

Demand Side Analytics

DATA DRIVEN RESEARCH AND INSIGHTS

FINAL REPORT

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SDG&E Small Commercial Time Varying Pricing and Commercial Thermostat Evaluation for Program Year 2017



Josh Bode & Alana Lemarchand

By Demand Side Analytics, LLC

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Principal Consultants

- Josh Bode
- Alana Lemarchand

SDG&E Team

- Leslie Willoughby
- Lizzette Garcia-Rodriguez
- Sean Weiss

ABSTRACT

This study quantifies the energy and demand impacts of three related interventions – time of use pricing with a critical peak pricing component, time of use pricing alone, and commercial thermostats. The study focuses on three primary research questions: What were the 2017 demand reductions due to dispatch operations? Are customers delivering non-dispatchable energy savings and 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. Time varying rates better reflect energy costs and incentivize customers to reduce electricity use or shift their use away from peak hours that drive the need for infrastructure expansion. As part of the transition, SDG&E offered customers smart thermostats, free of charge, to help them manage their energy bills and automate response to critical peak prices. Dispatchable demand reductions were analyzed separately from non-dispatchable energy savings and demand reductions. Both dispatchable critical peak pricing and commercial thermostats delivered statistically significant reductions totaling 7.6 MW, most of which were delivered by customers who signed up for event notification. The time varying rates and commercial thermostats also led to statistically significant non-dispatchable demand reductions of 8.2 MW (in addition to dispatchable reductions) during summer peak periods and annual energy savings of 22.2 GWh per year. Because the interventions included all small business and agricultural customers, they led to substantive changes in demand and energy use despite small percentage changes in energy use and peak demand.

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1 EXECUTIVE SUMMARY

Between November 2015 and April 2016, SDG&E transitioned over 120,000 small business customers from rates that did not vary by time of day onto time varying pricing. Customers were defaulted onto time of use rates with a critical peak component (CPP-TOU) and had the option to instead 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.

The study analyzes three different interventions – TOU-CPP, TOU only rates, and commercial thermostats – and focuses on three primary research questions:

- What were the 2017 demand reductions due to dispatch operations?
- Are customers delivering non-dispatchable energy savings and 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?

Table 1 summarizes the estimated demand reductions and energy savings for each of the interventions and distinguishes between dispatchable and non-dispatchable resources.

Table 1: Summary of Demand Reductions and Energy Savings

Rate or Technology Intervention	Sites	Dispatchable			Non-dispatchable	
		Load without DR (MW)	Load reduction (MW)	% Reduction	Demand Reduction (MW)	Annual Energy Savings (GWh)
TOU-CPP (11-6 pm events)	112,062	417.1	4.3	1.0%	6.0	7.5
TOU only	4,588	Not applicable			0.8	1.3
Commercial thermostats (2-6 pm events)	3,163	62.0	3.3	5.3%	1.5	13.4

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. The results are shown under both CAISO and SDG&E peaking conditions and reflect the reduction capability from 1-6 pm, which aligns with resource adequacy

requirements. For small CPP, the dispatchable reductions decrease due to projected decreases in enrollment. Over time, customers are expected to sort themselves between TOU-CPP and TOU rates. In contrast, ex ante impacts for commercial thermostats are expected to increase as additional thermostats are installed.

Table 2: Summary of Ex ante Dispatchable Demand Reductions

Year	Small CPP			Commercial Thermostats		
	Accts	MW (CAISO)	MW (SDG&E)	Accts	MW (CAISO)	MW (SDG&E)
2017	112,032	4.83	4.73	3,297	2.87	2.83
2018	111,587	4.81	4.71	3,385	2.97	2.92
2019	110,387	4.75	4.66	3,477	3.07	3.02
2020	108,612	4.68	4.58	3,574	3.18	3.13
2021	106,289	4.58	4.48	3,675	3.29	3.24
2022	103,455	4.46	4.36	3,781	3.41	3.35
2023	100,154	4.31	4.22	3,781	3.41	3.35
2024	96,436	4.15	4.07	3,781	3.41	3.35
2025	92,355	3.98	3.90	3,781	3.41	3.35
2026	87,970	3.79	3.71	3,781	3.41	3.35
2027	83,342	3.59	3.52	3,781	3.41	3.35
2028	78,532	3.38	3.31	3,781	3.41	3.35

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.

2.1 RATE AND TECHNOLOGIES EVALUATED

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

- TOU-CPP – 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.
- TOU rates – TOU rates provide a daily signal to customers regarding when electricity production costs are lower or higher and provide them an incentive to reduce or shift their use.
- Smart thermostats – 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. The program was known as the Small Commercial Technology Deployment (SCTD) and has been in operations since 2014. However, prior to 2017, customers were not required to be



on a CPP rate and, a result, includes participants who are only enrolled in TOU rates. The thermostats can be dispatched at any time between 11 am to 6 pm (on-peak hours) for a maximum of four consecutive hours. Historically, they have been dispatched from 2-6 pm.

Both the TOU-CPP 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 11 am and 6 pm during the summer. Appendix A provides additional details about the CPP-TOU, TOU, and pre-transition rates.

2.2 STUDY RESEARCH QUESTIONS

Table 3 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 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 3: Key Research Questions

	Research Question	TOU	CPP-TOU	Smart T-stats
Primary	1 What were the demand reductions due to dispatch operations in 2017 – for each event day and hour?		✓	✓
	2 Are customers delivering energy savings during non-event days due to the intervention?	✓	✓	✓
	3 What is the ex ante dispatchable 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?		✓	✓
Secondary	4 How do load impacts differ for customers who have enabling technology and/or are dually enrolled in other programs?	✓	✓	✓
	5 How does weather influence the magnitude of demand response?		✓	✓
	6 How do load impacts vary for different customer sizes, locations, and customer segments?	✓	✓	✓
	7 What concrete steps or experimental tests can be undertaken to improve program performance?		✓	✓

2.3 OVERVIEW OF METHODS

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

The change in energy use patterns was estimated using two primary methods:

- **Difference in differences with a matched control group.** This approach was used as the primary method for event impacts for critical peak events delivered by CPP-TOU and thermostat participants. The matched control group was developed using non-participants and relied on out of sample testing. A total of 12 matching models were specified and hot non-event days were split into training and testing days. The matching model used various combinations of hot non-event load data and customer characteristics. The quality of the match was assessed by comparing actual versus estimated aggregate hourly loads in the testing data. The analysis was implemented using a difference in differences panel regression with fixed effects. The technique corrects for remaining differences between the treatment and the matched control group, if any.
- **Synthetic control groups.** This approach was used as the primary method for estimating day to day energy savings (a non-dispatchable resource) for TOU impacts and commercial thermostats. The approach is implemented on a time series of aggregated loads. It relies on multiple non-equivalent control segments, plus weather and day characteristics, to estimate the counterfactual. The model weighs the various control segments based on their predictive power creating a synthetic control group out of multiple external controls. A total of 20 models, 10 without and 10 with synthetic controls were tested side by side using pre-transition data. The data was split in half, with one half used to develop the model, and the other half used to assess the accuracy of the model. Approaches that included synthetic controls outperformed models that relied exclusively on pre and post data on energy use and weather.

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

Figure 1: Out of Sample Process for Matching Model Selection

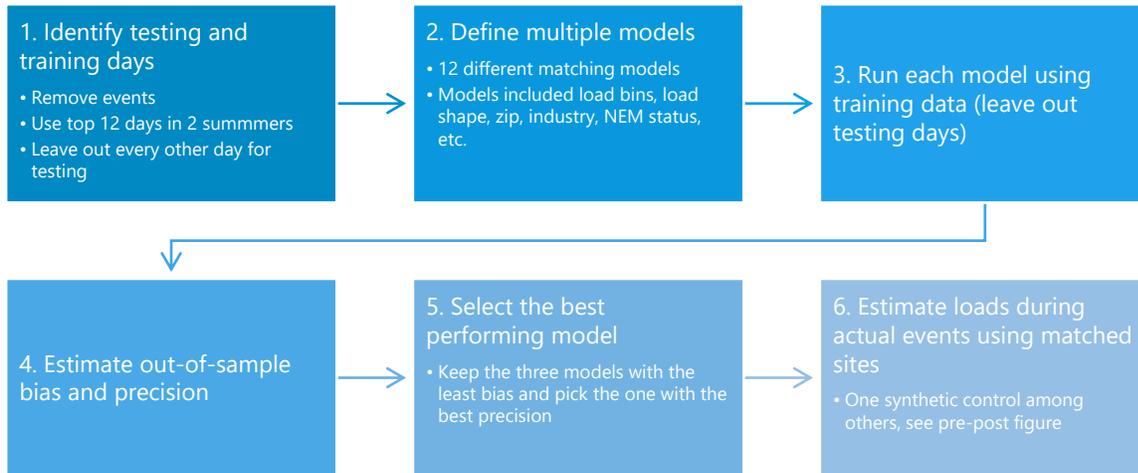


Figure 2: Out of Sample Process for Pre-post Model with Synthetic Controls

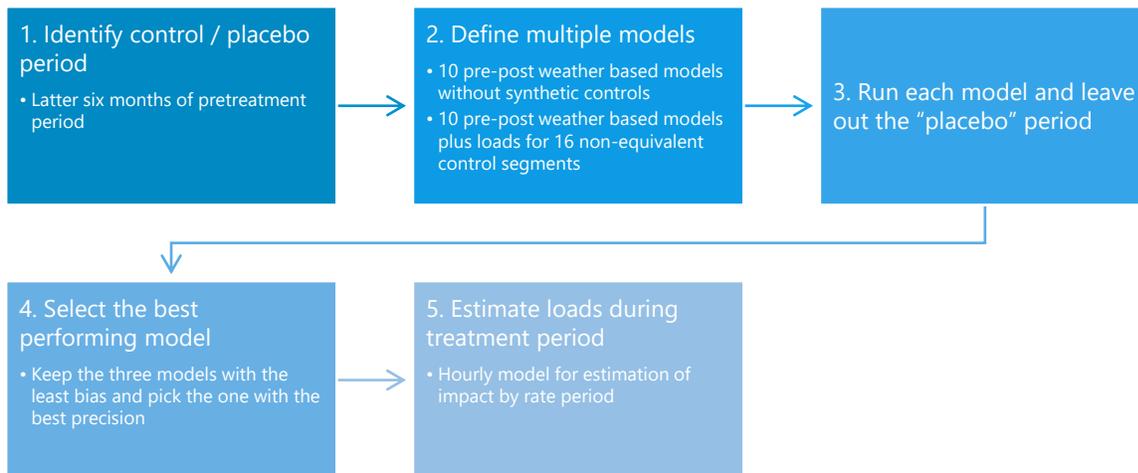


Figure 2 summarizes the multi-step out of sample process used to select pre-post models before finally estimating counterfactual post-treatment loads. For energy savings, the out-of-sample approach uses the first half of the pre-treatment period to predict loads for the second half of the pre-treatment period. This was done with each model tested and then model performance was assessed by comparing model estimates to actual loads. A total of 20 models were tested. The first 10 models did not include external control groups but relied on participant load patterns and weather data before the intervention to model the counterfactual (i.e., within-subjects models). The second 10 models were these same weather-based models with the addition of 16 different non-equivalent comparison groups. The non-equivalent control groups did not experience the same TOU rate transition as the small commercial

group. The model assigns weights to the various non-equivalent comparison groups based on their predictive power, creating a synthetic control group out of multiple external controls.

Table 4 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 deliver demand reductions and energy savings – such as customers who sign up for event notification or technology to automate response – from customers who were expected to deliver little or no demand reductions and energy savings. Additional segments were analyzed, after the fact, as part of exploratory analysis, but the core results presented are based on the segmentation detailed below.

Table 4: Evaluation Methods

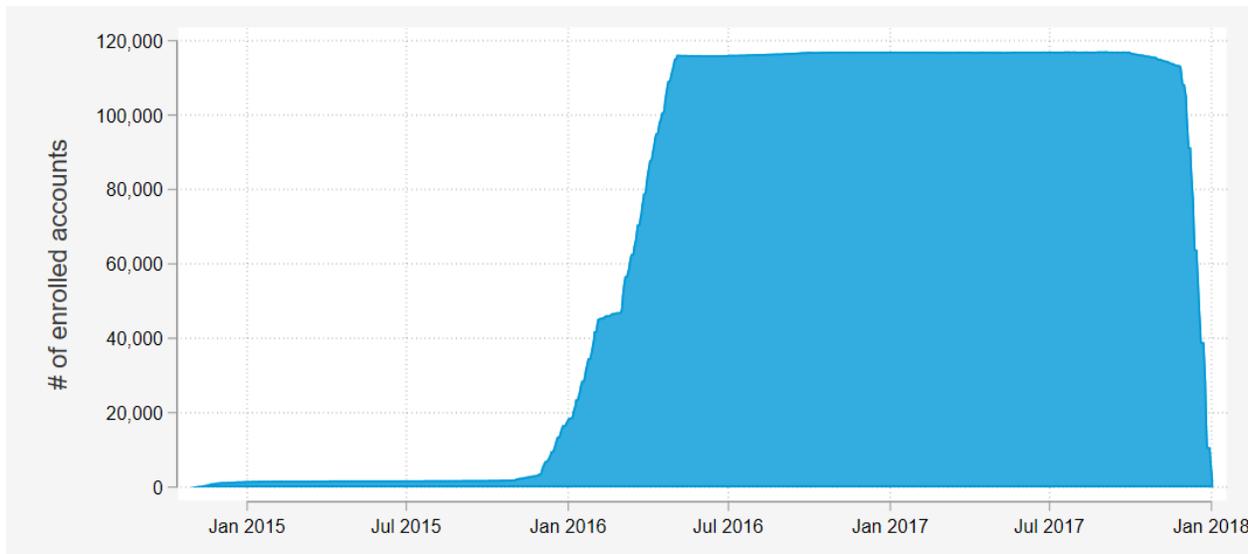
	TOU	CPP	Commercial Thermostats
Data sources / samples	<ul style="list-style-type: none"> ▪ 3 years (2015-2017) of hourly data for: <ul style="list-style-type: none"> ✓ ~6,400 TOU participants ✓ ~117k CPP-TOU participants ✓ ~3,310 Ag TOU participants ✓ 5,000 residential customers ✓ 15,000 large and medium customers that did not experience a change in rates 	<ul style="list-style-type: none"> ▪ Hottest 20 weekdays and weekends over two summers, plus any additional event days for: <ul style="list-style-type: none"> ✓ ~117k Small Comm participants ✓ ~6,400 CPP-TOU opt outs (used for match control group) ✓ 31 Ag participants ✓ 3,310 Ag non-participants 	<ul style="list-style-type: none"> ▪ 3 years of hourly data for participants and control group candidates for energy savings ▪ Hottest 20 weekdays and weekends over two summers, plus any additional event days, for event day impacts
Segmentation	<ul style="list-style-type: none"> ▪ Rate ▪ Enrollment in event notification (Y/N) ▪ Enabling technology (Y/N) ▪ Dual enrollment (by program) ▪ Net metering status (Y/N) 		<ul style="list-style-type: none"> ▪ Size ▪ Rate type

	TOU	CPP	Commercial Thermostats
Estimation method: Ex post	Energy savings – Synthetic control group for each segment using medium business and residential segments to establish counterfactual	Event impacts – Diff-in-diff panel regression using matched control from opt-outs for each segment	Event impacts – Diff-in-diff panel regression using matched control from opt-outs for each segment Control group – Synthetic control group for each segment using medium business and residential segments to establish counterfactual
Estimation method: Ex ante	NA	<ul style="list-style-type: none"> ▪ Weather normalized customer regressions by segment for reference loads ▪ Apply average percent impacts from 2017 to load profiles for various temperature conditions 	<ul style="list-style-type: none"> ▪ Weather normalized customer regressions by segment for reference loads ▪ Apply average percent impacts from 2017 to load profiles for various temperature conditions

3 CRITICAL PEAK PRICING EVENT DAY IMPACTS

SDG&E defaulted over 117,000 small customer sites¹ onto CPP-TOU rates between November 2015 and April 2016. Roughly 5% of these customers opted-out and were placed on TOU rates. Figure 3 shows this cumulative enrollment in CPP, net of the opt-outs.

Figure 3: Small Non-Residential Critical Peak Pricing Enrollment



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

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

3.1 PARTICIPANT AND EVENT CHARACTERISTICS

CPP event impacts were assessed by site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The

¹ Here and through this report a site is defined as a premise and service point combination

segmentation, summarized in Table 5, was developed based on rate class, program, and technology characteristics which may influence impacts. Analysis was performed at the segment level so these granular impacts could therefore be summed, yielding aggregate impacts in addition to the segment specific impacts.

The segmentation criteria were defined as follows:

- **Rate class:** what type of rate was the site on throughout the study period?
- **Notification:** did the customer associated with the site receive any event notifications for any site?
- **Technology:** did the site have smart thermostat enabling technology installed?
- **Dual enrollment:** was the site enrolled in other demand response programs during the study period (Summer Saver, PTR, CBP)?
- **Solar:** was the site on a net metered rate during the study period?

Table 5: Critical Peak Pricing Population Segments

Rate class	Notification	Tech	Dually enrolled	Solar	Total Sites	Sites in analysis
Small Commercial	No	No	No	No	40,397	40,348
			Yes	Yes	499	495
			No	No	1,393	1,392
		Yes	No	No	268	268
			Yes	Yes	11	10
			Yes	No	29	29
	Yes	No	No	No	70,248	70,147
			Yes	Yes	878	865
			No	No	2,424	2,423
			Yes	Yes	40	40
		Yes	No	No	797	797
			Yes	Yes	37	36
			No	No	74	74
			Yes	Yes	4	4
TOTAL SMALL COMMERCIAL					117,118	116,945
Small Agricultural	No	No	No	No	16	11
			Yes	Yes	1	1
	Yes	No	No	No	22	17
			Yes	Yes	1	1
			Yes	No	2	1
TOTAL SMALL AGRICULTURAL					42	31

Sites are premise and service point combinations

Table 5 summarizes the total number of sites in each segment and the final number of sites used for analysis once data cleaning was completed². For most segments, the vast majority of sites were included in the analysis. Aggregate ex post analysis results were scaled up to match the total number of sites before data cleaning.

Because other programs also modify loads, those event days cannot be used for counterfactual estimation for dually enrolled CPP participants. Days which were not CPP events but which were events for other DR programs were excluded for dual participants, leaving fewer days for counterfactual estimation. High load days from both 2016 and 2017 were used to develop the CPP counterfactual.

Table 6 shows the three PY 2017 CPP event days, including the maximum daily temperature weighted by participating sites. These consecutive events occurred during a statewide heat wave on the Thursday, Friday, and Saturday before Labor Day. Though the SDG&E peak often differs from the rest of the state, Friday September 1 was the system peak for both SDG&E and CAISO. The second highest load day for both systems was Saturday September 2, which was hotter than the previous day and also a weekend day.

Table 6: Critical Peak Pricing Events in 2017

Event day	Day of week	Event start	Event end	Max daily temp (F)	SDG&E system load (MW)
8/31/2017	Thursday	11:00 AM	6:00 PM	89.4	4,190
9/1/2017	Friday	11:00 AM	6:00 PM	94.1	4,481
9/2/2017	Saturday	11:00 AM	6:00 PM	94.6	4,353

3.2 DATA SOURCES AND ANALYSIS METHOD

Table 7 summarizes the five data sources used to conduct the CPP analysis. The analysis was done by site on hourly load data. Various data sources were used to classify sites into the study segments. While different segments were developed for the various analyses in this report (rate versus technology based, event and non-event), the characteristic definitions used to build segments were consistent across analyses.

² The cleaning algorithm ensured that complete data was available for the study period. Sites for which high quality matches could not be found were also excluded.

Table 7: Critical Peak Pricing Evaluation Data Sources

Source	Comments
Hourly interval data	<ul style="list-style-type: none"> Summer 2017 (June 1 through October 31) All analysis done by site (premise id-service point id pair)
Customer characteristics	<ul style="list-style-type: none"> Treatment: All small non-residential (Commercial and Agricultural) CPP rates (117,160 sites) Control: TOU only rates (13,381 sites) Industry, zip codes, NEM status used in matching model selection NEM status and SCTD and DR program enrollment used for segmentation
SDG&E hourly system loads	<ul style="list-style-type: none"> Summer 2017 (June 1 through October 31) Used to identify non-event high system load days
Ex post weather data by weather station	<ul style="list-style-type: none"> Used to derive cooling degree days for impact evaluation panel model
Event notification	<ul style="list-style-type: none"> List of notifications sent to each account for each event day Rolled up by customer to identify customers who had received notifications at any site (used for segmentation)

Propensity score matching was used to select a matched control for the roughly 117,000 TOU-CPP sites among a control candidate pool of roughly 13,000 TOU sites (e.g., those that opted out of TOU-CPP). A difference-in-difference panel regression model with fixed effects was then used to assess impacts and standard errors for each event and each study segment. The matches selected were highly accurate and unbiased, as detailed in the Appendix. Details about the regression used for assessing impacts are also in the Appendix.

3.3 EX POST LOAD IMPACTS

Weekend loads are typically different than weekday patterns, reflecting different activities and usage patterns for these different types of day. Because of this, the weekday events have been summarized separately from the weekend event which may not be comparable.

Table 8 summarizes the load impacts by segment for the two weekday events (August 31 and September 1) for the 11 am to 6 pm event window. In aggregate, these events delivered 4.57 MW of load reduction across the small commercial and small agricultural rate classes. The small CPP portfolio total, excluding impacts for commercial thermostats and customer dually enrolled in other DR programs, was 4.31 MW. While aggregate impacts were significant, segmentation of load impacts

actually shows that impacts were concentrated in key segments. Customers who signed up for event notification delivered the vast share of demand reductions. Percentage impacts for weekday events were about 50% higher for the groups that received some form of event notification. Customers who did not sign up for notification also delivered reductions, albeit smaller ones. 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. Though very small in absolute, solar segments produced very high percentage impacts, primarily because they have smaller net loads (i.e., a small denominator).

Table 8: CPP Weekday Event Impacts (11 am to 6pm)

Rate class	Notification	Tech	Dually enrolled	Solar	Sites	Load without DR (MW)	Load w DR (MW)	Impact (MW)	% Impact	Std. Error	t	Significant (90% CI)	
Small Commercial	No	No	No	No	40,397	141.39	139.77	-1.63	-1.1%	0.242	-6.70	Yes	
			Yes	499	0.61	0.65	0.04	6.4%	0.035	1.10	No		
			Yes	No	1,393	7.43	7.46	0.02	0.3%	0.052	0.42	No	
		Yes	No	19	0.03	0.03	0.00	3.1%	0.007	0.14	No		
			Yes	No	268	2.00	1.88	-0.11	-5.7%	0.031	-3.73	Yes	
			Yes	Yes	11	0.06	0.05	-0.01	-11.9%	0.005	-1.33	No	
	Yes	No	No	No	70,248	273.10	270.40	-2.71	-1.0%	0.321	-8.42	Yes	
			Yes	878	1.98	1.96	-0.02	-1.0%	0.064	-0.30	No		
			Yes	No	2,424	13.71	13.68	-0.03	-0.2%	0.079	-0.36	No	
		Yes	No	40	0.18	0.18	0.00	0.3%	0.018	0.03	No		
			Yes	No	797	6.70	6.59	-0.11	-1.7%	0.050	-2.21	Yes	
			Yes	Yes	37	0.24	0.22	-0.01	-5.2%	0.011	-1.11	No	
	Yes	Yes	No	No	74	0.52	0.50	-0.03	-5.4%	0.015	-1.89	Yes	
			Yes	Yes	4	0.00	0.01	0.00	45.5%	0.006	0.35	No	
	TOTAL SMALL COMMERCIAL					117,118	448.19	443.61	-4.57	-1.0%	0.423	-10.76	Yes
	TOTAL SMALL COMMERCIAL (portfolio only)					112,062	417.11	412.80	-4.31	-1.0%	0.408	-10.53	Yes
	Small Agricultural	No	No	No	No	16	0.01	0.01	0.01	71.7%	0.004	0.99	No
				Yes	1	0.00	0.00	0.00	2469.0%	0.001	-1.99	Yes	
Yes		No	No	No	22	0.01	0.01	0.00	-31.4%	0.003	-1.17	No	
			Yes	Yes	1	0.00	0.00	0.00	12.7%	0.000	-0.68	No	
TOTAL SMALL AGRICULTURAL					42	0.02	0.02	0.00	-2.3%	0.006	-0.06	No	

Sites are premise and service point combinations

Very high percent impacts for some solar subgroups a function of low net loads.

Table 9 summarizes the load impacts by segment for the single weekend event, Saturday, September 2, for the 11 am to 6 pm event window. In aggregate, this event delivered 2.08 MW of load reduction across the small commercial and small agricultural rate classes.

The impact for this weekend event was substantially lower in overall magnitude than the weekday impacts due to lower weekend loads and small load increases among customers who did not sign up for notification. The call for event reduction made the news on the weekday events but not on the

weekend. This stands in contrast to the impacts produced by those receiving notification – notified participants produced weekend impacts similar in magnitude to their weekday impacts.

Table 9: CPP Weekend Event Impacts

Rate class	Notifi- cation	Tech	Dually enrolled	Solar	Sites	Load without DR (MW)	Load w DR (MW)	Impact (MW)	% Impact	Std. Error	t	Significant (90% CI)	
Small Commercial	No	No	No	No	40,397	105.75	106.19	0.45	0.4%	0.395	1.13	No	
			Yes	499	-0.03	-0.03	0.00	8.1%	0.138	-0.02	No		
		Yes	No	No	1,393	5.90	6.10	0.20	3.4%	0.082	2.44	Yes	
			Yes	Yes	19	-0.01	-0.01	-0.01	100.7%	0.011	-0.45	No	
		Yes	No	No	No	268	1.43	1.42	-0.01	-0.7%	0.042	-0.24	No
				Yes	Yes	11	0.01	0.01	0.00	29.1%	0.010	0.26	No
	Yes		No	No	29	0.21	0.23	0.02	9.1%	0.015	1.33	No	
			Yes	Yes	No	70,248	208.02	205.14	-2.88	-1.4%	0.518	-5.55	Yes
	Yes	No	No	No	878	-0.37	-0.30	0.07	-18.3%	0.075	0.88	No	
			Yes	No	2,424	10.73	10.95	0.22	2.0%	0.129	1.70	Yes	
		Yes	No	Yes	Yes	40	-0.05	-0.03	0.02	-44.1%	0.030	0.77	No
				Yes	No	797	5.33	5.16	-0.17	-3.2%	0.082	-2.06	Yes
			Yes	No	Yes	37	0.02	0.00	-0.02	-88.1%	0.013	-1.49	No
				Yes	No	74	0.42	0.45	0.04	8.5%	0.021	1.66	Yes
	Yes	Yes	Yes	4	0.00	0.00	-0.01	-381.9%	0.006	-1.15	No		
	TOTAL SMALL COMMERCIAL					117,118	337.38	335.30	-2.08	-0.6%	0.695	-2.99	Yes
TOTAL SMALL COMMERCIAL (portfolio only)					112,062	313.39	311.03	-2.36	-0.8%	0.670	-3.52	Yes	
Small Agricultural	No	No	No	No	16	0.01	0.02	0.01	49.5%	0.003	1.38	No	
			Yes	1	0.00	0.00	0.00	62.7%	0.001	-0.70	No		
	Yes	No	No	No	22	0.01	0.01	0.00	-12.3%	0.003	-0.30	No	
			Yes	Yes	1	0.00	0.00	0.00	44.2%	0.000	-2.26	Yes	
Yes	Yes	Yes	No	2	0.00	0.00	0.00	-99.8%	0.000	-6.07	Yes		
TOTAL SMALL AGRICULTURAL					42	0.02	0.02	0.00	0.6%	0.005	0.02	No	

Sites are premise and service point combinations

Very high percent impacts for some solar subgroups a function of low net loads.

The three events are summarized in greater detail in the following three figures (Figure 4, Figure 5, Figure 6). Note that each figure, extracted from the Ex Post Load Impact Tables, are for the CPP portfolio impacts which exclude participants dually enrolled in other DR programs and those with commercial thermostats. Each figure shows the aggregate hourly loads (actual and counterfactual) for CPP sites. The tables accompanying each figure show aggregate impacts for the 11 am to 6 pm event window as well as for the future 2 pm to 6 pm event window. Each event produced distinctly different load impacts:

- The August 31 and September 1 events produced relatively consistent load reductions for the duration of the event, with load reductions of 4.00 MW on August 31 and 4.62 MW (or about 16% higher) on September 1 (which was also the system peak load day).
- The 2.36 MW impacts for the Saturday, September 2 event were statistically significant for the CPP portfolio population, despite a small load increase from participants not receiving notification.

Figure 4: CPP Event Summary for 8/31/2017

Table 1: Menu options

Type of results	Aggregate
Category	CPP portfolio
Subcategory	Yes
Event date	8/31/2017

Table 2: Event day information

Event start	11:00 AM
Event end	6:00 PM
Total enrolled accounts	112,062
Avg load reduction 11AM-6PM (MW)	4.00
% Load reduction 11AM-6PM	1.0%
Avg load reduction 2PM-6PM (MW)	4.38
% Load reduction 2PM-6PM	1.1%

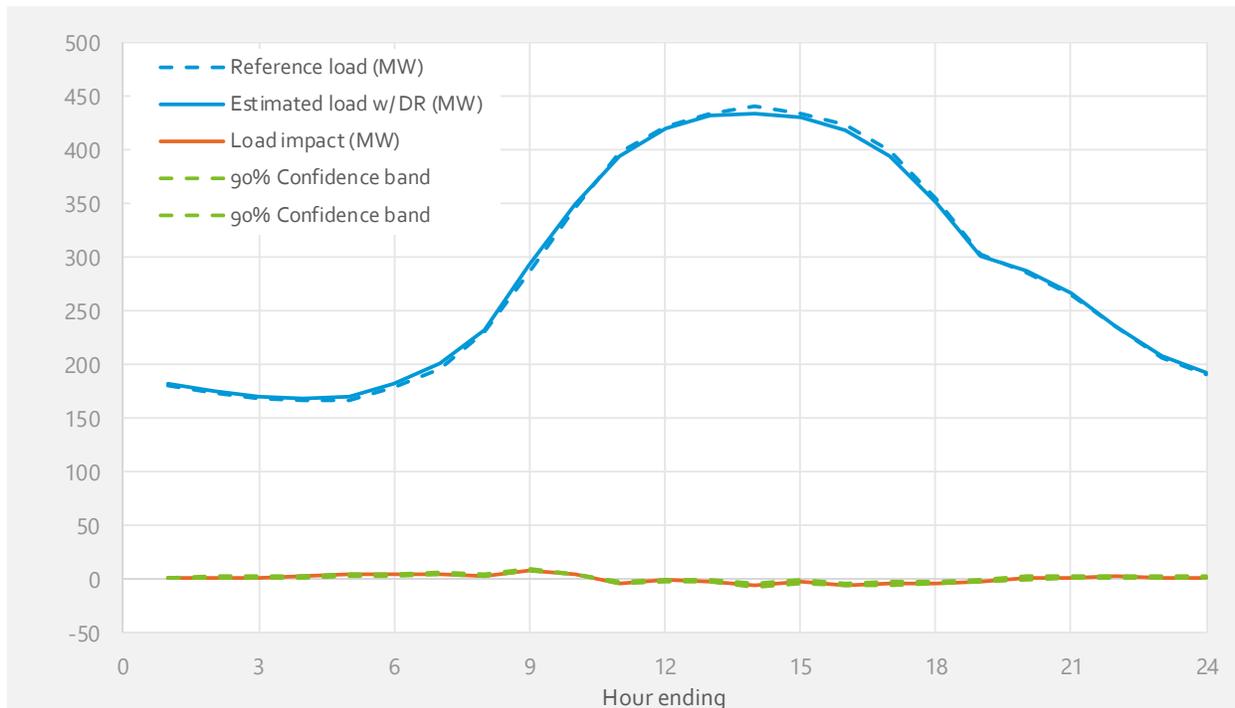


Figure 5: CPP Event Summary for 9/1/2017

Table 1: Menu options

Type of results	Aggregate
Category	CPP portfolio
Subcategory	Yes
Event date	9/1/2017

Table 2: Event day information

Event start	11:00 AM
Event end	6:00 PM
Total enrolled accounts	112,062
Avg load reduction 11AM-6PM (MW)	4.62
% Load reduction 11AM-6PM	1.1%
Avg load reduction 2PM-6PM (MW)	4.66
% Load reduction 2PM-6PM	1.2%

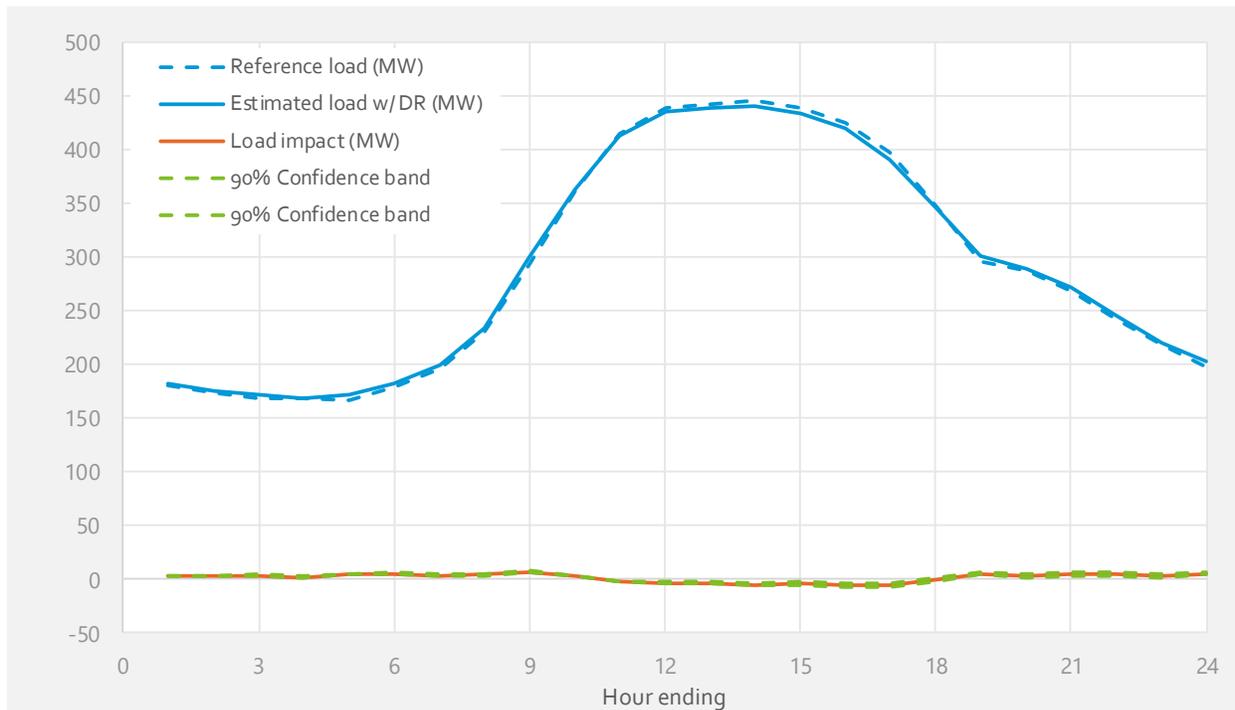


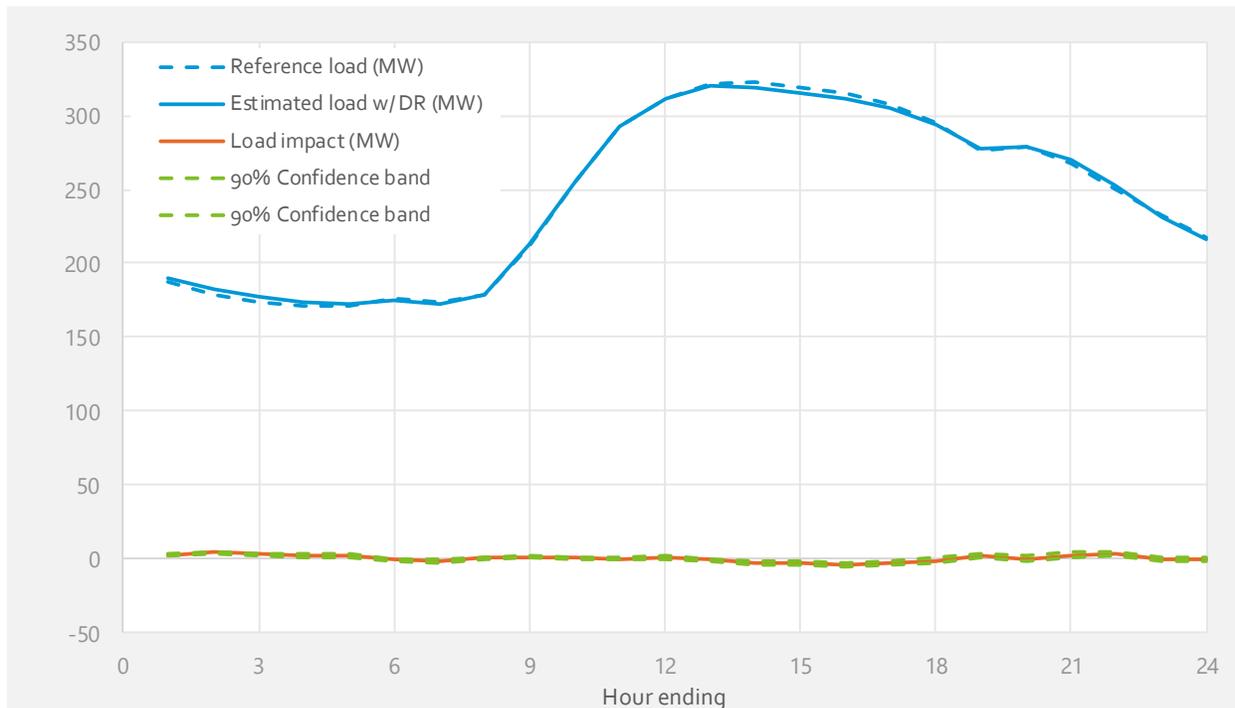
Figure 6: CPP Event Summary for 9/2/2017

Table 1: Menu options

Type of results	Aggregate
Category	CPP portfolio
Subcategory	Yes
Event date	9/2/2017

Table 2: Event day information

Event start	11:00 AM
Event end	6:00 PM
Total enrolled accounts	112,062
Avg load reduction 11AM-6PM (MW)	2.36
% Load reduction 11AM-6PM	0.8%
Avg load reduction 2PM-6PM (MW)	3.19
% Load reduction 2PM-6PM	1.0%



3.4 EX ANTE LOAD IMPACTS

A key objective of the 2017 evaluation is to quantify the relationship between demand reductions, temperature and hour of day. Ex ante impacts are estimated load reductions as a function of weather conditions, time of day, and forecasted changes in enrollment. By design, they reflect planning

conditions defined by normal (1-in-2) and extreme (1-in-10) peak demand weather conditions. The historical load patterns and performance during actual events are used the reductions for a standardized set of weather conditions.

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

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

3.4.1 RELATIONSHIP OF CUSTOMER LOADS AND PERCENT REDUCTIONS TO WEATHER

Figure 7 summarizes the relationship between weather and CPP participant loads in 2016 and 2017. 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 the daily 1 pm to 6 pm average loads. The 1 pm to 6 pm period was selected because it coincides with hours that count towards resource adequacy requirements. Overall, energy demand and discretionary load increases with hotter weather.

Figure 8 shows the relationship between small commercial CPP loads and SDG&E and CAISO daily peaks loads. Not surprisingly, small commercial customers use more power when it is extremely hot and contribute to peak demand, which drives the need for additional generation, transmission, and distribution infrastructure. Based on our analysis, we estimated that loads from small commercial CPP participants account for approximately 10% of SDG&E's peak load absent demand response. Because small commercial loads are a major driver of SDG&E peaks, if managed, they can reduce the need to build additional infrastructure to accommodate additional peak load. Because more discretionary load is in use during peaking conditions, reductions from CPP participants can be larger precisely when resources are needed most.

Figure 7: Weather Sensitivity of Small Commercial CPP Loads

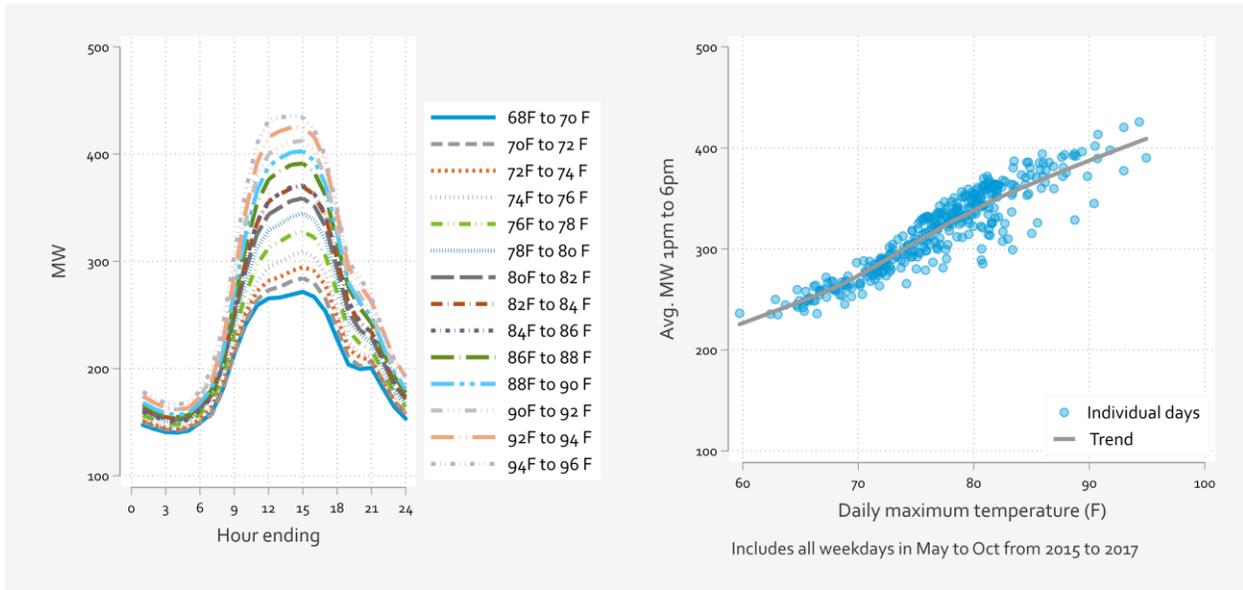
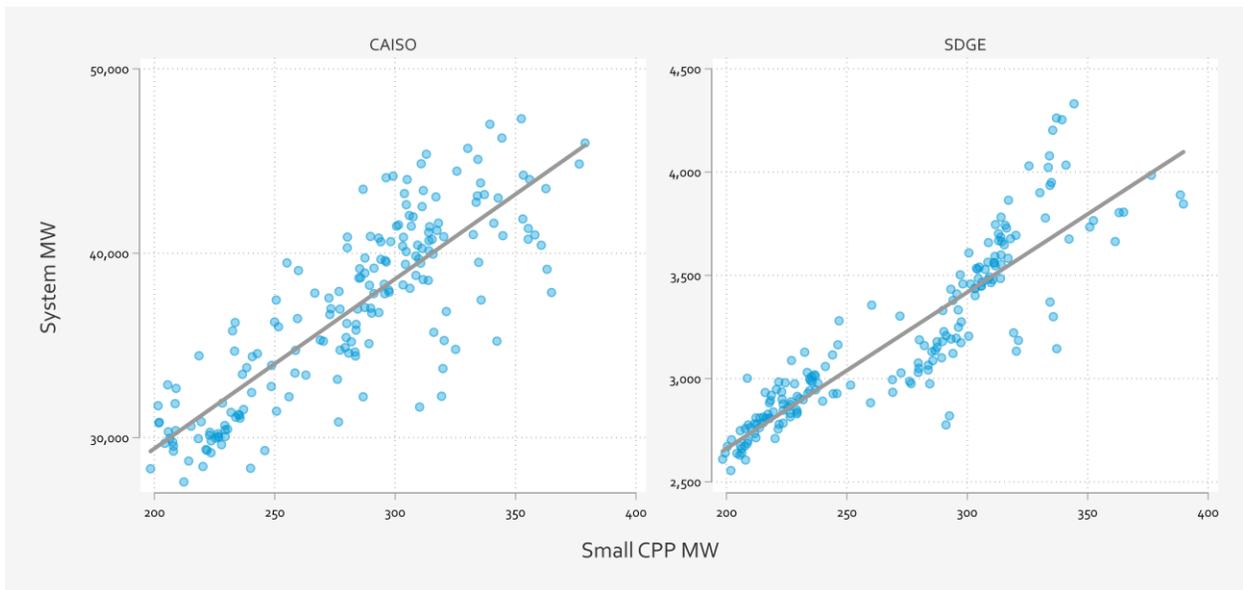


Figure 8: Small CPP Load versus System Daily Peaks



Because of the limited history of default CPP events, the main driver of differences in ex ante impacts are differences in loads. Since the implementation of default CPP, a total of four events have been called. The first, on September 26, 2016 was unusual. The heat wave occurred near the end of summer, on a Monday, when the share of customers signed up for event notification was lower. Of the three 2017 events, one was on the weekend and has limited value in helping estimate weekday peak reduction capability. As a result, the August 31 and September 1, 2017 events were used to estimate the

average hourly percent change in demand. The percent change in energy use was estimate for each of the ex post segments defined in Table 4 and applied to 1-in-2 and 1-in-10 weather year customer loads.

3.4.2 EX ANTE LOAD IMPACTS

Table 10 summarizes the ex ante demand reduction capability by forecast year and planning condition. The tables reflect dispatchable demand reductions available from 1 pm to 6 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 or the technology deployment, known as portfolio impacts.

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

Year	Accts	CAISO		SDG&E	
		1-in-2	1-in-10	1-in-2	1-in-10
2017	112,032	4.83	4.75	4.73	4.96
2018	111,587	4.81	4.73	4.71	4.94
2019	110,387	4.75	4.68	4.66	4.89
2020	108,612	4.68	4.60	4.58	4.81
2021	106,289	4.58	4.50	4.48	4.70
2022	103,455	4.46	4.38	4.36	4.58
2023	100,154	4.31	4.24	4.22	4.43
2024	96,436	4.15	4.09	4.07	4.27
2025	92,355	3.98	3.91	3.90	4.09
2026	87,970	3.79	3.73	3.71	3.89
2027	83,342	3.59	3.53	3.52	3.69
2028	78,532	3.38	3.33	3.31	3.48

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

3.4.3 COMPARISON OF EX POST AND EX ANTE LOAD IMPACTS

Table 11 compares the demand reductions from 2017 events to the reduction expected under the 1-in-2 and 1-in-10 weather conditions used for planning. The small differences between ex post and ex ante values are due to different reporting hours, weather conditions and day of week effects. In 2017, small CPP customers delivered 4.31 MW during the dispatch period of 11 am to 6 pm. However, demand reductions were larger, 4.81 MW, for the 1-6 pm period used for resource adequacy and planning. When similar hours are compared, the ex post impacts align well with the ex ante resource estimates. Because 2017 event day weather conditions were between an SDG&E 1-in-2 and a 1-in-10 weather year, the realized demand reductions fall between the two ex ante values. Some small differences are also due to differences in customer loads by day of week. The two 2017 events included a Friday, when business loads tend to be lower than in other weekdays. In contrast, the ex ante estimates assume an average weekday. Finally, the CAISO ex ante weather conditions are cooler. CAISO peak days are more heavily influenced by larger utilities and do not always coincide with SDG&E peaks.

Table 11: Small CPP Comparison of Ex Post and Ex Ante Load Impacts for 2017

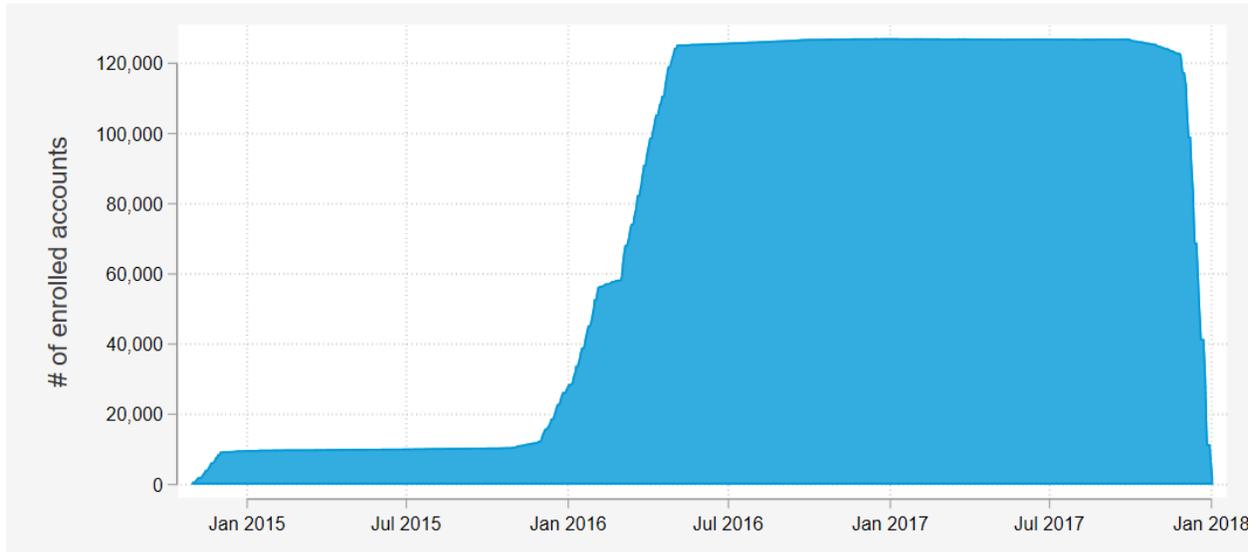
Result Type	Day Type and Period	Accts	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex Post Avg. Weekday	Event Period (11am to 6pm)	111,889	417.1	4.31	1.0%	91.5
	Resource Adequacy Period (1 to 6pm)	111,889	410.4	4.81	1.2%	91.5
Ex ante SDG&E	1-in-2 Weather August Peak (1 to 6pm)	112,032	408.9	4.73	1.2%	88.9
	1-in-10 Weather August Peak (1 to 6pm)	112,032	427.5	4.96	1.2%	92.7
Ex ante CAISO	1-in-2 Weather August Peak (1 to 6pm)	112,032	416.9	4.83	1.2%	88.8
	1-in-10 Weather August Peak (1 to 6pm)	112,032	411.0	4.75	1.2%	88.6

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

4 TIME OF USE PRICING DEMAND AND CONSUMPTION IMPACTS (NON-DISPATCHABLE)

By April 2016, all electric rate options available for small commercial and agricultural customers had a time varying component. Rates that did not differentiate prices by time of day were no longer available. Over 130,000 small customer sites³ were defaulted onto CPP-TOU rates. Though roughly 5% of these customers opted-out, they were placed on TOU rates so the full population is now on rates with a TOU component. Figure 9 shows this cumulative enrollment in TOU, including both CPP-TOU and TOU. This analysis assesses the energy impacts for sites that transitioned between November 2015 and April 2016, but it excludes the handful of customers who were already on TOU rates or who transitioned afterwards.

Figure 9: Small Non-Residential TOU Enrollment⁴



4.1 POPULATION

TOU impacts were assessed by site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in Table 12, was developed based on rate class, rate type (inclusion of CPP), and technology characteristics which may influence impacts. Analysis was performed at the segment

³ Here and through this report a site is defined as a premise and service point combination

⁴ Includes CPP-TOU

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

The segmentation criteria were defined as follows:

- **Rate class:** what type of rate class (agricultural or commercial) was the site on throughout the study period?
- **Rate:** was the site on a rate with a CPP component during the study period?
- **Tech:** did the site have commercial thermostats installed?
- **Solar:** was the site on a net metered rate during the study period?
- **Notification:** did the customer associated with the site receive any event notifications for any site?

Table 12 summarizes the total number of sites in each segment and the final number of sites used for analysis once data cleaning was completed⁵. For most segments, the vast majority of sites were included.

Table 12: Time of Use Population Segments

Rate class	CPP	Tech	Solar	Notify	Total Sites	Sites in analysis
Small Commercial	No	No	No	No	3,243	3,053
			Yes	Yes	1,160	1,050
		Yes	No	No	97	83
			Yes	No	48	44
			No	Yes	80	76
			Yes	Yes	14	14
	Yes	No	No	No	15	14
			Yes	Yes	2	2
		Yes	No	No	45,107	41,674
			Yes	No	74,339	65,987
			No	No	691	537
			Yes	Yes	963	836
			No	No	332	309
			Yes	Yes	880	746
Yes	No	No	17	14		
	Yes	Yes	43	37		

⁵ The cleaning algorithm ensured that complete data was available for the study period. The key reason for excluding a site was lack of pretreatment data: only sites with a full 12 months of data from November 2014 through October 2015 were included.

Rate class	CPP	Tech	Solar	Notify	Total Sites	Sites in analysis
TOTAL					127,031	114,476
Small Agricultural	No	No	No	No	2,461	2,417
			Yes	Yes	795	770
		Yes	No	No	139	134
			Yes	Yes	42	33
	Yes	No	No	No	1	0
			Yes	No	33	29
		Yes	No	Yes	36	27
			Yes	No	2	2
TOTAL					3,510	3,413

Sites are premise and service point combinations

4.2 DATA SOURCES AND ANALYSIS METHOD

Table 13 summarizes the four data sources used to conduct the TOU analysis. The analysis was done by site on hourly load data and various data sources were used to classify sites into the study segments. While different segments were developed for the various analyses (rate versus technology based, event and non-event), the characteristic definitions used to build segments were consistent across analyses.

Table 13: Time of Use Pricing Non-Event Day Evaluation Data Sources

Source	Comments
Hourly interval data	<ul style="list-style-type: none"> ▪ Pretreatment (Oct 2014-Sep 2015) and post-treatment thereafter (on a rolling basis) through Sep 2017 ▪ All analysis done by site (premise id-service point id pair) ▪ Only sites with full pretreatment data were included in the analysis
Customer characteristics	<ul style="list-style-type: none"> ▪ All small non-residential (Commercial and Agricultural) CPP rates and TOU only rates ▪ Medium non-residential TOU⁶ and large residential used for synthetic control (adjacent but non-equivalent groups with some predictive power for treatment loads)

⁶ While medium non-residential sites have been on mandatory TOU for some time, these sites did not experience the rate change experienced by the treatment group. As shown in the appendix, though not equivalent to the analysis population pre-treatment these groups have significant predictive power all the same.

Source	Comments
Ex post weather data by weather station	<ul style="list-style-type: none"> Used for ex post weather model
Event notification	<ul style="list-style-type: none"> 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

A synthetic control group approach was used to assess impacts for the roughly 130,000 TOU-CPP and TOU small non-residential sites. This approach is structured as a pre-post analysis with the inclusion of loads from 16 non-equivalent comparison groups which did not experience a rate transition. For example, if loads from large residential or medium commercial sites are correlated with loads from small commercial sites, they can be used as predictors for counterfactual loads since these comparison groups did not experience the same TOU rate transition as the small commercial group. The model assigns weights to the various non-equivalent comparison groups based on their predictive power, creating a synthetic control group. Model structure and performance are detailed in the Appendix.

4.3 DEMAND AND ENERGY SAVING IMPACTS

The impact estimation model was run at the hourly level, by segment, allowing for time and segment differentiated results. Table 14 summarizes the energy and demand savings by rate period for three key rate groups. Notably, energy consumption increased for the small agricultural customers. However, there is an important caveat. The transition to TOU rates coincided with drought conditions and changes to irrigation restrictions. This exogenous factor may have had an influence on water pumping behaviors and in turn on electricity usage, meaning the increase in electricity usage in the treatment period may be due to factors other than the TOU transition⁷.

For small commercial customers, a 0.6% decrease in energy usage overall was detected. This decrease was significant for all but one segment and equates to an aggregate energy savings of nearly 8.80 GWh and 6.82 MW. Though the energy savings are small in percentage terms, they are applied to a very large pool of customers, resulting in a large volume of energy savings. Percent savings are highest in off-peak

⁷ In addition, while the synthetic control approach worked particularly well for the small commercial segments, model performance was not as strong for the small agricultural segment, suggesting that it may be more difficult to find an appropriate comparison group for this segment.

periods—especially in the summer—but savings were observed in all rate periods. Percent savings are highest for sites on TOU rates without a CPP component.

Table 14: Time of Use Impacts by Rate Period

Rate group	Season	Day type	Rate period	Sites	Aggregate impacts			Average site impacts		
					Percent reduction	Demand reduction (MW)	Energy savings (GWh)	Demand reduction (kW)	95% CI Lower Bound	95% CI Upper Bound
Small Commercial: TOU	Summer	Weekday	Peak	4,588	0.4%	0.03	0.02	0.006	-0.063	0.075
			Off-peak	4,588	3.2%	0.16	0.34	0.034	-0.034	0.102
		Weekends & Holidays	Off-peak	4,588	3.9%	0.18	0.24	0.039	-0.027	0.106
	Winter	Weekday	Peak	4,588	1.8%	0.19	0.17	0.042	-0.042	0.126
			Off-peak	4,588	2.5%	0.18	0.39	0.039	-0.044	0.123
		Weekends & Holidays	Off-peak	4,588	1.7%	0.11	0.14	0.023	-0.060	0.107
Small Commercial: TOU-CPP	Summer	Weekday	Peak	119,078	0.1%	0.19	0.17	0.002	-0.004	0.007
			Off-peak	119,078	-0.1%	-0.15	-0.32	-0.001	-0.007	0.004
		Weekends & Holidays	Off-peak	119,078	1.8%	2.63	3.48	0.022	0.016	0.028
	Winter	Weekday	Peak	119,078	0.4%	0.89	0.78	0.007	0.002	0.013
			Off-peak	119,078	0.1%	0.21	0.44	0.002	-0.004	0.007
		Weekends & Holidays	Off-peak	119,078	1.7%	2.20	2.95	0.018	0.012	0.024
SMALL COMMERCIAL TOTAL				123,666	0.6%	6.82	8.80	0.06	0.04	0.07
Small Agricultural: all	Summer	Weekday	Peak	3,444	-12%	-0.66	-0.59	-0.193	-0.227	-0.158
			Off-peak	3,444	-15%	-0.99	-2.16	-0.288	-0.322	-0.255
		Weekends & Holidays	Off-peak	3,444	-16%	-0.89	-1.17	-0.258	-0.293	-0.223
	Winter	Weekday	Peak	3,444	8%	0.39	0.34	0.114	0.074	0.155
			Off-peak	3,444	1%	0.05	0.12	0.016	-0.023	0.055
		Weekends & Holidays	Off-peak	3,444	0%	0.00	0.00	0.001	-0.040	0.041
SMALL AGRICULTURAL TOTAL				3,444	-6.6%	-2.09	-3.46	-0.61	-0.70	-0.52

Sites are premise and service point combinations
Positive percentages indicate energy savings.

Table 15 and Table 16 summarize percent and aggregate GWh energy savings, respectively, by rate period for each study segment. Grey text indicates impacts that are not significant. Savings vary widely by segment and rate period and some segments increased energy usage overall. Large percent impacts were detected for a few, very small segments with distributed generation due to small net loads (percent impacts are a percent of net load).

The greatest savings, 14.3 GWh, were produced by the TOU-CPP segment with no solar or commercial thermostat technology but which opted to receive event notification⁸. Energy usage for most other groups either increased or did not significantly change, resulting in aggregate savings of 8.8 GWh across all segments.

⁸ Because a single customer can manage multiple sites, the notification classification was applied at the customer level, resulting in a handful of non-CPP sites being classified as receiving notification.

Table 15: Time of Use Impacts by Rate Period and Segment (Percent Savings)

Rate	Tech	Solar	Notify	Sites	Summer			Winter			Overall	
					Weekday		Weekends & Holidays	Weekday		Weekends & Holidays		
					Peak	Off-peak	Off-peak	Peak	Off-peak	Off-peak		
Small Commercial: TOU	No	No	No	3,189	-0.4%	-0.2%	1.9%	1.8%	1.0%	1.0%	0.7%	
			Yes	1,144	-1.0%	4.4%	3.7%	1.5%	5.5%	3.0%	2.7%	
		Yes	No	97	210.0%	34.8%	65.6%	163.8%	16.5%	28.9%	58.6%	
			Yes	47	-58.2%	-34.3%	-52.6%	-65.3%	-44.9%	-76.1%	-51.8%	
	Yes	No	No	80	3.2%	5.0%	7.3%	3.2%	0.2%	-0.2%	3.2%	
			Yes	14	3.2%	12.4%	11.1%	10.3%	16.1%	20.0%	10.6%	
		Yes	No	15	20.1%	22.4%	27.7%	7.3%	4.3%	6.5%	15.2%	
			Yes	2	-77.1%	-46.7%	-469.1%	-134.7%	-43.1%	-78.2%	-75.5%	
			No	No	43,124	-0.2%	-1.4%	0.3%	-0.5%	-1.6%	-0.5%	-0.6%
				Yes	73,198	0.3%	0.5%	2.5%	1.0%	1.2%	2.9%	1.2%
Small Commercial: TOU-CPP	No	Yes	No	569	-88.0%	-18.4%	-45.8%	-133.1%	-37.4%	-86.5%	-45.9%	
			Yes	929	-49.2%	-12.1%	-30.6%	-83.6%	-27.6%	-76.5%	-32.5%	
		Yes	No	No	321	-3.8%	-6.4%	-7.3%	-1.4%	-2.9%	-4.3%	-4.0%
				Yes	878	-1.5%	-2.0%	-0.2%	-0.6%	-1.6%	-0.5%	-1.1%
	Yes		No	17	-20.9%	-9.0%	-26.9%	-142.3%	-24.3%	-420.4%	-32.2%	
			Yes	42	-1.3%	-6.8%	3.2%	-7.7%	-21.8%	-50.0%	-10.0%	
	TOTAL				123,666	0.1%	0.0%	1.9%	0.5%	0.3%	1.7%	0.6%

Sites are premise and service point combinations

Positive percentages indicate energy savings. Estimates not significant at the 90% level have been greyed out.

Table 16: Time of Use Impacts by Rate Period and Segment (GWh Savings)

Rate	Tech	Solar	Notify	Sites	Summer			Winter			Overall	
					Weekday Peak	Weekday Off-peak	Weekends & Holidays Off-peak	Weekday Peak	Weekday Off-peak	Weekends & Holidays Off-peak		
Small Commercial: TOU	No	No	No	3,189	(0.010)	(0.008)	0.040	0.107	0.090	0.047	0.266	
			Yes	1,144	(0.031)	0.258	0.134	0.040	0.313	0.108	0.822	
		Yes	No	97	0.062	0.085	0.057	0.030	0.029	0.019	0.282	
			Yes	47	(0.029)	(0.062)	(0.035)	(0.026)	(0.066)	(0.042)	(0.260)	
	Yes	No	No	80	0.012	0.022	0.018	0.009	0.001	(0.000)	0.062	
			Yes	14	0.003	0.014	0.007	0.007	0.016	0.011	0.058	
		Yes	No	15	0.019	0.032	0.020	0.005	0.005	0.004	0.086	
			Yes	2	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.015)	
			No	No	43,124	(0.076)	(0.625)	0.083	(0.135)	(0.791)	(0.139)	(1.684)
				Yes	73,198	0.628	1.391	3.932	1.409	2.905	4.068	14.333
Small Commercial: TOU-CPP	Yes	No	569	(0.113)	(0.370)	(0.228)	(0.171)	(0.600)	(0.381)	(1.862)		
		Yes	929	(0.139)	(0.480)	(0.230)	(0.273)	(0.892)	(0.512)	(2.527)		
	No	No	No	321	(0.058)	(0.112)	(0.075)	(0.017)	(0.044)	(0.037)	(0.343)	
			Yes	878	(0.066)	(0.105)	(0.006)	(0.019)	(0.077)	(0.014)	(0.288)	
		Yes	No	17	(0.004)	(0.009)	(0.002)	(0.007)	(0.019)	(0.014)	(0.055)	
			Yes	42	(0.001)	(0.010)	0.001	(0.007)	(0.038)	(0.020)	(0.074)	
TOTAL				123,666	0.194	0.019	3.714	0.949	0.829	3.095	8.801	

Sites are premise and service point combinations

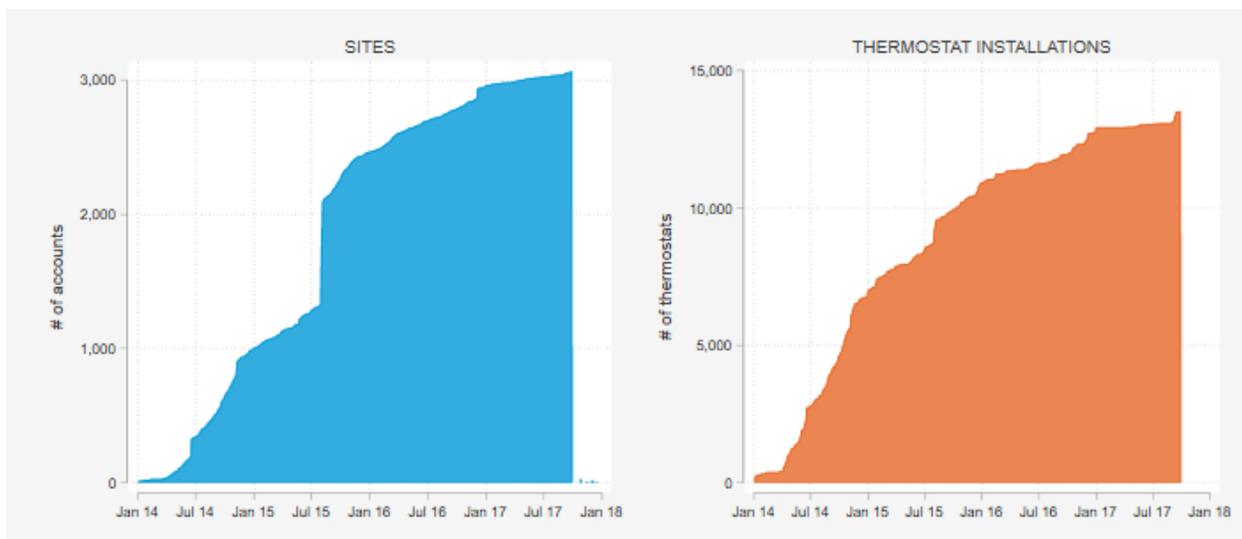
Positive percentages indicate energy savings. Estimates not significant at the 90% level have been greyed out.

5 COMMERCIAL THERMOSTAT EVENT DAY IMPACTS

The commercial thermostat program currently provides Ecobee devices free of charge to commercial customers. The technology deployment program has been in operations since 2014. However, beginning in 2017, customers are required to be on a CPP-TOU rate – either CPP-D (large commercial), TOU-A-P (small commercial), or CPP-D-Ag (agricultural). Because the requirement to be on a CPP-TOU rate was not in place before, a significant number of participants are not enrolled in a CPP-TOU rate. The devices are curtailed on the CPP event days or on Reduce Your Use (RYU) days for customers not enrolled on a CPP-TOU rate. The thermostats can be dispatched at any time between 11 am to 6 pm (on-peak hours) for a maximum of four consecutive hours. Historically, they have been dispatched from 2-6 pm.

Figure 10 shows cumulative program enrollment over time, in terms of sites (left) and in numbers of devices (right). There are over 14,000 devices installed at over 3,000 non-residential sites. This includes nearly 1,100 “quasi-residential” sites, most of which deployed thermostats within a one-week period at the end of July 2015, as indicated by the sharp increase in enrolled sites in that time frame (see large jump in the blue chart). The full program population also includes small, medium, and large non-residential sites. Together, these sites produced significant, consistent impacts during all three RYU days, on the order of 5.4% during the 2 pm to 6 pm window, with larger impacts on weekdays than on weekends. This is in contrast to reductions of 1.0% for small non-residential sites without enabling technology but on a CPP rate (covered in a previous section). Those sites, which experienced events on the same day as the commercial thermostat population, produced impacts which were significant overall but much smaller in magnitude than those produced by sites with enabling technology.

Figure 10: Commercial Thermostat Cumulative Installations



5.1 TECHNOLOGY AND EVENT CHARACTERISTICS

The Ecobee thermostats used as the enabling device receive a signal from SDG&E to curtail usage during events. Across the enrolled devices there was a variety of curtailment strategies, including raising thermostat temperatures by a designated number of degrees and cycling the thermostat on and off at regular intervals. Both of these approaches are 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.

Commercial thermostat event impacts were assessed by site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in Table 17, 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 rate⁹) was the site classified as throughout the study period?

Table 17: Commercial Thermostat Population Segments

Rate	Size	Total sites	Average # of devices per site	Sites in event analysis
TOU	Large	38	39	33
	Medium	87	14	86
	Small	112	5	95
	Quasi residential	1,099	1	1,099
TOU-CPP	Large	68	39	58

⁹ 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.

Rate	Size	Total sites	Average # of devices per site	Sites in event analysis
	Medium	506	11	484
	Small	1,253	3	1,218
TOTAL		3,163	5	3,073

Sites are premise and service point combinations

Table 17 also summarizes the total number of sites in each segment and the final number of sites used for event analysis once data cleaning was completed¹⁰. As one might expect, smaller sites are more numerous but larger sites have more devices per site. Of particular note is the quasi-residential group, which comprises over 1,000 sites with an average of one device per site. Analysis of loads showed that usage across quasi-residential sites was very highly correlated and analysis of participant data showed that over 80% of these devices were installed for the same customer – a commercial short-term housing operator – at the same location, in the same period. Another 17% were installed by two customers in a similar geographically clustered manner. Because of this, the quasi-residential customers were analyzed separately from the other segments using an approach more suited to highly correlated data.

Another attribute of the commercial thermostat sites is the long installation period which spanned over three-year period. This long installation period was an important consideration for the energy savings analysis (which requires pre-installation data, as covered in the next chapter). This is not the case for the event impact analysis which develops a counterfactual load estimate using non-event days from the time frame as event days.

Table 18 shows the three PY 2017 CPP event days, including the maximum daily temperature weighted by participating commercial thermostat sites¹¹. These consecutive events occurred during a statewide heat wave on the Thursday, Friday, and Saturday before Labor Day. Though the SDG&E peak often differs from the rest of the state, Friday September 1 was the system peak for both SDG&E and CAISO. The second highest load day for both systems was Saturday September 2, which was hotter than the previous day.

¹⁰ The cleaning algorithm ensured that complete data was available for the study period. Sites for which high quality matches could not be found were also excluded—about 10% of the sample. Loads and impacts were scaled to address the non-matched sites.

¹¹ The participant-weighted temperatures are lower than for the Small commercial CPP sites on the same days due to much higher representation in the cooler coastal climate zone.

Table 18: Commercial Thermostat Events in 2017

Event day	Day of week	Event start	Event end	Max daily temp (F)	SDG&E system load (MW)
8/31/2017	Thursday	2:00 PM	6:00 PM	85.3	4,190
9/1/2017	Friday	2:00 PM	6:00 PM	90.8	4,481
9/2/2017	Saturday	2:00 PM	6:00 PM	90.9	4,353

5.2 DATA SOURCES AND ANALYSIS METHOD

Table 19 summarizes the five data sources used to conduct the commercial thermostat event impact analysis. The analysis was done by site on hourly load data. Various data sources were used to classify sites into the study segments. While different segments were developed for the various analyses in this report (rate versus technology based, event and non-event), the characteristic definitions used to build segments were consistent across analyses.

Table 19: Commercial Thermostat Event Impact Evaluation Data Sources

Source	Comments
Hourly interval data	<ul style="list-style-type: none"> Summer 2017 All analysis done by site (premise id-service point id pair)
Customer characteristics	<ul style="list-style-type: none"> 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, Residential sample used as control pool for quasi residential treatment sites Industry, zip codes, climate zones used in matching model selection
Thermostat installation data	<ul style="list-style-type: none"> Installation and active dates
SDG&E hourly system loads	<ul style="list-style-type: none"> Summer 2017 Used to identify non-event high system load days
Ex post weather data by weather station	<ul style="list-style-type: none"> Used to derive cooling degree days for impact evaluation panel model

The primary analysis method was a differences-in-differences panel regression with a matched control group. The statistical matching approach used selected a matched control for the roughly 2,200 non-

residential thermostat sites among a control candidate pool of roughly 11,000 TOU sites who were not enrolled in CPP or other DR programs which might influence energy use. A difference-in-difference regression model was then used to assess impacts and standard errors for each event and each study segment.

A population comprising of about 1,100 quasi-residential sites was analyzed separately using a regression model that used non-event days to estimate the counterfactual. Quasi-residential customers were mainly temporary apartments for a specific industry at a handful of buildings, with a high level of distributed solar penetration. While there were roughly 1,100 sites, there were only eight distinct locations, each of which had highly correlated and predictable loads within the building. Because of their unique nature, a control group was not feasible.

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

5.3 EX POST LOAD IMPACTS

Weekend loads are typically different than weekday patterns, reflecting different activities and usage patterns for these different types of day. Because of this, the weekday events have been summarized separately from the weekend event which may not be comparable.

Table 20 summarizes the load impacts by segment for the two weekday events (August 31 and September 1) for the 2 pm to 6 pm event window. In aggregate, these events delivered 3.86 MW of load reduction across all rates including quasi-residential and Small Commercial CPP participants. Impacts were significant in aggregate and across every segment except large customers on TOU only rates. While the largest percent impacts were estimated for small and quasi-residential customers, the largest aggregate savings were estimated for the large and medium CPP sites, which delivered 0.91 MW and 1.05 MW of reductions respectively. Impacts were also distributed differently among segments for the weekday and weekend events.

Table 20: Smart Thermostat Weekday Event Impacts (2-6 pm)

Rate	Size	Sites	Load without DR (MW)	Load w DR (MW)	Impact (MW)	% Impact	Std. Error	t	Significant (90% CI)
TOU	Large	38	16.34	16.21	-0.12	-0.8%	0.40	-0.27	No
	Medium	87	3.11	2.93	-0.19	-6.1%	0.12	-1.58	No
	Small	112	0.86	0.76	-0.10	-12.1%	0.02	-4.20	Yes
	Quasi residential	1,099	0.84	0.32	-0.52	-62.3%	0.04	-12.40	Yes
TOU-CPP	Large	68	19.34	18.12	-1.22	-6.3%	0.26	-3.95	Yes
	Medium	506	21.56	20.40	-1.16	-5.4%	0.25	-4.38	Yes
	Small	1,253	9.64	9.09	-0.55	-5.7%	0.08	-6.70	Yes
TOTAL (w/ Small CPP)		3,163	71.68	67.82	-3.86	-5.4%	0.63	-6.09	Yes
TOTAL (w/o Small CPP)		1,910	62.04	58.73	-3.32	-5.3%	0.56	-5.95	Yes

Sites are premise and service point combinations

Table 21 summarizes the load impacts by segment for the one weekend event (September 2) during the 2 pm to 6 pm event window. In aggregate, this event delivered 1.29 MW of load reduction – about 40% of the reduction measured for the weekday events. Also of note is that while most other segments produced weekend load reductions about 20% to 50% lower than weekday reductions, the quasi-residential group contributed about 0.5 MW on the weekend and the weekday events. This group, largely consisting of managed residential sites, produced over a third of the weekend impacts.

Table 21: Smart Thermostat Weekend Event Impacts (2-6 pm)

Rate	Size	Sites	Load without DR (MW)	Load w DR (MW)	Impact (MW)	% Impact	Std. Error	t	Significant (90% CI)
TOU	Large	38	11.30	12.14	0.84	7.4%	0.37	1.94	Yes
	Medium	87	2.43	2.36	-0.07	-2.8%	0.11	-0.59	No
	Small	112	0.63	0.52	-0.11	-17.3%	0.04	-2.57	Yes
	Quasi residential	1,099	0.98	0.49	-0.49	-50.2%	0.09	-5.77	Yes
TOU-CPP	Large	68	16.44	16.15	-0.30	-1.8%	0.46	-0.54	No
	Medium	506	19.44	18.61	-0.83	-4.3%	0.32	-2.51	Yes
	Small	1,253	7.57	7.23	-0.34	-4.5%	0.12	-2.65	Yes
TOTAL (w/ Small CPP)		3,163	58.79	57.50	-1.29	-2.2%	0.79	-1.63	No
TOTAL (w/o Small CPP)		1,910	51.23	50.27	-0.96	-1.9%	0.69	-1.38	No

Sites are premise and service point combinations

The three events are summarized in greater detail in the following three figures (Figure 11, Figure 12, and Figure 13). Note that each figure, extracted from the Ex Post Load Impact Table, is for the full commercial thermostat participant population. Each figure shows the aggregate hourly loads (actual and counterfactual) for commercial thermostat sites. The tables accompanying each figure show aggregate impacts for the 2 pm to 6 pm event window. Load impacts were relatively consistent across each event:

- The August 31 and September 1 event produced relatively consistent load reductions for the duration of the event, with very similar load reductions of 3.88 MW and 3.99 MW, respectively.

Pre-event loads were about 4 MW higher on September 1, which was also the system peak load day.

- Impacts for the Saturday, September 2 event were 1.29 MW and were not significant, though this was due to load increases by large sites not on a CPP rate. The reference load shape for the weekend event was also relatively flat during event hours, notably different than the downward sloping shape for the weekday events. This underscores the non-comparability of weekday and weekend loads and events.

Figure 11: Commercial Thermostat Event Summary for 8/31/2017

Table 1: Menu options

Type of results	Aggregate
Category	All
Subcategory	All study segments
Event date	8/31/2017

Table 2: Event day information

Event start	2:00 PM
Event end	6:00 PM
Total enrolled accounts	3,163
Avg load reduction 11AM-6PM (MW)	1.69
% Load reduction 11AM-6PM	2.3%
Avg load reduction 2PM-6PM (MW)	3.88
% Load reduction 2PM-6PM	5.5%

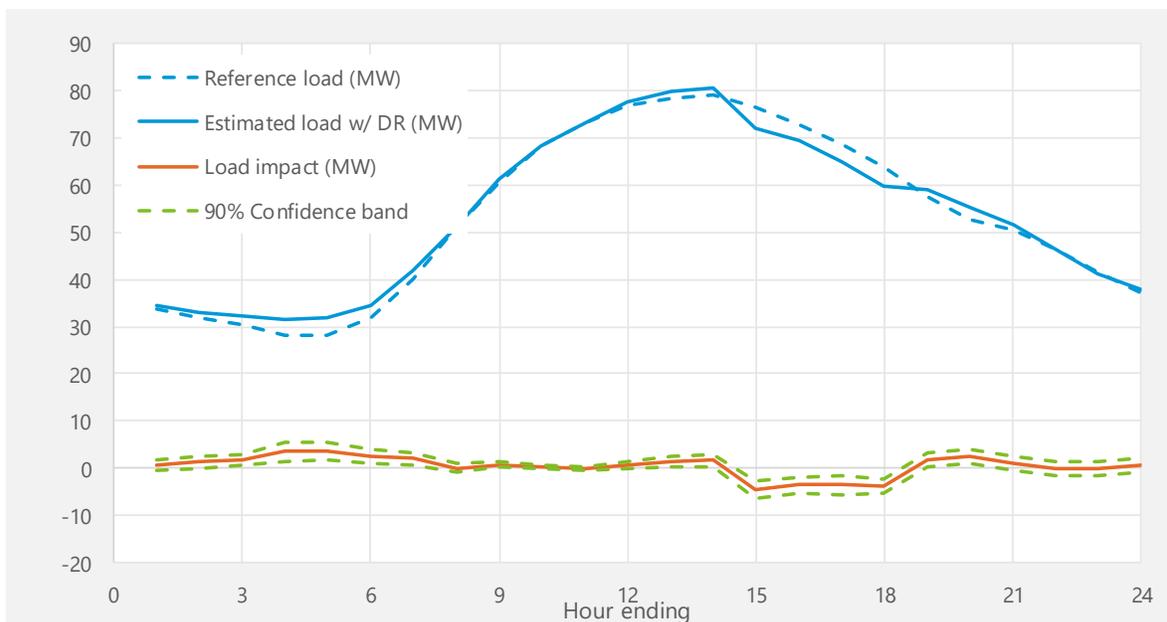


Figure 12: Commercial Thermostat Event Summary for 9/1/2017

Table 1: Menu options

Type of results	Aggregate
Category	All
Subcategory	All study segments
Event date	9/1/2017

Table 2: Event day information

Event start	2:00 PM
Event end	6:00 PM
Total enrolled accounts	3,163
Avg load reduction 11AM-6PM (MW)	1.90
% Load reduction 11AM-6PM	2.5%
Avg load reduction 2PM-6PM (MW)	3.99
% Load reduction 2PM-6PM	5.5%

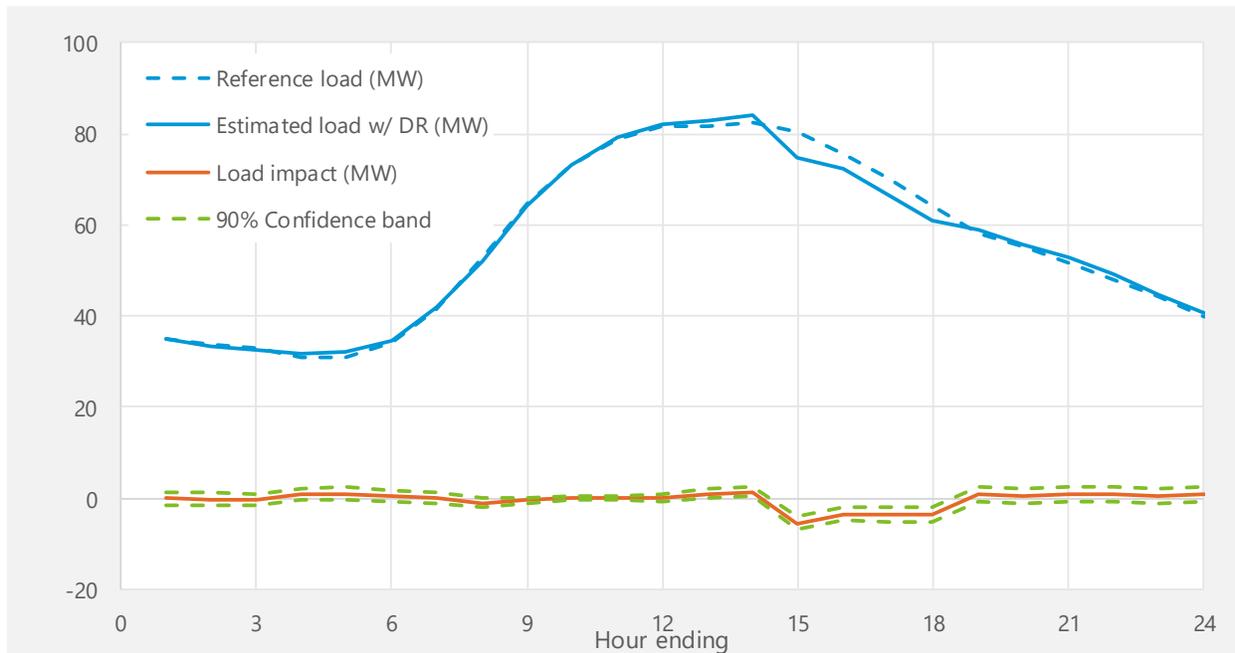


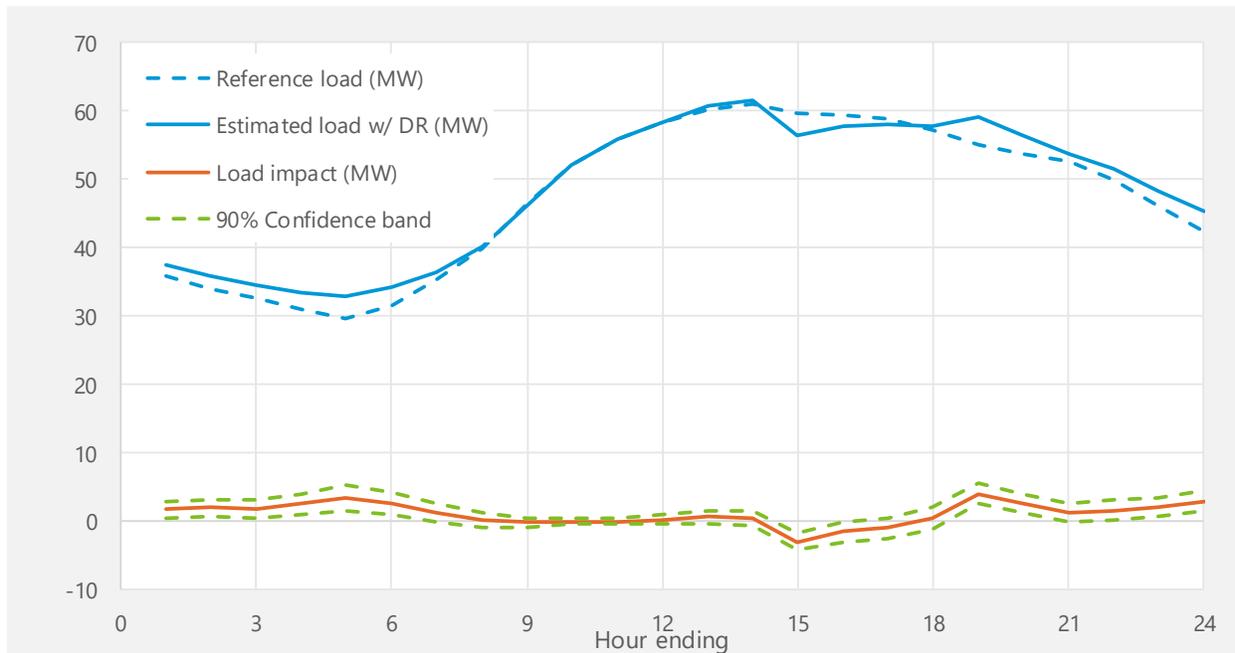
Figure 13: Commercial Thermostat Event Summary for 9/2/2017

Table 1: Menu options

Type of results	Aggregate
Category	All
Subcategory	All study segments
Event date	9/2/2017

Table 2: Event day information

Event start	2:00 PM
Event end	6:00 PM
Total enrolled accounts	3,163
Avg load reduction 11AM-6PM (MW)	0.56
% Load reduction 11AM-6PM	1.0%
Avg load reduction 2PM-6PM (MW)	1.29
% Load reduction 2PM-6PM	2.2%



5.4 EX ANTE LOAD IMPACTS

A key objective of the 2017 evaluation is to quantify the relationship between demand reductions, temperature, and hour of day. Ex ante impacts are estimated load reductions as a function of weather conditions, time of day, and forecasted changes in enrollment. By design, they reflect planning conditions defined by normal (1-in-2) and extreme (1-in-10) peak demand weather conditions. The

historical load patterns and performance during actual events are used the reductions for a standardized set of weather conditions.

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

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

5.4.1 RELATIONSHIP OF CUSTOMER LOADS AND PERCENT REDUCTIONS TO WEATHER

Figure 14 summarizes the relationship between weather for commercial customers with commercial thermostats in 2016 and 2017. Only days when the smart thermostat 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 the daily 1 pm to 6 pm average loads. The 1 pm to 6 pm period was selected because it coincides with hours that count towards resource adequacy requirements. Overall, energy demand and discretionary load increases with hotter weather.

Figure 15 shows the relationship between small thermostat participant loads and SDG&E and CAISO daily peaks loads. Not surprisingly, smart thermostat participants use more power when it is extremely hot and contribute to peak demand, which drives the need for additional generation, transmission, and distribution infrastructure. Because cooling loads are a major driver of SDG&E peaks, if managed, they can reduce the need to build additional infrastructure to accommodate additional peak load. Air conditioner use is higher during peaking conditions and, as a result, reductions from commercial thermostats are larger precisely when resources are needed most.

Because the commercial thermostats are dispatched automatically for events, the main driver of differences in ex ante impacts are differences in loads. The percent change in energy use was estimated for each hour and for each of the ex post segments defined in Table 4 and applied to 1-in-2 and 1-in-10 weather year customer loads.

Figure 14: Weather Sensitivity of Small Commercial CPP Loads

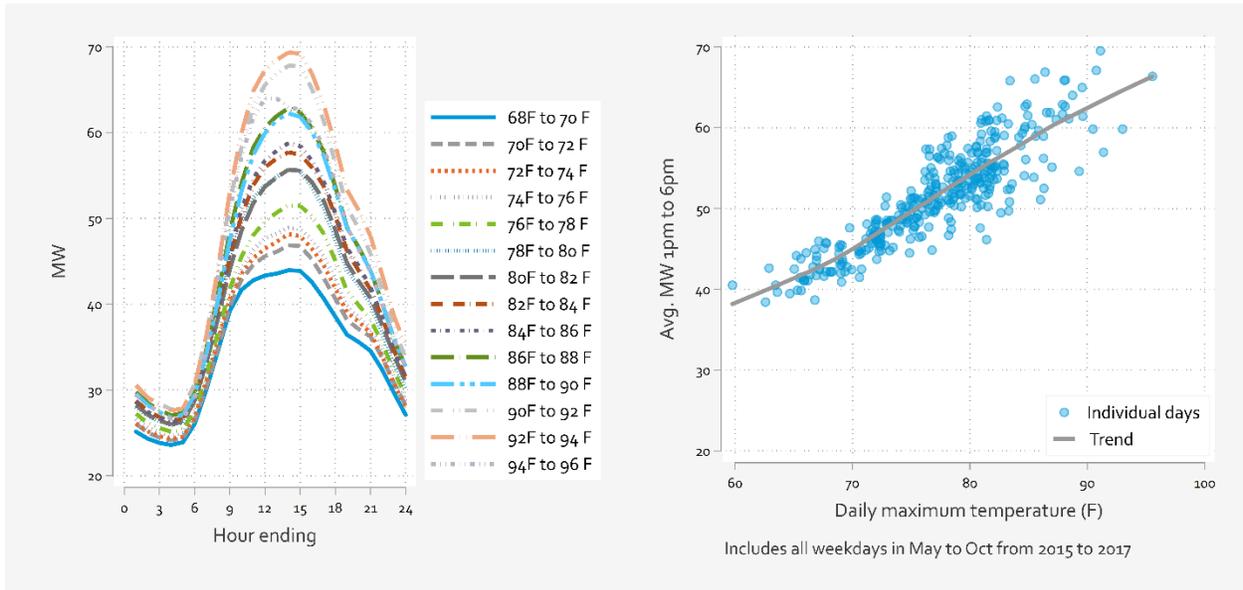
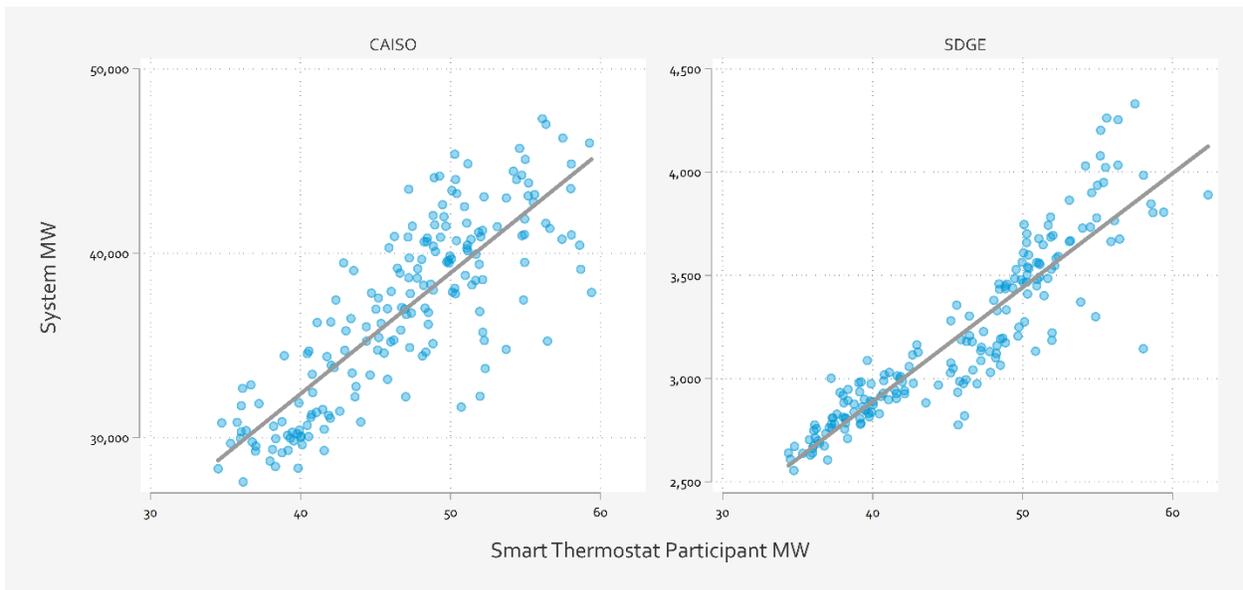


Figure 15: Commercial Thermostat Customer Loads During System Daily Peaks



5.4.2 EX ANTE LOAD IMPACTS

Table 22 summarizes the ex ante demand reduction capability by forecast year and planning condition. The tables reflect dispatchable demand reductions available from 1 pm to 6 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 was developed by SDG&E and shows moderate increases in the number of thermostats over time.

Table 22: Non-residential Smart Thermostat Portfolio Impacts for August Monthly Peak Day

Year	Accts	CAISO		SDG&E	
		1-in-2	1-in-10	1-in-2	1-in-10
2017	3,297	2.87	2.86	2.83	2.94
2018	3,385	2.97	2.95	2.92	3.04
2019	3,477	3.07	3.05	3.02	3.14
2020	3,574	3.18	3.16	3.13	3.25
2021	3,675	3.29	3.27	3.24	3.37
2022	3,781	3.41	3.39	3.35	3.49
2023	3,781	3.41	3.39	3.35	3.49
2024	3,781	3.41	3.39	3.35	3.49
2025	3,781	3.41	3.39	3.35	3.49
2026	3,781	3.41	3.39	3.35	3.49
2027	3,781	3.41	3.39	3.35	3.49
2028	3,781	3.41	3.39	3.35	3.49

5.4.3 COMPARISON OF EX POST AND EX ANTE LOAD IMPACTS

Table 23 compares the demand reductions from 2017 events to the reduction expected under the 1-in-2 and 1-in-10 weather conditions used for planning. The small differences between ex post and ex ante values are due to different reporting hours, weather conditions and customer counts. In 2017, small CPP customers delivered 3.86 MW during the dispatch period of 2 pm to 6 pm. However, because thermostat resources were not dispatched from 1-2 pm, demand reductions are smaller, 2.76 MW, for the 1-6 pm period used for resource adequacy and planning. When similar hours are compared, the ex post impacts align well with the ex ante resource estimates. The remaining differences are due to different number of sites (6.8%) and due to weather. As expected, available resources are larger under 1-in-10 SDG&E peaking conditions than under 1-in-2 conditions. However, this pattern does not hold for CAISO peak days, which are more heavily influenced by larger utilities and do not always coincide with SDG&E peaks.

Table 23: Commercial Thermostat Comparison of Ex Post and Ex Ante Load Impacts for 2017

Result Type	Day Type and Period	Accts	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex post Avg. Weekday	Event Period (2 to 6 pm)	3,073	71.7	3.86	5.4%	89.0
	Resource Adequacy Period (1 to 6 pm)	3,073	73.5	2.76	3.8%	89.0
Ex ante SDG&E	1-in-2 Weather August Peak (1 to 6 pm)	3,297	69.4	2.83	4.1%	88.1
	1-in-10 Weather August Peak (1 to 6 pm)	3,297	72.4	2.94	4.1%	92.1
Ex ante CAISO	1-in-2 Weather August Peak (1 to 6 pm)	3,297	70.7	2.87	4.1%	88.3
	1-in-10 Weather August Peak (1 to 6 pm)	3,297	69.9	2.86	4.1%	88.2

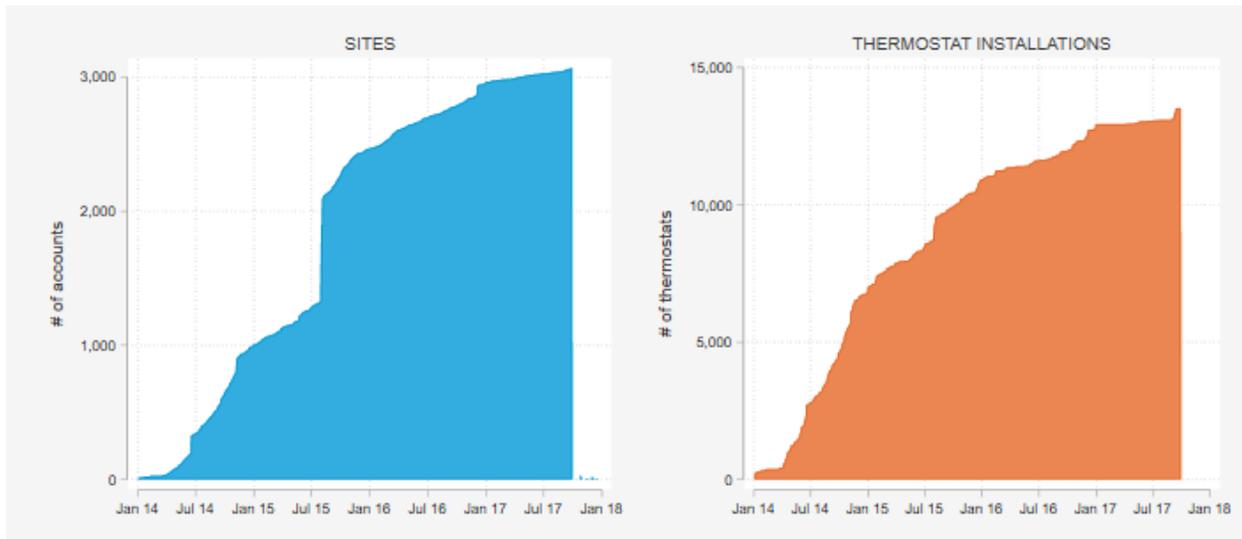
*Table shows portfolio impacts. To avoid double counting, it excluded commercial thermostats and customers dually enrolled in other DR programs.

6 COMMERCIAL THERMOSTAT DEMAND AND CONSUMPTION IMPACTS (NON-DISPATCHABLE)

The commercial thermostat program currently provides Ecobee thermostats free of charge to commercial customers. The technology deployment program has been in operation since 2014. Smart thermostats can help program schedules and detect occupancy, potentially reducing energy use during periods when the building is unoccupied. The goal of this analysis was to measure whether the installation of commercial thermostats led to energy or demand savings on non-event days.

Figure 16 shows cumulative program enrollment over time, in terms of sites (left) and in numbers of devices (right). There are over 14,000 devices installed at over 3,000 non-residential sites. This includes nearly 1,100 “quasi-residential” sites, mostly commercial apartments which deployed thermostats within a one-week period at the end of July 2015, as indicated by the sharp increase in enrolled sites in that time frame (see the blue chart). The full program population also includes small, medium, and large non-residential sites.

Figure 16: Commercial Thermostat Cumulative Installations



6.1 TECHNOLOGY AND PARTICIPANT CHARACTERISTICS

The Ecobee thermostats are programmable and controllable via the device and also via an online portal and a mobile app. Temperature set points can be automatically adjusted via an occupancy sensor and a detailed schedule can be set to manage energy usage.

The changes in energy usage were evaluated using hourly whole building data for each site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in Table 24, was developed

based on rate size and on rate characteristics. 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 rate¹²) was the site classified as throughout the study period?

Table 24: Commercial Thermostat Population Segments

Rate	Size	Total sites	Average devices per site	Sites in energy analysis
TOU	Large	38	39	13
	Medium	87	14	36
	Small	112	5	47
	Quasi residential	1,099	1	644
TOU-CPP	Large	68	39	15
	Medium	506	11	176
	Small	1,253	3	70
TOTAL		3,163	5	1,001

Sites are premise and service point combinations

Table 24 also summarizes the total number of sites in each segment and the final number of sites used for the energy savings analysis once data cleaning was completed¹³. Due to the long installation period spanning from January 2014 into 2017, a majority of sites did not have sufficient pre-treatment data for inclusion in the analysis. The analysis was thus conducted on a subset of sites, about 30% overall, which had an installation date after July 2015, allowing ten months of pretreatment data.¹⁴ Of particular note is that the quasi-residential segment comprises about two thirds of the sites included in the energy savings analysis. To ensure the results represented the participants mix, the analysis was implemented

¹² 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.

¹³ The cleaning algorithm ensured that complete data was available for the study period. Sites for which high quality matches could not be found were also excluded—about 10% of the sample. Loads and impacts were scaled to address the non-matched sites.

¹⁴ The analysis dataset extended to October 2014

by segment, and weighted to scale up to the population. In addition, analysis of loads showed that usage across quasi-residential sites was very highly correlated and analysis of participant data showed that over 80% of these devices were installed at the same temporary housing property, in the same period (about 70% devices were installed in the last week of July 2015). Another 17% were installed by two customers in a similar geographically clustered manner.

6.2 DATA SOURCES AND ANALYSIS METHOD

Table 25 summarizes the four data sources used to conduct the smart thermostat non dispatchable energy impacts analysis. The analysis was done on aggregated load data for the treatment and control groups. 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 25: Smart Thermostat Non-Dispatchable Energy Impact Evaluation Data Sources

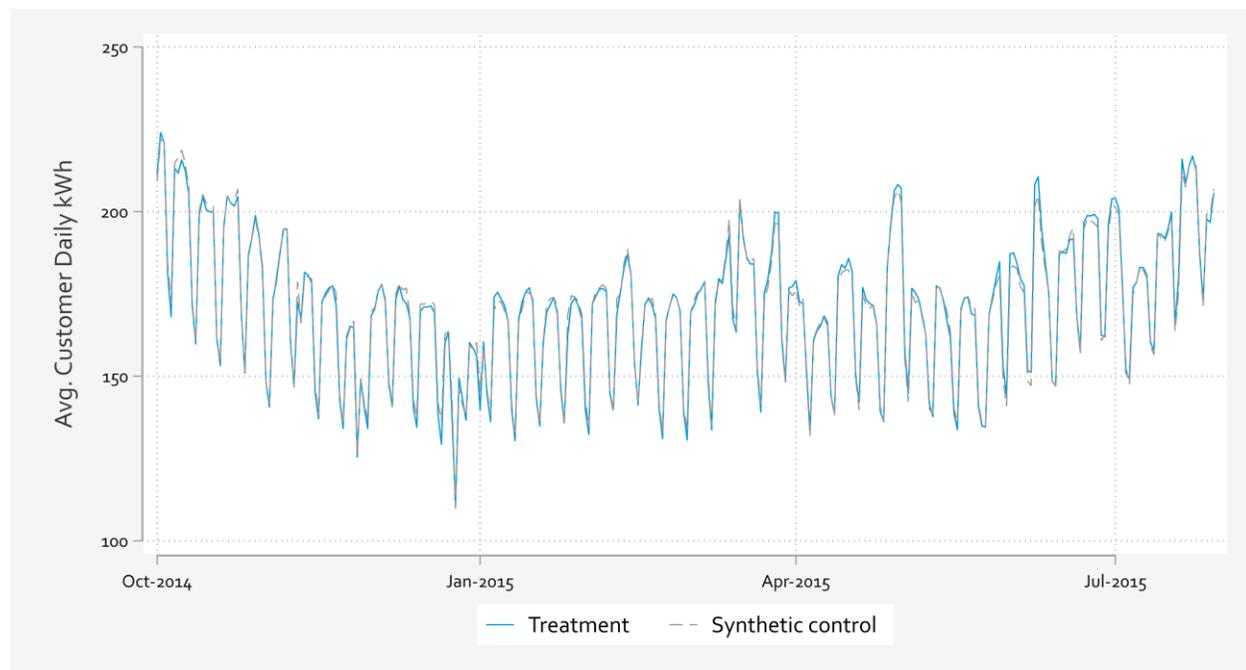
Source	Comments
Hourly interval data	<ul style="list-style-type: none"> ▪ Pretreatment (Oct 2014-Jul 2015¹⁵) and post-treatment thereafter (with installations on a rolling basis) through Sep 2017 ▪ All analysis done by site (premise id-service point id pair) ▪ Only sites with full pretreatment data were included in the analysis
Customer characteristics	<ul style="list-style-type: none"> ▪ Treatment: All customers with commercial thermostats and at least 10 months of pre-treatment data ▪ Control: All non-residential sites that did not install commercial thermostats via SDG&E's program. ▪ Pre-treatment data, load shapes, industry, zip codes, climate zones, solar installation and rate type used in matching model selection
Thermostat installation data	<ul style="list-style-type: none"> ▪ Installation and active dates
Weather data by weather station	<ul style="list-style-type: none"> ▪ Used to model energy use

¹⁵ Artificially selected for analysis purposes to ensure sufficient pre-treatment data. Though installations began in January 2014, sites with installation dates prior to August 2015 were excluded.

The impact analysis relied on an aggregated times series with weather, day, and season characteristics, and the loads of the matched control group and the 16 non-equivalent control segments as explanatory variables. The approach was selected to be consistent with the TOU energy savings analysis and because the quasi-residential group was challenging to match due to its unique nature (high solar penetration and clustered sites). An out of sample approach was also used to select the regression model, as summarized in Figure 2. The out-of-sample approach essentially used the first half of the pre-treatment period (November 2014 to April 2015) to predict loads for the second half of the pre-treatment period (May 2015 to July 2015). This was done with each model tested, then model performance was assessed by comparing modeled to actual loads. A total of 20 models were tested, 10 with and 10 without the control groups. Model structures and performance are detailed in the Appendix, highlighting that the synthetic control constructed from non-equivalent groups was the most accurate and precise.

Figure 17 shows how closely the model tracked the treatment group total daily consumption during the pre-treatment period. Differences between the two groups are nearly indistinguishable.

Figure 17: Comparison of Actual Loads and Model Estimates During Pre-treatment Period



6.3 DEMAND AND ENERGY SAVING IMPACTS (NON-DISPATCHABLE)

Figure 18 shows the differences between the synthetic control and the treatment group before and after installation of smart thermostats. Prior to installation, the differences were centered on zero, with some day to day differences. As the penetration of smart thermostat grows in the treatment group, the difference in daily energy use between the sites with commercial thermostats and the synthetic control group grows. The installation of thermostats coincides with the decreases in energy use.

Figure 18: The Difference in Daily Energy Use Grows Wider with the Penetration of Smart Thermostats

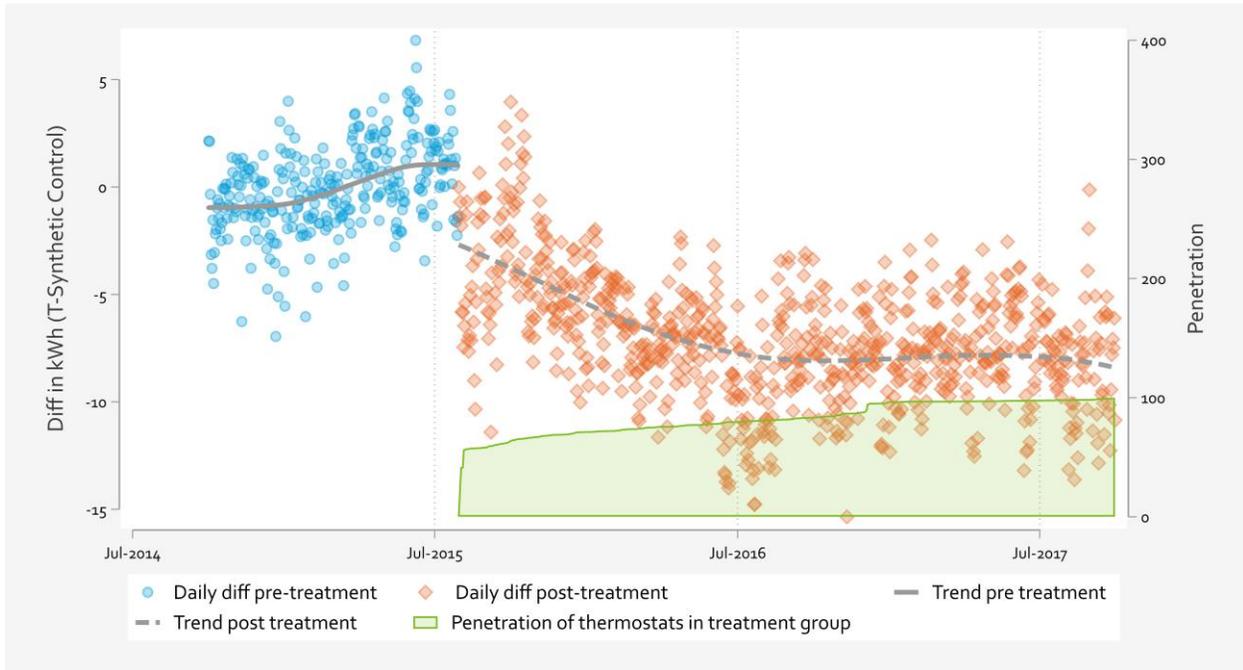


Figure 19: Commercial Thermostat Difference in Energy Use as a Function of Weather

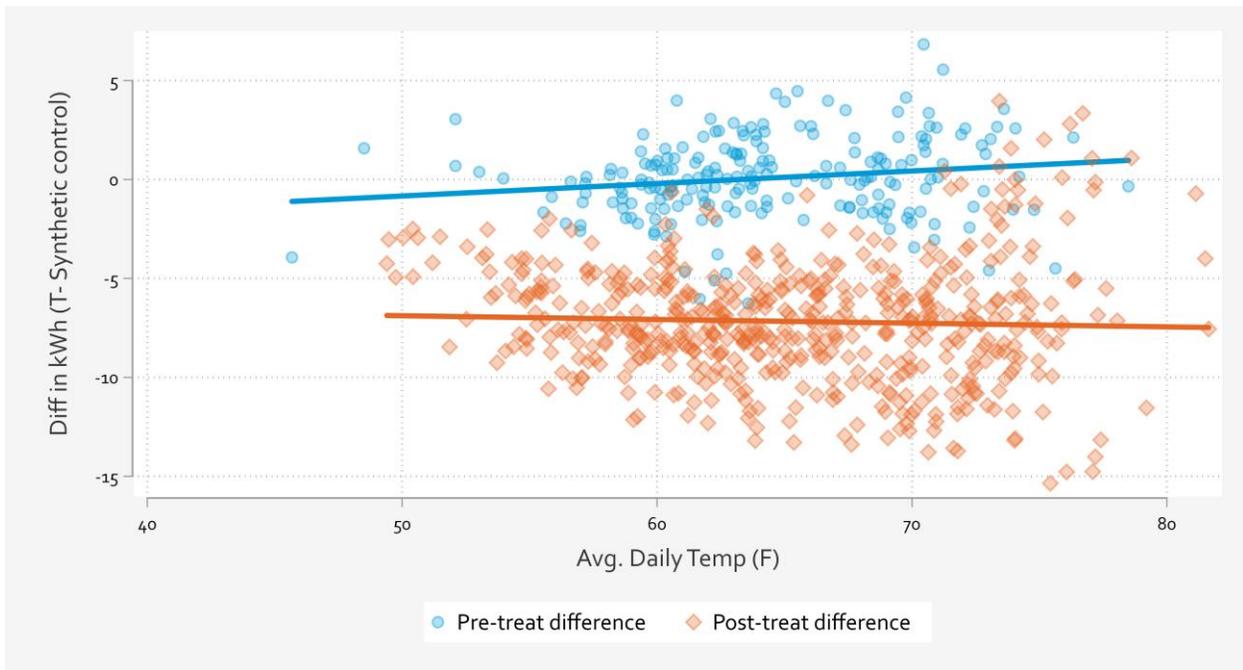


Figure 19 shows the differences in daily energy use between the synthetic control group and the participants before and after installation of commercial thermostats as a function of weather. Prior to the installation, the difference in energy use is effectively zero. With the thermostats in place, the reduction in energy use is clearly evident.

The impact estimation model was run at the hourly level, by segment, allowing for time and segment differentiated results. Table 26 summarizes the energy and demand savings by rate period for the two key rate groups. Significant savings of about 6.8% were detected for commercial thermostat sites, adding up to demand reductions of about 1.6 MW during the summer peak period and annual savings of about 13.5 GWh for October 2016 through September 2017. Despite the overall savings, we recommend caution in applying the savings estimates elsewhere. The population included in the analysis was unique, with a large number of commercial, short-term apartments with high penetration of solar. Due to the lower net loads from solar, the whole building percent impacts are smaller than they would be for sites without solar.

Table 26: Time of Use Impacts by Rate Period

Rate group	Season	Day type	Rate period	Sites	Aggregate impacts			Average site impacts		
					Percent reduction	Demand reduction (MW)	Energy savings (GWh)	Demand reduction (kW)	95% CI Lower Bound	95% CI Upper Bound
TOU	Summer	Weekday	Peak	1,336	0.7%	0.04	0.04	-0.022	-0.846	0.802
			Off-peak	1,336	4.2%	0.16	0.34	-0.104	-0.913	0.704
		Weekends & Holidays	Off-peak	1,336	1.6%	0.05	0.07	-0.005	-0.814	0.804
	Winter	Weekday	Peak	1,336	-0.4%	-0.02	-0.02	0.072	-0.739	0.882
			Off-peak	1,336	-1.8%	-0.06	-0.13	0.116	-0.686	0.917
		Weekends & Holidays	Off-peak	1,336	-6.3%	-0.17	-0.23	0.221	-0.583	1.024
TOU SUBTOTAL				1,336	0.2%	0.01	0.07	0.00	-0.80	0.79
TOU-CPP	Summer	Weekday	Peak	1,827	5.5%	1.59	1.41	-0.979	-1.830	-0.127
			Off-peak	1,827	8.7%	1.60	3.46	-0.985	-1.834	-0.135
		Weekends & Holidays	Off-peak	1,827	9.3%	1.58	2.09	-1.003	-1.864	-0.142
	Winter	Weekday	Peak	1,827	6.7%	1.62	1.42	-0.990	-1.782	-0.198
			Off-peak	1,827	8.5%	1.42	3.02	-0.857	-1.648	-0.067
		Weekends & Holidays	Off-peak	1,827	9.8%	1.47	1.98	-0.905	-1.701	-0.109
TOU-CPP SUBTOTAL				1,827	8.1%	1.54	13.38	-1.25	-2.16	-0.34
TOTAL				3,163	6.8%	1.54	13.45	-0.66	-0.72	-0.60

Sites are premise and service point combinations
Positive percentages indicate energy savings.

Table 27 and Table 28 summarize percent energy and GWh savings by rate period for each study segment. Grey text indicates impacts that are not significant. Savings vary widely by segment and rate period. Large percent impacts were detected for the quasi-residential segment in particular which produced average energy savings of 29% across rate periods. Further analysis of underlying loads showed patterns indicative of active energy management. Large and medium customers on TOU-CPP rates were the other segments which delivered energy savings, 3% and 12% respectively on average across rate periods. Medium and small segments showed significant increases in energy use and were highest in off peak periods, echoing the small non-residential TOU energy savings analysis which also showed savings similarly concentrated in the CPP sites (note that quasi-residential sites were not transitioned to TOU and are on flat rates).

Table 27: Time of Use Energy Savings, Percent Savings by Rate Period and Segment

Rate group	Size	Sites	Summer			Winter			Overall
			Weekday		Weekends & Holidays	Weekday		Weekends & Holidays	
			Peak	Off-peak	Off-peak	Peak	Off-peak	Off-peak	
TOU	Large	38	-0.4%	-1.4%	-6.2%	-7.4%	-15.0%	-27.4%	-8.0%
	Medium	87	-3.6%	-8.4%	-11.8%	-0.8%	-7.3%	-13.0%	-7.3%
	Small	112	-5.7%	-4.5%	-15.6%	-7.7%	-18.8%	-36.3%	-12.6%
	Quasi residential	1,099	15.6%	30.4%	25.0%	28.4%	35.6%	30.9%	28.8%
TOU-CPP	Large	68	2.5%	2.8%	8.7%	2.9%	1.0%	5.3%	3.4%
	Medium	506	8.7%	13.2%	11.4%	10.9%	13.8%	13.2%	12.1%
	Small	1,253	0.4%	2.5%	1.7%	-0.2%	1.7%	3.0%	1.5%
TOTAL		3,163	4.7%	8.0%	8.1%	5.5%	6.8%	7.3%	6.8%

Sites are premise and service point combinations

Positive percentages indicate energy savings. Estimates not significant at the 90% level have been greyed out.

Table 28: Time of Use Energy Savings, GWh by Rate Period and Segment

Rate group	Size	Sites	Summer			Winter			Overall
			Weekday		Weekends & Holidays	Weekday		Weekends & Holidays	
			Peak	Off-peak	Off-peak	Peak	Off-peak	Off-peak	
TOU	Large	38	-0.01	-0.06	-0.11	-0.16	-0.47	-0.37	-1.17
	Medium	87	-0.05	-0.16	-0.13	-0.01	-0.12	-0.12	-0.55
	Small	112	-0.03	-0.03	-0.05	-0.03	-0.11	-0.10	-0.36
	Quasi residential	1,099	0.13	0.57	0.34	0.19	0.58	0.36	2.15
TOU-CPP	Large	68	0.17	0.32	0.50	0.16	0.09	0.25	1.39
	Medium	506	1.27	3.09	1.63	1.27	2.84	1.64	11.56
	Small	1,253	0.02	0.17	0.06	-0.01	0.09	0.09	0.42
TOTAL		3,163	1.45	3.80	2.16	1.40	2.89	1.75	13.45

Sites are premise and service point combinations

Positive GWh values indicate energy savings. Estimates not significant at the 90% level have been greyed out.

7 CONCLUSIONS AND RECOMMENDATIONS

The three different interventions – CPP-TOU, TOU, and commercial thermostats – each delivered statistically significant demand reduction and energy savings. But there is room for improvement. The recommendations below may not be funded, and costs need to be considered alongside other research and program priorities.

- **Notifications rates for small CPP can be improved further.** 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. From 2016 to 2017, the notification rate improved from under 25% to 44%. Because many customers have multiple sites (and don't always sign up all sites), customers for roughly 60% sites received notification. Despite the improvement, there is further room to improve notifications.
- **More events need to be called to better define response as a function of temperature.** A total of four events were called in the past two years. By calling more events, SDG&E will have more data points to better understand the resource capability and better assess response to dispatch events. The number of events and the event conditions play a significant role in the ability to evaluate impacts and better understand ex ante demand reduction capability. The treatment effect is easier to detect if there are multiple events.
- **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. 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.
- **Assess if it is cost-effective to further expand commercial thermostat installation.** The commercial thermostats not only delivered dispatchable demand reduction but also led to substantial energy savings. Because the participant population was unique, however, we caution that it is important to understand if similar savings can be replicated with other customers and if the savings persist over multiple years.

APPENDIX

A. MATCHING MODELS

Propensity score matching identifies the closest match from a pool of candidates that did not experience the intervention based on observable characteristics. The various characteristics to a score and the candidate with the nearest score is identified as the match. The matching model used various combinations of hot non-event load data and customer characteristics. The matched control groups were developed using non-participants and relied on out of sample testing. Multiple matching models were specified and hot non-event days were split into training and testing days. The matching was done in two stages. First, all sites were classified into 10 groups from largest to smallest, each with approximately 20% of the total load (5 size bins). This helped ensure large customers were matched to large customers. Second, a separate propensity score model was developed for each size bin and closest statistical doppelganger was identified from within the size bins. In cases where a large number of sites had behind the meter solar, matching was done separately for them because of their distinctive load shapes and different consumption patterns (e.g., large customers with solar can have low consumption).

The below equation shows the general specification of the matching models.

$$\Pr(y = 1)_i = a + B \cdot \text{Nontreatment load variables}_i + C \cdot \text{Site characteristics}_i + \varepsilon_i$$

Table 29 describes the non-event load variables and site characteristics that were included in the various models. Table 30 shows the variables were included in each model.

Table 29: Matching Model Variable Definitions

Variables	Description
kw_1 - kw_24	Weekday average hourly loads during hot non-event days (control days). It includes all 24 hours of the day.
kw_12 - kw_18	Weekday average hourly loads during hot non-event days (control days) from 11am to 6pm.
kw_1_wkend - kw_24_wkend	Weekend average hourly loads during hot non-event days (control days). It includes all 24 hours of the day.
kw_12_wkend - kw_18_wkend	Weekend average hourly loads during hot non-event days (control days) from 11am to 6pm.
loadshape1 – loadshape6	The load shape cluster. Customer were classified into 6 distinct load shape using k-means clustering based on the percentage of their demand that occurred in each hour.
Percentile	The percentile or rank of the customers non-event day loads relative to other treatment and control candidates.

Variables	Description
Average kW	The average kW during hot non-events.
NEM	Is a binary variable indicating if a customer is net metered, which typically means they have behind the meter solar.
zip3digit	This was a set of binary variables for location. The first 3 digits of the zip code center around larger cities.
naics2digit	A set of binary variable for business type, as defined by the first two digits of the North American Industrial Classification System. Business types that made up less than 2% of the population were reclassified into other. A total of 15 business classifications were employed.
ε_i	The error term for each individual customer.

Table 30: Matching Models – Variables Included in Each Model

Variables	Model											
	1	2	3	4	5	6	7	8	9	10	11	12
kw_1 - kw_24	●		●		●		●		●		●	
kw_12 - kw_18		●		●		●		●		●		●
kw_1_wkend - kw_24_wkend							●		●		●	
kw_12_wkend - kw_18_wkend								●		●		●
loadshape1 – loadshape6			●	●	●	●			●	●	●	●
Percentile	●	●	●	●	●	●	●	●	●	●	●	●
Average kW												
NEM			●	●	●	●			●	●	●	●
zip3digit					●	●					●	●
naics2digit					●	●					●	●
ε_i												

B. DIFFERENCE-IN-DIFFERENCES PANEL REGRESSION MODEL

Event impacts were estimated using matched control groups and a difference-in-differences panel regression. The differences-in-differences model estimates reductions as the difference between the participant and control groups, net any pre-existing differences that may not have been captured in the matching process. The difference-in-differences model can be enhanced through additional explanatory variables to improve precision. With a difference-in-difference model, one should observe:

- Very similar energy use patterns for participant and control group customers 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 control group.
- The timing of the change should coincide with the introduction of intervention.

The use differences in differences model is prudent because it corrects for pre-existing differences between the control and treatment groups that are not addressed through matching. The equation for the model is presented below. A separate model was implemented for each intervention and hour of the day for each of the analysis segments identified as part of the evaluation plan.

$$kW_{i,t} = a + b \cdot Treatment_i + \sum_{n=1}^{max} c_n \cdot Event_n + \sum_{n=1}^{max} d_n \cdot (Event_n \cdot Treatment_i) + e \cdot CDD_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t}$$

Where:

$kW_{i,t}$	Is the usage by for each individual customer and time period
a	Is the model intercept
b	Corrects for pre-existing differences between treatment and control group customers
c	Controls for differences between event and non-event days that are common to both CPP participants and control group members
d	Represents the impact, or treatment effect, after controlling for pre-existing differences and other factors. This is estimated for each event day and hour.
e	Is the parameter for weather sensitivity of loads
$Treatment_i$	Is a binary variable to indicate if a customer is part of the participant or control group. It remains static throughout the analysis period. In practice, this variable drops out whenever fixed effects are included because fixed effects account for all unique customer characteristics that remain static.
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.

γ_i	Represents customer specific fixed effects. They account for all unique customer characteristics that remain static.
δ_t	Represents time effects for each time periods. This account for observed and unobserved factors that vary by time but affect all customers equally.
$\varepsilon_{i,t}$	Represents the error term for each individual customers and time period.

C. SYNTHETIC CONTROL GROUP AND WITHIN-SUBJECT MODELS

Synthetic control groups were used as the primary method for estimating day to day energy savings (a non-dispatchable resource) for TOU impacts and commercial thermostats. The approach is implemented on a time series of aggregated loads. It relies on multiple non-equivalent control segments that did not experience the intervention, plus weather and day characteristics, to estimate the counterfactual. The model weighs the various control segments based on their predictive power creating a synthetic control group out of multiple external controls. A total of 20 models, 10 without and 10 with synthetic controls were tested side by side using pre-transition data. The pre-treatment data was split in half, with one half used to developed the model, and the other half used to assess the accuracy of the model.

The general equation for the model is presented below. A separate model was implemented for each intervention and hour of the day using the segmentation identified as part of the evaluation plan. The models were implemented using a feasible GLS model to account for auto-correlation.¹⁶

$$kW_t = a + b \cdot \text{Treatment} + c \cdot \text{Weather Variables}_t + d \cdot \text{Day characteristics}_t + e \cdot \text{Nonequivalent controls}_t + \varepsilon_t$$

Table 31 describes the non-event load variables and site characteristics that were included in the various models. Table 32 shows the variables were included in each model.

¹⁶ In addition to feasible GLS, ARIMA and Newey-West Models were considered to account for auto-correlation. The two alternatives produced nearly identical coefficients and standard errors but were less robust to gaps in data (e.g., weekends) and therefore less practical.

Table 31: Within Subject and Synthetic Control Models Variable Definitions

Variables		Description
Weather	CDD (Base 65°F)	Cooling degree days measures the temperatures above which cooling is used and is defined on a daily basis. It is defined as the maximum of zero and the average daily temperature minus the base temperature.
	HDD (Base 55° F)	Heating degree days measures the temperatures below which heating is used. It is defined as the maximum of zero and the base temperature minus the average daily temperature.
	Mean 17	The average temperature for the hours before 5 pm (the first 17 hours of the day)
	CDH (Base 70°F)	Cooling degree hours measure the temperature above which cooling is used and is defined on an hourly basis. It is defined as the maximum of zero and the hourly temperature minus the base temperature.
	CDH 3 hour moving average	The moving average of cooling degree hours for the 3 hours immediately preceding the hour in question. It measures heat buildup.
	CDH 6 hour moving average	The moving average of cooling degree hours for the 6 hours immediately preceding the hour in question. It measures heat buildup.
	CDH 12 hour moving average	The moving average of cooling degree hours for the 12 hours immediately preceding the hour in question. It measures heat buildup.
	HDH (Base 60°F)	Heating degree hours measure the temperature above which heating is used and is defined on an hourly basis. It is defined as the maximum of zero and the hourly temperature minus the base temperature.
	HDH 3 hour moving average	The moving average of heating degree hours for the 3 hours immediately preceding the hour in question. It measures heat buildup.
	HDH 6 hour moving average	The moving average of heating degree hours for the 6 hours immediately preceding the hour in question. It measures heat buildup.
HDH 12 hour moving average	The moving average of heating degree hours for the 12 hours immediately preceding the hour in question. It measures heat buildup.	
Day characteristics	Day of week	Is a set of binary variables, one for each of the day.
	Month	This was a set of binary variables, one for each month of year, designed to identify seasonal patterns.
	YM	Year and month. A trend variable designed to quantify the change in energy use independent of the treatment and other explanatory variables.
Non-equivalent control groups	kw_1-kw16	Loads for the non-equivalent control groups that did not experience the treatment. They are weighted based on their predictive power.
Error		The error term for each time period.

Table 32: Within Subject and Control Group Models

Type	Variable	Model																				
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
Weather	CDD (Base 65°F)	●						●				●						●				
	HDD (Base 55° F)	●						●				●						●				
	Mean 17						●										●					
	CDH (Base 70°F)		●					●	●	●	●		●					●	●	●	●	●
	CDH 3 hour moving average			●						●					●					●		
	CDH 6 hour moving average				●					●					●						●	
	CDH 12 hour moving average					●					●						●					●
	HDH (Base 60°F)		●					●	●	●	●	●		●				●	●	●	●	●
	HDH 3 hour moving average			●											●							
	HDH 6 hour moving average				●										●							
	HDH 12 hour moving average					●											●					
	Day characteristics	Day of week	●	●	●	●	●	●	●	●	●		●						●			
Month		●	●	●	●	●	●	●	●	●		●						●				
YM		●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Non-equivalent control groups											●	●	●	●	●	●	●	●	●	●	●	

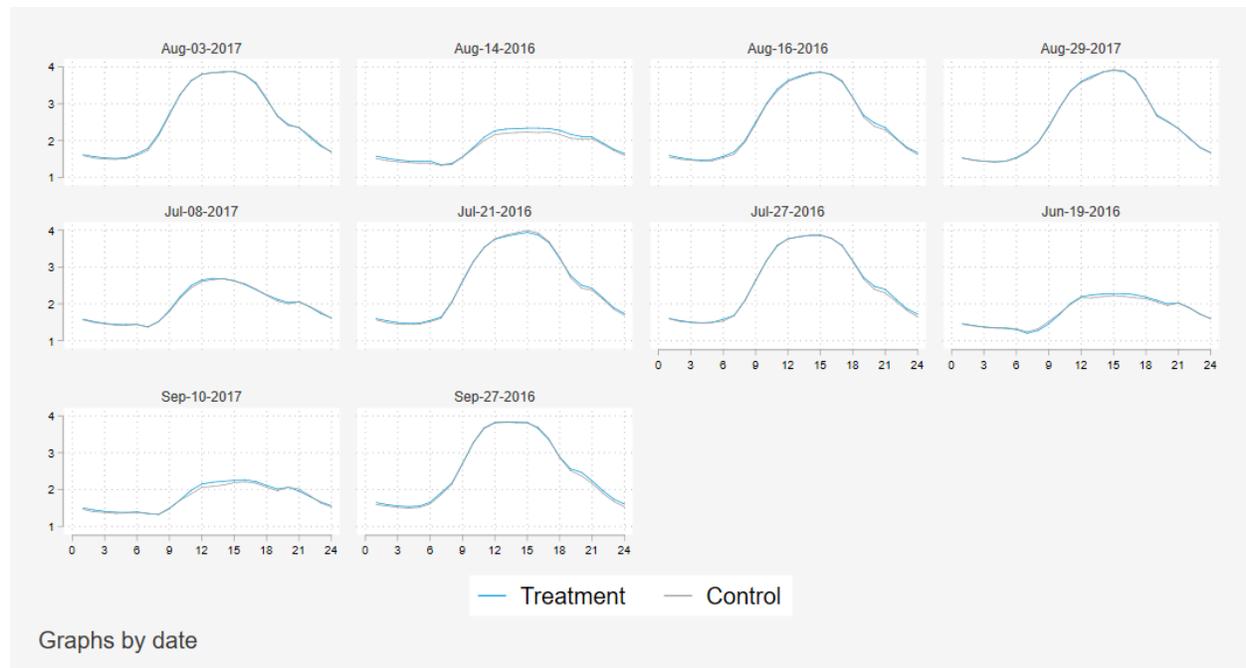
D. COMPARISON OF CONTROL AND TREATMENT GROUPS – SMALL COMMERCIAL DISPATCHABLE RESOURCES

The quality of the match was assessed by comparing the aggregated hourly loads of the treatment and control groups (i.e., date and hour of day) using the testing data (which was not used for matching). Below are the bias and fit metrics for all models tested. The model with the best fit (RMSE) among those with the top three with the least bias (Model 12) was selected.

Table 33: Small Commercial CPP Matching Model Assessment Statistics

Model	Avg. kW	Avg. Error	Mean Squared Error	Relative Root Mean Squared Error	% Bias	Abs % Bias
6	2.969317	.0161457	.0048784	.0235225	.0054375	.0054375
5	2.969078	.0269046	.0047593	.0232354	.0090616	.0090616
12	2.96998	.0276828	.0028436	.0179549	.0093209	.0093209
10	2.969113	.0303724	.003023	.018518	.0102295	.0102295
11	2.968771	.034981	.0039754	.021238	.011783	.011783
9	2.968063	.051022	.0040696	.0214932	.0171903	.0171903
8	2.969284	.0532765	.0051972	.0242792	.0179426	.0179426
3	2.970117	.0718609	.0070201	.0282096	.0241947	.0241947
1	2.970086	.0753799	.0143576	.0403434	.0253797	.0253797
7	2.968795	.0798968	.0086937	.0314067	.0269122	.0269122
2	2.968073	.1001989	.0196311	.047206	.0337589	.0337589
4	2.970931	.1087297	.0176481	.0447153	.0365979	.0365979

Figure 20: Treatment and Control Loads on Proxy Days, Selected Model



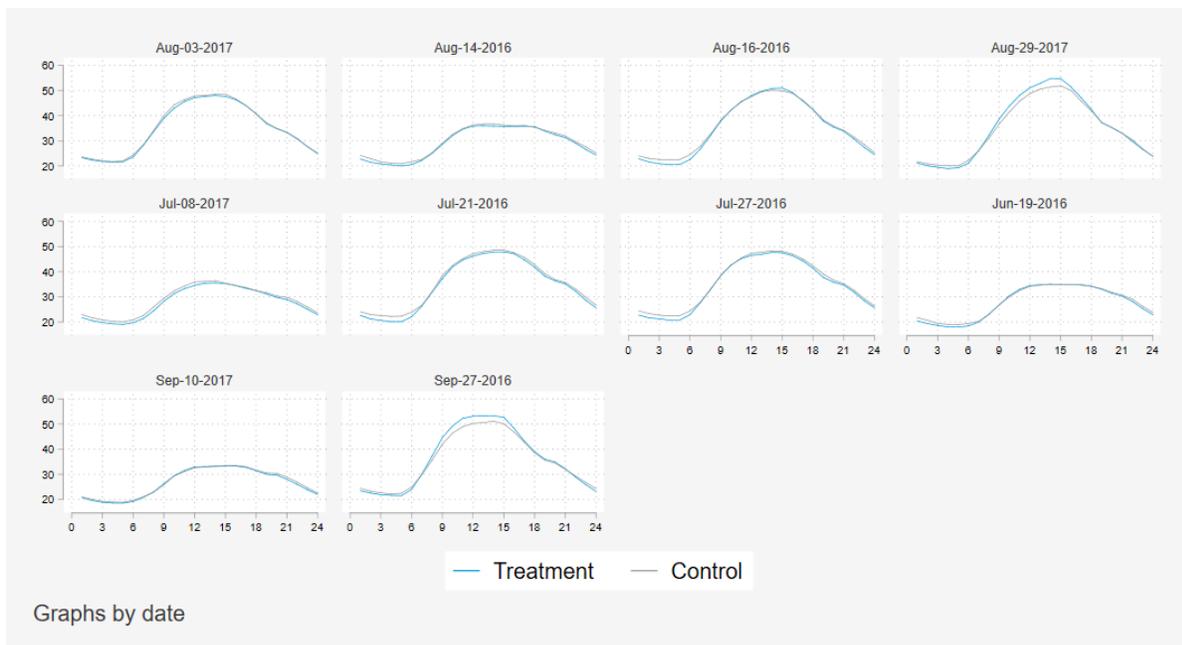
E. COMPARISON OF CONTROL AND TREATMENT CUSTOMERS – COMMERCIAL THERMOSTAT EVENTS

The quality of the match was assessed by comparing the aggregated hourly loads of the treatment and control groups using the testing data. The model with the best fit (RMSE) among those with the top three with the least bias (Model 11) was selected.

Table 34: Commercial Thermostat Event Matching Model Assessment Statistics

Model	Avg. kW	Avg. Error	MSE	Relative RMSE	% Bias	Abs % Bias
11	40.59091	.0179255	.9750575	.0243269	.0004416	.0004416
1	46.06397	-.1087559	5.597601	.0513617	-.002361	.002361
3	43.77487	.1074605	2.332191	.0348865	.0024548	.0024548
5	41.73522	-.1926723	8.938592	.0716361	-.0046165	.0046165
7	41.50603	-.2383966	2.717625	.0397176	-.0057437	.0057437
10	44.73293	.3328576	2.049462	.0320031	.007441	.007441
4	44.9217	.3371213	2.982354	.0384435	.0075046	.0075046
12	40.57112	-.7953912	3.498494	.0461024	-.0196049	.0196049
2	47.04164	1.074951	4.361097	.0443931	.022851	.022851
6	43.10268	1.695083	4.458417	.0489876	.0393266	.0393266
8	44.76113	-1.980755	7.908326	.0628263	-.0442517	.0442517
9	40.57227	-2.29842	9.086158	.0742952	-.05665	.05665

Figure 21: Treatment and Control Loads on Proxy Days, Selected Model



F. NON DISPATCHABLE ENERGY SAVINGS MODEL SELECTION – BIAS AND FIT METRICS FOR CPP-TOU AND TOU

The quality of the models was assessed by comparing the accuracy of predictions for time periods that were not used in model development (i.e., the testing data). Below are the bias and fit metrics for all models tested. The model with the best fit (RMSE) among those with the top three with the least bias (Model 11) was selected. The best model was selected for each segment. The table below show the results if the same model had been implemented for each segment.

Table 35: CPP-TOU and TOU Non-Dispatchable Impacts Model Selection Metrics

model	Avg. kW	Avg. Error	% Bias	MAPE	MSE	RRMSE
17	1.8907	-0.0005	-0.0003	0.0281	0.0043	0.0349
18	1.8907	-0.0010	-0.0005	0.0283	0.0044	0.0349
13	1.8907	-0.0011	-0.0006	0.0285	0.0044	0.0350
12	1.8907	-0.0011	-0.0006	0.0283	0.0044	0.0350
19	1.8907	-0.0011	-0.0006	0.0283	0.0043	0.0349
16	1.8907	-0.0012	-0.0006	0.0283	0.0044	0.0350
11	1.8907	-0.0012	-0.0007	0.0283	0.0044	0.0350
14	1.8907	-0.0014	-0.0007	0.0285	0.0044	0.0350
20	1.8907	-0.0015	-0.0008	0.0278	0.0043	0.0347
6	1.8907	0.0016	0.0008	0.1842	0.1529	0.2068
15	1.8907	-0.0020	-0.0011	0.0280	0.0043	0.0348
7	1.8907	0.1462	0.0773	0.3243	0.4402	0.3509
1	1.8907	0.1584	0.0838	0.4031	0.6847	0.4376
5	1.8907	0.1679	0.0888	0.4026	0.6682	0.4323
10	1.8907	0.1853	0.0980	0.3544	0.5004	0.3741
4	1.8907	0.1993	0.1054	0.4001	0.6434	0.4242
9	1.8907	0.2079	0.1099	0.3731	0.5498	0.3922
3	1.8907	0.2107	0.1114	0.3877	0.5959	0.4083
8	1.8907	0.2142	0.1133	0.3764	0.5587	0.3953
2	1.8907	0.2168	0.1147	0.3779	0.5614	0.3963

Figure 22 shows the correlation between the average pretreatment TOU participant usage (kwh) and each of the non-equivalent control groups.

Figure 22: Correlation between TOU Group and Non-Equivalent Controls (Pre-treatment)

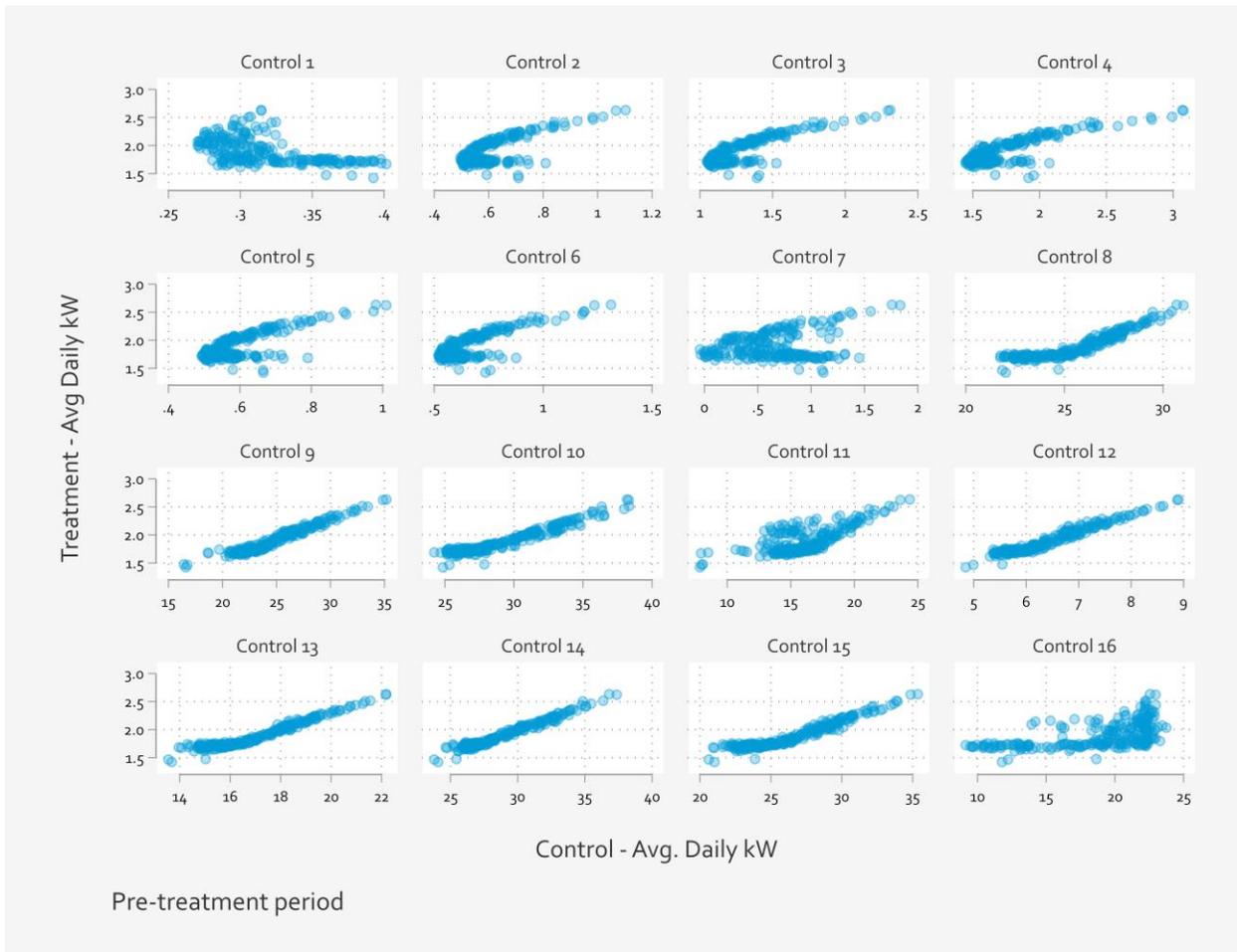
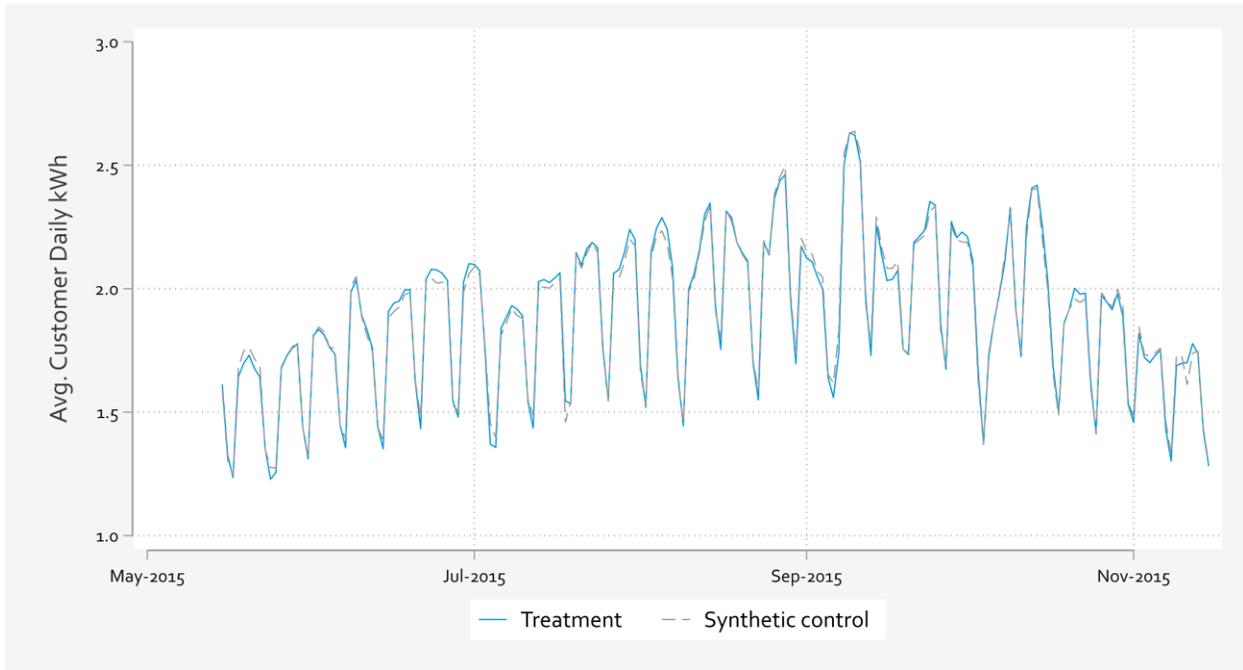


Figure 23 compares the TOU-CPP and TOU combined customer loads to the synthetic control group prior to the implementation of TOU. Differences between the two groups are nearly indistinguishable.

Figure 23: TOU Pre-treatment Comparison with Synthetic Control (Out-of-Sample)



G. NON DISPATCHABLE ENERGY SAVINGS MODEL SELECTION – BIAS AND FIT METRICS FOR COMMERCIAL THERMOSTATS

The quality of the models was assessed by comparing the accuracy of predictions for time periods that were not used in model development (i.e., the testing data). Below are the bias and fit metrics for all models tested. The model with the best fit (RMSE) among those with the top three with the least bias (Model 11) was selected.

Table 36: Commercial Thermostat Non-Dispatchable Impacts Model Selection Metrics

Model	Avg. kW	Avg. Error	MSE	Relative RMSE	% Bias	Abs % Bias	Model
20	7.438019	-.0036602	.0473004	.0226286	-.0004921	.0292398	.0004921
14	7.438019	-.0038636	.0470282	.0225437	-.0005194	.0291556	.0005194
13	7.438019	-.0038696	.0470157	.0225332	-.0005202	.0291517	.0005202
19	7.438019	-.0038698	.0472015	.0225941	-.0005203	.0292093	.0005203
16	7.438019	-.0039086	.0489735	.023041	-.0005255	.0297525	.0005255
17	7.438019	-.0039763	.0485559	.0228566	-.0005346	.0296254	.0005346
15	7.438019	-.0039879	.0479607	.0227533	-.0005361	.0294432	.0005361
18	7.438019	-.004051	.0470967	.0225572	-.0005446	.0291768	.0005446
12	7.438019	-.0040899	.0486024	.0228827	-.0005499	.0296395	.0005499
6	7.438019	-.0044789	.0976143	.0316742	-.0006022	.0420049	.0006022
11	7.438019	-.0050999	.050072	.0232072	-.0006857	.0300843	.0006857
10	7.438019	-.0052419	.0971398	.0311567	-.0007047	.0419026	.0007047
4	7.438019	-.005316	.0959756	.0310321	-.0007147	.0416508	.0007147
5	7.438019	-.0053193	.0969921	.0310642	-.0007151	.0418708	.0007151
3	7.438019	-.0054085	.0973539	.0312931	-.0007271	.0419488	.0007271
7	7.438019	-.0054639	.0985662	.0315649	-.0007346	.0422092	.0007346
9	7.438019	-.0054686	.0943326	.0305752	-.0007352	.0412927	.0007352
8	7.438019	-.005696	.0946509	.0306187	-.0007658	.0413623	.0007658
2	7.438019	-.0057171	.0994115	.0314991	-.0007686	.0423898	.0007686
1	7.438019	-.0061101	.0989736	.0313146	-.0008215	.0422963	.0008215

Figure 24 shows the correlation between the average commercial thermostat customer (kwh), the matched control group, and each of the non-equivalent control groups. Note that correlation is highest for the matched control group (0.99). Only data from the pre-treatment period is included.

Figure 24: Correlation between TOU Group and Non-Equivalent Controls (Pre-treatment)

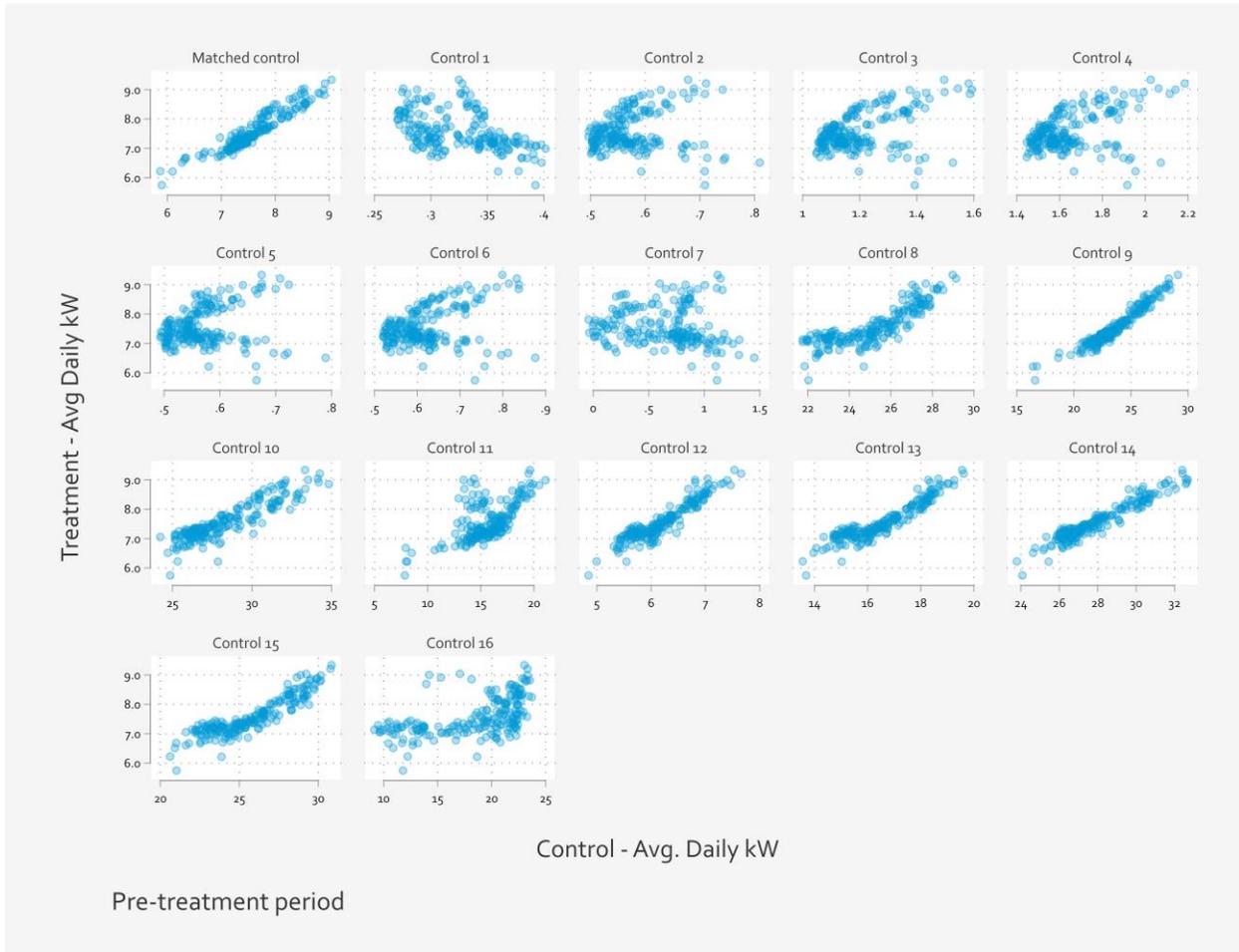


Figure 25 compares the commercial thermostat group to the synthetic control prior to installation of the thermostat. To assess the quality of the synthetic control, the pre-treatment data was split into a training period, used to develop the model, and a testing period, used to assess the accuracy of the estimates (out of sample). Differences between the two groups are nearly indistinguishable.

Figure 25: Commercial Thermostat Pre-treatment Comparison with Synthetic Control (Out-of-Sample)

