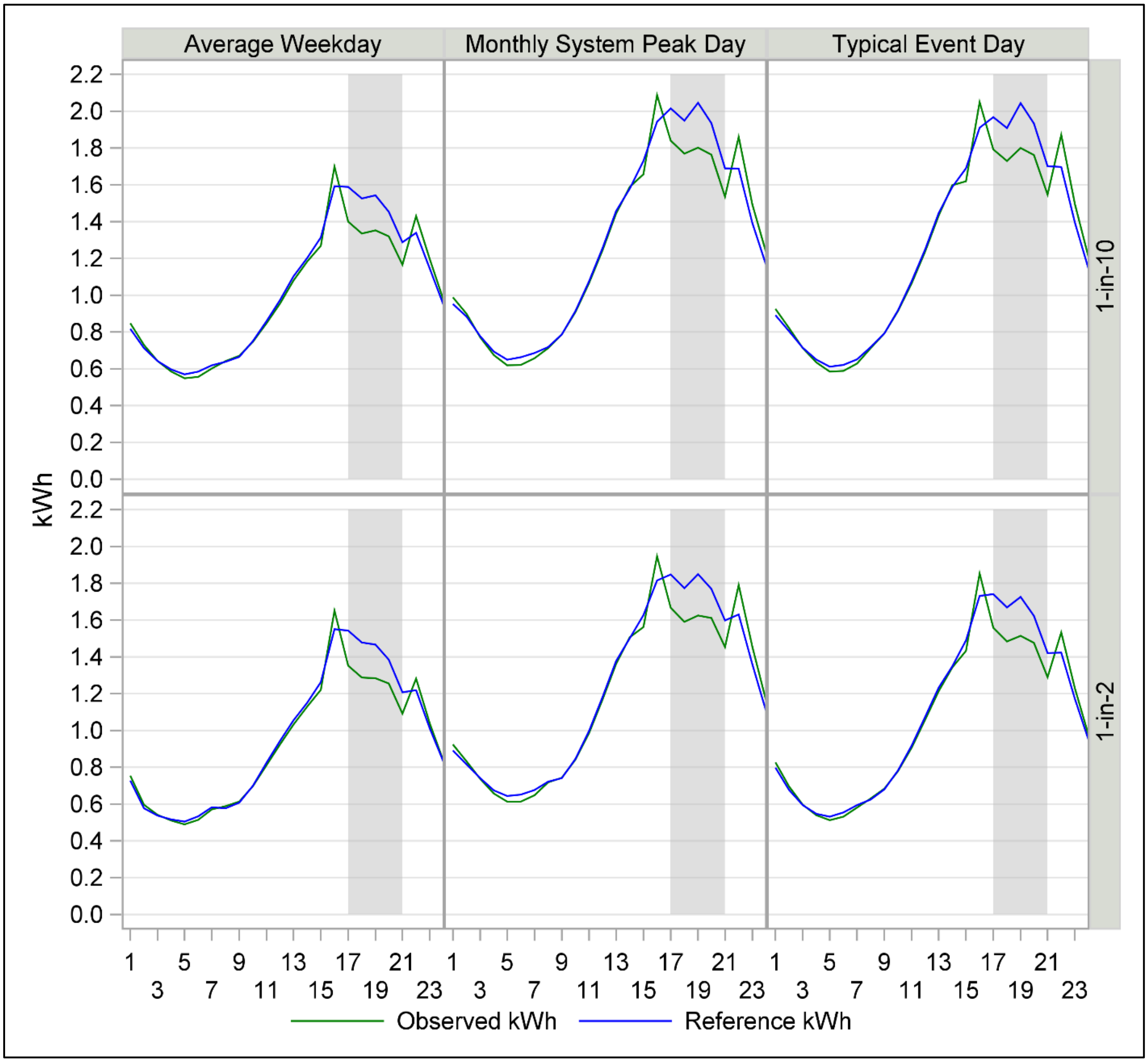


Table 6-10: 2019 Ex ante Hourly Load Impact Results – AC Saver Day Ahead

Control Strategy	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)
BYOT	Average Weekday	Jun	0.86	0.70	0.167	19.4%	1.68	0.63	0.49	0.133	21.2%	1.33
		Jul	1.32	1.12	0.201	15.1%	2.11	1.13	0.96	0.172	15.2%	1.80
		Aug	1.42	1.21	0.203	14.3%	2.23	1.36	1.17	0.194	14.2%	2.12
	Monthly System Peak Day	Jun	1.48	1.22	0.260	17.6%	2.61	0.90	0.73	0.167	18.6%	1.68
		Jul	1.68	1.43	0.251	14.9%	2.64	1.41	1.20	0.214	15.1%	2.25
		Aug	1.86	1.60	0.266	14.3%	2.91	1.69	1.45	0.245	14.5%	2.69
	Typical Event Day	Aug	1.84	1.57	0.267	14.5%	2.93	1.58	1.35	0.226	14.3%	2.48
Free	Average Weekday	Jun	0.92	0.81	0.116	12.6%	0.67	0.62	0.50	0.118	19.1%	0.68
		Jul	1.46	1.35	0.116	7.9%	0.69	1.24	1.12	0.118	9.5%	0.70
		Aug	1.57	1.46	0.117	7.4%	0.73	1.49	1.37	0.119	8.0%	0.74
	Monthly System Peak Day	Jun	1.58	1.47	0.109	6.9%	0.62	0.95	0.83	0.119	12.6%	0.68
		Jul	1.87	1.76	0.114	6.1%	0.68	1.54	1.43	0.116	7.5%	0.69
		Aug	2.01	1.90	0.115	5.7%	0.72	1.87	1.76	0.114	6.1%	0.71
	Typical Event Day	Aug	2.01	1.90	0.112	5.6%	0.70	1.72	1.60	0.116	6.8%	0.72

6.5.2 Comparison of 2018 and 2017 *Ex ante* Estimates

Table6-11,

Figure6-3 and

Figure4 show the comparisons between the ex ante estimates in the current evaluation and those reported in the previous evaluation for the forecast year 2019. The estimated impacts for the AC Saver participants in the current analysis decreased from previous evaluation forecast. For the participants, the previous analysis found estimates of 0.45 kW on 1-in-2 event days and 0.47 kW on 1-in-10 event days. The current analysis projects 0.17 kW on 1-in-2 event days and 0.19 kW on 1-in-10 event days. The percentage load reduction estimates under the current analysis are also much lower. For example, in the 1-in-2 year, the previous results had load reductions of 24.4%, while the current estimates are 10.5%.

Shown in Figure 6-3 and figure 6-4, the hourly load shapes for each of the groups are noticeably different between evaluation years. On average, the participants' observed loads are at similar level, but reference loads are higher in the previous evaluation. Last year, three events were called on three consecutive days, and all of which were of high temperature. This year, on the other hand, many more events were called, eighteen to be exact, the days were spread out, the temperatures varied significantly, and the event hours were during a later part of the day. All of these contributed to the difference in model estimations, which, in turn, led to different forecasting.

Table 6-11: Comparison of 2018 and 2017 Ex ante Estimates Per Customer – Forecast Year 2019 System Peak Days and typical event day – AC Saver

		Current				Previous			
		Average Hourly Reference Load	Average Hourly Observed Load	Average Hourly Impact	Percent Load Reduction	Average Hourly Reference Load	Average Hourly Observed Load	Averag e Hourly Impact	Percent Load Reduction
1-in-10	**August System Peak Day**	1.93	1.74	0.18	9.6%	2.19	1.72	0.47	21.5%
	Typical Event Day	1.91	1.73	0.19	9.7%	2.15	1.67	0.47	22.0%
1-in-2	**August System Peak Day**	1.77	1.59	0.18	10.1%	2.01	1.54	0.47	23.2%
	Typical Event Day	1.64	1.46	0.17	10.5%	1.85	1.40	0.45	24.4%

Figure 6-3: Comparison of 2018 and 2017 Ex ante Hourly Load Profiles – AC Saver program Average Customer– August System peak day

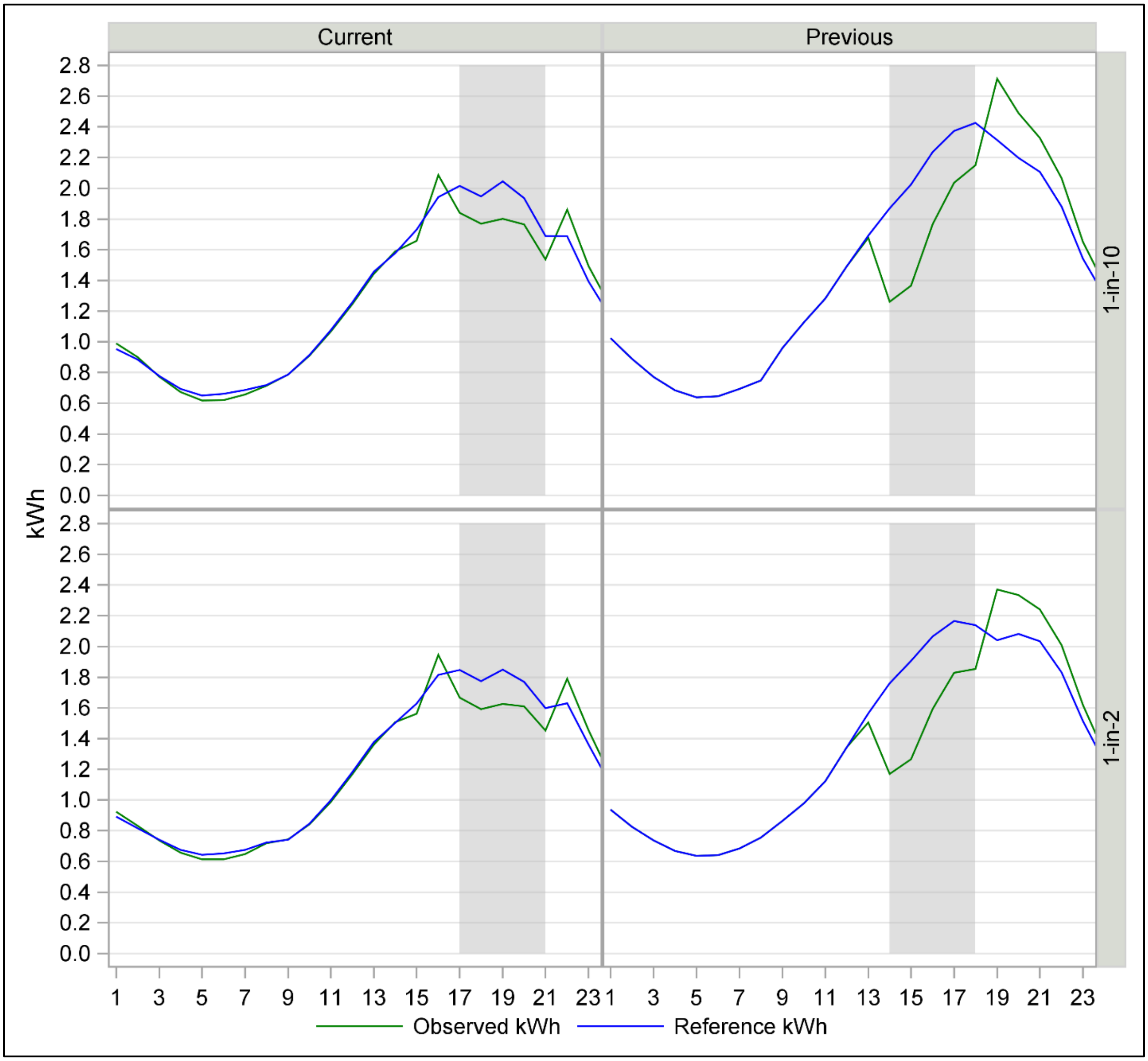
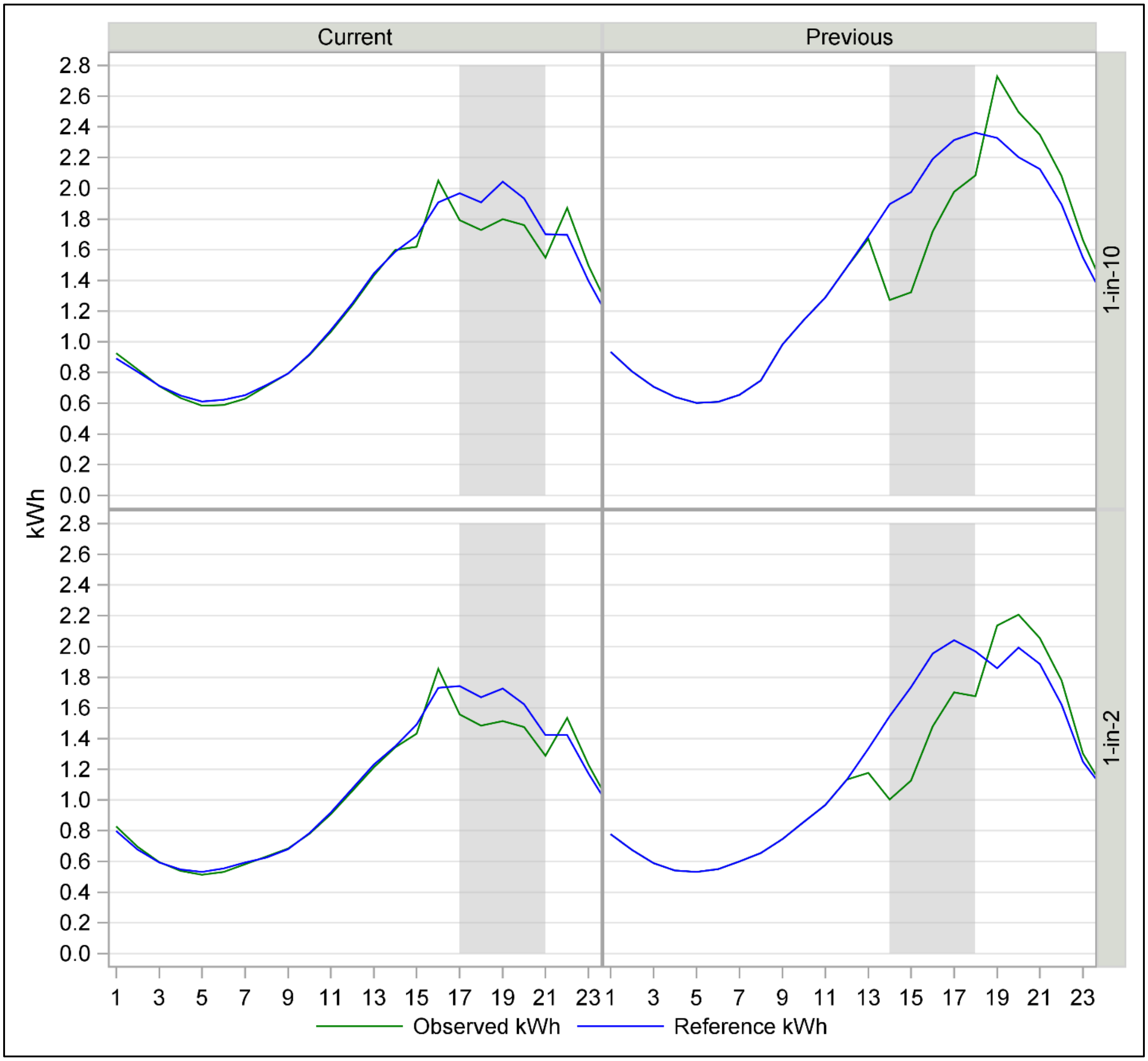


Figure 6-4: Comparison of 2018 and 2017 Ex ante Hourly Load Profiles – AC Saver program Average Customer – Typical Event Day



6.6 *Relationship between Ex post and Ex ante Estimates*

Table 6-12 shows comparisons between the ex ante and ex post estimates from the PY2018 evaluation. For the AC Saver program, the impacts were modeled as a function of cooling degree days, and hence the predicted impacts are vary given different temperatures. The ex post estimates are a little bit lower for the Free sub-group, and higher for the BYOT sub-group. Overall, the average ex post estimates for the whole program is 0.17 kW, same as predicted using 1-in-2 typical day weather data, and slightly lower than predicted using 1-in-10 typical event day weather data, which is about 0.19 kW. Yet, percentage wise, the ex post impact is the highest, 11.6%, comparing to 9.7% for 1-in-10 typical event days and 10.5% for 1-in-2 typical

Table 6-12: Comparison of Ex ante and Ex Post Estimates per Customer

Participant Segment	Control Strategy	Weather Year	Day / Type	Average Hourly Reference Load (kW)	Average Hourly Observed Load (kW)	Average Hourly Impact (kW)	Percent Load Reduction	Average °F
AC Saver	BYOT	1-In-10	August System Peak Day	1.86	1.60	0.27	14.3%	86.86
			Typical Event Day	1.84	1.57	0.27	14.5%	86.38
		1-In-2	August System Peak Day	1.69	1.45	0.24	14.5%	83.58
			Typical Event Day	1.58	1.35	0.23	14.3%	81.33
		Ex Post	Ex Post	1.36	1.12	0.25	18.1%	77.98
	Free	1-In-10	August System Peak Day	2.01	1.90	0.11	5.7%	87.79
			Typical Event Day	2.01	1.90	0.11	5.6%	87.69
		1-In-2	August System Peak Day	1.87	1.76	0.11	6.1%	85.18
			Typical Event Day	1.72	1.60	0.12	6.8%	82.33
		Ex Post	Ex Post	1.54	1.46	0.08	5.0%	79.31
	ALL	1-In-10	August System Peak Day	1.93	1.74	0.18	9.6%	87.20
			Typical Event Day	1.91	1.73	0.19	9.7%	86.85
		1-In-2	August System Peak Day	1.77	1.59	0.18	10.1%	84.16
			Typical Event Day	1.64	1.46	0.17	10.5%	81.69
		Ex Post	Ex Post	1.44	1.28	0.17	11.6%	78.59

Note: The Ex Post results for comparison to ex ante are from 34 out of 43 event hours. These 34 hours represent events that ran from hour 18 and 19 only between June 11th and Sep 26th, 2018. The other event hours only represented a couple of events, and hence the estimations were not robust.

7 Small Commercial Time Varying Pricing and AC Saver Day Ahead[26]

Most small business (SMB) customers across the U.S. have the same price throughout the day and do not have an incentive to consider the timing of their energy consumption and the degree to which consumption during peak hours drives energy and infrastructure costs. Between November 2015 and April 2016, SDG&E transitioned over 120,000 small business customers onto time of use rates with a critical peak component (CPP-TOU). While customers were defaulted onto TOU-CPP rates, they could elect to opt-out to a time-of-use (TOU) rate and 5% of them did. In tandem, SDG&E also transitioned small agricultural customers from flat rates onto time of use rates and offered a CPP-TOU rate on a voluntary (opt-in) basis. By April 2016, electricity rates without a time varying component were no longer available for small commercial and agricultural customers. In the years leading up to and after the rate transition, SDG&E offered customers smart thermostats, free of charge, to help them manage their energy bills and automate response to critical peak prices.

The transition to time varying rates encourages customers to consider when they consume power in addition to how much they consume. Customers can save by modifying when they use energy and by reducing energy use. The rates also better align the prices customers face and with the cost of supplying power. Prior to the transition, SDG&E implemented an outreach and education campaign designed to increase awareness and improve understanding of the new rate.

A total of two related but distinct interventions were assessed as part of the evaluation:

- CPP-TOU – Critical peak prices are designed to incentivize customers to reduce or shift electricity use from peak hours on a handful of days that drive the need for building additional power infrastructure. Customers receive rate reductions during summer non-event days to offset the higher prices during critical peak events (less than 1% of hours). At SDG&E, the CPP rates are layered on top of TOU rates. Historically, the event window was 11am to 6pm but beginning in 2018 the window was narrowed to 2 to 6pm.

- Smart thermostats – Through 2017, customers undergoing the transition to time varying rates were eligible for free Ecobee thermostats to help automated price

[26] The Small Commercial CPP and TD evaluation was conducted by Demand Side Analytics. This section of the Executive Summary contains excerpts from the following evaluation: Bode, J., Lemarchand, A., DSA (2019). “SDG&E Small Commercial Time Varying Pricing and Technology Deployment Evaluation for Program Year 2018”.

response during critical peak periods. The thermostats also can help reduce electricity consumption when a business is unoccupied. After the 2017 event season the program was shifted to a rebate design and expanded to allow additional thermostat models. There are four Technology Deployment programs of which some variants have been in operation since 2014. Prior to 2017, customers were not required to be on a CPP rate, customers on TOU only rates are in the AC Saver Day Ahead (ACSDA) programs—one for non-residential customers and one for quasi-residential customers. Historically, all thermostats were dispatched from 2 to 6pm on CPP event days. Beginning in 2018, ACSDA events were called separately and did not necessarily overlap with CPP event days. ACSDA thermostats can be dispatched at any time between 12 pm to 9 pm (on-peak hours) for a maximum of 4 consecutive hours and most events in 2018 were called from 6-8pm. For Technology Deployment customers on CPP rates (CPPTD) thermostats are still dispatched from 2-6pm on CPP event days. The two rate-based programs are Peak shift at Work (PSW, for small commercial customers) and CPP-D (for medium and large commercial customers). Both and ACSDA devices are curtailed by raising the thermostat temperature set point 4 degrees during the event window.

Both the CPP-TOU and TOU rates provide customers an incentive to reduce or shift electricity use away from peak hours. The CPP-TOU rates include higher prices during critical peak events, an event adder, which is applicable to usage during critical peak events which can be called between the hours of 2 pm and 6 pm during the summer.

7.1 Overview of Methods

The primary challenge of impact evaluation is the need to accurately detect changes in energy consumption while systematically eliminating plausible alternative explanations for those changes, including random chance. Did the introduction of time of use (TOU) rates or smart learning thermostats cause a change in critical peak period demand? Or can the differences be explained by other factors? To estimate energy savings, it is necessary to estimate what energy consumption would have been in the absence of the intervention—the counterfactual or reference load.

The change in energy use patterns was estimated using the following primary method:

- ✓ Difference in differences with a matched control group. This approach was used as the primary method for event impacts for critical peak events delivered by CPP-TOU and thermostat participants. The matched control group was developed using non-participants and relied on out of sample testing. A total of 12 matching models were specified and hot non-event days were split into training and testing days. The matching model used various combinations of hot non-event load data and customer characteristics. The quality of the match was assessed by comparing actual versus estimated aggregate hourly loads in the testing data. The analysis was implemented using a difference in differences panel regression with fixed effects. The technique corrects for remaining differences between the treatment and the matched control group, if any.

Figure 7-1 summarizes the out of sample testing process used to select matched control groups. Essentially, the out of sample process is an iterative approach whereby data is systematically left out of the matching model then used to assess model performance—a well performing matching model should produce matches for loads on days which were not used for the match. The final match control group is identified based on least bias (% Bias) and best fit (Relative RMSE) metrics.

Figure 7-1: Out of Sample Process for Matching Model Selection

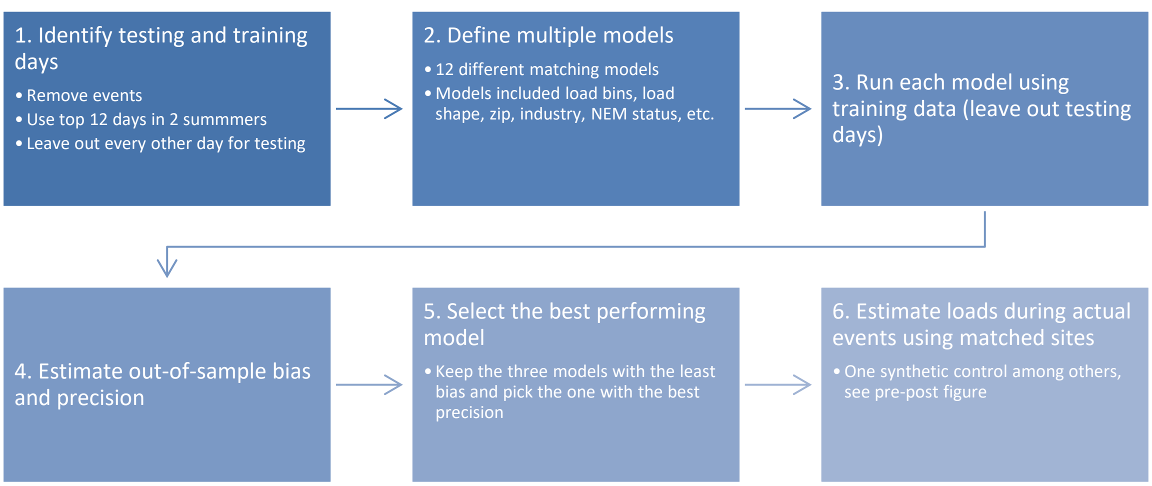


Table7-2 summarizes the data sources, segmentation, and estimation methods used for each program. The segmentation was defined in advance of the analysis and is of importance because the evaluation used a bottom up approach to estimate impacts and to ensure that aggregate impacts across segments equaled the sum of the parts. Because impacts for each segment were added together, the segmentation was structured to be mutually exclusive and completely exhaustive. In other words, every customer was assigned to exactly one segment. By design, the segmentation differentiated customers who were expected deliver demand reductions and energy savings – such as customers who sign up for event notification or technology to automate response – from customers who were expected to deliver little or no demand reductions and energy savings. Additional segments were analyzed, after the fact, as part of exploratory analysis, but the core results presented are based on the segmentation detailed below.

Table 7-2: Evaluation Methods

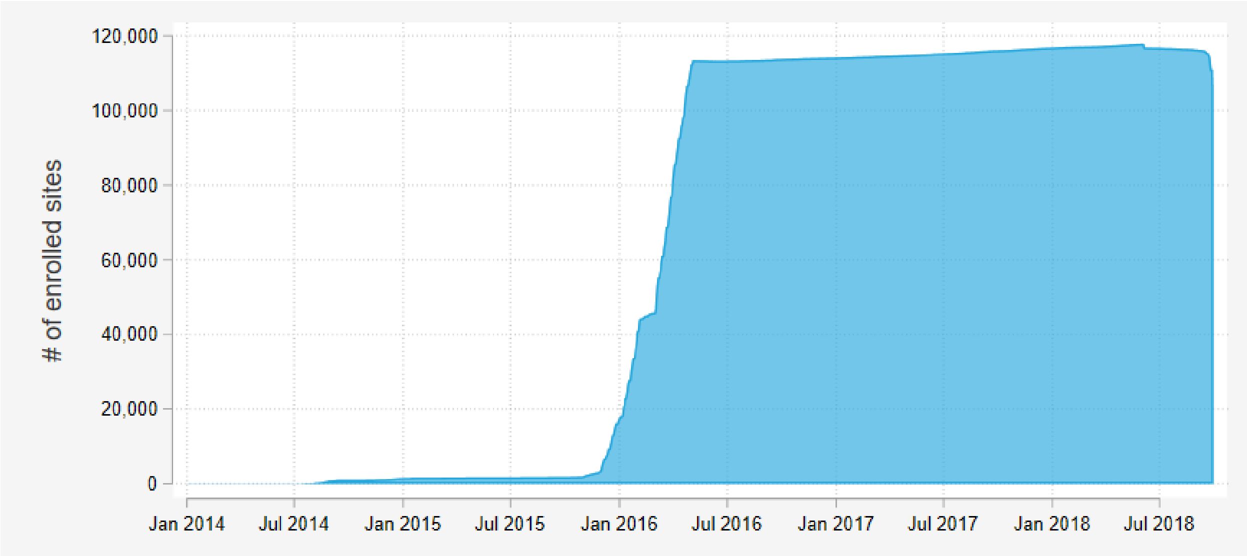
	CPP-TOU	TD Programs
Data sources / samples	▪ Hottest 20 weekdays and weekends over the past three summers (2015-2018), plus any additional event days for: ✓ 115k Small Comm ✓ 5.5k CPP-TOU opt outs (to be used for match control group[27]) ✓ 11 Ag participants ✓ 2.5k Ag participants (to be used for match control group[28])	▪ 3 years of hourly data weekends over the past three summers (2015-2018), for participants and control group candidates for energy savings ▪ Hottest 20 weekdays and weekends over the past three summers (2015-2018), plus any additional event days, for event day impacts
Segmentation	▪ Rate ✓ Small Commercial vs Ag ▪ Enrollment in event notification (Y/N) ▪ Climate zone (Coastal vs Inland) ▪ Dual enrollment (other DR programs) ▪ Net metering status (Y/N)	▪ Rate ✓ CPP-TD: PSW (Small) vs CPP-D (Med & Large) ✓ ACSDA: Small vs Med vs Large vs Quasi-residential ▪ Climate zone (Coastal vs Inland)
Estimation method: Ex post	Fixed effects diff-in-diff regression using matched control from opt-outs for each segment	Matched control groups analyzed using fixed effects diff-in-diff regression for each segment.
Estimation method: Ex ante	▪ Weather normalized customer regressions by segment for reference loads	▪ Weather normalized customer regressions by segment for reference loads ▪ Regression of historical event percent impacts versus weather for percent reductions

[27] Excludes 2.3k sites for customers receiving notifications to ensure no treatment effects for the control pool
[28] Excludes 830 sites for customers receiving notifications to ensure no treatment effects for the control pool

7.2 *Critical Peak Pricing Event Day Impacts*

SDG&E defaulted over 117,000 small customer sites29 onto CPP-TOU rates between November 2015 and April 2016. Roughly 5% of these customers opted-out and were placed on TOU rates. Figure7-2 shows this cumulative enrollment in CPP, net of the opt-outs.

Figure 7-2: Small Non-Residential Critical Peak Pricing Enrollment



The first event season for CPP was in 2016, but only one CPP event was called that year. It was called on SDG&E's peak day, Monday, September 27th. The PY 2016 evaluation for small customers found that the ex post load impacts for this lone CPP event were not statistically significant. The event was atypical. SDG&E had a low notification rate at the time – less than 25% of customers had elected to provide contact information to SDG&E –notifications were sent the Friday prior to the Monday event, and the event occurred near the end of the summer season.

In PY 2017, there were three consecutive CPP events, including one weekend event, and significant impacts were identified. In addition, roughly 45% of sites signed up for event notification but, because several customers had multiple sites (but only signed up some), approximately 60% of sites received event notification. In PY 2018, six CPP events were called in July and August. The rates of notification were similar.

CPP event impacts were assessed by site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in Table 7-3, was developed based on rate class, program, and technology characteristics which may influence impacts. Analysis was performed at the segment

[29] Here and through this report a site is defined as a premise and service point combination

level, so these granular impacts could therefore be summed, yielding aggregate impacts in addition to the segment specific impacts.

The segmentation criteria were defined as follows:

- ✓ Rate class: what type of rate was the site on throughout the study period?
- ✓ Notification: did the customer associated with the site receive any event notifications for any site?
- ✓ Climate zone: in which SDG&E climate zone was the site located?
- ✓ Dual enrollment: was the site enrolled in other demand response programs during the study period (Summer Saver, PTR, CBP)?
- ✓ Solar: was the site on a net metered rate during the study period?

Table 7-3: Critical Peak Pricing Population Segments

Rate class	Notification	Climate zone	Dually enrolled	Solar	Total Sites	Sites in analysis
Small Commercial	No	Coastal	No	No	23,814	23,601
				Yes	146	109
			Yes	No	589	593
				Yes	3	3
		Inland	No	No	16,683	16,110
				Yes	247	191
			Yes	No	723	721
				Yes	8	6
	Yes	Coastal	No	No	42,633	41,841
				Yes	524	382
			Yes	No	1,121	1,117
				Yes	29	21
		Inland	No	No	26,486	25,135
				Yes	605	442
			Yes	No	1,275	1,253
				Yes	26	17
Small Agricultural	No	Inland	No	No	5	4
				Yes	1	1
	Yes			No	6	6
Total sites					114,924	111,552

Table7-3 summarizes the total number of sites in each segment and the final number of sites used for analysis once data cleaning was completed30. For most segments, the vast majority of sites were included in the analysis. Aggregate ex post analysis results were scaled up to match the total number of sites before data cleaning.

Because other programs also modify loads, those event days cannot be used for counterfactual estimation for dually enrolled CPP participants. Days which were not CPP events, but which were events for other DR programs were excluded for dual participants, leaving fewer days for counterfactual estimation. High load days from 2018 were used to develop the CPP counterfactual.

Table7-4 shows the six PY 2018 CPP event days, including the maximum daily temperature weighted by participating sites. These events occurred on various days of week in July and August. The SDG&E system peak occurred on August 9, 2018 and all but one event (July 25, 2018) were in the top seven SDG&E system peak days.

Table 7-4: Critical Peak Pricing Events in 2018

Event day	Day of week	Event start	Event end	Max daily temp (F)	SDG&E system load (MW)
7/6/2018	Friday	2:00 PM	6:00 PM	99.5	4,300
7/24/2018	Tuesday	2:00 PM	6:00 PM	88.2	4,182
7/25/2018	Wednesday	2:00 PM	6:00 PM	85.0	3,906
8/6/2018	Monday	2:00 PM	6:00 PM	88.4	4,218
8/7/2018	Tuesday	2:00 PM	6:00 PM	91.7	4,249
8/9/2018	Thursday	2:00 PM	6:00 PM	91.1	4,358

7.3 Data Sources and Analysis Method

Table 3-5 summarizes the five data sources used to conduct the CPP analysis. The analysis was done by site on hourly load data. Various data sources were used to classify sites into the study segments. While different segments were developed for the various analyses in this report (rate versus technology based, event and non-event), the characteristic definitions used to build segments were consistent across analyses.

[30] The cleaning algorithm ensured that complete data was available for the study period. Sites for which high quality matches could not be found were also excluded.

Table 3-5: Critical Peak Pricing Evaluation Data Sources

Source	Comments
Hourly interval data	▪ Summer 2018 (June 1 through October 31) ▪ All analysis done by site (premise id-service point id pair)
Customer characteristics	▪ Treatment: All small non-residential (Commercial and Agricultural) CPP rates (114,923 sites) ▪ Control: TOU only rates (9.3k sites) ▪ Industry, zip codes, climate zone, NEM status used in matching model selection ▪ NEM status, climate zone, and DR program enrollment used for segmentation
SDG&E hourly system loads	▪ Summer 2018 (June 1 through October 31) ▪ Used to identify non-event high system load days
Ex post weather data by weather station	▪ Used to derive cooling degree days for impact evaluation panel model
Event notification	▪ List of notifications sent to each account for each event day ▪ Rolled up by customer to identify customers who had received notifications at any site (used for segmentation)

Propensity score matching was used to select a matched control for the roughly 115,000 TOU-CPP sites among a control candidate pool of roughly 9,300 TOU sites (e.g., those that opted out of TOU-CPP and are no longer receiving notifications). A difference-in-difference panel regression model with fixed effects was then used to assess impacts and standard errors for each event and each study segment. The matches selected were highly accurate and unbiased, as detailed in the Appendix. Details about the regression used for assessing impacts are also in the Appendix.

7.3.1 Ex Post Load Impacts

CPP event impacts were assessed by site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in Table7-6, was developed based on rate class, program, and technology characteristics which may influence impacts. Analysis was performed at the segment level, so these granular impacts could therefore be summed, yielding aggregate impacts in addition to the segment specific impacts.

The segmentation criteria were defined as follows:

- Rate class: what type of rate was the site on throughout the study period?
- Notification: did the customer associated with the site receive any event notifications for any site?
- Climate zone: in which SDG&E climate zone was the site located?
- Dual enrollment: was the site enrolled in other demand response programs during the study period (Summer Saver, PTR, CBP)?
- Solar: was the site on a net metered rate during the study period?

Table 7-6: Critical Peak Pricing Population Segments

Rate class	Notification	Climate zone	Dually enrolled	Solar	Total Sites	Sites in analysis
Small Commercial	No	Coastal	No	No	23,814	23,601
				Yes	146	109
			Yes	No	589	593
				Yes	3	3
		Inland	No	No	16,683	16,110
				Yes	247	191
			Yes	No	723	721
				Yes	8	6
	Yes	Coastal	No	No	42,633	41,841
				Yes	524	382
			Yes	No	1,121	1,117
				Yes	29	21
		Inland	No	No	26,486	25,135
				Yes	605	442
			Yes	No	1,275	1,253
				Yes	26	17
Small Agricultural	No	Inland	No	No	5	4
				Yes	1	1
	Yes			No	6	6
Total sites					114,924	111,552

Table7-6 summarizes the total number of sites in each segment and the final number of sites used for analysis once data cleaning was completed31. For most segments, the vast majority of sites were included in the analysis. Aggregate ex post analysis results were scaled up to match the total number of sites before data cleaning.

Because other programs also modify loads, those event days cannot be used for counterfactual estimation for dually enrolled CPP participants. Days which were not CPP events, but which were events for other DR programs were excluded for dual participants, leaving fewer days for counterfactual estimation. High load days from 2018 were used to develop the CPP counterfactual.

Table7-7 shows the six PY 2018 CPP event days, including the maximum daily temperature weighted by participating sites. These events occurred on various days of week in July and August. The SDG&E system peak occurred on August 9, 2018 and all but one event (July 25, 2018) were in the top seven SDG&E system peak days.

Table 7-7: Critical Peak Pricing Events in 2018

Event day	Day of week	Event start	Event end	Max daily temp (F)	SDG&E system load (MW)
7/6/2018	Friday	2:00 PM	6:00 PM	99.5	4,300
7/24/2018	Tuesday	2:00 PM	6:00 PM	88.2	4,182
7/25/2018	Wednesday	2:00 PM	6:00 PM	85.0	3,906
8/6/2018	Monday	2:00 PM	6:00 PM	88.4	4,218
8/7/2018	Tuesday	2:00 PM	6:00 PM	91.7	4,249
8/9/2018	Thursday	2:00 PM	6:00 PM	91.1	4,358

Table 7-8 summarizes the portfolio load reductions for all Small Non-Residential sites on CPP rates (and not dually enrolled in other DR programs) for the six weekday events and 2 pm to 6 pm reductions for the average event. The average event aggregate load reduction was 2.72 MW across all 111,149 portfolio sites and the average reduction per site was 0.06 kW. Reductions were significant at the 95% level for four of the six events and for the average event. The greatest reduction was for the event on 8/9/2018 with an aggregate reduction of 7.10 MW and a per site reduction of 0.06 kW.

[31] The cleaning algorithm ensured that complete data was available for the study period. Sites for which high quality matches could not be found were also excluded.

Table 7-8: CPP Program Specific Event Reductions

Event Date	Event Window	Avg Event Temp (F)	Sites Enrolled	Reductions Aggregate (MW)	Reductions Average Site (kw)	Significant (90% CI)	Significant (95% CI)
7/6/2018	Avg. 2 to 6 pm	96.2	111,149	-0.49	0.00	No	No
7/24/2018	Avg. 2 to 6 pm	85.4	111,149	4.82	0.04	Yes	Yes
7/25/2018	Avg. 2 to 6 pm	82.1	111,149	3.33	0.03	Yes	Yes
8/6/2018	Avg. 2 to 6 pm	86.9	111,149	0.28	0.00	No	No
8/7/2018	Avg. 2 to 6 pm	89.6	111,149	1.30	0.01	Yes	Yes
8/9/2018	Avg. 2 to 6 pm	88.2	111,149	7.10	0.06	Yes	Yes
Average Event	**Avg. 2 to 6 pm**	**88.1**	**111,149**	**2.72**	**0.02**	**Yes**	**Yes**

Reductions were also segmented by rate class, climate zone, and customers who signed up for event notifications32. Table7-9 details the reference loads and load reductions overall and by each of these study segments33 for the average 2 pm to 6 pm CPP event window. Both aggregate reductions and average reductions per site are shown. Commercial portfolio impacts for the average event were 2.70 MW in aggregate or 0.7% of whole building load, while program specific impacts were 3.15 MW—0.8% of whole building load including sites enrolled in other DR programs.

Segmentation of load impacts shows that reductions were concentrated in key segments. Customers in the Inland climate zone who signed up for event notification delivered the vast share of demand reductions—2.86 MW or 2.9%—while Inland sites that weren't notified delivered 1.12 MW or 2.1%. In contrast, reductions for Coastal sites—where the average event temperatures were about 5 degrees lower than in the Inland zone—program specific were negative, regardless of whether customers received event notifications. However, the increase in usage during events was very small in magnitude and not statistically significant for Coastal sites receiving event notifications. As a whole, program specific impacts for the 111,138 Small Commercial sites were 2.70 MW, though notably impacts for Inland sites specifically were 3.98 MW. Program reductions for the 11 Agricultural sites were directionally positive but not statistically significant. Sites dually enrolled in other DR programs are excluded from program reductions, but these sites delivered 0.43 MW of reductions or 2.1% of whole building load. As noted above, program specific impacts, which include dually enrolled sites were 3.15 MW.

[32] Sites were classified as receiving notifications if any site under the parent customer received notifications. There were multiple indirect channels where sites that did not directly sign up for notification could become aware of them. SDG&E publicized the events via mass media channels – radio and TV – and customers at many smaller sites that did not sign up for notification also had medium and large facilities that were signed for event notification.

[33] Results for more granular segments including NEM status and dual enrollment in other DR programs are included in the appendix.

Table 7-9: CPP Program Average Event Reductions by Segment

Subcategory	Temp	Sites	Aggregate (MW)				Average Site (kw)			t-stat
			Ref Load	Reduction	% Reduction	Std Error	Ref Load	Reduction	Std Error	
Comm: Coastal & received notification	85.8	43,157	158.16	-0.38	-0.2%	0.39	3.66	-0.01	0.01	-0.97
Comm: Coastal & no notification	85.7	23,960	84.36	-0.90	-1.1%	0.13	3.52	-0.04	0.01	-7.06
Comm: Inland & received notification	91.6	27,091	98.81	2.86	2.9%	0.17	3.65	0.11	0.01	17.31
Comm: Inland & no notification	91.8	16,930	53.92	1.12	2.1%	0.14	3.19	0.07	0.01	8.12
Commercial portfolio	88.1	111,138	395.25	2.70	0.7%	0.35	3.56	0.02	0.00	7.74
Agricultural portfolio	94.3	11	0.09	0.02	21.9%	0.01	7.91	1.73	1.21	1.43
Dual enrolled	89.2	3,774	20.19	0.43	2.1%	0.07	5.35	0.11	0.02	5.78
All study segments	**88.1**	**114,923**	**415.53**	**3.15**	**0.8%**	**0.36**	**3.62**	**0.03**	**0.00**	**8.80**

The load shape for the average event day is summarized in greater detail in Figure7-3. Note that the figure, extracted from the Ex Post Load Impact Table, is for the small CPP portfolio population. The figure shows the aggregate hourly loads (actual and counterfactual) for these sites. The tables accompanying each figure show aggregate impacts for the 2 pm to 6 pm event window. Load was reduced by 0.7% during the average event window, similar in magnitude with past years and in line with reductions for CPP rates with no enabling technology.

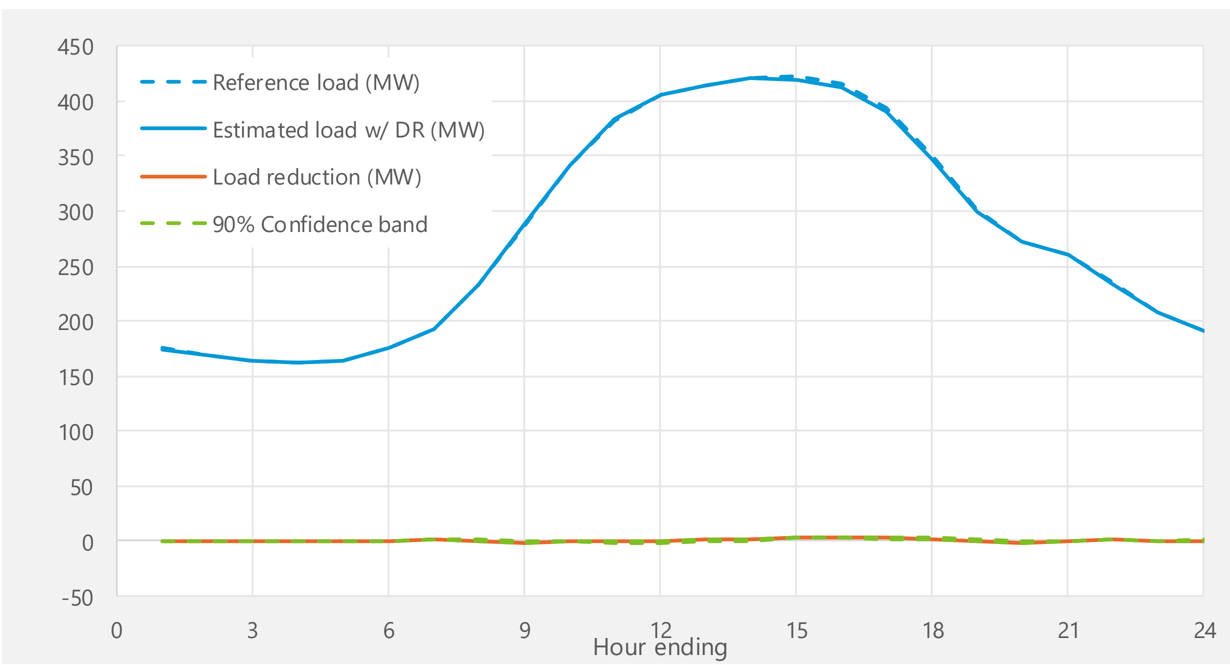
Figure 7-3: CPP Program Specific Impacts

Table 1: Menu options

Type of results	Aggregate
Category	Portfolio impacts
Subcategory	Portfolio (excludes dual enrolled)
Event date	Avg. Weekday Event 2018

Table 2: Event day information

CPP Event start	2:00 PM
CPP Event end	6:00 PM
Total enrolled accounts	111,149
Avg load reduction 11AM-6PM	1.80
% Load reduction 11AM-6PM	0.4%
Avg load reduction 2PM-6PM	2.72
% Load reduction 2PM-6PM	0.7%



7.4 Default Small Commercial CPP & TOU Rates Ex ante Evaluation Methodology

A key objective of the 2018 evaluation is to quantify the relationship between demand reductions, temperature and hour of day. Ex ante impacts are estimated load reductions as a function of weather conditions, time of day, and forecasted changes in enrollment. By design, they reflect planning conditions defined by normal (1-in-2) and extreme (1-in-10) peak demand weather conditions. The historical load patterns and performance during actual events are used the reductions for a standardized set of weather conditions.

At a fundamental level, the process of estimating ex ante impacts included five main steps:

1. Estimate the relationship between customer loads (absent DR) and weather
2. Use the models to predict customers loads (absent DR) for 1-in-2 and 1-in-10 weather year conditions
3. Apply the average percent reductions, at an hourly level, from historical events. The average reduction was employed because experience with small business default CPP is limited and there is less of a history of program performance across events.
4. Estimate reductions for 1-in-2 and 1-in-10 weather year conditions
5. Incorporate the enrollment forecast

7.5 Default Small Commercial CPP Ex ante Load Impact Estimates

Table 7-10 summarizes the ex ante demand reduction capability by forecast year and planning condition. The tables reflect dispatchable demand reductions available from 4 pm to 9 pm on August monthly peaking conditions for 1-in-2 and 1-in-10 weather conditions. They align with the planning conditions used for resource adequacy attribution. To avoid double counting, the table only includes resources that are not dually enrolled in other DR programs, known as portfolio impacts.

Table 7-10: Small CPP Portfolio Impacts for August Monthly Peak Day (1-6 pm)

Year	Sites	CAISO		SDG&E	
		1-in-2	1-in-10	1-in-2	1-in-10
2018	111,151	2.23	2.21	2.14	2.38
2019	107,605	2.15	2.14	2.07	2.30
2020	104,172	2.09	2.07	2.01	2.23
2021	100,848	2.02	2.01	1.94	2.16
2022	97,630	1.95	1.94	1.88	2.09
2023	94,516	1.89	1.88	1.82	2.02
2024	91,500	1.83	1.82	1.76	1.96
2025	88,581	1.77	1.76	1.71	1.90
2026	85,755	1.72	1.71	1.65	1.83
2027	83,019	1.66	1.65	1.60	1.78
2028	80,370	1.61	1.60	1.55	1.72
2029	77,806	1.56	1.55	1.50	1.66

The enrollment forecast was developed by SDG&E and shows a declining number of customers enrolled in CPP. Over time, customers are expected to sort themselves between TOU-CPP and TOU rates. For ex ante impacts, reduction in enrollment forecasts are assumed to have a proportional effect of the magnitude of demand reduction resources. This assumption is conservative. In past implementations, less price responsive customers opted out of default CPP rates, leading to lower enrollment rates, but a limited effect on reduction capability.

7.6 Comparison of Ex Post and Ex Ante Load Impacts

Table 7-11 compares the demand reductions from 2018 events to the reduction expected for the 1-in-2 weather conditions used for planning. Results are shown for both the new 4 to 9 pm and old 1 to 6 pm resource adequacy windows to highlight the differences under the later window. The small differences between ex post and ex ante values for 1 to 6 pm are due to different reporting hours and weather conditions. In 2018, small CPP customers delivered 2.72 MW during the dispatch period of 2 to 6 pm. Demand reductions were somewhat lower, 2.45 MW, for the old 1-6 pm period used for resource adequacy and planning. The 4 to 9 pm ex post reductions are much lower, 0.69 MW, because CPP events can only be called from 2 to 6 pm. When similar hours are compared, ex ante resource estimates are somewhat higher than the ex post impacts align due to higher impacts modeled for previous years. With such small impacts (on the order of 1%) such variability is to be expected.

Table 7-11 Small CPP Comparison of Ex Post and Ex Ante Load Impacts for 2018

Result Type	Day Type and Period	Sites	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex Post Avg. Weekday	Event Period (2 to 6pm)	111,149	395.33	2.72	0.7%	90.4
	Old Resource Adequacy Period (1 to 6pm)	111,149	400.61	2.45	0.6%	90.4
	New Resource Adequacy Period (4 to 9pm)	111,149	315.03	0.69	0.2%	90.4
Ex ante SDG&E	1-in-2 Weather August Peak (1 to 6pm)	111,151	410.33	4.82	1.2%	88.6
	1-in-2 Weather August Peak (4 to 9pm)	111,151	321.56	2.14	0.7%	88.6
Ex ante CAISO	1-in-2 Weather August Peak (1 to 6pm)	111,151	417.57	5.08	1.2%	88.6
	1-in-2 Weather August Peak (4 to 9pm)	111,151	326.26	2.23	0.7%	88.6

*Table shows portfolio impacts. To avoid double counting, it excluded commercial thermostats and customers dually enrolled in other DR programs.

8 Summary of the AC Saver Day Ahead Commercial Program[34]

8.1 AC Saver Day Ahead Commercial Overview

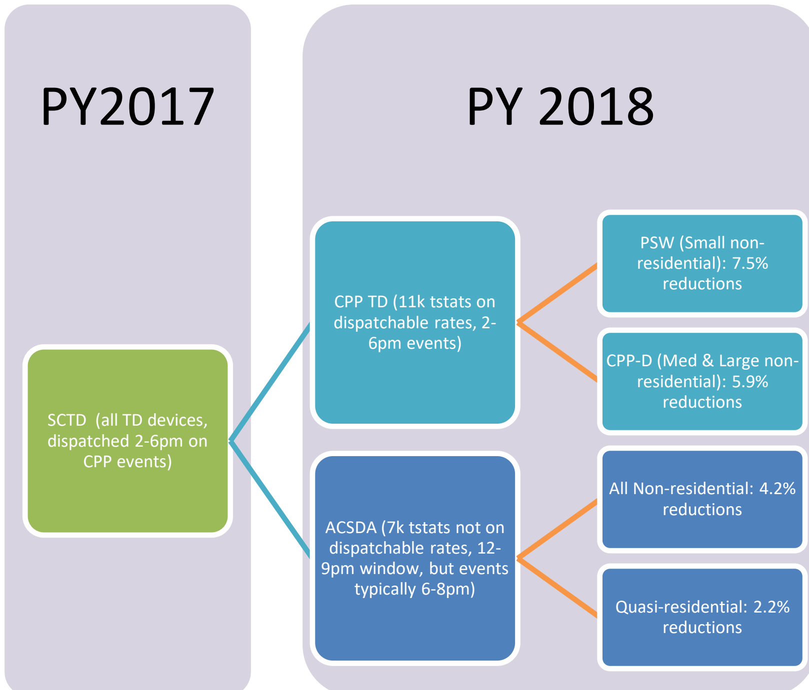
Customers undergoing the transition to time varying rates were eligible for free Ecobee thermostats to help automated price response during critical peak periods. The thermostats can also help reduce electricity consumption when a business is unoccupied. The program was

[34] The AC Saver Day Ahead Commercial Program was conducted by Demand Side Analytics (DSA). This section of the Executive Summary contains excerpts from the following evaluation: Bode, J. & Lemarchand, A. (2019). "SDG&E Small Commercial Time Varying Pricing and Technology Deployment Evaluation for Program Year 2018"

known as the Small Commercial Technology Deployment (SCTD) and has been in operation since 2014. However, prior to 2017, customers were not required to be on a CPP rate and, as a result, SCTD also included participants who are enrolled in TOU only rates with no dispatchable component. Historically, all thermostats were dispatched from 2-6 pm and Technology Deployment events coincided with CPP events, of which there were one in 2016 and three in 2017.

In 2018, the program changed from a free thermostat to a rebate model and was broadened to include additional thermostat models. Figure8-1 summarizes four the specific program designations for the PY 2018 evaluation. There are two programs (and accompanying rates) for customers on CPP-TOU rates: Peak Shift at Work (PSW) for Small non-residential customers and CPP-D for Medium and Large non-residential customers. Devices enrolled in these programs are dispatched during CPP events, which had a dispatch window of 2 to 6 pm in program year 2018 (PY 2018). For customers who are not on dispatchable rates, there are also two programs AC Saver Day Ahead (ACSDA) for non-residential customers and ACSDA for quasi-residential customers (who are on residential rates). ACSDA events are typically called from 6 to 8 pm and do not necessarily overlap with CPP event days. ACSDA thermostats can be dispatched at any time between 12 pm to 9 pm (on-peak hours) for a maximum of 4 consecutive hours and most events in 2018 were called from 6-8pm. For all four programs, devices are curtailed by raising the thermostat temperature set point 4 degrees during the event window. Notably during one event (7/6/2018), devices were dispatched using a 100% cycling approach rather than the 4-degree setback.

Figure 8-1: Summary of TD Program Taxonomy



There are over 18,000 devices installed at over 3,000 non-residential sites. Roughly 11,000 devices are installed at sites on dispatchable rates (small commercial on PSW and medium and large on CPP-D) and the remaining 7,000 are installed at non-residential and quasi-residential sites on non-dispatchable rates enrolled in AC Saver Day Ahead (ACSDA). The sites on dispatchable rates produced significant, consistent, and meaningful reductions of 6 to 7.5% of whole building load during all six CPP event days. In contrast, reductions for ACSDA sites, while statistically significant on average, were much smaller in magnitude (2 to 4%) and less consistent across the seventeen ACSDA event days called. These differences can mostly be explained by the later ACSDA dispatch window (6 to 8pm for most events compared to 2 to 6pm for CPP events) and cooler weather (over half of ACSDA event were called on days with max temperatures below 87.4F compared to just one CPP event).

A key finding was that only about half of installed devices were connected during the PY 2018 event season. Because only connected devices can receive signals and curtail AC load this lack of connectivity has direct implication for load impacts delivered by the Technology Deployment programs. The decline in connectivity appears to be substantial and relatively steady over time, ranging from 13% to 23% per year for most programs[35]. Because of the decline impacts were derived at a per connected thermostat basis so they could be applied to enrollment forecasts

[35] With the exception of ACSDA quasi-residential sites where hundreds of sites managed by a single customer were disconnected around the same time in late 2017.

reflecting numbers of connected devices in addition to enrolled sites. Future efforts to reconnect disconnected devices, particularly among programs or customer segments delivering greater reductions, could substantially increase future load reduction potential for the Technology Deployment programs.

Reductions for the technology enabled programs on dispatchable rates also stand in contrast to reductions of 0.7% for small non-residential sites without enabling technology but on a CPP rate (covered in a previous section). Those sites, which experienced events on the same day as the commercial thermostat population on dispatchable rates, produced impacts which were significant overall but much smaller in magnitude than those produced by sites with enabling technology.

8.2 AC Saver Day Ahead Commercial Analysis Method

Table 8-2 summarizes the five data sources used to conduct the commercial thermostat event impact analysis. The analysis was done by site on hourly load data. Various data sources were used to classify sites into the study segments. While different segments were developed for the various analyses in this report (rate versus technology based, event and non-event), the characteristic definitions used to build segments were consistent across analyses.

Table 8-2: Commercial Thermostat Event Impact Evaluation Data Sources

Source	Comments
Hourly interval data	▪ Summer 2018 ▪ All analysis done by site (premise id-service point id pair)
Customer characteristics	▪ Treatment: All non-residential (Commercial and Agricultural) commercial thermostat participants, including quasi-residential sites ▪ Control: All non-residential sites not on CPP or other DR programs ▪ Industry, zip codes, climate zones used in matching model selection
Thermostat installation data	▪ Installation and last connected dates
SDG&E hourly system loads	▪ Summer 2018 ▪ Used to identify non-event high system load days
Ex post weather data by weather station	▪ Used to derive cooling degree days for impact evaluation panel model

The primary analysis method was a differences-in-differences panel regression with a matched control group. The statistical matching approach used selected a matched control for the roughly 3,300 non-residential thermostat sites among a control candidate pool of roughly 17,000 TOU sites who were not enrolled in CPP or other DR programs which might influence energy use. A difference-in-difference regression model was then used to assess impacts and standard errors for each event and each study segment.

To identify which model best predicted customer loads absent demand reductions, an out of sample approach was still used to select the regression model. The model selection relied on testing how well each model estimated loads for hot non-event days out-of-sample. Because there was, in fact, no event, it was possible to assess how close model estimates were to the correct answer and the most accurate model. A total of ten weather-based models were tested.

8.3 AC Saver Day Ahead Commercial Ex post Load Impact Estimates

8.3.1 *Peak Shift at Work: Small Non-Residential CPP with Technology*

Table8-3 summarizes the load reductions for all PSW sites for the six weekday events and 2 pm to 6 pm reductions for the average event. In aggregate, these events delivered 0.55 MW of load reduction across all 1,184 enrolled sites and the average reduction per site was 0.78 kW. Though 3,132 devices were installed at enrolled sites, only 1,599 devices on average were connected during the PY 2018 event season. Because only connected devices can be dispatched, all reductions are delivered by these connected devices. The average reduction per connected device was 0.34 kW.

Reductions were strongly significant on average (t value=12.38) and for each event (t value≥4.99). Reductions were about higher during the 7/6/2018 event than during all the other events, in part because the event temperature during the event was several degrees hotter and in part because devices were dispatched using a 100% cycling approach while for other events AC load was curtailed by raising the thermostat temperature set point 4 degrees during the event window.

Table 8-3: PSW Program Event Reductions

Event Date	Event Window	Avg Event Temp (F)	Sites Enrolled	Installed Devices	Connect-ed Devices	Reduction: Aggregate (MW)	Reduction: Average Site (kw)	Reduction: Average Connected Tstat (kw)	t-stat	Significant (90% CI)
7/6/2018	2 to 6 pm	96.7	1,184	3,132	1,650	1.00	1.44	0.61	7.74	Yes
7/24/2018	2 to 6 pm	86.2	1,184	3,132	1,604	0.44	0.63	0.28	5.47	Yes
7/25/2018	2 to 6 pm	83.0	1,184	3,132	1,604	0.47	0.67	0.29	4.99	Yes
8/6/2018	2 to 6 pm	87.6	1,184	3,132	1,585	0.38	0.54	0.24	5.22	Yes
8/7/2018	2 to 6 pm	90.3	1,184	3,132	1,576	0.43	0.62	0.27	5.30	Yes
8/9/2018	2 to 6 pm	88.6	1,184	3,132	1,576	0.56	0.80	0.35	5.65	Yes
Avg Event	**2 to 6 pm**	**88.8**	**1,184**	**3,132**	**1,599**	**0.55**	**0.78**	**0.34**	**12.38**	**Yes**

Reductions were also analyzed within climate zone segment. Table8-4 details the reference loads and load reductions overall and by segment for the average 2 pm to 6 pm event window. In addition to aggregate reductions, average reductions per connected thermostat are also shown. Note that the reference load for aggregate impacts includes the whole building load across all enrolled sites as recorded at the meter; the reference load for the average connected thermostat is the cooling load per connected thermostat, estimated by isolating the weather sensitive portion of whole building load. In aggregate, 7.5% of whole building was curtailed during the average event, while 31% of cooling load was curtailed per connected device.

In aggregate, about 67% of connected devices were in the Coastal zone and these devices delivered about 57% of the 0.55 MW of reductions for the PSW program. While percent reductions per connected were very similar in the two climate zones, connected devices in the Inland zone delivered 0.44 kW per device compared to 0.29 kW for devices in the Coastal zone. Devices in the Inland zone, where event temperatures were also higher, delivered more per connected device largely because there was more AC load available for curtailment. In hotter environments, AC units must run more often to maintain a comfortable set point, meaning more runtime and load can be avoided by raising the set point than in the face of cooler outdoor temperatures where the AC is already running less often.

Table 8-4: PSW Program Average Event Reductions by Segment

Size	Climate zone	Event Window	Avg Event Temp (F)	Sites Enrolled	Installed Devices	Connect-ed Devices	Aggregate (MW) Ref load (whole bldg)	Aggregate (MW) Reduc-tion	Aggregate (MW) % Reduc-tion	Average connected tstat (kW) Ref load (cooling)	Average connected tstat (kW) Reduc-tion	Average connected tstat (kW) % Reduc-tion	t-stat
Small	Coastal	2 to 6 pm	86.4	693	1,911	1,071	4.31	0.31	7.3%	0.98	0.29	30%	10.37
	Inland	2 to 6 pm	91.8	491	1,221	528	2.95	0.23	7.9%	1.34	0.44	33%	7.42
All	All	2 to 6 pm	88.8	1,184	3,132	1,599	7.26	0.55	7.5%	1.12	0.34	31%	12.38

The average event day load shape is summarized in greater detail in Figure8-2. Note that the figure, extracted from the Ex Post Load Impact Table, is for the CPPTD (PSW) participant population. The left panel shows the aggregate hourly loads (actual and counterfactual) for these sites. The right panel shows impacts per connected thermostat as a function of cooling load. The tables accompanying each figure show impacts for the 2 pm to 6 pm event window. Load impacts were evident for the average event window with a 7.5% aggregate reduction and a 30.6% cooling load reduction per connected thermostat.

Figure 8-2: CPPTD Peak Shift at Work: Summary for Average Event

Table 1: Menu options

Program	CPPTD (PSW)
Type of result	Aggregate
Type of site	All
Category	All
Subcategory	All study segments
Event date	Avg. Weekday Event 2018

Table 2: Event day information

Event start	2:00 PM
Event end	6:00 PM
Total sites	1,184
Total installed thermostats	3,132
Total connected thermostats	1,599
Percent of thermostats connected	51%
Avg load reduction 2PM-6PM	0.55
% Load reduction 2PM-6PM	7.5%
Avg load reduction 6PM-8PM	
% Load reduction 6PM-8PM	

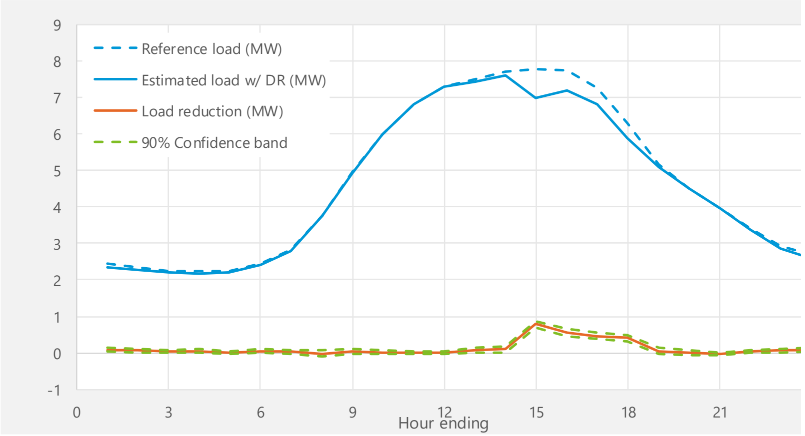
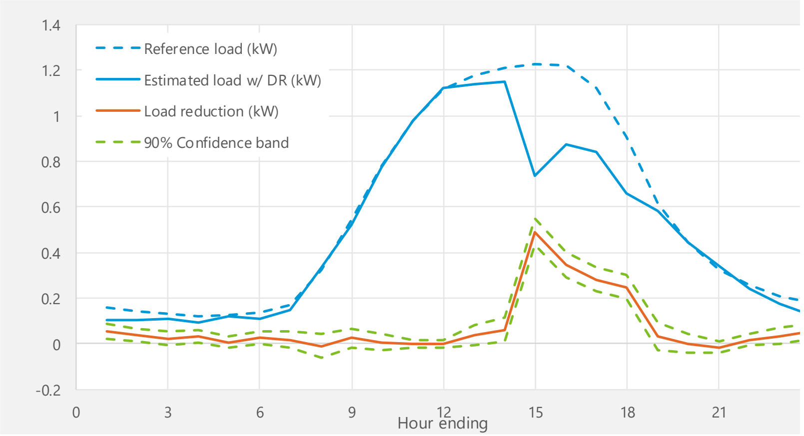


Table 1: Menu options

Program	CPPTD (PSW)
Type of result	Average Connected Thermostat (Cooling load)
Type of site	Connected
Category	All
Subcategory	All study segments
Event date	Avg. Weekday Event 2018

Table 2: Event day information

Event start	2:00 PM
Event end	6:00 PM
Total sites	698
Total installed thermostats	2,171
Total connected thermostats	1,599
Percent of thermostats connected	74%
Avg load reduction 2PM-6PM	0.34
% Load reduction 2PM-6PM	30.6%
Avg load reduction 6PM-8PM	
% Load reduction 6PM-8PM	



8.3.2 CPP-D: Medium & Large Non-Residential CPP with Technology

Table 8-5 summarizes the load reductions for the Medium and Large Non-Residential sites on the CPP-D rate with thermostats for the six weekday events and 2 pm to 6 pm reductions for the average event. The average event aggregate load reduction was 1.82 MW across the 592 sites. The average reduction per site was 4.39 kW. Though 7,853 devices were installed at enrolled sites, only 4,071 devices on average were connected during the PY 2018 event season. Because only connected devices can be dispatched, all reductions are delivered by these connected devices. The average reduction per connected device was 0.45 kW.

Reductions were strongly significant on average (t value=12.77) and for each event (t value≥5.05). Reductions were much higher during the 7/6/2018 event than during all the other events, in part because the temperature during the event was several degrees hotter and in part because devices were dispatched using a 100% cycling approach while for other events AC load was curtailed by raising the thermostat temperature set point 4 degrees during the event window.

Table 8-5: CPP-D Program Event Reductions

Event Date	Event Window	Avg Event Temp (F)	Sites Enrolled	Installed Devices	Connect-ed Devices	Reduction			t-stat	Significant (90% CI)
						Aggregate (MW)	Average Site (kw)	Average Connected Tstat		
7/6/2018	2 to 6 pm	96.4	592	7,849	4,242	3.06	7.37	0.72	7.27	Yes
7/24/2018	2 to 6 pm	86.0	592	7,854	4,079	1.60	3.85	0.39	5.65	Yes
7/25/2018	2 to 6 pm	82.7	592	7,854	4,078	1.62	3.89	0.40	6.76	Yes
8/6/2018	2 to 6 pm	87.3	592	7,854	4,028	1.82	4.39	0.45	5.77	Yes
8/7/2018	2 to 6 pm	89.9	592	7,854	4,000	1.21	2.91	0.30	5.05	Yes
8/9/2018	2 to 6 pm	88.3	592	7,854	3,999	1.62	3.90	0.41	5.16	Yes
Avg Event	**2 to 6 pm**	**88.4**	**592**	**7,853**	**4,071**	**1.82**	**4.39**	**0.45**	**12.77**	**Yes**

Reductions were also analyzed within climate zone segment. Table8-6 details the reference loads and load reductions overall and by segment for the average 2 pm to 6 pm event window. In addition to aggregate reductions, average reductions per connected thermostat are also shown. Note that the reference load for aggregate impacts includes the whole building load across all enrolled sites as recorded at the meter; the reference load for the average connected thermostat is the cooling load per connected thermostat, estimated by isolating the weather sensitive portion of whole building load. In aggregate, 5.9% of whole building was curtailed during the average event, while 27% of cooling load was curtailed per connected device.

In aggregate, about 72% of connected devices were installed at medium customer sites and these devices delivered about 77% of the 1.82 MW of reductions for the CPP-D program. In addition to comprising many more sites and connected devices, medium customers in the coastal zone also delivered more reductions per connected device— 38% compared to 13% per connected device for large sites in the coastal zone. In addition, only 37% of devices installed at large sites in the coastal zone were connected during PY 2018, decreasing the aggregate savings potential for large customers.

Table 8-6: CPP-D Program Average Event Reductions by Segment

							Aggregate (MW)			Average connected tstat (kW)			
Size	Climate zone	Event Window	Avg Event Temp (F)	Sites Enrolled	Installed Devices	Connect-ed Devices	Ref load (whole bldg)	Reduc-tion	% Reduc-tion	Ref load (cooling)	Reduc-tion	% Reduc-tion	t-stat
Large	Coastal	2 to 6 pm	85.2	39	1,528	559	8.82	0.18	2.0%	2.49	0.32	13%	2.95
	Inland	2 to 6 pm	93.9	27	896	592	3.40	0.24	7.2%	1.50	0.41	28%	2.96
Medium	Coastal	2 to 6 pm	85.1	309	3,409	1,941	11.80	0.92	7.8%	1.26	0.48	38%	12.66
	Inland	2 to 6 pm	93.2	218	2,020	979	6.73	0.48	7.1%	1.63	0.49	30%	8.10
All	**All**	**2 to 6 pm**	**88.4**	**592**	**7,853**	**4,071**	**30.75**	**1.82**	**5.9%**	**1.66**	**0.45**	**27%**	**12.77**

The average event day load shape is summarized in greater detail in Figure8-3. Note that the figure, extracted from the Ex Post Load Impact Table, is for the CPP-D participant population. The left panel shows the aggregate hourly loads (actual and counterfactual) for these sites. The right panel shows impacts per connected thermostat as a function of cooling load. The tables accompanying each figure show impacts for the 2 pm to 6 pm event window. Load impacts were evident for the average event window with a 5.9% aggregate reduction and a 27.0% cooling load reduction per connected thermostat.

Figure 8-3: CPP-D Summary for Average Event

Table 1: Menu options

Program	CPPTD (CPP-D)
Type of result	Aggregate
Type of site	All
Category	All
Subcategory	All study segments
Event date	Avg. Weekday Event 2018

Table 2: Event day information

Event start	2:00 PM
Event end	6:00 PM
Total sites	592
Total installed thermostats	7,853
Total connected thermostats	4,071
Percent of thermostats connected	52%
Avg load reduction 2PM-6PM	1.82
% Load reduction 2PM-6PM	5.9%
Avg load reduction 6PM-8PM	
% Load reduction 6PM-8PM	

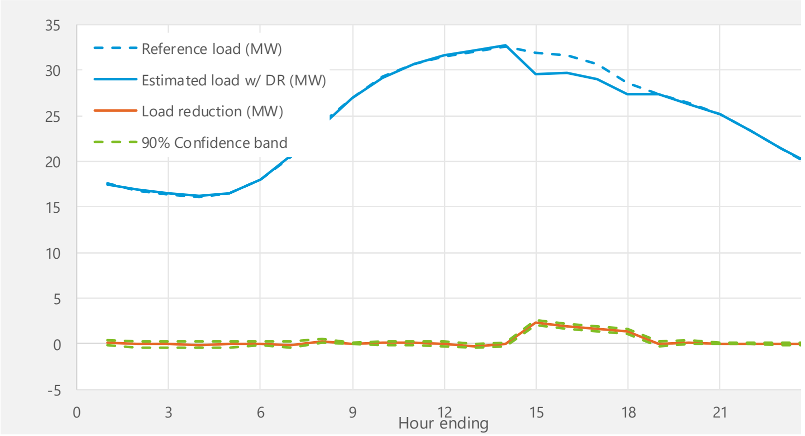
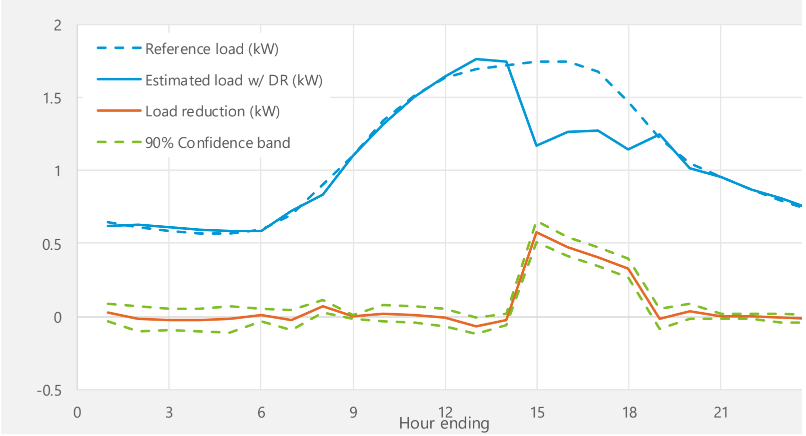


Table 1: Menu options

Program	CPPTD (CPP-D)
Type of result	Average Connected Thermostat (Cooling load)
Type of site	Connected
Category	All
Subcategory	All study segments
Event date	Avg. Weekday Event 2018

Table 2: Event day information

Event start	2:00 PM
Event end	6:00 PM
Total sites	416
Total installed thermostats	6,576
Total connected thermostats	4,071
Percent of thermostats connected	62%
Avg load reduction 2PM-6PM	0.45
% Load reduction 2PM-6PM	27.0%
Avg load reduction 6PM-8PM	
% Load reduction 6PM-8PM	



8.3.3 AC Saver Day Ahead: Commercial with Technology

The AC Saver program called 17 events during PY 2018. The ACSDA events were typically called from 6 to 8 pm, though three were called during slightly different windows. In addition to being called later in the day when commercial AC loads are lower several ACSDA events were also called later in the season on cooler days. Load reductions were not significant for many individual events and for the average event were significant but low on a percentage basis. These factors resulted in relatively minimal impacts for this program. Greater impacts may be achieved by calling events earlier in the day or on hotter days and by reconnecting disconnected devices.

Table8-7 summarizes the load reductions for all Non-Residential ACSDA sites for the 17 weekday events and 6 pm to 8 pm reductions for the average event. The full event hours for the three non-standard event days are provided at the bottom of Table. The event on 9/27/2018 did not include the 6 to 8 pm window and is therefore not included in the calculations for the average event. For the other non-standard events, the 6 to 8 pm impacts were included in the average event calculations, and the relevant contribution is provided by date above the "Avg Event" row. The average aggregate load reduction for all event days from 6 to 8 pm was 0.71 MW across all 385 enrolled sites and the average reduction per site was 2.45 kW. Though 6,009 devices were installed at enrolled sites, only 3,866 devices on average were connected during the PY 2018 event season. Because only connected devices can be dispatched, all reductions are delivered by these connected devices. The average reduction per connected device was 0.18 kW. Notably, non-residential loads tend to be lower during the typical 6 pm to 8 pm dispatch window and events were also called on cooler days. Average temperatures during the last three events were below 70 F. Impacts tended to be larger for events where the average event temperature was higher.

Reductions were marginally significant and very small in magnitude on average, with six events producing reductions significant at the 90% level though all with t-statistics below 3.22 and the average event with a t-statistic of 4.09, indicating some degree of statistical noise in the results. Aggregate reductions for significant events range from 0.81 MW (July 20 and August 7) to 1.46 MW (July 17). These dates, respectively, also exhibited the highest and lowest average site reductions and average connected thermostat reductions of the significant events.

Table 8-7: ACSDA Commercial Program Event Reductions

Event Date	Event Window	Avg Event Temp (F)	Sites Enrolled	Installed Devices	Connect-ed Devices	Reduction Aggregate (MW)	Reduction Average Site (kw)	Reduction Average Connected Tstat (kw)	t-stat	Significant (90% CI)
7/6/2018	6 to 8 pm	88.9	385	5,993	3,944	0.81	2.80	0.21	2.59	Yes
7/12/2018	6 to 8 pm	75.0	385	6,003	3,939	0.53	1.82	0.13	0.63	No
7/16/2018	6 to 8 pm	73.1	385	6,003	3,937	0.33	1.15	0.08	0.77	No
7/17/2018	6 to 8 pm	71.9	385	6,003	3,937	1.46	5.07	0.37	2.54	Yes
7/19/2018	6 to 8 pm	74.4	385	6,003	3,921	0.35	1.22	0.09	0.71	No
7/20/2018	6 to 8 pm	74.4	385	6,003	3,914	0.33	1.15	0.09	0.79	No
7/25/2018	6 to 8 pm	76.8	385	6,003	3,865	0.13	0.47	0.03	0.34	No
7/30/2018	6 to 8 pm	79.9	385	6,003	3,855	0.76	2.64	0.20	1.56	No
7/31/2018	6 to 8 pm	78.4	385	6,003	3,855	0.87	3.01	0.23	2.00	Yes
8/6/2018	6 to 8 pm	82.3	385	6,020	3,855	0.70	2.43	0.18	1.23	No
8/7/2018	6 to 8 pm	82.5	385	6,020	3,854	0.81	2.80	0.21	2.28	Yes
8/9/2018	6 to 8 pm	84.7	385	6,020	3,851	0.95	3.29	0.25	1.57	No
9/18/2018	6 to 8 pm	69.6	385	6,020	3,763	0.77	2.67	0.20	1.58	No
9/20/2018	6 to 8 pm	66.4	386	6,020	3,763	1.04	3.58	0.28	2.22	Yes
9/26/2018	6 to 8 pm	67.6	386	6,020	3,739	0.53	1.83	0.14	1.36	No
Avg Event	**6 to 8 pm**	**76.4**	**385**	**6,009**	**3,866**	**0.71**	**2.45**	**0.18**	**4.09**	**Yes**
7/6/2018	4 to 8 pm	93.3	385	5,993	3,944	0.98	3.39	0.25	3.22	Yes
7/17/2018	5 to 9 pm	72.4	385	6,003	3,937	1.36	4.72	0.35	2.56	Yes
9/27/2018	5 to 7 pm	73.0	386	6,020	3,733	1.39	4.82	0.37	2.19	Yes

Reductions were also analyzed within climate zone for Small, Medium, and Large customers in the ACSDA program. Table8-8 details the reference loads and load reductions overall and by size-climate zone segment for the average 6 pm to 8 pm event window. In addition to aggregate reductions, average reductions per connected thermostat are also shown. Note that the reference load for aggregate impacts includes the whole building load across all enrolled sites as recorded at the meter; the reference load for the average connected thermostat is the cooling load per connected thermostat, estimated by isolating the weather sensitive portion of whole building load. In aggregate, 4.2% of whole building load was curtailed during the average event, while 22% of cooling load was curtailed per connected device.

In aggregate, about 34% of connected devices were in the coastal zone and these devices delivered 0.26 MW of the 0.71 MW—about one third—of reductions for the ACSDA Non-Res program. Large customers exhibited the largest reference loads in aggregate and per connected thermostat. Significant load reductions were not found for small customers in either climate zone. Small sites in the inland zone actually exhibited substantial load increases (negative reductions). Explorations of load patterns on individual event days revealed distinct load control notch patterns from 2 to 6 pm for small customer sites specifically on CPP event days but no visually noticeable impacts during hours where ACSDA events were dispatched. This implies that small ACSDA sites may have erroneously been dispatched during CPP events rather than during ACSDA days. Based on inspection of event day load shapes for small sites, the significant load increases for small customers in the inland zone appear mostly to be due to snap back during the 6 to 8 pm window on ACSDA events where CPP events were called earlier in the day.

Table 8-8: ACSDA Commercial Program Average Event Reductions by Segment

Size	Climate zone	Event Window	Avg Event Temp (F)	Sites Enrolled	Installed Devices	Connect-ed Devices	Aggregate (MW)			Average connected tstat (kW)			
							Ref load (whole bldg)	Reduc-tion	% Reduc-tion	Ref load (cooling)	Reduc-tion	% Reduc-tion	t-stat
Large	Coastal	6 to 8 pm	73.3	29	1,096	611	6.50	0.16	2.4%	1.74	0.26	15%	1.93
	Inland	6 to 8 pm	77.6	42	1,722	1,248	4.59	0.43	9.4%	0.71	0.34	48%	4.13
Medium	Coastal	6 to 8 pm	74.5	68	804	492	2.41	0.09	3.8%	0.99	0.18	19%	2.12
	Inland	6 to 8 pm	78.3	100	1,727	1,099	2.68	0.10	3.7%	0.49	0.09	18%	2.06
Small	Coastal	6 to 8 pm	74.0	64	348	216	0.31	0.01	3.8%	0.24	0.05	22%	0.84
	Inland	6 to 8 pm	78.0	82	311	201	0.24	-0.08	-33.0%	0.37	-0.40	-108%	-4.18
All	**All**	**6 to 8 pm**	**76.4**	**385**	**6,009**	**3,866**	**16.73**	**0.71**	**4.2%**	**0.83**	**0.18**	**22%**	**4.09**

The average event day load shape is summarized in greater detail in Figure8-3. Note that the figure, extracted from the Ex Post Load Impact Table, is for the ACSDA Non-residential participant population for the average event day. The average event day reflects days where event hours covered the 6 to 8 pm window, including days such as July 6 where the event window began earlier (4pm). The left panel shows the aggregate hourly loads (actual and counterfactual) for these sites. The right panel shows impacts per connected thermostat as a function of cooling load. The tables accompanying each figure show aggregate impacts for the 6 pm to 8 pm event window. Load reductions, though statistically significant, are much smaller on a percentage basis than for the CPP Technology Deployment Programs. As noted above this is due primarily to the later window and cooler event temperatures for ACSDA events. Though aggregate load reductions are 4.2%, reductions are 22.2% of cooling load per connected thermostat. However, this 22% reduction translates to 0.18 kW per connected thermostat because events were called later in the day when non-residential loads, especially cooling loads, are lower.

Figure 8-3: ACSDA Commercial Summary for Average Event

Table 1: Menu options

Program	ACSDA (non-res)
Type of result	Aggregate
Type of site	All
Category	All
Subcategory	All study segments
Event date	Avg. Weekday Event 2018

Table 2: Event day information

Event start	6:00 PM
Event end	8:00 PM
Total sites	385
Total installed thermostats	6,009
Total connected thermostats	3,866
Percent of thermostats connected	64%
Avg load reduction 2PM-6PM	0.21
% Load reduction 2PM-6PM	1.1%
Avg load reduction 6PM-8PM	0.71
% Load reduction 6PM-8PM	4.2%

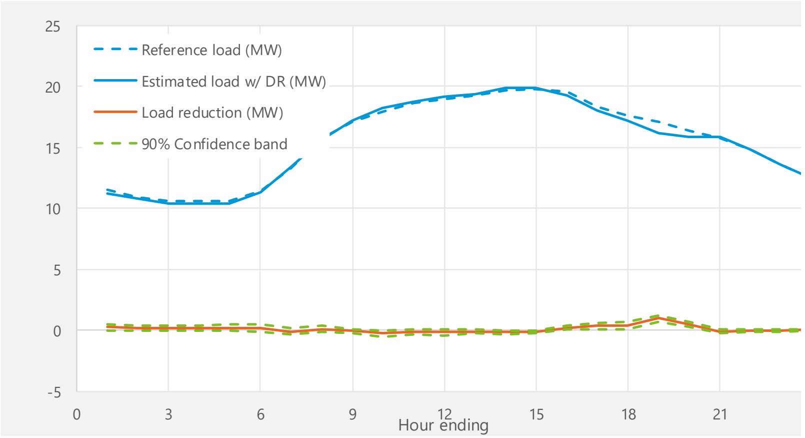
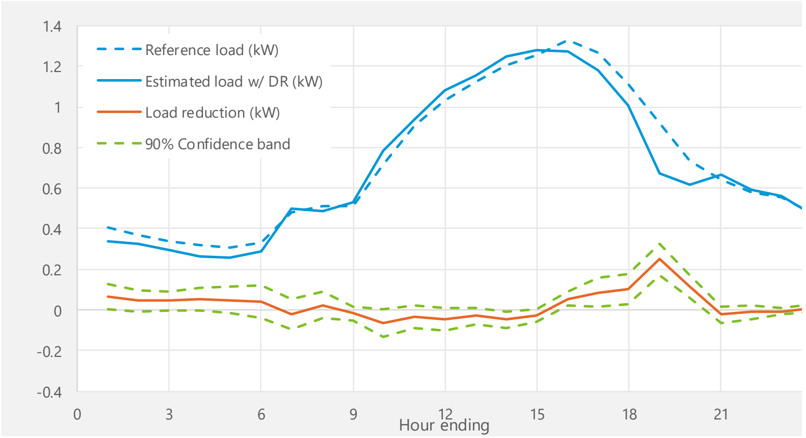


Table 1: Menu options

Program	ACSDA (non-res)
Type of result	Average Connected Thermostat (Cooling load)
Type of site	Connected
Category	All
Subcategory	All study segments
Event date	Avg. Weekday Event 2018

Table 2: Event day information

Event start	6:00 PM
Event end	8:00 PM
Total sites	289
Total installed thermostats	5,509
Total connected thermostats	3,866
Percent of thermostats connected	70%
Avg load reduction 2PM-6PM	0.05
% Load reduction 2PM-6PM	4.4%
Avg load reduction 6PM-8PM	0.18
% Load reduction 6PM-8PM	22.2%



8.3.4 AC Saver Day Ahead: Quasi-Residential with Technology

Seventeen events were called for the AC Saver Day Ahead program during PY 2018. As with enrolled non-residential sites, no meaningful reductions found for quasi-residential enrolled sites. As noted in the non-residential ACSDA section events were called later in the day and on cool days late in the season when cooling loads are already relatively low, likely contributing to the lack of reductions. In addition, only 209 thermostats were connected during PY 2018, making it difficult to detect any reductions. Greater impacts may be achieved by calling events earlier in the day or on hotter days and by reconnecting disconnected devices.

In addition, clusters of dozens or even hundreds of quasi-res sites are often managed by a single customer, reflecting the fact that quasi-residential customers are often property management companies. Based on observation, loads tend to be relatively correlated across sites managed by the same customer which further presents a challenge for detecting load reductions. However, most of the disconnected devices were managed by a single customer and were disconnected on or around the same date in 2017. In PY 2017 quasi-residential sites were analyzed using a slightly different, within-subjects methodology, but since so few devices remained connected for PY 2018 they were analyzed using the same methodology as the other Technology Deployment programs.

Table8-9 summarizes the load reductions for all ACSDA Quasi-Residential sites for the 17 weekday events and 6 pm to 8 pm reductions for the average event. As described in the non-residential ACSDA section, three events occurred during a different window than the rest. These three events are presented in full below the Average Event details, and for the events that included the 6 to 8 pm window, the applicable timeframe from that event is provided to show its impact on the Average Event calculations. The average aggregate load reduction was 0.03 MW across all 1,174 enrolled sites and the average reduction per site was 0.18 kW and this was significant at the 90% confidence level (t-value = 3.43). Of 1,255 devices installed at enrolled sites, only 209 devices on average were connected during the PY 2018 event season. Because only connected devices can be dispatched, all reductions are delivered by these connected devices. The average reduction per connected device was 0.15 kW.

Reductions were marginally significant and very small in magnitude on average, with five events producing reductions significant at the 90% level. Significant reductions were not correlated with higher event temperatures and also largely occurred in the latter half of September, indicating there may have been a shift in usage patterns unrelated to the program. This is all the more likely given that the majority of the connected devices are located at sites managed by a single customer.

Table 8-9: ACSDA Quasi-Residential Program Event Reductions

Event Date	Event Window	Avg Event Temp (F)	Sites Enrolled	Installed Devices	Connect-ed Devices	Reduction Aggregate (MW)	Reduction Average Site (kw)	Reduction Average Connected Tstat (kw)	t-stat	Significant (90% CI)
7/6/2018	6 to 8 pm	99.2	1,173	1,254	209	0.04	0.25	0.20	2.18	Yes
7/12/2018	6 to 8 pm	76.9	1,174	1,255	209	0.03	0.15	0.12	0.84	No
7/16/2018	6 to 8 pm	74.9	1,174	1,255	209	-0.01	-0.06	-0.05	-1.13	No
7/17/2018	6 to 8 pm	74.9	1,174	1,255	209	0.05	0.30	0.25	1.44	No
7/19/2018	6 to 8 pm	76.9	1,174	1,255	209	0.10	0.56	0.47	2.83	Yes
7/20/2018	6 to 8 pm	76.4	1,174	1,255	209	0.01	0.08	0.07	0.71	No
7/25/2018	6 to 8 pm	82.9	1,174	1,255	209	0.00	0.00	0.00	-0.10	No
7/30/2018	6 to 8 pm	82.9	1,173	1,254	209	0.00	0.01	0.01	0.01	No
7/31/2018	6 to 8 pm	80.9	1,172	1,252	209	0.03	0.16	0.14	1.37	No
8/6/2018	6 to 8 pm	85.4	1,174	1,255	208	-0.01	-0.04	-0.03	-0.14	No
8/7/2018	6 to 8 pm	85.9	1,174	1,255	208	0.00	0.01	0.00	0.03	No
8/9/2018	6 to 8 pm	85.9	1,174	1,255	208	0.01	0.08	0.06	0.51	No
9/18/2018	6 to 8 pm	66.6	1,174	1,255	208	0.13	0.76	0.64	4.08	Yes
9/20/2018	6 to 8 pm	65.0	1,174	1,255	208	0.04	0.24	0.20	2.28	Yes
9/26/2018	6 to 8 pm	66.5	1,174	1,255	208	0.03	0.17	0.14	0.99	No
Avg Event	**6 to 8 pm**	**78.8**	**1,174**	**1,255**	**209**	**0.03**	**0.18**	**0.15**	**3.43**	**Yes**
7/6/2018	4 to 8 pm	103.9	1,173	1,254	209	0.05	0.27	0.22	2.04	Yes
7/17/2018	5 to 9 pm	75.4	1,174	1,255	209	0.05	0.31	0.26	1.77	Yes
9/27/2018	5 to 7 pm	78.4	1,174	1,255	208	-0.03	-0.18	-0.15	-1.04	No

Quasi-Residential reductions were also analyzed by climate zone segment. Table8-10 details the reference loads and load reductions overall and by segment for the average 6 pm to 8 pm event window. In addition to aggregate reductions, average reductions per connected thermostat are also shown. Note that the reference load for aggregate impacts includes the whole building load across all enrolled sites as recorded at the meter; the reference load for the average connected thermostat is the cooling load per connected thermostat, estimated by isolating the weather sensitive portion of whole building load. In aggregate, 2.2% of whole building was curtailed during the average event, while 13% of cooling load was curtailed per connected device. Notably, half of reductions were delivered by the two devices at a single site in the Coastal Zone, which also happened to have a distinct solar generation load shape which may also interfere somewhat with detecting load reductions. For all these reasons load reduction results for ACSDA quasi-residential sites should be viewed with caution.

Table 8-10: ACSDA Quasi-Residential Program Average Event Reductions by Segment

Size	Climate zone	Event Window	Avg Event Temp (F)	Sites Enrolled	Installed Devices	Connect-ed Devices	Aggregate (MW) Ref load (whole bldg)	Aggregate (MW) Reduc-tion	Aggregate (MW) % Reduc-tion	Average connected tstat (kW) Ref load (cooling)	Average connected tstat (kW) Reduc-tion	Average connected tstat (kW) % Reduc-tion	t-stat
Quasi-res	Coastal	6 to 8 pm	74.8	905	972	5	0.86	0.01	1.0%	1.18	1.80	153%	3.15
	Inland	6 to 8 pm	78.8	269	283	204	0.53	0.02	4.1%	0.98	0.11	11%	2.89
All	All	6 to 8 pm	78.8	1,174	1,255	209	1.40	0.03	2.2%	1.11	0.15	13%	3.43

The average event day load shape is summarized in greater detail in Figure8-5. Note that the figure, extracted from the Ex Post Load Impact Table, is for the ACSDA quasi-residential participant population for the average event day. The average event day reflects days where event hours covered the 6 to 8 pm window, including days such as July 6 where the event window began earlier (4pm). The left panel shows the aggregate hourly loads (actual and counterfactual) for these sites. The right panel shows impacts per thermostat as a function of cooling load. The tables accompanying each figure show impacts for the 6 pm to 8 pm event window. Load reductions, though statistically significant, are much smaller on a percentage basis than for the CPP Technology Deployment Programs. As noted above this is due primarily to the later window and cooler event temperatures for ACSDA events. The load shape for quasi-residential site is visibly distinctive and indicative of highly correlated site loads across sites managed by a few customers. Though aggregate load reductions are 2.2%, reductions are 13.2% of cooling load per connected thermostat.

Figure 8-5: ACSDA Quasi-Residential Summary for Average Event

Table 1: Menu options

Program	ACSDA (quasi-res)
Type of result	Aggregate
Type of site	All
Category	All
Subcategory	All study segments
Event date	Avg. Weekday Event 2018

Table 2: Event day information

Event start	6:00 PM
Event end	8:00 PM
Total sites	1,174
Total installed thermostats	1,255
Total connected thermostats	209
Percent of thermostats connected	17%
Avg load reduction 2PM-6PM	0.00
% Load reduction 2PM-6PM	0.3%
Avg load reduction 6PM-8PM	0.03
% Load reduction 6PM-8PM	2.2%

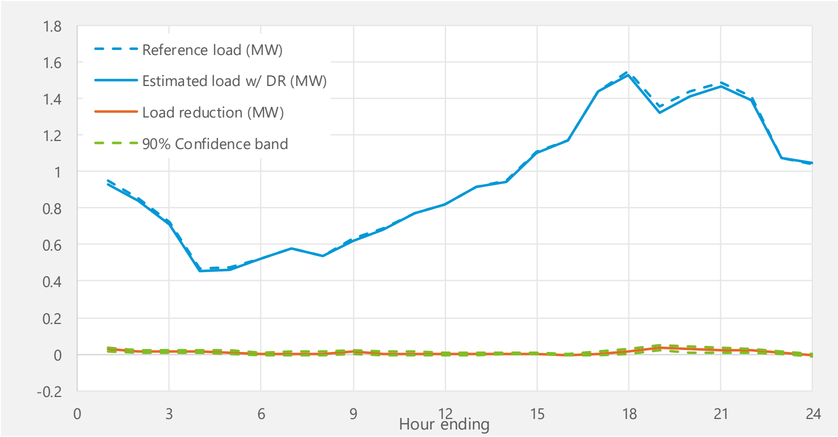
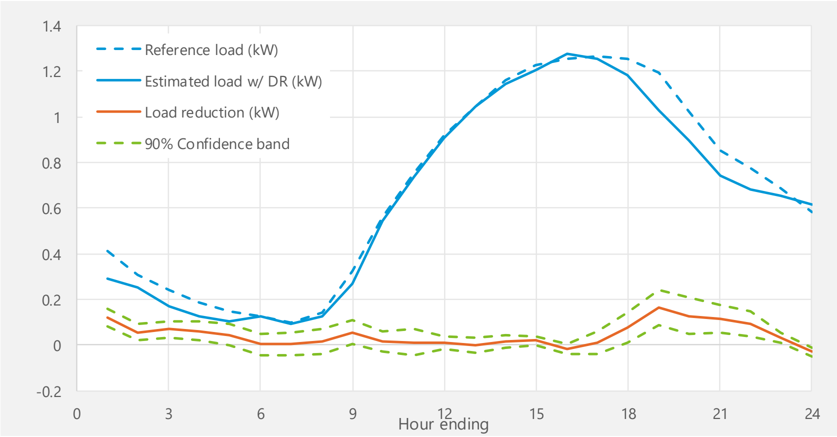


Table 1: Menu options

Program	ACSDA (quasi-res)
Type of result	Average Connected Thermostat (Cooling load)
Type of site	Connected
Category	All
Subcategory	All study segments
Event date	Avg. Weekday Event 2018

Table 2: Event day information

Event start	6:00 PM
Event end	8:00 PM
Total sites	174
Total installed thermostats	187
Total connected thermostats	209
Percent of thermostats connected	112%
Avg load reduction 2PM-6PM	0.02
% Load reduction 2PM-6PM	1.7%
Avg load reduction 6PM-8PM	0.15
% Load reduction 6PM-8PM	13.2%



8.4 *Commercial Thermostats Ex ante Load Impact Estimates*

Table8-11 summarizes the ex ante demand reduction capability by forecast year for 1-in-2 SDG&E weather planning conditions across all four Technology Deployment programs. The tables reflect dispatchable demand reductions available from 4 pm to 9 pm on August monthly peaking conditions. They align with the planning conditions used for resource adequacy attribution. They incorporate an enrollment forecast developed by SDG&E reflecting moderate growth in enrollment for sites on dispatchable rates. The enrollment forecast also incorporates declines in device connectivity in line with the historical average discussed at the beginning of this chapter.

Table 8-11: Non-residential Smart Thermostat Portfolio Impacts for 1-in-2 August Monthly Peak Day

Year	CPP-TD		ACSDA		Total
	PSW	CPP-D	Non-Res	Quasi-Res	
2018	0.10	0.45	1.22	0.01	1.78
2019	0.09	0.40	1.08	0.01	1.58
2020	0.08	0.37	0.96	0.00	1.41
2021	0.07	0.34	0.85	0.00	1.27
2022	0.07	0.33	0.76	0.00	1.16
2023	0.05	0.26	0.66	0.00	0.98
2024	0.04	0.21	0.58	0.00	0.83
2025	0.03	0.17	0.50	0.00	0.70
2026	0.02	0.14	0.44	0.00	0.59
2027	0.02	0.11	0.38	0.00	0.50
2028	0.01	0.09	0.33	0.00	0.43
2029	0.01	0.07	0.29	0.00	0.37

Table8-12 and Table8-13 summarize the ex ante demand reduction capability by forecast year for different planning conditions, respectively, for sites on dispatchable rates (CPP-TD) and those that are not (ACSDA). The tables reflect dispatchable demand reductions available from 4 pm to 9 pm on August monthly peaking conditions for 1-in-2 and 1-in-10 weather conditions. They align with the planning conditions used for resource adequacy attribution. The enrollment forecast for the number of enrolled sites was developed by SDG&E was also applied to the counts of installed thermostats and shows moderate increases in the number of thermostats over time. The number of thermostats connected reflects the decline in connectivity observed historically and overlays this decline on the total population of installed thermostats. Impacts are a function of connected thermostats and therefore also decline over time.

Table 8-12: CPP-TD Portfolio Impacts for August Monthly Peak Day

Year	Sites	Tstats installed	Tstats connected	CAISO		SDG&E	
				1-in-2	1-in-10	1-in-2	1-in-10
2018	1,777	10,985	5,670	0.58	0.54	0.55	0.62
2019	1,867	11,538	5,044	0.51	0.48	0.49	0.55
2020	1,961	12,119	4,578	0.47	0.44	0.45	0.50
2021	2,060	12,729	4,238	0.43	0.41	0.42	0.46
2022	2,164	13,369	4,000	0.41	0.39	0.39	0.44
2023	2,164	13,369	3,172	0.33	0.31	0.31	0.35
2024	2,164	13,369	2,517	0.26	0.24	0.25	0.28
2025	2,164	13,369	1,997	0.21	0.19	0.20	0.22
2026	2,164	13,369	1,586	0.17	0.16	0.16	0.18
2027	2,164	13,369	1,259	0.13	0.12	0.13	0.14
2028	2,164	13,369	1,001	0.11	0.10	0.10	0.11
2029	2,164	13,369	795	0.08	0.08	0.08	0.09

Table 8-13: ACSDA Portfolio Impacts for August Monthly Peak Day

Year	Sites	Tstats installed	Tstats connected	CAISO		SDG&E	
				1-in-2	1-in-10	1-in-2	1-in-10
2018	1,559	7,264	4,075	1.25	1.21	1.23	1.30
2019	1,563	7,324	3,562	1.11	1.07	1.09	1.15
2020	1,567	7,385	3,130	0.98	0.94	0.96	1.02
2021	1,571	7,447	2,765	0.87	0.84	0.85	0.90
2022	1,575	7,509	2,454	0.78	0.75	0.76	0.81
2023	1,575	7,509	2,126	0.68	0.65	0.66	0.70
2024	1,575	7,509	1,844	0.59	0.57	0.58	0.61
2025	1,575	7,509	1,600	0.51	0.49	0.50	0.53
2026	1,575	7,509	1,389	0.44	0.43	0.44	0.46
2027	1,575	7,509	1,206	0.39	0.37	0.38	0.40
2028	1,575	7,509	1,048	0.34	0.32	0.33	0.35
2029	1,575	7,509	911	0.29	0.28	0.29	0.30

8.5 *Commercial Thermostats Comparison between Ex post and Ex ante Estimates*

Table8-14 compares the demand reductions from 2018 events to the reduction expected for the 1-in-2 weather conditions used for planning. Results are shown for both the new 4 to 9 pm and old 1 to 6 pm resource adequacy windows to highlight the differences under the later window for CPPTD programs. In 2018, CPPTD customers delivered 2.37 MW during the dispatch period of 2 pm to 6 pm and 1.90 MW during the old 1 pm to 6 pm resource adequacy window, after factoring in an hour with no reductions from 1 to 2 pm. For the new 4 to 9 pm resource adequacy window, which extends three hours beyond the CPP dispatch window, ex post reductions are much lower because they include three hours with no reductions, from 6 to 9 pm. Ex ante impacts for the old and new resource adequacy windows are lower than the corresponding ex post impacts. This is in part because ex ante temperatures for 1-in-2 weather conditions shown here are two degrees lower than for the events called in 2018 (ex post). Ex post results also reflect a changing mix of connected devices over the course of the summer and the unique hourly temperature profiles of each event, whereas ex ante impacts assume a fixed number of connected devices and weather for a single peak day.

Table 8-14: CPPTD Comparison of Ex Post and Ex Ante Load Impacts for 2018

Result Type	Day Type and Period	Sites	Tstats connected	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex Post Avg. Weekday	Event Period (2pm to 6pm)	1,776	5,670	38.01	2.37	6.2%	90.9
	Old Resource Adequacy Period (1 to 6pm)	1,776	5,670	38.48	1.90	4.9%	90.9
	New Resource Adequacy Period (4 to 9pm)	1,776	5,670	33.07	0.79	2.4%	90.9
Ex ante SDG&E	1-in-2 Weather August Peak (1 to 6pm)	1,777	5,670	38.29	1.41	3.7%	88.9
	1-in-2 Weather August Peak (4 to 9pm)	1,777	5,670	32.35	0.55	1.7%	88.9

Table 8-14: CPPTD Comparison of Ex Post and Ex Ante Load Impacts for 2018 (Continued)

Result Type	Day Type and Period	Sites	Tstats connected	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex ante CAISO	1-in-2 Weather August Peak (1 to 6pm)	1,777	5,670	38.97	1.47	3.8%	88.9
	1-in-2 Weather August Peak (4 to 9pm)	1,777	5,670	32.85	0.58	1.8%	88.9

*Table shows portfolio impacts. To avoid double counting, it excluded commercial thermostats and customers dually enrolled in other DR programs.

Table8-15 makes a similar comparison for ACSDA programs. An important difference is that ex post impacts are shown on average only across events with average temperature surpassing 70 F. Excluding the cooler events makes for a more meaningful comparison with ex ante results. In 2018, ACSDA customers delivered 0.68 MW during the typical dispatch period of 6 pm to 8 pm. However, because thermostat resources were largely only dispatched for two hours during the five-hour window, ex post reductions during the new 4 to 9 pm resource adequacy window were lower (0.42 MW). In contrast, ex ante reference loads and impacts are greater for the both the old 1 to 6 pm window and for the new 4 to 9 pm window, mostly because they assume four hours of dispatch—the maximum for the program. In addition, temperatures were somewhat higher for 1-in-2 planning conditions than for the PY 2018 events. Further, it is important to note that percent reductions for ACSDA were relatively low and there is a greater degree of uncertainty with small percentage impacts. As with the CPPTD programs, ex post results also reflect a changing mix of connected devices over the course of the summer and the unique hourly temperature profiles of each event, whereas ex ante impacts assume a fixed number of connected devices and weather for a single peak day.

Table 8-15: ACSDA Comparison of Ex Post and Ex Ante Load Impacts for 2018

Result Type	Day Type and Period	Sites	Tstats connected	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex Post Avg. Weekday**	Event Period (6pm to 8pm)	1,559	4,091	18.30	0.68	3.7%	90.9
	Old Resource Adequacy Period (1 to 6pm)	1,559	4,091	20.18	0.18	0.9%	90.9
	New Resource Adequacy Period (4 to 9pm)	1,559	4,091	18.64	0.42	2.2%	90.9
Ex ante SDG&E	1-in-2 Weather August Peak (1 to 6pm)	1,559	4,075	20.94	1.70	8.1%	92.1
	1-in-2 Weather August Peak (4 to 9pm)	1,559	4,075	18.87	1.23	6.5%	92.1
Ex ante CAISO	1-in-2 Weather August Peak (1 to 6pm)	1,559	4,075	21.29	1.69	8.0%	91.6
	1-in-2 Weather August Peak (4 to 9pm)	1,559	4,075	19.13	1.25	6.5%	91.6

*Table shows portfolio impacts. To avoid double counting, it excludes commercial thermostats and customers dually enrolled in other DR programs.
**For comparability to ex ante, only includes events with average event temperature above 70F

9 Summary of the Voluntary Residential TOU-DR-P and GTOU-DR-P Rate[36]

9.1 Voluntary Residential TOU-DR-P and GTOU-DR-P Rate Overview

This section documents the program year 2018 (PY 2018) load impacts for SDG&E's time varying pricing tariffs for residential customers, including:

- Voluntary CPP-TOU residential customers (non-event) (TOU-DR)
- Voluntary CPP-TOU residential customers (event based) (TOU-DR-P)
- Voluntary Grand fathered CPP-TOU residential customers (GTOU-DR-P)

The TOU periods for the two non-grandfathered rates are centered around an on-peak period of 4 p.m. to 9 p.m. on non-holiday weekdays, which is surrounded by morning and evening off-peak periods, and an overnight super-off-peak period. The super-off-peak hours are longer for weekend and holidays as well as during the months of March and April. The CPP rate may be called during the 2 p.m. to 6 p.m. period on any day (including weekends) throughout the year. SDG&E called six CPP events in 2018: 7/6, 7/24, 7/25, 8/6, 8/7, and 8/9.

For grandfathered customers, the summer TOU on-peak period is 11 a.m. to 6 p.m. on non-holiday weekdays, which is surrounded by morning and evening semi-peak periods, and an overnight off-peak period. On winter weekdays, the on-peak period is 5 p.m. to 8 p.m., with semi-peak periods in the morning, afternoon and evening hours, and an overnight off-peak period. Weekend and holiday hours are all off-peak.

These are collectively referred to as the residential smart pricing project (SPP) rates. The SPP rates became active in February of 2015, with the exception of the grandfathered TOU periods which became effective on Dec 1st, 2017.

a) Time Periods for CPP

The CPUC approved SDG&E's GRC application for the following changes for SDG&E Residential CPP and TOU. Changes were effective on December 1st, 2017:

[36] The Voluntary Residential CPP evaluation was conducted by Christensen. This section of the Executive Summary contains excerpts from the following evaluation: Crowley, N., & Hansen, D. & Clark, M. Christensen Associates (2019). "2018 Load Impact Evaluation of San Diego Gas and Electric's Voluntary Residential Critical Peak Pricing (CPP) and Time-of-Use (TOU) Rates"

All time periods listed are applicable to local time. The definition of time will be based upon the date service is rendered.

RYU Event Days

RYU Event Period 2:00 p.m. – 6:00 p.m. any day of the year on RYU Days

Non-RYU Event

TOU Period – Weekdays	Summer	Winter
On-Peak	4:00 p.m. – 9:00 p.m.	4:00 p.m. – 9:00 p.m.
Off-Peak	6:00 a.m. – 4:00 p.m.; 9:00 p.m. – midnight	6:00 a.m. – 4:00 p.m. Excluding 10:00 a.m.–2:00 p.m.in March and April; 9:00 p.m. - midnight
Super-Off-Peak	Midnight – 6:00 a.m.	Midnight – 6:00 a.m. 10:00 a.m. – 2:00 p.m. in March and April

TOU Period – Weekends and Holidays	Summer	Winter
On-Peak	4:00 p.m. – 9:00 p.m.	4:00 p.m. – 9:00 p.m.
Off-Peak	2:00 p.m. – 4:00 p.m.; 9:00 p.m. – midnight	2:00 p.m. – 4:00 p.m. 9:00 p.m. - midnight
Super-Off-Peak	Midnight – 2:00 p.m.	Midnight – 2:00 p.m.

Seasons:

Summer June 1 – October 31

Winter November 1 – May 31

b) Event Triggers:

a. RYU events for all residential customers may be triggered at the same time.

b. A RYU event may also be triggered as warranted by extreme system conditions such as special alerts issued by the California Independent System Operator, Utility system emergencies related to grid operations, or under conditions of high forecasted California spot market prices or for testing/evaluation purposes.

c. 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.

d. The Utility will evaluate and consider all relevant conditions including temperature and system load conditions, as well as other system operating conditions, energy market conditions and other emergency conditions in determining whether to trigger a RYU event.

c) Time Periods for TOU

The approved changes for SDG&E TOU effective on December 1st, 2017:

TOU Period Grandfathering: Pursuant to D.17-01-006 and D.17-10-018, TOU Period Grandfathering permits certain eligible behind-the-meter solar customers to continue billing under grandfathered TOU period definitions for a specific period of time after new TOU Periods are implemented.

TOU Period Grandfathering Eligible Customer Generator (Residential): a residential customer with an on-site solar system, who opts into a TOU tariff prior to July 31, 2017. In addition, the customer must have filed an initial interconnection application by January 31, 2017. The on-site solar system must be designed to offset at least 15% of the customer's current annual load. Pursuant to D.17-01-001, TOU Period Grandfathering, does not apply to residential solar customers who take service under Schedule NEM-ST and are already permitted to stay on a TOU rate for five years pursuant to D.16-01-044.

TOU Period Grandfathering Term (Residential): Upon SDG&E's implementation of updated TOU periods adopted in D.17-08-030, TOU Grandfathering Eligible Customer Generators will continue to be billed under prior existing TOU periods and resulting rates for the remainder of their applicable TOU Grandfathering Term, which begins upon issuance of a permission to operate customer's on-site solar system and continues for 5 years. In no event shall the duration a customer's grandfathering term extend beyond July 31, 2022. Upon expiration of a customer's TOU period Grandfathering Term, the customer will be billed using his otherwise applicable TOU periods and associated rates beginning with the customer's the next billing cycle.

TOU Grandfathering Time Periods

All time periods listed are applicable to local time. The definition of time will be based upon the date service is rendered.

RYU Event Days	
RYU Event Period	2 p.m. – 6 p.m. any day of the week, year-round
Non-RYU Event Days	
Summer	
On-Peak	11 a.m. – 6 p.m. weekdays, excluding holidays
Semi-Peak	6 a.m. – 11 a.m. weekdays, excluding holidays
	6 p.m. – 10 p.m. weekdays, excluding holidays
Off-Peak	10 p.m. – 6 a.m. weekdays, and all hours on weekends & holidays

Seasons:

Summer	June 1 – October 31
Winter	November 1 – May 31

d) Residential Opt-In and Default TOU pilots

In 2016 SDG&E conducted an opt-in residential TOU pilot to test SDG&E's new TOU periods and resulting rates. One of the primary goals of the opt-in TOU pilot was to assess hardship for certain customers – those living in hot climate zones, low income, and other vulnerable customers. In 2018 SDG&E launched a default TOU pilot that implemented its 3 period TOU rate with updated time of use periods to approximately 140,000 residential customers. SDG&E is evaluating the Residential 2018 default TOU for the 2018 summer period in section 10 of this report. The load impact evaluation of the TOU-DR-P will include an estimate of load impacts from the TOU portion of the TOU-DR-P for non-event days.

9.2 Voluntary Residential CPP Rate Ex post Evaluation Methodology

The ex post impact evaluations for the TOU and CPP rates apply difference-in-differences analysis 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 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, solar PV size, and enrollment in SDG&E's Peak Time Rebate Reduce Your Use, or PTR-RYU, program), based on the closest match of load profiles.

9.2.1 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 produces load impact estimates for each hour of every event:

$$kWh_{c,d} = \beta_0 + \Sigma_{Evts(i)}\,(\beta_{1,i} \text{ x } CPP_{c,d} \text{ x } Evt_{i,d}) + \beta_2 \text{ x } \mathrm{CPP}_{c,d} + \Sigma_{Evts(i)}\,(\beta_{3,i} \text{ x } TD_{c,d} \text{ x } Evt_{i,d}) + \Sigma_{Cust}\,(\beta_{4,Cust} \text{ x } C_c) + \Sigma_{day}\,(\beta_{5,day} \text{ x } D_{day,d}) + \beta_6 \text{ x } SS\_Evt_{c,d} + \varepsilon_{c,d}$$

The variables and coefficients in the equation are described in the following table. Results are then scaled to enrollment numbers because a portion CPP customers are removed from the analysis based upon load quality and NEM customer restrictions.

Symbol	Description
$kWh_{c,d}$	Load in a particular hour for customer *c* on day *d*
$CPP_{c,d}$	Variable indicating whether customer *c* is only a *CPP* customer (*i.e.*, not also dually enrolled in *TD*) on day *d* (1 = yes, 0 if not)
$Evt_{i,d}$	Variable indicating that day *d* is the i^{th} event day (1=i^{th} event, 0 if not)
$TD_{c,d}$	Variable indicating whether customer *c* is a dually enrolled *CPP* and *TD* customer on day *d* (1 = yes, 0 if not)
$SS\_Evt_{c,d}$	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* for *CPP* only customers
β_2	Estimated non-event day response for incremental *CPP* customers
$\beta_{3,d}$	Estimated load impact for event *d* for dually enrolled *CPP* and *TD* customers
$\beta_{4,Cust}$ and $\beta_{5,day}$	Customer and day fixed-effects
β_6	Estimated average *Summer Saver* load impact
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

9.2.2 Ex post models for estimating TOU load impacts

To obtain TOU load impacts (for TOU-DR, TOU-DR-P, and GTOU-DR-P customers), a distinct model for each required result is estimated. For example, to obtain the average TOU load impacts on August non-holiday weekdays, a model is estimated that includes only days of that day-type. In this case, the model is simplified 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 rate (e.g., TOU-DR, TOU-DR-P, GDRTOPH), hour, month, day-type (i.e., average weekday versus peak month day), applicable customer groups (e.g., climate zone, NEM), where the customer-level fixed-effects models are of the following form:

$$kWc,d = \beta 0 + \beta 1\ x\ (TOUc\ x\ Postc,d) + \Sigma Cust\ (\beta 2,Cust\ x\ Cc) + \Sigma days\ (\beta 3,day\ x\ Dday)$$
$$+ \beta 4\ x\ Evtc,d + \beta 5\ x\ SS\_Evtc,d + \beta 6\ x\ TD\_Evtc,d + \varepsilon c,d$$

The variables and coefficients in the equation are described in the following table. Incremental customers are used to estimate the TOU load impacts in each regression. Results are then scaled to the program level of enrollments.

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* [37]
$Post_{c,d}$	Variable indicating that day *d* is in the post-enrollment period for customer *c*
$TD\_Evt_{c,d}$	Variable indicating that day *d* is a *TD* 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 *TD* 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

9.2.3 Control Group Matching

The difference-in-differences evaluation is a quasi-experimental approach that compares the usage of treatment and matched control group customers on relevant days or time periods, 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 a 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. The initial samples of eligible control group customers were developed as seven-to-one samples by segment from the eligible population of SDG&E residential customers.

The matching process differed for customers on the two rates. Since the CPP (TOU-DR-P) customers experienced TOU rates on all non-event days, and the CPP rate on event days, customers are treated as CPP customers when evaluating CPP load impacts, and as TOU customers when evaluating TOU impacts.

For analyzing CPP impacts, the 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 days).

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[37] 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.

For analyzing TOU impacts, for both CPP and TOU customers, only incremental treatment customers were used in the analysis and matched based on loads in the pre-treatment period (October 2016 through September 2017). Only incremental customers were used in the TOU load impact study because these customers have enough pre-treatment data to provide a quality difference-in-difference analysis. The matching and regression analysis are separated by season, thus allowing different threshold dates that define incremental customers.[38] Specifically, incremental customers for the winter analysis are those that enrolled after June 1, 2017 while incremental customers for the summer analysis are those that enrolled after October 1, 2017. The incremental TOU customers were matched 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 2016 through May 2017, while that for the *summer* season used data for October 2016 and June through September of 2017.

The grandfathered rate prevents new customers from joining the rate. As a result, all grandfathered customers are already treated during the pre-treatment matching periods mentioned above. To estimate TOU load impacts for these customers, PY2017 TOU load impacts were estimated using PY2017 incremental customers that are now grandfathered customers. The PY2017 pre- and post-treatment analysis periods cover October 2015 through September 2017. Current grandfathered customers that enrolled in either DR-TOD or DR-TOD-PSH after May 1, 2016 are incremental customers for the grandfathered winter analysis and those that enrolled after September 1, 2016 are incremental customers for the grandfathered summer analysis.

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 as shown in the equation below.

$$Distance_{T,C} = \sqrt{(T_1 - C_1)^2 + (T_2 - C_2)^2 \dots + (T_n - C_n)^2}$$

In this equation, the *T* variables represent treatment customer characteristics and the *C* variables represent the corresponding eligible control group customer characteristics. As described, separate matches and therefore sets of variables are used for the for the CPP and TOU analyses. For matching in the CPP analysis, the customer characteristics include the average hourly usage on event-like non-event weekdays (24 variables). For the TOU analysis, the customer characteristics include the average hourly usage on weekdays and hot/cold days for the

[38] The seasons defined for matching are summer (June through October) and winter (November through May).

summer/winter match (48 variables).[39] Treatment and potential control customers are also segmented by climate zone, CARE status, and enrollment in RYU. Each enrolled customer is compared to each potential control group customer within their segment, 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 with replacement (*i.e.*, matched to multiple enrolled customers).

NEM customers are matched similarly, with three major distinctions. First, only customers that are NEM for the entire analysis period are included. Second, NEM treatment customers must be matched to NEM control customers that have comparable solar photovoltaic generation capacity sizes.[40] Third, customers with large changes in net profiles between periods are not used in the analysis because the differences are more likely caused by unobserved structural changes to a customer's solar PV system. Each of these requirements helps prevent estimating load impacts (TOU or CPP) that are confounded by differences in solar generation capacity between periods and/or between the treatment and control groups, as opposed to only a behavioral response to TOU rates or CPP events.[41]

9.2.4 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). Statistics such as the mean absolute percentage error (MAPE) and mean percent error (MPE) are reported, which provide formal estimates of the percent differences between treatment and control group loads. The MAPE offers a measure of accuracy while MPE offers a measure of bias.

[39] Hot/cold days are among the highest/lowest 20th percentile in terms of CDD or HDD temperature values. Hot/cold days are selected separately by climate zone.

[40] NEM customers are segmented only by solar PV size, rounded to the next integer level (capacity sizes greater than 12 kW are a separate segment).

[41] For example, a large load-usage treatment customer with a larger solar generation system may be matched to a smaller load-usage control customer with a smaller solar generation system based on similar net load profiles. If conditions are met so that solar generation is larger in the post-period, then any analysis based on net load profiles will exhibit that the treatment customer reduced their usage, relative to their own pre-treatment usage as well as relative to the control customer's usage.

9.3 Voluntary Residential CPP Rate & TOU Ex post Load Impacts

This section documents the findings from the ex post load impact evaluation analysis of the CPP portion of the TOU-DR-P and GDRTODPH rates. 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 four-hour event window from 2 p.m. to 6 p.m.), in aggregate and per-customer, for each event day. Results of the analysis of the TOU portion of the rate (i.e., peak load impacts on non-event days) are presented in Section 10.3.2, along with results for the TOU rate.

9.3.1 Voluntary Residential CPP and Grandfather CPP Rates *Ex post* Load Impact Estimates

This section summarizes average event-hour reference loads and load impacts, at an aggregate and per-customer basis, for the six 2018 CPP events called on July 6, July 24, July 25, August 6, August 7, and August 9. Each event had an event-window of 2 p.m. to 6 p.m. (HE 15-18). This section contains only the results for CPP customers; CPP load impacts for Grandfathered CPP customers are reported in Section 4.3 of the full report.[42]

Table 9-1 summarizes reference load and CPP load impact results for CPP customers, by climate zone. The first three columns show the climate zone, event date, and numbers of enrolled customers. The next two columns show aggregate estimated reference loads and load impacts for the average event hour, in MWh/h. The next two columns show the same variables for the average customer, in units of kWh/h. The last two columns show the load impacts as a percentage of the reference loads and the average temperature during the event window.

[42] 2018 Load Impact Evaluation of San Diego Gas and Electric's Voluntary Residential Critical Peak Pricing (CPP) and Time-of-Use (TOU) Rates, Crowley, N., & Hansen, D. & Clark, M. Christensen Associates (2018).

Table 9-1: Average CPP Event-Hour Load Impacts

Climate Zone	Date	Enrolled	Aggregate Ref. Load (MWh/h)	Aggregate Load Impact (MWh/h)	Per-Customer Ref. Load (kWh/h)	Per-Customer Load Impact (kWh/h)	% Load Impact	Ave. Event Temp.
Coastal	Jul 6, 2018	3,981	4.89	0.68	1.23	0.17	14%	96
	Jul 24, 2018	4,051	4.47	0.64	1.10	0.16	14%	85
	Jul 25, 2018	4,063	4.15	0.52	1.02	0.13	13%	82
	Aug 6, 2017	4,166	4.67	0.74	1.12	0.18	16%	87
	Aug 7, 2017	4,175	4.81	0.62	1.15	0.15	13%	90
	Aug 9, 2017	4,193	5.35	0.94	1.28	0.22	17%	89
	Typical Event Day	**4,105**	**4.72**	**0.69**	**1.15**	**0.17**	**15%**	**88**
Inland	Jul 6, 2018	2,600	4.64	0.66	1.78	0.25	14%	103
	Jul 24, 2018	2,649	4.32	0.75	1.63	0.28	17%	92
	Jul 25, 2018	2,655	3.94	0.58	1.48	0.22	15%	89
	Aug 6, 2017	2,728	4.41	0.91	1.61	0.33	21%	93
	Aug 7, 2017	2,743	4.50	0.76	1.64	0.28	17%	94
	Aug 9, 2017	2,774	4.70	0.81	1.70	0.29	17%	91
	Typical Event Day	**2,692**	**4.42**	**0.75**	**1.64**	**0.28**	**17%**	**94**
All	Jul 6, 2018	6,581	10.13	1.36	1.54	0.21	13%	99
	Jul 24, 2018	6,700	9.46	1.42	1.41	0.21	15%	89
	Jul 25, 2018	6,718	8.61	1.12	1.28	0.17	13%	86
	Aug 6, 2017	6,894	9.84	1.67	1.43	0.24	17%	90
	Aug 7, 2017	6,918	9.93	1.40	1.44	0.20	14%	92
	Aug 9, 2017	6,967	10.82	1.76	1.55	0.25	16%	90
	Typical Event Day	**6,796**	**9.14**	**1.45**	**1.35**	**0.21**	**16%**	**91**

Program enrollment was 6,581 customers for the first event, skewed somewhat toward the Coastal climate zone. On a Typical Event Day (i.e., the average event), the per-customer reference load during event hours for all customers was 1.35 kWh/h. Per-customer load impacts averaged 0.17 kWh/h for customers in the Coastal climate zone, representing 15 percent of their reference load, and 0.28 kW, or 17 percent, for the Inland climate zone. Average event-window temperatures were somewhat cooler in the Coastal zone, at 88 degrees, than the 94-degree temperature for the Inland zone. Both customer groups, inland and climate, respond similarly in percentage terms to the average weekday event. The first event-day, July 6, had the hottest event-window temperature but not the largest per-customer load impact.

This section summarizes average event-hour reference loads and load impacts, at an aggregate and per-customer basis, for the six 2018 CPP events for the Grandfathered CPP customers. Table 9-2 summarizes reference load and CPP load impact results for Grandfathered CPP customers, by climate zone. Program enrollment remained fairly constant between events. The average per-customer load impact is larger for customers in the inland climate zone. Percentage load impacts are not presented because all grandfathered customers are NEM customers that can have near zero reference loads, resulting in misleading percentage load impacts. Customers in the coastal climate exhibited an average increase in usage for the second event, July 24, 2018. For the average weekday event, the per-customer level load impact of grandfathered customers is larger than non-grandfathered CPP customers.

Table 9-2: Average Grandfathered CPP Event-Hour Load Impacts

Climate Zone	Date	Enrolled	Aggregate		Per-Customer		Ave. Event Temp.
			Ref. Load (MWh/h)	Load Impact (MWh/h)	Ref. Load (kWh/h)	Load Impact (kWh/h)	
Coastal	Jul 6, 2018	181	0.09	0.01	0.51	0.05	96
	Jul 24, 2018	181	-0.01	0.00	-0.04	-0.01	85
	Jul 25, 2018	181	-0.03	0.01	-0.14	0.03	82
	Aug 6, 2017	181	0.03	0.05	0.15	0.29	86
	Aug 7, 2017	181	0.07	0.04	0.36	0.24	89
	Aug 9, 2017	180	0.22	0.04	1.25	0.20	89
	Typical Event Day	**181**	**0.06**	**0.02**	**0.35**	**0.13**	**88**
Inland	Jul 6, 2018	246	0.36	0.10	1.46	0.42	106
	Jul 24, 2018	246	0.19	0.07	0.79	0.29	94
	Jul 25, 2018	246	0.14	0.06	0.58	0.26	91
	Aug 6, 2017	245	0.19	0.09	0.78	0.37	95
	Aug 7, 2017	245	0.18	0.06	0.75	0.23	96
	Aug 9, 2017	245	0.41	0.11	1.68	0.44	92
	Typical Event Day	**246**	**0.25**	**0.08**	**1.01**	**0.33**	**95**
All	Jul 6, 2018	427	0.45	0.12	1.07	0.28	106
	Jul 24, 2018	427	0.19	0.07	0.45	0.18	94
	Jul 25, 2018	427	0.12	0.07	0.28	0.17	91
	Aug 6, 2017	426	0.22	0.15	0.52	0.35	95
	Aug 7, 2017	426	0.25	0.10	0.58	0.23	96
	Aug 9, 2017	425	0.64	0.14	1.50	0.34	92
	Typical Event Day	**426**	**0.31**	**0.11**	**0.73**	**0.26**	**95**

9.3.2 Technology Deployment Load Impacts

This section compares the CPP load impact estimates for customers that were dually enrolled in CPP and the Technology Deployment ("TD") program during 2018. Customers dually enrolled in TD and CPP experienced the same CPP events and event-window (July 6, July 24, July 25, August 6, August 7, and August 9; 2 p.m. to 6 p.m.).

Table 9-3 summarizes reference loads and load impacts for customers by enrollment status during the event-hour window, bifurcating results for customers enrolled solely in CPP ("CPP

Only") and customers dually enrolled in CPP and TD ("Dually Enrolled CPP+TD"). The number of dually enrolled customers by the last event date was 1,192 (which is about 9% of all CPP customers). On average, customers dually enrolled in TD have larger reference loads and load impacts. For example, the average weekday event reference load and load impact for dually enrolled customers was 1.60 kWh/h and 0.59 kWh/h, respectively. While the average weekday event reference load and load impact for non-dually enrolled customers was 1.33 kWh/h and 0.19 kWh/h, respectively. The load impact percentage of dually enrolled customers is more than double that of non-dually enrolled customers for each event.

The lowest dually enrolled customer load impact of 0.54 kWh/h occurred on July 25th, the event with the lowest average event-hour temperature.

Table 9-3: Comparison of Average CPP Event-Hour Load Impacts for TD and CPP Enrollment Type

Enrollment Type	Date	Enrolled	Aggregate		Per-Customer		% Load Impact	Ave. Event Temp.
			Ref. Load (MWh/h)	Load Impact (MWh/h)	Ref. Load (kWh/h)	Load Impact (kWh/h)		
CPP Only	Jul 6, 2018	6,004	9.17	1.08	1.53	0.18	12%	99
	Jul 24, 2018	6,111	8.57	1.14	1.40	0.19	13%	89
	Jul 25, 2018	6,128	7.78	0.86	1.27	0.14	11%	86
	Aug 6, 2018	6,292	8.91	1.35	1.42	0.21	15%	90
	Aug 7, 2016	6,312	9.00	1.11	1.43	0.18	12%	92
	Aug 9, 2018	6,356	9.81	1.43	1.54	0.22	15%	90
	Typical Event Day	**6,201**	**8.23**	**1.16**	**1.33**	**0.19**	**14%**	**91**
Dually Enrolled CPP + TD	Jul 6, 2018	577	0.98	0.33	1.70	0.58	34%	100
	Jul 24, 2018	589	0.93	0.34	1.58	0.57	36%	89
	Jul 25, 2018	590	0.86	0.32	1.46	0.54	37%	86
	Aug 6, 2018	602	0.96	0.39	1.59	0.64	40%	90
	Aug 7, 2018	606	0.95	0.34	1.58	0.56	36%	92
	Aug 9, 2018	611	1.03	0.39	1.68	0.63	38%	90
	Typical Event Day	**596**	**0.95**	**0.35**	**1.60**	**0.59**	**37%**	**91**

9.3.3 TOU *Ex post* Load Impact Estimates

This sub-section shows ex post TOU load impact results for those customers enrolled in the TOU (TOU-DR) rate. Table 9-4 summarizes the average reference loads and TOU load impacts for the TOU peak period (i.e., 4 p.m. to 9 p.m.), 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 2017). The winter months are indicated by light blue shading. Enrollment continued throughout the period, with the numbers of enrolled customers rising from 1,019 in October 2017 to 2,869 in September 2018. The estimation methodology for TOU non-NEM customers included applying seasonal (March and April as a separate season) percentage load impacts to monthly reference loads. The seasonal level load impacts are similarly used for NEM customers. Therefore, differences in percentage load impacts across seasons is driven by load impacts of NEM customers. The per-customer load impacts are largest during the summer months, followed by the March and April season, and lowest for the remaining winter period. The largest per-customer load impact of 0.156 kWh/h occurs in August, which also has the largest average event-hour temperature.

Table 9-4: TOU Peak Load Impacts for TOU Customers – *Average Weekday by Month*

			Aggregate		Per-Customer			
Month	Climate Zone	Enrolled	Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	% Peak Load Impact	Ave. Peak Temp.
Oct-17	All	1,019	1.13	0.07	1.11	0.07	6.0%	74
Nov-17	All	1,103	1.02	0.01	0.93	0.01	1.4%	66
Dec-17	All	1,233	1.26	0.02	1.02	0.01	1.4%	62
Jan-18	All	1,290	1.20	0.02	0.93	0.01	1.3%	62
Feb-18	All	1,290	1.15	0.01	0.89	0.01	1.2%	59
Mar-18	All	1,298	1.03	0.04	0.80	0.03	4.1%	63
Apr-18	All	1,335	0.99	0.04	0.74	0.03	3.6%	65
May-18	All	1,535	1.08	0.00	0.71	0.00	-0.4%	65
Jun-18	All	1,729	1.52	0.18	0.88	0.10	11.6%	70
Jul-18	All	1,917	2.91	0.27	1.52	0.14	9.3%	78
Aug-18	All	2,456	3.96	0.38	1.61	0.16	9.7%	79
Sep-18	All	2,869	3.31	0.44	1.15	0.16	13.5%	73

Table 9-5 shows results by season and climate zone. The coastal climate had at least one and a half times larger level and percentage load impacts for each season

Table 9-5: 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 (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)		
Summer	Coastal	1,102	1.28	0.16	1.17	0.14	12.1%	74
	Inland	896	1.25	0.08	1.40	0.09	6.6%	76
	All	1,998	2.54	0.24	1.27	0.12	9.4%	75
Winter	Coastal	742	0.61	0.02	0.82	0.02	2.5%	63
	Inland	556	0.50	0.01	0.89	0.01	1.1%	63
	All	1,298	1.11	0.02	0.85	0.02	1.9%	63

Voluntary Residential CPP and Grandfather CPP Rates & TOU Ex ante Methodology

9.4.1 Per-customer load impacts

In cases where multiple events have been called in the historical period for event-based programs such as CPP, a relationship is developed between the estimated event-day *ex post* load impacts and the weather conditions that held on those days. That relationship is used to produce weather-sensitive *ex ante* load impacts for the relevant weather scenarios. In 2018 SDG&E called six RYU/CPP events, which means there are six events on which to base the *ex ante* forecasts. The percentage load impact is used for the average weekday event to simulate the *ex ante* CPP load impact. CPP load impacts are developed for different weather scenarios by applying the estimated percentage load impact from the *ex post* analysis to weather-sensitive reference loads.

Load Impacts are also reported at the portfolio-level for instances when a CPP event is called on the same day as a Summer Saver or TD event. For such days, it is assumed that Summer Saver and TD customers do not provide a load impact that can be attributable to CPP and therefore remove dually enrolled customers from the reference load and load impacts for portfolio-level estimates. The proportion of Summer Saver and TD customers is assumed to be equivalent to *ex post* enrollment numbers and is held constant throughout the *ex ante* forecast.

An additional issue in producing the *ex ante* load impact forecasts is that the Protocols call for estimating load impacts for the RA hours of 4 to 9 p.m., while the CPP events are called during the program hours of 2 p.m. to 6 p.m. year-round. Load impacts are simulated using the event hours that are indicated by the tariff, load impacts are then summarized across the RA window as required.

For TOU load impacts (TOU-DR and TOU-DR-P customers), the percentage peak load impacts are applied from the *ex post* analysis (monthly values for CPP and seasonal values for TOU) to weather-sensitive reference loads that are developed as described in the following sub-section.

NEM customer reference loads and load impacts are estimated separately from non-NEM customers. For both TOU and CPP load impacts, *ex post* seasonal TOU load impacts and average CPP event-day load impacts are applied to reference loads and scaled to the count of enrolled customers. The proportion of NEM customers is assumed to remain constant throughout the forecast period. Non-NEM and NEM results are customer weighted to produce program TOU and CPP outcomes.

9.1.2 Per-customer reference loads

Weather-sensitive reference loads for the average customer in each of the two climate zones were developed through a regression analysis of hourly load data for weekday non-event days for the period of October 2017 through September 2018 for the CPP and TOU customers. Customers are first sorted as weather sensitive or not.[43] Regression models were estimated separately for each hour of the day, by weather sensitivity, using daily observations for weekdays, and a form similar to that of the *ex post* load impact models. The primary differences between this analysis compared to the *ex post* analysis are:

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[43] Customer-specific regressions are implemented to categorize customers as weather sensitive or not. Weather sensitive customers change usage in response to changes in the weather, while non-weather sensitive customers do not. Determining which customers are non-weather sensitive allows for a more parsimonious regression model by not including weather variables as explanatory variables for these customers. The following regression specification is used to determine whether a customer is weather sensitive:

$$Q_t = b^{Weather} \times Weather_t + \sum_{i=2}^{5}\left(b_i^{DTYPE} \times DTYPE_{i,t}\right) + \sum_{i=7}^{9}\left(b_i^{MONTH} \times MONTH_{i,t}\right) + \sum_{i=1}^{EVT}\left(b_i^{EVT} \times EVT_{i,t}\right) + e_t$$

, where Q_t represents the average customer usage during event hours on day t in the summer months of June through September. $DTYPE_{i,t}$ represents the day of week, while $MONTH_{i,t}$ represents each month. The $EVT_{i,t}$ variables control for any event days a customer faces (DBP, BIP, CPP, etc.). The variable of importance is $Weather_t$, which is defined as CDD55, CDD60, or CDD65, each as a separate regression. The regression is estimated for each customer and weather specification. A customer is identified as weather sensitive if the weather coefficient ($b^{Weather}$) is positive and statistically significant for any of the three separate weather specifications.

- The analysis included only the treatment customers;
- Weather variables were included (Mean17, CDH60, and HDH60)[44];
- Data for all months were included, rather than estimating separate models by month or season; and
- Month-year indicator variables were added to account for monthly and yearly differences in usage patterns.

The resulting equations allow the simulation of "observed" (*i.e.*, post TOU load impacts) loads under the four different weather scenarios. Reference loads for the alternative scenarios were then obtained by adjusting the above observed loads by the relevant estimated percentage TOU load impacts from the *ex post* analysis (seasonal values for TOU, and monthly values for CPP).[45] For NEM customers, reference loads are calculated by adjusting observed loads by the relevant seasonal *ex post* level load impacts. The process for obtaining simulated reference and observed loads is completed separately for each reporting category.[46]

9.5 Voluntary Residential CPP and Grandfather CPP Rates & TOU 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. The forecasts are based on analyses of per-customer load impact findings from *ex post* evaluations, development of weather-sensitive reference loads, and incorporation of utility forecasts of program enrollments.

9.5.1 Voluntary Residential CPP Enrollment Forecast

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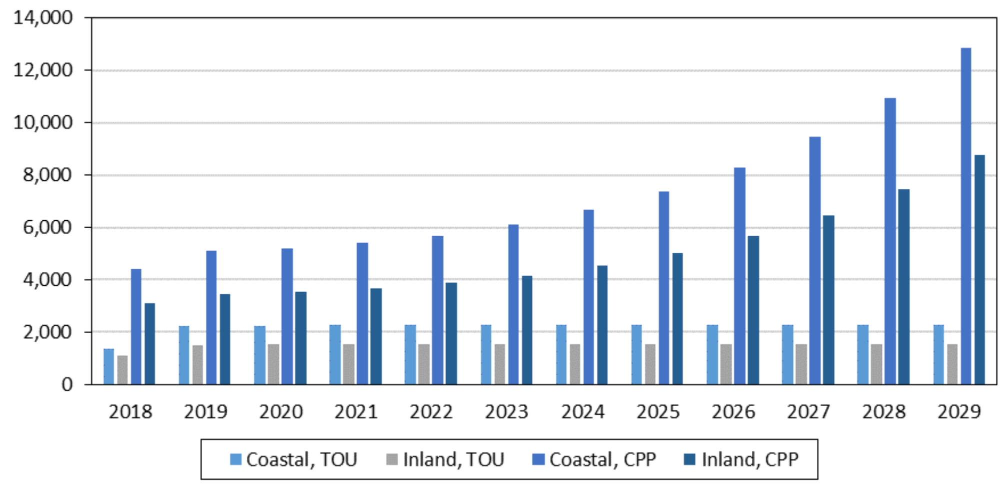
[44] Mean17 is the average temperature in degrees Fahrenheit during the first 17 hours of the day. Cooling degree hours (CDH) for each hour of the day are defined as: CDH60 = max (0, Temperature in °F – 60). Likewise, heating degree hours (HDH) for each hour of the day are defined as: HDH60 =max (0, 60 – Temperature in °F).

[45] The adjustment takes the form of Reference = Observed / (1 - %TOULoadImpact). Christensen examined several alternative approaches to developing the weather-sensitive reference load, including the same type of regression analysis using load data for the matched control group customers. The resulting reference loads were not very sensitive to the data and approach used, although the selected approach produced more accurate loads during the swing months.

[46] The use of panel regressions limits results to only apply to the customer type included in the regressions, as opposed to customer-specific regressions for which sub-categories can created by combining pieces from the individual regressions. Therefore, any sub-categorization of results needs to be processed separately to account for possible differences in weather sensitivity and load profiles. For example, customers dually enrolled in CPP and TD have larger loads. Therefore, separate panel regressions including only dually enrolled CPP and TD customers would be estimated to simulate reference and observed loads for these customers.

Figure 9-1 shows SDG&E's enrollment forecasts for the TOU and CPP rates. Enrollment is anticipated to be essentially flat for TOU, while enrollment in CPP is forecasted to nearly triple by the end of the forecast period. TOU load impact Enrollment is expected to be somewhat greater in the Coastal climate zone than in the Inland for both rates which is consistent with ex post. Enrollment for grandfathered customers (GDRTOPH) is assumed to remain constant at 418 customers until the grandfathering term expires on July 31, 2027.

Figure 9-1: Enrollments in TOU and CPP



9.5.2 Residential CPP *Ex ante* Load Impacts

Figure 9-2 illustrates the aggregate reference load, event-day load, and estimated load impact for an August peak day in 2020 for the SDG&E 1-in-2 weather scenario. The average event-period percentage load impact is 16 percent.

Figure 9-2: Aggregate Hourly Loads and CPP Load Impacts (MWh/h) – (*August 2020 SDG&E 1-in-2 Peak Day*)

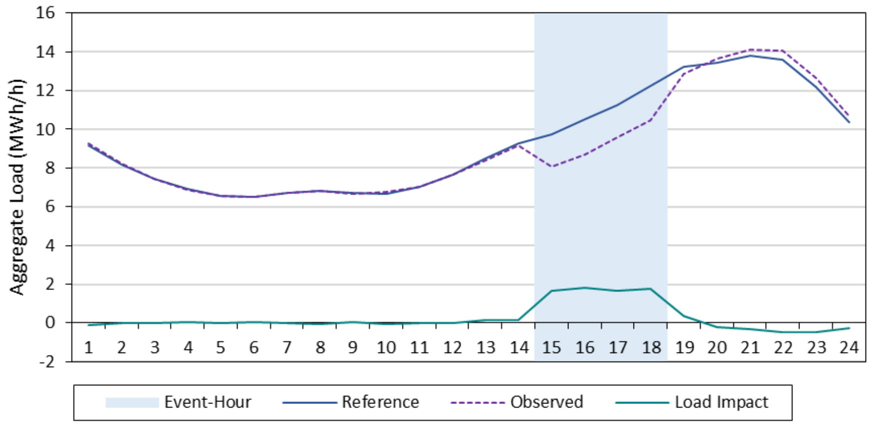
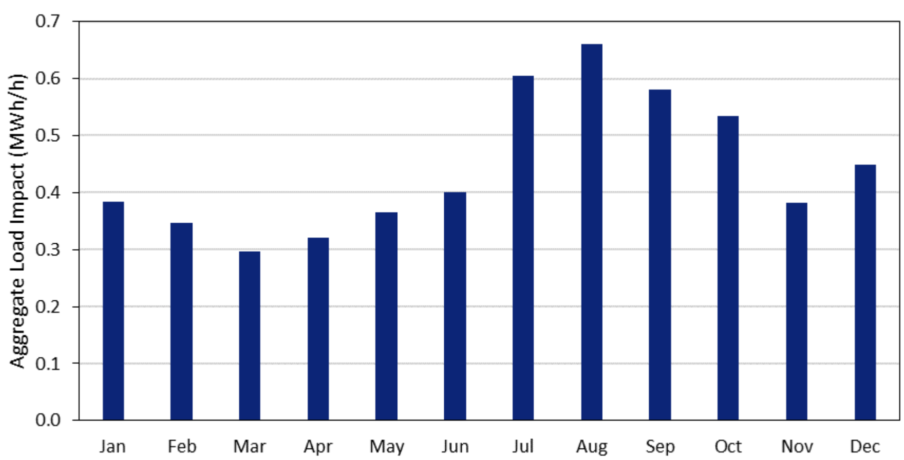


Figure 9-3 shows the monthly pattern of aggregate average ex ante load impacts (RA window) in 2020 for the SDG&E 1-in-2 peak day. Load impacts are greatest in the summer months, reaching a maximum in August. The difference in load impacts between months also indicates the seasonal pattern in customer reference loads.

Figure 9-3: Aggregate CPP Load Impacts (MWh/h), by Month – (*2020 SDG&E 1-in-2 Peak Day, RA Window*)



9.5.3 Residential TOU *Ex ante* Load Impacts

Figure 9-4 shows aggregate loads and load impacts for TOU and CPP customers, in 2020 for an August SDG&E 1-in-2 average weekday. The average peak load impact is 9 percent of the reference load.

Figure 9-4: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *TOU-DR and TOU-DR-P Customers,* (*August 2020 SDG&E 1-in-2 Peak Day*)

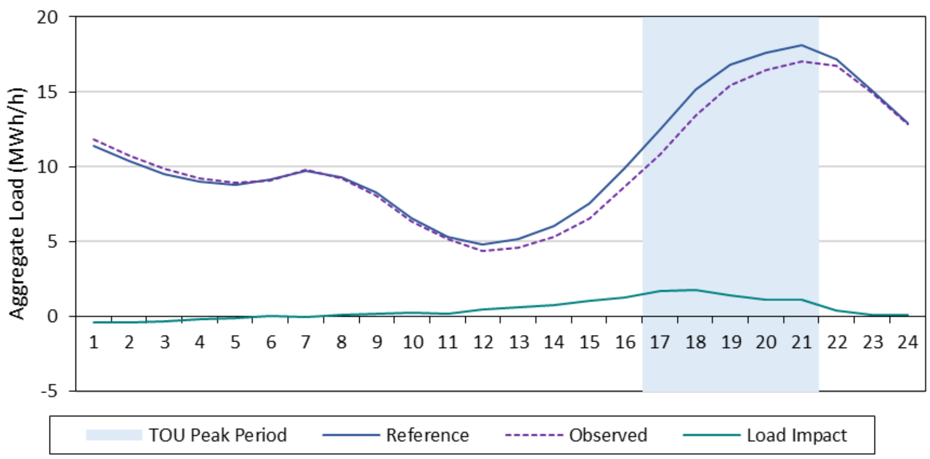
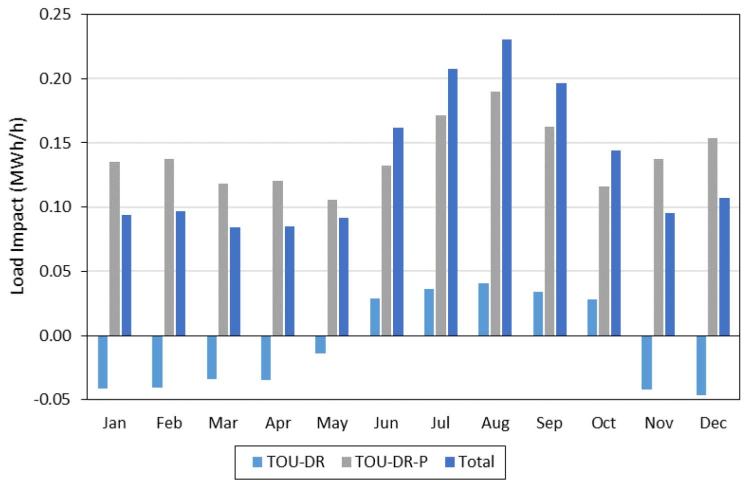


Figure 9-5 shows the monthly distributions of the peak-period TOU load impacts (TOU peak period aligns with the RA window) for TOU and CPP customers. Load impacts for are greatest in the summer months, June through October. Results for the winter months are considerably smaller, with a near zero change in November and even an increase in usage for the months of February and December. One would expect higher peak load impacts to occur during the summer months based on the higher peak-hour prices, relative to the standard non-TOU rate prices, of the summer rate schedule.

Figure 9-5: Aggregate TOU Load Impacts (MWh/h) by Month – *TOU-DR and TOU-DR-P Customers, (2029 SDG&E 1-in-2 Average Weekday,* RA Window)



9.6 Voluntary Residential CPP and Grandfather and TOU Comparison of current Ex post versus Ex ante

9.6.1 *Residential CPP*

Comparison of PY2017 Ex Post to Current Ex Post Load Impacts

Table 9-6 shows the average event-hour reference loads and CPP load impacts for the average weekday event during the current and previous program years. The event hours were longer in the *ex post* PY2017 study, lasting from 11 a.m. to 6 p.m., as opposed to the current event hours of 2 p.m. to 6 p.m. The aggregate enrollments increased in the current program which also increase reference loads and CPP load impacts. The per-customer reference load and load impact in the PY2018 study is slightly smaller, corresponding to slightly lower average event hour temperatures. The percentage load impact is slightly larger in the current study at 16 percent versus 13 percent in the PY2017 study. The current study also includes the load impacts of dually enrolled TD customers. The percentage load impact of CPP only customers was 14% for the current study, which is closer to the PY2017 study.

Table 9-6 Comparison of PY2017 *Ex post* and Current *Ex post* Load Impacts, *CPP Event*

Result	Ex post for 2017 Weekday Event from PY2017 Study	Ex post for 2018 Weekday Event from PY2018 Study
# Enrolled	4,935	6,796
Reference (MWh/h)	6.76	9.14
Load Impact (MWh/h)	0.90	1.45
Per-customer reference (kWh/h)	1.37	1.35
Per-customer load impact (kWh/h)	0.18	0.21
% Load Impact	13%	16%
Temperature	91.6	91.0

Previous ex ante versus current *ex ante*

In this sub-section, the ex ante forecast prepared following PY2017 (the "previous study") are compared to the ex ante forecast contained in this study (the "current study"). Table 9-7 reports the average event-hour load impacts for the August 2019 system peak day under utility-specific 1-in-2 weather conditions. The current study ex ante forecast has larger percentage load impacts, which results from including dually enrolled customer load impacts in the current forecast, as mentioned in the previous section. Per-customer reference loads are lower in the current study. The lower temperature in the current study causes a lower reference load; however, an increase in the proportion of NEM customers has also reduced the per-customer reference loads during event hours.

Table 9-7 Comparison of PY2017 *Ex ante* 2019 Forecast and Current *Ex ante* 2019 Forecast Load Impacts, *CPP Event*

Result	Ex ante for 2019 System Peak Day from PY2017 Study	Ex ante for 2019 System Peak Day from PY2018 Study
# Enrolled	5,721	8,568
Reference (MWh/h)	7.88	10.72
Load Impact (MWh/h)	1.05	1.69
Per-customer reference (kWh/h)	1.38	1.25
Per-customer load impact (kWh/h)	0.18	0.20
% Load Impact	13%	16%
Temperature	87.1	86.9

Previous *ex ante* versus current *ex post*

Table 9-8 provides a comparison of the ex ante forecast of 2018 load impacts prepared following PY2017 and the PY2018 load impacts estimated as part of this study, averaged over the CPP event-window. The ex ante forecast shown in the table represents the August peak day during a utility-specific 1-in-2 weather year. The ex post load impacts are based on the 2018 average CPP event day. The increase in aggregate loads and load impacts in from the PY2018 study is mostly driven by difference in enrollment numbers. The percentage load impact is also higher which is partly explained by hotter temperatures realized in ex post, as well as the inclusion of dually enrolled customer load impacts. Even with hotter PY2018 temperatures, the per-customer reference load is lower in the PY2018 study because of the increase proportion of NEM customers.

Table 9-8 Comparison of PY2017 *Ex ante* 2018 Forecast and Current *Ex post* Load Impacts, *CPP Event*

Result	Ex ante for 2018 System Peak Day from PY2017 Study	Ex post for 2018 Weekday Event from PY2018 Study
# Enrolled	5,611	6,796
Reference (MWh/h)	7.72	9.14
Load Impact (MWh/h)	1.03	1.45
Per-customer reference (kWh/h)	1.38	1.35
Per-customer load impact (kWh/h)	0.18	0.21
% Load Impact	13.3%	15.9%
Temperature	87.1	91.0

Current *ex post* versus current *ex ante*

Table 9-9 compares the CPP *ex post* load impacts for the average weekday event against the *ex ante* load impacts for 2019 (of the SDG&E 1-in-2 August peak day), from this study. The *ex post* and first set of *ex ante* load impacts are averaged over the CPP event hours (HE 15-18) while the second set of *ex ante* load impacts are summarized over the RA window (HE 17-21). Since our *ex ante* CPP load impacts are built on the 2018 *ex post* values, the per-customer load impact percentages are similar during the event window. The RA window includes non-event hours-ending 19 through 21, which reduces the percentage load impacts. Aggregate reference loads and load impacts increase in *ex ante* because of the increase in enrollments. The results are consistent between the *ex post* and *ex ante* analyses. Per-customer reference loads decrease in *ex ante* over the event window because of the lower temperatures; however, the *ex ante* per-customer reference loads are larger during the RA window because the average load profile displays rising hourly loads during event and RA window.

Table 9-9: Comparison of Current *Ex post* and *Ex ante* Load Impacts, *CPP Event*

Result	Ex post for 2018 (Event Window)	Ex ante for 2019 Peak Day (Event Window)	Ex ante for 2019 Peak Day (RA Window)
# Enrolled	6,796	8,568	8,568
Reference (MWh/h)	9.14	10.72	12.54
Load Impact (MWh/h)	1.45	1.69	0.65
Per-customer reference (kWh/h)	1.35	1.25	1.46
Per-customer load impact (kWh/h)	0.21	0.20	0.08
% Load Impact	16%	16%	5%
Temperature	91.0	86.9	82.8

Table 9-10 compares the key components of the two analyses. As the table describes, the two largest sources of differences between the *ex post* and *ex ante* load impacts are the enrollment level and the summary over the RA window for *ex ante* versus the actual event hours for the *ex post* impacts.

Table 9-10: *Ex post* versus *Ex ante* Factors, *CPP Event*

Factor	*Ex post*	*Ex ante*	Expected Impact
Weather	91 degrees Fahrenheit during HE 15-18.	82.8 degrees Fahrenheit during HE 17-21 of a utility-specific 1-in-2 August peak day.	Cooler *ex ante* weather decreases the reference load and load impact.
Event window	HE 15-18 for the average weekday event.	RA Window: HE 17-21. Event Window: HE 15-18.	The RA window covers HE 19-21 which are not event hours, resulting in a lower load impact over the RA window.
% of resource dispatched	The entire program was dispatched on each of the days that comprise the average weekday event.	Assume all customers are called.	None. The *ex ante* method assumes that all enrolled customers are dispatched.
Enrollment	6,796 customers enrolled.	8,568 customers.	The increase in *ex ante* enrollments increases the total load impact proportionately relative to *ex post*.
Methodology	Climate-zone-specific regressions using a matched control-group and difference-in-differences analysis on event and event-like non-event days.	Treatment only customer regressions to estimate observed loads.	No effect to percentage load impacts. The *ex post* percentage load impacts are applied to reference loads of the various scenarios in the *ex ante* study.

9.6.2 Residential TOU

Previous versus current *ex post*

Table 9-11 shows the average reference loads and load impacts for the average August and January weekday day during the current and previous program years, averaged over the RA window. Enrollment numbers have increased resulting in higher aggregate reference loads. The per-customer reference loads are larger in during the summer in the current study because the RA window is HE 17-21, whereas the RA window for the summer period in the PY2017 analysis was HE 14-18. The TOU peak periods were also different between the PY2017 and PY2018 *ex post* analyses, shifting to the now later TOU peak-period of HE 17-21.

Table 9-11 Comparison of PY2017 *Ex post* and PY2018 *Ex post* TOU Load Impacts

Season	Result	Ex post for 2017 Avg. Weekday from PY2017 Study	Ex post for 2018 Avg. Weekday from PY2018 Study
Summer (August)	# Enrolled	6,396	9,944
	Reference (MWh/h)	6.77	13.87
	Load Impact (MWh/h)	0.19	1.17
	Per-customer reference (kWh/h)	1.06	1.39
	Per-customer load impact (kWh/h)	0.03	0.12
	% Load Impact	2.9%	8.5%
	Temperature	79.8	78.9
Winter (January)	# Enrolled	4,006	6,097
	Reference (MWh/h)	4.01	5.61
	Load Impact (MWh/h)	0.04	0.06
	Per-customer reference (kWh/h)	1.00	0.92
	Per-customer load impact (kWh/h)	0.01	0.01
	% Load Impact	0.9%	1.1%
	Temperature	56.1	62.4

Previous versus current ex ante

In this sub-section, the ex ante forecast was prepared following PY2017 (the "previous study") to the ex ante forecast contained in this study (the "current study"). Table 9-12 reports the average RA-window load impacts for the August and January 2019 average weekday under utility-specific 1-in-2 weather conditions. The TOU peak-period remains the same in both forecasts; however, the RA-window is HE 17-21 for all months in the PY2018 study, whereas the PY2017 summer period had an RA window of HE 14-18. The later summer RA window leads to larger per-customer reference loads. The winter per-customer reference loads, on the other hand, remain fairly similar between forecasts. The current study percentage load impacts are larger in the summer period and smaller in the winter months when compared to the PY2017 *ex ante* forecast. One significant difference between studies is the inclusion of increased NEM customers in the analysis.

Table 9-12 Comparison of PY2017 *Ex ante* 2019 Forecast and PY2018 *Ex ante* 2019 Forecast TOU Load Impacts

Season	Result	Ex ante for 2019 Avg. Weekday from PY2017 Study	Ex ante for 2019 Avg. Weekday from PY2018 Study
Summer (August)	# Enrolled	7,221	12,305
	Reference (MWh/h)	7.44	15.79
	Load Impact (MWh/h)	0.23	1.39
	Per-customer reference (kWh/h)	1.03	1.28
	Per-customer load impact (kWh/h)	0.03	0.11
	% Load Impact	3.1%	8.8%
	Temperature	80.6	76.6
Winter (January)	# Enrolled	7,221	12,305
	Reference (MWh/h)	6.43	12.26
	Load Impact (MWh/h)	0.09	0.04
	Per-customer reference (kWh/h)	0.89	1.00
	Per-customer load impact (kWh/h)	0.01	0.00
	% Load Impact	1.5%	0.3%
	Temperature	61.0	61.0

9.6.2.1 Previous *ex ante* versus current *ex post*

Table 9-13 provides a comparison of the *ex ante* forecast of 2018 TOU load impacts prepared following PY2017 and the PY2018 *ex post* TOU load impacts estimated as part of this study. The *ex ante* forecast shown in the table represents the August and January average weekday during a utility-specific 1-in-2 weather year. The *ex post* load impacts are based on August and January weekdays. Increased enrollments lead to larger aggregate load impacts and reference loads. However, the enrollments for January were smaller than the PY2017 forecast, resulting in smaller aggregate reference loads and load impacts. The current *ex post* analysis also has larger percentage load impacts in August and smaller percentage load impacts in January.

Table 9-13 Comparison of PY2017 *Ex ante* 2018 Forecast and PY2018 *Ex post* TOU Load Impacts

Season	Result	Ex ante for 2018 Avg. Weekday from PY2017 Study	Ex post for 2018 Avg. Weekday from PY2018 Study
Summer (August)	# Enrolled	7,096	9,944
	Reference (MWh/h)	8.40	13.87
	Load Impact (MWh/h)	0.44	1.17
	Per-customer reference (kWh/h)	1.18	1.39
	Per-customer load impact (kWh/h)	0.06	0.12
	% Load Impact	5%	8%
	Temperature	76.6	78.9
Winter (January)	# Enrolled	7,096	6,097
	Reference (MWh/h)	6.31	5.61
	Load Impact (MWh/h)	0.09	0.06
	Per-customer reference (kWh/h)	0.89	0.92
	Per-customer load impact (kWh/h)	0.01	0.01
	% Load Impact	1.4%	1.1%
	Temperature	61.0	62.4

9.6.2.2 Current *ex post* versus current *ex ante*

Table 9-14 compares the PY2018 *ex post* TOU load impacts for the August average weekday with the corresponding *ex ante* forecast for 2019 (of the SDG&E 1-in-2 August average weekday) produced in this study. The TOU load impacts are presented for all TOU customers and are averaged over the RA window, which perfectly overlaps with the TOU peak period. The *ex ante* load impacts are based upon *ex post* percentage load impacts for each TOU period. Difference in percentage load impacts between *ex post* and *ex ante* occur because of changes in customer composition. For example, the January *ex post* percentage load impact is 1.1% versus 0.3% for *ex ante*. The proportion of NEM customers was about 5% and January and increased to 15% in September. The *ex ante* forecast assumes the same proportion of NEM customers recorded in the last month. Therefore, a greater proportion of NEM customers affect the January *ex ante* load impacts, and NEM customers exhibited lower winter TOU load impacts.

Table 9-14: Comparison of Current *Ex post* and *Ex ante* TOU Load Impacts

Season	Result	Ex post for 2018 Avg. Weekday from PY2018 Study	Ex ante for 2019 Avg. Weekday from PY2018 Study
Summer (August)	# Enrolled	9,944	12,305
	Reference (MWh/h)	13.87	15.79
	Load Impact (MWh/h)	1.17	1.39
	Per-customer reference (kWh/h)	1.39	1.28
	Per-customer load impact (kWh/h)	0.12	0.11
	% Load Impact	8%	9%
	Temperature	78.9	76.6
Winter (January)	# Enrolled	6,097	12,305
	Reference (MWh/h)	5.61	12.26
	Load Impact (MWh/h)	0.06	0.04
	Per-customer reference (kWh/h)	0.92	1.00
	Per-customer load impact (kWh/h)	0.01	0.00
	% Load Impact	1.1%	0.3%
	Temperature	62.4	61.0

9.6.3 Grandfathered Customers

This section compares the *ex post* with *ex ante* load impacts for grandfathered customers. No other comparisons for grandfathered customers can be made because this is their first program year.

9.6.3.1 Current ex post versus current ex ante, CPP load impacts

Table 9-15 compares the grandfathered customers' CPP *ex post* load impacts for the average weekday event against the *ex ante* load impacts for 2019 (of the SDG&E 1-in-2 August peak day), from this study. The *ex post* and first set of *ex ante* load impacts are averaged over the CPP event hours (HE 15-18) while the second set of *ex ante* load impacts are summarized over the RA window (HE 17-21). Since our *ex ante* CPP load impacts are built on the 2018 *ex post* values, the per-customer load impact nearly identical during the event window. Any differences between *ex post* and *ex ante* stem from changes in the number of customers between climate zones because this is the only source of differentiation in the load impact estimates. The RA window includes non-event hours-ending 19 through 21, which reduces the level load impacts. Aggregate reference loads and load impacts decrease because of program enrollment attrition.

Table 9-15: Comparison of Current *Ex post* and *Ex ante* Load Impacts, *CPP Event* for Grandfathered Customers

Result	Ex post for 2018 (Event Window)	Ex ante for 2019 Peak Day (Event Window)	Ex ante for 2019 Peak Day (RA Window)
# Enrolled	426	418	418
Reference (MWh/h)	0.31	0.42	1.01
Load Impact (MWh/h)	0.11	0.10	0.02
Per-customer reference (kWh/h)	0.73	1.00	2.42
Per-customer load impact (kWh/h)	0.26	0.25	0.06
Temperature	95.4	88.1	83.5

9.6.3.2 Current ex post versus current ex ante, TOU load impacts

Table 9-16 compares the grandfathered customers' PY2018 *ex post* TOU load impacts for the August average weekday with the corresponding *ex ante* forecast for 2019 (of the SDG&E 1-in-2 August average weekday) produced in this study. The grandfathered customers' TOU load impacts are presented for all grandfathered customers and are averaged over the RA window, which perfectly overlaps with the TOU peak period. Similar to the CPP load impacts for grandfathered customers, any differences between *ex post* and *ex ante* load impacts stem from changes in the number of customers within climate zones. As well, smaller *ex ante* enrollment numbers lead to a decrease in aggregate reference loads and load impacts.

Table 9-16: Comparison of Current *Ex post* and *Ex ante* TOU Load Impacts for Grandfathered Customers

Season	Result	Ex post for 2018 Avg. Weekday from PY2018 Study	Ex ante for 2019 Avg. Weekday from PY2018 Study
Summer (August)	# Enrolled	430	418
	Reference (MWh/h)	0.85	0.71
	Load Impact (MWh/h)	0.02	0.01
	Per-customer reference (kWh/h)	1.98	1.70
	Per-customer load impact (kWh/h)	0.04	0.03
	Temperature	79.4	77.2
Winter (January)	# Enrolled	469	418
	Reference (MWh/h)	0.66	0.58
	Load Impact (MWh/h)	0.01	0.01
	Per-customer reference (kWh/h)	1.41	1.40
	Per-customer load impact (kWh/h)	0.03	0.02
	Temperature	62.1	60.9

10 Summary of the Residential Default TOU Pilot[47]

10.1 Default TOU Pilot Overview

San Diego Gas & Electric Company's residential default time-of-use (TOU) pricing pilot was implemented in response to California Public Utilities Commission (CPUC) Decision 15-07-001. A key objective of the pilot is to develop insights that will help guide SDG&E's approach to implementation of default TOU pricing for the majority of residential electricity customers and the CPUC's policy decisions regarding default pricing.

The pilot tested two different TOU rate options and was structured as a randomized encouragement design (RED) experiment. Approximately 113,000 customers were assigned to Rate 1 and 27,000 were assigned to Rate 2. An additional 169,000 were retained in the study on the standard tiered rate to act as a control group for those who were placed on the new tariffs. After receiving multiple notifications regarding the fact that their rate will change if they did not

[47] The Residential Default TOU Pilot was conducted by Nexant, Inc. This section of the Executive Summary contains excerpts from the following evaluation: George, S., Bell, E., Savage, A., Nexant Inc. (2019). "Default Time-of-Use Pricing Pilot Interim Evaluation"

take action by a certain date, customers had the choice of staying on their otherwise applicable tariff or selecting an alternative TOU rate plan. If a customer took no action, they were placed on the default rate associated with their assigned group.

Based on pre-treatment validations it was determined that an error had occurred in the pilot implementation and the control groups were not statistically equivalent to the treatment groups. Without pre-treatment statistical equivalence between the treatment and control groups, the RED analysis framework was no longer valid. SDG&E selected a revised control group for each rate from the original pool of eligible customers. The revised control group for Rate 2 was statistically equivalent to the treatment group. However, the Rate 1 control group was not. As a result, statistical matching was implemented to select a revised control group for the Rate 1 population. Impact estimates for both rates were estimated using a difference-in-differences regression model.

Figure 100-1 and

Figure 100-2 show the timing of the rate periods for Rates 1 and 2 and the prices[48] in each period. Rate 1 is a three-period rate in summer and winter. Prices are the same on weekdays and weekends, but weekends have a longer super off-peak period relative to weekdays. The peak period in both summer and winter is from 4 to 9 PM. The rate structure for winter is the same as summer except for the months of March and April where there is an additional super off-peak period from 11 AM to 2 PM. The peak-to-super-off-peak price ratio in summer is 1.9:1 for usage above the baseline quantity. In winter, the peak and off-peak prices are very similar, as super off-peak prices are nearly 5% lower than peak-period prices. The structure of Rate 2 is simpler compared to Rate 1 as there are only two rate periods that don't vary throughout the year or on weekdays or weekends. The peak period is the same as Rate 1 (4 PM to 9 PM) and the remaining period is an off-peak period from 9 PM to 4 PM.

Figure 100-1: Default Pilot Rate 1

[48] Prices do not reflect the baseline credit of $0.20 per kWh for electricity usage up to 130% of the customer's baseline allocation.

Day Type	Season	Hour Ending																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Weekday	Summer	Super Off-Peak (36¢)						Off-Peak (42¢)										Peak (67¢)							
	Winter	Super Off-Peak (39¢)						Off-Peak (40¢)										Peak (41¢)							
	March - April	Super Off-Peak (39¢)						Off-Peak (40¢)										Peak (41¢)							
Weekend	Summer	Super Off-Peak (36¢)																Peak (67¢)							
	Winter	Super Off-Peak (39¢)																Peak (41¢)							

Figure 100-2: Default Pilot Rate 2

Day Type	Season	Hour Ending																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Weekday	Summer	Off-Peak (41¢)																Peak (64¢)							
	Winter	Off-Peak (40¢)																Peak (41¢)							
Weekend	Summer	Off-Peak (41¢)																Peak (64¢)							
	Winter	Off-Peak (40¢)																Peak (41¢)							

The interim evaluation focused on the first summer of SDG&E's default TOU pilot, covering the time period from June through October 2018. Load impacts were estimated for three different climate regions in SDG&E's service territory (hot, moderate, and cool). For the moderate and cool climate regions, estimates were also made for two customer segments, CARE/FERA customers and Non-CARE/FERA customers. CARE/FERA customers in the hot climate region were not allowed to be enrolled on TOU tariffs using default recruitment. Ex ante impacts were not estimated as part of the evaluation.

10.2 Default TOU Pilot Ex post Methodology

In order to have a valid comparison group for Rate 1, Nexant developed a matched control group using propensity score matching. In this procedure, a probit model is used to estimate a score for each customer based on a set of observable variables. A probit model is a regression model designed to estimate probabilities – in this case, the probability that a customer would be assigned to Rate 1 for the default TOU pilot. Each customer in the Rate 1 population was matched with a customer in the eligible (but untreated) population that has the closest propensity score. A control group was developed for each season (summer and winter) and day type (average weekday, average weekend, and monthly system peak day). Matches were based on a set of variables that characterize load shape and the magnitude of electricity use on each day type for each season.

Load impacts for each segment were estimated using a difference-in-differences (DiD) methodology following the completion and validation of the matching assignments. This method estimates impacts by subtracting treatment customers' loads from control customers' loads in each hour or time period after the treatments are in place and subtracts from this value the difference in loads between treatment and control customers for the same time period in the pretreatment period. Subtracting any difference between treatment and control customers prior to the treatment going into effect adjusts for any difference between the two groups that might occur due to inaccuracies in the matching algorithms.

The DiD calculation can be done arithmetically using simple averages or can be done using regression analysis. Customer fixed effects regression analysis allows each customer's mean usage to be modeled separately, which reduces the standard error of the impact estimates without changing their magnitude. A typical regression specification for estimating impacts is shown below:

$$kW_{i,t} = \alpha_i + \delta \mathrm{treat}_i + \gamma \mathrm{post}_t + \beta(\mathrm{treatpost})_{i,t} + v_i + \varepsilon_{i,t}$$

In the above equation, the variable $kW_{i,t}$ equals electricity usage during the time period of interest, which might be each hour of the day, peak or off-peak periods, daily usage or some other period. The index i refers to customers and the index t refers to the time period of interest. The estimating database would contain electricity usage data during both the pretreatment and post-treatment periods for both treatment and control group customers. The variable treat is equal to 1 for treatment customers and 0 for control customers, while the variable post is equal to 1 for days after the TOU rate has been implemented and a value of 0 for days during the pretreatment period. The treat post term is the interaction of treat and post and its coefficient β is a difference-in-differences estimator of the treatment effect that makes use of the pretreatment data. The primary parameter of interest is β, which provides the estimated demand impact during the relevant period. The parameter a_i is equal to mean usage for each customer for the relevant time period (e.g., hourly, peak period, etc.). The v_i term is the customer fixed effects variable that controls for unobserved factors that are time-invariant and unique to each customer.

Rate 1 was analyzed via a matched control group due to the pilot implementation challenges, but Rate 2 was analyzed as a RED. With a RED structure involving a single rate treatment of interest (for simplicity), the study sample is randomly divided into two groups. One group is offered the treatment and the other is not. The group offered the treatment is referred to as the encouraged group and the group not offered the treatment is referred to as the control group. Some people in the encouraged group will accept the treatment and others will not. With a RED, impacts for those who accept the treatment offer are estimated through a two-step process. In the first step, loads by time period for the encouraged group are subtracted from loads for the control group.

As stated above, the encouraged group includes both those who accept the encouragement (that is, those who enroll on the new rate) and those who do not. The estimated load impact based on these two groups of customers is referred to as the intention-to-treat (ITT) effect. In the second analysis step, the ITT estimate is divided by the percent of the encouraged group who take up the treatment offer. This value represents the impact for those who took the treatment (referred to as the impact of the treatment on the treated).[49] For Rate 2, the first stage ITT impact was estimated using the same DiD analysis used for Rate 1.

10.3 Default TOU Pilot Ex post Load Impact Estimates

The first summer of SDG&E's default TOU pilot has produced a large amount of information that will help guide SDG&E's approach to implementation of default TOU pricing. However, it must be kept in mind that these load impact findings are based on only the summer months. Load impacts are going to differ significantly during winter months and the actions of TOU pilot participants may be quite different over the course of a full year.

Table 100-1 and Table 100-2 present the average summer weekday peak period load reduction for each pilot rate. On average, default customers on both Rates 1 and 2 produced small, but statistically significant, peak-period load reductions. Peak period load reductions averaged roughly 1.5% for Rate 1 and 2.0% for Rate 2. Load reductions were greater for Rate 2 than for Rate 1, despite having the same peak period time period (4 PM to 9 PM) and despite Rate 1 having higher peak-period prices than Rate 2. While the difference between Rate 1 and Rate 2 impacts are statistically significant, it is important to keep in mind that the estimates were calculated using different estimation techniques and the populations are not equivalent due to the exclusion of NEM customers from Rate 2.

[49] This second stage calculation relies on an assumption that decliners are not influenced by the fact that they received an offer. If, for example, decliners shifted load simply because they received an offer to go on a new rate, load impact estimates for non-decliners would be biased upward.

Table 100-1: Peak Period Load Reductions on Average Summer Weekday – Rate 1

Climate	Segment	Enrolled Customers	Ref. kW	kW Impact	90% Conf. Interval		% Impact
All	All	88,169	0.86	0.01	0.01	0.01	1.5%
All	Non-CARE/FERA	71,874	0.90	0.01	0.01	0.02	1.5%
Moderate & Cool	CARE/FERA	16,295	0.69	0.01	0.01	0.01	1.2%
Hot	Non-CARE/FERA	570	1.34	0.05	0.02	0.08	3.6%
Moderate	Non-CARE/FERA	26,882	1.03	0.02	0.01	0.02	1.7%
	CARE/FERA	7,854	0.80	0.01	0.01	0.02	1.5%
Cool	Non-CARE/FERA	44,422	0.82	0.01	0.01	0.01	1.3%
	CARE/FERA	8,441	0.58	0.01	0.00	0.01	0.9%

Table 100-2: Peak Period Load Reductions on Average Summer Weekday – Rate 2

Climate	Segment	Enrolled Customers	Ref. kW	kW Impact	90% Conf. Interval		% Impact
All	All	20,781	0.87	0.02	0.02	0.02	2.0%
All	Non-CARE/FERA	16,972	0.91	0.02	0.02	0.02	2.2%
Moderate & Cool	CARE/FERA	3,809	0.69	0.00	0.00	0.01	0.7%
Hot	Non-CARE/FERA	131	1.27	0.09	0.05	0.13	7.0%
Moderate	Non-CARE/FERA	6,257	1.04	0.02	0.02	0.03	2.2%
	CARE/FERA	1,848	0.81	0.01	0.00	0.01	1.0%
Cool	Non-CARE/FERA	10,580	0.83	0.02	0.02	0.02	2.2%
	CARE/FERA	1,961	0.58	0.00	0.00	0.01	0.4%

The pattern of load reductions across climate regions in absolute terms was consistent between the two rates but was slightly different in percentage terms. Absolute peak period load reductions were largest in the hot climate region, but these segments did not include CARE/FERA customers. Absolute impacts were smallest in the cool climate region, which included CARE/FERA and Non-CARE/FERA customers.

In the moderate and cool climate regions, Non-CARE/FERA customers typically had statistically significantly greater absolute peak-period impacts compared to CARE/FERA customers. Survey findings help explain some of this difference[50]. After being on the rate for the full summer, 58% of Non-CARE/FERA customers reported that they were on a TOU rate while only 38% of CARE/FERA customers identified their current rate plan as a TOU rate. Identification of the correct peak hours was also much higher among Non-CARE/FERA customers (69.4%)[51] versus CARE/FERA customers (58.2%). Efforts to more effectively educate CARE/FERA customers regarding their TOU rate plan could improve load reductions for this customer segment.

At the territory level, customers on Rate 1 increased their net daily electricity consumption on average summer weekdays and weekends. The increases were small but statistically significant. Similarly, customers on Rate 2 increased their daily consumption on the average summer weekend by a statistically significant amount at the territory level and on the average weekday and weekend in the moderate climate region. Increases in net daily electricity consumption were driven by statistically significant increases in electricity usage during the off-peak and super off-peak periods. Customer surveys found that 32% of customers stated they shifted their electricity usage compared to 18% of customers stating they reduced electricity usage, indicating that load shifting was a driver of the off-peak load increases. Another possible explanation for the estimated increase in daily usage is the fact that control customers were subject to a High Usage Charge (HUC) for monthly usage exceeding a certain threshold whereas TOU customers were not. 2018 was the first summer in which the HUC was in effect. This difference could cause some control customers to reduce usage, thus producing a downward bias in the reference load. If this bias is large enough, it could lead to an estimated increase in daily

[50] SDG&E "Default TOU Pilot Survey 1, Working Group Report" presented to the TOU Working Group on June 13, 2018;

SDG&E “Default TOU Pilot Survey 2 Report” presented to the TOU Working Group on January 28, 2019

[51] This value represents the average percent of customers that correctly identified each of the peak period hours as in the peak period.

usage that might otherwise have shown up as no change or a decline in daily usage had both treatment and control customers been treated the same.

During 2019 SDG&E plans to default approximately 750,000 residential customers onto its TOU-DR1 rate. The transition began in March of 2019 and will continue throughout 2019. SDG&E will conduct a full load impact evaluation on its residential default TOU customers that will be served on April 1st 2020. This evaluation will include both An Ex Post and Ex Ante estimates and will be compliant with the Demand Response Load Impact Protocols.

11 References

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