Public Version. Redactions from 2024 CPP Load Impact Evaluation CONFIDENTIAL version removed and blacked out [redacted]

Demand Side Analytics
DATA DRIVEN RESEARCH AND INSIGHTS

FINAL REPORT

CALMAC ID: SDG0370

2024 Load Impact Evaluation for San Diego Gas & Electric's Small Commercial & Agricultural Critical Peak Pricing Program

Prepared for SD&GE
By Demand Side Analytics, LLC
March 1, 2025

ACKNOWLEDGEMENTS

Demand Side Analytics Team

- Alana Lemarchand
- Tim Larsen
- Candace Yee

SDG&E Team

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

ABSTRACT

This study quantifies the load impacts of the Critical Peak Pricing (CPP) rate plans SDG&E's Small (< 20 kW demand) customers in the commercial and agricultural rate classes for PY2024. CPP rates charge increased prices during peak hours on event days in exchange for lower rates during other summer hours. CPP rates are the default commercial rates for SDG&E.

The study focuses on two primary research questions: 1) *Ex post*, what were the 2024 demand reductions from 4 to 9 p.m. on event days? 2) *Ex ante*, what is the magnitude of future load reduction by CPP customers under 1-in-2 weather conditions?

Ex post, SDG&E's three events produced an average demand reduction of 1.2 MW from 16,000 customers in the Small Commercial and Agricultural groups. Ex ante, Small CPP customers would be expected to deliver estimated demand reductions of 0.9 MW in 2025, with impacts growing slightly over time with changes in forecasted enrollments. These impacts are somewhat lower than those estimated through PY 2022, when enrollments were much higher.

TABLE OF CONTENTS

Figures

Tables

1 EXECUTIVE SUMMARY

SDG&E's Critical Peak Pricing (CPP) is a dynamic rate for commercial and agricultural customers. CPP rates are time-of-use (TOU) rates that include price adders from 4 to 9 p.m. during event days. Customers pay lower rates during the other, non-event hours in the summer. Event days are called based on system demand, and customers can sign up to receive day-ahead or day-of notifications. TOU rates with a CPP component are the default rates for Small Commercial (< 20kW demand) customers, and an optional rate for Small Agricultural customers. Small Commercial customers can opt out of the rates at any time.

The study analyzes two primary research questions:

- What were the 2024 demand reductions on CPP event days?
- What is the magnitude of load reduction capability for 1-in-2 weather planning conditions?

In 2024, SDG&E called three CPP event days – all came during a September heat wave, on consecutive business days (September 5, 6, 9) around the SDG&E system peak on Sunday September 8.

Table 1-1 summarizes the estimated ex-post load impact estimates and distinguishes between agricultural and commercial customers. In PY 2024, Small Commercial customers delivered an average reduction of 0.44 MW per event hour across SDG&E's three event days. [redacted]

Table 1-1: Summary of 2024 Average Weekday Event Ex Post Load Impact Estimates

Group	Sites	Load without DR (MW)	Load reduction (MW)	% Reduction	Significant (90% CI)	Significant (95% CI)
Agricultural - Small (Below 20 kW)	[redacted]					
Commercial - Small (Below 20 kW)	16,059	38.39	0.44	1.1%	Yes	Yes

Table 1-2 and Table 1-3 summarize the small CPP ex ante reductions under August Worst Day conditions for a 1-in-2 weather year for agricultural sites and commercial sites. Results are shown under both CAISO and SDG&E peaking conditions and reflect the reduction capability from 4-9 p.m. PY 2023 impacts were combined with PY 2024 impacts for the ex ante estimates.

Small Agricultural sites are expected to deliver reductions of 0.45 to 0.46 MW per hour on event days, with this impact growing slightly over time with increased enrollments. Small Commercial sites are expected to deliver a similar 0.40 to 0.41 MW per hour on event days, with this impact growing over time to 0.47 to 0.48 MW.

Table 1-2: Summary of Ex ante Dispatchable Demand Reductions – Agricultural

Weather Type	Year	Sites	CAISO		SDG&E	
			Program	Portfolio Adj	Program	Portfolio Adj
1-in-2	2024	59	0.46	0.46	0.45	0.45
1-in-2	2025	62	0.49	0.49	0.48	0.48
1-in-2	2026	62	0.49	0.49	0.48	0.48
1-in-2	2027	62	0.49	0.49	0.48	0.48
1-in-2	2028	64	0.51	0.51	0.50	0.50
1-in-2	2029	66	0.52	0.52	0.51	0.51
1-in-2	2030	67	0.52	0.52	0.51	0.51
1-in-2	2031	72	0.56	0.56	0.55	0.55
1-in-2	2032	72	0.56	0.56	0.55	0.55
1-in-2	2033	76	0.59	0.59	0.58	0.58
1-in-2	2034	79	0.63	0.63	0.62	0.62

Table 1-3: Summary of Ex ante Dispatchable Demand Reductions – Commercial

Weather Type	Year	Sites	CAISO		SDG&E	
			Program	Portfolio Adj	Program	Portfolio Adj
1-in-2	2024	16,046	0.40	0.40	0.41	0.41
1-in-2	2025	15,709	0.39	0.39	0.40	0.40
1-in-2	2026	16,007	0.40	0.40	0.41	0.41
1-in-2	2027	16,372	0.41	0.41	0.42	0.42
1-in-2	2028	16,781	0.42	0.42	0.43	0.43
1-in-2	2029	17,243	0.43	0.43	0.44	0.44
1-in-2	2030	17,758	0.44	0.44	0.45	0.45
1-in-2	2031	18,340	0.46	0.46	0.47	0.47
1-in-2	2032	19,001	0.47	0.47	0.48	0.48
1-in-2	2033	19,745	0.49	0.49	0.50	0.50
1-in-2	2034	20,597	0.51	0.51	0.52	0.52

2 INTRODUCTION

SDG&E's Critical Peak Pricing is a dynamic rate for commercial and agricultural customers. CPP rates are time-of-use rates that include price adders from 4 to 9 p.m. during event days. Customers pay lower rates during the other, non-event hours in the summer. Event days are called based on system demand, and customers can sign up to receive day-ahead or day-of notifications. [1]

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). SDG&E has since 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. Participation in recent years has decreased through the expansion of Community Choice Aggregations (CCAs), which do not offer CPP rates, but TOU rates with a CPP component remain the default rate for commercial customers.

CPP rates are designed to incentivize customers to reduce electricity use during peak hours on the handful of days that drive utilities' needs for additional power infrastructure. This evaluation seeks to quantify the load reductions during peak hours (4 to 9 p.m.) during PY 2024 event days.

2.1 CPP PROGRAM FEATURES

The following table outlines several relevant features of SDG&E's CPP rates for Small Commercial and Small Agricultural customers.

Table 2-1: SDG&E Small CPP Program Details

Program Feature	Details
Eligible Customers	Commercial and Agricultural customers with < 20 kW demand
Peak Window	4-9 p.m. year-round
CPP Rate Adder	Various; generally $1.17 per kWh for Small CPP sites
Incentive	Lower rates during other summer peak hours

[1] 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

Program Feature	Details
Bill Protection	Yes, for first year
Program Changes	Peak window was earlier in past years (originally 11 a.m. to 6 p.m., then 2 to 6 p.m.; 4-9 p.m. window began in PY 2022)
Default rate for C&I customers (bundled)?	Yes
Groups ineligible?	CCAs, Direct Access (DA) customers
Min./Max. Possible Events	Max. 18 (no Min.)
Event Triggers	Day-ahead system load forecast > 4,000 MW Can also be triggered for high temp.'s, extreme conditions, emergencies
Number of Events - PY2024	3, all in September

2.2 STUDY RESEARCH QUESTIONS

Table 2-2 summarizes the key research questions for the evaluation:

Table 2-2: Key Research Questions

	Research Question
1	What were the demand reductions for CPP event days in 2024?
2	How do load impacts differ for customers that 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 weather conditions? 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 CPP rate performance?

3 DATA & METHODS

The CPP event day impacts were primarily estimated using differences-in-differences with a matched control group. Site-specific individual regression models were also used in cases where there were too few customer sites in a given segment. Table 3-1 lists further detail on the evaluation data and methods:

Table 3-1: Ex Post Evaluation Method Details

Utility/ Program	SDG&E
Analysis Method	Differences-in-Differences with matched control group Individual customer regressions if too few sites in customer segment
Loads Analyzed	Net loads (almost all sites) Delivered loads only for power generators
Groups	By rate class (Small Agricultural, Small Commercial)
Geographic segmentation	Climate Zone (Coastal, Inland)
Other segmentation	Industry, NEM, Power generators
Analyze event notifications?	Yes

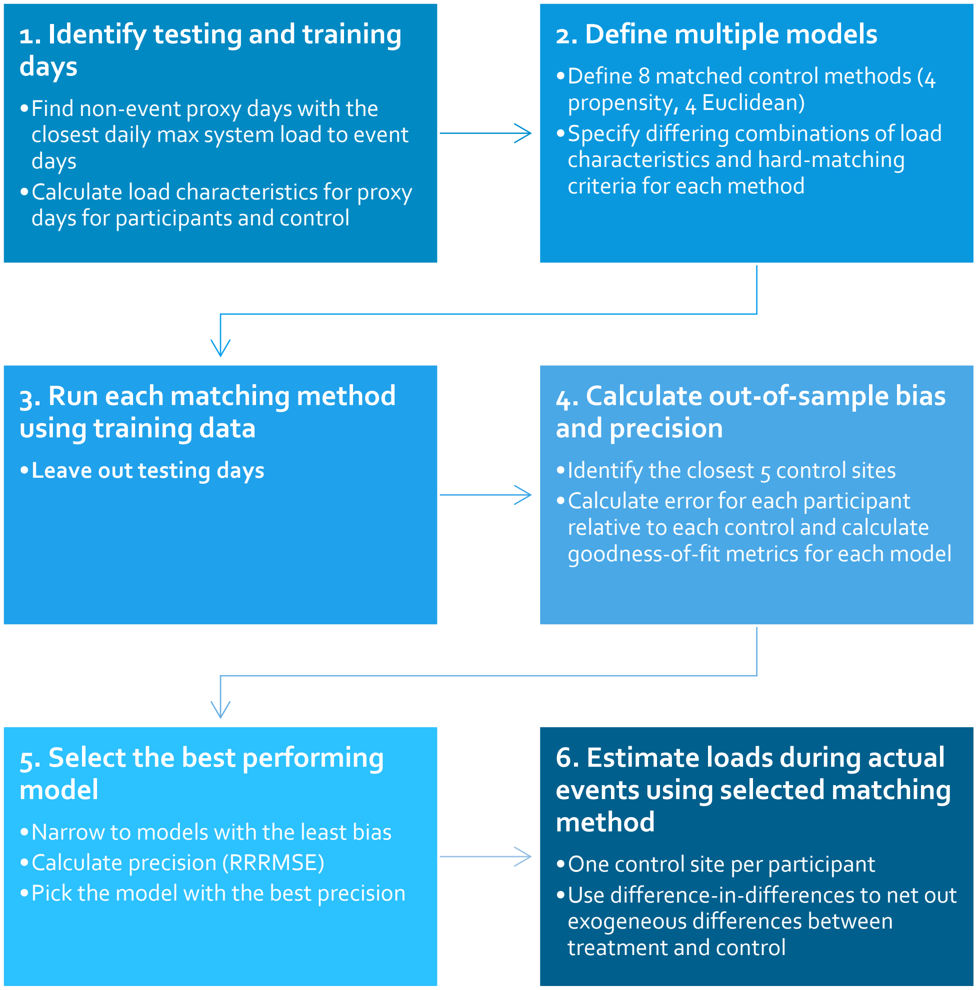
3.1 EX POST METHODOLOGY

3.1.1 CONTROL GROUP SELECTION

Figure 3-1 summarizes the process used to select matched controls for the difference-in-difference analyses. First, several event-like, proxy days were chosen, with similar weather and system conditions to event days. CPP customers were then matched to non-CPP sites with similar energy-use patterns on the proxy days. More detail on proxy day selection can be found in Appendix B.

Matching methods included different combinations of proxy day load characteristics such as load factor, load shape, and weather sensitivity. Customers were always matched with control candidates in the same climate zone, net metering status, and size bin. Size bins were constructed using average usage on event-like, proxy days. For solar customers, size bins were constructed based on system size.

Figure 3-1: Out of Sample Process for Control Group Selection



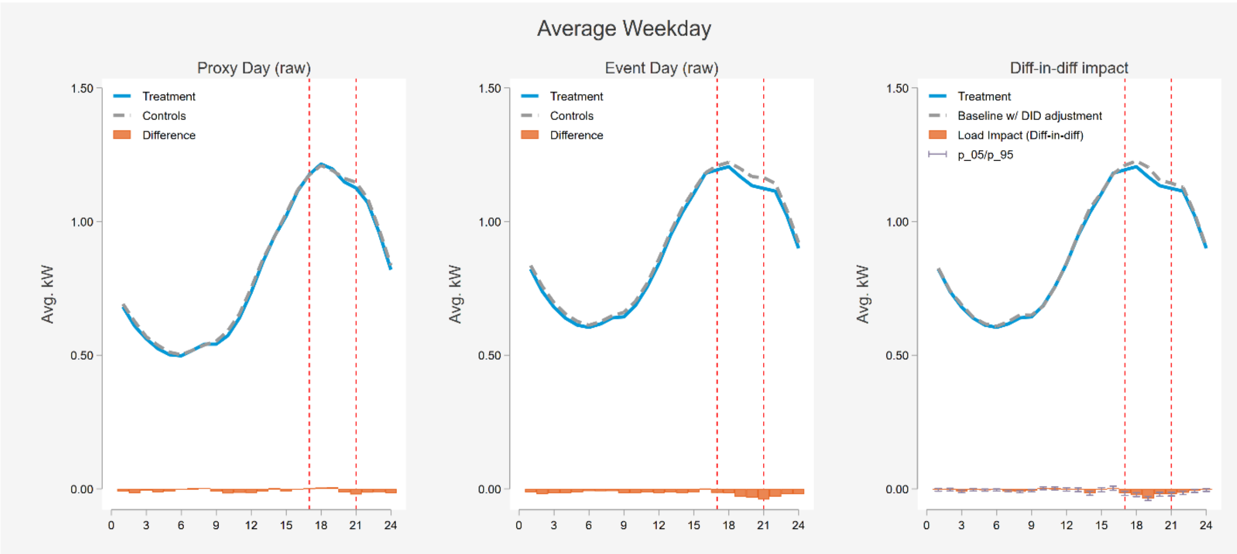
Matches were evaluated and the process was iterated as necessary until strong matches were achieved for each group. Matching was assessed using bias and goodness-of-fit metrics.

The difference-in-differences approach used the matches collectively as a control group to net out changes in energy usage patterns not due to the CPP events. The individual customer regressions also test for the inclusion of matched control sites as explanatory variables, representing the usage patterns on event days from similar sites. As such, regardless of evaluation methodology, each CPP site was matched to one or more non-CPP using a matching tournament where match quality was compared across eight different matching models to identify the best performing model.

3.1.2 Differences-in-Differences

Figure 3-2 below demonstrates the mechanics of a difference-in-difference calculation. The data shown is generic and not specific to any group in this evaluation. In the first panel, average observed loads on proxy days are shown for customers and for their matched controls. The difference between these two is the first "difference" and quantifies underlying differences between CPP customers and their controls not attributable to event participation. Note that this first difference is very small, indicative of a high-quality match and sufficient sample size to neutralize the noise inherent in individual customer loads.

Figure 3-2: Difference-in-Differences Calculation Example



The second panel shows the average observed CPP customer and matched control loads on event days. The gap between these two is the second "difference" which includes both the difference due to event participation and the underlying first difference observable on non-event days.

The third panel shows the average event day loads after netting out the proxy day difference from the event day control load. The result is the difference-in-differences impact, or the change in customers' usage on event days vs. proxy days, net of any observed differences in the control group on those same days.

3.1.3 Individual Customer Regressions

In cases where a difference-in-differences approach was not possible due to insufficient sample size in the required matching categories, site-specific individual customer regression models were used.

For sites requiring individual customer regressions, an out of sample tournament was used to select site specific regression models among 120 possible specifications across 4 parameters:

- Industry profiles, constructed of loads for other similar commercial and industrial customers[2]
- Local solar irradiance data from nearest weather station
- Number of control sites (up to five matched controls from the matching process above)
- Lags of load data[3]

The industry profiles (based on NAICS codes) and control sites (up to five matches, from the matching process described above) are included as explanatory variables to include the event-day usage patterns of similar sites. A variety of within-subjects lagged loads (1 day, 1 week, 2 weeks) were also included in the model testing.

To implement out of sample testing, the top 50 system load days, excluding event days, were randomly divided into testing and training datasets. Bias and fit metrics were calculated using the testing dataset and the model with the best fit (lowest Root Mean Squared Error) was selected among models with the least bias (Mean Absolute Error[4]). Site-specific load impacts were estimated with using the winning model for each site.

The figures below show the explanatory variables included in the site-specific model tournament and the number of sites for which each parameter was included in the winning model. The wide spread across parameters indicates that it was important to allow for individually-tailored models to be selected for each participating site.

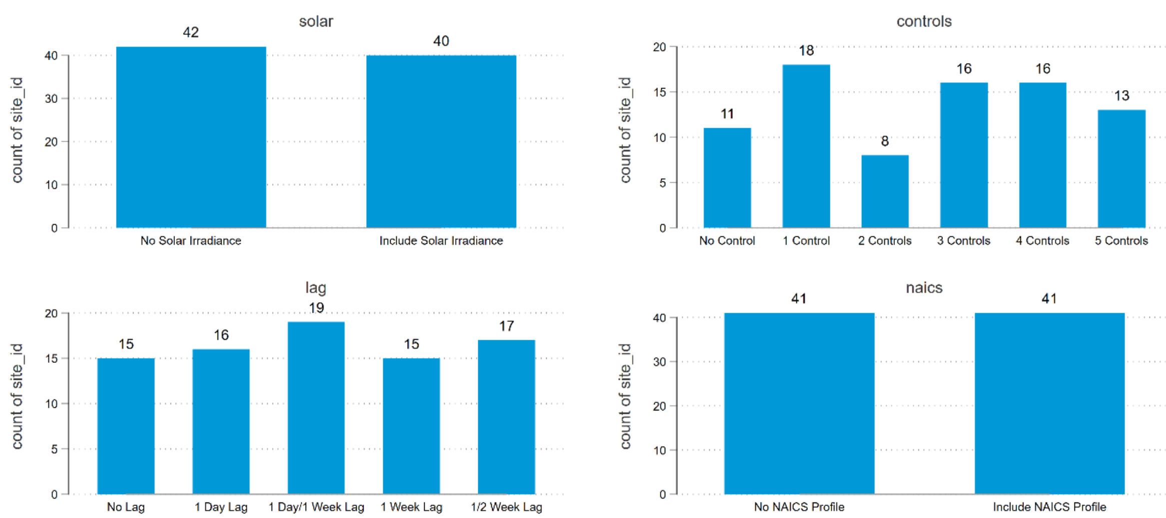
---

[2] Selected from granular load profiles within climate zone and industry segment constructed and maintained by Demand Side Analytics for SDG&E population NMEC settlement validation.
[3] Lags were designed to capture the tendency of large commercial and industrial customers to operate on daily, weekly, or bi-weekly schedules irrespective of weather or time of year.
[4] MAE was used rather that Mean Average Percent Error (MAPE) to ensure robustness for sites with loads very close to zero, common for sites with solar or other generation.

Figure 3-3: Variables Included in Best-Performing Site-Specific Models – Small Agricultural

[redacted]

Figure 3-4: Variables Included in Best-Performing Site-Specific Models – Small Commercial



Further detail on the exact regression specification can be found in Appendix A. Only a small percentage of this evaluation's estimates were generated by the individual customer regressions, however.

3.2 EX ANTE METHODOLOGY

A key objective of DR evaluations is to quantify the relationship between demand reductions, temperature, and hour-of-day. The purpose of doing so is to establish the demand reduction capability under 1-in-2 weather conditions for planning purposes and, increasingly, for operations. When possible, we rely on the historical event performance to forecast ex-ante impacts for future years for different operating conditions.

3.2.1 Ex Ante Model Inputs

For ex ante projections, we use a top-down enrollment model that includes PY2023 – PY2024 ex post percent impact estimates, system loads, and the CPP enrollment forecast from SDG&E. Weather and event-hour impacts were also tested for both CPP groups, but there were no significant trends in either of these measures on the PY2024 impact estimates, so they were not included. More detail on weather and event hour impacts can be found in the ex ante section of this report.

Table 3-2 provides an overview the ex ante methods:

Table 3-2: Ex Ante Analysis Details

Data/Parameter	Detail
Reference loads	SDG&E, CAISO 1-in-2 weather year loads
PY2024 Ex Post impacts included?	Yes, by event/hour/group if statistically significant (otherwise set to 0)
Historical impact estimates included?	Yes, PY2023
Weather impacts?	No, based on testing
Different percent impacts by event hour?	No, based on testing
Enrollment forecast	10 years (2025-2034), supplied by SDG&E

3.2.2 Portfolio-Adjusted Impacts

For ex ante estimates, program-specific and portfolio-adjusted impacts are developed for each subgroup. Since customers may be able to participate in more than one energy-saving program, an attribution of savings estimates to separate DR programs is essential. This prevents double-counting savings for planning purposes. Ex post results are properly attributed by calculating the incremental impacts, or the load reduction beyond what was predicted or committed on dually called event hours. Modelling for ex ante is based solely on these incremental impacts.

For PY 2024, however, there was little dual-program participation with CPP. The only exception was ELRP. Because SDG&E counts CPP impacts before ELRP impacts in their portfolio aggregation, incremental impacts accounting for dual CPP-ELRP participation are handled in that evaluation. Any impacts for dual CPP-ELRP participants are therefore wholly attributed to CPP in this evaluation.

As such, in all cases the portfolio-adjusted impacts reported in this evaluation are equal to the program-specific impacts. Ex ante results will generally be presented as "portfolio-adjusted", since these are the impacts used for planning, but they are equivalent to the program-specific values.

For clarity, Table 3-3 lists each program reviewed for dual-participation:

Table 3-3: Eligible Dually Enrolled Programs for Ex Ante Considerations

BIP	CBP	Thermostat Programs	ELRP
N/A	No dual participants	N/A	Adjustments made in ELRP evaluation

4 EX POST IMPACTS

4.1 CUSTOMERS AND EVENT CHARACTERISTICS

SDG&E defaulted over 120,000 small customer sites onto CPP-TOU rates between November 2015 and April 2016. In 2021, many Small CPP customers switched to receiving their energy from a Community Choice Aggregator, which removed them from CPP rates. Since the large wave of unenrollment in 2021, customer counts have fallen further, from around 44,000 customers in 2022 to around 16,000 customers in 2024.

SDG&E CPP event days are generally called under extreme weather conditions by design. In PY2024, three events were called during a September heat wave, listed in Table 4-1 below. These were called on consecutive weekdays surrounding the SDG&E system peak, which occurred Sunday September 8th at 6:45 p.m. Demand conditions were similarly high for each event day. In PY2023, there was only one CPP event called in August. In PY2022, there were five CPP events all called within one week in September.

Table 4-1: SDG&E CPP Events in 2024

Event date	Day of week	Max SDG&E system load (MW)	Event window	All groups
9/5/2024	Thursday	4,633	4 to 9 p.m.	✓
9/6/2024	Friday	4,381	4 to 9 p.m.	✓
9/9/2024	Monday	4,698	4 to 9 p.m.	✓

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. Table 4-2, summarizes the total number of sites in each group and the final number of sites used for analysis once data cleaning was completed. Due to the small population of the Small Agricultural group, the group was not further segmented. Aggregate ex post analysis results were scaled up to match the total number of sites

Table 4-2: Small Critical Peak Pricing Population Segments

Group	Rate Class	Total sites	Sites in analysis*
Small Agricultural	Agricultural	[redacted]	
Small Commercial	Commercial	16,059	15,795
Total		**16,121**	**15,857**

4.2 DATA SOURCES AND ANALYSIS METHOD

Table 4-3 summarizes the five data sources used to conduct the Small 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.

Table 4-3: Small Critical Peak Pricing Evaluation Data Sources

Source	Comments
Hourly interval data	▪ Summer 2024 (June 1 through October 31) ▪ All analysis done by site (Premise ID x 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 customers or control sites were excluded from the analysis
Customer characteristics	▪ Treatment: All small non-residential (Commercial and Agricultural) CPP rates (16k sites) ▪ Control: CPP-TOU opt outs ▪ 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 2024 (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 modeling
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 difference-in-differences with matched controls. The distance matching approach used selected one matched control site for each of the roughly 23,000 non-residential Small CPP sites among a matched control candidate pool of roughly 5,000 Small

Commercial CPP opt-outs and 900 Small Agricultural CPP opt-outs. These customers were not enrolled in CPP or other DR programs which might influence energy use and excluded sites that were recently defaulted to a CCA. The difference-in-differences model was then used to assess impacts and standard errors for each event and each study segment.

4.3 EX POST LOAD IMPACTS

Table 4-4 and Table 4-5 summarize the load reductions for all Small Commercial and Small Agricultural CPP customers for the September 5th, September 6th, and September 9th events, all of which occurred from 4 to 9 p.m. For Small Commercial sites, the aggregate hourly load reduction for an average weekday event was 0.4 MW across 16,000 sites. Reductions were statistically significant at the 10% level for the September 6th and September 9th events (90% confidence interval for the estimate does not include zero).

For Small Agricultural sites, the hourly load reduction for an average weekday event was [redacted] In the tables, the orange bars show a visual comparison of the reductions that are numerically labeled on the left of the bars.

Table 4-4: CPP Small Commercial Load Reductions by Event Day

Event Date	Event Window	Avg Event Temp (F)	Sites Enrolled	Reductions (Ex Post)			Significant (90% CI)	Significant (95% CI)
				Aggregate (MW)	% Reduction	Average Site (kW)		
9/5/2024	4 to 9 pm	86.8	16,059	0.2	0.6%	0.0	No	No
9/6/2024	4 to 9 pm	82.1	16,059	0.3	0.9%	0.0	Yes	No
9/9/2024	4 to 9 pm	85.6	16,059	0.7	1.8%	0.0	Yes	Yes
Avg Weekday 4-9 pm	**4 to 9 pm**	**84.8**	**16,059**	**0.4**	**1.1%**	**0.0**	**Yes**	**Yes**

Table 4-5: CPP Small Agricultural Load Reductions by Event Day

Event Date	Event Window	Avg Event Temp (F)	Sites Enrolled	Reductions (Ex Post)			Significant (90% CI)	Significant (95% CI)
				Aggregate (MW)	% Reduction	Average Site (kW)		
9/5/2024	4 to 9 pm	[redacted]						
9/6/2024	4 to 9 pm	[redacted]						
9/9/2024	4 to 9 pm	[redacted]						
Avg Weekday 4-9 pm	**4 to 9 pm**	[redacted]						

Reductions were further segmented by climate zone and for customers who signed up for event notifications[5]. Table 4-6 details the reference loads and load reductions overall and by each of these study segments[6] for the average 4 p.m. to 9 p.m. weekday CPP event.

Segmentation of load impacts shows minor differences in three of the commercial segments. Inland customers produced higher percent and absolute reductions than coastal customers in the Small Commercial group. [redacted] Since most customers were enrolled to received notifications, notified customers delivered greater aggregate impacts, though not in percentage terms.

Table 4-6: Small CPP Average Event Reductions by Subgroup

Subcategory	Temp	Sites	Aggregate (MW)				Average Site (kW)			t-stat
			Ref Load	Reduction	% Reduction	Std Error	Ref Load	Reduction	Std Error	
Ag Coastal	83.0	[redacted]								
Ag Inland	86.0									
Ag Received notification	85.2									
Ag All	85.2									
Comm Coastal	82.7	8,189	19.05	0.12	1%	0.11	2.27	0.01	0.01	1.15
Comm Inland	87.2	7,524	19.10	0.29	2%	0.12	2.49	0.04	0.02	2.54
Comm No notification	84.8	1,142	2.63	0.05	2%	0.03	1.97	0.04	0.02	1.65
Comm Received notification	84.8	14,571	35.46	0.36	1%	0.15	2.41	0.02	0.01	2.39
Comm All	84.8	15,713	38.16	0.41	1%	0.16	2.38	0.03	0.01	2.65

Hourly load shapes for an average event day for commercial and agricultural customers are shown in Figure 4-1 and Figure 4-2, respectively. The figures show the aggregate hourly loads (actual and counterfactual) for these sites. As shown above, both groups saw significant reductions during the event hours (4 to 9 p.m.). For Small Commercial customers, impacts begin ahead of the 4 to 9 p.m. window, possibly a holdover from previous years when the previous event window was from 2 p.m. to 6 p.m.

[5] 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.

[6] Results for more granular segments including NEM status and industry are included in the ex post table generators.

Figure 4-1: Small CPP Commercial Program Specific Impacts

Table 1a: Menu options

Type of results	Aggregate
CPP Group	Below 20 kW
Category	Rate Class
Subcategory	Commercial/Industrial
Event date	Avg Weekday 4-9 pm
Type of impact	Total
Hour Ending View	HE (Prevailing Time)

Table 1: Event day information

CPP Event start, HE (Prevailing Time)	4:00 PM
CPP Event end, HE (Prevailing Time)	9:00 PM
Total enrolled accounts	16,059
Load reduction (Event Window, MWh/h)	0.41
% load reduction (Event Window)	1.1%
Reduction significant (95% confidence level)	Yes

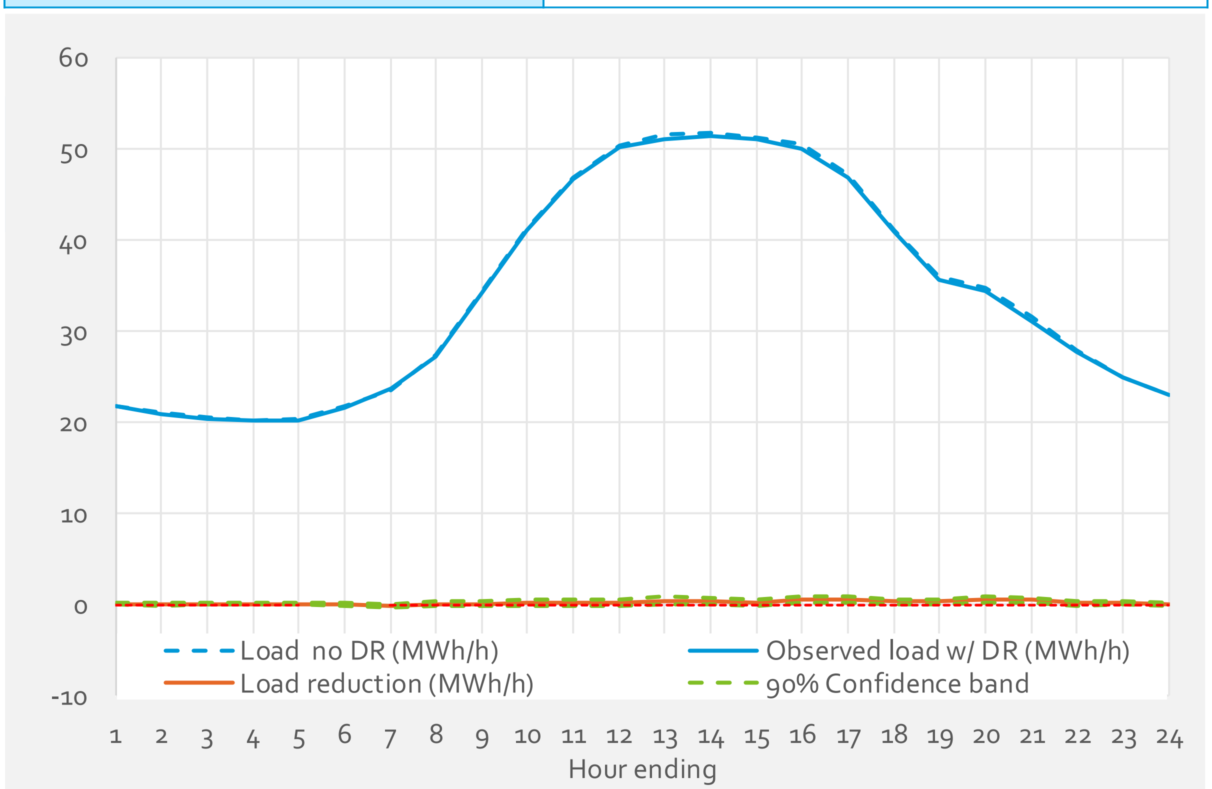


Figure 4-2: Small CPP Agricultural Program Specific Impacts

[redacted]

4.4 EX ANTE LOAD IMPACTS

A key objective of the evaluation is to project, *ex ante*, the load reductions that CPP customers can deliver on future event days. These are intended to reflect performance under normal (1-in-2) worst day demand weather conditions for both CAISO and the SDG&E system.

In general, ex ante forecasts rely on the estimated ex post impacts for current or recent program years, as well as any relationship between weather and event hour to load reductions. For PY2024, ex ante modeling incorporated both PY2023 and PY2024 ex post impact estimates, but it did not include any differential impacts based on weather or the event hour. The included ex post impact estimates for both PY2023 and PY2024 are significant impacts (in percentage terms) by group and event day. Insignificant ex post estimates are also included but set to zero to prevent projecting noise into future years' estimates.

4.4.1 Ex Ante Model Inputs

For PY2024, the key inputs for ex ante impact model are:

- PY2023 ex post impact estimates (percent impacts)
- PY2024 ex post impact estimates (percent impacts)
- 1-in-2 system weather data for both CAISO and SDG&E
- CPP enrollment forecast through 2034

The following factors were also considered, but ultimately were not included in the ex ante model:

- Weather impacts on percent reductions
- Event-hour impacts on percent reductions

Note that while event hour and weather do not impact the percent reductions in the ex ante model, both hotter temperatures and earlier event hours result in larger aggregate impact estimates, since percent reductions are applied to larger reference loads in each case.

PY 2024 Impact Estimates

Statistically significant ex post impact estimates by event, hour, and rate class are the primary input. Any individual estimates on these same margins that are not statistically significant are set to zero in the ex ante analysis to prevent projecting noise forward. Note that even if group-level or program-level ex post estimates are insignificant, there may be underlying events, hours, and rate class combinations where significant impacts were seen, and these are included individually in the model.

Historical Impact Estimates

PY2023 ex post impacts were included in the ex ante model along with the current year ex post estimates. PY2024 impacts differed from those estimated in PY 2023, and the low number of event days (three) likely impacted the variance in the estimates over time. As such, the PY2023 percent impacts were included to add more data to the model.

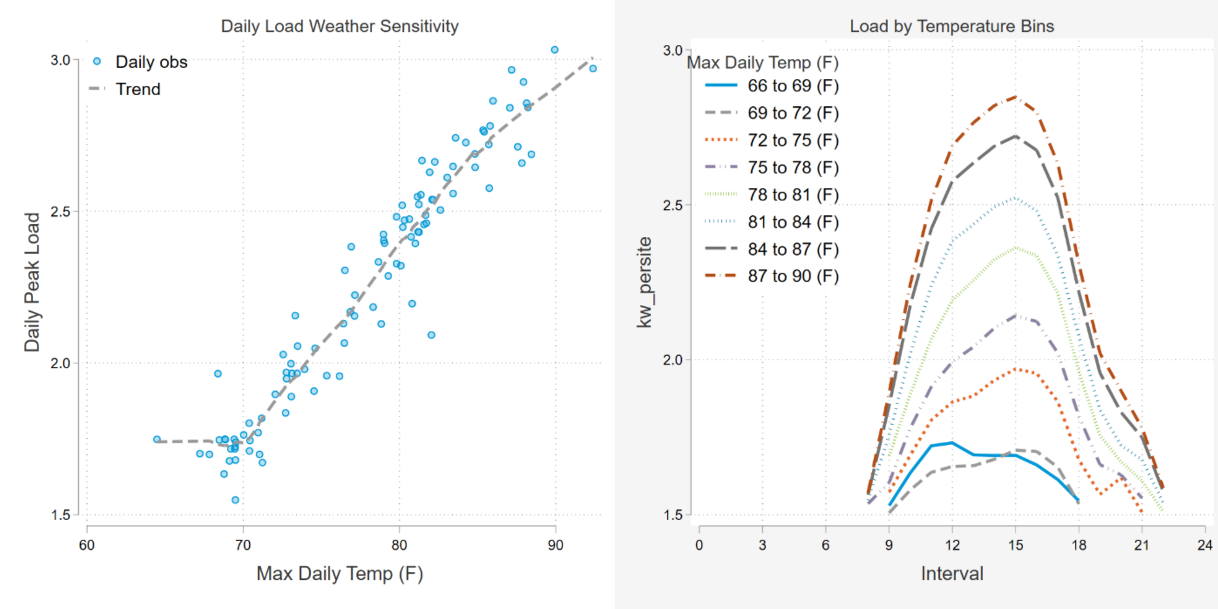
Impact estimates from PY2022 were not included since the number of customers has changed dramatically since that year: current CPP enrollments are less than 50% of what they were in the summer of 2022. These large decreases (due to the CCA expansion) likely affected not only the number of customers but also the composition of the customer pool. As such, the 2022 results would be less applicable to the customer populations that SDG&E can expect going forward.

Weather Impacts

Figure 4-3 summarizes the relationship between weather and Small Commercial customer loads in 2024. Only non-event days are included. The left panel in Figure 4-3 shows average hourly loads for current customers for different temperature bins, defined by the daily maximum temperature. The right panel shows the relationship between daily maximum temperatures and hourly loads. The hottest temperature day in the right panel is the highest load curve. In 2024 we see the expected pattern that energy demand and discretionary load increases with hotter weather.

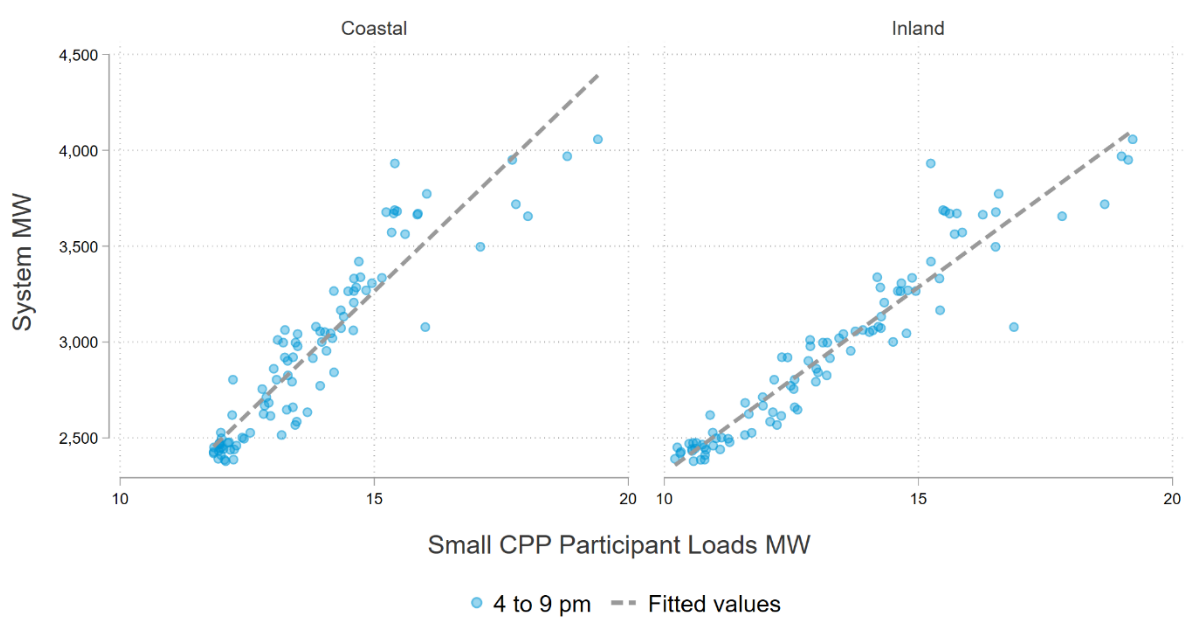
Figure 4-4 shows the relationship between aggregate Small Commercial CPP loads and SDG&E daily peak loads. Small Commercial CPP loads are highly correlated with system load daily peaks during the 4 to 9 p.m. window. However, Small Commercial loads peak around 3 p.m. (HE 15) (Figure 4-3) and drop sharply thereafter, leaving relatively little discretionary load to curtail after about 6 p.m. (HE 18). This remains a challenge since the shift of the CPP window from 2 to 6 p.m. to 4 to 9 p.m. Essentially, about half of Small Commercial load has dissipated by the time system peaks typically occur. Small CPP customers are therefore not in a strong position to provide reductions when resources are needed most.

Figure 4-3: Weather Sensitivity of Small Commercial CPP Loads



2024 May to mid-Oct loads, excluding weekends/holidays and events

Figure 4-4: Small Commercial CPP Load versus System Daily Peaks

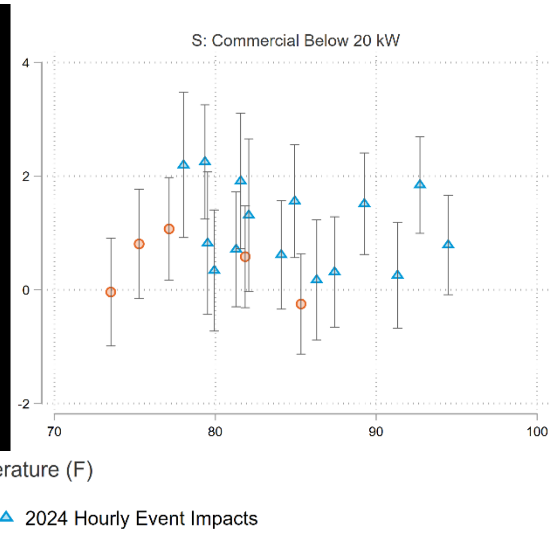


Both PY 2023 and PY 2024 impacts were used to model ex ante impacts for PY 2024. Figure 4-5 shows hourly event percent reductions for these events as a function of hourly temperatures, separately for

Agricultural and Commercial customers. The symbols indicate 2023 and 2024 impact estimates, with bars showing a 95% confidence interval around each (where confidence intervals that include zero being statistically insignificant). Overall there is no clear trend in the impacts as temperatures rise.

Figure 4-5: Small Commercial CPP Hourly Reductions and Temperatures with Uncertainty

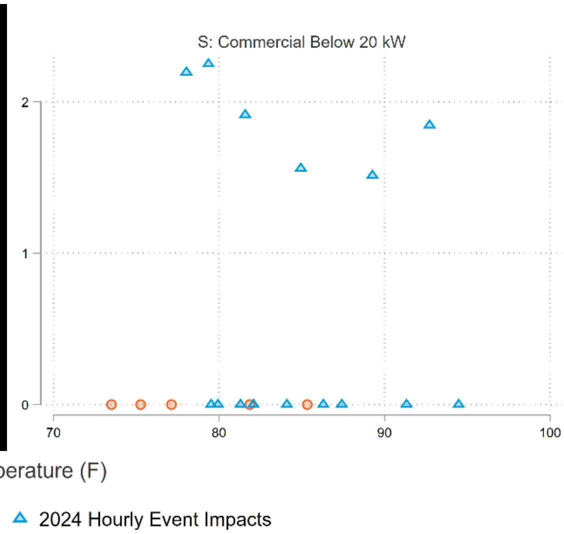
[redacted]



In practice, PY 2024 and PY 2023 ex post impacts which were not statistically significant were assumed to be zero in the ex ante modeling. Figure 4-6 shows the resulting impacts and trends.

Figure 4-6: Small Commercial CPP Hourly Reductions and Temperatures Used for Ex Ante

[redacted]



4.4.2 Ex Ante Load Impacts

Table 4-7 and Table 4-8 summarize the ex ante demand reduction capability by forecast year and planning condition for the Small Commercial and Small Agricultural groups. The tables reflect hourly demand reductions available from 4 p.m. to 9 p.m. on an August Worst Day under 1-in-2 weather conditions. Since no dual-participant groups were estimated separately for this evaluation, the values in the table reflect both the program-specific and portfolio-adjusted ex ante reductions.

Table 4-7: Small Commercial Ex Ante Impacts for August Worst Day (MW)

Weather Type	Year	Sites	CAISO		SDG&E	
			Program	Portfolio Adj	Program	Portfolio Adj
1-in-2	2024	16,046	0.40	0.40	0.41	0.41
1-in-2	2025	15,709	0.39	0.39	0.40	0.40
1-in-2	2026	16,007	0.40	0.40	0.41	0.41
1-in-2	2027	16,372	0.41	0.41	0.42	0.42
1-in-2	2028	16,781	0.42	0.42	0.43	0.43
1-in-2	2029	17,243	0.43	0.43	0.44	0.44
1-in-2	2030	17,758	0.44	0.44	0.45	0.45
1-in-2	2031	18,340	0.46	0.46	0.47	0.47
1-in-2	2032	19,001	0.47	0.47	0.48	0.48
1-in-2	2033	19,745	0.49	0.49	0.50	0.50
1-in-2	2034	20,597	0.51	0.51	0.52	0.52

Table 4-8: Small Agricultural Ex Ante Impacts for August Worst Day (MW)

Weather Type	Year	Sites	CAISO		SDG&E	
			Program	Portfolio Adj	Program	Portfolio Adj
1-in-2	2024	59	0.46	0.46	0.45	0.45
1-in-2	2025	62	0.49	0.49	0.48	0.48
1-in-2	2026	62	0.49	0.49	0.48	0.48
1-in-2	2027	62	0.49	0.49	0.48	0.48
1-in-2	2028	64	0.51	0.51	0.50	0.50
1-in-2	2029	66	0.52	0.52	0.51	0.51
1-in-2	2030	67	0.52	0.52	0.51	0.51
1-in-2	2031	72	0.56	0.56	0.55	0.55
1-in-2	2032	72	0.56	0.56	0.55	0.55

Weather Type	Year	Sites	CAISO		SDG&E	
			Program	Portfolio Adj	Program	Portfolio Adj
1-in-2	**2033**	76	0.59	0.59	0.58	0.58
1-in-2	**2034**	79	0.63	0.63	0.62	0.62

The enrollment forecast was developed by SDG&E and shows an increasing number of customers enrolled in the Small CPP groups. The slight drop in Small Commercial sites in 2025 is due to de-enrollments since PY 2024 ended. For 2025 – 2034, there is no modelling for de-enrollments from CCA expansion.

4.4.3 Comparison of Ex Post And Ex Ante Load Impacts

Table 4-9 and Table 4-10 compare the average site's ex post demand reductions to their expected, ex ante reductions under 1-in-2 planning conditions. Results are shown for the 4 to 9 p.m. window. The ex post demand reductions in the tables are the values applied in the ex ante modeling – these include PY 2023 ex post estimates along with the PY 2024 estimates, and statistically insignificant estimates by climate zone and event day are reset to zero so that noise is not projected forward in the model.

In PY 2024, the average Small Commercial customer delivered 0.01 MW (0.6%) per hour during the from 4 to 9 p.m. The expected load reduction capability for 2024 under SDG&E and CAISO 1-in-2 weather conditions is similarly 0.01 MW. [redacted]

Table 4-9: Comparison of PY 2024 – Small Commercial

Result Type	Day Type	Period	Load without DR (avg site kWh/h)	Load Reduction (avg site kWh/h)	% Reduction	Event Avg Temp (F)
Ex Post	Avg Weekday Event	4 to 9 p.m.	2.38	0.01	0.6%	83.3
Ex Ante (CAISO)	Aug Worst Day, 1-in-2	4 to 9 p.m.	2.20	0.01	0.6%	82.1

Result Type	Day Type	Period	Load without DR (avg site kWh/h)	Load Reduction (avg site kWh/h)	% Reduction	Event Avg Temp (F)
Ex Ante (SDG&E)	Aug Worst Day, 1-in-2	4 to 9 p.m.	2.25	0.01	0.6%	83.7

*Ex Post impacts reflect significant, incremental impacts, e.g. those used for ex ante impact model. Historical impacts weighted by number of current customers in a given event.
**Ex Ante impacts reflect portfolio impacts.

Note that, in these tables, ex ante impacts are similar across weather conditions because only the reference loads are assumed to vary by weather. Ex post results also reflect the unique hourly temperature profiles of each event, whereas ex ante impacts assume a fixed number of sites and weather for a single peak day.

Table 4-10: Comparison of PY 2024 Ex Post and Ex Ante Load Impacts – Small Agricultural

Result Type	Day Type	Period	Load without DR (avg site kWh/h)	Load Reduction (avg site kWh/h)	% Reduction	Event Avg Temp (F)
Ex Post	Avg Weekday Event	4 to 9 p.m.	[redacted]			
Ex Ante (CAISO)	Aug Worst Day, 1-in-2	4 to 9 p.m.	9.15	3.92	42.6%	82.6
Ex Ante (SDG&E)	Aug Worst Day, 1-in-2	4 to 9 p.m.	8.96	3.84	42.6%	84.9

*Ex Post impacts reflect significant, incremental impacts, e.g. those used for ex ante impact model. Historical impacts weighted by number of current customers in a given event.
**Ex Ante impacts reflect portfolio impacts.

4.4.4 Ex Ante Load Impact Slice-of-Day Tables

Table 4-11 and Table 4-12 show the 2024 ex ante aggregate hourly impacts for each month under CAISO and SDG&E monthly peaking conditions, respectively. The load impacts in the table represent the sum of Small CPP Commercial and Small CPP Agricultural aggregate impacts by hour.

CPP tariffs only allow for dispatch from 4 p.m. to 9 p.m. so the Slice-of-Day table shows impacts aligned with the tariffed event window. The estimated reductions are typically larger in the hotter summer months and smaller in the cooler winter months. While the percent impacts underlying these estimates do not vary by weather or event hour, the aggregate impacts reported in the table vary by month and hour based on the reference loads.

Table 4-11: Slice of Day Table for CAISO 1-in-2 Weather Year Monthly Worst Day (Aggregate Impacts, (MW)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.25	0.25	0.13	0.17	0.16	0.34	0.39	0.42	0.43	0.44	0.40	0.28
18	0.29	0.29	0.29	0.35	0.34	0.35	0.38	0.40	0.41	0.42	0.41	0.34
19	0.33	0.33	0.33	0.38	0.37	0.38	0.42	0.45	0.46	0.47	0.45	0.37
20	0.37	0.37	0.37	0.39	0.39	0.39	0.41	0.43	0.45	0.45	0.44	0.42
21	0.46	0.46	0.46	0.43	0.43	0.43	0.42	0.45	0.46	0.47	0.48	0.52
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Demand reductions are positive (Blue)

Load increases are negative (Orange)

Table 4-12: Slice of Day Table for SDG&E 1-in-2 Weather Year Monthly Worst Day (Aggregate Impacts, MW)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.25	0.25	0.14	0.18	0.17	0.34	0.42	0.43	0.48	0.44	0.40	0.28
18	0.29	0.29	0.31	0.37	0.36	0.35	0.40	0.41	0.44	0.42	0.41	0.34
19	0.33	0.33	0.34	0.40	0.39	0.38	0.44	0.45	0.49	0.47	0.45	0.37
20	0.37	0.37	0.38	0.40	0.39	0.39	0.42	0.43	0.46	0.44	0.44	0.42
21	0.46	0.46	0.45	0.43	0.43	0.43	0.43	0.44	0.45	0.47	0.48	0.52
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Demand reductions are positive (Blue)
Load increases are negative (Orange)

5 CONCLUSIONS AND RECOMMENDATIONS

Since 2021, the Small CPP groups had been delivering fewer demand reductions as the enrolled populations declined due to CCA expansion. Impact estimates for PY 2024, however, were slightly higher than for PY2023, with ex post impacts averaging 1.0% across the two groups. Greater impacts were also found for agricultural customers and the Inland climate zone.

Based on the PY 2024, the following recommendations may aid program operations in future years. The recommendations may not be currently funded, and costs need to be considered alongside other research and program priorities.

- **Assess whether additional communications encouraging response improve reductions using randomized controlled trials.** A post event survey on event awareness and response barriers was conducted of Small Commercial CPP customers (N=163) in September and October 2024. Results clearly showed that respondents (N=136) recalled the events and were familiar with the 4 to 9 p.m. event window, and that most of these respondents (N=116) took some action. The remainder were unable to shift load away from peak hours beyond what they do on a day-to-day basis for their TOU rate or because the loads were for critical equipment.

  Of the respondents that did report shifting, 47% adjusted their thermostat settings. 58% were interested in additional shifting and in receiving information about how to shift. This suggests that offering education on load shifting along with event notifications may improve load impacts for this subset of customers.

  Most sites already receive event notifications, but the impacts of additional communications is unknown. We recommend testing the effectiveness of education on event response using randomized control trials, where certain customers would be randomly selected to either receive additional education with event notifications or not.

- **Study how individual CPP prices impact event impacts**. SDG&E's Small CPP in some cases qualify for different rates with different CPP event-day adders. They can also choose monthly subscriptions per kW for reservation capacities. Since customers in the rates face different CPP pricing, estimating differential responses to events by price could be useful.

APPENDIX

A. INDIVIDUAL SITE REGRESSIONS WITH SYNTHETIC CONTROLS

Individual site regressions with synthetic controls and site-specific specifications were used as a supplementary method for estimating load impacts for PY 2024 impacts for CPP customers. The approach is implemented on hourly customer site loads. It relies on control sites that did not experience the intervention (up to five matched to each customer site), lagged customer site usage, an industry usage profile, solar irradiance, plus weather and time characteristics, to estimate the counterfactual. The model estimates a counterfactual load using weather and these various synthetic controls and predictors. A separate model is estimated for each hour of day and all modeling excludes event days. Reductions are the difference between the observed customer site and predicted counterfactual loads. With a regression model with synthetic controls, one should observe:

- Very similar energy use patterns for CPP sites and counterfactual loads when the intervention is not in place.
- A change in demand patterns for CPP customers on event days, but no similar change for the counterfactual load.
- The timing of the change should coincide with the introduction of intervention.

The use of individually specified site specific regression models allows for incorporation of a subset of possible parameters that best predict out of sample loads for each site and does not rely on finding a single ideal match. The model equation including the full set up possible parameters is presented below in Equation A-1 and Table A-1. In practice the model used for each site and included a varying subset of these parameters. A separate model was estimated for each hour of the day.

Equation A-1: Ex Post Regression Model for Non-Residential ELRP

$$kW_t = \mathrm{a} + \sum_{n=1}^{max} \mathrm{b} \cdot kW\_0_{n,t} + \sum_{n=1}^{max} \mathrm{c}_n \cdot kW\_1_{t-n} + \sum_{n=1}^{max} \mathrm{d}_n \cdot month_n + \sum_{n=1}^{max} \mathrm{e}_n \cdot dow_n + \mathrm{f} \cdot solar_t + \mathrm{g} \cdot industry_t + \sum_{n=1}^{max} \mathrm{h}_{n,t} \cdot spline_{n,t} + \delta_t + \varepsilon_{i,t}$$

Where:

Table A-1: Ex Post Regression Elements for Non-Residential ELRP

$\mathrm{kW_t}$	Is the site usage for each time period.
$\mathrm{kW\_0_t}$	Is the synthetic control usage for up to 5 matched controls for each time period. The specific number of controls used varied by site. These synthetic controls were selected based on Euclidean distance matching (the winning matching method in a tournament of 8 methods). They did not experience the treatment.

kW_1_{t-n}	Is the lagged customer site usage and could by one of: no lags, 1 day, 1 week, 2 weeks, 1 day and 1 week, and 1 and 2 weeks. The specific lags used varied by site.
a	Is the model intercept.
b	Coefficients for the synthetic control loads. The specific number of controls used varied by site and ranged from 0 to 5.
c	Coefficients for the customer site usage lags. The specific lags used varied by site.
d	Coefficients for each month.
e	Coefficients for each day of week.
f	Coefficient for solar irradiance across for each time period. Inclusion of this parameter varied by site.
g	Coefficient for industry load profile: normalized hourly loads (scaled from 0 to 1) for control sites in the same industry as the customer site. Industry grouping developed using NAICS code and customer names indicative of industry activity. Inclusion of this parameter varied by site.
h	Coefficients for weather sensitivity of loads, based on a 2 knot spline of 24 hour moving average of temperature, averaged across customer sites for each time period.
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. PROXY DAY SELECTION

For the differences-in-differences estimates, customers are compared both over time (event days vs. non-event days) and with a pool of similar, non-CPP customers (the matched control group). Proxy days, the non-event days used for comparison, are selected to be as similar as possible to actual event days. In general, these are often the hottest non-holiday weekdays of the summer.

Proxy days are selecting by matching customers pre-event loads on event days (through 2 p.m.) to loads for the same hours on non-event days. Matches are tested and selected as the group that minimizes bias between the event day and non-event day loads.

A t-test can show the likelihood that two data series in fact different from each other. For proxy day selection, better matches should produce results with a higher probability that the two series are not different from each other.

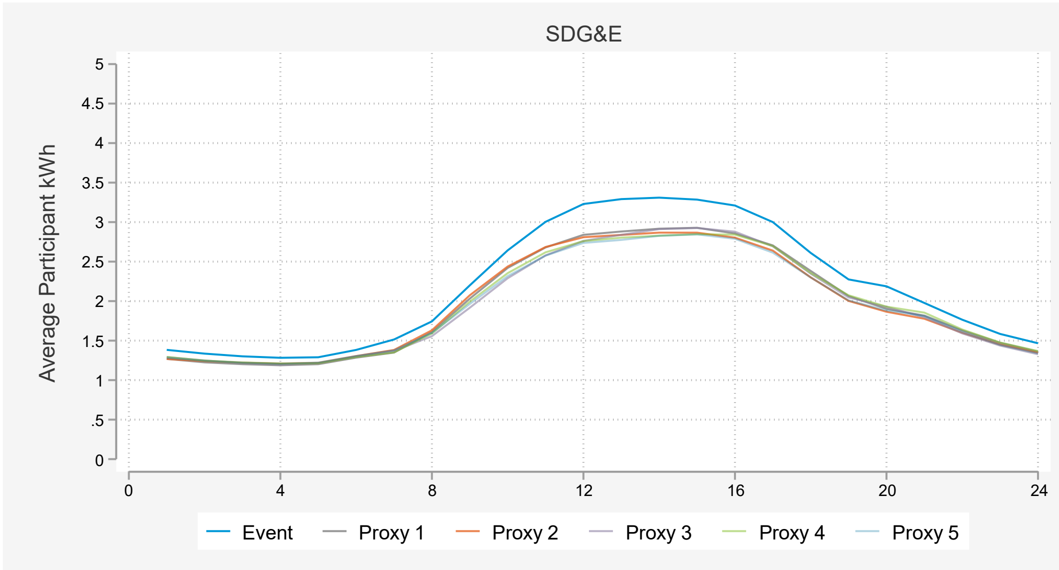
The following tables report the p-values from t-tests of the hypothesis that pre-event hour loads on event days and proxy days are the same. Values are greater than 0.05, corresponding to the 95% confidence level, meaning the hypothesis of similar loads cannot be rejected at the 95% confidence level.

Table A-2: SDG&E Proxy and Event Day Matching: p-Values from t-Tests

Event Date	p-Value
09-05	0.360
09-06	0.303
09-09	0.109

p-values closer to one would give greater confidence in the proxy days' similarity to event days, however. SDG&E's event days were very extreme, so some difference with the best proxy days can be expected. To highlight the potential difference, Figure A-1 shows proxy day and event day loads for Small CPP customers:

Figure A-1: Event Day and Proxy Day Loads for Small Commercial CPP Customers



Even if very closely matching proxy days cannot be found, differences-in-differences can still be the best estimation method for a DR evaluation. In such cases, dissimilarities between event days and proxy days may simply mean that the event days are very different from other summer days. Differences-in-differences then would still allow for comparison to a control group on these very hot days, with the control group serving as a proxy for the types of loads seen on those extreme days.

Regression modeling would instead require a very precise model to extrapolate each site's usage on an extremely hot day, based only on their behavior on other, milder days. The small impacts observed for CPP groups (0-1%) make this type of prediction with regression modeling even more difficult. For this reason, differences-in-differences were still used wherever possible for SDG&E's event day impacts.