FINAL REPORT

CALMAC ID: SDG0339

2021 Load Impact Evaluation for San Diego Gas and Electric's Small Commercial and Agricultural Critical Peak Pricing and Commercial Technology Deployment Program

Prepared for SD&GE
By Demand Side Analytics, LLC

April 1, 2022

ACKNOWLEDGEMENTS

Demand Side Analytics Team

- Alana Lemarchand
- Josh Bode
- Alex Xie

SDG&E Team

- Leslie Willoughby
- Lizzette Garcia-Rodriguez
- Jordi Lopez
- Erich Kevari

ABSTRACT

This study quantifies the demand impacts of three related interventions – time of use pricing with a critical peak pricing component, the shift in a time of use pricing window, and commercial thermostats. The study focuses on three primary research questions: What were the 2021 demand reductions due to dispatch operations? Are customers delivering non-dispatchable demand reductions due to the interventions? What is the magnitude of dispatchable load reduction capability for 1-in-2 and 1-in-10 weather planning conditions?

SDG&E transitioned the full population of approximately 120,000 small business and agricultural customers from rates that did not vary by time of day to time varying rates in 2016. As part of the transition, in 2017 and part of 2018, SDG&E offered customers smart thermostats, free of charge, to help them manage their energy bills and automate response to critical peak prices. After the transition was complete the program was transitioned to a rebate model and split by customers on dispatchable rates (Peak Shift at Work (PSW) and Critical Peak Pricing – Default (CPP-D) for medium commercial and Industrial customers) versus those that aren't (AC Saver Day Ahead (ACSDA)). Dispatchable demand reductions were analyzed separately from non-dispatchable energy savings and demand reductions. In 2021, no events were called for the AC Saver Day Ahead program and no events were called for CPP program.

TABLE OF CONTENTS

Figures

Tables

1 EXECUTIVE SUMMARY

Between November 2015 and April 2016, SDG&E defaulted over 120,000 small business customers from rates that did not vary by time of day onto time varying pricing with a critical peak pricing component (CPP-TOU). If these customers did not want critical peak pricing, they had the option to elect a time-of-use rate (TOU) without a critical peak component. Approximately 95% of customer sites remained on TOU-CPP rate and 5% elected the TOU only option. In tandem, SDG&E also transitioned small agricultural customers from rates that did not vary by time of day onto default time of use rates. A CPP-TOU rate was offered to customers 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. 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. This commercial thermostat program has now transitioned to a rebate model and has been separated into two program types: one for sites on dispatchable (CPP) rates and ones that are not.

The study analyzes two primary research questions:

- What were the 2021 demand reductions due to dispatch operations?[1]
- What is the magnitude of dispatchable load reduction capability for 1-in-2 and 1-in-10 weather planning conditions?

Table 2 summarizes the small CPP and commercial thermostat dispatchable ex ante reductions under August monthly peaking conditions for a 1-in-2 weather year[2]. The results are shown under both CAISO and SDG&E peaking conditions and reflect the reduction capability from 4-9 pm, which aligns with resource adequacy requirements. For small CPP, the dispatchable reductions decrease due to projected decreases in enrollment due to CCA transition. The Community Choice Aggregator transition is expected to reduce the Small CPP population by an overwhelming majority. There was an initial transition during April-May 2021. Customers that shift from CPP rates to a CCA can no longer be on SDG&E CPP rates, so these sites with smart thermostats that were on CPP rates will be migrated to the non-residential ACSDA program. Over time, customers are expected to sort themselves between TOU-CPP and TOU rates. Despite new installations projected for commercial thermostats, ex ante impacts for commercial thermostats are also expected to decrease given that thermostat connection rates decline over time faster than new thermostats are projected to be added.

Small CPP and commercial thermostat customers on CPP rates are dispatched during the 2 to 6pm event window. There were no CPP events in PY 2021. Commercial thermostat customers on ACSDA were called during a variety of event windows and later in the day, typically from 6 to 8 pm. There were

[1] No events were called in PY 2021 so this annual evaluation question is not addressable for PY 2021

[2] Though no CPP events were called in PY 2021, ex ante estimates for dispatchable rates were developed using impacts from previous years, updated to reflect PY 2021 enrollment forecasts and device connectivity

no ACSDA events in PY 2021. Historically, ex post impacts per thermostat have been much lower for ACSDA than for commercial thermostats on dispatchable rates. However, ex ante impacts per thermostat and per site, as shown in Table 1-1, are higher for ACSDA than for CPP-TD. This is primarily because CPP-TD, as a program for dispatchable rates with a fixed window, is assumed to deliver impacts only during the 2pm to 6pm critical peak window, which only has two hours of overlap with the 4pm to 9pm resource adequacy window. In contrast, the ACSDA program can be dispatched any time between 1pm and 9pm. As such, the ACSDA ex ante impacts assume reductions are delivered for the full duration of the 4pm to 9pm resource adequacy window.

Table 1-1: Summary of Ex ante Dispatchable Demand Reductions

Year	Small CPP			Tech Deployment: CPP rates			Tech Deployment: ACSDA		
	Sites	MW (CAISO)	MW (SDG&E)	Sites	MW (CAISO)	MW (SDG&E)	Sites	MW (CAISO)	MW (SDG&E)
2021	52,081	0.20	0.17	383	0.38	0.36	676	0.64	0.63
2022	51,393	0.19	0.17	415	0.39	0.37	650	0.61	0.60
2023	35,221	0.13	0.12	463	0.42	0.39	612	0.56	0.55
2024	22,681	0.09	0.08	514	0.44	0.41	576	0.52	0.51
2025	16,886	0.06	0.06	569	0.47	0.44	542	0.48	0.48
2026	12,522	0.05	0.04	630	0.50	0.47	511	0.45	0.44
2027	9,232	0.03	0.03	695	0.53	0.50	481	0.41	0.41
2028	6,784	0.03	0.02	717	0.53	0.50	471	0.40	0.39
2029	4,961	0.02	0.02	717	0.52	0.49	471	0.39	0.39
2030	3,593	0.01	0.01	717	0.51	0.48	471	0.38	0.38
2031	2,566	0.01	0.01	717	0.49	0.46	471	0.38	0.37
2032	1,795	0.01	0.01	717	0.48	0.45	471	0.37	0.37

2 INTRODUCTION

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.

In subsequent years, the portion of non-residential sites opting out of CPP-TOU rates onto TOU only rates continued to be in the low single digits and about 112,000 small commercial customers were on CPP-TOU rates at the end of 2020. In spring 2021, all customer sites in the City of San Diego were defaulted onto a Customer Choice Aggregation (CCA) energy supply option which precludes staying on SDG&E CPP-TOU rates. As of the PY 2021 event season, about 51,000 small commercial sites (45%) remain on the CPP-TOU rate. The CCA transition also affected TD sites on CPP rates as they will no longer be signaled during CPP events. This transition does not affect TD sites in ACSDA programs since those participants are not on CPP-TOU rates.

2.1 RATE AND TECHNOLOGIES EVALUATED

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. The CPP event window will shift again in PY 2022 to 4 to 8pm to better align with the 4 to 9pm resource adequacy window.

Outreach and education will be key to help current participants shift response to the later window, particularly for behavioral response.

- Smart thermostats – Through 2017, 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 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.[3] There are four Technology Deployment programs of which some variants have been in operation since 2014[4]. 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 CPP 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.

2.2 STUDY RESEARCH QUESTIONS

Table 2-1 summarizes the key research questions for each intervention. Both CPP-TOU and commercial thermostats are dispatchable resources that also can lead to daily changes in energy use. Because

---

[3] SDG&E had a limited number of free thermostats available in 2018 that were provided on first serve basis, the remainder of the 2018 thermostats were purchased by the customer and rebates were issued.
[4] Expanded from the former Small Customer Technology Deployment (SCTD) program

dispatchable resources are used for operations, the impacts associated with event dispatch are estimated and reported separately from daily, non-dispatchable changes in energy use.

Table 2-1: Key Research Questions

	Research Question	CPP-TOU	TD Programs
1	What were the demand reductions due to program operations and interventions in 2021 – for each event day and hour? [5]	✓	✓
2	How do load impacts differ for customers who have enabling technology and/or are dually enrolled in other programs?	✓	✓
3	How does weather influence the magnitude of demand response?	✓	✓
4	How do load impacts vary for different customer sizes, locations, and customer segments?	✓	✓
5	What is the ex ante load reduction capability for 1-in-2 and 1-in-10 weather conditions? And how well does it align with ex post results and prior ex ante forecasts?	✓	✓
6	What concrete steps or experimental tests can be undertaken to improve program performance?	✓	✓

2.3 OVERVIEW OF METHODS

Because no CPP or ACSDA events were called in PY 2021, there is no ex post analysis to describe. However, historical impacts from PY 2020 events were used as inputs to ex ante modeling. Detailed description of the methodology and results can be found in the PY 2020 evaluation report (CALMAC: SDG0324). The methodology summary provided here for reference comes from that report.

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 varying 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.

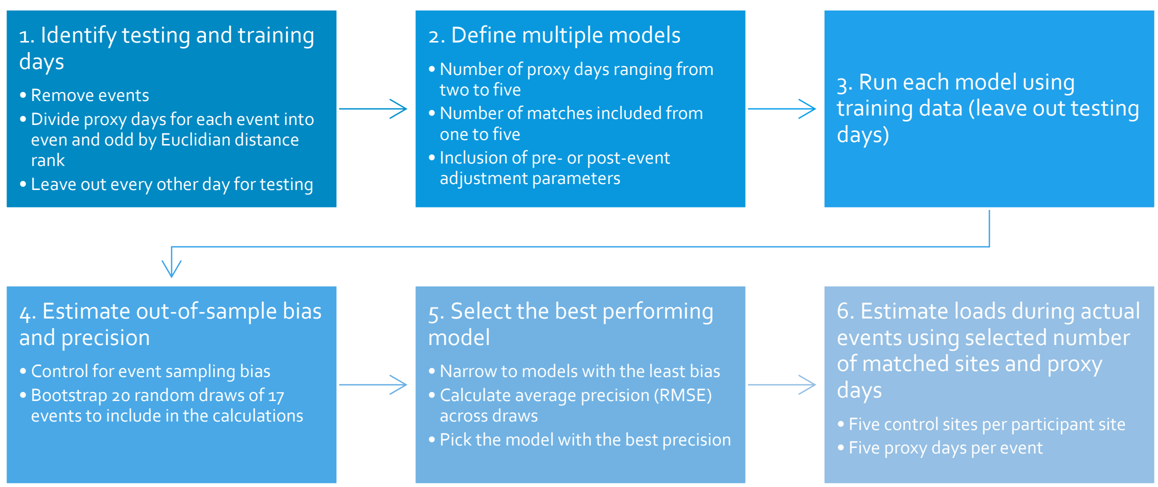
[5] No events were called in PY 2021 so this annual evaluation question is not addressable for PY 2021

The change in energy use patterns was estimated using a panel regression with multiple control groups, each matched to a participant. Key modeling design components are as follows:

- **Multiple matched controls:** For each participant, five control sites were identified based on how closely their loads matched the participant on event-like proxy days (e.g. using Euclidian distance matching). A total of five matched control sites were selected for each participant site, ranked by their closeness of fit across all proxy days.
- **Panel regression model with event and non-event day and participants and matched controls:** The data was structured as a time series for each participant. The control loads, weather, and day characteristics were used to predict participant loads. The model coefficients for each control site essentially weight the various control sites based on their predictive power creating a more accurate prediction out of multiple controls. This approach was used as the primary method for event impacts for critical peak events delivered by AC Saver Day Ahead thermostat participants.
- **Event specific models:** Given the wide range of temperature conditions during events, five proxy days were selected for each event based on the how closely the proxy day conditions, measured by system load, matched the event days (e.g. using Euclidean distance matching). A separate model was estimated for each event including only loads for the event day and the proxy days selected for that event. The number of proxy days included was validated using the model validation process described below.
- **Pre and post event adjustment:** The impact regression also included pre and post event loads to adjust the model for differences. A two hour pre- and post-adjustment period with a two hour pre- and post-buffer was used. Inclusion of these parameters was validated using the model validation process described below.
- **Model validation:** The choice of the number of proxy days (ranging from two to five), of the number of matched control sites (ranging from one to five), and of the inclusion of pre and post event adjustment parameters was validated using a placebo effect approach: a subset of proxy days was used to predict load on the remaining proxy days for each event. In the absence of events, the difference between predicted and actual error should be zero and any deviation is a direct reflection of modeling error. In each case the approach with the least error and best fit was selected.

Figure 2-1 summarizes the out of sample testing process used to select the number of proxy days, controls, and adjustments to be used for modeling. 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 model should produce matches for loads on days which were not used for the model. The final model is identified based on least bias (% Bias) and best fit (Relative RMSE) metrics. As an example, Figure 2-2 summarizes the model selection analysis for the non-residential TD programs[6]. Each row shows a different adjustment model and each cluster of bars shows results for a selected number of proxy days. Each individual bar in a cluster shows results for a selected number of control sites per participant site. Note that across the 60 models tested, the one with the best precision (lowest RMSE) is the one with a pre and post adjustment, using five proxy days and five control sites. This is the model that was selected for estimating counterfactual loads during events. Using multiple proxy days, matched controls and, adjustments systematically increased model precision though there are diminishing returns to including additional proxy days and matched controls. The model elements tested exhibit a directional improvement trend for additional proxy days and controls. However, this trend diminishes with each the marginal improvement. This trend is likely why the same model was selection as in the prior evaluation.

Figure 2-1: Out of Sample Process for Model Selection



[6] Analogous results for Small CPP are summarized in Appendix B

Figure 2-2: TD Program Model Selection Results

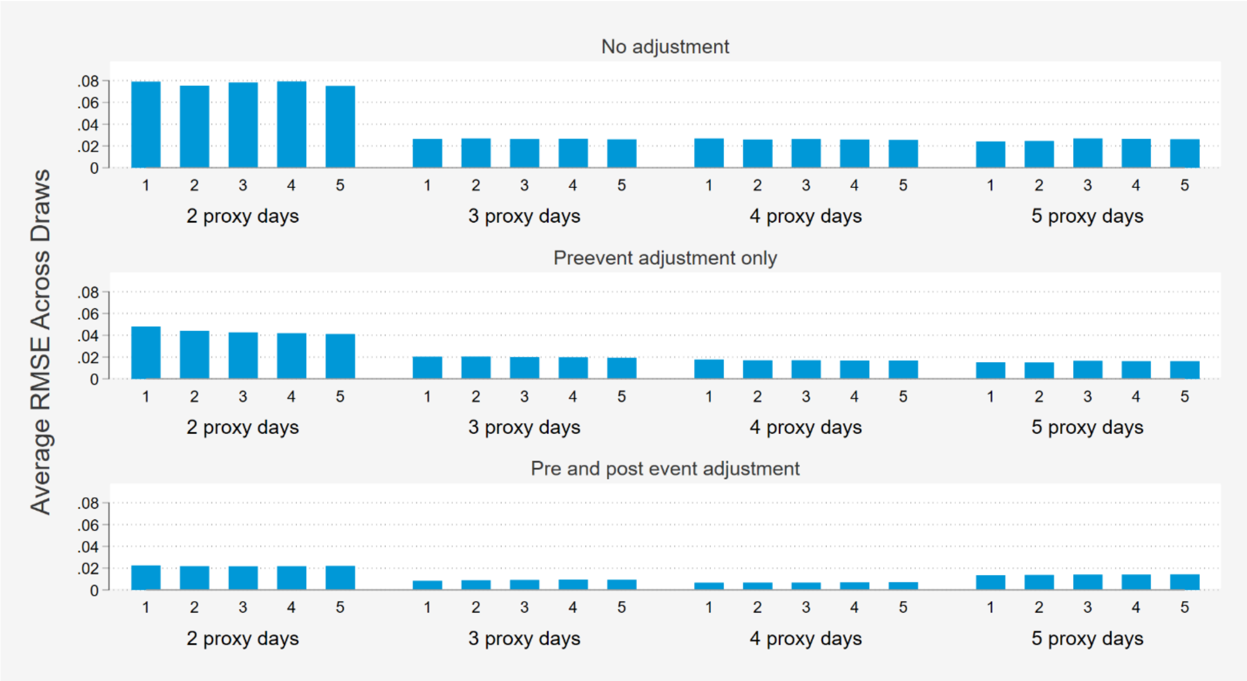


Table 2-2 summarizes the data sources, segmentation, and estimation methods used for each program. The segmentation was defined in advance of the analysis and is of particular importance because the evaluation used a bottom up approach to estimate impacts and to ensure that aggregate impacts across segments 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 to deliver demand reductions– 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. Additional segments were analyzed, after the fact, as part of exploratory analysis, but the core results presented are based on the segmentation detailed below. Importantly, the segmentation categories for Small CPP were simplified in PY 2020 relative to previous years. This introduces a source of difference with the previous methodology but yields more robust results given that simpler segmentation results in many more sites (sample points) per segment. Segments with very few sites were effectively eliminated.

Table 2-2: Evaluation Methods[7]

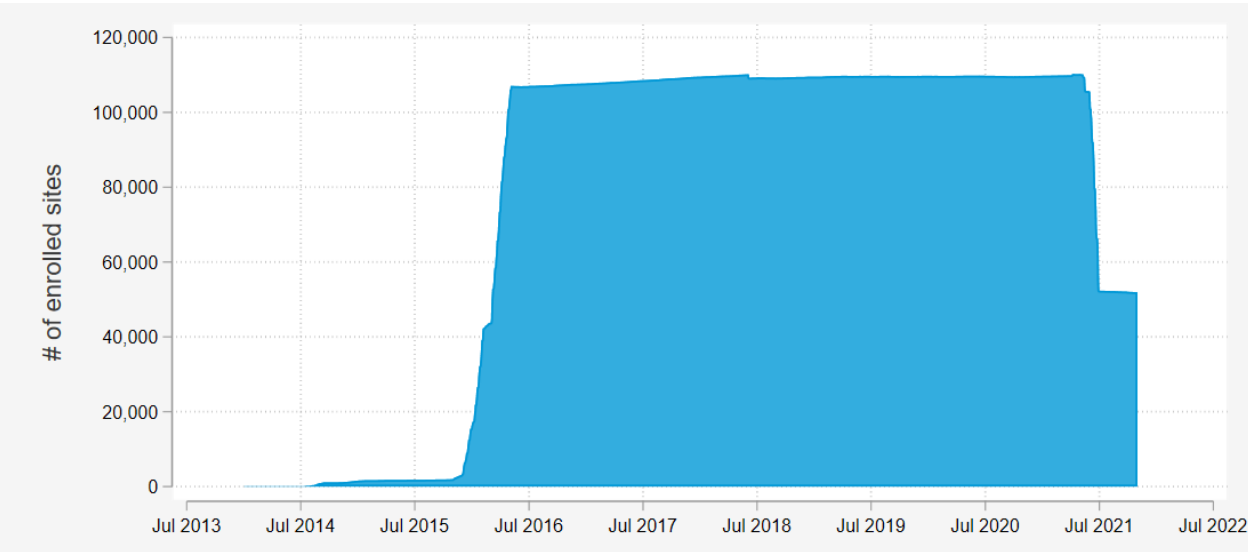
	CPP-TOU	TD Programs
Data sources / samples	▪ Load data for June through October: ✓ 51k Small Commercial ✓ 161 Ag participants	▪ Load data for June through October ✓ 383 CPP-TD sites ✓ 676 ACSDA sites
Segmentation	▪ Rate ✓ Small Commercial vs Ag ▪ Enrollment in event notification (Y/N) ▪ Climate zone (Coastal vs Inland)	▪ 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 (from PY 2020)	Fixed effects diff-in-diff regression using matched control from opt-outs for each segment	CPP-TD: Matched control groups analyzed using fixed effects diff-in-diff regression for each segment ACSDA: Panel regression with multiple matched control group for each customer.
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 ▪ CPP-TD: Used 2020 impacts ▪ ACSDA: Used 2020 impacts

[7] All counts provided are for the PY 2021 ex ante analysis. Counts relevant to the PY 2020 ex post impacts used for ex ante modeling can be found in the PY 2020 evaluation report

3 CRITICAL PEAK PRICING EVENT DAY IMPACTS

SDG&E defaulted over 120,000 small customer sites[8] onto CPP-TOU rates between November 2015 and April 2016. Roughly 5% of these customers opted-out and were placed on TOU rates. In spring 2021, roughly 55% of the remaining 112,000 small customer sites moved to the CCA option for energy supply which also precludes staying on CPP rates. Figure 3-1 shows this cumulative enrollment in CPP, net of the opt-outs, and the subsequent CCA transition which left about 51,000 small sites on CPP rates.

Figure 3-1: 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 2018, six CPP events were called in July and August while in PY 2019, there were no CPP events. In PY 2020, there were nine CPP events in August through October. In PY 2021, there were no CPP events.

[8] Here and throughout this report a site is defined as a premise and service point combination. Note that this figure is slightly higher than the number of sites used for the PY 2020 ex post impact analysis which only included sites still on CPP-TOU rates in PY 2020.

3.1 PARTICIPANT AND EVENT CHARACTERISTICS

In previous program years, Small CPP (Commercial and Agricultural) event impacts were assessed by site (premise and service point combination). These historical ex post impacts are used for the PY 2021 ex ante estimation.

Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in Table 3-1, 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. Customers on CPP rates and in the TD program are covered in Section 4. Dually enrolled customers, those in the Small CPP program and either Summer Saver or CBP, were omitted from the analysis.

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?

Table 3-1: PY 2020 Small Critical Peak Pricing Population Segments

Rate class	Climate zone	Notification	Sites in analysis
Small Commercial	Coastal	No	13,493
		Yes	7,825
	Inland	No	18,889
		Yes	10,717
Small Agricultural	All	All	161
Total sites			51,085

Table 3-1 summarizes the total number of sites in each segment used for development of PY 2021 reference loads. PY 2020 segments were mirrored to facilitate application of PY 2020 impacts to PY 2021 reference loads.

3.2 DATA SOURCES AND ANALYSIS METHOD

Table 3-2 summarizes the six data sources used to conduct the PY 2020 Small CPP analysis. The resulting impacts from that evaluation were used to develop ex ante impacts for PY 2021 and are provided below for reference. The PY 2020 ex post analysis conducted in 2021 and reported in the PY 2020 evaluation report 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 3-2: Small Critical Peak Pricing Evaluation Data Sources

Source	Comments

Hourly interval data	▪ PY 2020 ex post impacts
	  o Summer 2020 (June 1 through October 31)
	▪ PY 2021 ex ante reference loads
	  o Summer 2021 (June 1 through October 31)
	▪ All analysis done by site (premise id-service point id pair)

Outage information	▪ PSPS and CAISO emergency outage data details which customers and what timeframes were impacted by outages ▪ Outage days which affected participants or control sites were excluded from the analysis

Customer characteristics	▪ PY 2020 ex post impacts
	  o Treatment: All small non-residential (Commercial and Agricultural) CPP rates (108,079 sites)
	  o Control: TOU only rates (10k commercial sites, 3.5k Ag sites)
	▪ PY 2021 ex ante reference loads
	  o All small non-residential (Commercial and Agricultural) CPP rates (52,081 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	▪ PY 2020 ex post impacts
	  o Summer 2020 (June 1 through October 31)
	▪ PY 2021 ex ante reference loads
	  o Summer 2021 (June 1 through October 31)
	▪ Used to identify non-event high system load days

Source	Comments
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 in segmentation)

The primary analysis method was a panel regression with a multiple matched control groups. The distance matching approach used selected five matched control sites for each of the roughly 108,000 non-residential Small CPP sites among a matched control candidate pool of roughly 13,500 small commercial and small agricultural TOU sites who were selected in PY 2020. These customers were not enrolled in CPP or other DR programs which might influence energy use. The panel 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 model specification. The model selection relied on testing how well each model estimated loads for event-like 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 80 models were tested to select the number of proxy days, number of matched controls, and structure of same day adjustments to use. The regression model structure and out of sample testing are detailed in Appendix B. Reference loads were developed using pre-2020 and 2020 data to show the differences caused by COVID.

3.3 EX POST LOAD IMPACTS

No CPP events were called in PY 2021 so there are no event impacts to assess. PY 2020 impacts were used to estimate ex ante impacts.

3.4 EX ANTE LOAD IMPACTS

A key objective of the 2021 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 to estimate the reductions for a standardized set of weather conditions. Since no new events were called during PY 2021, historical impacts during events from 2020 were used. Prior impacts were not used to avoid including pre-COVID data.

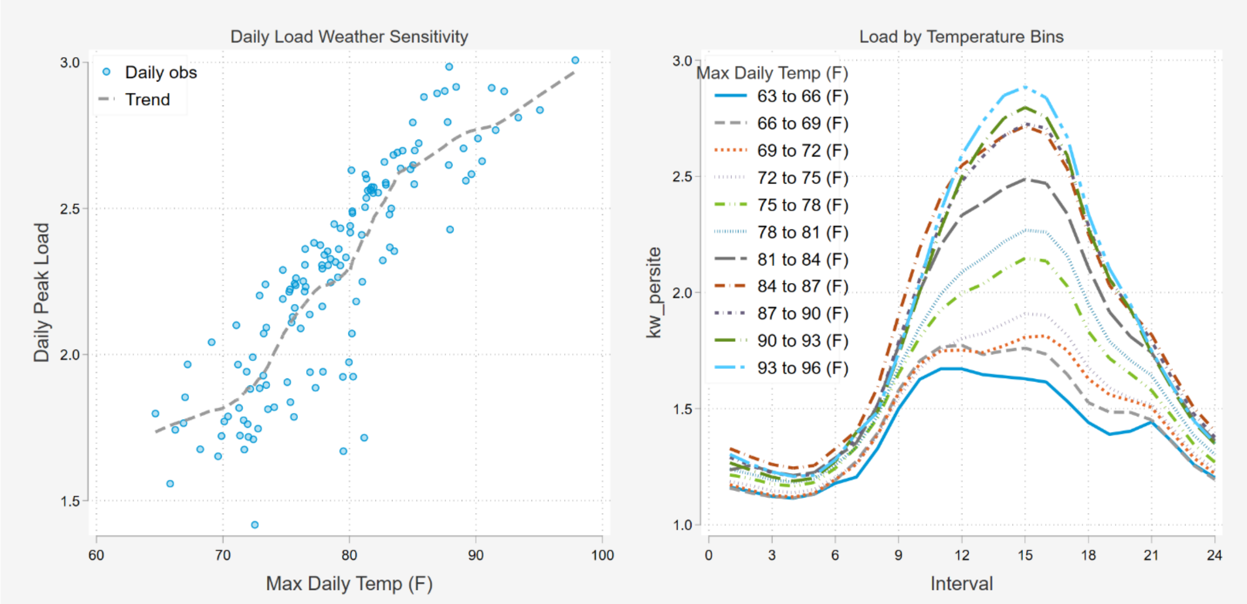
At a fundamental level, the process of estimating ex ante impacts included five main steps:

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

3.4.1 Relationship of Customer Loads and Percent Reductions to Weather

Figure 3-2 summarizes the relationship between weather and CPP participant loads in 2021. Only days when CPP resources were not dispatched are included. The panel to the left shows average hourly loads for current participants for different temperature bins, defined by the daily maximum temperature. The panel to the right shows the relationship between daily maximum temperatures and hourly loads. The hottest temperature day in the right panel is not the highest load curve. Generally, energy demand and discretionary load increases with hotter weather.

Figure 3-2: Weather Sensitivity of Small Commercial CPP Loads



2021 May to mid-Oct loads, excluding weekends/holidays and events

Figure 3-3 shows the relationship between aggregate small commercial CPP loads and SDG&E daily peak loads. Importantly, most system peak net loads are now occurring after 4pm, after solar production begins to wane. Daily peaks that occurred before 4pm are shown in blue and those that occurred later are shown in grey. Daily peaks that occur later in the day (after 4pm) are now larger in magnitude.

Figure 3-3: Small Commercial CPP Load versus System Daily Peaks

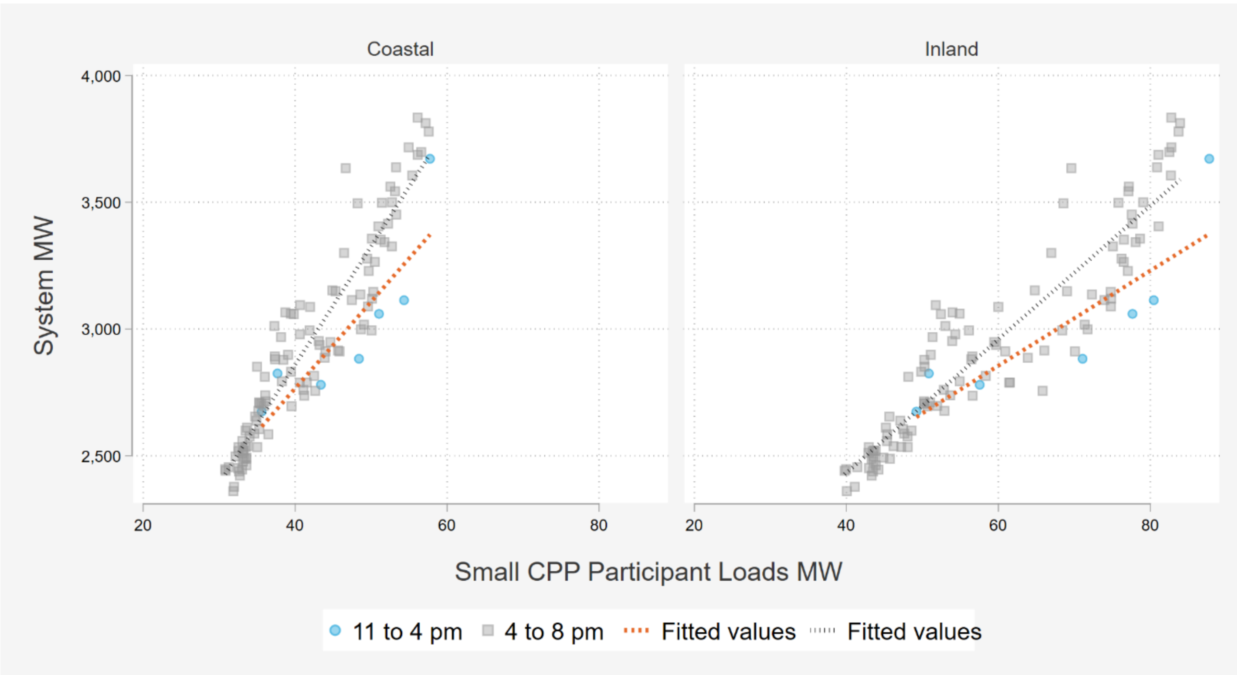


Figure 3-4 shows the range of aggregate small commercial CPP loads for each climate zone during the daily system peak hours. The boxes show the inter quartile range of loads and the lines that extend above show the more extreme loads in each hour. Notably the highest loads occur from 3 to 4pm (hour 16) and from 4 to 5pm (hour 17). At their highest, coastal loads comprise about 50 to 60 MW and Inland about 80 to 90 MW for a total of 130 to 150 MW. However, after 5pm loads drop by about a third, reflecting minimized the load reduction potential from small CPP customers. This is important context when considering the planned shift of the CPP event window from 2 to 6 pm to 4 to 8 pm. Historically, more discretionary load was in use during peaking conditions, and large reductions from CPP participants during the 2 to 6 pm could be deployed could be larger precisely when resources are needed most. However, the planned shift of the CPP window to the later 4 to 8pm window is likely to capture part of this peaking load in the first hour or two of the event window, but potential is expected substantially taper off in later hours along as small commercial loads decline.

Figure 3-4: Small Commercial CPP Hourly Loads at System Daily Peaks

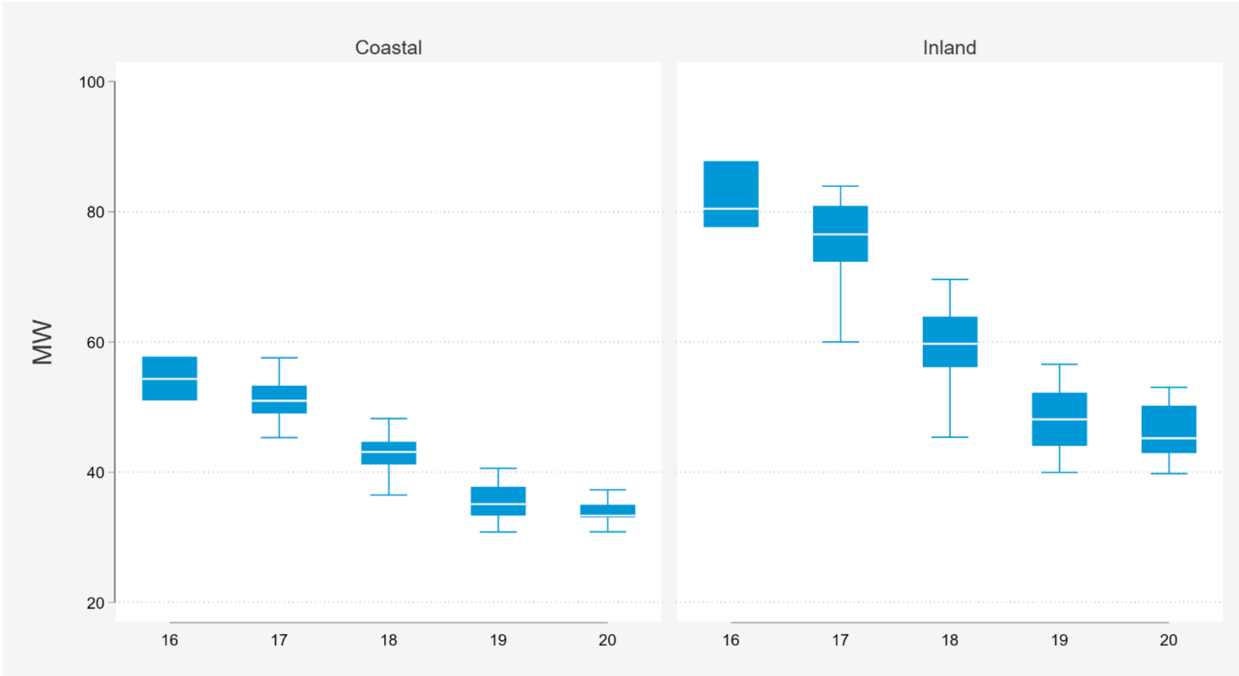
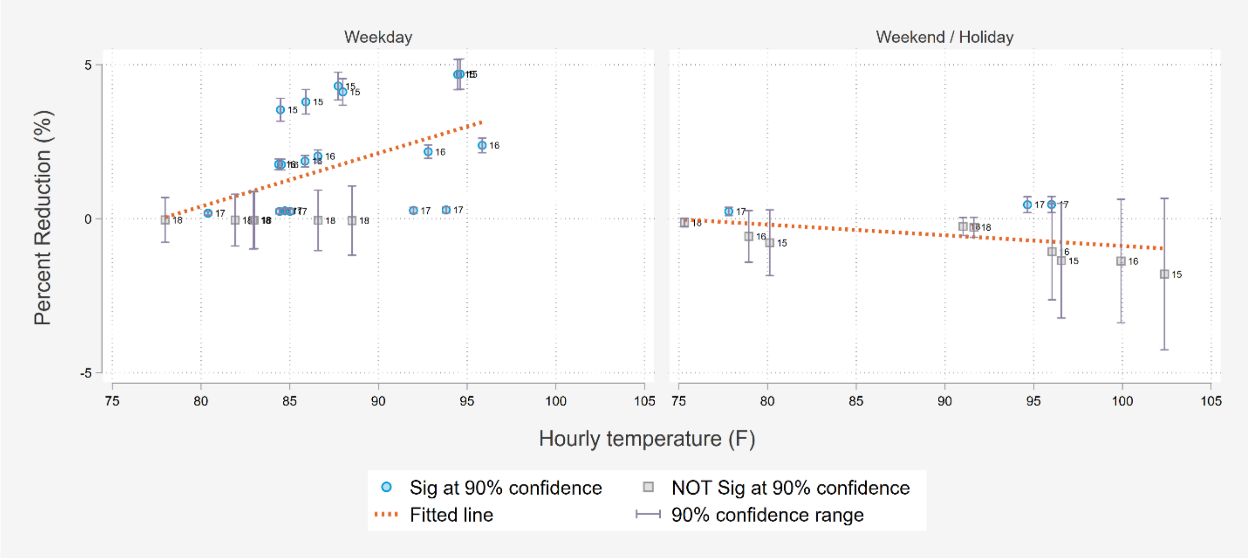


Figure 3-5 shows hourly event percent reductions for these events as a function of hourly temperatures. The left panel shows weekdays and the right shows the weekend and holiday event hours from PY 2020. Note that while most reductions are positive in magnitude, a handful are negative or near zero (and not statistically significant). Weekdays show a positive trend as warmer temperatures result in larger percent reductions. The hour of day is also noted in the figure, showing that hour 15, the first event hour, is larger than subsequent hours, regardless of temperature. The weekend and holiday events are mostly insignificant, and there are too few observations from which to deduce any trends. An important note is that past ex post evaluations consistently showed that small CPP customers continue to deliver load reductions in line with the original 11 am to 6 pm event window, despite the shift to 2 to 6 pm. In effect, customers are responding to event notifications, but not during the correct window and reductions are largely zero for most event hours. The ex ante analysis assumed that this pattern will continue. Given this and the observations about reduced small CPP load reduction potential after 5pm, load reductions are anticipated to be very low during the new 4 to 9pm window.

Figure 3-5: PY 2020 Small Commercial CPP Hourly Reductions and Temperatures



3.4.2 COVID-19 Load Considerations

Beginning in March 2020, shutdowns began across the United States as a response to the COVID-19 pandemic. As commercial businesses closed, many workers either lost their jobs or began working from home. The shutdown impacted sectors at different levels of intensity and during different time periods, but all PY 2020 Small CPP events are assumed to have occurred under COVID-19 conditions. As such, PY 2020 reference loads were modeled under COVID-19 conditions.

During PY 2021, DSA and SDG&E analysis showed that COVID-19 effects have largely subsided and any remaining effects are small. For instance, many workers have returned in-person to their commercial businesses, although there are some who still work remotely or have left the workforce. Therefore, we assume loads are a "new normal" going forward.

3.4.3 Ex Ante Enrollment Forecast

To derive the aggregate forecast, site level reference loads and percent impacts are scaled to the population expected to be enrolled in each planning year. The CPP-TOU enrollment forecast for small commercial and agricultural customers was developed by SDG&E and incorporated the following assumptions:

- 2021 end of year starting point based on the number of small commercial and agricultural sites on CPP-TOU rates not served by CCAs
- Continued migration toward CCAs: 2% migration in 2022, 46% in 2023, and 25% annually thereafter

- Linear mensualization of annual enrollment expectations

The Small CPP-TOU evaluation further allocates the overall forecast between commercial and agricultural sites by applying the 2021 split[9] then subtracts the enrollments forecasted by the evaluator for small sites with smart thermostats on CPP rates, e.g. PSW on TD, covered in more detail in section 4.4.3.

3.4.4 Ex Ante Load Impacts

Table 3-3 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 3-3: Small CPP Portfolio Impacts for August Monthly Peak Day (4-9 pm)[10]

Year	Sites	CAISO		SDG&E	
		1-in-2	1-in-10	1-in-2	1-in-10
2021	52,081	2	0.20	0.18	0.17
2022	51,393	2	0.19	0.17	0.17
2023	35,221	2	0.13	0.12	0.12
2024	22,681	2	0.09	0.08	0.08
2025	16,886	2	0.06	0.06	0.06
2026	12,522	2	0.05	0.04	0.04
2027	9,232	2	0.03	0.03	0.03
2028	6,784	2	0.03	0.02	0.02
2029	4,961	2	0.02	0.02	0.02
2030	3,593	2	0.01	0.01	0.01
2031	2,566	2	0.01	0.01	0.01
2032	1,795	2	0.01	0.01	0.01

The enrollment forecast was developed by SDG&E and shows a declining number of customers enrolled in small non-residential CPP. The steep drop in sites over the coming years is due to the continued defaulting of non-residential sites to Community Choice Aggregation energy suppliers. The expectation is that the overwhelming majority of Small CPP participants will be eventually served by CCAs. This

[9] About 51 thousand commercial sites to 161 agricultural sites

[10] Small commercial impacts only. Excludes 161 Agricultural sites for which aggregate loads and impacts are negligible. Results for Agricultural sites are available in the accompanying ex ante table generator.

transition will result in disenrollment from SDG&E's CPP rates, which precludes participation in SDG&E's CPP events. Note that participants served by CCAs will remain on SDG&E's distribution TOU rates. For ex ante impacts, reduction in enrollment forecasts are assumed to have a proportional effect on 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.

3.4.5 Comparison of Ex Post and Ex Ante Load Impacts

Table 3-4 compares the demand reductions from 2020 events to the reduction expected for the 1-in-2 weather conditions used for planning. Results are shown for both the 4 to 9 pm resource adequacy window. In PY 2020, the most recent year where CPP events were called, small CPP customers delivered 5.23 MW during the dispatch period of 2 to 6 pm. The 4 to 9 pm ex post reductions were much lower, -0.46 MW, in part 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. With such small impacts (on the order of 1%) such variability is to be expected.

Table 3-4: Small CPP Comparison of PY 2020 Ex Post and PY 2021 Ex Ante Load Impacts

Result Type	Day Type and Period	Sites	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex Post Avg. Weekday (PY 2020 Results)	Event Period (2pm to 6pm)	108,138	302.35	5.23	1.7%	90.4
	Resource Adequacy Period (4 to 9pm)	108,138	239.44	-0.46	-0.2%	90.4
Ex ante SDG&E	1-in-2 Weather August Peak (4 to 9pm)	52,081	120.13	0.17	0.1%	91.1
Ex ante CAISO	1-in-2 Weather August Peak (4 to 9pm)	52,081	123.00	0.20	0.2%	90.9

*Table shows portfolio impacts. To avoid double counting, it excluded commercial thermostats and customers dually enrolled in other DR programs. Also excludes 161 Agricultural sites for which aggregate loads and impacts are negligible.

4 COMMERCIAL THERMOSTAT EVENT DAY IMPACTS

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 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. Thermostats are dispatched from 2-6 pm and Technology Deployment events historically coincided with CPP events, of which there were one in 2016 and three in 2017. In PY 2020, nine CPP events were called, but they did not all fall on ACSDA event days. In PY 2021, there were no CPP events.

In 2018, the program changed from a free thermostat to a rebate model and was broadened to include additional thermostat models. Figure 4-1 summarizes four the specific program designations for the PY 2019 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, of which there were none in PY 2019. 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. 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 2019 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.

Figure 4-1: Summary of TD Program Taxonomy

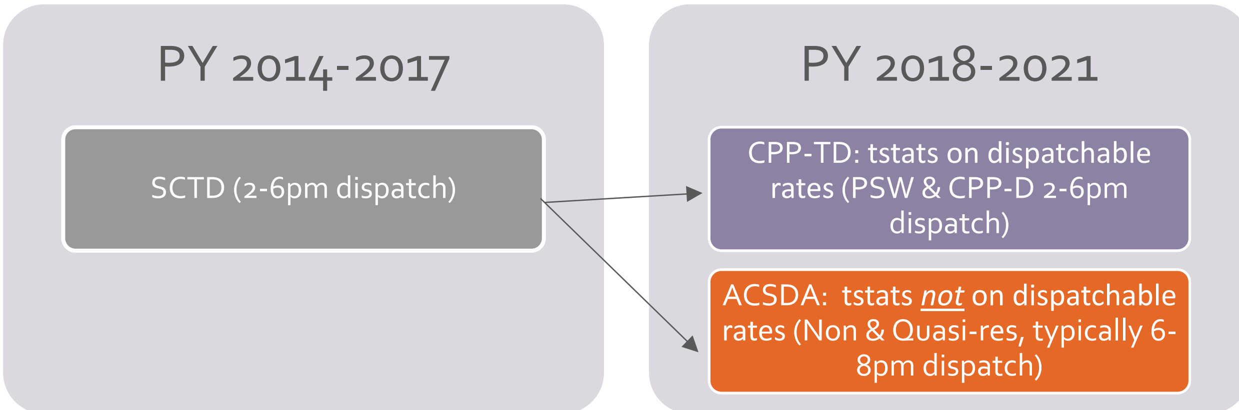


Table 4-1 shows the customer site counts and aggregate percent reduction for the previous four program years for each of the Commercial TD programs. The reductions in PSW and CPP-D sites reflects the CCA transition because CCA customers could not stay on CPP-TOU rates. Some migrated to the ACSDA program and many unenrolled altogether, with overall TD enrollment dropping form over 3,000 sites in PY 2020 to about 1,000 sites in PY 2021

Table 4-1: Historical Program Overview

	Count of Sites (Aggregate Percent Reductions)			
Program	2018	2019	2020	2021
PSW	1,184 (7.5%)	No Events	773 (7.0%)	253 (No Events)
CPP-D	592 (5.9%)	No Events	431 (6.6%)	130 (No Events)
ACSDA Non-Residential	385 (4.2%)	355 (2.9%)	397 (3.0%)	661 (No Events)
ACSDA Quasi-Res	1,174 (2.2%)	1,097 (1.0%)	544 (1.5%)	15 (No Events)

In PY 2021, there were nearly 8,000 devices installed at over 1,000 non-residential sites. Roughly 2,000 devices were installed at sites on dispatchable rates (small commercial on PSW and medium and large on CPP-D) and the remaining 6,000 were installed at non-residential and quasi-residential sites on non-dispatchable rates enrolled in AC Saver Day Ahead (ACSDA). As noted above, no events were called for any non-residential TD program in PY 2021.

Device connectivity is a key driver of realized load impacts because only connected thermostats can receive dispatch signals and deliver load reductions. As such connectivity has been closely monitored since PY 2018. In PY 2018 and PY 2019 roughly half of devices were not connected. However, much of this was due to the auto-enrollment of new accounts moving into a site with a previously enrolled thermostat. In practice the device is often no longer connected and simply ends up diluting results. In PY 2020 SDG&E discontinued the practice of auto-enrollment and removed inactive thermostats from the dispatch portal. This has enabled separation of site attrition, primarily driven by move-outs, from thermostat connectivity. There is still a steady decline in connectivity over time and it is an important consideration for forecasting future impacts but it is smaller in magnitude after controlling for site attrition. Impacts continue to be derived at a per connected thermostat basis so they can be applied to enrollment forecasts 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.

4.1 TECHNOLOGY AND EVENT CHARACTERISTICS

The thermostats used as the enabling device receive a signal from SDG&E to curtail usage during events. Historically, thermostats were controlled by raising the setpoint temperature by 4 degrees. This approach is intended to reduce energy usage by air conditioning units. However, to receive the curtailment signals, the devices must be connected to the internet and registered in the SDG&E dispatch portal. This is initially set up during the device installation process, but connectivity can be affected by internet reliability. Once connected, the device can receive and execute curtailment signals, and it can also communicate event notifications to users before the beginning of an event. Participating, connected devices were sent event notifications 24 hours prior to an event.

The PY 2019 evaluation highlighted the issue of disconnected devices and the dampening effect this had on average "per-site" and "per-device" impacts. The failure rate described in the past incorporated two threads of failure-site attrition and thermostat failure. Site attrition occurs when a site, or customer, un-enrolls from a program or moves outside of the service territory. Thermostat failure occurs when a customer changes a setting that disconnects their thermostat from the internet. This could be caused by a change in the internet router, a new password, a new internet service provider or any other simple disconnection where the customer fails to reconnect their device.

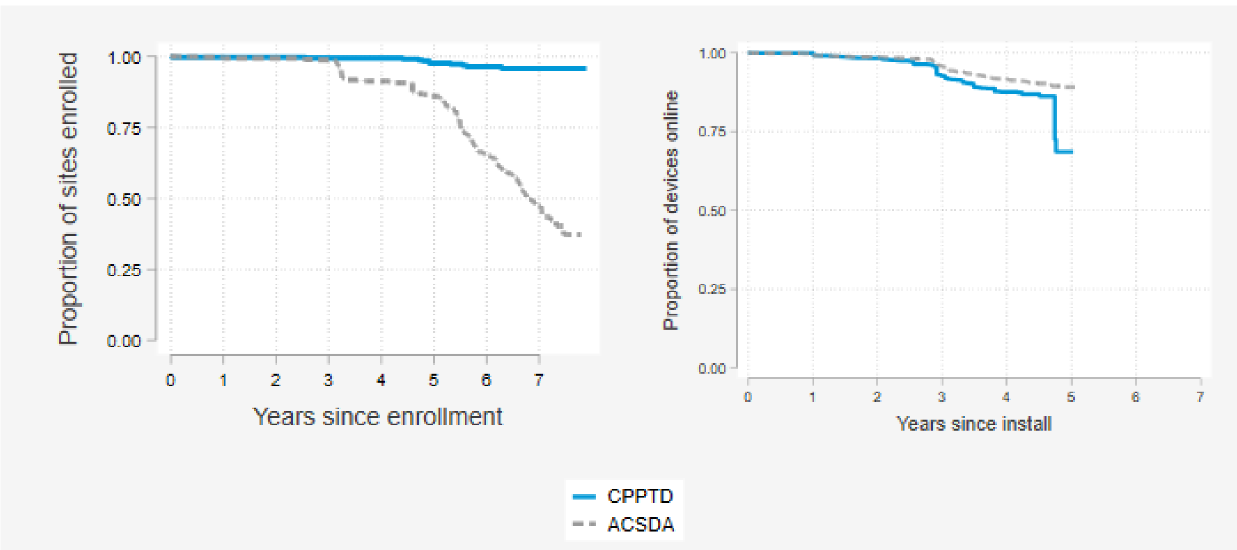
For PY 2020, site attrition and thermostat disconnections were disaggregated. In part, this helped distinguish between de-enrollments, presumably largely due to move-outs, and device disconnections which may possibly be remedied through participant outreach. This was important for modeling enrollment going forward since historically customers moving into an enrolled site were automatically enrolled in the program, but in practice the device was no longer connected or receiving dispatch signals. Functionally, this artificially lowered the observed thermostat survival rate because it was conflated with site move-outs. Just prior to the PY 2020 event season the practice of automatic enrollment at move-in was discontinued and roughly 2,000 sites were unenrolled that had previously been enrolled due to this practice.

Table 4-2 and Figure 4-2 show the failure rates updated using PY 2021 data on device connectivity and survival trends based on years since enrollment and years since installation, respectively. Note that thermostat survival only includes thermostats for enrolled sites. Essentially, the site survival trend reflects the rate at which sites remain enrolled over time while the thermostat survival trend shows the rate over time at which thermostats at enrolled sites remain connected. Note that site attrition, which is a function of site move ins and move outs as well as intentional unenrollment varies more than thermostat disconnection rates which are a function of technology.

Table 4-2: Failure Rates by Cause

Program	Site Attrition			Tstat Disconnection		
	Expected	Lower bound	Upper bound	Expected	Lower bound	Upper bound
CPPTD	0.5%	0.3%	1.0%	2.6%	2.2%	3.0%
ACSDA	5.8%	5.1%	6.8%	1.7%	1.5%	1.9%

Figure 4-2: Survival Rates Over Time



In previous program years, TD 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. These historical ex post impacts are used for the PY 2021 ex ante estimation and PY 2020 segments were mirrored to facilitate application of PY 2020 impacts to PY 2021 reference loads. Table 4-3 summarizes the total number of sites in each segment used for development of PY 2021 reference loads.

The segmentation was developed based on rate size and on rate characteristics which may influence impacts. The 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:** was the site on a rate with a CPP component during the study period?
- **Rate size**: what size (demand level for rate[11]) was the site classified as throughout the study period?
- **Climate zone:** in which SDG&E climate zone was the site located?

Table 4-3: PY 2021 Small Critical Peak Pricing Population Segments

Program Rate	Size	Climate zone	Total sites	Total Connected sites	Total installed devices	Total connected devices
CPPTD (PSW)	Small	Coastal	93	88	231	150
		Inland	160	157	415	260
CPPTD (CPP-D)	Large	Coastal	6	6	89	55
		Inland	6	6	180	117
	Medium	Coastal	48	47	549	322
		Inland	70	68	659	421
ACSDA (non-res)	Large	Coastal	25	24	550	307
		Inland	19	19	721	440
	Medium	Coastal	156	155	1,752	918
		Inland	119	117	1,513	952
	Small	Coastal	209	201	719	395
		Inland	133	129	353	220
ACSDA (quasi-res)	Quasi-res	Coastal	7	6	13	8
		Inland	8	7	8	6
TOTAL			**1,059**	**1,030**	**7,752**	**4,570**

4.2 DATA SOURCES AND ANALYSIS METHOD

Table 4-4 summarizes the six data sources used to conduct the PY 2020 commercial thermostat event impact analysis. The resulting impacts from that evaluation were used to develop ex ante impacts for PY 2021 and are provided below for reference. The PY 2020 ex post analysis conducted in 2021 and reported in the PY 2020 evaluation report was done by site on hourly load data. Various data sources

[11] Small sites are on AS rates (such as ATOU and ASTODPSW) and have maximum demand below 20 kW—classification was assigned by rate. Medium and large sites are on AL rates or PA CP2 rates (such as ALTOU or PATODCP2). Medium sites were distinguished from Large sites by applying a maximum demand cutoff of 200 kW.

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 4-4: Commercial Thermostat Event Impact Evaluation Data Sources

Source	Comments

Hourly interval data	▪ PY 2020 ex post impacts
	  ○ Summer 2020
	▪ PY 2021 ex ante reference loads
	  ○ Summer 2021
	▪ All analysis done by site (premise id-service point id pair)

Outage information	▪ PSPS and SDG&E emergency outage data details which customers and what timeframes were impacted by outages ▪ Outage days which affected participants or control sites were excluded from the analysis
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	▪ PY 2020 ex post impacts
	  ○ Summer 2020
	▪ PY 2021 ex ante reference loads
	  ○ Summer 2021
	▪ Used to identify non-event high system load days

Ex post weather data by weather station	▪ Used to derive cooling degree hours for impact evaluation panel model

The primary analysis method was a panel regression with a multiple matched control groups. The distance matching approach used selected five matched control sites for each of the non-residential ACSDA sites among a matched control candidate pool of roughly 11,000 TOU sites. These customers were not enrolled in CPP or other DR programs which might influence energy use. The panel 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 model specification. The model selection relied on testing how well each model estimated loads for event-like 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 60 models were tested to select the number of proxy days, number of matched controls, and structure of same day adjustments to use. The regression model structure is detailed in Appendix A. The model selection process and results are covered more in depth in section 2.3.

4.3 EX POST LOAD IMPACTS

4.3.1 PEAK SHIFT AT WORK: SMALL NON-RESIDENTIAL CPP WITH TECHNOLOGY

No TD events were called in PY 2021 so there are no event impacts to assess. PY 2020 impacts were used to estimate ex ante impacts.

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

No TD events were called in PY 2021 so there are no event impacts to assess. PY 2020 impacts were used to estimate ex ante impacts.

4.3.3 AC Saver Day Ahead: Non-Residential with Technology

No ACSDA Non-Residential events were called in PY 2021 so there are no event impacts to assess. PY 2020 impacts were used to estimate ex ante impacts.

4.3.4 AC Saver Day Ahead: Quasi-Residential with Technology

No ACSDA Quasi-Residential events were called in PY 2021 so there are no event impacts to assess. PY 2020 impacts were used to estimate ex ante impacts.

4.4 EX ANTE LOAD IMPACTS

A key objective of the 2021 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. Since no new events were called during PY 2021, historical impacts during events from 2020 were used. Prior impacts were not used to avoid including pre-COVID data.

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

1. Estimate the relationship between cooling load per thermostat (absent DR) and weather by hour of day
2. Estimate the relationship between cooling load percent reduction, temperature, and hours into an event using historical event data
3. Predict cooling loads and percent reductions for 1-in-2 and 1-in-10 weather year conditions
4. Combine the loads and percent reductions to estimate impacts per connected thermostat
5. Incorporate the enrollment/device forecast and device connectivity forecast

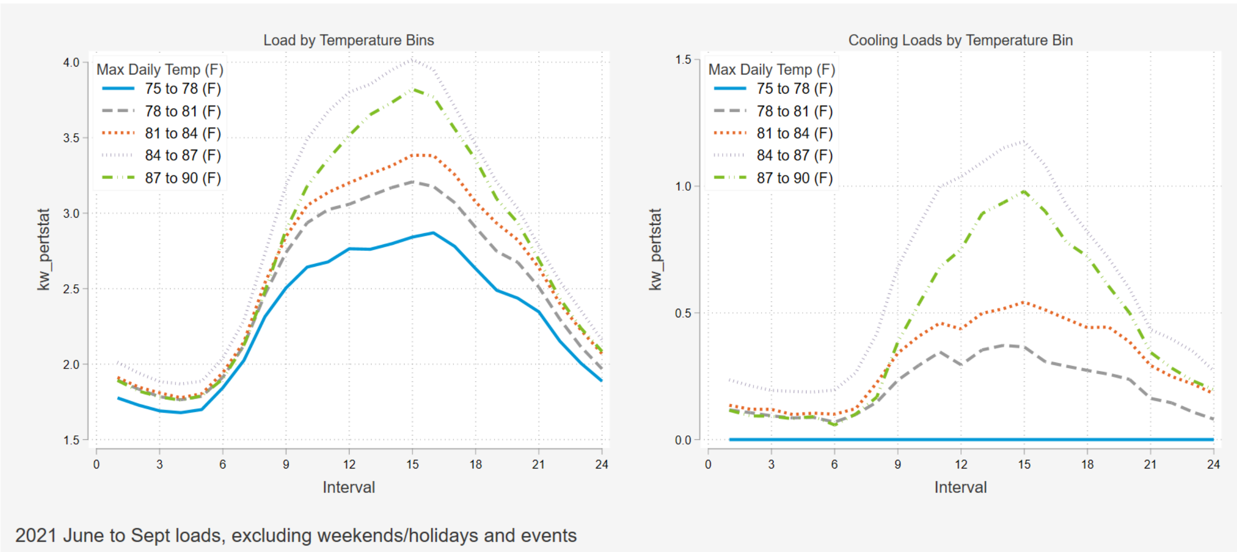
4.4.1 RELATIONSHIP OF CUSTOMER LOADS AND PERCENT REDUCTIONS TO WEATHER

Figure 4-3 summarizes the relationship between weather for commercial customers with commercial thermostats on CPP rates. Figure 4-4 does the same for ACSDA customers (excluding quasi-residential). Only days when the smart thermostat resources were not dispatched are included. Generally, energy demand and discretionary load increases with hotter weather.

These figures also provide an estimate for typical cooling loads for commercial thermostat sites by assessing how whole building loads per thermostat vary with temperature (left panel). The baseload is estimated by the load on cooling neutral days (max daily temperatures around 75-78 degrees, e.g. blue line in left panel). Net cooling loads (right panel) are total loads for each weather bin minus the baseload. Note that hotter temperature bands were available for plotting for ACSDA devices which skew less heavily toward the Coastal zone than do devices on dispatchable rates.

Due to small sample size for the CPPTD program, the peak temperature band (green) is not actually the highest load in the visual (light gray). However, on days with the highest usage (the 87-90 max daily temperature band[12]) average whole building load per thermostat for CPPTD devices is about 4.5 kW during 4 to 9 pm resource adequacy planning window, closely aligned with the 4 to 8 pm CPP event window planned for PY 2022. Cooling loads from 4 to 9 pm are only 37% of whole building loads, or about 0.6 kW per thermostat. On days with 87-90 max daily temperature (Figure 4-4 light gray curve) average cooling load per thermostat for non-residential ACSDA devices is about 3.1 kW during the 4 to 9 pm period that counts towards resource adequacy requirements, and cooling load is about 0.7 kW during this time frame. ACSDA events are typically called later in the day but can be called anytime from 12pm to 9pm. Because impacts are directly driven by connected thermostats controlling cooling loads, ex ante impacts were estimated as a function of cooling loads on a per thermostat basis.

Figure 4-3: Weather Sensitivity of CPPTD Program Participant Loads



[12] Negligible difference relative to the 84-87F band

Figure 4-4: Weather Sensitivity of ACSDA Non-residential Program Participant Loads

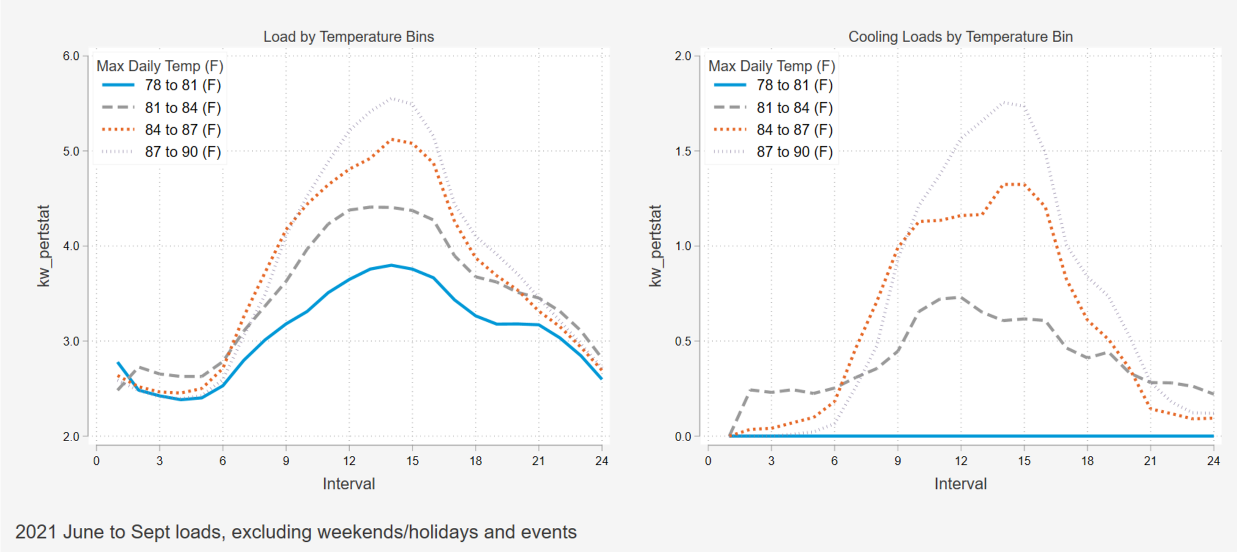


Figure 4-5 shows the relationship between aggregate loads for Technology Deployment sites and SDG&E daily peak loads during PY 2021. Daily peaks that occurred before 5pm (typically at 4 or 5pm) are shown in blue and those that occurred later are shown in grey. The patterns are similar for Technology Deployment sites on CPP rates and those on ACSDA. Importantly, most system peak net loads are now occurring after 4pm, after solar production begins to wane. Daily peaks that occurred before 4pm are shown in blue and those that occurred later are shown in grey. Daily peaks that occur later in the day (after 4pm) are now larger in magnitude but they occur when TD program participants have less load reduction potential.

Figure 4-5: 2021 Commercial Thermostat Customer Loads During System Daily Peaks

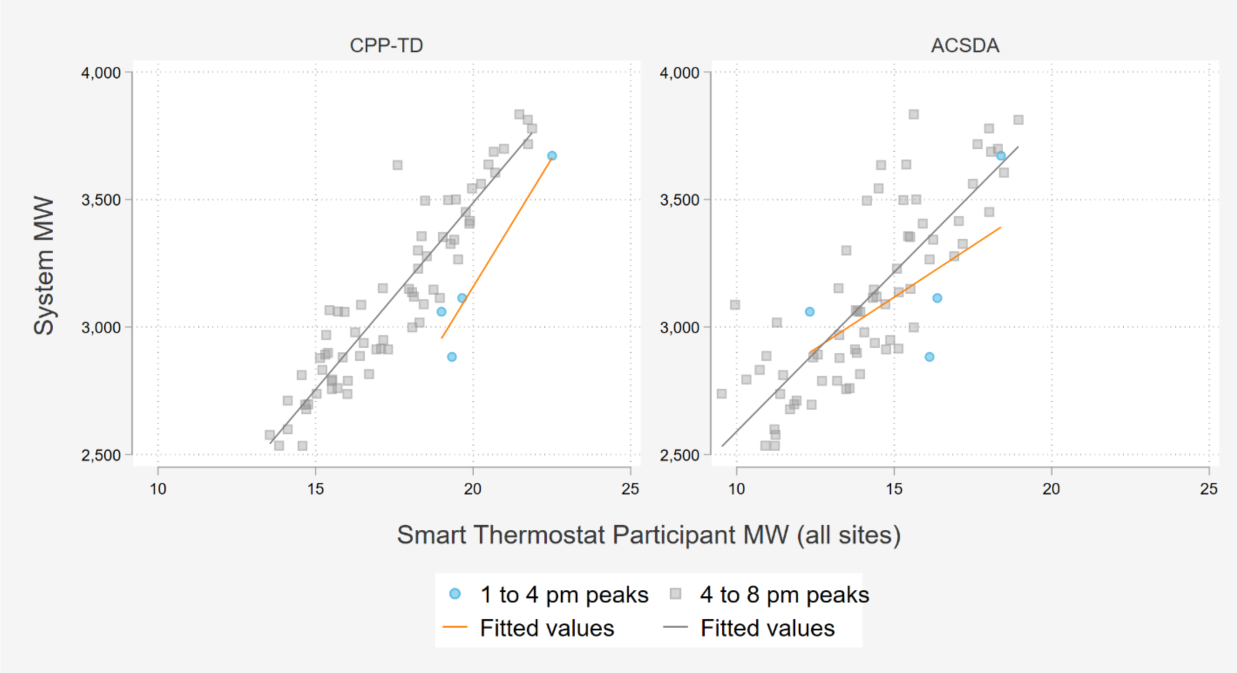
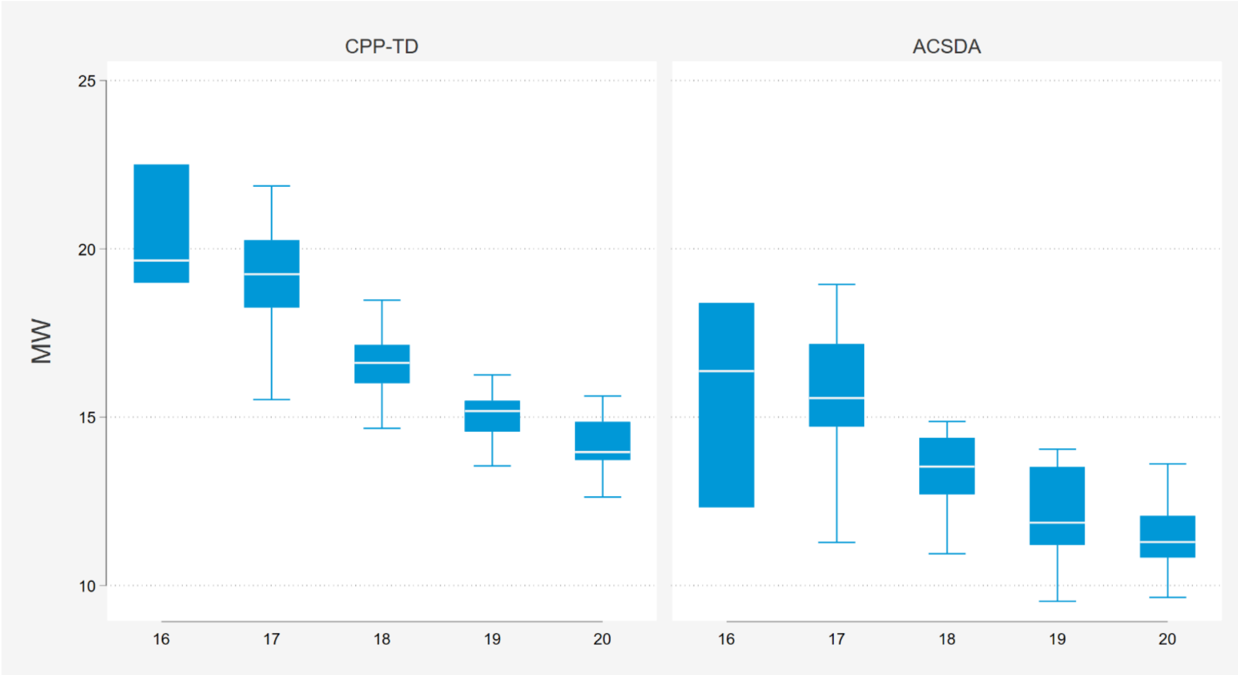


Figure 4-6 shows the range of aggregate TD program loads for each climate zone during the daily system peak hours. The boxes show the inter quartile range of loads and the lines that extend above show the more extreme loads in each hour. Notably the highest loads occur from 3 to 4pm (hour 16) and from 4 to 5pm (hour 17). At their highest, CPP-TD loads comprise around 20 MW and ACSDA about 18 MW for a total of about 38 MW. However, after 5pm loads drop by about a third, reflecting minimized the load reduction potential from non-residential customers. This is important context when considering the planned shift of the CPP event window from 2 to 6 pm to 4 to 8 pm. Historically, more discretionary load was in use during peaking conditions, and large reductions from CPP-TD participants during the 2 to 6 pm could be deployed could be larger precisely when resources are needed most. However, the planned shift of the CPP window to the later 4 to 8 pm window is likely to capture part of this peaking load in the first hour or two of the event window, but potential is expected substantially taper off in later hours along as small commercial loads decline. This known pattern already reduces the load reduction potential for the ACSDA program for which the typical event is called from 6 to 8 pm.

Figure 4-6: TD Program Hourly Loads at System Daily Peaks



Because the commercial thermostats are dispatched automatically for events, the main driver of differences in ex ante impacts are differences in loads. Since no CPPTD or ACSDA events were called in PY 2021, PY 2020 events were included in the ex ante model estimation. The percent change in energy use was estimated for each of the ex post segments defined in **Error! Reference source not found.** and a pplied to 1-in-2 and 1-in-10 weather year customer loads.

Figure 4-7 and Figure 4-8 show hourly event percent reductions for historical weekday events as a function of hourly temperatures for sites on each Technology Deployment program. Reductions are largely positive in magnitude, a handful are near zero (and not statistically significant) and few are negative, indicating an increase in load, but insignificant. All programs show the positive relationship between temperature and load reductions.

Figure 4-7: PY 2020 CPPTD Hourly Reductions and Temperatures

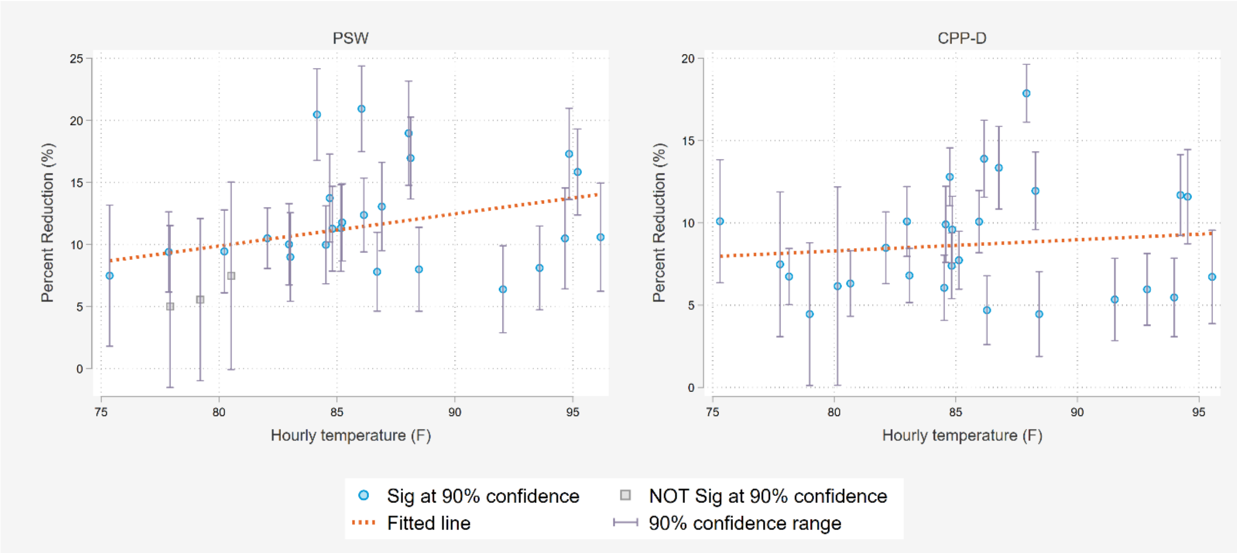
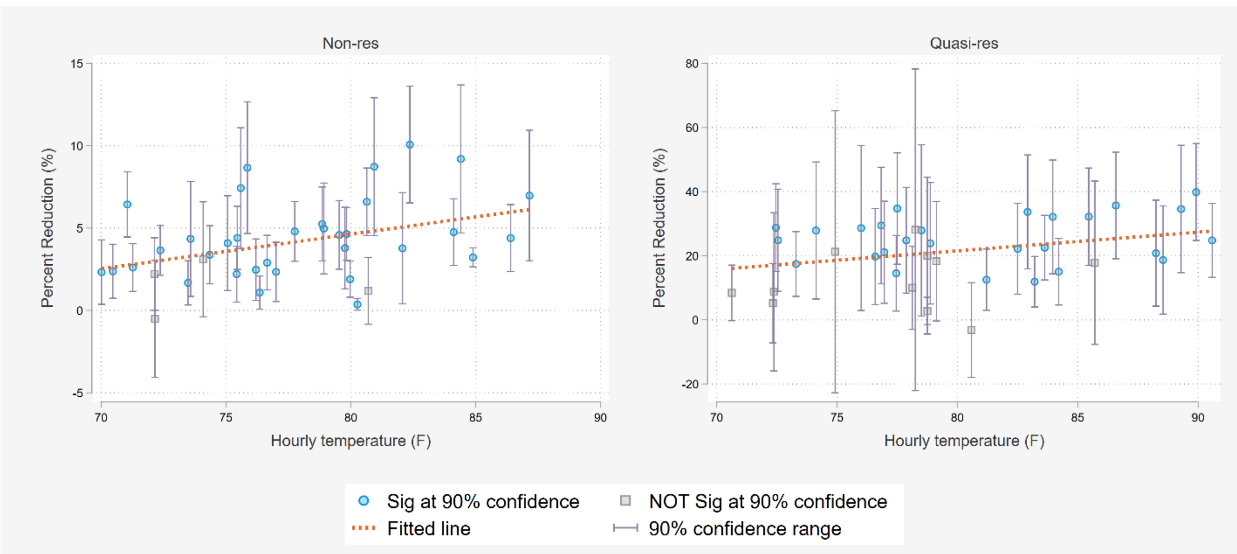


Figure 4-8: PY 2020 ACSDA Hourly Reductions and Temperatures



4.4.2 COVID-19 CONSIDERATIONS

Beginning in March 2020, shutdowns began across the United States as a response to the COVID-19 pandemic. As commercial businesses closed, many workers either lost their jobs or began working from home. The shutdown impacted sectors at different levels of intensity and during different time periods, but all PY 2020 TD events are assumed to have occurred under COVID-19 conditions. As such, PY 2020 reference loads were modeled under COVID-19 conditions.

During PY 2021, DSA and SDG&E analysis showed that COVID-19 effects have largely subsided and any remaining effects are small. For instance, many workers have returned in-person to their commercial businesses, although there are some who still work remotely or have left the workforce. Therefore, we assume loads are a "new normal" going forward.

4.4.3 Ex Ante Enrollment Forecast

To derive the aggregate forecast and reference and loads percent impacts per connected thermostat and are scaled to the site and connected device population expected to be enrolled in each planning year. The enrollment forecast for all four non-residential TD programs was developed by the evaluator and incorporates:

- Expected new site enrollments per year
- Expected site retention
- Expected number of thermostats per site
- Expected retention of thermostat connectivity per year

Figure 9 summarizes the enrollment model architecture.

Figure 9: ACSDA Enrollment Model Architecture

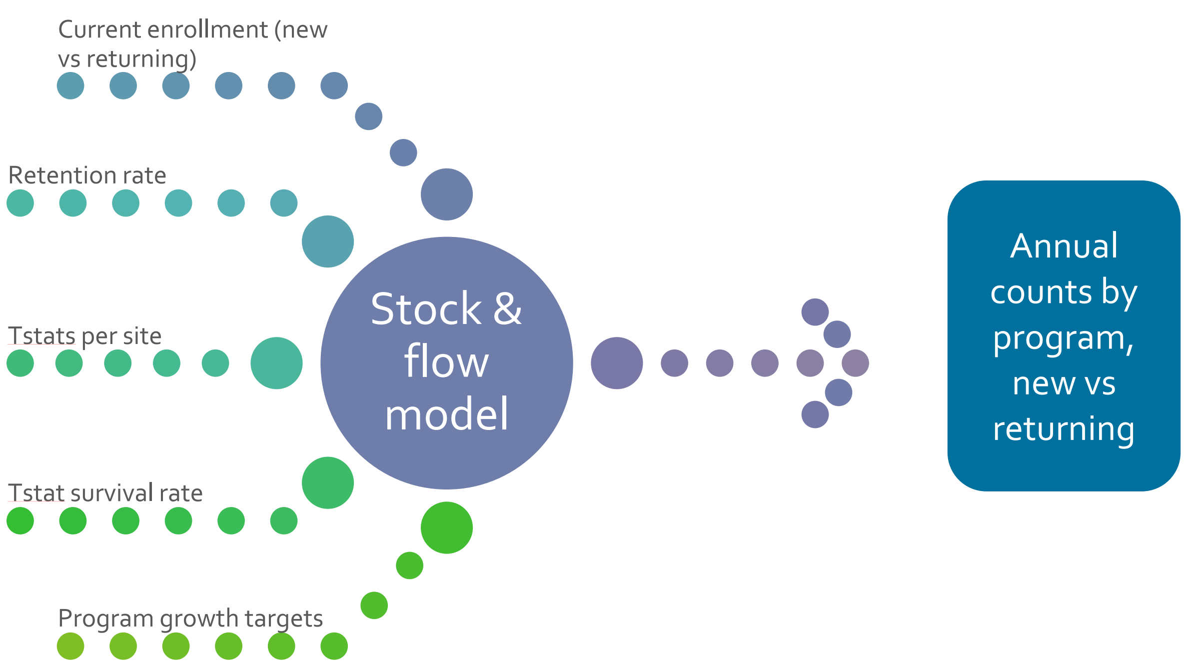


Table 5 summarizes retention, connectivity, thermostats per site, and annual new site enrollments used to derive the enrollment forecasts for PY 2021 using the enrollment model described above. Note that site attrition and device connectivity rates are the same figures described in section 4.1.

Table 5: Non-Residential TD Program Enrollment Forecast Assumptions

Program	Program Type	Site retention rate	Tstat failure rate	Tstats per site (current) [13]	Tstats per site (capped) [14]	Projected New Enrollment
CPPTD (PSW)	CPPTD	98.5%	2.6%	2.6	2.0	40
CPPTD (CPP-D)	CPPTD	98.5%	2.6%	11.4	3.2	10
ACSDA (non-res)	ACSDA	94.2%	1.7%	8.5	2.6	0
ACSDA (quasi-res)	ACSDA	94.2%	1.7%	1.4	1.4	0

Table 6 below summarizes key assumptions incorporated into the forecast used.

Table 6: Key Forecast Assumptions TD Program Enrollment Model

Assumption	Description
New participant forecast	Assumed to be zero for ACSDA and very modest for PSW (40) and CPP-D (10).
Long term flattening out of enrollments	Assume enrollments stabilize starting in 2028 (no new enrollments, no attrition, only change to connected thermostats is from connectivity)
Ramping of enrollments to mirror expected smart thermostat uptake	Thermostat market share of smart thermostats assumed to grow by 10% a year from 2023 through 2026, conservative application of market forecast projecting 18% annual growth[15]. Enrollment growth is ramped to mirror this market share growth.
Thermostats enrolled per site	Also assume future enrollments reflect historical average, but cap historical figures at 4 thermostats per site before taking the average.

[13] Reflects average thermostat counts for existing participants. This is the figure applied to current enrollments

[14] Reflects average thermostat counts for existing participants if total thermostats per participant is capped at 4. This is the figure applied to future enrollments

[15] https://www.freedoniagroup.com/industry-study/smart-and-connected-thermostats-3659.htm

Assumption	Description
Monthly ramp of enrollments	Annual forecast changes spread linearly across months

4.4.4 Ex Ante Load Impacts

Table 4-7 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 under August 1-in-2 peaking conditions in alignment with the planning conditions used for resource adequacy attribution. They incorporate an enrollment forecast for sites and devices described above.

Table 4-7 summarizes expected August peak day 1-in-2 reductions for the four TD programs. Ultimately, forecasted ex ante load reductions reflect load reductions are delivered by connected devices among enrolled sites. Reductions are a function of the number of enrolled sites (which decrease over time), the connectivity rate over time for installed devices (which decreases over time), and the estimated load reduction per connected device (which stays constant over time on a percentage basis). The estimated load reductions are also influenced by reference loads. CPP-TD impacts are assumed to slowly increase over time as new enrollments are forecasted until 2028, while ACSDA impacts are assumed to slowly decrease over time as participants un-enroll (or move out) and thermostats become disconnected.

Table 4-7: Non-residential Smart Thermostat Portfolio Impacts for 1-in-2 SDG&E Weather Conditions, August Monthly Peak Day

Year	CPP-TD		Total	ACSDA		Total
	PSW	CPP-D		Non-Res	Quasi-Res	
2021	0.07	0.29	0.36	0.62	0.01	0.63
2022	0.07	0.30	0.37	0.59	0.01	0.60
2023	0.08	0.31	0.39	0.55	0.00	0.55
2024	0.09	0.32	0.41	0.51	0.00	0.51
2025	0.10	0.34	0.44	0.47	0.00	0.48
2026	0.11	0.36	0.47	0.44	0.00	0.44
2027	0.12	0.37	0.50	0.40	0.00	0.41
2028	0.13	0.38	0.50	0.39	0.00	0.39
2029	0.12	0.37	0.49	0.38	0.00	0.39
2030	0.12	0.36	0.48	0.38	0.00	0.38
2031	0.12	0.35	0.46	0.37	0.00	0.37
2032	0.11	0.34	0.45	0.36	0.00	0.37

Table 4-8 and Table 4-9 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 an initial increase followed by a decrease in sites, installed devices, and connected devices over time for the ACSDA programs. For the CPP-TD programs, all three categories show a decrease in forecasted enrollment. 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 as well as the reference load. These confounding impacts cause the irregular trend in the CPP-TD impacts over time, while ACSDA shows a clear decrease in impacts each year.

Table 4-8: CPP-TD Portfolio Ex Ante Impacts for August Monthly Peak Day

Year	Sites	Tstats installed	Tstats connected	Average Reference Load	CAISO		SDG&E	
					1-in-2	1-in-10	1-in-2	1-in-10
2021	383	2,124	1,326	5.19	0.38	0.36	0.36	0.39
2022	415	2,192	1,389	5.19	0.39	0.37	0.37	0.41
2023	463	2,293	1,481	5.19	0.42	0.40	0.39	0.43
2024	514	2,401	1,579	5.19	0.44	0.42	0.41	0.45
2025	569	2,520	1,688	5.19	0.47	0.44	0.44	0.48
2026	630	2,649	1,807	5.19	0.50	0.47	0.47	0.51
2027	695	2,789	1,936	5.19	0.53	0.50	0.50	0.55
2028	717	2,837	1,946	5.19	0.53	0.51	0.50	0.55
2029	717	2,837	1,896	5.19	0.52	0.49	0.49	0.53
2030	717	2,837	1,847	5.19	0.51	0.48	0.48	0.52
2031	717	2,837	1,800	5.19	0.49	0.47	0.46	0.51
2032	717	2,837	1,753	5.19	0.48	0.46	0.45	0.49

Table 4-9: ACSDA Portfolio Ex Ante Impacts for August Monthly Peak Day

Year	Sites	Tstats installed	Tstats connected	Average Reference Load	CAISO		SDG&E	
					1-in-2	1-in-10	1-in-2	1-in-10
2021	676	5,629	3,246	8.96	0.64	0.61	0.63	0.60
2022	650	5,409	3,085	8.96	0.61	0.58	0.60	0.57
2023	612	5,093	2,856	8.96	0.56	0.53	0.55	0.53

2024	576	4,796	2,644	8.96	0.52	0.49	0.51	0.49
2025	542	4,515	2,447	8.96	0.48	0.46	0.48	0.45
2026	511	4,251	2,265	8.96	0.45	0.42	0.44	0.42
2027	481	4,003	2,097	8.96	0.41	0.39	0.41	0.39
2028	471	3,922	2,020	8.96	0.40	0.38	0.39	0.38
2029	471	3,922	1,986	8.96	0.39	0.37	0.39	0.37
2030	471	3,922	1,952	8.96	0.38	0.37	0.38	0.36
2031	471	3,922	1,919	8.96	0.38	0.36	0.37	0.36
2032	471	3,922	1,887	8.96	0.37	0.35	0.37	0.35

4.4.5 COMPARISON OF EX POST AND EX ANTE LOAD IMPACTS

Table 4-10 compares the observed demand reductions from PY 2020 events to the PY 2021 reductions expected for the 1-in-2 weather conditions used for planning. Results are shown for the 4 to 9 pm resource adequacy window. In 2020, CPPTD customers delivered 1.54 MW during the dispatch period of 2 pm to 6 pm and 0.37 MW during the 4 to 9 pm resource adequacy window, which extends three hours beyond the CPP dispatch window. Ex post reductions during the resource adequacy window are much lower because they include three hours with no reductions, from 6 to 9 pm. Ex ante impacts for the resource adequacy window are much greater than the corresponding ex post impacts. 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 4-10: CPPTD Comparison of PY 2020 Ex Post and PY 2021 Ex Ante Load Impacts

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 (PY 2020 Results)	Event Period (2pm to 6pm)	1,204	4,676	23.00	1.54	6.7%	90.7
	Resource Adequacy Period (4 to 9pm)	1,204	4,676	19.30	0.37	1.9%	90.7
Ex ante SDG&E	1-in-2 Weather August Peak (4 to 9pm)	383	1,326	6.04	0.36	5.9%	91.2
Ex ante CAISO	1-in-2 Weather August Peak (4 to 9pm)	383	1,326	6.25	0.38	6.1%	90.8

Result Type	Day Type and Period	Sites	Tstats connected	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)

*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
***Ex ante site counts are lower due to exclusion of sites with no associated thermostat

Table 4-11 makes a similar comparison for ACSDA programs, comparing the observed demand reductions from PY 2020 events to the PY 2021 reductions expected for the 1-in-2 weather conditions used for planning. 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 2020, ACSDA customers delivered 0.44 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 4 to 9 pm resource adequacy window were lower (0.15 MW). In contrast, ex ante reference loads and impacts are greater for the 4 to 9 pm window, mostly because they assume five hours of dispatch. In addition, temperatures were over four degrees higher for 1-in-2 planning conditions than for the PY 2020 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 4-11: ACSDA Comparison of PY 2020 Ex Post and PY 2021 Ex Ante Load Impacts

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** (PY 2020 Results)	Event Period (6pm to 8pm)	941	3,543	15.17	0.44	2.9%	85.6
	Resource Adequacy Period (4 to 9pm)	941	3,543	15.46	0.15	1.0%	85.6
Ex ante SDG&E	1-in-2 Weather August Peak (4 to 9pm)	676	3,246	32.13	0.63	2.0%	90.0
Ex ante CAISO	1-in-2 Weather August Peak (4 to 9pm)	676	3,246	33.03	0.64	1.9%	89.8

*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
***Ex ante site counts are lower due to exclusion of sites with no associated thermostat

5 CONCLUSIONS AND RECOMMENDATIONS

The two different interventions – CPP-TOU and commercial thermostats – each delivered statistically significant demand reduction, but there is room for improvement. The recommendations below may not be currently funded, and costs need to be considered alongside other research and program priorities. For clarity, we present the recommendations for technology deployment programs and critical peak pricing separately.

5.1 TECHNOLOGY DEPLOYMENT RECOMMENDATIONS

- **If possible, avoid bidding sites that lack connected thermostats into the CAISO markets.** Sites with loads that cannot be controlled or dispatched do not deliver any detectable demand reduction. They simply dilute the demand reductions and make them harder to detect. SDGE& should continue ongoing efforts to remove inactive devices from the dispatch portal.

- **Continue to monitor loads and assumptions about the effect of COVID-19 on loads.** Analyze load data and public health data to evaluate the appropriateness of the "new normal" assumption going forward.

- **Anticipate lower load reductions for CPP-TD with the new 4 to 8 pm CPP event window.** Commercial loads decline substantially after 5pm as does load reduction potential.

- **Develop and deploy a robust outreach and education plan to inform participants regarding the new CPP window due to start in PY 2022.** The event window is planned to change from 2 to 6 pm to 4 to 8 pm for PY 2022. Outreach may not be critical for the technology enabled CPP-TD programs, but participants should be informed and doing so will help ensure any behavioral response that is layered on the technology response will not be lost.

5.2 SMALL COMMERCIAL CRITICAL PEAK PRICING RECOMMENDATIONS

- **Develop and deploy a robust outreach and education plan to inform participants regarding the new CPP window due to start in PY 2022.** The event window is planned to change from 2 to 6 pm to 4 to 8 pm for PY 2022. However, small CPP participants appear to still be responding to the original 11 am to 6 pm window. For the behavioral Small CPP program it will be critical to help participants understand that load reductions are needed after 4 pm. Multiple communication modes should be used to deliver this messaging.

- **Assess if additional communications encouraging response improve reductions using randomized controlled trials.** The magnitude of demand reductions during events is small on a percentage basis, about 1%, providing ample room to improve reductions. However, most reductions were delivered by sites receiving event notifications. Additional communications require resources and their effectiveness at improving price response is unknown. Because of the potential, however, we recommend testing the effectiveness of more education regarding event response. It is critical, however, for the test to be implemented using randomized control trials, so it is possible to assess if the communications had any impact on price response.

- **Notification rates for small CPP can be improved.** Customers elect whether or not to sign up for notifications and by which channels they receive notification. Because notification is closely linked to response, additional efforts to improve notification rates are recommended. The share of sites enrolled to receive notifications has dropped somewhat since PY 2018 when CPP events were last called. In PY 2018 roughly 60% of sites received event notifications while that number dropped to 43% in PY 2020. Sites receiving event notifications tend to produce greater impacts so an increase in notification rates has the potential to meaningfully increase load reductions.

- **Continue to monitor loads and assumptions about the effect of COVID-19 on loads.** Analyze load data and public health data to evaluate the appropriateness of the "new normal" assumption going forward.

APPENDIX

A. PANEL REGRESSION MODELS WITH MULTIPLE CONTROLS: TD PROGRAMS

Panel regressions with multiple control groups were used as the primary method for estimating load impacts for PY 2020 impacts for TD programs. The approach is implemented on a time series of individual customer loads. It relies on multiple non-equivalent control sites that did not experience the intervention, plus weather and day characteristics, to estimate the counterfactual. The panel model estimates a counterfactual load using weather and loads for the matched control sites. A separate model is estimated for each hour of day. Reductions are the difference between the participant and counterfactual loads with a panel model, one should observe:

- Very similar energy use patterns for participant and counterfactual loads when the intervention is not in place.
- A change in demand patterns for customers who are dispatched or subject to time varying prices, but no similar change for the counterfactual load.
- The timing of the change should coincide with the introduction of intervention.

The use of a panel model allows for incorporation of multiple control sites and does not rely on finding a single ideal match. The equation for the model is presented below in Equation A 0-1 and Table A 0-1. A separate model was estimated for each intervention and hour of the day for each of the analysis segments identified as part of the evaluation plan. Pre and post event terms (single hour with two-hour buffer) were added to the Technology Deployment models to implement the same calibration for these load control programs.

Equation A 0-1: Ex Post Regression Model for TD Programs

$$kW_{i,t} = \mathrm{a} + \mathrm{b} \cdot kW\_1 - kW\_5_i + \sum_{n=1}^{max} \mathrm{c}_n \cdot Event_n + \mathrm{d} \cdot CDH_{i,t} + \delta_t + \varepsilon_{i,t}$$

Where:

Table A 0-1: Ex Post Regression Elements for TD Programs

$\mathrm{kW}_{\mathrm{i,t}}$	Is the usage for each individual customer and time period
a	Is the model intercept
b	Loads for the five most closely matched control sites based on Euclidean distance matching. They did not experience the treatment and are weighted based on their predictive power.
c	Controls for differences between event and non-event days
d	Is the parameter for weather sensitivity of loads
Event	Is a binary variable indicating if day is an event. Separate variables are used for each event so impacts are estimated for each event. It has a value of zero on event-like proxy days. The five closest non-event days

	were included as proxy days for each event. Separate proxy days were selected for each event using Euclidean distance matching.
δ_t	Represents time effects for each time period. This accounts for observed and unobserved factors that vary by time but affect all customers equally.
$\varepsilon_{i,t}$	Represents the error term for each individual customer and time period.

B. PANEL REGRESSION MODELS WITH MULTIPLE CONTROLS: SMALL CPP

Panel regressions with multiple control groups were used as the primary method for estimating load impacts for PY 2020 impacts for Small CPP. The approach is implemented on a time series of individual customer loads. It relies on multiple non-equivalent control sites that did not experience the intervention, plus weather and day characteristics, to estimate the counterfactual. The panel model estimates a counterfactual load using weather and loads for the matched control sites. A separate model is estimated for each hour of day. Reductions are the difference between the participant and counterfactual loads with a panel model, one should observe:

- Very similar energy use patterns for participant and counterfactual loads when the intervention is not in place.
- A change in demand patterns for customers who are dispatched or subject to time varying prices, but no similar change for the counterfactual load.
- The timing of the change should coincide with the introduction of intervention.

The use of a panel model allows for incorporation of multiple control sites and does not rely on finding a single ideal match. The equation for the model is presented below in Equation B 0-2 and $kW_{i,t} = \mathrm{a} + \sum_{n=1}^{5} \mathrm{b}_n \cdot Control_{\,i,t,n} + \mathrm{c} \cdot kW_{i,t-5} + \mathrm{d} \cdot CDH_{i,t} + \delta_t + \varepsilon_{i,t}$

Where:
Table B 0-2. A separate model was estimated for each intervention, each hour of the day, and each of the analysis segments identified as part of the evaluation plan.

Equation B 0-2: Ex Post Regression Model for Small CPP

$$kW_{i,t} = \mathrm{a} + \sum_{n=1}^{5} \mathrm{b}_n \cdot Control_{\,i,t,n} + \mathrm{c} \cdot kW_{i,t-5} + \mathrm{d} \cdot CDH_{i,t} + \delta_t + \varepsilon_{i,t}$$

Where:

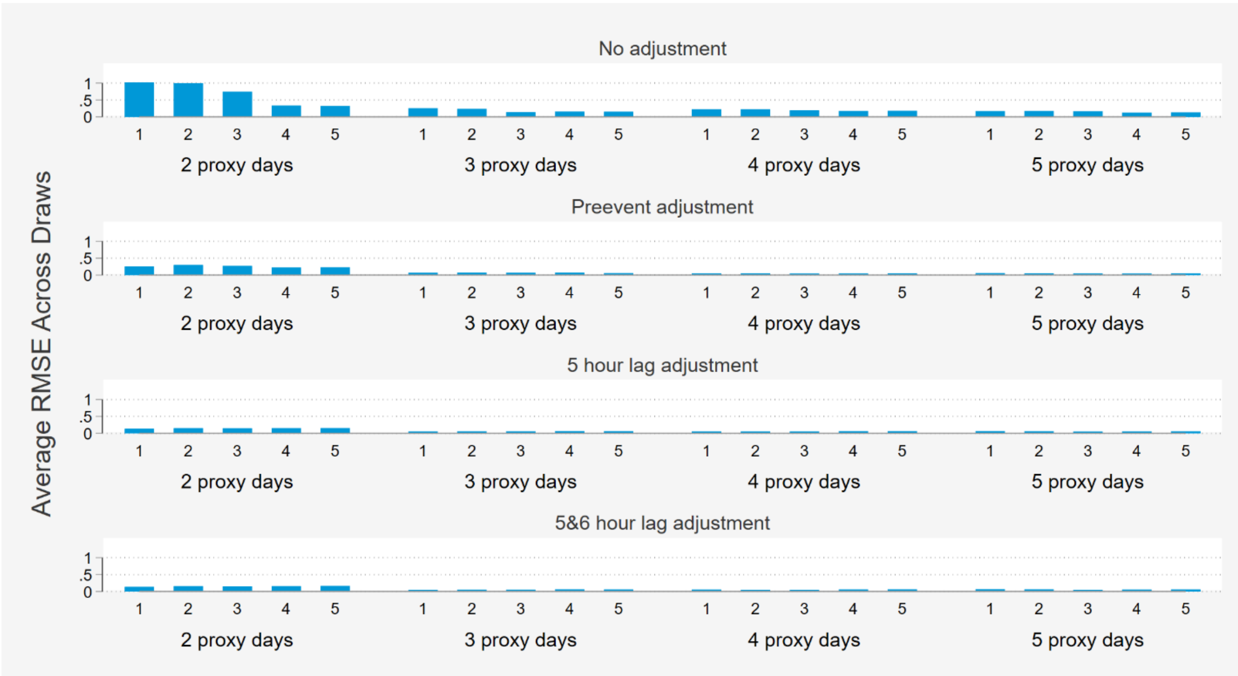
Table B 0-2: Ex Post Regression Elements for Small CPP

$kW_{i,t}$	Is the usage for each individual customer and time period

$Control_{i,t,n}$	The hourly used for five control sites, with each match
Event	Is a binary variable indicating if day is an event. Separate variables are used for weekday and weekend events so weather sensitivity of loads is estimated separately for weekday vs for weekend events. It has a value of zero on event-like proxy days. The five closest non-event days were included as proxy days for each event. Separate proxy days were selected for each event using Euclidean distance matching.
a	Is the model intercept
b	Loads for the five most closely matched control sites based on Euclidean distance matching. They did not experience the treatment and are weighted based on their predictive power.
c	5-hour lagged site load
d	Parameters for weather sensitivity of loads on event days vs on non-event days
δ_t	Represents time effects for each time period. This accounts for observed and unobserved factors that vary by time but affect all customers equally.
$\varepsilon_{i,t}$	Represents the error term for each individual customer and time period.

As with the TD Program analysis, out of sample testing was used for model selection. Figure B 0-1 summarizes the model variants tested and resulting RMSE. Also as modeled for the TD Program analysis, variants included the number of event proxy days (2 through 5), the number of control sites (1 through 5), and the same day adjustments. The adjustment variants tested included no adjustment, a two hour prevent adjustment, a 5-hour lag adjustment, and a 5 and 6-hour lag adjustment. All adjustments performed similarly, on the order of 0.05 to 0.06 RMSE, and produced markedly lower RMSE than applying no adjustment. The lag 5-hour lag approach was ultimately selected over the pre-event adjustment given the observed response in hours leading up to event start.

Figure B 0-1: PY 2020 Small CPP Model Selection Results



The key load impact coefficient for this regression model is the interaction of event impacts with weather sensitivity, e.g. the expected load impact (kW) for each cooling degree hour. This approach is described in the California Load Impact Protocols[16] and has the advantage of producing ex post results which directly reflect the weather impact relationship that is a key input to ex ante load impacts.

This relationship was modeled for each hour and day type (weekdays and weekends). The example regression summary in Figure B 0-2 below shows the results for hour ending 15 for weekday events. The highlighted term represents the event day weather sensitivity term: for each cooling degree hour average load is expected to drop by 0.00659 kW.

---

[16] http://www.calmac.org/events/FinalDecision_AttachementA.pdf, pages 70-72

Figure B 0-2: PY 2020 Ex Post Regression Example for Small CPP

```
Linear regression, absorbing indicators         Number of obs      =  1,619,729
Absorbed variable: site_id                      No. of categories  =    109,051
                                                F(   8,1510670)    =     694.66
                                                Prob > F           =     0.0000
                                                R-squared          =     0.9811
                                                Adj R-squared      =     0.9797
                                                Root MSE           =     2.4618

------------------------------------------------------------------------------------------
                    |               Robust
                kwh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------------
eventday_cpp#c.cdh65|
                  1 |  -.0065894   .0003153   -20.90   0.000    -.0072074   -.0059715
                    |
                kwh |
                L5. |   1.509874   .0301685    50.05   0.000     1.450745    1.569003
                    |
       _kwh_match_1 |   .0756694   .0390454     1.94   0.053    -.0008582    .1521971
       _kwh_match_2 |   .1397278   .0398529     3.51   0.000     .0616176     .217838
       _kwh_match_3 |   .0063335   .0125676     0.50   0.614    -.0182986    .0309656
       _kwh_match_4 |   .0240203   .0209156     1.15   0.251    -.0169736    .0650142
       _kwh_match_5 |   -.004661   .0101335    -0.46   0.646    -.0245223    .0152003
              cdh65 |   .0306782   .0008337    36.80   0.000     .0290442    .0323122
                    |
            daytype |
           Weekday  |          0  (omitted)
                    |
     daytype#c.cdh65|
           Weekday  |          0  (omitted)
                    |
              _cons |  -1.912648   .1893787   -10.10   0.000    -2.283823   -1.541472
------------------------------------------------------------------------------------------
```

Table B 0-3 below shows how this weather sensitivity regression coefficient is converted to kW and percent impacts. Essentially, though the relationship between load and weather is the same across events, the load impact varies across events as a function of weather (CDH) on each event. To derive load impacts the weather sensitivity coefficient (kW per CDH) for weekday events during hour ending 15 is multiplied by the CDH in that hour for a given event.

Table B 0-3: PY 2020 Ex Post Impact Calculation Example for Small CPP

(A) Event Date	(B) Sites	(C) Avg Ref Load (kW)	(D) Avg kW Impact per CDH	(E) CDH	(F=D*E) Avg Impact (kW)	(G=B*F) Total Impact (MW)	(H=F/C) % Impact (%)
17-Aug-20	108,595	2.89	-0.00659	22.7	-0.150	-16.3	-5.2%
18-Aug-20	108,606	2.98	-0.00659	19.5	-0.128	-13.9	-4.3%
19-Aug-20	108,595	2.99	-0.00659	20.9	-0.138	-15.0	-4.6%
20-Aug-20	108,583	3.04	-0.00659	23.0	-0.151	-16.4	-5.0%
30-Sep-20	107,039	3.34	-0.00659	29.5	-0.195	-20.8	-5.8%
1-Oct-20	107,057	3.39	-0.00659	29.9	-0.197	-21.1	-5.8%
Avg Weekday Event	*108,079*	*3.10*	*-0.00659*	*24.2*	*-0.160*	*-17.3*	*-5.2%*