2015 Load Impact Evaluation of California's Statewide Nonresidential Critical Peak Pricing Program

Public Version

April 1, 2016

Prepared for
Pacific Gas and Electric Co.
Southern California Edison Co.
San Diego Gas and Electric Co.

Prepared by
Stephen George,
Senior Vice President

Eric Bell, *Senior Consultant*

Marshall M. Blundell,
Lead Analyst

Adriana Ciccone,
Senior Analyst

CALMAC ID PGE0376
Nexant, Inc.

Table of Contents

1 Executive Summary

This report presents the 2015 ex post load impact estimates for the nonresidential critical peak pricing (CPP) tariffs that are implemented by California's three electric investor-owned utilities (IOUs): Pacific Gas and Electric Co. (PG&E); Southern California Edison (SCE); and San Diego Gas and Electric Co. (SDG&E). Ex ante estimates for 2016 through 2026 are also presented.

CPP is an electric rate in which a utility charges a higher price for consumption of electricity during peak hours on selected days, referred to as critical peak days or event days. PG&E markets their CPP rate as Peak Day Pricing, while SCE markets their CPP rate as Summer Advantage Incentive. SDG&E does not market the program under a different name, and refers to it as Critical Peak Pricing. Typically, CPP hours coincide with the utility's peak demand and CPP days are called 5 to 15 times a year when demand is high and supply is short. The higher price during peak hours on critical event days is designed to encourage reductions in demand and reflects the fact that electric demand during those hours drives a substantial portion of electric infrastructure costs. Compared with non-CPP tariffs, the higher CPP prices are typically offset by reductions in energy prices during non-peak hours, reductions in demand charges or both.

Most customers[1] that faced CPP rates in California in 2015 were defaulted onto CPP from pre-existing TOU rates that already provided incentives to shift or reduce electricity use during peak periods. In 2014, all three IOUs also offered CPP rates to small and medium businesses (SMB) on a voluntary basis. PG&E began defaulting SMB customers onto CPP in 2014. SDG&E will begin to default their SMB customers onto CPP in 2016, and SCE will begin to default their SMB customers onto CPP starting in 2018. The customers who have been defaulted to the CPP rate are the primary focus of this evaluation. Most customers on CPP rates are provided with the opportunity to hedge against bill volatility by protecting a portion of their load from the higher prices during the peak period on critical event days.

This evaluation is designed to address several research questions, including:

- How much demand reduction did CPP participants deliver at each utility during 2015 events (i.e., what are the ex post load impacts)?
- Did the estimated demand reductions vary across events and did they vary by temperature conditions?
- How do the number of accounts, load, demand reductions and performance vary across industries, location and customer size categories?
- Do demand reductions vary based on the presence of enabling technology and/or participation in other DR programs?
- Have customer demand reductions grown, decreased or remained constant across years?

[1] The term "customer" is used synonymously with "service account" throughout this report.

- What amount of demand reduction can CPP rates provide under normal (1-in-2) and extreme (1-in-10) peaking conditions (i.e., what are the ex ante load impacts)?
- How are CPP demand reduction resources forecasted to change in future years? How much of the forecasted change is due to changes in program enrollment versus differences in weather between ex post and ex ante weather conditions?
- What is the effect of in-season support on load impacts for PG&E SMB CPP customers?

Table 1-1 summarizes the 2015 program year default CPP results for PG&E, SCE and SDG&E and compares them with the 2014 program year impacts.

Table 1-1: Summary of 2014 and 2015 Statewide Default CPP Impacts for Large C&I Customers (Average Event Hour)

Utility	Year	Number of Events Called	Approximate Customer Count	Temperature (°F)	Reference Load (MW)	Load Impact (MW)	Percent Impact (%)
PG&E	2014	10	1,815	88.4	504.6	41.0	8.12%
	2015	15	2,093[2]	91.4	557.8	29.8	5.34%
SCE	2014	12	2,670	86.7	594.4	29.6	4.98%
	2015	12	2,677	86.5	581.5	29.0	4.99%
SDG&E	2014	6	1,142	82.7	290.6	25.4	8.76%
	2015	5	1,207	90.8	305.5	25.3	8.29%
Total	2014	–	5,627	–	1,389.6	96.0	6.91%
	2015	–	5,977	–	1,444.8	81.4	5.63%

Table 1-2: Summary of 2015 PG&E SMB Default CPP Impacts Average Event Hour

Segment	Approximate Customer Count	Avg. Event Temperature (°F)	Reference Load (kW)	Load Impact (kW)	Percent Impact (%)	Aggregate Load Impact (MW)
SMB Default	148,782	92.6	5.1	0.04	0.8%	5.8
Early Enrollment Customers	4,016	90.9	5.3	0.13	2.4%	0.5

[2] This number represents Large Default customers. Impacts for Small & Medium Businesses, Opt In customers and Early Enrollment groups are reported in the PG&E Ex Post section of this report.

While CPP rates at all three utilities are conceptually similar, any cross-utility comparisons must be made with caution due to differences in the rates, event patterns, customer mix and penetration of other DR programs prior to implementation of default CPP. For example, PG&E, SCE and SDG&E called 10, 12 and 5 CPP events, respectively. Two event days were called across all three territories; September 9 and September 10, 2015. In addition, SDG&E has a longer critical peak period—11 AM to 6 PM—than PG&E or SCE and also dispatches CPP on Saturdays, due to its system load patterns.

Default enrollment of large, nonresidential customers for all three IOUs combined was higher in 2015 than in 2014 by approximately 6%.[3] However, the aggregate reference load only increased approximately 4%. Overall, approximately 5,977 large customers were enrolled on default CPP for the 2015 summer.

Between 2014 and 2015, enrollment in opt-in CPP at PG&E increased from around 4,700 service accounts to around 7,332;[4] and at SCE enrollment grew from approximately 800 service accounts to approximately 880. However, the results are not representative of future demand response expected when SMB customers are defaulted onto CPP.

A number of PG&E SMB customers were defaulted onto the CPP rate on November 2014. These customers are referred to as the SMB default CPP population. The average number of PG&E SMB default CPP customers participating in the 2015 events was 148,782.

Starting in November 2013 and through early 2014, PG&E engaged in a marketing effort to SMB customers who were due to be defaulted onto PG&E's CPP tariff in November 2014 to encourage them to enroll early in the CPP tariff on an opt-in basis. This customer group, which this report refers to as the Early Enrollment Group (EEG), yielded an average of 4,760 EEG CPP customers in 2014, of which 4,016 remained on the rate and participated in the 15 events in 2015.

Table 1-3 summarizes PG&E, SCE and SDG&E ex ante load impacts for forecast years 2016 and 2026 under 1-in-2 weather conditions. Enrollments, and consequently aggregate reference loads, are forecasted to increase substantially in the next 10 years as default CPP is introduced to small and medium C&I customers. The magnitude of ex ante impacts from small and medium customers under default dynamic pricing is far less certain than it is for large customers. Due to the limited empirical data, small and medium C&I ex ante impact estimates should be interpreted with caution.

---

[3] All customers who were defaulted onto the program or would have been defaulted onto CPP due to their size are referred to as default CPP customers in this report.

[4] The majority of the new opt-in customers were SMB customers subject to an early enrollment campaign prior to default.

Table 1-3: Summary of 2016 and 2026 Ex Ante Load Impacts (1 to 6 PM) 1-in-2 Weather Conditions for August System Peak Day

Utility	Demand Size	Year	Enrollment Forecast	Reference Load (MW)	Load Impact (MW)	Percent Impact (%)
PG&E (1-6 PM)	Large	2016	2,483	722.8	35.6	4.93%
		2026	3,154	914.5	45.7	5.00%
	Medium	2016	33,118	822.7	6.0	0.73%
		2026	69,474	1,784.1	13.1	0.73%
SCE (1-6 PM)	Large	2016	2,718	623.7	27.7	4.44%
		2026	2,813	645.4	28.6	4.44%
	Medium	2016	0	-	-	-
		2026	13,918	452.3	3.3	0.73%
SDG&E (1-6 PM)	Large	2016	1,271	286.8	22.1	7.71%
		2026	1,419	320.2	24.6	7.69%
	Medium	2016	19,308	631.6	5.8	0.92%
		2026	16,260	531.9	4.9	0.92%
Total	Large	2016	6,472	1,633.3	85.4	5.23%
		2026	7,387	1,880.1	99.0	5.27%
	Medium	2016	52,426	1,454.2	11.9	0.81%
		2026	99,652	2,768.3	21.3	0.77%

Key findings for PG&E include the following:

- **A reduction in year over year performance on a per customer basis was observed in all groups compared with prior year impacts**. This large reduction was driven by much lower event performance in the latter event days for persistent customers (e.g., those in the program for multiple years) and changes in customer mix. Large default PDP had an average event impact of 29.8 MW (5.3%) and SMB default PDP had an average event impact of 5.8 MW (0.8%), 0.04 kW per customer. EEG participants had an average event impact of 0.5 MW (2.4%), a reduction of more than 50% compared with 2014. Legacy opt-in PDP had an average event impact of 1.4 MW (8.4%), an increase of 0.1 MW relative to 2014. 2015 opt-In customers that enrolled on or after October 1, 2015 had an average event impact of 1.2 MW (5.9%).
- **The differences between individual 2015 event day results and the average event day results are not statistically significant for large customers.** Estimated demand reductions for large default customers vary from 17.7 MW to 49.7 MW for individual events. On a percentage basis, demand reduction estimates vary from 3.1% to 9.0%. The confidence bands for individual event days are relatively wide and reflect the addition of new customers to the program who exhibited highly variable event performance. While it is technically accurate that the difference between any single event day and the average event day was not statistically significant at a 90% confidence level, the single event day results were obviously different from one another in a significant way. This will be discussed in greater detail in Section 4.1.

- **Manufacturing, Ag, and Utilities sectors accounted for the majority of the large customer aggregate impact and were the only industries to provide a percent reduction above 2.7%.** Impacts for Offices, Institutional/Government, Schools, and Other are low and statistically insignificant.
- **Due to their relatively low performance, large default Greater Bay Area customers accounted for only 24% of the aggregate impact, but 45% of customers in default PDP**. The results are the opposite for the Other LCA, which accounted for 32% of the aggregate impact and only 18% of customers.
- **Across the 15 events in 2015, Default SMB customers delivered between -9.7MW and 26.5MW of aggregate impact,** ranging from -1.3% to 3.3%. These customers improved their performance in the program significantly during the last third of the season.
- **1-in-2 August ex ante load impacts for large customers are expected to grow from 35.6 MW in 2016 to 45.7 MW in 2026**. This growth is expected partly because PG&E expects additional large customers to default onto CPP.
- **Default CPP load impacts for medium C&I customers under 1-in-2 August ex ante conditions are expected to grow from 6.0 MW in 2016 to 13.1 MW in 2026**. This growth is expected because PG&E expects to approximately double the population of default medium customers on CPP.
- **Small C&I Default CPP load impacts under 1-in-2 August ex ante conditions are expected to grow from 1.8 MW in 2016 to 2.4 MW in 2026**. This growth is expected because PG&E expects the population of default small customers on CPP to increase by approximately 40%.

Key findings for SCE include the following:

- **In aggregate, default CPP participants reduced demand by 5.0% across the 2 to 6 PM event window for the average event day, delivering 29.0 MW of demand reduction.**
- **The differences between individual event day results and average event day results are not statistically significant for any of the 12 event days.** Estimated demand reductions vary from 21.8 MW to 37.0 MW for individual events. On a percentage basis, demand reduction estimates vary from 3.8% to 6.5%. While day-to-day performance can vary, much of the variation across days is explained by statistical uncertainty.
- **Demand reductions were highly concentrated in specific industry segments—Manufacturing, and Wholesale, Transport & Other Utilities.** These customers make up 45% of program enrollment and 45% of program load at SCE, but contribute 83% of the estimated demand reductions. Manufacturing customers reduce a larger share of their demand than the average CPP customer, delivering a reduction of 11.7%.
- **The estimated load impacts for 2015 are statistically indistinguishable from 2014 estimated impacts.**

- **In aggregate, opt-in CPP participants reduced demand by 0.9% across the 2 to 6 PM event window for the average event day, delivering 0.2 MW of demand reduction.**

- **Under SCE's current enrollment projections, the load reduction capability for large default CPP customers is expected to exhibit only slight growth.** 2016 aggregate load impacts at SCE during an August event for the 1-in-2 weather year scenario is estimated to be 27.7 MW.

- **Default CPP load impacts for small and medium C&I customers are highly uncertain.** The estimate developed by assuming a modest percentage impact informed by PG&E's default SMB customers assumes they will deliver approximately 10.2 MW in 2018.

Key findings for SDG&E include the following:

- **In aggregate, participants reduced demand by 8.3% across the 11 AM to 6 PM event window for the average event, delivering 25.3 MW of demand reduction.**
- **The differences between three of the individual event day results and average event day results are not statistically significant.** Results on September 9 were significantly higher than average, and those on September 11 were significantly lower, which is attributed to the 11th being a pseudo holiday, with some businesses closed, as well as it being the third consecutive event day. Estimated demand reductions vary from 16.4 MW to 35.9 MW for individual events. On a percentage basis, estimated demand reductions vary from 5.5% to 11.0%.
- **Demand reductions were concentrated in wholesale, transport and other utilities and institutional/government sectors.** These customers make up 25.3% of program enrollment and 19.4% of the program reference load, but account for 55.3% of the estimated demand reductions. On a percentage basis, the highest-performing industry was agriculture, mining and construction, with average load reductions of 30%; however, there is still a large amount of uncertainty in the estimate as the sector is comprised of only 15 customers. These customers accounted for just 1% of both program enrollment and reference load.
- **Ex ante impacts for SDG&E's large customers grow moderately from year to year.** The aggregate 1-in-2 weather year August demand reductions are forecasted to grow from 22.9 MW in 2016 to 25.5 MW in 2026.
- **Default CPP load impacts for medium C&I customers are highly uncertain.** The estimate developed by applying percentage impact forecasts from PG&E's medium customers indicates that they will deliver approximately 5.8 MW in 2016 to 4.9MW in 2026 under a 1-in-2 SDG&E weather scenario.

2 Introduction

The 2015 statewide evaluation of California's nonresidential Critical Peak Pricing (CPP) programs is designed to meet multiple objectives. The primary objective is to develop ex post and ex ante load impact estimates for each utility. The ex post estimates presented in this report represent CPP performance for events called in the 2015 calendar year and reflect the specific system, dispatch, enrollment, weather and economic conditions that were in effect at each utility on those event days. These estimated impacts are not necessarily reflective of what could be expected under conditions that may occur in the future. Ex ante load impacts are forward looking and are designed to reflect the load reduction capability of the CPP program under a standard set of system and resource planning conditions. Typically, ex ante estimates are based on the ex post analysis, but the ex ante estimates require adjustments to reflect appropriate ex ante conditions. Ex ante load impacts are not only important for system and resource planning, but also for comparing load impacts across CPP programs and for cost-effectiveness analyses.

This evaluation is designed to address the following research questions:

- How much demand reduction did CPP participants deliver at each utility during 2015 events (i.e., what are the ex post load impacts)?
- Did the estimated demand reductions vary across events and did they vary by temperature conditions?
- How do the number of accounts, load, demand reductions and performance vary across industries, location and customer size categories?
- Do demand reductions vary based on the presence of enabling technology and/or participation in other DR programs?
- Have customer demand reductions grown, decreased or remained constant across years?
- What amount of demand reduction can CPP rates provide under normal (1-in-2) and extreme (1-in-10) peaking conditions (i.e., what are the ex ante load impacts)?
- How are CPP demand reduction resources forecasted to change in future years? How much of the forecasted change is due to changes in program enrollment versus differences in weather between ex post and ex ante weather conditions?
- What is the effect of in-season support on load impacts for PG&E SMB CPP customers?

2.1 Nonresidential CPP Programs at California IOUs

CPP is an electric rate in which a utility charges a higher price for consumption of electricity during peak hours on selected days, referred to as CPP days or event days. Typically, peak hours coincide with a utility's peak demand and CPP days are called 5 to 15 times per year when demand is high and supply is short. The higher price during peak hours on CPP days is designed to encourage reductions in demand and reflect the fact that electric demand during those hours drives a substantial portion of electric infrastructure costs. Compared with non-CPP tariffs, the higher CPP prices are typically offset by reductions in energy prices during non-peak hours, reductions in demand charges or both. Most customers that faced CPP rates in California in 2015 were defaulted onto CPP from pre-existing TOU rates that already provided incentives to shift or reduce electricity use during peak periods. Large C&I customers were defaulted onto CPP, starting in 2008.[5] In 2014, all three IOUs also offered CPP rates to small and medium businesses (SMB) on a voluntary basis. PG&E began defaulting SMB customers onto CPP in late 2014. SDG&E plans to start defaulting SMB customers onto CPP in 2016, and SCE will start its SMB default in 2018.

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

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

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

PG&E, SCE and SDG&E have developed CPP tariffs that adhere to the principles and direction provided by D.10-02-032. However, many details of the CPP tariffs vary across utilities. Among the important differences are:

- The rate design window schedule for each IOU caused the CPP rates to be implemented at different times. SDG&E was the first to default customers onto a CPP tariff, on May 1, 2008. SCE began defaulting customers onto CPP 18 months later in October 2009 and PG&E began defaulting customers in May 2010;
- SDG&E defaulted customers whose maximum demand exceeded 20 kW for the prior 12 consecutive months. PG&E defaulted customers with maximum demand that exceeded 200 kW for three consecutive months in the prior year. In addition, PG&E transitioned approximately 110 small customers that had voluntarily enrolled on SmartRate, a pure CPP tariff, to the new CPP tariff. SCE required only that a customer's monthly maximum demand exceed 200 kW;

[5] In this report, definitions of large, medium and small C&I customers are consistent with demand response reporting to the California Public Utilities Commission (CPUC). Accounts with peak demand of 200 kW or more are considered large C&I, while accounts between 20 kW and 200 kW are referred to as medium C&I. Small commercial customers include all accounts with annual peak demands under 20 kW. This is in contrast to how PG&E and SCE rate schedules define customers. At these utilities, customers with annual peak demand above 500 kW are categorized as large C&I and those with demands between 200 kW to 500 kW are categorized as medium.

- At SDG&E, customers are locked into the CPP rate for a full year if they do not opt out prior to going on the default rate, while customers can opt out at any time at PG&E and SCE;
- SCE and PG&E share the same event hours, 2 to 6 PM. SCE and PG&E also share the same TOU peak period hours, noon to 6 PM, Monday through Friday. For SDG&E, both the CPP event period hours and TOU summer peak period hours are from 11 AM to 6 PM. Off-peak prices apply on the weekends at all three IOUs, unless a CPP event is called on a weekday;
- PG&E and SDG&E can call CPP events throughout the calendar year and on any day of the week, while SCE only calls events on non-holiday weekdays. PG&E is committed to a minimum of 9 and a maximum of 15 events each year. SCE plans to call 12 events each year and SDG&E is committed to a maximum of 18 events with no minimum; and
- PG&E notifies customers of CPP events via phone, email, pager or text by 2 PM on the day before an event, while SCE and SDG&E notify customers by 3 PM the day before.

There is one key feature that is common to the CPP tariffs for all three IOUs. PG&E, SCE and SDG&E all offer customers the ability to hedge part or all of their demand against higher CPP prices, a feature known as a capacity reservation level (CRL).

The default enrollment process differed significantly across utilities. At PG&E, more than 5,000 accounts were scheduled to be defaulted onto CPP, but the majority of them migrated to a TOU rate before being placed on the CPP tariff. By the end of summer 2011, approximately 1,750 PG&E accounts remained on default CPP. PG&E's CPP enrollment averaged: 1,627 customers in 2012; 1,717 customers in 2013; 1,815 customers in 2014, and 2,093 customers in 2015.

In November 2013, PG&E engaged in a marketing effort to SMB customers who were due to be defaulted onto PG&E's CPP tariff in November 2014 to encourage them to enroll early in the CPP tariff on an opt-in basis. This initiative is referred to as the Early Enrollment Group (EEG). Two waves of customers were recruited: one through email outreach at the end of 2013 and the other through direct mail early in 2014. This yielded an average of 4,760 EEG CPP customers in 2014, of which 4,016 remained on the rate and participated in the 15 PG&E CPP events in 2015. A subset of the EEG population was also involved in a program during the 2014 season to test the effectiveness of in-season education and feedback on event day performance. Prior to and on the day of each CPP event, participating customers received emails notifying them of the event and offering tips on how to reduce energy usage. Customers were also directed to a website that allowed them to develop an event day plan. Following each event, customers were given feedback about how they performed. PG&E has continued offering in-season support to customers enrolled in CPP.

At SCE, most of the 8,000 eligible accounts were placed on default CPP in fall 2009, but nearly half of them opted out to TOU before the first summer. By the end of summer 2011, roughly 3,000 accounts remained on default CPP. Notably, SCE customers transitioned to default CPP at the same time that a 3.1% rate reduction was implemented for large customers. During CPP events, CPP enrollment at SCE averaged 2,496 customers in 2013, 2,670 customers in 2014, and 2,677 customers in 2015. In 2018 SCE will begin defaulting SMB customers to CPP.

By the end of 2011, SDG&E had almost 1,300 accounts—or roughly 60% of eligible customers—on CPP and enrollment averaged 1,063 customers in 2013. In 2014, CPP enrollment averaged 1,142 customers, and grew to 1,207 customers by 2015. As indicated above, if a customer does not opt out within 45 days of becoming eligible for default CPP at SDG&E, they must stay on the rate for at least 12 months, whereas at PG&E and SCE, customers can opt out at any time.

All three utilities offer customers CPP bill protection during their default year, which ensures that the customer does not pay more for the energy commodity under CPP than they would have under the otherwise applicable tariff (OAT). The bill comparison is sent to customers at the end of their first year on the rate. If the bill comparison shows that the customer paid more under CPP than they would have if they were subject to the OAT, then the customer's account is credited the difference.

When assessing the impacts that are presented in subsequent sections, it is important to keep in mind that cross-utility comparisons of load impacts should be made with care. Each utility triggers CPP event days using their own protocols, which depend on forecasted conditions for their individual transmission and distribution system. Due to the climatic diversity in California, system load patterns across utilities are not always coincident, particularly between Northern and Southern California. For example, PG&E's system peaked on August 17, 2015, the SCE system peaked on September 8, 2015 while the SDG&E system peak occurred on September 9, 2015. Another key difference in ex post results is event duration. SDG&E uses a longer event window, 11 AM to 6 PM, than PG&E or SCE, which have a 2 to 6 PM window. Finally, another differentiator is the rates themselves. There are many differences in the details of the tariffs and the implementation processes across the three utilities. Although the basic structure of the rates is similar, tariff price levels themselves are fairly different.

Tables 2-1 and 2-2 provide examples of the default CPP and opt-out TOU rates at each utility. There are a number of different CPP rates at each utility, which vary with customer size and service voltage level. These various CPP rates also change over time due to periodic rate changes. Tables 2-1 and 2-2 illustrate that the rate components, credits and charges vary significantly across the utilities. Seasonal definitions also differ across the IOUs: PG&E defines summer as the period from May through October; while SDG&E defines summer as May through September; and SCE defines summer as June through September.

The critical peak price is typically an adder, in effect during CPP hours, which varies from a low of $1.20/kWh for PG&E E-19 and SDG&E AL-TOU to a high of $1.37/kWh for SCE TOU-GS-3 customers. The CPP credits take the form of reduced demand charges ($/kW), reduced consumption charges ($/kWh), or both. Customers on CPP experience on-peak demand credits that also vary substantially across utilities, ranging from: $6.37 per kW for PG&E E-19 customers; to $9.77 per kW for SDG&E AL-TOU customers; and $11.44 per kW for SCE customers on TOU-GS-3. While the utilities can offer energy credits for nonevent periods, for most participants, SCE does not and both PG&E and SDG&E's are currently set to $0 per kWh. SDG&E's peak energy and demand credits come in the form of a difference between the energy and demand rates that CPP customers pay and energy and demand rates under the OAT, rather than as explicit credits. The difference in summer on-peak demand charges is

$9.77 per kW and the differences in energy charges are $0.00 per kWh. The impact on customer bills is the same as that of an explicit credit.

Table 2-1: Example Summer Default CPP Rates at PG&E, SCE and SDG&E[6]

Season	TOU/CPP Component	Type of Charge/Credit	Period	Rate		
				PG&E E-19	SCE TOU-GS-3	SDG&E AL-TOU
Summer	TOU Component	Energy Charges (per kWh)	On-peak	$0.15	$0.14	$0.13
			Semi-peak	$0.11	$0.09	$0.12
			Off-peak	$0.08	$0.06	$0.09
		Demand Charges (per kW)	On-peak	$18.74	$18.83	$21.40
			Semi-peak	$5.23	$5.52	NA
			Maximum	$17.33	$16.14	$24.43
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.20	$1.37	$1.35
			On-peak	$0.00	NA	$0.000
			Semi-peak	$0.00	NA	$0.000
			Off-peak	NA	NA	$0.000
		Demand Credits (per kW)	On-peak	($5.92)	($11.44)	($11.03)
			Semi-peak	($1.46)	NA	NA
		Capacity Reservation Charge (per kW per month)	Summer	$12.17	$11.44	$6.07

6 Tables 2-1 and 2-2 do not include all CPP rates at each utility, and the rates shown are presented for illustrative purposes only. Rates may vary over the course of the program year, by customer size and service voltage level. The rates shown are for customers at the secondary service voltage level. E-19 is mandatory for PG&E customers who fail to meet the requirements of E-20, but have monthly maximum billing demand above 499 kW and is voluntary for PG&E customers with maximum billing demand greater than 200 kW and less than 500 kW; TOU-GS-3 is mandatory for SCE customers with maximum demand greater than 200 kW and less than 500 kW; and AL-TOU applies to all SDG&E customers whose monthly maximum demand equals, exceeds, or is expected to equal or exceed 20 kW. This example PG&E E-19 rate was effective March 1, 2016; the SCE TOU-GS-3 rate was effective April 1, 2014; and the SDG&E rates were effective May 1, 2014. Please consult each utility's website to obtain the CPP rates that were in effect for specific time periods.

Table 2-2: Example Winter Default CPP Rates at PG&E, SCE and SDG&E

Season	TOU/CPP Component	Type of Charge/Credit	Period	Rate		
				PG&E E-19	SCE TOU-GS-3	SDG&E AL-TOU
Winter	TOU Component	Energy Charges (per kWh)	On-peak	NA	NA	$0.12
			Semi-peak	$0.10	$0.09	$0.10
			Off-peak	$0.09	$0.07	$0.08
		Demand Charges (per kW)	On-peak	NA	$0.00	$7.66
			Semi-peak	$0.13	$0.00	NA
			Maximum	$17.33	$16.14	$24.43
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.20	NA	$1.35
			On-peak	NA	NA	$0.000
			Semi-peak	NA	NA	$0.000
			Off-peak	NA	NA	$0.000
		Demand Credits (per kW)	On-peak	NA	NA	NA
			Semi-peak	NA	NA	NA
		Capacity Reservation Charge (per kW per month)	Winter	NA	NA	$6.07

All IOUs offer the capacity reservation option, which is a type of insurance contract in which a customer pays a fee (paid per kW) to set a level of demand below which it will be charged the non-CPP, TOU price during event periods. Above the set level, a customer will pay the normal CPP price during an event. Customers choosing this option will pay the capacity reservation fee whether or not events are called and whether or not they actually reach their specified level of demand. SDG&E charges $5.44 per kW per month, year-round, for this option and the default level for SDG&E customers is 50% of a customer's maximum on-peak demand from the prior summer. Default CRLs are set to zero for those customers with no SDG&E summer usage history.

Not all CPP participants are offered the CRL option at PG&E. Customers on the A-10 rate cannot specify a CRL, but they can opt for a longer event window (12 to 6 PM) and/or to only be subject to every other CPP event. The longer event window results in a two thirds reduction in CPP charges and the every-other-event option results in a 50% reduction in CPP rate credits. PG&E sets the default level to 50% of the average on-peak demand from the prior summer, or to zero for those customers with no summer usage history. The capacity reservation charge only applies in the summer months at PG&E, and equals $12.94 per kW per summer month.

SCE's CRL options work much like PG&E's—the CRL is only available to customers with demands greater than 200 kW. Customers with demand less than 200 kW are instead offered a CPP-lite option that simply halves both the CPP credits and the CPP event-related charges. Once enrolled in CPP-lite, the customer must stay on the option for 12 consecutive months. Customers with demands greater than 200 kW may opt for a CRL. For those customers that come to CPP from CPP-Lite, SCE sets the default CRL at 50% of the customer's average summer on-peak demand. All other customers defaulted to CPP at SCE will have a default CRL set to zero. There is no explicit CRL charge in the SCE CPP tariff. Customers who elect a CRL do not earn summer CPP nonevent credits on the kW subject to CRL.

PG&E and SCE allow CPP customers to change their CRL once a year. SDG&E customers may only change their CRL upon their default to CPP or on their annual default anniversary.

2.2 Report Organization

The remainder of this report proceeds as follows. Section 3 discusses the methodology employed to estimate ex post and ex ante load impacts. PG&E's ex post and ex ante load impacts are presented in Sections 4 and 5; SCE's in Sections 6 and 7; and SDG&E's in Sections 8 and 9. Section 10 concludes this report with Nexant's evaluation-related recommendations for CPP. The appendices include additional details about the methodology and portfolio-adjusted estimates. Appendix A contains the candidate probit models for selecting the matched control group. Appendix B contains output from the matching model selection process and identifies the final model used to match the control group. Appendix C outlines the difference-in-differences regression model specifications. Appendix D provides an overview of the individual regression models. Portfolio-adjusted ex ante load impact forecasts are shown in Appendix E. Appendices F and G present the ex ante reference load and load impact regression models. Ex post and ex ante tables showing hourly load impacts for individual event days and across customer segments are provided as an electronic appendix.

3 Methodology

This section summarizes the methodologies used to estimate ex post and ex ante load impacts for the statewide CPP tariffs, as well as the process used to develop the two sets of weather conditions used in the ex ante forecast. One set of weather is meant to represent normal and extreme weather conditions that coincide with utility specific peak operating conditions. Utility-specific operating conditions were the basis for weather scenarios in all prior impact evaluations in California, although even these weather conditions were updated this year based on revised methods and more current weather data. The second set of weather is meant to represent normal and peak weather conditions that coincide with the California Independent System Operator (CAISO) peak operating conditions. The extent to which a utility's peak demands coincide with CAISO peak demands will determine how different these weather conditions and the resulting ex ante load impacts will be.

CPP tariffs introduce two changes in pricing. First, participants pay a higher price for electricity during peak hours on critical event days, which is designed to encourage reductions in demand. Second, participants receive a discount during nonevent hours. The rate discount for large and medium customers has been implemented at all three utilities primarily in the form of a reduction in summer on-peak demand charges.

The impacts estimated for 2015 focus on the incremental effect of event day prices on demand relative to peak period demand on non-CPP days. The impact of the rate discount on nonevent days is not estimated for three reasons: 1) prior analyses in 2010 and 2011 did not find statistically significant impacts due to the rate discount; 2) the pre-enrollment data needed to quantify the effect of the rate discount is too far in the past (four or five years prior) to be used; and 3) any changes are by now embedded in system load forecasts (and not incremental).

The methodology discussed in this section mainly concerns the estimation of impacts for historically large, defaulted CPP customers; while the methodology for SMB and EEG customers differed slightly. Load impacts for SMB and EEG customers were estimated solely using difference-in-differences with a matched control group. This approach was particularly suitable given the homogeneity of these customers' loads and the availability of a large pool of control candidates.

The remainder of this section:

- Describes the ex post evaluation methodology;
- Describes the matching model selection approach used;
- Describes the primary regression models and estimating sample used for ex post evaluation;
- Explains the methodology used to develop ex ante load impacts; and
- Summarizes the development of the ex ante weather conditions based on both utility specific and CAISO operating conditions.

3.1 Ex Post Evaluation Methodology

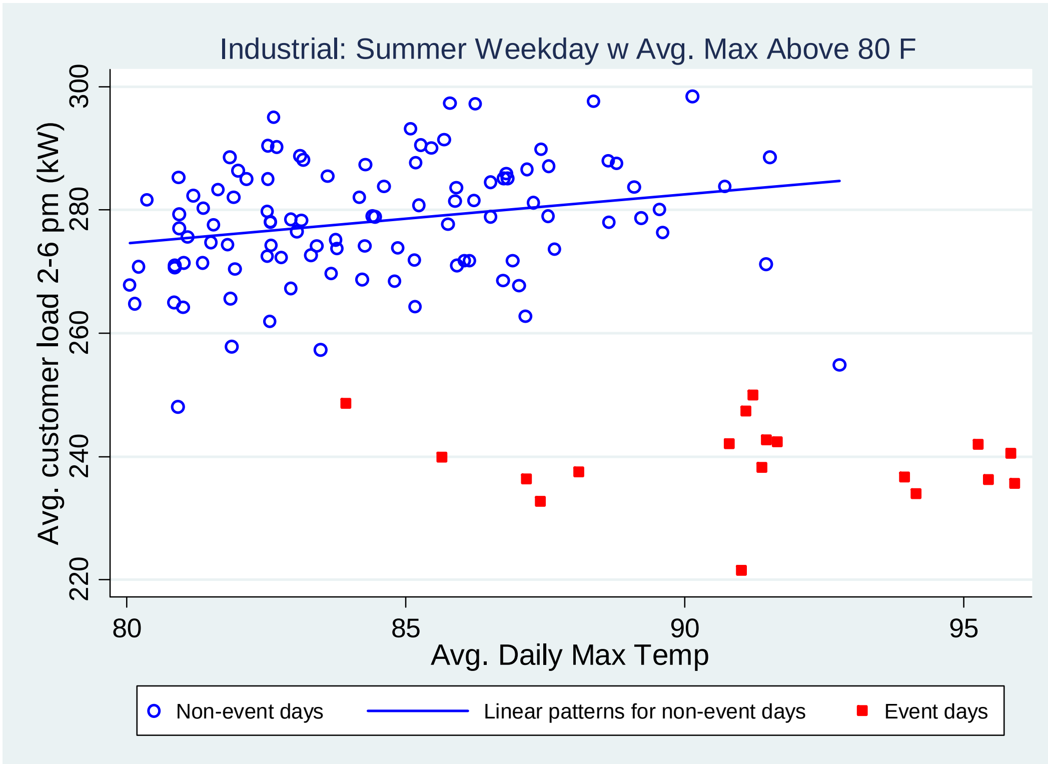
Ex post evaluation is designed to estimate demand reductions on event days when higher CPP prices are in effect. Ex post impacts reflect the enrollment mix, weather, dispatch strategy and program rules in effect at the time of each event and, as a result, may not reflect the full demand reduction capability of a resource. For example, if a resource is weather-sensitive and delivers larger demand reductions on hotter days, ex post events under cooler weather conditions understate the resource's capability.

To calculate load reductions for demand response programs, customers' load patterns in the absence of higher event-day prices—the reference load—must be estimated. Reference loads can be estimated using pre-enrollment data, by observing differences in behavior during event and nonevent days (i.e., a within-subjects design), by using an external control group (a between-subjects design) or through a combination of the above. Load impacts are estimated for 2015 using a combination of customer specific regressions and difference-in-differences. For the majority of customers we estimate difference-in-differences panel regressions that make use of both an external control group and nonevent day data. However, for CPP customers for which a similar control customer is unavailable, we estimate customer specific regressions—that is, we rely exclusively on each customer's electricity usage patterns on nonevent days to estimate reference load for event days.

Prior to the 2012 CPP evaluation, CPP load impacts had been estimated exclusively using the individual customer regression approach. Individual customer regressions have the benefit of easily producing impact estimates for any number of customer segments. However, applying a within-subjects evaluation approach to CPP in California suffers from drawbacks that stem from the fact that CPP events target the top system peak days of the year, which are almost by definition different from nonevent days. The 5 to 15 top days of the year are typically distinguished by higher temperatures and higher loads than those that occur on hot nonevent days—indeed, in California the very hottest weather drives the very highest system load days. The primary challenge this presents for evaluating CPP is that a within-subjects approach uses a customer's load on nonevent days to predict what load would have been in the absence of CPP on event days, but the nonevent days available for estimating reference load are not as hot as the event days. This puts the evaluator in the position of using individual regression models to predict out of sample, that is, to infer reference loads under temperature conditions not recently observed without CPP events in effect.

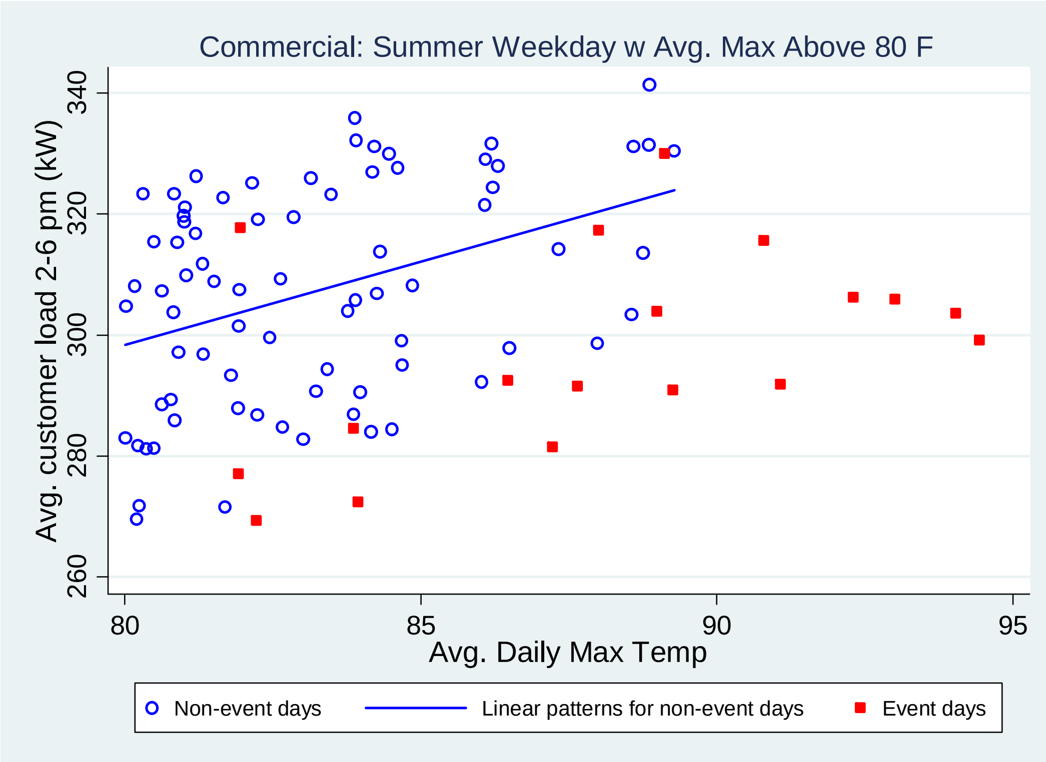
Since PG&E's historically large, defaulted CPP population is still mostly comprised of large C&I customers, it may be hypothesized that CPP load impacts are not weather sensitive. However, the CPP population is comprised of a diverse cross section of industry segments where some segments are known to be weather-sensitive and some are not. The CPP population is split roughly evenly between commercial and industrial customers. Figure 3-1 shows average industrial customer load on summer weekdays where the enrollment-weighted, average maximum temperature across three years is greater than 80°F. The customers included in this graphic are only those that have two years of experience on the PG&E CPP rate in both 2014 and 2015. Figure 3-1 shows that across the 12-degree swing in temperature (80°F to 92°F), the linear pattern for industrial load only increases by about 9.5 kW, or 0.79 kW per degree.

Figure 3-1: Average PG&E Industrial Customer Load (2–6 PM) on Hot Days



On the other hand, Figure 3-2 shows the same information for commercial CPP customers with two years of CPP history in 2014 and 2015. Across a narrower temperature range (80°F to 89°F) the linear pattern for these customers' load increased by 24.8 kW, or 2.75 kW per °F.

Figure 3-2: Average PG&E Commercial Customer Load (2–6 PM) on Hot Days



When estimating load impacts, getting the reference load right is crucial: a -5% error in reference load estimation for a 250 kW customer that reduces load by 10% results in a 50% understatement of load impact.[7] This concern was the main reason why, in 2012, the primary evaluation method transitioned from a within-subjects analysis involving individual customer regressions to a difference-in-differences estimate based on a selection of statistically matched control group. The accuracy of load impacts based on within-subjects regression analysis is highly dependent on accurately modeling the relationship between weather and load, which is challenging. With a matched control group and a difference-in-differences methodology, there is no need to specify a relationship between weather and load for ex post impact estimation and, therefore, no possibility of introducing a weather related specification error or bias into the impact estimation process. With this approach, the matched control group provides an estimate of what CPP customer load shapes would have looked like in the absence of the CPP event—under the very same weather conditions that CPP customers faced with respect to temperature, day of week, month and a host of unobservable factors that influence load patterns and load impacts. This event-day difference (the difference between the electric load observed in the control group and the treatment group) is corrected with an adjustment that takes into account differences in load that occur on nonevent days. The compound result (the difference-in-

[7] In this example, the customer's observed load would be 225 kW (250 kW reference load minus a 10% load impact equals 225 kW). The biased reference load would be 0.95 times the true reference load, which is 237.5 kW. The estimated load impact based on the biased reference load would then be 237.5 kW minus 225 kW, which equals 12.5 kW. This biased load impact is 50% lower than the actual load impact of 25 kW.

differences) is a simple and transparent approach that does not suffer from the specification error that can be a problem for individual regression modeling. Nonetheless, the matched control group approach rests on the assumption that usage on hot nonevent days is an accurate indicator of event day usage for control group customers and a reliable proxy for how treatment customers would have behaved on event days had they not been on CPP. This assumption is reasonable, but if for whatever reason it does not hold true (e.g., the relationship between event day and nonevent day usage is different for control group customers), there could be some bias in the results.

The key to the success using the matched control group approach, however, is a good match. An important factor in identifying a control group that looks like and behaves like CPP customers during nonevent days is the availability of a large pool of control candidates that contains comparable untreated individuals. In recent years, the prevalence of other events for other demand response programs such as AMP and CBP on CPP days and hot nonevent days has limited the size and scope of available control pool customers. In particular, it affected the ability to select suitable controls for industrial customers, which are generally larger and more difficult to match due to their often unique load patterns. The quality of a match is also influenced by the model class[8] and specification used to select potential matches. Unlike the adequacy of the control pool, which is fixed, the matching model can be selected to achieve a good match for as many customers as possible.

As described in more detail below, Nexant employed a rigorous approach to selecting an appropriate matching model that provides accurate matched control group counterparts for as many CPP customers as possible. Multiple models and their associated control groups were assessed in a cross-validation process that quantifies how well a control group predicts load on hot event-like days (proxy days) that were not used to match (an out-of-sample test). This approach was used to select among a set of carefully chosen models.

The subsections that follow describe the work to select a matching model and the subsequent control group selection. The load impact estimation procedure is then described.

3.1.1 Proxy Day Selection

Proxy event days are selected by matching historical events to nonevent days based on system loads, temperature conditions, month, and day of week[9].[10] CPP event days tend to differ from

---

[8] The class of model is the particular type of statistical model used. For example, probit and logistic regression models are two classes of model.

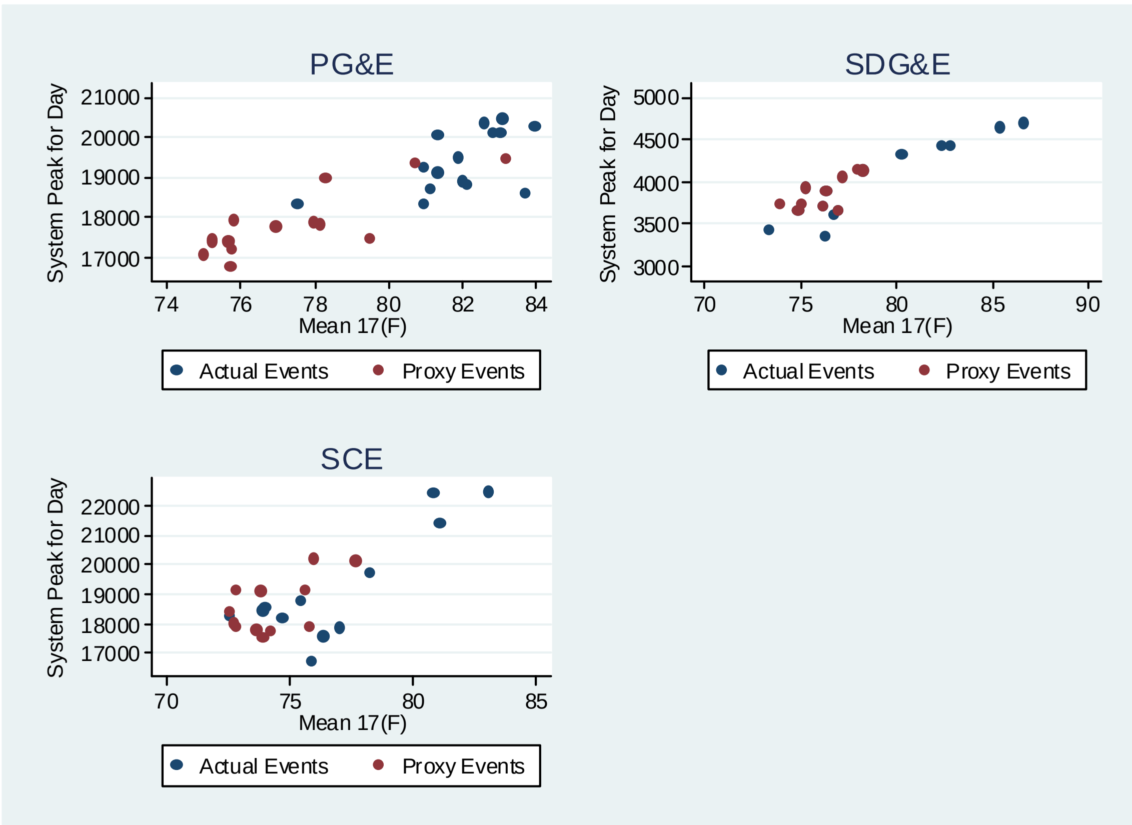
[9] To better represent schools in the SDG&E territory, separate proxy days were chosen. Because schools are typically closed during summers and open by early fall, any proxy day from the summer months will not be comparable in usage to the event days, which are all in the late summer and early fall when school is likely to be in session. These school-specific proxy days were restricted to be high temperature and high-system peak nonevent weekdays during the months of September and October, instead of from the pool of days between May 2015 and September 2015 for the other SDG&E industries.

[10] For PG&E, the temperatures were calculated based on the 5-station simple average of the Concord, Fresno, Sacramento, Red Bluff and San Jose weather stations. These are the same weather stations PG&E uses in assessing whether or not to dispatch programs. For SDG&E, the temperatures were from the Miramar weather station, which is used to assess when to dispatch events. For SCE, we used the simple average of the 9 weather stations that most correlated (correlation above 0.80) with system loads across 2007-2012.

typical days. System loads are typically higher, the days are hotter and they are more likely to fall on specific weekdays. Most event days were matched to similar nonevent days, however, comparable nonevent days are not available for some of the days with the most extreme weather.

Figure 3-3 shows how the proxy event days compare to actual event days for each utility. It plots the system peak load and the temperature conditions for each event day and for each proxy event day. In all three cases, the proxy days often have lower temperatures and loads than most event days.

Figure 3-3: Comparison of Actual and Proxy Event Days by Utility 2015



3.1.2 Matching Model Selection

Propensity score matching using a probit model was used to select valid control groups for each utility and relevant customer segment. This method is a standard approach for identifying statistical look-alikes from a pool of control group candidates and is typically used to address self-selection based on observable differences between CPP participants and non-participants.[11] The model specification affects both the quality of the match and the number of

[11] For a discussion of the use of propensity score matching to identify control groups, see Imbens, Guido W. and Woolridge, Jeffrey M. "Recent Developments in the Econometrics of Program Evaluation." *Journal of Economic Literature* 47.1 (2009): 5-86.

participants matched given some threshold for the acceptable quality of a match. In the 2015 evaluation, model selection was conducted in a rigorous and quantitative fashion in order to achieve an accurate match for as many CPP customers as possible.

Nexant first developed a set of candidate models to test. A candidate model could vary based on its specification, its *hard match* criteria, and its caliper. A hard match is when a different probit model is estimated for each value of a categorical variable and matches are constrained within that value. This ensures that CPP customers in a certain industry, for example, are only matched to control group customers in that same industry. The caliper is a constraint placed on the maximum proximity of a potential control group match. A caliper of 0.05, for example, restricts potential matches to be within 0.05 of the CPP customer's propensity score. The model specifications tested were carefully selected with a focus on matching on load magnitude and shape. Load magnitude and shape capture the effect of many other variables such as weather and location, so sparser models that describe load were included rather than models that included many observables. Models that include many observable characteristics are likely to be over-fitted and produce a poor match on load in event hours. The set of candidate models is outlined in Appendix A.

The set of candidate models and their associated control groups were evaluated using a cross-validation process that assesses the quality of the match based on how well they predict for excluded proxy days that are not used to estimate the model. The rationale for such a strategy is that, if a probit model yields a control group that accurately predicts treatment load on proxy days, it is expected to provide an accurate counterfactual for event day load. A good control group's load can be said to predict that of the treatment group accurately if it yields an unbiased and precise fit to that of the treatment group. In years prior to 2014, the quality of a match was inspected visually using a second set of proxy days. This process posed several issues, which we identified and sought to improve. Often, finding a single group of proxy event days that was similar to event days in terms of load and temperature proved difficult. Load and temperature on the second set of days were invariably much lower than event days. Therefore, the approach assumed that if a match was adequate on significantly cooler days with much lower load, then it was also adequate on hotter, higher load event days, which is not necessarily the case. In this year's approach, a similar assumption is made, but the approach has improved because the proxy days are only chosen from the hottest set of nonevent days that are most similar to event days, so the difference in temperature between proxy days and event days is not as large. Furthermore, only fitting a model once and evaluating its outcome on one set of days produces a variable and biased estimator of fit. Finally, the prior models were developed and tested on an ad hoc basis, and a purely visual inspection did not lend itself to recording and comparing the accuracy of different models. The 2014 evaluation improved on this approach, and the same methodology was applied for 2015, using a more quantitative model selection process that employs a method called *leave one out cross validation* (LOOCV) over a single set of proxy days. That set of days is selected to be as similar to event days as possible. LOOCV is outlined below:

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

i. Develop explanatory variables using data from all proxy days except the nth;
ii. Fit mth model using explanatory variables and select its associate control group;
iii. Record load of control group and treatment group individuals on the nth proxy day not used to fit the model; and
iv. Record number of treatment customers without a match.
2. Compute metrics to measure bias and goodness-of-fit of a control group match.
3. Retain models that match at least 75% of treatment customers.

Note that we only retained models that provided matches for over 75% of CPP customers. This was done in order to estimate impacts using difference-in-differences with a matched control group for the vast majority of customers. As noted above, we evaluate the quality of a control group based on the bias and precision of its match with treatment group load on excluded days. Table 3-1 shows the metrics computed in step 2. All metrics were computed over the relevant CPP event hours for each IOU, as that was the principal period over which we had to estimate load impacts.

Table 3-1: Control Group Accuracy Statistics

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

The statistics above use the following nomenclature:

- y - treatment kWh

- $\hat{y}$ - control kWh
- i - customers
- t - each individual proxy day
- n - total number of proxy days

The ultimate model selection was not performed in a rule-based fashion, but outcomes from the selection procedure were used to inform decision making. For example, while other model parameters were allowed to vary, Nexant decided to perform a hard match within industry for each IOU's matching model. This decision was made to limit the seasonal variation that was observed in certain industries, such as schools, and on the basis of its intuitive sense. The final model was then selected on the basis of average percent error, taking into account both its absolute value and its deviation across the excluded days, provided that the absolute sum of errors was acceptable relative to other potential models. The final model and its associated summary statistics and rankings are presented in Appendix B. For purposes of comparison, the 50 best performing models of those tested are presented, as well as the worst performing.

The matching methodology, and in particular the final model selected used to match customers, are sources of variation in results from year to year. Nexant used the same metrics to select matching models as it did in the 2014 evaluation. This year's final model featured the following predictors: demand (kW) in hours ending 15 and 18 on proxy event days, average daily consumption (kWh) on peak days, and percent of consumption in peak hours on proxy event days. Last year's model featured the following predictors: average daily consumption (kWh) on summer days, and percent of consumption in peak hours on proxy event days. Both models matched with industry, proxy day usage 2-tiles. The models were therefore similar, with this year's model featuring additional terms that take into account demand on proxy event days. Both models exhibited good performance in the selection metrics. The 2015 model's value of event hours average percent error was 0.09% and the 2014 model's value was 0.28%.

3.1.3 Control Group Selection

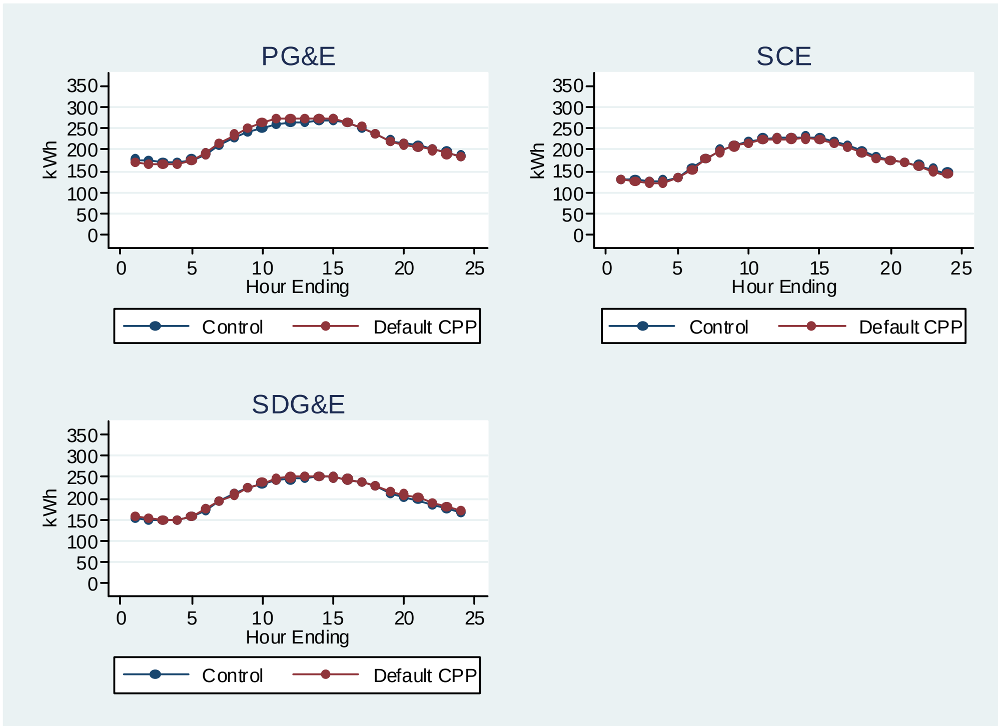
The control group was selected from customers who were not on CPP rates, but were on the otherwise applicable TOU tariff[12]. The best performing probit model and caliper were used to select customers from the control pool. The majority of CPP customers were successfully matched: 99% for PG&E[13]; 86% for SCE; and 93% for SDG&E. Customers who were not matched were moved to the individual customer regression group. Some control group customers were selected more than once—that is, if customer A was the best match for both customer B and customer C, it was chosen twice. Figure 3-4 shows load for the matched treatment and control customers on the average proxy event day. The loads match closely,

[12] Large customers who are on the otherwise applicable tariff opted-out of CPP. Due to CPP being the default rate, there is no pool of customers from which to select a control pool who are neither on CPP, nor haven't opted out of CPP.

[13] Match rate for Large Default customers for PG&E. Default SMB and EEG all found appropriate control customer counterparts during the matching process.

particularly during event hours. As explained in the next section, even these small differences are largely controlled for using the difference-in-differences methodology.

Figure 3-4: Comparison of Matched Treatment and Control Group Load on Average Proxy Event Day[14]



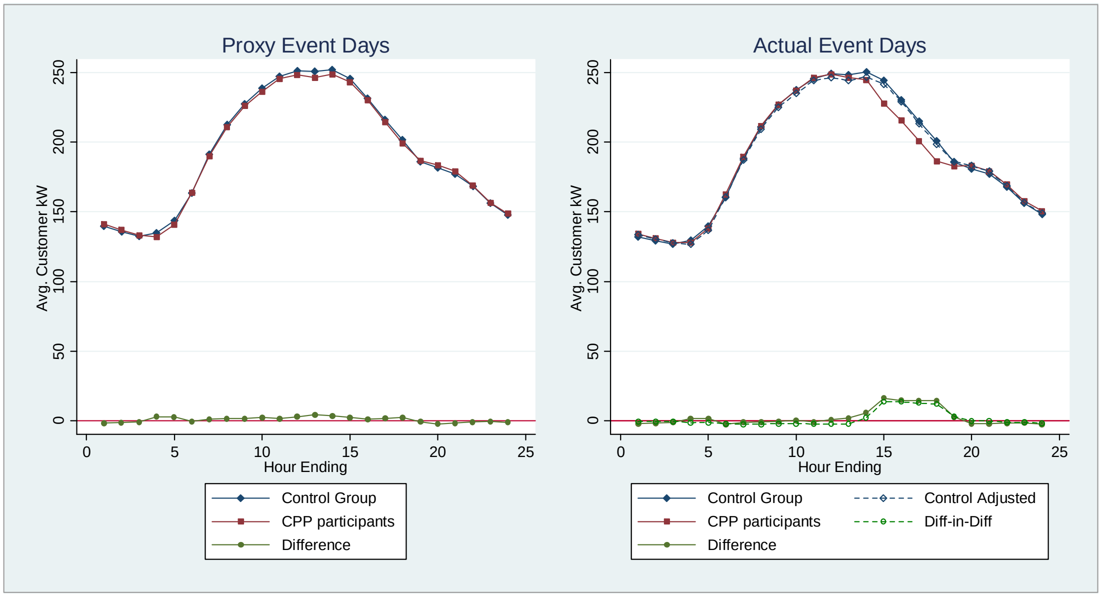
3.1.4 Difference-in-differences

Using the matched control groups, 2015 ex post CPP load impacts were estimated for the majority of customers with the difference-in-differences approach. Figure 3-5 illustrates the process conceptually. The left side of the figure shows hourly loads for CPP participants and control customers during proxy CPP days that have similar exogenous conditions, such as weather, as those that occur on event days. The loads on proxy days closely mirror each other for the two customer groups, indicating that the control group load is a good reference load for CPP participants.

The right side of Figure 3-5 shows the hourly loads for CPP participants and the control group on event days. As expected, the loads for the two groups diverge during event hours. Since the only known difference between the two groups is the fact that CPP customers face higher prices and control customers do not, the difference in observed loads can be attributed to the higher CPP prices on event days.

[14] Match for Large Default customers for PG&E shown

Figure 3-5: Example of Difference-in-differences Calculation (SCE)



The difference-in-differences calculation refines the impact estimates by netting out the small differences between the two groups observed during proxy event days (when CPP prices were not in effect for either group). This is illustrated on the right-hand side of Figure 3-6, at the bottom of the graph, where both the event-day weather difference and the difference-in-differences are shown. Overall, the adjustment is small, primarily because CPP participant and control group electricity use patterns are nearly identical during nonevent days. However, such differences can be larger for specific customer segments.

While load impact estimates using difference-in-differences calculations can be done arithmetically, that is, by subtracting the difference in observed loads between the two groups on proxy days from the difference on event days, the analysis can also be done using regressions. The regressions are used to produce correct standard errors. Importantly, the simple difference-in-differences regression produces exactly the same results as a hand calculation. This approach makes full use of nonevent and event day data for CPP and control group customers. It takes into account whether peak load patterns changed for CPP customers and whether load patterns changed for customers who did not experience CPP prices. It also accounts for differences between CPP participants and the control group observed during nonevent days.

The regression analysis employed a simple model that relies on no explanatory variables other than customer fixed effects and time effects.[15] This model does not rely on modeling the relationship between customers' electricity usage and other factors such as weather; it

15 Fixed effects account for unobserved time invariant customer characteristics. They also place all customers on the same scale. Time effects account for unobserved factors that are the same across all customers but unique to a specific time period.

is informed by control group customers that experience the event day weather, but do not experience the CPP event day prices. A second model was tested that included weather to assess if it affected the precision of the standard errors or changed the results. The second model produced results that were nearly identical to the first, indicating that the control group and the difference-in-differences adjustment provided nearly all of the explanatory power. Appendix C describes the mathematical representation of the model. It also includes the hourly regression coefficients, standard errors and R-squared values for the average event day regressions for each of the utilities.

3.1.5 Individual Customers Regressions

As its name suggests, this type of analysis consists of applying regression models to the hourly load data for each individual customer. The estimated coefficients vary for each customer, as does the amount of data used for each customer. The fact that each customer has its own parameters automatically accounts for variables that are constant for each customer, such as industry and geographic location. Customer specific regressions were only used for customers for which an adequate control group match could not be found.[16]

For each customer, we:

- Analyzed hot weekdays from 2015. To the extent possible, the regressions for each customer excluded cooler days, which typically do not provide much information about behavior under event conditions. For example, if the lowest event day maximum temperature a customer experienced was 100°F, only days that exceed 85% of 100°F (or 85°F) were included.
- Estimated 10 different regression models and used them to predict out-of-sample for event-like days where, in fact, CPP events were not called. This allowed us to identify the regression model that produced the most accurate results for each customer. The 10 models vary in how weather variables were defined, if at all, and in the inclusion of monthly or seasonal variables.
- Selected the most accurate model specification and used it to estimate demand reductions during actual event days.

Appendix D provides more detail regarding the regression model specifications tested.

3.2 Ex Ante Load Impact Estimation

The process to estimate ex ante load impacts differed for large C&I customers (peak demands above 200 kW) and small/medium customers (peak demands between 20 and 200 kW) and by utility. For large customers, the ex ante estimation process began by re-estimating ex post load impacts for customers with data for all events, using the same estimation model. Estimates may be sensitive to modeling variation and customer churn, so this

[16] At PG&E, individual customer regressions were performed for 35 customers. 34% of these customers were in the 5th usage quintile, which was disproportionately represented. At SCE, individual customer regressions were performed for 484 customers. These customers tended to be in the 1st and 5th usage quintles. At SDG&E, individual customer regressions were performed for 90 customers. These customers tended to be in the 1st usage quintile. SDG&E Wholesale, Transport and Other Utilities were disproportionately represented as they made up 26% of unmatched customers, but only 12% of the defaulted CPP population. There were no strong trends by industry at PG&E or SCE.

re-estimation is necessary to derive impacts that can be used to reliably model a relationship with temperature. PG&E estimates relied upon all customers who were in the large demand category, who were still enrolled in the program at the end of the season, and who had a complete set of data. The significant difference in performance between the persistent customers (with two years of data) and the large population of new customers led to using this approach rather than modeling only the persistent customers as implemented in prior evaluations. Using two years of data from the persistent customers is generally the preferable approach, however there isn't a clear explanation of what drove the significant differences in performance in 2015 compared to 2014. Seasonality issues due the events late in the season, or the sheer number of events are possible drivers. However, without a concrete explanation to explain the year over year differences, it isn't appropriate to dismiss the possibility that a similar situation couldn't occur again next year. Based on this reasoning, it was decided to use one year of ex post data for all customers, rather than two years of data for the persistent customers. SCE and SDG&E had relatively stable large customer populations, so the persistent customers with two years of data were used to develop their ex ante estimates, consistent with prior years. Estimates for persistent customers are more likely to reflect reductions delivered by customers that remain on CPP in years to come. Therefore, the persistent customer approach using multiple years of event data is the preferred approach, unless there is significant change in the customer population; such as the case with PG&E.

For default SMB customers at PG&E, ex post impacts were not re-estimated, the average percent reduction across the ex post event hours for the average event was calculated. Percent reductions were calculated separately for the small and medium customer groups. The same percentage impacts were later made available for the SCE and SDG&E ex ante forecasts given there have not been any events for SMB default customers at either of those utilities yet.

Nexant then modeled reference loads for 1-in-2 and 1-in-10 weather conditions. Reference loads are estimated separately for the large and small/medium C&I customer classes. For the large C&I customer class, hourly default CPP customer load, by LCA, is modeled as a function of temperature and month. For the small/medium C&I customer class, hourly load for a representative sample of small/medium C&I customers is modeled by LCA as a function of temperature and month.[17] Temperature is represented by daily average of the first 17 hours (*mean17*), which is used to capture heat buildup in the daylight hours. Appendix F provides details of the regression model used. Once these models are estimated, we can predict reference load for each month of the year under both 1-in-2 and 1-in-10 weather conditions.

The next step in ex ante estimation is modeling the relationship of ex post load impacts to temperature conditions. This step is only performed for large customers. Load impacts from 2014 and 2015 for large persistent customers for SCE and SDG&E were modeled as a function of temperature for each LCA. Just as in the reference load modeling, temperature is represented by *mean17*, which is used to capture heat buildup in the daylight hours. For PG&E the ex ante percent impact estimates are based on the average event percent reductions in the ex post analysis. The flat temperature relationship was applied in this year's evaluation due to

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

the significant change in ex post event performance in the first two-thirds and latter third of the events as noted in Section 4.4.1. This performance shift led to spurious relationships between load impact magnitude and temperature. Certain industries also exhibited inconsistent performance either due to seasonality, or other unknown factors. Because of these two factors, it was decided that allowing impacts to vary by LCA was the next best approach at allowing impacts to vary across program participants, without implementing an approach that led to unrealistic results. Appendix G gives details of the regression model used. Given that the large C&I default CPP population has been subject to CPP for so many years, projecting ex post load impacts into the future is fairly simple since the load impacts by LCA are representative of the large C&I default CPP population in each LCA.

Around 170,000 SMB customers were defaulted onto CPP in November 2014 at PG&E. SCE and SDG&E small and medium customers have yet to be defaulted onto CPP. The percent load reductions from the default SMB customers at PG&E provide information on how small and medium customers respond to CPP. Nexant therefore used the PG&E SMB CPP percent reductions as the expected response of defaulted small and medium customers at SCE and SDG&E. The ex post percent reduction for medium customers was 0.9%, with small customers exhibiting a 0.5% impact. Small CPP customers at SDG&E are covered in a separate report, so their ex ante impacts are not reported here.

The predicted percent reductions were then combined with the predicted reference loads for different weather conditions. Even though percent reductions are assumed to be fixed for SCE and SDG&E small and medium customers, there is variation in ex ante kW impacts for those customers because of variations in reference loads that are modeled in relationship to weather conditions. A summary of the ex ante analysis methodology specific to each utility is available in the introduction section of each utility's respective ex ante chapter.

3.2.1 Estimating Ex Ante Weather Conditions

The CPUC Load Impact Protocols[18] require that ex ante load impacts be estimated assuming weather conditions associated with both normal and extreme utility operating conditions. Normal conditions are defined as those that would be expected to occur once every two years (1-in-2 conditions) and extreme conditions are those that would be expected to occur once every 10 years (1-in-10 conditions). Since 2008, the IOUs have based ex ante weather on system operating conditions specific to each individual utility. However, ex ante weather conditions could alternatively reflect 1-in-2 and 1-in-10 year operating conditions for the California Independent System Operator (CAISO) rather than the operating conditions for each IOU. While the protocols are silent on this issue, a letter from the CPUC Energy Division to the IOUs dated October 21, 2014 directed the utilities to provide impact estimates under two sets of operating conditions starting with the April 1, 2015 filings: one reflecting operating conditions for each IOU; and one reflecting operating conditions for the CAISO system.

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

To meet this requirement, California's IOUs contracted with Nexant to develop ex ante weather conditions based on the peaking conditions for each utility and for the CAISO system. The previous ex ante weather conditions for each utility were developed in 2009 and were updated this year along with the development of the new CAISO based conditions. Both sets of estimates use a common methodology, which is documented in a report delivered to the IOUs.[19]

The extent to which utility-specific ex ante weather conditions differ from CAISO ex ante weather conditions largely depends on the correlation between individual utility and CAISO peak loads. Figure 3-6 shows the correlations between each of the three California investor-owned utilities' daily peaks and CAISO system-wide daily peaks. Because the focus is on peaking conditions, the graph includes the 25 days with the highest CAISO loads in each year from 2006 through 2013 (25 days per year for 8 years, leading 200 observations per utility).

SCE peak loads are more closely related to CAISO peak loads than are PG&E or SDG&E peak loads. Part of the explanation is simply that SCE constitutes a larger share of CAISO load than do the other two utilities and therefore has more influence on the overall CAISO loads. However, there are additional reasons for the differences. PG&E's northern California service territory experiences different weather systems and is more likely to peak earlier in the year than the overall CAISO system. SDG&E weekday loads and weather patterns are also unique. A larger share of SDG&E's load is residential and less of it is industrial. Temperatures peak earlier in the day than load does at SDG&E, and the diurnal swing between overnight and peak temperatures is smaller.

While IOU and CAISO loads do not peak at the same time all the time, the relationship between CAISO loads and utility peaking conditions is weakest when CAISO loads are below 45,000 MW. For example, CAISO loads often reach 43,000 MW when SCE and SDG&E loads are extreme, but PG&E loads are moderate (or vice-versa). However, whenever CAISO loads exceed 45,000 MW, loads are typically high across all three IOU's.

[19] See *Statewide Demand Response Ex Ante Weather Conditions*. Nexant, Inc. January 30, 2015.

Figure 3-6: Relationship between CAISO and Utility Peak Loads CAISO Top 25 Peak Days per Year (2006–2013)

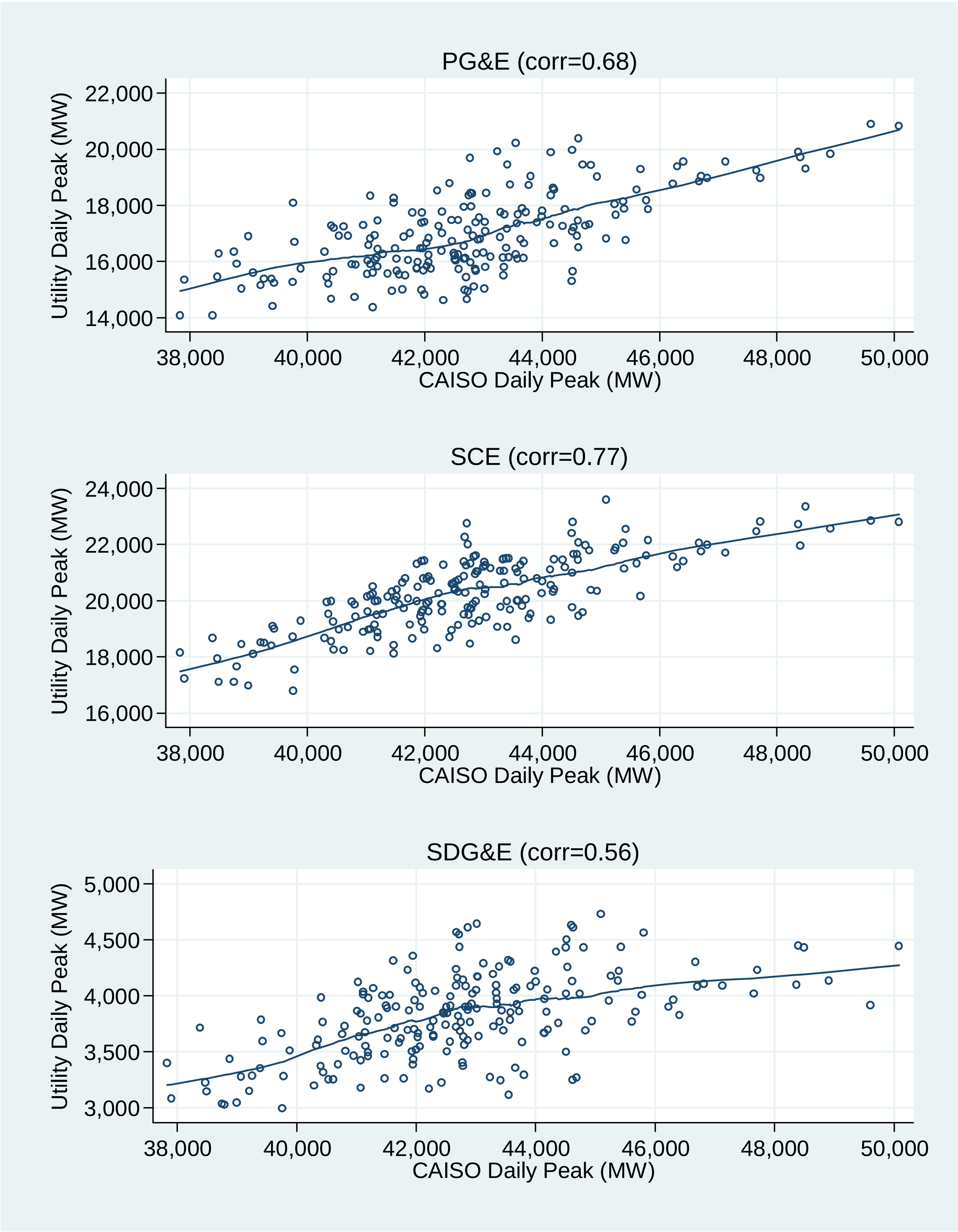


Table 3-2 shows the CPP enrollment-weighted value for *mean17* (the weather variable used in the ex ante model), for the typical event day and the monthly system peak day under the four sets of weather for which load impacts are estimated for each utility. As seen, the differences in weather conditions based on utility specific and CAISO peak conditions, and normal and extreme weather, vary significantly in some cases, less so in others. For PG&E, the CAISO weather conditions were typically cooler in the summer months and warmer in the winter months compared with weather conditions based on PG&E's operating conditions. On the typical event day, the difference in *mean17*, which is the average temperature across the hours from midnight to 5 PM, was more than 2 degrees under 1-in-2 year conditions and 3 degrees under 1-in-10 year conditions. In the winter, the CAISO-based average temperatures were higher than the PG&E-based averages. For SDG&E, the CAISO-based conditions on the typical event day were slightly higher in a normal weather year and lower in a 1-in-10 weather year. For SCE, the CAISO-based conditions were largely similar to the weather conditions based on the utility specific peak. As shown in later sections, these differences in weather across utility specific and CAISO ex ante scenarios can lead to significant differences in load impacts in some cases.

Table 3-2: Enrollment Weighted Ex Ante Weather Values (*mean17*) by Utility, Month and Weather Scenario

Ex Ante Scenario	PG&E				SCE				SDG&E			
	Utility Weather		CAISO Weather		Utility Weather		CAISO Weather		Utility Weather		CAISO Weather	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Typical Event Day	77.4	81.1	75.1	78.1	75.8	80.2	77.1	80.1	72.5	77.5	73.2	76.0
January Peak Day	42.7	40.6	44.2	40.8	53.1	46.7	48.4	44.0	52.4	49.0	52.2	47.3
February Peak Day	47.0	45.8	49.7	48.7	55.7	53.6	50.7	52.3	53.6	54.0	54.9	55.0
March Peak Day	49.9	52.5	51.5	60.3	56.0	63.8	51.1	65.5	56.3	64.8	54.8	66.6
April Peak Day	67.5	74.2	66.9	72.5	67.3	75.1	66.5	75.1	65.7	74.5	64.2	74.0
May Peak Day	71.3	80.2	70.0	74.4	69.4	78.2	67.6	76.6	67.7	75.9	64.5	72.9
June Peak Day	77.6	82.1	77.3	77.4	71.8	76.4	72.5	76.8	68.2	73.2	68.7	73.0
July Peak Day	77.6	82.4	76.2	80.8	75.5	79.8	78.8	79.0	71.9	77.9	71.6	73.7
August Peak Day	77.7	81.2	73.7	78.9	79.7	81.9	78.8	81.1	75.0	78.7	76.0	76.6
September Peak Day	76.7	78.8	73.0	75.4	76.2	82.9	78.3	83.3	75.1	80.2	76.4	80.7
October Peak Day	69.5	75.6	69.4	72.9	74.9	77.5	71.0	77.6	70.9	76.1	68.3	74.8
November Peak Day	51.4	55.5	57.5	59.7	65.8	73.7	63.4	67.5	64.2	72.6	63.0	69.7
December Peak Day	44.2	40.1	49.3	43.1	48.3	47.6	53.2	46.0	55.5	51.0	56.8	51.0

4 PG&E Ex Post Load Impacts

This section summarizes the ex post load impact estimates for customers on PG&E's CPP tariff. PG&E called 15 CPP events in 2015. The first event occurred on June 12 and the last was held on September 11.

Several distinct customer segments are enrolled on PG&E's CPP tariff. The load impacts described in this report pertain primarily to customers subject to the CPP rate on a default basis. This includes large C&I customers, some of which enrolled in the legacy voluntary CPP program prior to the default in 2010 or were defaulted to CPP and remained on CPP even though their load dropped below 200 kW. This group is referred to as the large C&I default CPP population in this report. The average number of large C&I default CPP customers participating in the 15 events in 2015 was 2,093. There was some slight variation in the number of large C&I default CPP customers participating in each event due to customer churn; some customers departed and others enrolled in CPP during summer 2015. The highest 2015 enrollment, 2,107 customers, occurred on the first event. The lowest enrollment, 2,082 customers, occurred on the August 28 event.

A large number of SMB customers were defaulted onto the CPP rate as of November 2014. We refer to these customers as the SMB default CPP population. The average number of SMB default CPP customers participating in the 15 events was 148,782. There was some variation in the number of customers participating in each event due to customer churn. The highest 2015 enrollment, 152,399 customers, occurred on the first event. The lowest enrollment, 146,280 customers, occurred on the last event.

Nexant also estimated ex post load impacts for SMB customers who enrolled in CPP on a voluntary basis through PG&E's 2014 early enrollment campaign. This group of customers is referred to as the EEG CPP population. The EEG targeted SMB customers who were due to be defaulted onto PG&E's CPP tariff in November 2014. Because they enrolled early on a voluntary basis, EEG CPP customers are not included in the SMB default CPP analysis. Two waves of EEG CPP customers were recruited, one through email outreach at the end of 2013 and the other through direct mail early in 2014. This yielded an average of 4,760 EEG CPP customers in 2014, of which 4,016 remained on the rate and participated in the 15 PG&E CPP events in 2015. Load impacts for EEG CPP customers are presented at the end of this section.

There are also voluntary customers who opted in on or after October 1st 2014. These customers were analyzed separately because the majority are SMB customers who were due to be defaulted onto the rate but were subject to PG&E's 2015 early enrollment campaign. These customers are referred to as 2015 opt-in customers.

Voluntary customers who were not a part of either of PG&E's early enrollment campaigns prior to the 2015 PDP season are referred to as legacy opt-in CPP customers. A large number of these service accounts are associated with a single business entity.

These opt-in CPP participants are not included in this section or used for modeling in the ex ante analysis because they are not representative of the overall SMB population. Load impacts for these customers are presented in the PG&E electronic ex post load impact table generator.

4.1 Large C&I Default Ex Post Load Impacts

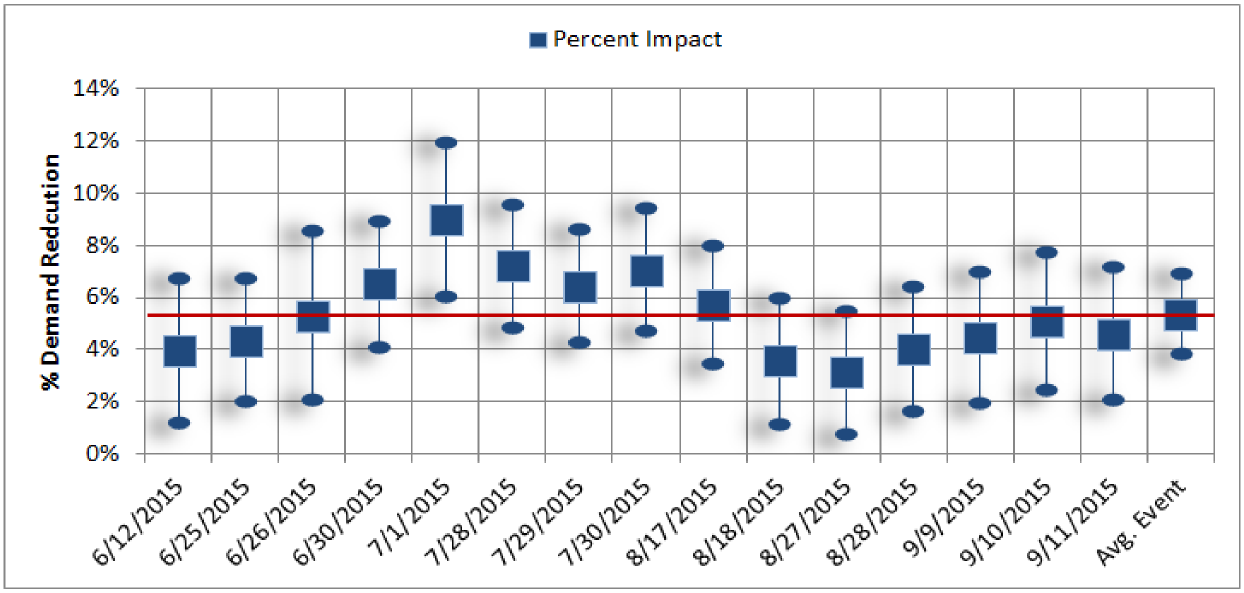
Table 4-1 shows large C&I default ex post load impact estimates for each event day and for the average event day in 2015. The participant-weighted average temperature during the event period ranged from a low of 86.9°F to a high of 96.1°F. Percent impacts range from 3.1% to 9.0%; average impacts range from 8.5 kW to 23.6 kW; and aggregate impacts range from 17.7 MW to 49.7 MW. On the average event day, the average participant reduced peak period load by 5.3%. In aggregate, PG&E's CPP customers reduced load by an average of 29.8 MW across the 15 event days in 2015.

Table 4-1: Large C&I Default CPP Ex Post Load Impact Estimates by Event Day PG&E 2015 CPP Events (2 to 6 PM)

Event Date	Day of Week	Accounts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Average Customer Impact (kW)	Aggregate Impact (MW)	% Reduction (%)	Avg. Event Temp. (°F)	Daily Max. Temp. (°F)
6/12/2015	Fri	2,107	248.4	238.6	9.8	20.7	3.9%	88.2	101.8
6/25/2015	Thu	2,103	256.2	245.0	11.1	23.4	4.4%	91.3	105.0
6/26/2015	Fri	2,105	250.3	237.0	13.3	27.9	5.3%	88.5	107.0
6/30/2015	Tue	2,106	266.0	248.6	17.3	36.5	6.5%	93.9	106.5
7/1/2015	Wed	2,106	262.7	239.1	23.6	49.7	9.0%	87.9	102.0
7/28/2015	Tue	2,091	264.3	245.3	19.0	39.8	7.2%	93.1	102.0
7/29/2015	Wed	2,092	262.7	245.8	16.9	35.3	6.4%	92.3	107.5
7/30/2015	Thu	2,091	258.3	240.1	18.2	38.0	7.0%	87.7	103.0
8/17/2015	Mon	2,089	277.5	261.7	15.8	33.1	5.7%	93.0	108.0
8/18/2015	Tue	2,089	264.3	254.9	9.4	19.6	3.6%	86.9	104.0
8/27/2015	Thu	2,083	272.3	263.8	8.5	17.7	3.1%	92.8	103.5
8/28/2015	Fri	2,082	275.9	264.9	11.0	23.0	4.0%	93.5	106.0
9/9/2015	Wed	2,083	283.9	271.3	12.7	26.4	4.5%	96.1	104.0
9/10/2015	Thu	2,084	283.6	269.2	14.4	30.0	5.1%	94.6	105.0
9/11/2015	Fri	2,084	271.7	259.2	12.5	26.1	4.6%	91.2	101.0
Avg. Event		2,093	266.5	252.2	14.2	29.8	5.3%	91.4	103.7

Figure 4-1 also presents the ex post load impact estimates for the 2015 CPP event days and the average 2015 event day, but here the 90% confidence intervals are shown with the point estimates. The wider confidence bands around the individual event day estimates, in comparison to the average event day, illustrate the noise inherent in measuring load impacts for individual event days. Average event day load impact estimates are more precise; individual day impacts are noisier.

Figure 4-1: Large C&I Default CPP Ex Post Load Impact Estimates with 90% Confidence Intervals PG&E 2015 CPP Events (2 to 6 PM)



The individual event day results are less precise because of the lack of repeated observations. In general, smaller percent demand reductions are harder to distinguish from the inherent day-to-day variation in loads that occur because of changes in occupancy, operational schedules or other unobservable factors. A large amount of the variation in load impact estimates across event days is unexplained noise. However, load impacts of individual event days are generally not significantly different from the average event.

4.1.1 Average Event Day Impacts

Figure 4-2 shows the aggregate hourly impacts for all large C&I default PG&E CPP customers for all hours of the day for the average event day. This figure is an example of the output from the electronic table generator, which is filed with the CPUC along with this evaluation report. Percent reductions in each hour vary modestly across the four-hour event window, ranging from a high of 5.5% in the second event hour to a low of 5.2% in the first hour. The highest aggregate impact, 31.3 MW, occurs in the second hour and the lowest impact, 27.8 MW, occurs in the last hour. The decline in impacts coincides with the decline in the aggregate reference load. This represents a typical usage pattern for nonresidential customers: a relatively steep decline in late afternoon and early evening that coincides with when many businesses begin shutting down at the end of the work day.

The hourly load impacts for the average 2015 event day are similar in shape to the 2014 hourly load impacts: stronger in the first two hours of the event and weaker at the end of the event. The average impact (14.2 kW) and percent impact (5.3%) are lower than the 2014 estimates (22.6 kW and 8.1%). The aggregate impact on the typical event day (29.8 MW) is also lower in 2015 compared with the 2014 value (41 MW) despite enrollment increasing by roughly 300 participants. The largest increase in enrollment was from the agricultural sector at 100 customers, a 38% increase in that industry's population.

Figure 4-2: Aggregate Impact for the Average Event Day in 2015
Large C&I Default CPP Ex Post Load Impacts

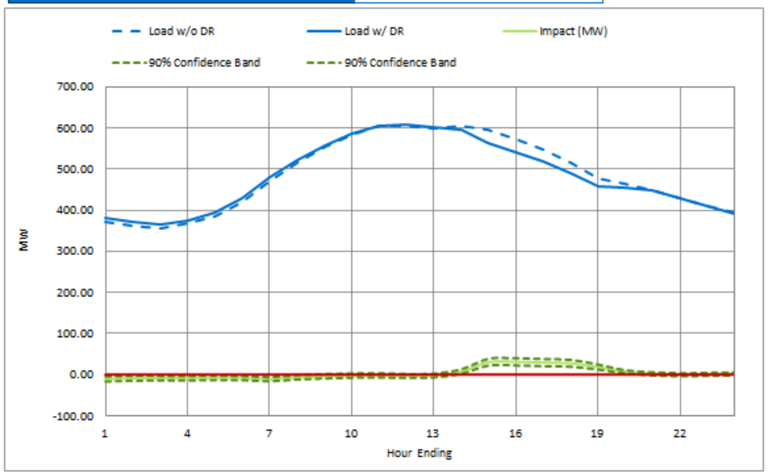
Pacific Gas & Electric
2015 Ex Post Load Impacts - CPP

Menu Options

Result Type	Aggregate
Subprogram Type	Large Default
Customer Segment	All Customers
Event Date	Average Event

Event Day Impact Summary

Event Start Time	2:00 PM
Event End Time	6:00 PM
Average Temperature for Event Window (°F)	91
Aggregate Load Reduction Across Event Window (MW)	29.8
% Load Reduction	5.3%
# of Customers Called for Event	2,093
# of Customers Enrolled in Program	2,093



Hour Ending	Load w/o DR (MW)	Load w/ DR (MW)	Impact (MW)	Impact (%)	Avg. Temp (°F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1	371.1	381.3	-10.2	-2.8%	73.1	-14.9	-12.2	-10.2	-8.3	-5.6
2	363.3	371.9	-8.6	-2.4%	71.8	-13.5	-10.6	-8.6	-6.7	-3.8
3	356.9	365.0	-8.1	-2.3%	70.6	-12.5	-9.9	-8.1	-6.3	-3.7
4	366.9	375.2	-8.3	-2.3%	69.4	-12.7	-10.1	-8.3	-6.5	-3.8
5	385.7	393.2	-7.5	-1.9%	68.3	-11.8	-9.3	-7.5	-5.7	-3.1
6	419.8	427.8	-8.1	-1.9%	67.5	-12.0	-9.7	-8.1	-6.4	-4.1
7	470.1	481.0	-10.8	-2.3%	67.4	-14.7	-12.4	-10.8	-9.3	-7.0
8	515.5	521.9	-6.4	-1.2%	69.4	-10.5	-8.1	-6.4	-4.7	-2.3
9	554.4	558.1	-3.7	-0.7%	73.0	-7.8	-5.4	-3.7	-2.0	0.4
10	581.9	584.0	-2.1	-0.4%	77.0	-6.1	-3.7	-2.1	-0.4	2.0
11	604.1	605.8	-1.8	-0.3%	80.9	-5.9	-3.4	-1.8	-0.1	2.4
12	605.3	608.4	-3.1	-0.5%	84.4	-6.9	-4.7	-3.1	-1.6	0.7
13	598.3	600.4	-2.0	-0.3%	87.4	-5.7	-3.5	-2.0	-0.5	1.6
14	603.3	595.6	7.7	1.3%	89.8	3.4	5.9	7.7	9.4	11.9
15	593.6	563.0	30.6	5.2%	91.2	24.1	27.9	30.6	33.2	37.0
16	573.4	542.1	31.3	5.5%	92.0	24.5	28.5	31.3	34.1	38.1
17	548.2	518.7	29.5	5.4%	91.7	22.7	26.7	29.5	32.3	36.3
18	515.9	488.0	27.8	5.4%	90.6	21.3	25.2	27.8	30.5	34.4
19	476.3	457.4	18.9	4.0%	88.3	14.1	16.9	18.9	20.8	23.6
20	462.5	455.4	7.1	1.5%	84.6	4.1	5.8	7.1	8.3	10.1
21	448.8	446.8	2.0	0.4%	81.0	-1.1	0.7	2.0	3.2	5.0
22	429.5	429.5	-0.1	0.0%	78.2	-2.9	-1.2	-0.1	1.1	2.8
23	410.6	409.7	1.0	0.2%	75.9	-1.9	-0.2	1.0	2.2	3.9
24	393.8	391.6	2.2	0.6%	74.3	-0.7	1.0	2.2	3.4	5.0
	Reference Energy Use (MWh)	Estimated Energy Use w/ DR (MWh)	Total Load Impact (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Event	557.8	528.0	29.8	5.3%	91.4	23.1	27.1	29.8	32.5	36.5

Note: A positive value % Daily Load Change indicates the use of less energy for the day.

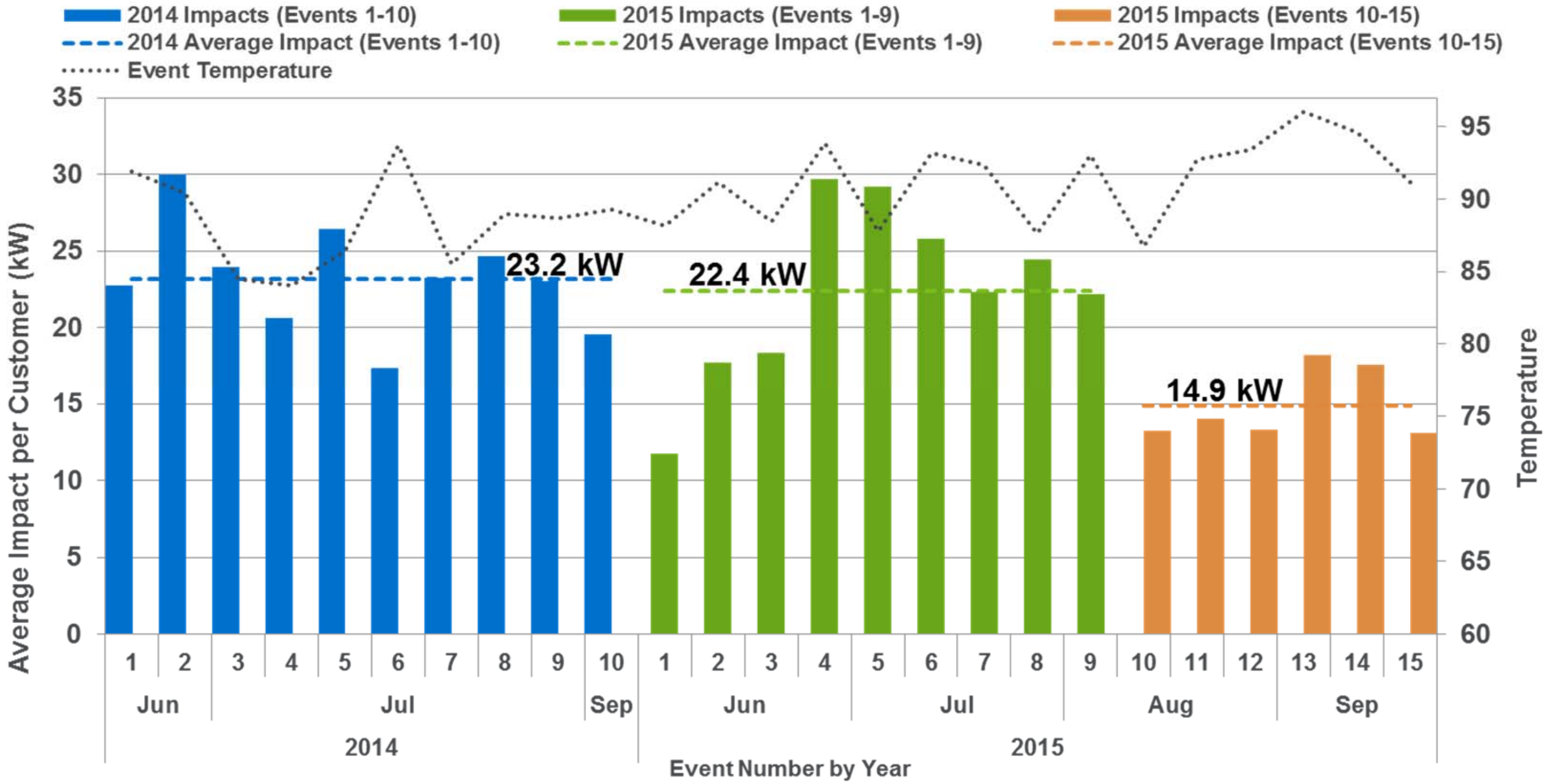
4.1.2 Comparison between 2014 and 2015

The average ex post load impact per customer was 23.2 kW in 2014; compared to 14.2 kW per customer in 2015. This year-over-year reduction in performance is attributable to the difference in performance between persistent customers (customers who were enrolled in CPP for both 2014 and 2015) and non-persistent customers (customers either new to CPP in 2015 or reclassified to default CPP based on newly available data). These two groups of customers exhibited remarkably different performance in the first two-thirds of the season compared to the latter third of the season.

2015 was unique in that 15 events were called, compared to only 10 in 2014. The 50% increase in the number of events compared to 2014 increased the possibility of event fatigue, but also resulted in a different allocation of events by month across the season. In 2014, the events were largely contained to July, with 7 events; only 2 events occurred in June, and 1 event took place in September. In contrast, 2015 had events more evenly distributed; with 4 events each in the months of June, July, and August; and 3 events in September. This resulted in 2015 having 7 events in August or September, compared to only a single event in September in 2014. This indicates that not only could the number of events be influencing performance, but also the time of year during which the events took place as well.

To better understand the difference in average performance in 2014 and 2015, persistent and non-persistent customers were examined separately. Persistent customers tended to perform well during the first 9 events, but performance dropped significantly for the last 6 events, as shown in Figure 4-3. In fact, the performance in 2015 for the first 9 events was comparable to the 10 events from 2014 at 23.2 kW and 22.4 kW for 2014 and 2015, respectively. In contrast, the last 6 events exhibited an average load impact of only 14.9 kW, approximately a third lower. The reduction in performance during the August and September time period could be attributable to event fatigue, or it could also be attributed to seasonality and the business cycles of some industries.

Figure 4-3: Large Default CPP Persistent Customers 2014 vs 2015 Comparison- Average Impact (2 to 6 PM)

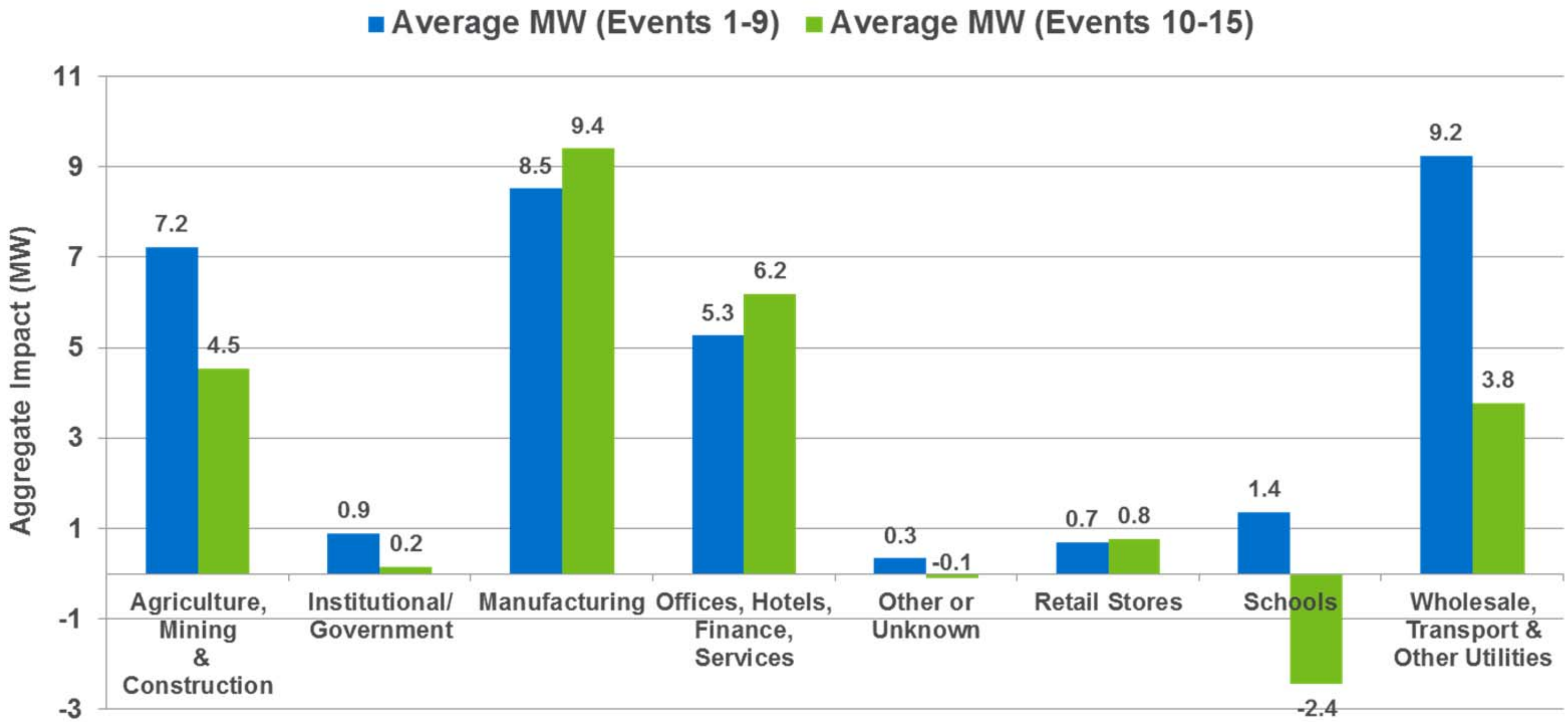


To better understand the underlying drivers of late season performance, aggregate load impacts by industry were compared for the first 9 events, when impacts were comparable to 2014, and the last 6 events, when the results were lower. As seen in Figure 4-4, this comparison identified three industries with significantly lower aggregate[20] load impacts in the latter six events: Agriculture, Mining &

[20] The difference is being reported in aggregate (MW) to facilitate identifying the industries driving the change. Other industries experienced changes in average impacts per customer, but weren't significantly driving the overall results due to their smaller contribution to overall load.

Construction: -2.7 MW; Schools: -3.8 MW; and Wholesale, Transport & Other Utilities: -5.4 MW. The cause for the performance decreases in these industries is unknown. Further research into these industries may be informative; however, it is outside of the scope of the evaluation at this time.

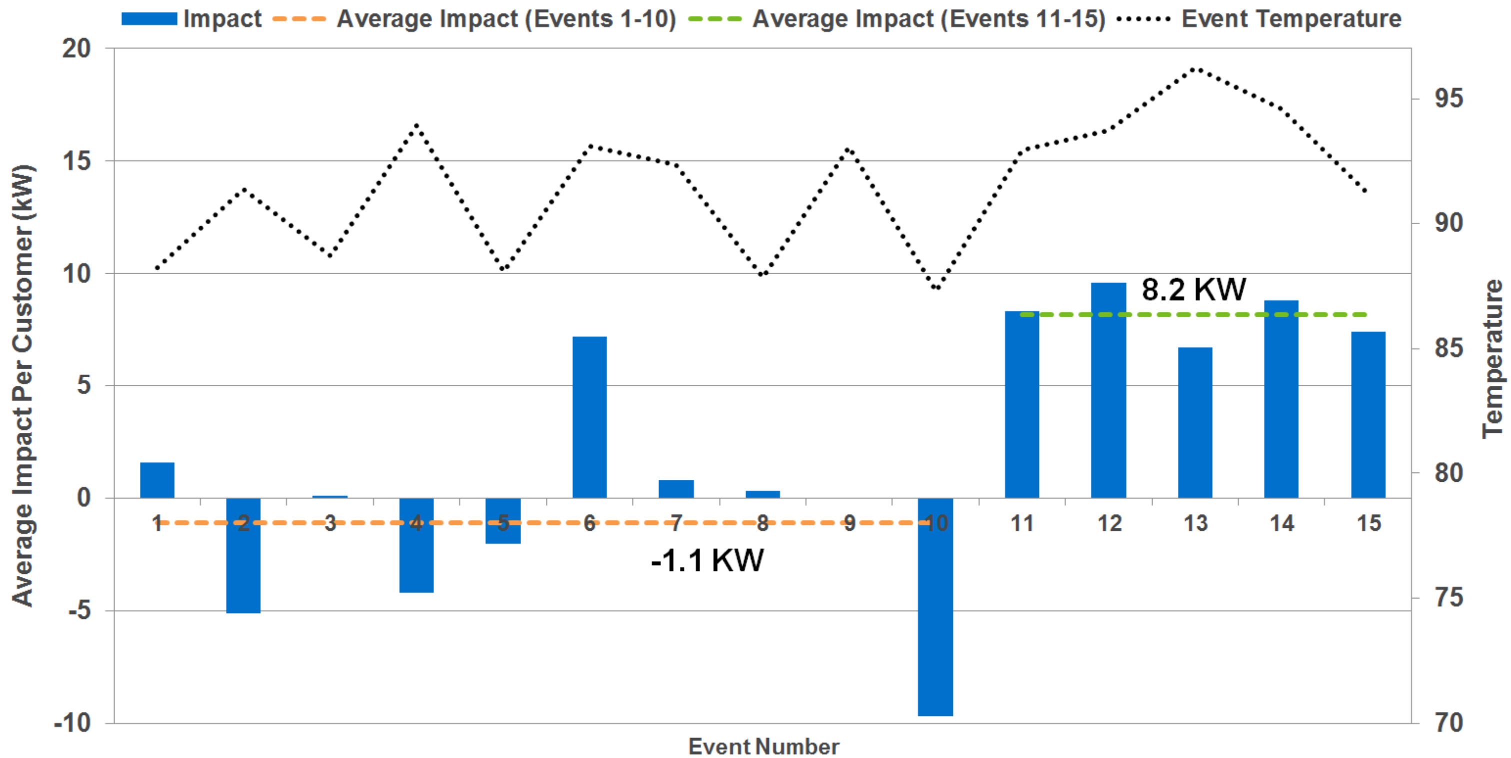
Figure 4-4: Large Default CPP Persistent Customers Events 1-9 vs 10-15 Comparison - Average Impact (2 to 6 PM)



Non-persistent customers exhibited an almost completely opposite pattern of event performance across the 2015 event season, as shown in Figure 4-5. In the first two-thirds of the season, the average load impact per customer was negative, indicating customers largely weren't responding to event signals. The latter third of the season showed remarkable improvement with an average impact of 8.2 kW per customer. Two-thirds of the non-persistent customers were new to CPP, so it is possible this improved performance reflected customers learning how to reduce event period load. It may also reflect the impact of customers receiving their first bill with

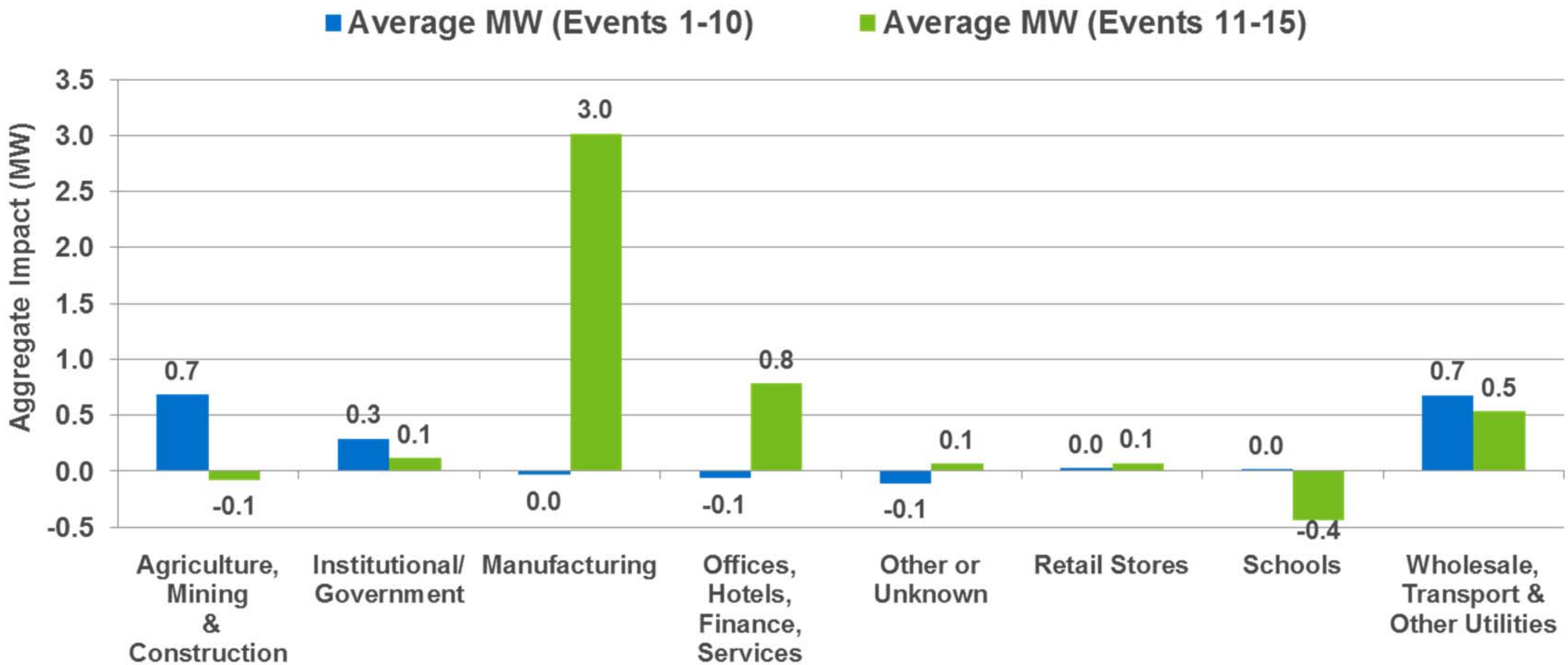
CPP charges and then adjusting their peak period usage to better manage energy costs. A preliminary review of notification success rates indicated a consistent proportion of customers were notified throughout the season so the performance difference was not due to issues with the notification system. PG&E's program teams indicated the timing of its customer outreach is unlikely to have accounted for this performance difference.

Figure 4-5: Large Default CPP Non-Persistent Customers Events 1-10 vs 11-15 Comparison - Average Impact (2 to 6 PM)



The performance by industry for the non-persistent customers was compared for the first ten and the last five events, as shown in Figure 4-6. Interestingly, the performance increase in the latter events was almost completely driven by two industries: Manufacturing: +3 MW; and Offices, Hotels, Finance: +0.9 MW. These two industries also showed increases in the latter events for the persistent customers, indicating seasonality was a possible factor. However, the persistent customers in those two industries exhibited large, significant, impacts in the earlier events, compared to impacts near zero for the earlier events for non-persistent customers. This indicates that perhaps seasonality and learning were both contributing factors.

Figure 4-6: Large Default CPP Non-Persistent Customers by Industry Events 1-10 vs 11-15 Comparison - Average Impact (2 to 6 PM)



Poor late-season event performance from the Agriculture, Mining & Construction; Schools; and Wholesale, Transport & Other Utilities persistent customers; and poor, inconsistent, early-season performance from non-persistent customers combined to create significant variability in the aggregate load impacts across event days. This ultimately resulted in the lower 2015 average event load impacts when comparing results between 2014 and 2015.

Non-persistent customer event performance variability also affected the confidence intervals for the large default CPP customer group as a whole. The wider confidence intervals in this year's evaluation compared to last year reflect greater uncertainty in the load impact estimates. While it is technically accurate that the difference between any single event day and the average event day was not statistically significant at a 90% confidence level, the single event day results were obviously different from one another in a significant way. Table 4-2 compares the 90% confidence intervals for the persistent customers for 2014 and 2015, and the non-persistent customers from 2015. The key takeaway from this exercise is that the non-persistent customers are the main driver for the increase in uncertainty in the 2015 evaluation load impacts.

Table 4-2: Confidence Intervals by Customer Type

Customer Type	90% Confidence Interval
2014 Persistent Customers	Impact +/- 27%
2015 Persistent Customers	Impact +/- 29%
2015 Non-Persistent Customers	Impact +/- 77%

4.1.3 Load Impacts by Industry

Table 4-3 compares the reference load, load impact and the number of accounts, in percentage terms, across industry segments. It also shows the share of demand reduced by the average customer within each industry and whether or not the demand reduction was statistically significant at the 90% confidence level. The industries are presented in rank order based on the aggregate demand reduction.

About 45% of the accounts came from three industry segments: Manufacturing; Wholesale, Transport & Other Utilities; and Agriculture, Mining & Construction. These three industries had the highest percent impact and highest average impact per customer. Combined, they accounted for 40.5% of the reference load (226 MW), but produced 81% of the impacts. CPP participants in the Manufacturing sector provided 9.3 MW of aggregate load reduction on the average event day, while the Agriculture, Mining & Construction segment provided 7.6 MW of aggregate load impact, reducing loads by 8.9% and 11.3%, respectively.

The Offices, Hotels, Finances & Services sector has the largest number of enrolled accounts, but also has small load reductions on both a percentage and absolute basis. The reference load for the program is also concentrated in this sector, typically comprised of office buildings. They accounted for 39% of the estimated reference load, but produced 13.4% of the load reduction (4 MW). On average, offices reduced load by 1.8%.

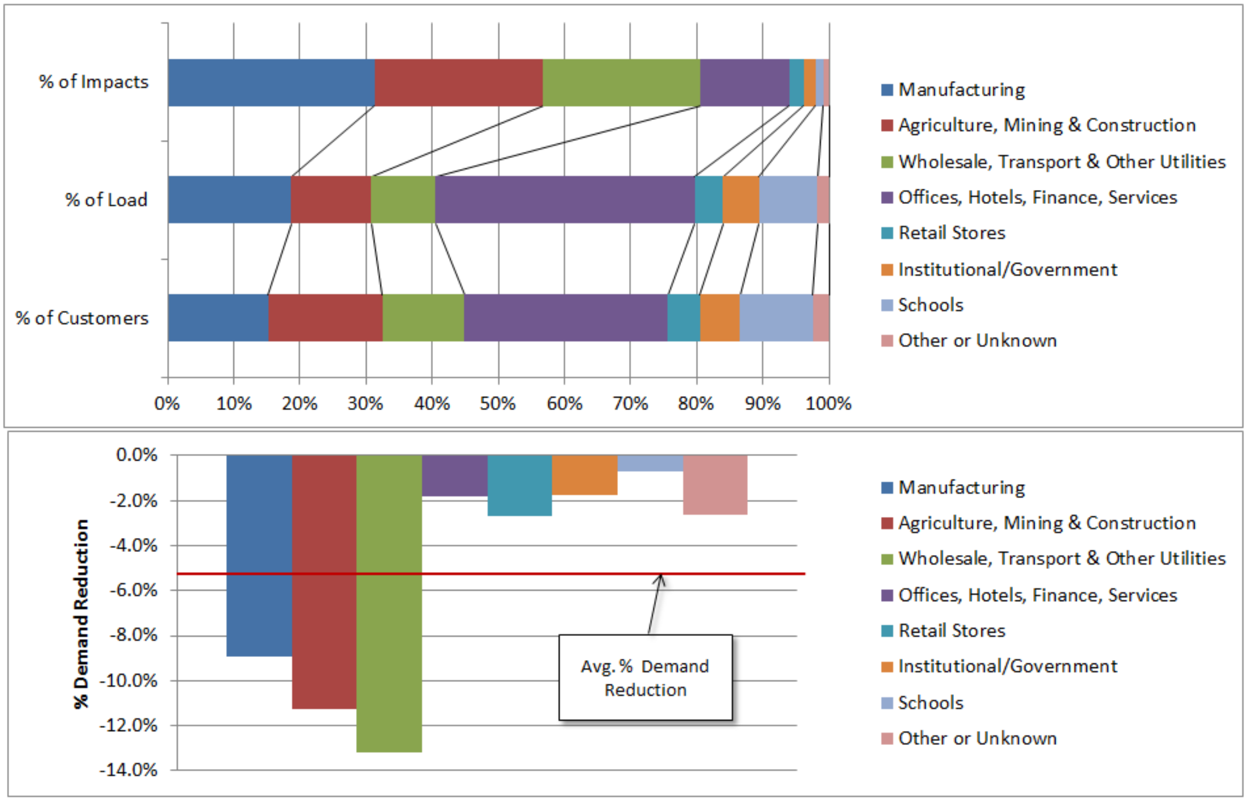
Table 4-3: Large C&I Default CPP Ex Post Load Impact Estimates by Industry Average 2015 PG&E CPP Event (2-6 PM)*

Industry	Accounts		Aggregate Reference Load		Aggregate Impact		Average Customer Impact	% Reduction	Stat. Sig?
	Enrollment	% of Program	MW	% of Program	MW	% of Program	kW		
Manufacturing	317	15.2%	104.3	18.7%	9.3	31.3%	29.4	8.9%	Yes
Agriculture, Mining & Construction	361	17.3%	67.5	12.1%	7.6	25.5%	21.1	11.3%	Yes
Wholesale, Transport & Other Utilities	260	12.4%	54.1	9.7%	7.1	23.9%	27.4	13.2%	Yes
Offices, Hotels, Finance, Services	643	30.8%	218.1	39.1%	4.0	13.4%	6.2	1.8%	No
Retail Stores	102	4.9%	24.1	4.3%	0.6	2.2%	6.3	2.7%	Yes
Institutional/Government	126	6.0%	30.1	5.4%	0.5	1.8%	4.2	1.8%	No
Schools	230	11.0%	49.1	8.8%	0.3	1.2%	1.5	0.7%	No
Other or Unknown	51	2.4%	10.0	1.8%	0.3	0.9%	5.2	2.7%	No

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

Figure 4-7 presents the same information visually, but better illustrates the concentration of load impacts in specific industries. The benefit of Figure 4-7 is that it readily shows how a large percentage of PG&E's CPP program impacts are provided by a relatively small group of customers, and vice versa, that participants in sectors that make up a large portion of CPP enrollment contribute a smaller share of the program's total load impacts.

**Figure 4-7: Large C&I Default CPP Enrollment, Load, Impact and Percent Demand Reduction by Industry
Average 2014 PG&E CPP Event (2 to 6 PM)**



Six of the eight industry segments had lower load impacts in 2015 than in 2014. Before addressing these differences, we note that comparisons across years must be made conservatively, as the matching and modeling across years varies. The matching model in 2015 differed from that in 2014, so some difference may be an artifact of modeling. Manufacturing delivered 13.8 MW in 2014 and 9.3 MW in 2015, a 33% reduction. Wholesale, Transport & Other Utilities delivered 10.1 MW in 2014 and 7.1 MW in 2015, a 30% reduction. The other industry segments with decreased load impacts, Offices, Hotels, Finance, Services; Retail Stores; Schools and Other, made up 25% of aggregate impacts in 2014, and now make up 18%. The two segments that had larger load impacts in 2015 were the Agriculture, Mining & Construction segment, which increased aggregate load impacts by 0.9 MW, a 13% increase from the segment's 2014 impact, and Institutional/Government which increased aggregate load impacts by 0.3 MW, a 230% increase. The increased load impacts delivered by the Agriculture, Mining & Construction sector are predominantly the effect of larger percent reductions; percent reductions increased from 9.5% in 2014 to 11.3% in 2015. Although enrollment in the Agriculture, Mining & Construction segment increased from 261 accounts in 2014 to 361 in 2015, new customers were small (average reference load for new Ag. customers was 143.1 kW) and did not deliver large load impacts (see Figure 4-6). On the other hand, persistent customers in the Agriculture, Mining & Construction segment performed relatively well and accounted for the larger load impacts in 2015. The same 217 Ag customers who were enrolled in 2014 increased their percent impacts from 10.3% to 13.4% in 2015. Their average reference load, which was 204.5 kW in 2014, increased to 211.1 kW in 2015. Therefore, despite a large number of new customers in the Agriculture, Mining & Construction segment that did not deliver large load impacts, strong performance from existing customers increased delivered load impacts in the sector in 2015.

4.1.4 Load Impacts by Local Capacity Area and Customer Size

PG&E is comprised of seven geographic planning zones known as local capacity areas (LCAs). An eighth region, designated as the Other LCA, is comprised of customers that are not located in any of the seven LCAs. The ex post load impacts differ by geographic location due to differences in the total population, industry mix, and climate.

Table 4-4 presents the estimated ex post load impacts by LCA. Participants in the Greater Bay Area provided 7.1 MW of aggregate load impact during the average event day, while customers in the Other LCA provided 9.6 MW of aggregate load reduction. The Greater Bay Area had the lowest average impact per customer of 7.7 kW, while customers in the Other LCA provided an average impact of 25.7 kW, which was the second highest. Combined, these LCAs comprise 56% of aggregate load impact. Customers in the Greater Bay Area had the highest average reference load of any LCA, at 319 kW, while customers in the Kern LCA had the lowest average reference load (168.9 kW). Figure 4-8 illustrates how large the Bay Area and Other LCAs are on a customer and reference load basis—these two segments comprise 63% of enrolled accounts and 70% of enrolled load. Differences in percent impacts across LCAs is largely driven by differences in the industry mix. The Offices, Hotels, Finance, and Services sector, which delivers modest percent reductions, comprises 51% of accounts in the Greater Bay Area. On the other hand, Kern, which deliver large percent impacts, is made up of 37% Agricultural customers, and only 20% Offices, Hotels, Finance, and Services customers. Other LCA has a similarly high incidence of Agricultural customers, at 35%.

Table 4-4: Large C&I Default CPP Ex Post Load Impact Estimates by LCA Average 2015 PG&E CPP Event (2 to 6 PM)*

Local Capacity Area	Accounts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Average Customer Impact (kW)	Aggregate Impact (MW)	% Reduction (%)	Avg. Temp (°F)	Stat. Sig.?
Greater Bay Area	931	319.3	311.7	7.7	7.1	2.4%	84.6	Yes
Greater Fresno Area	252	243.2	231.8	11.4	2.9	4.7%	102.9	Yes
Humboldt	27	179.8	145.8	33.9	0.9	18.9%	86.6	Yes
Kern	268	168.9	150.4	18.6	5.0	11.0%	100.9	Yes
LCA: Other	375	246.8	221.1	25.7	9.6	10.4%	89.9	Yes
North Coast and North Bay	24	204.9	185.4	19.4	0.5	9.5%	92.9	No
Sierra	85	183.3	170.8	12.5	1.1	6.8%	98.5	Yes
Stockton	127	276.0	254.7	21.3	2.7	7.7%	98.7	Yes

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

Figure 4-8: Large C&I Default CPP Enrollment, Load and Impact by LCA Average 2015 PG&E CPP Event (2 to 6 PM)

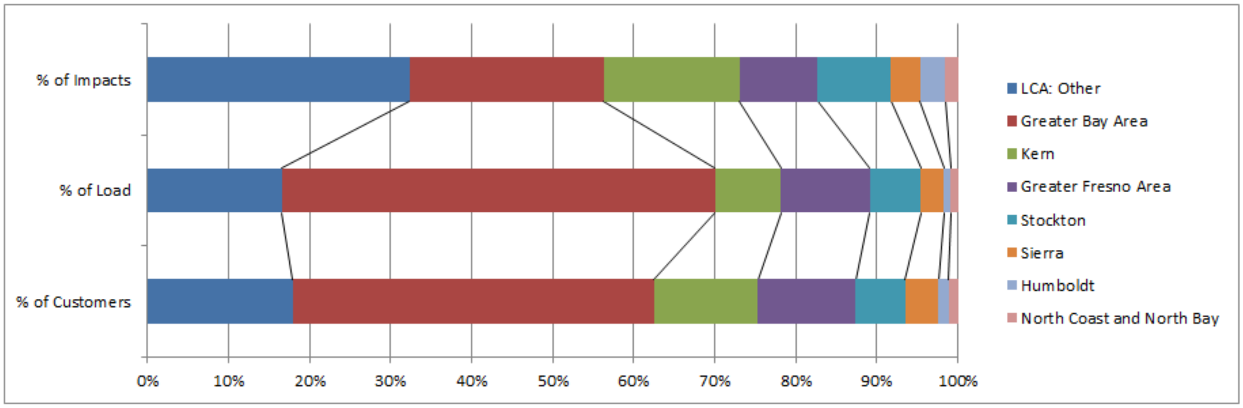


Table 4-5 shows the estimated ex post load impact by customer size, using two different size categorization methods. First, load impacts are reported for the three demand size categories: greater than 200 kW; 20 kW to 200 kW; and less than 20kW. The other size categorization is by usage quintile, in which large C&I default CPP customers were assigned to a usage quintile based on annual consumption. This metric of customer size is more useful than the demand response size categories because it provides estimates for a broad spectrum of customer sizes, where the segments all have sample sizes large enough to support reasonable estimates, which is a shortcoming of using the demand response size categories for default CPP. In fact, the load impact for the < 20 kW size category is insignificant, owing principally to the fact that there are only 65 customers in that category. Customers in the smallest two usage quintiles, and the largest usage quintile, have the largest percentage load impacts. The 4th quintile has the lowest percentage load impacts.

Table 4-5: Large C&I Default CPP Ex Post Load Impact Estimates by Customer Size Average 2015 PG&E CPP Event (2 to 6 PM)*

Categorization	Size Category	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig.?
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
By Demand Size	Greater than 200kW	1,833	293.8	278.0	15.8	28.9	5.4%	90.9	Yes
	20 kW to 199kW	193	97.6	93.7	3.8	0.7	3.9%	93.4	Yes
	Less than 20kW	65	2.2	0.8	1.4	0.1	65.2%[21]	100.2	No
By Annual Consumption Quintiles	5th Quintile	416	667.4	627.4	40.0	16.6	6.0%	88.8	Yes
	4th Quintile	417	280.7	273.8	6.9	2.9	2.5%	88.8	Yes
	3rd Quintile	420	202.0	194.1	7.9	3.3	3.9%	90.7	Yes
	2nd Quintile	416	132.8	124.4	8.4	3.5	6.3%	94.1	Yes
	1st Quintile	421	53.1	44.9	8.2	3.4	15.4%	94.5	Yes

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

4.1.5 Load Impacts for Multi-DR Program Participants

PG&E CPP participants are allowed to dually enroll in certain other DR programs. To avoid double counting load impacts when multiple DR programs are called, it is necessary to estimate the demand response under the CPP tariff for customers that are dually enrolled in other programs. CPP customers at PG&E may also participate in the following DR programs:

- **Aggregator Managed Portfolio (AMP):** A non-tariff program that consists of bilateral contracts with aggregators to provide PG&E with price-responsive demand response. AMP events are called at PG&E's discretion. Each aggregator is responsible for designing and implementing its own program, including customer acquisition, marketing, sales, retention, support, event notification and payments. Customers taking CPP may only dually enroll in the same day notification AMP products.
- **Base Interruptible Program (BIP):** Pays customers an incentive to reduce load to or below a preselected, customer-specific level known as the firm service level (FSL). Failure to reduce load to the FSL on BIP event days results in penalties.
- **Capacity Bidding Program (CBP):** A monthly incentive is paid to reduce energy use to a pre-determined amount once an electric resource generation facility reaches or exceeds heat rates of 15,000 Btu (British thermal units) per kWh. Load reduction commitment is on a month-by-month basis, with nominations made five days prior to the beginning of each month. Customers must enroll with (or as) a third-party aggregator to join the Capacity Bidding Program. Customers can choose between day-ahead and day-of notification. Only customers with day-of notification can be dually enrolled in CPP.

[21] This number is correct, although the number of customers is small and the result is statistically insignificant.

Table 4-6 shows large C&I default CPP load impacts for customers that are dually enrolled in other demand response programs. A word of caution is needed in reviewing Table 4-6. There are relatively few dually enrolled customers in any single DR program. For example, there are only 33 customers enrolled in both CPP and CBP. The significant variation in average and aggregate load impacts across dual enrollment categories probably has less to do with dual enrollment than it does with fundamental differences in the average characteristics and price responsiveness of the few customers who happen to be in each category. The estimates are useful for adjusting portfolio impact estimates under assumptions that both programs are called on the same day, but it is not appropriate to claim that customers dually enrolled in CPP and BIP are more than twice as price responsive compared with customers dually enrolled in CPP and AMP because the BIP program somehow supports CPP demand response better than the AMP program. Said another way, while dual enrollment in CPP and BIP appears to correlate with above average load reductions, there is no basis to infer that any combination of dual enrollment listed in Table 4-6 causes CPP customers to respond better.

Table 4-6: Large C&I Default CPP Ex Post Load Impact Estimates for Dually-enrolled Participants
Average 2015 PG&E CPP Event (2 to 6 PM)*

Dually Enrolled DR	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp.	Stat. Sig.?
		(kW)	(kW)	(kW)	(MW)	%	°F	
AMP	143	387.0	327.7	59.3	8.5	15%	89.7	Yes
BIP	42	435.6	205.4	230.2	9.7	53%	95.3	Yes
CBP	33	243.5	225.2	18.4	0.6	8%	88.4	Yes
Not Dually-enrolled	1,872	253.7	248.1	5.7	10.6	2%	91.5	Yes

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

4.1.6 TI and AutoDR Load Impacts and Realization Rates

The Technical Incentive (TI) and Automated Demand Response (AutoDR) programs offered by PG&E are designed to increase demand response for participating customers on CPP rates and to provide greater certainty regarding the amount of load shed during an event. These programs involve a multi-step process that begins with technical assistance (TA), which is an audit to determine the potential for installing energy saving technology or changing processes at a particular premise. A technical incentive is paid if a customer installs equipment or reconfigures processes and demonstrates that the investments and changes produce load reductions. Although the response is automated, customers must still decide whether and when to drop load. AutoDR provides an incremental incentive to encourage customers to allow PG&E to remotely dispatch the automated load reduction.

From a policy perspective, it is important to understand if customers enrolled in these programs reach their approved load shed on event days. The realization rate describes the percent of approved load shed that is met by the estimated impacts on event days. It assumes that load reductions are due to automated reduction technology and not due to demand reductions from other end-uses.

A statistically valid assessment of TI is hampered by the very small number of customers that participate in this complementary program. There were only two PG&E accounts on the CPP tariff that received TI payments. Table 4-7 shows the load impact of the average customer on each of these programs on the average event day. [redacted]

Table 4-7: Default CPP Ex Post Load Average Customer Impact Estimates of TI and AutoDR Participants
Average 2014 PG&E CPP Event (2 to 6 PM)*

Enabling Technology	Accounts	Load Impact	% Reduction	90% Confidence Interval		Approved kW	Realization Rate
		(kW)	%	Lower	Upper		
TI/LIA**	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
No TI or AutoDR	2,090	14.3	5.3%	10.2	18.3	NA	NA

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

The realization rate estimates were developed by taking the average impact for customers who were enrolled in TI or AutoDR and dividing it by the average of the approved TI or AutoDR load shed. TI realization rates depend on whether the equipment is typically used during events and whether customers decide to drop load on CPP event days.

4.2 SMB Default Ex Post Load Impacts

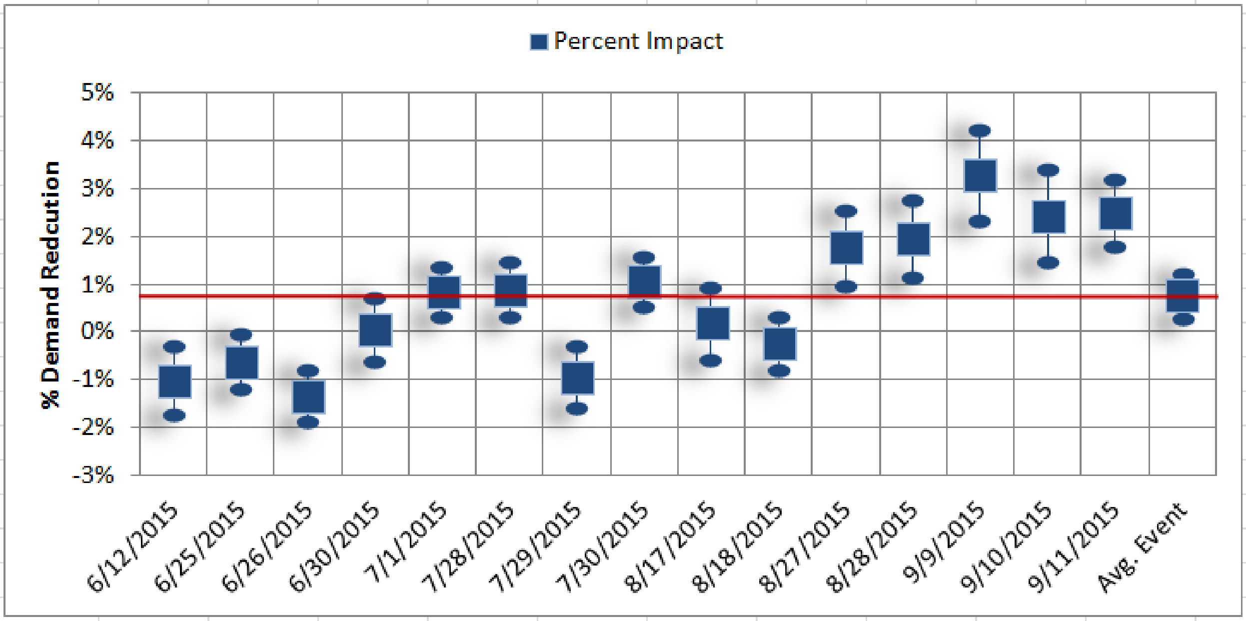
Table 4-8 shows SMB default ex post load impact estimates for each event day and for the average event day in 2015. The participant-weighted average temperature during the event period ranged from a low of 87.5°F to a high of 96.9°F. Percent impacts ranged from -1.3% to 3.3%; average impacts ranged from -0.1 kW to 0.2 kW; and aggregate impacts ranged from -9.7 MW to 26.5 MW. On the average event day, the average participant reduced peak period load by 0.8%. In aggregate, PG&E's SMB default CPP customers reduced load by an average of 5.8 MW across the 15 event days in 2015.

Table 4-8: SMB Default CPP Ex Post Load Impact Estimates by Event Day PG&E 2015 CPP Events (2 to 6 PM)

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Event Temp.	Daily Max. Temp.
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	(°F)
6/12/2015	Fri	152,399	4.7	4.8	0.0	-7.4	-1.0%	90.1	90.8
6/25/2015	Thu	150,899	5.0	5.1	0.0	-4.7	-0.6%	92.5	92.9
6/26/2015	Fri	150,817	4.8	4.9	-0.1	-9.7	-1.3%	90.1	90.8
6/30/2015	Tue	150,687	5.2	5.2	0.0	0.5	0.1%	95.4	96.0
7/1/2015	Wed	150,540	5.0	4.9	0.0	6.2	0.8%	89.3	89.7
7/28/2015	Tue	148,998	5.1	5.1	0.0	6.8	0.9%	94.4	94.9
7/29/2015	Wed	148,921	5.2	5.2	0.0	-7.2	-0.9%	94.1	94.6
7/30/2015	Thu	148,851	5.0	4.9	0.1	7.9	1.1%	89.2	89.8
8/17/2015	Mon	147,883	5.2	5.2	0.0	1.4	0.2%	94.4	95.2
8/18/2015	Tue	147,812	5.0	5.0	0.0	-1.7	-0.2%	87.5	88.1
8/27/2015	Thu	147,436	5.3	5.2	0.1	13.7	1.8%	93.5	94.5
8/28/2015	Fri	147,358	5.3	5.2	0.1	15.2	2.0%	94.0	95.6
9/9/2015	Wed	146,489	5.5	5.3	0.2	26.5	3.3%	96.9	97.6
9/10/2015	Thu	146,373	5.5	5.3	0.1	19.5	2.4%	95.7	96.2
9/11/2015	Fri	146,280	5.1	5.0	0.1	18.6	2.5%	92.2	93.2
Avg. Event		148,782	5.1	5.1	0.0	5.8	0.8%	92.6	93.2

Figure 4-9 also presents the ex post load impact estimates for the 2015 CPP event days and the average 2015 event day, but here the 90% confidence intervals are shown with the point estimates. The wider confidence bands around the individual event day estimates, in comparison to the average event day, illustrate the noise inherent in measuring load impacts for individual event days. Average event day load impact estimates are more precise; individual day impacts are noisier. The average event impact is statistically significant at the 10% level, as are many of the individual event day impacts. Load impacts towards the end of the summer tend to be larger than those earlier in the summer. This could be as a result of learning behavior on the part of participants.

Figure 4-9: SMB Default CPP Ex Post Load Impact Estimates with 90% Confidence Intervals PG&E 2015 CPP Events (2 to 6 PM)



The individual event day results are less precise because of the lack of repeated observations. In general, smaller percent demand reductions are harder to distinguish from the inherent day-to-day variation in loads that occur because of changes in occupancy, operational schedules, or other unobservable factors. A large amount of the variation in load impact estimates across event days is unexplained noise.

4.2.1 Average Event Day Impacts

Figure 4-10 shows the aggregate hourly impacts for all SMB default PG&E CPP customers for all hours of the day for the average event day. This figure is an example of the output from the electronic table generator, which is filed with the CPUC along with this evaluation report. Percent reductions in each hour vary modestly across the four-hour event window, ranging from a high of 0.9% in the third event hour to a low of 0.6% in the first hour. The highest aggregate impact, 6.5 MW, occurs in the third hour and the lowest impact, 5.1 MW, occurs in the last hour. The decline in impacts coincides with the decline in the aggregate reference load. This represents a typical usage pattern for nonresidential customers: a relatively steep decline in late afternoon and early evening that coincides with when many businesses begin shutting down at the end of the work day.

Figure 4-10: Aggregate Impact for the Average Event Day in 2015 SMB Default CPP Ex Post Load Impacts

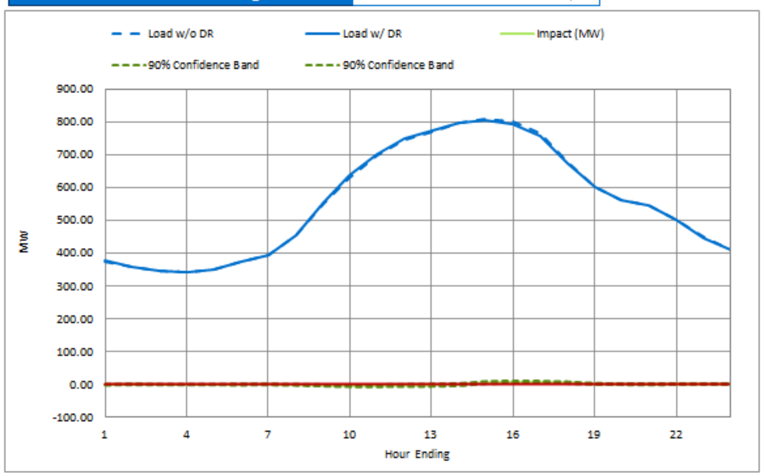
Pacific Gas & Electric
2015 Ex Post Load Impacts - CPP

Menu Options

Result Type	Aggregate
Subprogram Type	SMB Default
Customer Segment	All Customers
Event Date	Average Event

Event Day Impact Summary

Event Start Time	2:00 PM
Event End Time	6:00 PM
Average Temperature for Event Window (°F)	93
Aggregate Load Reduction Across Event Window (MW)	5.8
% Load Reduction	0.8%
# of Customers Called for Event	148,782
# of Customers Enrolled in Program	148,782

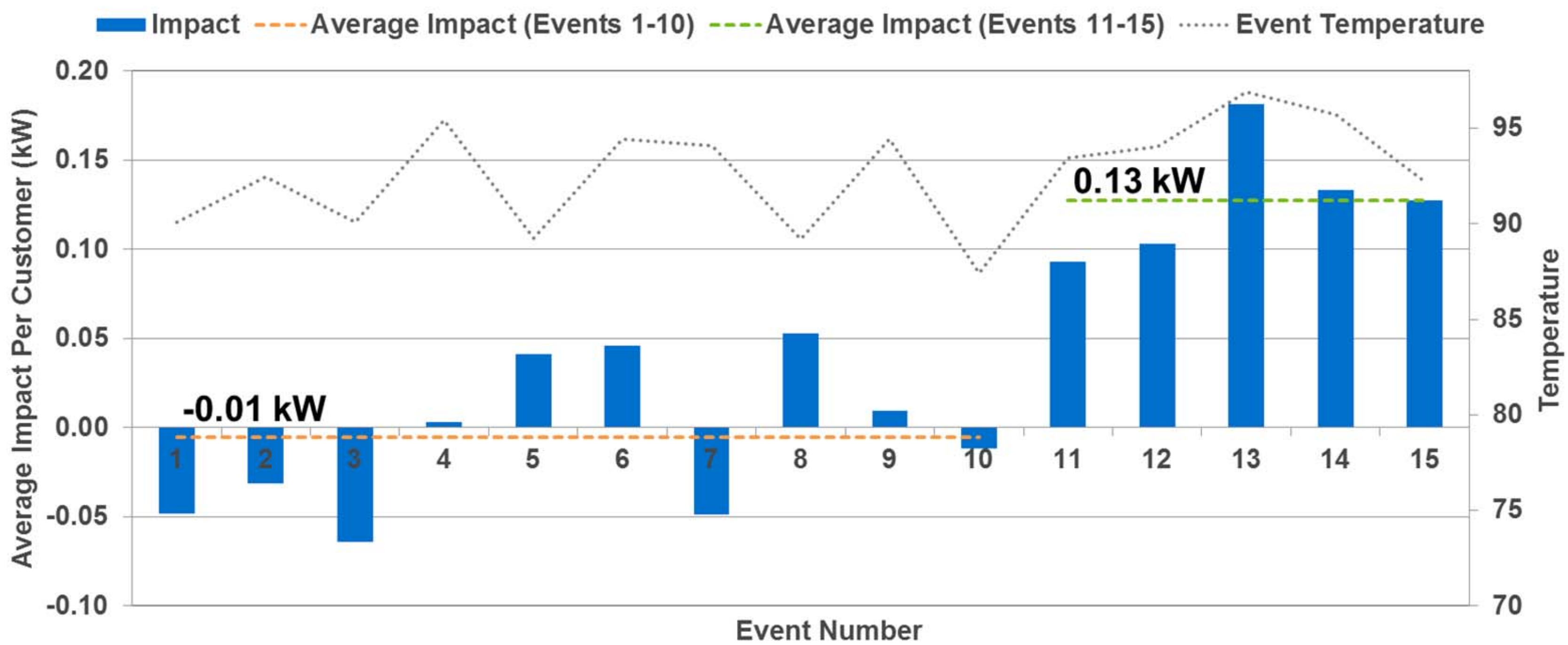


Hour Ending	Load w/o DR (MW)	Load w/ DR (MW)	Impact (MW)	Impact (%)	Avg. Temp (°F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1	374.9	376.3	-1.3	-0.4%	73.0	-2.8	-1.9	-1.3	-0.7	0.2
2	358.7	358.9	-0.2	-0.1%	71.7	-1.8	-0.9	-0.2	0.4	1.4
3	345.8	346.9	-1.0	-0.3%	70.3	-2.1	-1.5	-1.0	-0.6	0.0
4	341.2	342.5	-1.3	-0.4%	69.1	-2.4	-1.8	-1.3	-0.9	-0.2
5	349.1	350.2	-1.2	-0.3%	68.1	-2.3	-1.6	-1.2	-0.7	0.0
6	371.3	372.3	-0.9	-0.2%	67.3	-2.8	-1.7	-0.9	-0.1	1.0
7	394.6	395.0	-0.5	-0.1%	67.2	-2.1	-1.1	-0.5	0.2	1.1
8	452.1	453.8	-1.8	-0.4%	69.4	-3.4	-2.4	-1.8	-1.1	-0.1
9	548.9	552.5	-3.6	-0.7%	73.4	-5.6	-4.5	-3.6	-2.8	-1.6
10	630.2	635.1	-4.9	-0.8%	77.7	-7.4	-5.9	-4.9	-4.0	-2.5
11	697.0	701.6	-4.7	-0.7%	81.7	-7.4	-5.8	-4.7	-3.6	-1.9
12	745.3	748.9	-3.6	-0.5%	85.3	-6.6	-4.8	-3.6	-2.3	-0.5
13	768.5	771.5	-3.0	-0.4%	88.5	-6.1	-4.3	-3.0	-1.8	0.0
14	796.9	798.1	-1.2	-0.1%	90.9	-4.3	-2.5	-1.2	0.1	2.0
15	810.5	805.3	5.2	0.6%	92.4	2.1	3.9	5.2	6.5	8.3
16	799.8	793.5	6.2	0.8%	93.2	3.3	5.0	6.2	7.4	9.2
17	762.8	756.3	6.5	0.9%	93.0	3.8	5.4	6.5	7.6	9.2
18	676.6	671.5	5.1	0.7%	91.8	2.8	4.1	5.1	6.0	7.4
19	600.8	599.7	1.1	0.2%	89.4	-0.8	0.3	1.1	1.9	3.0
20	562.0	561.8	0.2	0.0%	85.4	-1.6	-0.5	0.2	0.9	2.0
21	544.1	544.4	-0.3	-0.1%	81.3	-2.2	-1.1	-0.3	0.4	1.5
22	502.2	501.8	0.4	0.1%	78.4	-1.1	-0.2	0.4	1.0	1.9
23	447.2	446.5	0.7	0.2%	76.0	-0.7	0.2	0.7	1.3	2.2
24	408.2	407.5	0.7	0.2%	74.3	-0.8	0.1	0.7	1.3	2.2
	Reference Energy Use (MWh)	Estimated Energy Use w/ DR (MWh)	Total Load Impact (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Event	762.4	756.7	5.8	0.8%	92.6	3.0	4.6	5.8	6.9	8.5

Note: A positive value % Daily Load Change indicates the use of less energy for the day.

The Default SMB load impact performance throughout the event season exhibited a pattern similar to the non-persistent Large Default CPP customers with a slightly negative average impact across the first ten events, and a positive 0.13 kW impact across the last five events, as shown in Figure 4-11. Approximately two-thirds of the non-persistent Large Default customers were new to the program, as were all of the Default SMB customers. PG&E observed similar results from their in-house analysis. As noted above, PG&E indicated that the timing of its customer outreach is unlikely to have caused the sudden increase in performance, nor were there any systematic problems with the notification system that appeared to align with the observed event performance increase. An analysis of performance by industry, as completed for the Large Default CPP customers, showed that Schools, which make up the majority of aggregate impacts, exhibit a seasonal pattern similar to that of observed impacts. Schools are not in session for most of the summer and return in late August when impacts increase. Customers in the Agricultural, Mining & Construction sectors exhibit a different trend, with large impacts occurring earlier in the summer. Certainly, not all industries deliver impacts late in the season, and the trend seems to be driven by schools. A further analysis might seek to determine if the timing of the customer billing cycles could be driving the observed pattern. The billing cycle could be a factor if event number 11 was the first event after customers received or paid a bill with substantial CPP charges from events earlier in the season.

Figure 4-11: Default SMB CPP Customers
Events 1-10 vs 11-15 Comparison - Average Impact (2 to 6 PM)



4.2.2 Load Impacts by Industry

Table 4-9 compares the reference load, load impact, and the number of accounts, in percentage terms, across industry segments. It also shows the share of demand reduced by the average customer within each industry and whether or not the demand reduction was statistically significant at the 90% confidence level. The industries are presented in rank order based on the aggregate demand reduction.

Five industries have a similar share of impacts: Schools; Other; Retail Stores; Wholesale, Transport & Other Utilities; and Manufacturing. About 47% of the accounts came from these five industry segments, and they have the highest percent impact and highest average impact per customer. Combined, they accounted for 44% of the reference load (333.6 MW), but produced 91% of the impacts. However, load impacts were not significant at the 10% level for Other, or Wholesale, Transport & Other Utilities sectors, despite their relatively large contribution to aggregate impacts.

The Offices, Hotels, Finances & Services sector has the most accounts enrolled, but also has small load reductions on both a percentage and absolute basis. The reference load for the program is also concentrated in this sector, typically comprised of office buildings. They accounted for 41% of the estimated reference load, but produced 3.5% of the load reduction (0.2 MW).

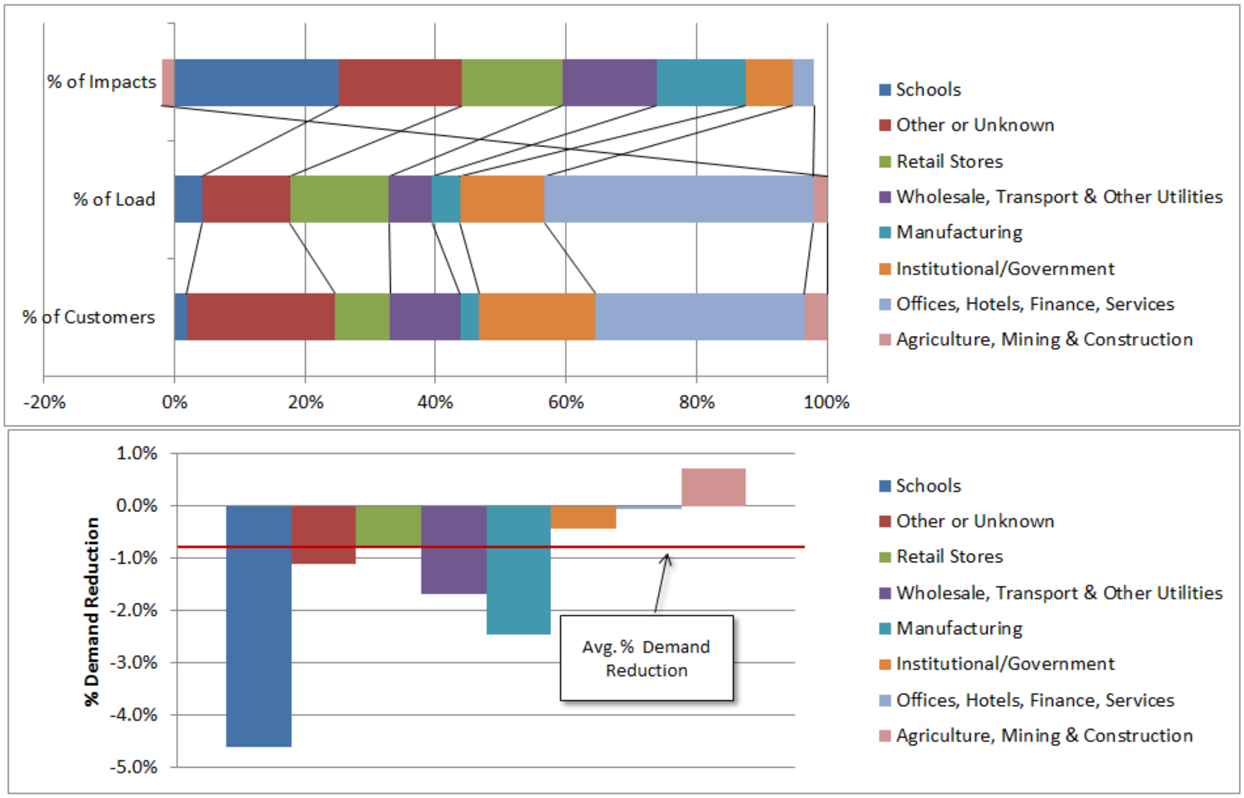
Table 4-9: SMB Default CPP Ex Post Load Impact Estimates by Industry Average 2015 PG&E CPP Event (2-6 PM)*

Industry	Accounts		Aggregate Reference Load		Aggregate Impact		Average Customer Impact	% Reduction	Stat. Sig?
	Enrollment	% of Program	MW	% of Program	MW	% of Program	kW		
Schools	2,698	1.8%	32.3	4.2%	1.5	26.1%	0.6	4.6%	Yes
Other or Unknown	33,949	22.8%	102.9	13.5%	1.1	19.8%	0.0	1.1%	No
Retail Stores	12,466	8.4%	114.8	15.1%	0.9	16.0%	0.1	0.8%	Yes
Wholesale, Transport & Other Utilities	15,961	10.7%	50.7	6.6%	0.9	15.0%	0.1	1.7%	No
Manufacturing	4,326	2.9%	32.9	4.3%	0.8	14.2%	0.2	2.5%	Yes
Institutional/Government	26,543	17.8%	98.6	12.9%	0.4	7.5%	0.0	0.4%	No
Offices, Hotels, Finance, Services	47,635	32.0%	314.4	41.2%	0.2	3.5%	0.0	0.1%	No
Agriculture, Mining & Construction	5,201	3.5%	15.9	2.1%	-0.1	-2.0%	0.0	-0.7%	No

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

Figure 4-12 presents the same information visually, but better illustrates the concentration of load impacts in specific industries. The benefit of Figure 4-7 is that it readily shows how a large percentage of PG&E's CPP program impacts are provided by a relatively small group of customers, and vice versa, that participants in sectors that make up a large portion of CPP enrollment contribute a smaller share of the program's total load impacts.

Figure 4-12: SMB Default CPP Enrollment, Load, Impact and Percent Demand Reduction by Industry Average 2014 PG&E CPP Event (2 to 6 PM)



4.2.3 Load Impacts by Local Capacity Area and Customer Size

PG&E is comprised of seven geographic planning zones known as LCAs. An eighth region, designated as the Other LCA, is comprised of customers that are not located in any of the seven LCAs. The ex post load impacts differ by geographic location due to differences in the total population, industry mix and climate.

Table 4-10 presents the estimated ex post load impacts by LCA. Participants in the Greater Bay Area provided 2.8 MW of aggregate load impact during the average event day, but this LCA had the lowest statistically significant average impact per customer of 0.04 kW. Customers in Kern and the Other LCA had relatively high average impacts per customer of 0.2 kW, and 0.1 kW, respectively. Combined, these LCAs comprise 103.5% of aggregate load impact.[22] Customers in Kern had the highest average reference load of any LCA, at 8.7 kW, while customers in the North Coast and North Bay had the lowest average reference load (3.8 kW).

[22] These LCAs accounts for over 100% of impacts because some LCAs delivered negative load impacts that were not statistically significant at the 90% confidence level.

Figure 4-13 illustrates how the Bay Area, Other and Kern LCAs make up the great majority of aggregate impacts, and to a lesser extent aggregate reference load and enrolled customers.

Table 4-10: SMB Default CPP Ex Post Load Impact Estimates by LCA Average 2015 PG&E CPP Event (2 to 6 PM)*

Local Capacity Area	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig.?
		(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
Greater Bay Area	63,386	5.2	5.2	0.0	2.8	0.8%	86.7	Yes
Greater Fresno Area	15,680	5.5	5.4	0.0	0.4	0.5%	102.9	No
Humboldt	2,449	3.9	3.7	0.2	0.4	4.1%	70.4	Yes
Kern	10,400	8.7	8.6	0.2	1.6	1.7%	100.8	Yes
LCA: Other	29,756	4.4	4.3	0.1	1.7	1.3%	94.2	Yes
North Coast and North Bay	4,353	3.8	3.8	0.0	0.0	-0.1%	92.2	No
Sierra	12,061	4.2	4.3	0.0	-0.6	-1.1%	98.3	No
Stockton	10,695	4.6	4.6	0.0	-0.4	-0.8%	98.7	No

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

Figure 4-13: SMB Default CPP Enrollment, Load and Impact by LCA Average 2015 PG&E CPP Event (2 to 6 PM)

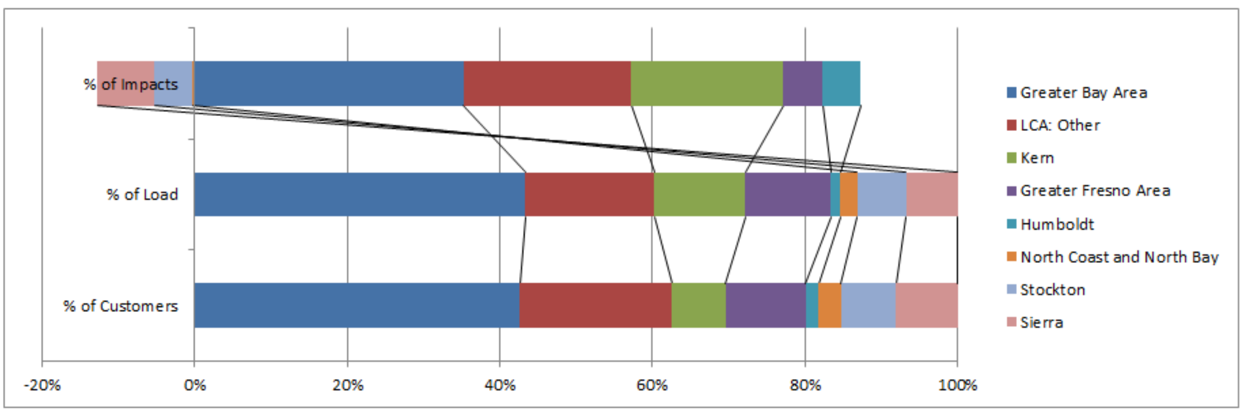


Table 4-11 shows the estimated ex post load impact by customer size. Load impacts are reported for two demand size categories: 20 kW to 200 kW; and less than 20kW. The load impact for the < 20 kW size category is insignificant, despite the large sample size. Table 4-11 shows that the 21,503 medium sized customers provided the vast majority of aggregate load reduction among the SMB default CPP population.

Table 4-11: SMB Default CPP Ex Post Load Impact Estimates by Customer Size Average 2015 PG&E CPP Event (2 to 6 PM)*

Categorization	Size Category	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig.?
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
By Demand Size	20 kW to 200 kW	21,503	21.6	21.4	0.2	4.3	0.9%	92.1	Yes
	Less than 20kW	127,279	2.3	2.3	0.0	1.5	0.5%	92.7	No

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

4.2.4 Load Impacts for Multi-DR Program Participants

Table 4-12 shows SMB default CPP load impacts for customers that are dually enrolled in other demand response programs. A word of caution is needed in reviewing Table 4-12. There are relatively few dually enrolled customers in any single DR program. For example, there are only 7 SMB default customers enrolled in both CPP and CBP. [redacted] The estimates are useful for adjusting portfolio impact estimates under assumptions that both programs are called on the same day, but it is not appropriate to claim that customers dually enrolled in CPP and CBP [redacted]. Said another way, while dual enrollment in CPP and CBP [redacted], there is no basis to infer that any combination of dual enrollment listed in Table 4-12 causes [redacted].

Table 4-12: SMB Default CPP Ex Post Load Impact Estimates for Dually-enrolled Participants Average 2015 PG&E CPP Event (2 to 6 PM)*

Dually Enrolled DR	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp.	Stat. Sig.?
		(kW)	(kW)	(kW)	(MW)	%	°F	
AMP	19	4.8	4.7	0.1	0.0	1%	92.1	Yes
CBP	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Not Dually-enrolled	148,755	5.1	5.1	0.0	5.7	1%	92.6	Yes

* Summations across segmentation categories may not equal totals presented for all customers on the average event day (Table 4-1). Sector specific estimates required estimation of separate difference-in-differences models and can result on rounding errors.

4.3 Early Enrollment Group Ex Post Load Impacts

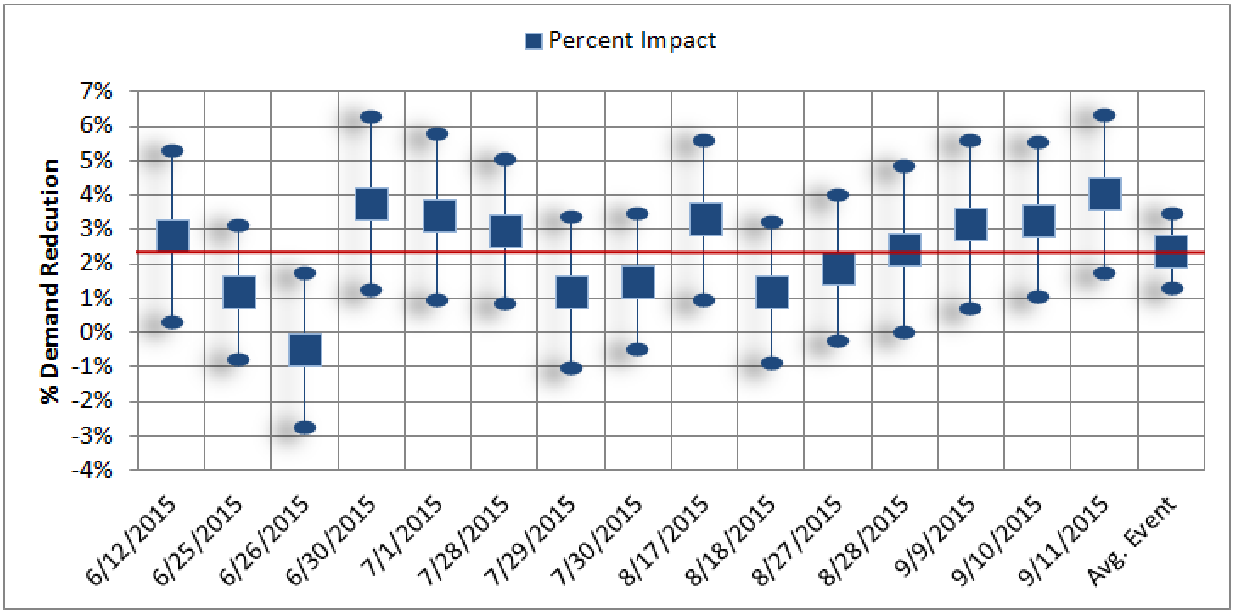
Table 4-13 shows the ex post load impact estimates for the EEG CPP customers for each event day and for the average event day in 2015. The average number of EEG CPP customers who participated in the 15 PG&E CPP events was 4,016. There is event-to-event variation in the number of EEG CPP customers due to some customers departing the CPP rate during summer 2015. The highest 2015 enrollment, 4,139 customers, occurred on the first event. The lowest enrollment, 3,951 customers, occurred on the last event. The participant-weighted average temperature during the event period ranged from a low of 85.6°F to a high of 95.7°F. Percent impacts ranged from -0.5% to 4.1%; average impacts ranged from 0.0 kW to 0.2 kW; and aggregate impacts ranged from -0.1 MW to 0.8 MW. On the average event day, the average participant reduced peak period load by 2.4%. In aggregate, PG&E's EEG CPP customers reduced load by an average of 0.5 MW across the 15 event days in 2015.

Table 4-13: EEG Ex Post Load Impact Estimates by Event Day PG&E 2015 CPP Events (2 to 6 PM)

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Event Temp.	Daily Max. Temp.
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	(°F)
6/12/2015	Fri	4,139	5.1	5.0	0.1	0.6	2.8%	88.3	89.0
6/25/2015	Thu	4,076	5.3	5.2	0.1	0.3	1.2%	90.4	90.9
6/26/2015	Fri	4,070	5.1	5.1	0.0	-0.1	-0.5%	87.9	88.7
6/30/2015	Tue	4,063	5.5	5.3	0.2	0.8	3.8%	93.5	94.0
7/1/2015	Wed	4,060	5.3	5.1	0.2	0.7	3.4%	87.4	87.9
7/28/2015	Tue	4,016	5.3	5.2	0.2	0.6	2.9%	93.1	93.6
7/29/2015	Wed	4,014	5.4	5.4	0.1	0.3	1.2%	92.1	92.6
7/30/2015	Thu	4,012	5.2	5.1	0.1	0.3	1.5%	87.5	88.1
8/17/2015	Mon	3,992	5.4	5.2	0.2	0.7	3.3%	92.4	93.2
8/18/2015	Tue	3,991	5.2	5.1	0.1	0.2	1.2%	85.6	86.2
8/27/2015	Thu	3,978	5.3	5.2	0.1	0.4	1.9%	92.1	93.2
8/28/2015	Fri	3,977	5.4	5.3	0.1	0.5	2.4%	92.6	94.4
9/9/2015	Wed	3,952	5.6	5.4	0.2	0.7	3.2%	95.7	96.6
9/10/2015	Thu	3,952	5.6	5.4	0.2	0.7	3.3%	94.0	94.7
9/11/2015	Fri	3,951	5.3	5.0	0.2	0.8	4.1%	90.7	91.8
Avg. Event		4,016	5.3	5.2	0.1	0.5	2.4%	90.9	91.6

Figure 4-14 also presents the PG&E EEG ex post load impact estimates for the 2015 CPP event days and the average 2015 event day, but here the 90% confidence intervals are shown with the point estimates. The wider confidence bands around the individual event day estimates, in comparison to the average event day, illustrate the noise inherent in measuring load impacts for individual event days—average event day load impact estimates are more precise; individual day impacts are noisier.

Figure 4-14: EEG Ex Post Load Impacts Estimates with 90% Confidence Intervals PG&E 2014 CPP Events (2 to 6 PM)



4.4 In Season Support Ex Post Load Impacts

PG&E provided In-Season (ISS) support (e.g. e-mail notifications and performance feedback) to nearly 38,000 SMB CPP customers throughout the event season. Table 4-14 provides a comparison between the average SMB default customer impacts without ISS support, with the impacts for customers with ISS. Customers with ISS exhibited a higher reference load than Non-ISS customers, and also produced significantly higher load impacts of 0.08 kW (1.3%) compared to Non-ISS customers with impacts of 0.02 kW (0.5%). Nexant also estimated impacts for 2015 opt-in customers with ISS. These 1,858 customers delivered impacts of .3 kW (4.9%) on average. Readers should refer to the load impacts table generator for more detailed results for 2015 opt-in customers with ISS.

Table 4-14: In-Season Support Impacts- SMB Default Customers

In-Season Support	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Event Temp.	Stat. Significant ?
		(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
In-Season Support	36,895	6.31	6.23	0.08	3.0	1.3%	92.8	Yes
Not In-Season Support	111,887	4.73	4.71	0.02	2.7	0.5%	92.6	Yes

Figure 4-15 provides a graphical comparison between ISS and Non-ISS customers. ISS impacts were generally positive throughout the season. However, Non-ISS impacts were negative on average for the first two-thirds of the season, but improved significantly in the latter third of the season. Ultimately, ISS and Non-ISS impacts were similar in percentage terms at the end of the season. A customer who defaulted onto PDP and chose to receive notifications by email was enrolled in ISS. As such, these impacts are valid for customers who are offered ISS in the same manner.

Figure 4-15: ISS & Non-ISS Impact Comparison (Non-incremental)- SMB Default Customers

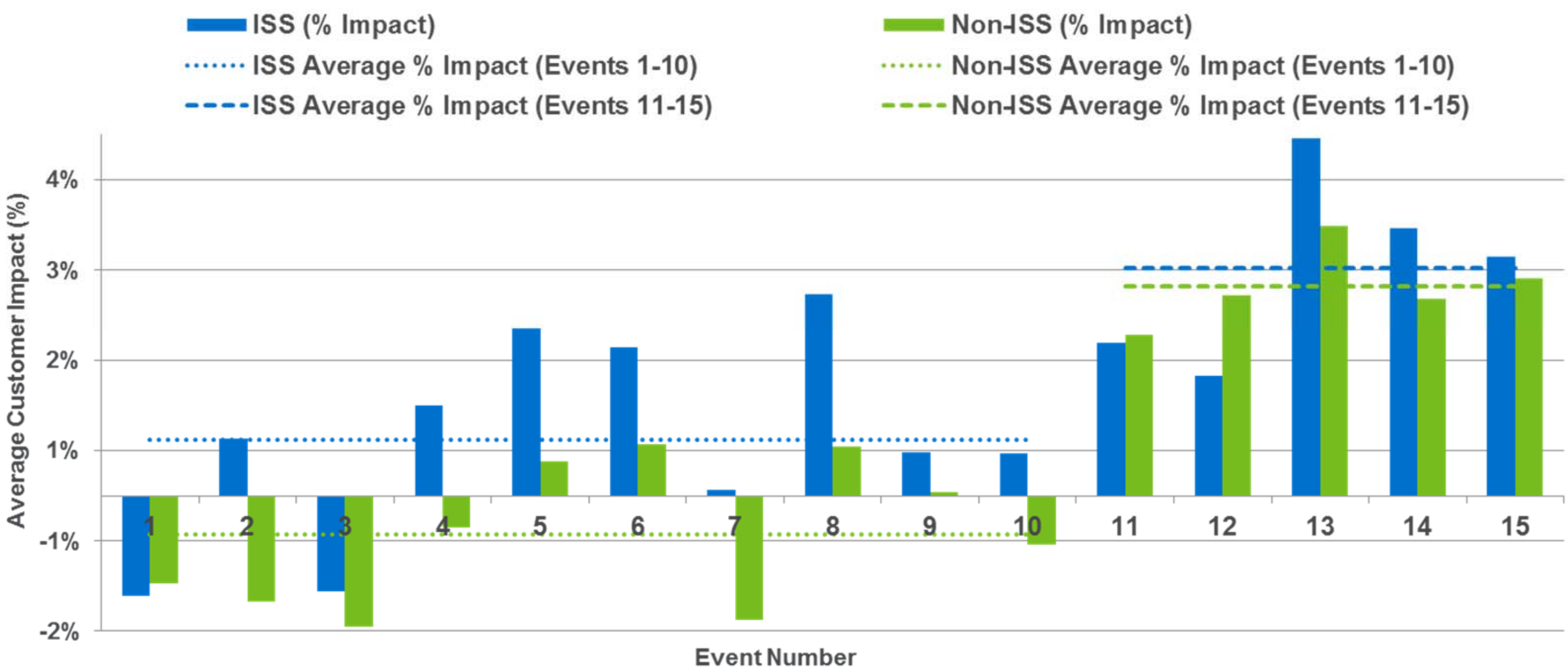


Table 4-15 presents the impact of ISS incremental or in addition to the typical SMB default customer impacts. For example, on the June 25 event ISS customers exhibited load reductions that was 0.06 kW larger than Non-ISS customers. Of particular interest is the statistical significance of the impacts throughout the season. In the earlier two-thirds of the season the incremental impacts are statistically significant more often than not. However, in the later third of the season the incremental impacts are almost exclusively not statistically significant. This implies that the effect of ISS was present towards the beginning of the season, but the Non-ISS customers effectively caught up, or learned through out the season, and this resulted in no effect from ISS in the later season events.

Table 4-15: ISS Incremental Impacts by Event Day- SMB Default Customers

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Stat.Sig?	Avg. Event Temp.	Daily Max. Temp.
			(kW)	(kW)	(kW)	(MW)	(%)		(°F)	(°F)
6/12/2015	Fri	37,975	5.8	5.9	-0.03	-1.0	-0.5%	No	90.3	91.0
6/25/2015	Thurs	37,543	6.2	6.1	0.06	2.2	0.9%	Yes	92.7	93.1
6/26/2015	Fri	37,511	6.0	5.9	0.01	0.5	0.2%	No	90.4	91.1
6/30/2015	Tues	37,466	6.4	6.3	0.05	1.8	0.8%	No	95.6	96.2
7/1/2015	Wed	37,422	6.0	6.0	0.06	2.2	1.0%	Yes	89.5	89.9
7/28/2015	Tues	36,901	6.2	6.1	0.05	2.0	0.9%	Yes	94.5	94.9
7/29/2015	Wed	36,882	6.4	6.3	0.06	2.4	1.0%	Yes	94.3	94.9
7/30/2015	Thurs	36,862	6.1	6.0	0.06	2.2	1.0%	Yes	89.4	90.0
8/17/2015	Mon	36,603	6.5	6.5	0.06	2.1	0.9%	No	94.6	95.4
8/18/2015	Tues	36,581	6.2	6.1	0.08	3.1	1.4%	Yes	87.7	88.3
8/27/2015	Thurs	36,494	6.4	6.4	0.02	0.6	0.3%	No	93.6	94.6
8/28/2015	Fri	36,468	6.4	6.5	-0.02	-0.8	-0.3%	No	94.1	95.7
9/9/2015	Wed	36,270	6.6	6.6	0.00	-0.1	-0.1%	No	97.0	97.7
9/10/2015	Thurs	36,234	6.6	6.6	-0.01	-0.3	-0.1%	No	95.9	96.4
9/11/2015	Fri	36,214	6.2	6.2	0.00	0.0	0.0%	No	92.4	93.4
Avg. Event		36,895	6.3	6.2	0.03	1.1	0.5%	Yes	92.8	93.4

Figure 4-16 provides a graphical representation of the incremental impacts shown in the previous table. As noted, the ISS incremental impacts (in orange) were generally positive and significant in the first two-thirds of the season. The blue bars represent the SMB total impact, including both the basic SMB impacts and the incremental ISS effect. The green SMB basic bars represent what impacts would have been expected had there not been ISS—the SMB total impact minus the ISS incremental effect. The diminishing effect of ISS can be observed in events 11-15 as the incremental ISS effect nearly disappears, and the load impacts between SMB total and SMB basic converge. A similar convergence can be observed in events 11-15 in Figure 4-15, where the percentage impacts between customers with and without ISS begin to align. The key takeaway from this analysis is that ISS customers tend to respond to events earlier in the season, but all customers ultimately ended up performing similarly in percentage terms by the end of the season.

Figure 4-16: Relative Impact of Incremental ISS- SMB Default Customers

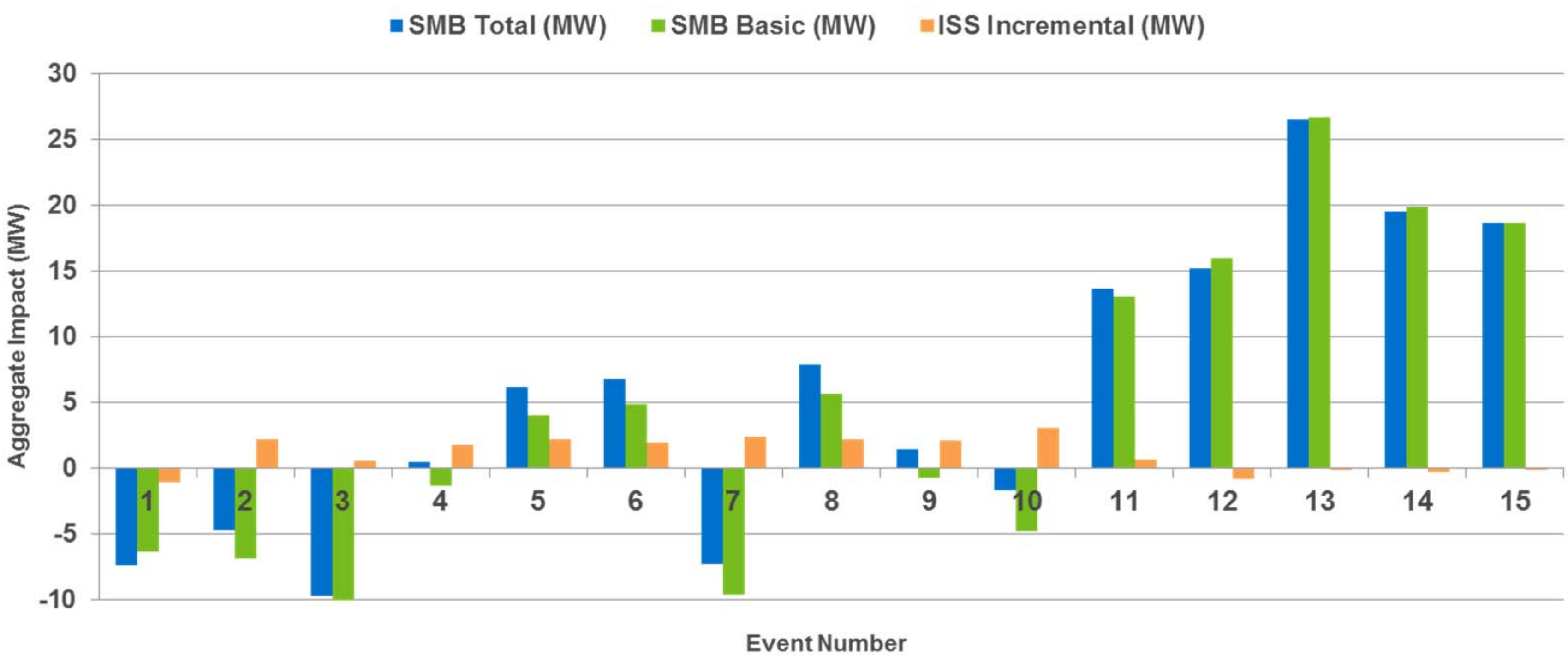


Table 4-16 presents the impact of 2015 opt-in customers with ISS incremental or in addition to the typical SMB default customer impacts. For example, on the June 25 event ISS customers exhibited load reductions that was 0.28 kW larger than Non-ISS default customers. The incremental impacts are almost exclusively not statistically significant on specific event days, with the exception of the July 29 event, but the incremental impact for the average event is statistically significant. These ISS customers were on CPP on an opt-in basis, and by comparing their impacts to those of SMB default customers, these results not only capture the effect of ISS, but any effect, behavioral or otherwise, related to the decision to opt-in.

Table 4-16: ISS Incremental Impacts by Event Day- 2015 Opt-in Customers

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Stat.Sig?	Avg. Event Temp.	Daily Max. Temp.
			(kW)	(kW)	(kW)	(MW)	(%)		(°F)	(°F)
6/12/2015	Fri	1,878	5.8	5.7	0.15	0.3	2.7%	No	82.7	83.1
6/25/2015	Thurs	1,864	6.0	5.7	0.28	0.5	4.7%	No	84.1	84.8
6/26/2015	Fri	1,864	5.8	5.6	0.13	0.2	2.2%	No	81.3	82.3
6/30/2015	Tues	1,861	6.2	5.9	0.30	0.6	4.8%	No	87.4	88.3
7/1/2015	Wed	1,858	6.0	5.7	0.27	0.5	4.5%	No	82.1	82.8
7/28/2015	Tues	1,833	6.0	5.9	0.13	0.2	2.2%	No	87.5	88.2
7/29/2015	Wed	1,830	6.3	5.9	0.35	0.6	5.6%	Yes	85.2	86.0
7/30/2015	Thurs	1,828	5.9	5.7	0.15	0.3	2.5%	No	82.7	83.3
8/17/2015	Mon	1,820	6.2	6.0	0.15	0.3	2.4%	No	85.4	86.3
8/18/2015	Tues	1,818	6.0	5.9	0.10	0.2	1.7%	No	80.8	81.6
8/27/2015	Thurs	1,810	6.4	6.2	0.22	0.4	3.4%	No	88.6	89.8
8/28/2015	Fri	1,809	6.4	6.1	0.33	0.6	5.1%	No	88.7	91.1
9/9/2015	Wed	1,802	6.5	6.3	0.18	0.3	2.7%	No	91.5	92.9
9/10/2015	Thurs	1,799	6.5	6.3	0.17	0.3	2.7%	No	88.7	89.8
9/11/2015	Fri	1,799	6.1	6.0	0.09	0.2	1.5%	No	86.2	87.4
Avg. Event		1,831	6.1	5.9	0.20	0.4	3.3%	Yes	85.5	86.5

5 PG&E Ex Ante Load Impacts

This section presents ex ante load impact estimates for PG&E's nonresidential CPP tariff. As discussed in Section 3, the main purpose of ex ante load impact estimates is to reflect the load reduction capability of a demand response resource under a standard set of conditions that align with system planning. These estimates are used in assessing alternatives for meeting peak demand, cost-effectiveness comparisons, and long-term planning. The ex ante impact estimates for PG&E are based on ex post load impacts of CPP events that occurred in 2015. Load impact estimates for the average 2015 event were used as input to the ex ante model. This departs from the approach used in prior years of basing impacts on two years of historical ex-post load impact estimates. As discussed in Section 3.2, the decision was made to base the ex ante forecast solely on 2015 results, which were substantially lower than prior year impacts. Lacking evidence to indicate the impacts will revert to their 2014 average, basing the impacts on the 2015 average is a more conservative approach. All load impact estimates presented here are incremental to the effects of the underlying TOU rates.

Ex ante load impact projections are shown separately for small, medium, and large customers projected to receive service under PG&E's default CPP tariff. The load reduction capability is summarized for each segment under annual system peak day conditions for a 1-in-2 and a 1-in-10 weather year for selected years (e.g., 2016, 2017, 2018 and 2026),[23] based on PG&E and CAISO weather scenarios. The estimates presented here are not adjusted for dual enrollment of CPP participants in other DR programs. Portfolio estimates that net out impacts for other programs if called at the same time are presented in Appendix E. Explanations of how CPP ex ante load impact estimates vary by geographic location and month under standardized ex ante conditions are also included in this section.

5.1 Large C&I Ex Ante Load Impacts

As discussed in Section 3, the ex ante load impact estimates for large C&I customers are based on a percent load reductions for the average 2015 event for each LCA. Variation in load impacts is based on the relationship of reference load and weather, as well as changes in the distribution of customers across LCAs over time. Before reviewing ex ante results, we provide an overview of the ex ante methodology. The steps involved in the analysis are as follows:

1. Use 2015 ex post results for large default customers[24] to calculate percent impacts for each hour of the average event day by LCA; [25];

---

[23] Enrollment is not forecasted to change substantially between 2017 and 2026, so the interim years didn't provide much additional information of interest. The electronic load impact tables contain estimates for each year over the forecast horizon.

[24] In prior years, 2 years of impact data from the persistent customers were used instead of a single year for all customers included in the ex post analysis. The rationale for this is covered in the methodology section 3.2.

[25] Percent impacts are applied to ex ante weather conditions (in this case the percent impacts are identical for each set of conditions; the relationship between percent load impacts and weather was not modeled for PG&E for reasons explained below and in Section 3.

2. Identify large ex post customers enrolled at the end of the summer in 2015 who are also in the large demand category and have a full panel of data for 2015, and model their reference load as a function of temperature;

3. Apply reference load model to ex ante weather conditions;

4. Combine percent impacts and reference load for each set of ex ante conditions to get kW impacts for the average customer;

5. Multiply average customer impacts by ex ante enrollment.

Table 5-1 shows the ex post load impact estimates for each LCA for large default customers. These percentage impacts are applied directly to the reference load that is predicted for ex ante weather conditions. Impacts at the LCA level reflect the weather, size of customers, and industry mix in each of PG&E's LCAs. PG&E does not expect the customer mix within the LCAs to change significantly over the forecast horizon[26]. Percent impacts range from 2.4% to 18.9%; average impacts range from 7.7 kW to 33.9 kW; and aggregate impacts range from 0.9 MW to 9.6 MW. The Greater Bay Area and Other LCAs account for the majority of aggregate load reduction. A more detailed discussion of impacts by LCA is presented in section 5.1.3.

Table 5-1: Default CPP Ex Post Load Impact Estimates for Large Customers by LCA for the Average 2015 Event (2 to 6 PM)

Local Capacity Area	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig.?
		(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
Greater Bay Area	931	319.3	311.7	7.7	7.1	2.4%	84.6	Yes
Greater Fresno Area	252	243.2	231.8	11.4	2.9	4.7%	102.9	Yes
Humboldt	27	179.8	145.8	33.9	0.9	18.9%	86.6	Yes
Kern	268	168.9	150.4	18.6	5.0	11.0%	100.9	Yes
LCA: Other	375	246.8	221.1	25.7	9.6	10.4%	89.9	Yes
North Coast and North Bay	24	204.9	185.4	19.4	0.5	9.5%	92.9	No
Sierra	85	183.3	170.8	12.5	1.1	6.8%	98.5	Yes
Stockton	127	276.0	254.7	21.3	2.7	7.7%	98.7	Yes

Figure 5-1 illustrates the ex post impacts from the table above after they have been applied to the ex ante conditions. For each LCA, the figure includes the percent demand reductions estimated under 1-in-2 and 1-in-10 year weather conditions (green squares) for the months of May to October based on the PG&E weather scenarios. Ex post percent reductions (blue circles) as a function of temperature are also included for each LCA. The ex ante percent

[26] There is expected to be a large increase in agricultural customers that will increase the share of those customers within the Greater Fresno Area, Kern, and Other LCAs. However, an analysis was completed evaluating the performance of persistent versus new agricultural customers. Newer agricultural customers didn't perform nearly as well as persistent customers. With the expectation of more, but lower performing agricultural customers joining the program, the increase in enrollment may be offset by the reduction in performance. Based off this information the assumption is these effects may net each other out. Therefore, the current % impacts by LCA are best information available until the actual performance of these new customers is observed.

reductions are identical to those in the table above. As discussed, the ex ante percent impact estimates are based on the average event percent reductions in the ex post analysis. The ex ante fitted values therefore exhibit a flat temperature relationship, which falls towards the center of the range of ex post impacts for each LCA. The flat temperature relationship was applied in this year's evaluation due to the significant change in ex post event performance in the first two-thirds and latter third of the events as noted in Section 4.4.1. This performance shift led to spurious relationships between load impact magnitude and temperature. Certain industries also exhibited inconsistent performance either due to seasonality, or other unknown factors. Because of these two factors, it was decided that allowing impacts to vary by LCA was the next best approach at allowing impacts vary across program participants, without implementing an approach that led to unrealistic results.

Figure 5-1: Comparison of 2015 CPP Load Impacts and Summer Ex Ante Load Impacts vs. Temperature by LCA

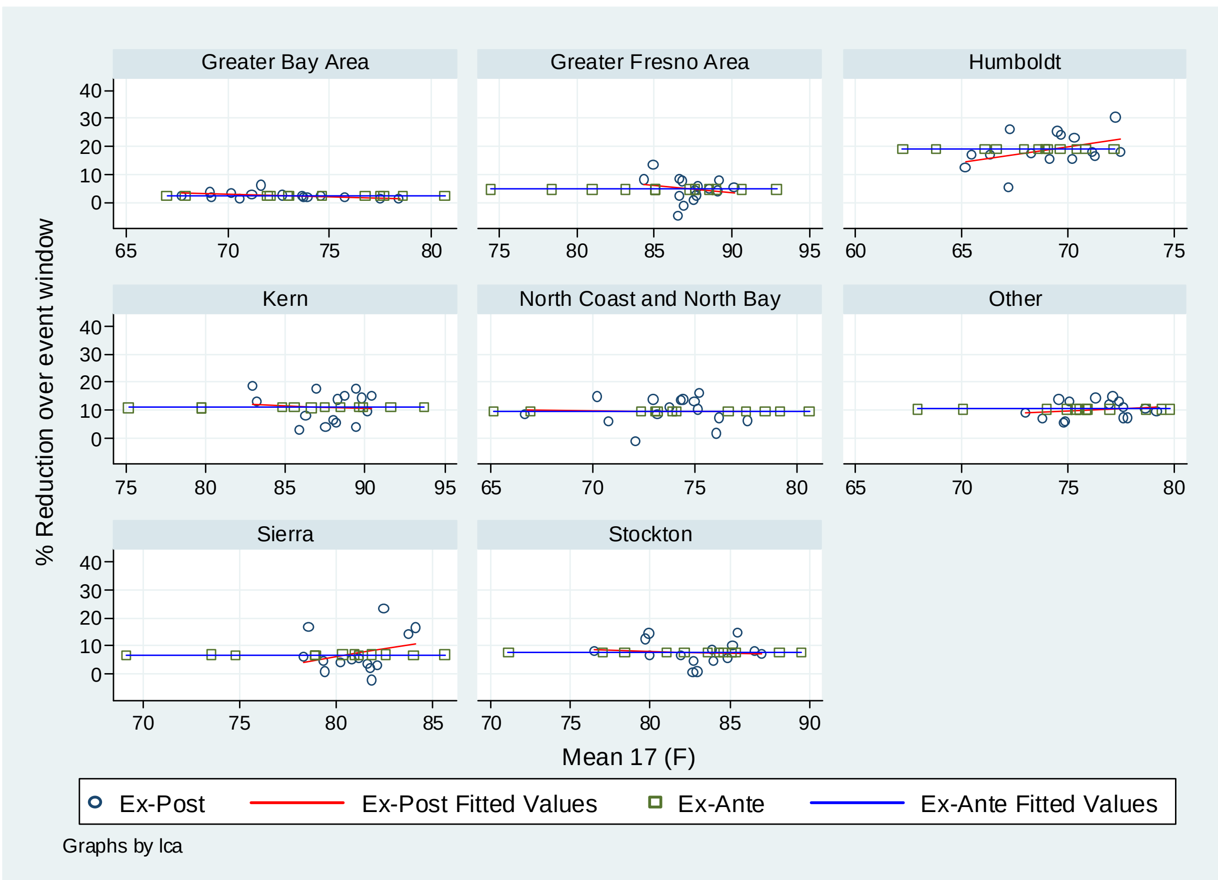


Figure 5-2 examines the sample used to model reference load, and compares the average large default ex post customer's load on nonevent days to the load of the average customer in the subset of large customers used in developing the ex ante reference load. The ex ante customers are the large customers identified as enrolled at the end of summer of 2015, which are used for reference load modeling in order to provide the most up to date picture of customers enrolled on CPP. Customers used for reference load modeling are also required to have a full panel of data for the year, and consist only of customers in the largest demand category. Therefore, the three reasons a large default ex post customer wouldn't be included in the ex ante reference load calculation are: 1) the customer is no longer in the program; or 2) the customer had incomplete data; or 3) the customer was defaulted but fell in size to a lower demand category. The 1,755 customers used for ex ante reference load modeling comprised 84% large default customers enrolled throughout summer 2015. The reference loads from nonevent days in May through October are included in the graph (weekends and holidays are excluded). The average nonevent day load is roughly 25 kW higher for ex ante customers than for the ex post customers for the same days and weather conditions. Furthermore, the nonevent day loads for ex ante customers show a slightly stronger relationship with temperature than those for all ex post customers.

Figure 5-2: Comparison of Nonevent Day Loads of All Large Default Ex Post Customers and Subset of Large Customers Used in Developing the Ex Ante Reference Load

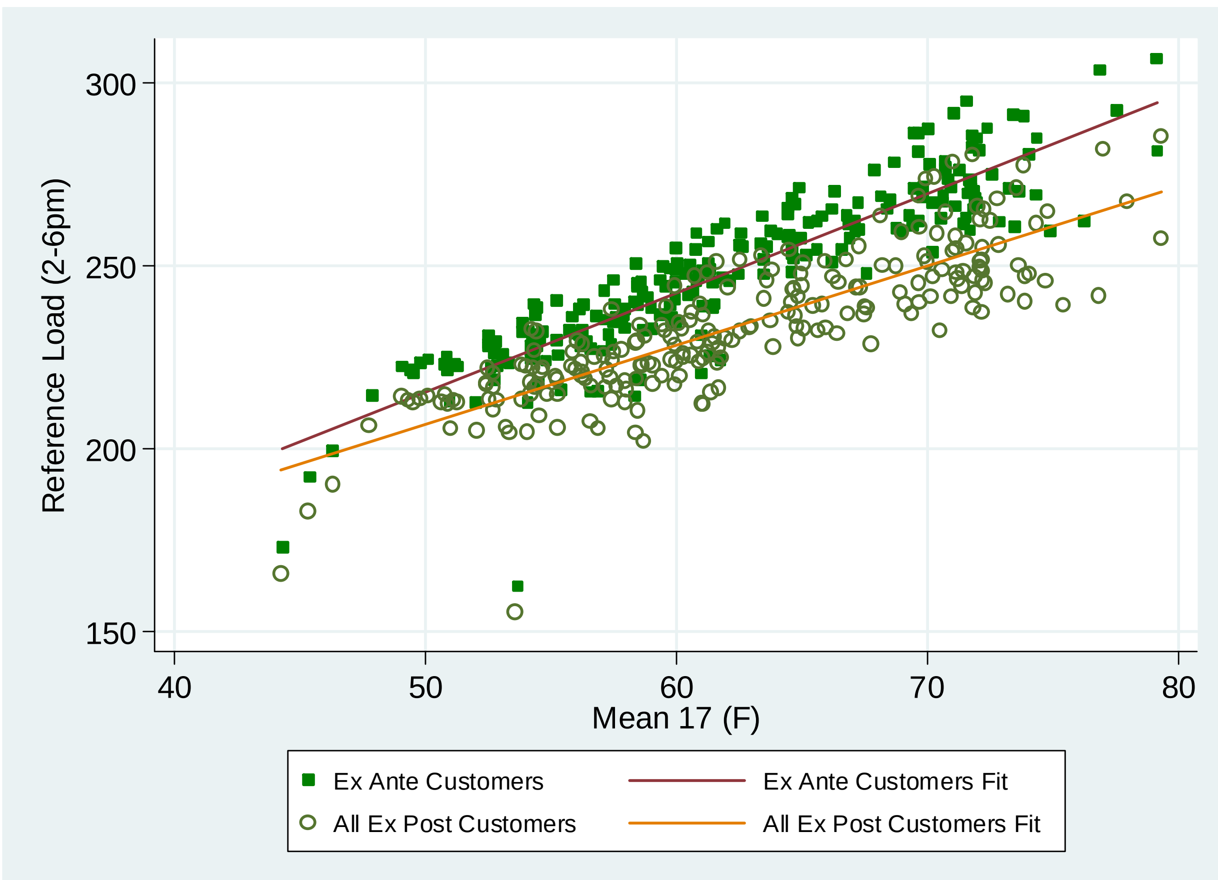


Figure 5-3 illustrates the reference load temperature relationship from the ex ante customers in the figure above after it has been applied to the ex ante conditions. It compares the customer reference loads during nonevent days in 2015 to the ex ante reference loads. The 1-in-2 and 1-in-10 reference loads from May through October are included in the graph. The ex ante reference loads follow the weather trend observed within each LCA during nonevent days.

Figure 5-3: Comparison of Ex Post Reference Loads on Nonevent Days to Ex-Ante Reference Loads for Large C&I

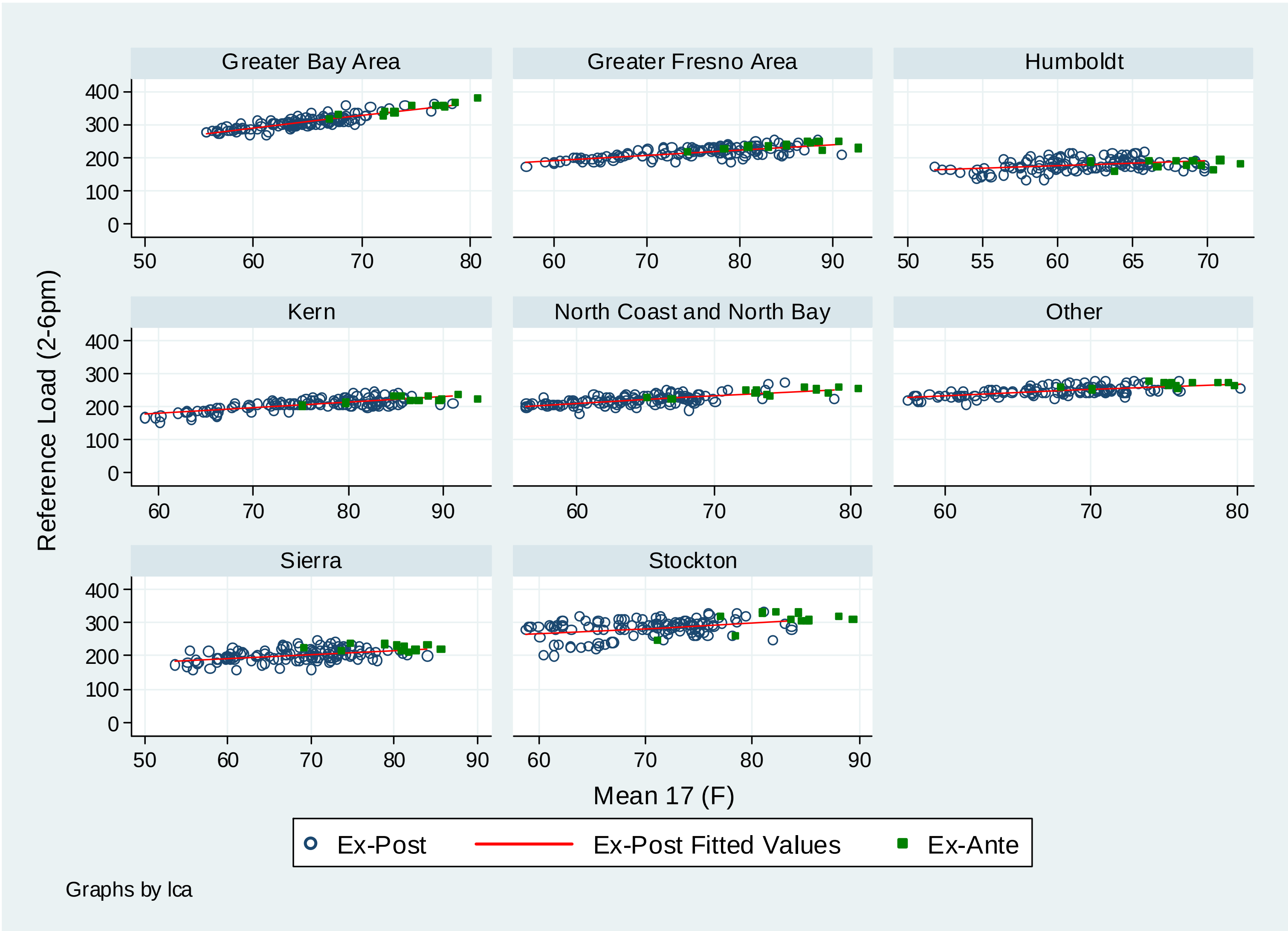


Table 5-2 shows PG&E's enrollment projections for large C&I CPP customers through 2026. Impacts for the average customer are scaled up by the enrollments below to yield aggregate impacts. PG&E developed the enrollment forecast using the company's near-term schedule of forthcoming PDP defaults and data from its longer term sales forecast. . Due to additional large customers that are scheduled to be defaulted onto CPP, PG&E projects that large C&I CPP enrollment will grow to 3,109 by November 2017 and will then remain essentially flat through 2026.

Table 5-2: PG&E Enrollment Projections for Large C&I CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2016	2,123	2,123	2,483	2,483	2,483	2,483	2,483	2,483	2,483	2,483	2,776	2,776
2017	2,776	2,776	3,011	3,011	3,011	3,011	3,011	3,011	3,011	3,011	3,109	3,109
2026	3,150	3,150	3,154	3,154	3,154	3,154	3,154	3,154	3,154	3,154	3,155	3,155

5.1.1 Annual System Peak Day Impacts

Table 5-3 summarizes the aggregate load impact estimates for large C&I customers on PG&E's CPP tariff for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios, based on both PG&E and CAISO weather scenarios. The table shows the average load reduction across the 1 to 6 PM event period for an August monthly system peak day. Looking first at the aggregate load impacts based on normal, PG&E-specific weather, load reductions based on 1-in-2 year PG&E weather conditions grow from roughly 35 MW to almost 46 MW between 2016 and 2026. Impacts based on 1-in-10 year PG&E weather conditions equal roughly 37 MW in 2016 and grow to 47 MW by 2026. These estimates equal roughly 5.0% of the aggregate reference load for large C&I customers. The percent impact is lower than the 5.3% observed for the average ex post event because the ex ante percent impact is calculated over the RA event window. Impact estimates based on CAISO weather 1-in-2 year conditions are roughly 3% less than the estimates based on PG&E weather. The CAISO 1-in-10 year weather values produce a load reduction that is about 2% less than the 1-in-10 year PG&E estimates.

Table 5-3: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I, PG&E August System Peak Day (1-6 PM)

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
PG&E	1-in-10	2016	2,483	749.4	712.7	36.7	4.9%	95.8
		2017	3,011	902.7	857.6	45.2	5.0%	96.0
		2026	3,154	947.9	900.8	47.1	5.0%	95.9
	1-in-2	2016	2,483	722.8	687.2	35.6	4.9%	92.3
		2017	3,011	871.1	827.2	43.9	5.0%	92.5
		2026	3,154	914.5	868.7	45.7	5.0%	92.5
CAISO	1-in-10	2016	2,483	731.0	694.9	36.1	4.9%	92.7
		2017	3,011	881.0	836.5	44.4	5.0%	93.1
		2026	3,154	924.8	878.5	46.3	5.0%	93.0
	1-in-2	2016	2,483	694.3	659.9	34.4	5.0%	89.2
		2017	3,011	837.0	794.6	42.4	5.1%	89.4
		2026	3,154	878.7	834.5	44.2	5.0%	89.4

5.1.2 Ex Ante Load Impact Uncertainty

Table 5-4 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for large C&I customers that are presented in Table 5-3. Ex ante impacts and the uncertainty in those estimates do not reflect uncertainty in the enrollment forecast. At first glance, the uncertainty appears large. For example, in 2016, the projected load impacts for August 1-in-2 year, PG&E weather have an 80% confidence interval of 26.9 MW to 44.4 MW. The large confidence intervals in the ex ante forecasts reflect the challenges of accurately estimating small percentage demand reductions and the variability in performance observed across events. It is harder to accurately estimate a smaller percent change from the variation inherent in day to day loads. Put in percentage terms, the uncertainty seems much smaller, with an 80% confidence interval of 4.0% to 6.6%. For this program in particular, small differences in the estimated percent demand reductions can appear to be large changes in the estimate MW reductions, if the uncertainty is not considered.

Table 5-4: Aggregate Default CPP Ex Ante Load Impact Estimates for Large C&I with Uncertainty, PG&E August System Peak Day (MW 1–6 PM)

Weather Type	Weather Year	Year	Expected Aggregate Load Impact (MW 1-6 PM)	Impact Uncertainty				
				10th	30th	50th	70th	90th
PG&E	1-in-10	2016	36.7	27.7	33.0	36.7	40.4	45.7
		2017	45.2	34.0	40.6	45.2	49.8	56.4
		2026	47.1	35.4	42.3	47.1	51.9	58.7
	1-in-2	2016	35.6	26.9	32.1	35.6	39.2	44.4
		2017	43.9	33.0	39.5	43.9	48.3	54.7
		2026	45.7	34.4	41.1	45.7	50.4	57.0
CAISO	1-in-10	2016	36.1	27.2	32.4	36.1	39.7	45.0
		2017	44.4	33.4	39.9	44.4	48.9	55.4
		2026	46.3	34.9	41.6	46.3	51.0	57.8
	1-in-2	2016	34.4	25.9	30.9	34.4	37.9	42.9
		2017	42.4	31.9	38.1	42.4	46.7	52.8
		2026	44.2	33.3	39.7	44.2	48.6	55.1

5.1.3 Ex Ante Impacts by Geographic Location and Month

Table 5-5 presents aggregate 2016 ex ante impacts for each LCA by month for large C&I customers. Load impacts are shown for the Resource Adequacy hours in effect for each month, which are 1 to 6 PM in the summer months and 4 to 9 PM in the winter months. As a result of the CPP event window ending at 6 PM, impacts are typically between 2 and 3 times larger in the summer months compared with winter months. It should also be noted that estimates for months outside of the June to September timeframe should be used with caution as PG&E has not called events in shoulder and winter months since the implementation of default TOU in 2010. As such, there is no real empirical data on how customers will respond in these periods, which vary significantly in terms of weather conditions and event window hours.

In aggregate, the load reductions are largest in the Greater Bay Area and Other LCAs. The 2016 enrollment forecast shows 40% of enrollments located in the Greater Bay Area LCA; and 23% are located outside of the primary LCAs and are classified as Other. Greater Bay Area CPP participants delivered 19% of the program's ex ante load reduction on an average event day while customers classified as Other LCA provided 38% of aggregate ex ante impacts despite only accounting for 23% of the total population. This pattern is similar to that observed in 2015 and 2014 ex post evaluations.

Table 5-5: Aggregate PG&E Ex Ante Load Impact Estimates by LCA Large C&I 2016 Monthly System Peak Days, PG&E Weather Scenarios[27]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4-9 pm Resource Adequacy Window				1-6 pm Resource Adequacy Window						4-9 pm	
1-in-10	All	12.0	12.4	17.1	22.7	36.3	36.4	35.4	36.7	36.5	35.3	20.3	15.4
	Greater Bay Area	3.5	3.5	3.7	4.6	7.3	7.5	7.0	7.1	7.1	7.1	4.5	3.8
	Greater Fresno	0.8	0.9	1.3	1.6	3.3	3.3	3.1	3.4	3.2	3.1	1.4	1.0
	Humboldt	0.4	0.4	0.4	0.4	0.7	0.8	0.8	0.9	0.9	0.9	0.4	0.4
	Kern	1.2	1.4	2.8	3.7	6.5	6.4	6.6	6.9	6.8	6.2	3.1	2.0
	Northern Coast	0.3	0.3	0.3	0.4	0.8	0.8	0.7	0.8	0.8	0.8	0.4	0.3
	Other	4.4	4.5	7.0	9.7	13.8	14.0	13.5	13.9	13.9	14.1	8.6	6.3
	Sierra	0.4	0.4	0.4	0.6	0.9	0.9	0.9	0.9	1.0	1.0	0.6	0.4
	Stockton	0.9	1.0	1.2	1.6	3.0	2.8	2.8	2.9	3.0	2.3	1.4	1.1
1-in-2	All	12.3	12.5	16.6	21.4	33.7	35.1	34.0	35.6	36.1	33.4	19.4	16.1
	Greater Bay Area	3.6	3.6	3.7	4.2	6.3	6.7	6.5	6.7	6.7	6.5	4.3	4.0
	Greater Fresno	0.8	0.9	1.2	1.6	3.1	3.4	3.0	3.3	3.2	3.0	1.3	1.1
	Humboldt	0.4	0.4	0.4	0.4	0.7	0.8	0.8	0.8	0.9	0.8	0.4	0.4
	Kern	1.2	1.4	2.7	3.6	6.2	6.5	6.4	6.8	6.8	6.0	2.8	2.1
	Northern Coast	0.3	0.3	0.3	0.4	0.7	0.7	0.7	0.7	0.8	0.7	0.4	0.4
	Other	4.6	4.6	6.8	9.1	12.9	13.4	13.0	13.5	13.8	13.2	8.2	6.6
	Sierra	0.4	0.4	0.4	0.6	0.9	0.9	0.9	0.9	1.0	0.9	0.5	0.4
	Stockton	1.0	1.0	1.1	1.5	2.9	2.7	2.7	2.8	3.0	2.2	1.3	1.1

5.1.4 Comparison of 2014 and 2015 Ex Ante Estimates

Table 5-6 compares the August ex ante estimates produced for the 2014 evaluation to those presented in this report. Because ex ante impacts take into account changes in utility enrollment forecasts, program design and customer mix as well as additional experience, the forecasts are adjusted each year. In general, forecasts a year out are more reliable while forecasts further in the future are less certain.

Table 5-6 summarizes the comparison between the prior year’s ex ante estimates and the current estimates. Notable differences are observed in the enrollment forecasts, which range from 4% lower to 19% higher than those produced by PG&E for the 2014 report estimates. This difference is highest in 2018-2026. The adjustment reflects more recent data about the number of customers who will be defaulted onto CPP in the future.

Notable differences are also observed in the reference loads, which are roughly 10% lower than those produced in the 2015 report. The difference in reference loads is consistent with the ex post results, and reflects changes in the customer mix.

27 Estimates based on CAISO weather scenarios have a similar pattern across months and LCAs. These values can be obtained from the electronic load impact tables that were submitted along with this report.

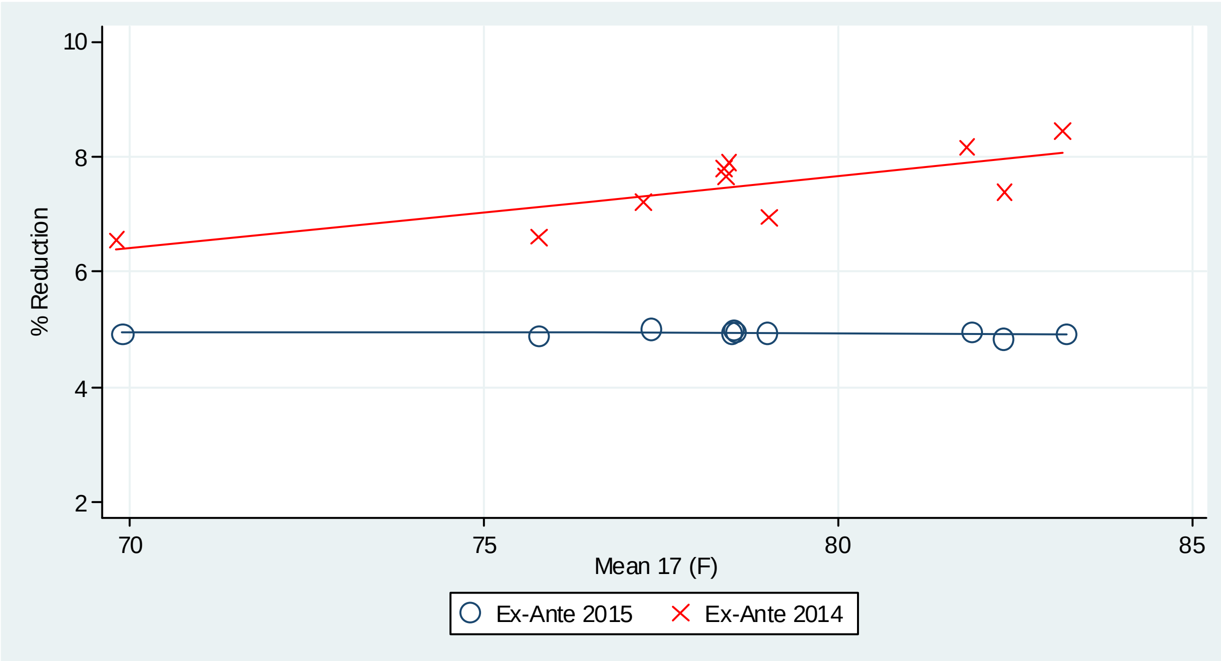
Most notably, the percent reductions in 2015 are lower than those in 2014. The 2015 ex post percent reductions (5.3%), which are used in the ex ante analysis, were lower than in previous evaluations (8.1%); this in turn translates to lower percent impacts in the ex ante estimates, shown below. A detailed discussion of the ex post percent reductions, including an analysis of differences from last year's results, is provided in section 4.1.1. The ex ante impacts were based on the 2015 ex post estimates in order that they reflect the most up to date information on customer response. The net effect of differences from 2014 is that this year's forecast for 2016 under 1-in-10 year weather conditions is 37 MW, which is 47% lower than last year's forecast of 70.9 MW, with most of the difference due to lower percent reductions, and some due to changes in PG&E's enrollment forecasts, and lower reference load. Further into the future, the differences in forecast aggregate impacts grow smaller, as the 2015 enrollment forecast is larger.

Table 5-6: Comparison of Large C&I August Ex Ante Estimates to Prior Year Estimates

Weather Year	Year	Accounts		Reference Loads (kW)		Percent Reductions		Aggregate Impacts (MW)	
		2014 Estimates	2015 Estimates	2014 Estimates	2015 Estimates	2014 Estimates	2015 Estimates	2014 Load Impact (MW)	2015 Load Impact (MW)
1-in-10	2016	2,594	2,483	335.5	301.8	8.1%	4.9%	70.9	36.7
	2017	2,624	3,011	335.7	299.8	8.1%	5.0%	71.8	45.2
	2018-2026	2,621	3,112	335.6	300.8	8.2%	4.9%	71.7	46.3
1-in-2	2016	2,594	2,483	322.4	291.1	7.7%	4.9%	64.0	35.6
	2017	2,624	3,011	322.6	289.3	7.7%	5.0%	64.8	43.9
	2018-2026	2,621	3,112	322.6	290.2	7.7%	5.0%	64.8	45.0

A graphical comparison between the summer ex ante load impacts for large C&I customers as estimated in the 2014 and 2015 load impact evaluation is shown in Figure 5-4. The 2014 ex ante estimates are larger than those estimated this year, and they show a stronger relationship with temperature.

Figure 5-4: Comparison of 2014 Ex Ante Load Impacts to 2015 Ex Ante Large C&I Summer Months Load Impacts vs. Temperature



5.1.5 Relationship between Ex Post and Ex Ante Estimates

The ex post estimates presented in Section 4 and the ex ante estimates presented in this section differ for a number of reasons, including differences in weather, enrollment, event window and estimation methodology. This section discusses the impact these factors have on the difference between ex post and ex ante impact estimates.

Table 5-7 summarizes the key factors that lead to differences between ex post and ex ante estimates for CPP and the expected influence that these factors have on the relationship between ex post and ex ante impacts. Given that the CPP load impacts are sensitive to variation in weather, even small changes in *mean17* between ex post and ex ante weather conditions can produce differences in load impacts. In 2015 event days were relatively hot, so large differences in *mean17* do not occur. For the typical event day, ex ante impacts are significantly higher when based on PG&E ex ante weather and similar to ex post values when based on CAISO weather conditions. Changes in enrollment between the values used for ex post estimation and the 2015 enrollment values increase impact estimates by about 17%. Finally, reference load for the ex ante population (large ex post customers enrolled at the end of the summer in 2015 who are also in the large demand category and have a full panel of data for 2015) which was used to model reference load for ex ante conditions, is about 25 kW higher on average than that of the ex post population. This will also result in higher ex ante load impacts.

Table 5-7: Summary of Factors Underlying Differences between Ex Post and Ex Ante Impacts for the Default CPP Customers for the Ex Ante Typical Event Day

Factor	Ex Post	Ex Ante	Expected Impact
Weather	Default CPP customers: 74.7 < event day mean17 < 80.7 Average event day mean17 = 77.9	Program specific mean17 for 1-in-2 typical event day = 78.1 and 75.9 for PG&E and CAISO weather, respectively Program specific mean17 for 1-in-10 typical event day = 81.5 and 78.8 for PG&E and CAISO weather, respectively	Ex ante estimates are sensitive to variation in mean17 (although percent impacts are invariant, reference load increases with mean17)– impacts will be higher based on PG&E weather and only slightly higher based on CAISO weather
Event window	All events called from 2 to 6 PM	Resource adequacy event window is 5 hours, from 1 to 6 PM, and 1 to 2 PM impact is basically zero because the CPP program event window does not include that hour	Average ex ante impacts will be lower
Enrollment	Enrollment remained fairly constant over the 2015 summer	2016 enrollment is forecast to be about 17% higher	Ex ante estimates will be about 17% higher than ex post
Methodology	2015 impacts based on combination of matched control groups and individual customer regressions	Impacts: 2015 ex post percent impacts from all large default customers. Reference Load: regression of kW against mean17 and date variables for each hour using large ex ante population from end of summer 2015	No difference in impacts by using 2015 ex post percent reductions. Reference load is higher for the ex ante population than for the ex post population, so impacts will in turn be higher.

Table 5-8 shows how aggregate load impacts change for large default CPP customers as a result of differences in the factors underlying ex post and ex ante estimates. Column B shows the 2015 ex post impacts shown in Table 4-1. The projected enrollment for August 2016 is applied to the ex post impacts to produce a scaled-up ex post impact estimate in Column C. This leads to an average increase in load reductions of about 19%. Column D shows what the ex ante model would produce using the same August 2016 enrollment figures and the ex post weather conditions for each event day. The ex ante model over predicts load reductions on average by about 17% compared with the 2015 ex post impacts. As discussed earlier, this is the result of the higher reference load for the ex ante population. The only a reasons a customer would not be included in the ex ante population for the large default customers are: 1) they dropped out of the program; 2) they didn't have complete data; or 3) they weren't actually large customers, but were originally defaulted as large customers and have since dropped to a lower demand category[28]. Column E presents what the ex ante model would produce using the same August 2016 enrollment figures and ex post weather conditions but with impacts calculated over the RA window that spans 1 to 6 PM as opposed to 2 to 6 PM. Impacts are slightly lower under the RA window as the impact from 1 to 2 PM is close to zero. The final four columns F through I show how aggregate load reductions vary with the different ex ante weather scenarios. On average across all event days, the impacts derived from the CAISO 1-in-2 conditions are most similar to those derived using the ex post weather conditions and RA event window, although for any given ex post event day, the impacts can differ significantly. Using the PG&E 1-in-2 year conditions increases the average impacts by about 0.6% compared with the impacts from the ex post weather conditions. The CAISO and PG&E 1-in-10 year weather conditions yield impacts of 5% and 2% larger than impacts derived from their respective 1-in-2 year weather conditions.

[28] The customers originally defaulted as large have traditionally be included in the large customer ex post analysis. However, due to the medium and small customers now also on CPP, this practice of including the previously defaulted, but no longer large, customers in the large customer cohort for the ex post analysis will be revisited for the next evaluation cycle.

Table 5-8: Differences in Large C&I Ex Post and Ex Ante Impacts Due to Key Factors

Date	Mean 17	Ex Post Impact	Ex Post Impact with Ex Ante Enrollment	Ex Ante Model Ex Post Weather and Event Window	Ex Ante Model Ex Post Weather RA Event Window	CAISO 1-in-2	PG&E 1-in-2	CAISO 1-in-10	PG&E 1-in-10
	(F)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
	A	B	C	D	E	F	G	H	I
6/12/2015	75.0	20.7	24.3	40.3	34.3	34.4	36.1	36.1	36.7
6/25/2015	76.7	23.4	27.7	40.9	34.8				
6/26/2015	76.8	27.9	32.9	40.9	34.8				
6/30/2015	78.3	36.5	43.0	41.6	35.4				
7/1/2015	78.6	49.7	58.6	41.7	35.5				
7/28/2015	77.0	39.8	47.3	40.9	34.8				
7/29/2015	78.8	35.3	41.9	41.6	35.4				
7/30/2015	76.3	38.0	45.2	40.8	34.7				
8/17/2015	79.6	33.1	39.3	41.9	35.7				
8/18/2015	74.7	19.6	23.3	40.1	34.2				
8/27/2015	78.3	17.7	21.1	41.6	35.4				
8/28/2015	80.7	23.0	27.4	42.4	36.1				
9/9/2015	80.1	26.4	31.4	42.1	35.8				
9/10/2015	79.9	30.0	35.8	42.2	35.9				
9/11/2015	78.3	26.1	31.1	41.6	35.4				
Avg.	77.9	29.8	35.4	41.4	35.2				

5.2 Medium C&I Ex Ante Impacts

Ex ante impacts for medium C&I customers are derived from the ex post impacts from the 2015 default population. Nexant used the medium size customer percent reductions from the average 2015 event for the expected response of all future medium size customer default participants. Medium C&I customers yielded percent reductions of 0.9%, which translates to a percent reduction of 0.7% over the RA event hours. The reference loads were developed by using a sample of interval data for current and future enrollees and estimating reference loads for them within LCA. We simply applied the percent reductions to the reference loads.

Table 5-9 presents PG&E's enrollment projections for medium C&I customers through 2026. In November 2016 and 2017, medium C&I customers with at least 24-months of experience on a TOU rate will be defaulted onto CPP, leading to the increase in enrollment during those months. By November 2017, the medium C&I population is expected to reach enrollment of 64,334 accounts, and 65,707 by November of 2018. The enrollment is expected to increase slowly thereafter as a result of growth in accounts. PG&E's medium C&I CPP enrollment forecast is based on the company's near-term schedule of forthcoming PDP defaults and data from its longer term sales forecast.

Table 5-9: PG&E Enrollment Projections for Medium C&I CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2016	33,118	33,118	33,118	33,118	33,118	33,118	33,118	33,118	33,118	33,118	58,283	58,283
2017	58,283	58,283	58,283	58,283	58,283	58,283	58,283	58,283	58,283	58,283	64,334	64,334
2018	64,334	64,334	64,334	64,334	64,334	64,334	64,334	64,334	64,334	64,334	65,707	65,707
2026	69,474	69,474	69,474	69,474	69,474	69,474	69,474	69,474	69,474	69,474	69,960	69,960

5.2.1 Annual System Peak Day Impacts

Table 5-10 summarizes the aggregate load impact estimates for medium C&I customers on PG&E's CPP rate for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios based on both PG&E and CAISO weather scenarios. The table shows the average load reduction across the 1 to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on PG&E-specific weather, August load reductions will grow from 6.4 MW to around 12.9 MW in 2018 under 1-in-10 weather conditions, and peak at 14 MW in 2026. This growth is due to the implementation of default CPP over two more Novembers as more medium C&I customers meet default criteria. After default CPP is fully implemented, medium customers are forecasted to reduce 0.7% of their demand under all weather conditions. The estimated percent reductions are constant as enrollment increases. Impact estimates based on CAISO weather 1-in-2 year conditions are roughly 7% less than the estimates based on PG&E weather. The CAISO 1-in-10 weather values produce a load reduction that is about 3% less than the 1-in-10 year PG&E estimates.

Table 5-10: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Medium C&I, PG&E August System Peak Day (1-6 PM)

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
PG&E	1-in-10	2016	33,118	876.2	869.8	6.4	0.7%	95.3
		2017	58,283	1586.5	1574.8	11.6	0.7%	94.9
		2018	64,334	1755.4	1742.5	12.9	0.7%	94.9
		2026	69,474	1897.9	1884.0	13.9	0.7%	94.8
	1-in-2	2016	33,118	822.7	816.6	6.0	0.7%	91.6
		2017	58,283	1491.1	1480.1	10.9	0.7%	91.2
		2018	64,334	1650.0	1637.9	12.1	0.7%	91.1
		2026	69,474	1784.1	1771.0	13.1	0.7%	91.1
CAISO	1-in-10	2016	33,118	841.9	835.8	6.2	0.7%	92.0
		2017	58,283	1524.2	1513.0	11.2	0.7%	91.5
		2018	64,334	1686.4	1674.0	12.4	0.7%	91.5
		2026	69,474	1823.3	1809.9	13.4	0.7%	91.4
	1-in-2	2016	33,118	765.2	759.6	5.6	0.7%	88.4
		2017	58,283	1390.0	1379.8	10.2	0.7%	88.0
		2018	64,334	1538.5	1527.2	11.3	0.7%	88.0
		2026	69,474	1663.8	1651.6	12.2	0.7%	88.0

5.2.2 Ex Ante Impacts by Geographic Location and Month

Table 5-11 summarizes aggregate 2018 ex ante impacts for each LCA by month for medium C&I CPP customers. It shows the per customer impacts for each monthly system peak day under PG&E 1-in-2 and 1-in-10 system peaking conditions. As a result of the CPP event window ending at 6 PM, impacts are typically between 3 and 4 times larger in the summer months compared with winter months. Although there is no real empirical data on how customers will respond in winter months, the load impacts in these months reflect the 0.7% impact from 2 to 6 PM that was assumed. Differences in impacts over months occur as a result of differences in reference load as well.

The variation in impact by LCA reflects the weather, size of customers and the industry mix in each of PG&E's LCAs, which in turn affect reference load. Impacts for 2018, when default CPP will have been fully implemented across PG&E's territory, are shown in Table 5-11. Like the large C&I ex ante load impacts by LCA, most of the load impacts will come from the Greater Bay Area and Other LCAs. The Greater Bay Area accounts for 48% of the forecasted 2018 medium C&I enrollment while the Other LCA accounts for 22%.

Table 5-11: Aggregate PG&E Ex Ante Load Impact Estimates by LCA Medium C&I 2018 Monthly System Peak Days (1 to 6 PM), PG&E Weather Scenarios[29]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4-9 pm Resource Adequacy Window				1-6 pm Resource Adequacy Window						4-9 pm	
1-in-10	All	3.5	3.5	3.7	5.0	12.3	13.1	12.9	12.9	12.1	11.1	3.9	3.5
	Greater Bay Area	2.0	2.0	2.1	2.7	6.6	7.1	6.6	6.6	6.6	6.2	2.2	2.0
	Greater Fresno	0.2	0.2	0.3	0.4	1.0	1.1	1.2	1.2	1.0	0.8	0.3	0.2
	Humboldt	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1
	Kern	0.2	0.2	0.2	0.2	0.6	0.6	0.7	0.7	0.6	0.5	0.2	0.2
	Northern Coast	0.1	0.1	0.1	0.1	0.3	0.4	0.3	0.3	0.3	0.3	0.1	0.1
	Other	0.7	0.7	0.7	1.0	2.5	2.7	2.8	2.8	2.4	2.2	0.7	0.7
	Sierra	0.1	0.1	0.1	0.2	0.5	0.5	0.5	0.6	0.5	0.4	0.1	0.1
	Stockton	0.0	0.1	0.2	0.2	0.5	0.5	0.5	0.5	0.5	0.4	0.2	0.1
1-in-2	All	3.4	3.5	3.6	4.4	10.4	11.9	11.8	12.1	11.6	9.9	3.7	3.5
	Greater Bay Area	2.0	2.0	2.0	2.4	5.4	6.1	5.9	6.2	6.1	5.5	2.1	2.0
	Greater Fresno	0.2	0.2	0.3	0.4	0.9	1.1	1.1	1.1	1.0	0.8	0.2	0.2
	Humboldt	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1
	Kern	0.2	0.2	0.2	0.2	0.5	0.7	0.6	0.7	0.6	0.5	0.2	0.2
	Northern Coast	0.1	0.1	0.1	0.1	0.3	0.3	0.3	0.3	0.3	0.3	0.1	0.1
	Other	0.7	0.7	0.7	0.9	2.2	2.6	2.6	2.6	2.4	1.9	0.7	0.6
	Sierra	0.1	0.1	0.1	0.1	0.4	0.5	0.5	0.5	0.4	0.4	0.1	0.1
	Stockton	0.0	0.1	0.2	0.2	0.5	0.5	0.5	0.5	0.5	0.3	0.2	0.1

29 Estimates based on CAISO weather scenarios have a similar pattern across months and LCAs. These values can be obtained from the electronic load impact tables that were submitted along with this report.

5.3 Small C&I Ex Ante Impacts

As was true for medium customers, ex ante estimates are based on ex post reductions for the average 2015 event day. Small C&I customers yielded a 0.5% load reduction on the average event day in 2015, which translates to a 0.4% load reduction under RA event hours.

Table 5-12 presents PG&E's enrollment projections for small C&I customers through 2026. As with medium C&I customers, small C&I customers with at least 24-months of experience on a TOU rate will be defaulted onto CPP in upcoming Novembers, leading to the increase in enrollment toward the end of 2016, 2017 and, but to a lesser extent, 2018. Of the customers who were already defaulted in November 2015, 184,027 small C&I customers are projected to remain on CPP. By November 2016, the small C&I population is expected to reach enrollment of 234,332 accounts, 260,751 by November 2017, and 273,457 by November 2018. The enrollment is expected to increase slowly thereafter as a result of growth in accounts. PG&E's small C&I CPP enrollment forecast is based on the company's near-term schedule of forthcoming PDP defaults and data from its longer term sales forecast.

Table 5-12: PG&E Enrollment Projections for Small C&I CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2016	184,027	184,027	184,027	184,027	184,027	184,027	184,027	184,027	184,027	184,027	234,332	234,332
2017	234,332	234,332	234,332	234,332	234,332	234,332	234,332	234,332	234,332	234,332	260,751	260,751
2018	260,751	260,751	260,751	260,751	260,751	260,751	260,751	260,751	260,751	260,751	273,457	273,457
2026	287,981	287,981	287,981	287,981	287,981	287,981	287,981	287,981	287,981	287,981	289,952	289,952

5.3.1 Annual System Peak Day Impacts

Table 5-13 summarizes the aggregate load impact estimates for small C&I customers on PG&E's CPP rate for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios, based on both PG&E and CAISO weather scenarios. The table shows the average load reduction across the 1 to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on PG&E-specific weather, August load reductions will grow from 1.8 MW in 2016 to 2.4 MW in 2018 under 1-in-10 weather conditions, and peak at around 2.6 MW in 2026. This growth is due to the implementation of default CPP over three more Novembers as more small C&I customers meet default criteria. After default CPP is fully implemented, small customers are forecasted to reduce 0.4% of their demand under all weather conditions. The estimated percent reductions are constant as enrollment increases. Impact estimates based on CAISO weather 1-in-2 year conditions are roughly 6% less than the estimates based on PG&E weather. The CAISO 1-in-10 weather values produce a load reduction that is about 6% less than the 1-in-10 year PG&E estimates.

Table 5-13: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Small C&I, PG&E August System Peak Day (1–6 PM)

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
PG&E	1-in-10	2016	184,027	453.2	451.4	1.8	0.4%	95.9
		2017	234,332	556.3	554.1	2.2	0.4%	95.9
		2018	260,751	610.1	607.7	2.4	0.4%	95.9
		2026	287,981	666.3	663.7	2.6	0.4%	95.8
	1-in-2	2016	184,027	415.1	413.5	1.6	0.4%	92.3
		2017	234,332	508.6	506.6	2.0	0.4%	92.3
		2018	260,751	557.4	555.2	2.2	0.4%	92.2
		2026	287,981	608.4	606.0	2.4	0.4%	92.2
CAISO	1-in-10	2016	184,027	429.9	428.2	1.7	0.4%	93.0
		2017	234,332	526.8	524.8	2.1	0.4%	93.0
		2018	260,751	577.4	575.1	2.3	0.4%	93.0
		2026	287,981	630.3	627.8	2.5	0.4%	93.0
	1-in-2	2016	184,027	372.9	371.4	1.5	0.4%	88.9
		2017	234,332	456.1	454.3	1.8	0.4%	88.9
		2018	260,751	499.5	497.6	2.0	0.4%	88.8
		2026	287,981	545.0	542.9	2.1	0.4%	88.8

5.3.2 Ex Ante Impacts by Geographic Location and Month

Table 5-14 summarizes aggregate 2018 ex ante impacts for each LCA by month for small C&I CPP customers. It shows the per customer impacts for each monthly system peak day under PG&E 1-in-2 and 1-in-10 system peaking conditions. As a result of the CPP event window ending at 6 PM, impacts are typically between 2 and 3 times larger in the summer months compared with winter months. Although there is no real empirical data on how customers will respond in winter months, the load impacts in these months reflect the 0.4% impact from 2 to 6 PM that was assumed. Differences in impacts over months occur as a result of differences in reference load as well.

The variation in impact by LCA reflects the weather, size of customers and the industry mix in each of PG&E's LCAs, which in turn affect reference load. Impacts for 2018, when default CPP is fully implemented across PG&E's territory, are shown in Table 5-14. Like the large C&I ex ante load impacts by LCA, most of the load impacts will come from the Greater Bay Area and Other LCAs. The Greater Bay Area accounts for 39% of the forecasted 2018 medium C&I enrollment while the Other LCA accounts for 28%.

Table 5-14: Aggregate PG&E Ex Ante Load Impact Estimates by LCA Small C&I 2018 Monthly System Peak Days (1 to 6 PM), PG&E Weather Scenarios[30]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4-9 pm Resource Adequacy Window				1-6 pm Resource Adequacy Window						4-9 pm	
1-in-10	All	1.0	0.9	0.8	1.2	2.2	2.5	2.5	2.4	2.2	2.0	1.0	1.1
	Greater Bay Area	0.5	0.4	0.4	0.6	1.1	1.2	1.1	1.1	1.1	1.0	0.5	0.5
	Greater Fresno	0.1	0.1	0.0	0.1	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1
	Humboldt	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
	Kern	0.0	0.0	0.0	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.0	0.0
	Northern Coast	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
	Other	0.2	0.2	0.2	0.3	0.5	0.6	0.7	0.7	0.6	0.5	0.2	0.3
	Sierra	0.1	0.0	0.0	0.1	0.1	0.2	0.2	0.1	0.1	0.1	0.0	0.1
	Stockton	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1
1-in-2	All	1.0	0.9	0.8	1.0	1.7	2.2	2.2	2.2	2.1	1.7	1.0	1.0
	Greater Bay Area	0.5	0.4	0.4	0.5	0.8	1.0	0.9	1.0	0.9	0.8	0.5	0.5
	Greater Fresno	0.1	0.1	0.0	0.1	0.1	0.2	0.2	0.2	0.2	0.1	0.1	0.1
	Humboldt	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0
	Kern	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
	Northern Coast	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0
	Other	0.2	0.2	0.2	0.2	0.5	0.6	0.6	0.6	0.5	0.4	0.2	0.2
	Sierra	0.0	0.0	0.0	0.0	0.1	0.2	0.2	0.1	0.1	0.1	0.0	0.1
	Stockton	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0

30 Estimates based on CAISO weather scenarios have a similar pattern across months and LCAs. These values can be obtained from the electronic load impact tables that were submitted along with this report.

6 SCE Ex Post Load Impacts

SCE called 12 CPP events in 2015, with the first occurring on July 1 and the last on September 21. The average number of default CPP customers participating in the 12 SCE CPP events through September was 2,677. There is some slight variation in the number of default customers participating in each event due to customer churn; some customers departed and others enrolled during summer 2015. The highest 2015 enrollment, 2,692 customers, occurred on the July 2 event. The lowest enrollment, 2,667 customers, occurred on the August 3, August 6, and August 18 events.

The load impacts described in this report pertain exclusively to customers subject to the CPP rate on a default basis, including customers enrolled in the legacy voluntary CPP program prior to default CPP going into effect in 2010 or who were defaulted to CPP at one point in time and remained on CPP even though their load dropped below 200 kW. This group of customers taking CPP in 2015 is referred to as the default CPP population.

There is also another group of customers who were on the CPP rate in 2015: small and medium business (SMB) customers enrolled on CPP on a purely voluntary basis. This group of customers is referred to as opt-in CPP customers, keeping in mind the distinction between these customers and the large C&I customers who took the legacy voluntary CPP rate prior to 2009 and who are included in the default CPP population. There were 797 opt-in CPP customers at SCE in 2014. In 2015, there were 882 and the majority of these service accounts are associated with a single business entity. These opt-in CPP participants are not included in the ex post load impact reporting presented in this report because the few SCE customers who take CPP on an opt-in basis are not representative of the SMB population that will be subject to CPP on a default basis beginning in 2018. Load impacts for these customers are presented in the SCE electronic ex post load impact table generator but it is important to remember that their load impacts do not reflect what would be expected from the SMB customer class in the future under default CPP.

Table 6-1 shows the ex post load impact estimates for each event day and for the average event day in 2015. The participant-weighted average temperature during the peak period on event days ranged from a low of 80.7°F to a high of 94.7°F. Daily maximum temperatures were higher, ranging from a low of 91.2°F to a high of 105.4°F.

Table 6-1: Default CPP Ex Post Load Impact Estimates by Event Day
SCE 2015 CPP Events (2–6 PM)

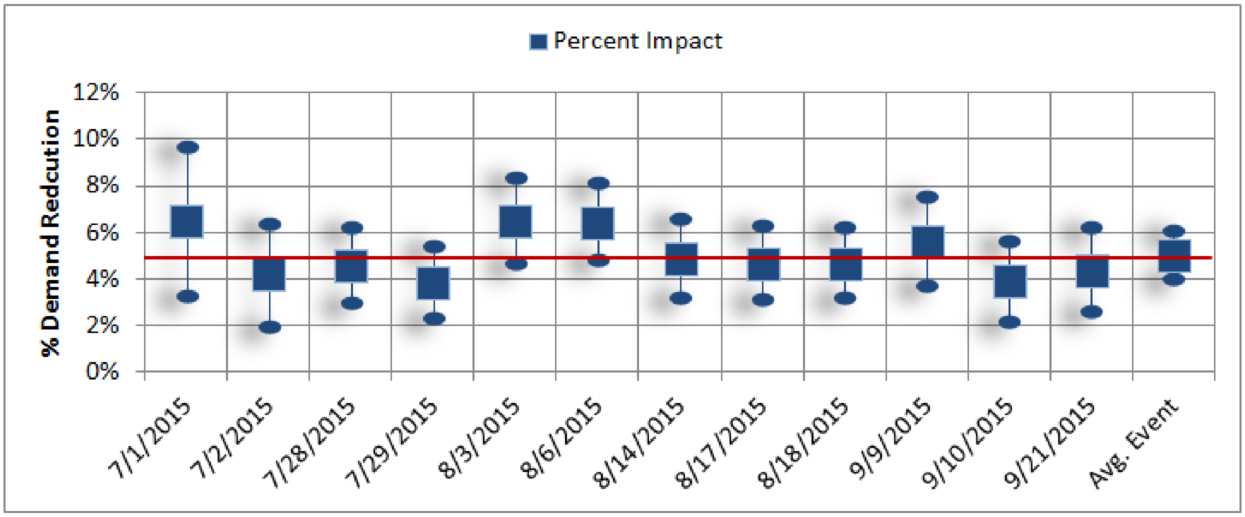
Event Date	Day of Week	Accounts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Average Customer Impact (kW)	Aggregate Impact (MW)	% Reduction (%)	Avg. Event Temp. (°F)	Daily Max. Temp. (°F)
7/1/2015	Wed.	2,690	208.8	195.4	13.5	36.3	6.5%	82.8	98.4
7/2/2015	Thu.	2,692	202.5	194.1	8.4	22.7	4.2%	84.8	100.1
7/28/2015	Tue.	2,679	208.8	199.2	9.5	25.5	4.6%	85.3	97.0
7/29/2015	Wed.	2,676	212.8	204.6	8.2	21.8	3.8%	85.8	104.5
8/3/2015	Mon.	2,667	214.6	200.7	13.9	37.0	6.5%	85.0	93.1
8/6/2015	Thu.	2,667	212.2	198.6	13.6	36.4	6.4%	83.3	91.2
8/14/2015	Fri.	2,669	216.2	205.7	10.5	28.0	4.8%	94.7	102.9
8/17/2015	Mon.	2,669	219.9	209.6	10.3	27.4	4.7%	85.1	105.4
8/18/2015	Tue.	2,667	216.4	206.3	10.1	26.8	4.7%	83.7	100.4
9/9/2015	Wed.	2,684	236.5	223.2	13.3	35.6	5.6%	93.0	102.5
9/10/2015	Thu.	2,684	240.0	230.7	9.3	25.0	3.9%	93.4	102.0
9/21/2015	Mon.	2,682	218.2	208.7	9.5	25.4	4.3%	80.7	99.9
Avg. Event		2,677	217.2	206.4	10.8	29.0	5.0%	86.5	98.1

Percent impacts ranged from 3.8% to 6.5%, average customer impacts ranged from 8.2 kW to 13.9 kW and aggregate impacts ranged from 21.8 MW to 37.0 MW. On the average event day, the average participant reduced peak period load by 5.0% or 10.8 kW. In aggregate, SCE's CPP customers reduced load by 29.0 MW on average across the 12 event days from July through September 2015.

Figure 6-1 shows the ex post load impact estimates for 2015 CPP event days and the average event day. The figure includes both the estimated percent demand reduction and the 90% confidence intervals around the point estimates. The confidence bands around the individual event day estimates are wider than the confidence band around the average event day load impact estimate. The individual event day results are less precise because the percent demand reductions are relatively small and hard to detect from the inherent day-to-day variation in loads. A large amount of the event-to-event variation in load impacts is unexplained noise. Due to the large number of events called, it is likely that some events may be significantly different from the average event by chance.[31]

[31] Since impacts were estimated for 12 events with 90% confidence bands, there is a 72% chance that at least one event is significantly different from the average.

Figure 6-1: Ex Post Load Impact Estimates with 90% Confidence Intervals SCE 2015 CPP Events (2–6 PM)



6.1 Average Event Day Impacts

Figure 6-2 shows the aggregate hourly impact for CPP customers for the average event in 2015. Percent reductions are similar across event hours. Demand reductions vary between 25.8 MW and 31.6 MW, depending on the event hour. Figure 6-2 also illustrates the electronic appendices filed in conjunction with this report, which present hourly results, with uncertainty bands for individual event days for the program as a whole and for each of the segments discussed in this report.

The hourly load impacts for the average 2015 event day are slightly stronger in the early hours of the event. The overall magnitude of the hourly load impacts is very similar to 2014: percent impact for the average event day in 2015 and 2014 were 5.0% and 5.0%, yielding 29.0 MW and 29.6 MW, respectively, of load impact.

Figure 6-2: Aggregate Hourly Default CPP Ex Post Load Impacts for the Average 2015 SCE CPP Event

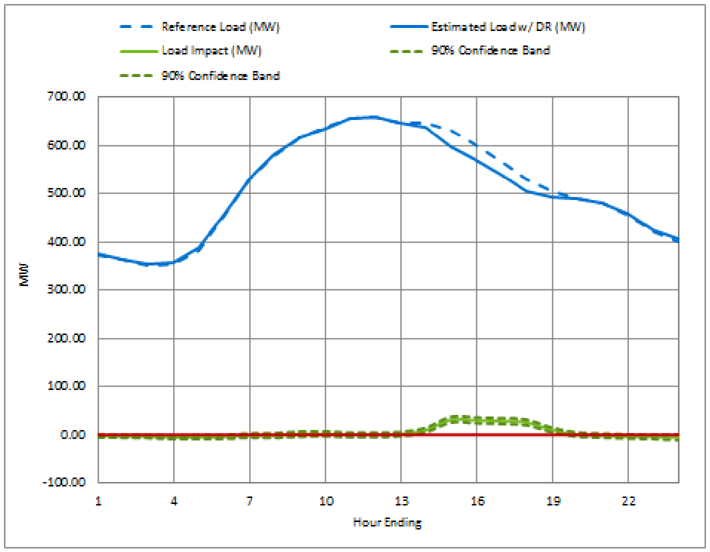
Southern California Edison
2015 Ex Post Load Impacts - CPP

TABLE 1: Menu Options

Type of Results	Aggregate
Enrollment Type	Default
Customer Category	All Customers
Event Date	Average Event

TABLE 2: Event Day Information

Event Start	2:00 PM
Event End	6:00 PM
Total Enrolled Accounts	2,677
Avg. Load Reduction for Event Window (MW)	29.0
% Load Reduction for Event Window	5.0%



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	% Load Reduction	Weighted Temp. (°F)	Uncertainty-adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1	373.8	375.6	-1.8	-0.5%	74.9	-4.0	-2.7	-1.8	-0.9	0.3
2	362.2	364.8	-2.6	-0.7%	73.9	-4.9	-3.6	-2.6	-1.6	-0.3
3	351.9	354.7	-2.8	-0.8%	73.2	-5.4	-3.9	-2.8	-1.8	-0.2
4	353.7	358.5	-4.8	-1.3%	72.5	-7.5	-5.9	-4.8	-3.6	-2.0
5	382.7	387.0	-4.3	-1.1%	71.9	-7.4	-5.6	-4.3	-3.1	-1.3
6	451.5	455.3	-3.7	-0.8%	71.6	-6.8	-5.0	-3.7	-2.5	-0.7
7	528.7	529.5	-0.8	-0.1%	71.2	-4.2	-2.2	-0.8	0.6	2.6
8	579.3	580.2	-0.9	-0.2%	71.4	-4.7	-2.4	-0.9	0.7	2.9
9	616.9	614.8	2.1	0.3%	73.3	-2.0	0.4	2.1	3.7	6.1
10	637.0	634.6	2.4	0.4%	76.4	-1.6	0.8	2.4	4.0	6.3
11	656.9	656.7	0.2	0.0%	79.7	-3.5	-1.3	0.2	1.7	3.9
12	658.8	658.6	0.2	0.0%	82.6	-3.3	-1.2	0.2	1.7	3.8
13	647.5	645.4	2.0	0.3%	84.8	-1.4	0.6	2.0	3.4	5.5
14	647.2	636.9	10.3	1.6%	86.1	6.7	8.8	10.3	11.8	14.0
15	629.4	597.8	31.6	5.0%	86.8	27.0	29.7	31.6	33.5	36.2
16	600.4	570.4	30.0	5.0%	86.9	25.3	28.1	30.0	31.8	34.6
17	565.8	537.2	28.6	5.1%	86.6	24.0	26.7	28.6	30.5	33.2
18	530.7	504.8	25.8	4.9%	85.7	21.3	24.0	25.8	27.7	30.4
19	503.7	493.5	10.2	2.0%	84.2	6.5	8.7	10.2	11.7	13.9
20	490.2	489.2	1.0	0.2%	82.3	-2.4	-0.4	1.0	2.4	4.4
21	480.3	481.4	-1.0	-0.2%	79.6	-4.4	-2.4	-1.0	0.3	2.3
22	454.7	457.7	-3.0	-0.7%	77.2	-6.3	-4.3	-3.0	-1.6	0.4
23	422.7	426.4	-3.7	-0.9%	75.8	-7.0	-5.1	-3.7	-2.4	-0.4
24	401.8	406.3	-4.5	-1.1%	74.6	-9.1	-6.4	-4.5	-2.7	0.0
	Reference Energy Use (MWh)	Estimated Energy Use w/ DR (MWh)	Total Load Impact (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)	Uncertainty-adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Event	581.5	552.5	29.0	5.0%	323.0	24.4	27.1	29.0	30.9	33.6

6.2 Load Impacts by Industry

Table 6-2 compares the reference load, load impact and the number of accounts, in percentage terms, across industry segments. It also shows the share of demand reduced by the average customer within each industry and whether or not the demand reduction was statistically significant with 90% confidence. The industries are presented in rank order based on the aggregate demand reduction. Figure 6-3 presents the same information visually and illustrates the concentration of load impacts in specific industries.

The estimated load impacts for the first six industries presented in Table 6-2 are statistically significant. The load impact for the Agriculture, Mining & Construction sector is not statistically significant. The largest industry segment in SCE's default CPP population is Manufacturing, with 758 enrolled accounts. These customers produced the strongest (statistically significant) percentage load impacts of 11.7%.

Table 6-2: Default CPP Ex Post Load Impact Estimates by Industry Average 2015 SCE CPP Event (2 to 6 PM)

Industry	Accounts		Aggregate Reference Load		Aggregate Impact		Average Customer Impact	% Reduction	Stat. Sig?
	Enrollment	% of Program	MW	% of Program	MW	% of Program	kW		
Manufacturing	758	28.3%	160.1	27.6%	18.7	64.7%	24.6	11.7%	Yes
Wholesale, Transport & Other Utilities	447	16.7%	100.1	17.2%	5.3	18.3%	11.8	5.3%	Yes
Offices, Hotels, Finance, Services	597	22.3%	150.8	26.0%	1.8	6.3%	3.0	1.2%	Yes
Retail Stores	216	8.1%	52.4	9.0%	1.3	4.6%	6.1	2.5%	Yes
Schools	336	12.6%	59.2	10.2%	0.8	2.9%	2.5	1.4%	Yes
Institutional/Government	233	8.7%	48.1	8.3%	0.6	2.2%	2.7	1.3%	Yes
Agriculture, Mining & Construction	88	3.3%	10.4	1.8%	0.3	1.1%	3.5	2.9%	No

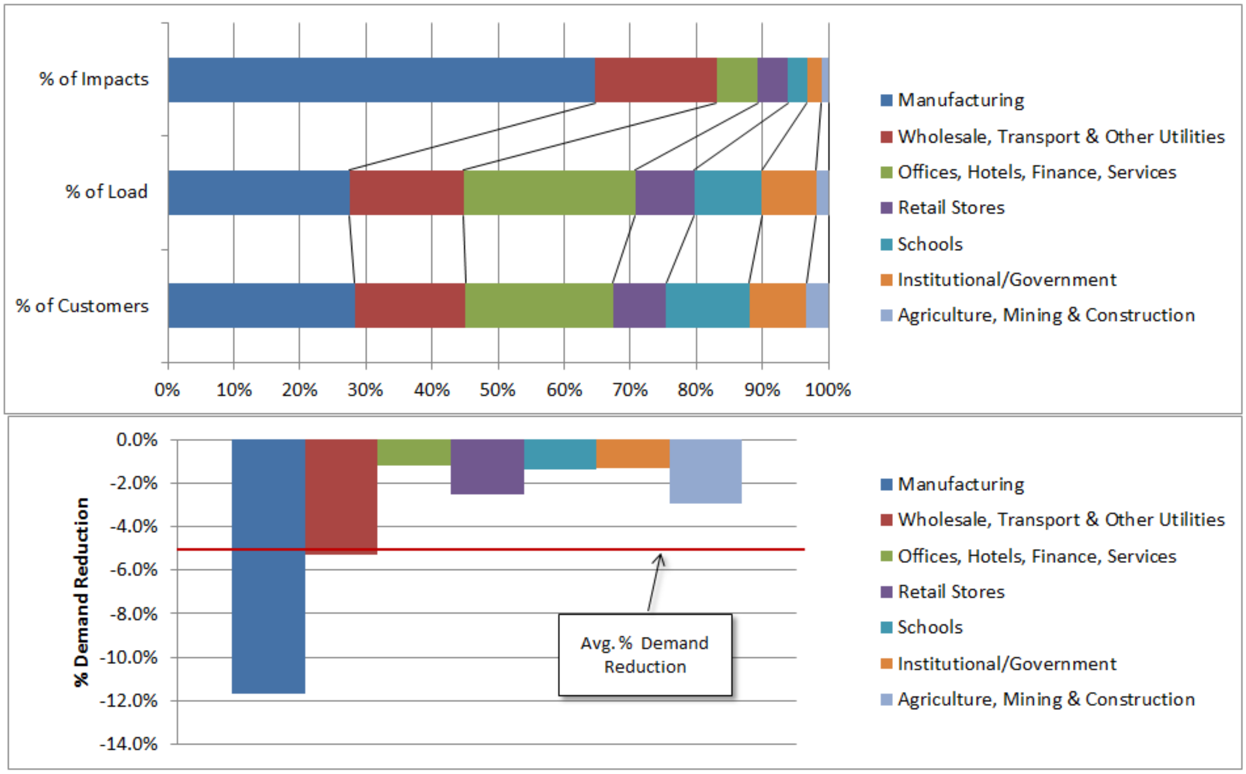
* Does not represent a conclusive finding for this reporting segment due to the uncertainty in the estimate.

Figure 6-3 shows that CPP demand reductions at SCE are concentrated among customers in the Manufacturing and Wholesale, Transport & Other Utilities segments. The pattern is similar to the industry concentration seen at PG&E, but program resources are even more highly concentrated among these two sectors at SCE. The manufacturing sector provides 65% of the aggregate load reduction on the average event day, while comprising only 28% of program enrollment. When combined with Wholesale, Transport & Other Utilities, the two segments account for 45% of enrollment but 83% of aggregate load reduction. Customers in these two industry sectors were not substantially bigger than the average customer; they simply reduced a larger share of demand during events.

Similar to CPP at PG&E and SDG&E, schools account for a relatively large percent of program participants but do not produce large percent load reductions. The Institutional/Government segment also showed small, but statistically significant results.

Agriculture, Mining & Construction did not yield statistically significant results. Combined, these three sectors account for 20% of the program load.

Figure 6-3: Default CPP Enrollment, Load, Impact and Percent Demand Reduction by Industry Average 2015 SCE CPP Event (2–6 PM)



Before addressing differences between 2014 and 2015 load impacts, we note that comparisons across years must be made conservatively, as the matching and modeling across years vary. The matching model in 2014 differed from that in 2015, so some difference may be an artifact of modeling. Relative to 2014, the industry with the most influence on CPP load impacts at SCE, Manufacturing, delivered weaker load impacts: 11.7% in 2015 versus 12.4% in 2014. There was little change in enrollment from 2014 to 2015. Wholesale, Transport and Other Utilities, and Institutional/Government, and Schools were the only sectors in which delivered load impacts increased. Average customer reference load decreased slightly across all sectors except Wholesale, Transport and Other Utilities and Institutional/Government, in which it increased by 7% and 1%, respectively.

6.3 Load Impacts by Local Capacity Area

Table 6-3 shows the estimated ex post load impacts by LCA. In total, 85% of enrolled customers and 88% of aggregate load reduction came from the Los Angeles Basin LCA. Customer size did not vary substantially by LCA and load impacts are highest in the LA Basin LCA.

Table 6-3: Default CPP Ex Post Load Impact Estimates by LCA
Average 2014 SCE CPP Event (2 to 6 PM)

Type of Category	Area	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig.?
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
LCA	LA Basin	2,273	220.7	209.5	11.2	25.4	5.1%	86.4	Yes
	Outside	144	205.7	197.4	8.3	1.2	4.0%	90.8	Yes
	Ventura	258	193.4	184.2	9.2	2.4	4.8%	85.0	Yes

6.4 Load Impacts by Customer Size

Table 6-4 shows ex post load impact estimates by customer size, using two different size categorization methods. First, load impacts are reported for the three demand response categories: greater than 200 kW, less than 200 kW and greater than 20 kW and less than 20 kW. The other size categorization is by usage quintile; all default CPP customers were assigned to a usage quintile based on annual consumption. This metric of customer size is more useful than the demand response categorization because it provides estimates for a broad spectrum of customer sizes, where the segments all have sample sizes large enough to support reasonable estimates, which is one shortcoming of using DMDRCAT status. Table 6-4 shows that percentage load impacts are largest in the top quintile.

Table 6-4: Default CPP Ex Post Load Impact Estimates by Customer Size
Average 2015 SCE CPP Event (2–6 PM)

Categorization	Size Category	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig.?
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
By Demand Category	Over 200kW	2,464	229.9	218.2	11.7	28.8	5.1%	86.4	Yes
	20 kW to 199 kW	201	74.0	72.8	1.2	0.2	1.6%	86.9	No
	Under 20 kW*								
By Annual Consumption Quintiles	5th Quintile	534	499.1	462.5	36.6	19.6	7.3%	86.5	Yes
	4th Quintile	534	227.6	223.6	4.0	2.1	1.7%	85.8	No
	3rd Quintile	538	170.1	163.8	6.3	3.4	3.7%	85.8	Yes
	2nd Quintile	539	132.0	127.0	5.0	2.7	3.8%	86.9	Yes
	1st Quintile	530	58.1	55.7	2.3	1.2	4.0%	87.3	Yes

6.5 Load Impacts for Multi-DR Program Participants

CPP customers can also enroll in several other DR programs at SCE, including the Base Interruptible Program (BIP), Demand Response Resource Contracts (DRRC), Capacity Bidding Program (CBP), and the Summer Discount Plan (SDP). Impacts for customers dually enrolled in some of these programs are not reported as there were too few accounts in the respective segmentation. In 2012, dually-enrolled customers accounted for a third of program impacts. By

2014, the relatively few dually-enrolled CPP customers accounted for 49% of CPP load impacts at SCE, and they still accounted for 47% in 2015.

In 2015, 267 accounts were dually enrolled in one of the four DR programs listed above. Dual enrollment in BIP grew from 34 to 41 customers from 2014 to 2015. Dual enrollment in aggregator programs stayed constant at 125 customers in both 2014 and 2015. Table 6-5 shows the estimated load impacts for the dually-enrolled customers in SCE's CPP and DR programs. Customers who enrolled in other programs delivered substantially larger percent demand reductions. Customers dually enrolled in BIP reduced demand by 42% during CPP events; customers dually enrolled in aggregator programs reduced loads by 38%. Further, the differences between load impacts from dually-enrolled customers and non-dually-enrolled customers should not be interpreted as an implication that dual participation causes increased CPP performance. Customers who are highly responsive may self-select into other DR programs. It is also quite plausible that aggregators target customers in industries that can deliver larger reductions. The higher percent demand reductions could also be due to BIP program administrators and/or aggregators helping customers identify how to reduce their demand during demand response events.

Table 6-5: Default CPP Ex Post Load Impact Estimates for Dually-enrolled Participants Average 2015 SCE CPP Event (2–6 PM)

Dually Enrolled DR	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp.	Stat. Sig.?
		(kW)	(kW)	(kW)	(MW)	%	°F	
BIP	41	372.4	217.6	154.8	6.3	42%	87.9	Yes
CBP	[redacted]							
DRC	107	339.8	286.7	53.1	5.7	16%	88.3	Yes
DRC, CBP	[redacted]							
SDP	101	157.6	153.0	4.7	0.5	3%	86.5	Yes
Other DR: None	2,406	210.1	203.7	6.4	15.4	3%	86.3	Yes

6.6 TI and AutoDR Load Impacts and Realization Rates

CPP customers are eligible to participate in Technical Assistance, Technical Incentives and AutoDR (TA/TI and AutoDR) programs. These programs involve a multi-step process that begins with TA, which consists of an audit to determine the potential for installing energy saving technology or processes at a particular premise. A TI is paid if a customer installs equipment or reconfigures processes and demonstrates that they produce load reductions. Although the response is automated, customers must still decide whether and when to drop load. AutoDR provides an incremental incentive to encourage customers to allow SCE to remotely dispatch the automated load reduction.

Historically, most CPP accounts that participated in the enabling technology program completed the process and fully automated the demand reduction to utility signals. However, over time, many of these customers have exited the CPP program. During 2015 CPP events, there were 54 customers enrolled in CPP with AutoDR, down from 59 in 2014. Load impact and realization rate estimates for AutoDR customers at SCE are presented in Table 6-6.

**Table 6-6: Default CPP Ex Post Load Impact Estimates of TI and AutoDR Participants for Average Customer
Average 2015 SCE CPP Event (2–6 PM)**

Enabling Technology	Accounts	Load Impact	% Reduction	90% Confidence Interval		Approved kW	Realization Rate
		(kW)	%	Lower	Upper		
AutoDR	54	83.2	16.1%	48.2	118.3	204.0	40.8%
No AutoDR	2,620	9.3	4.4%	7.2	11.4	NA	NA

7 SCE Ex Ante Load Impacts

This section presents ex ante load impact estimates for SCE's nonresidential CPP tariff. As discussed in Section 3, the main purpose of ex ante load impact estimates is to reflect the load reduction capability of a demand response resource under a standard set of conditions that align with system planning. These estimates are used in assessing alternatives for meeting peak demand, cost-effectiveness comparisons and long-term planning. The ex ante impact estimates for SCE are based on ex post load impacts of CPP events that occurred in 2014 and 2015 for the group of persistent customers that remained on the CPP tariff for both years. In total, load impact estimates for 24 events were used as input to the ex ante model. All load impact estimates presented here are incremental to the effects of the underlying TOU rates.

Ex ante load impact projections are shown separately for small, medium and large customers projected to receive service under SCE's default CPP tariff. The load reduction capability is summarized for each segment under annual system peak day conditions for a 1-in-2 and a 1-in-10 weather year for selected years (e.g., 2016, 2017, 2018 and 2026),[32] based on SCE and CAISO weather scenarios. The estimates presented here are not adjusted for dual enrollment of CPP participants in other DR programs. Portfolio estimates that net out impacts for other programs if called at the same time are presented in Appendix E. Explanations of how CPP ex ante load impact estimates vary by geographic location and month under standardized ex ante conditions are also included in this section.

7.1 Large C&I Ex Ante Load Impacts

As discussed in Section 3, the ex ante load impact estimates for large C&I customers are based on a regression model that relates impacts to weather conditions using the ex post impacts and weather to estimate model coefficients. The model is based on ex post data from both 2014 and 2015 for the group of persistent customers who were enrolled in all 2014 and 2015 event days. Before reviewing ex ante results, we provide an overview of the ex ante methodology. The steps involved in the analysis are as follows:

1. Identify persistent customers from 2014 and 2015;
2. Re-run 2014 and 2015 ex post analysis for just persistent customers to yield persistent customer ex post impacts by transmission planning area;
3. Model persistent customer ex post impacts as a function of weather by transmission planning area;
4. Apply percent impacts model to ex ante weather conditions;
5. Identify large ex post customers enrolled at the end of the summer in 2015 who are also in the large demand category and have a full panel of data for 2015, and model their reference load as a function of temperature, by transmission planning area;

[32] Enrollment is not forecasted to change substantially between 2018 and 2026 for large customers, so the interim years didn't provide much additional information of interest. The electronic load impact tables contain estimates for each year over the forecast horizon.

6. Apply reference load model to ex ante weather conditions;
7. Combine percent impacts and reference load for each set of ex ante conditions to get kW impacts for the average customer;
8. Multiply average customer impacts by ex ante enrollment.

Table 7-1 shows the ex post load impact estimates for each event day in 2014 and 2015 for large, persistent customers. The participant-weighted average temperature during the event period ranged from a low of 80.6°F to a high of 96.4°F. Percent impacts ranged from 3.6% to 7.9%; average impacts ranged from 7.5 kW to 17.0 kW; and aggregate impacts ranged from 16.3 MW to 36.8 MW.

Table 7-1: Default CPP Ex Post Load Impact Estimates for Persistent Customers by Event Day SCE 2014, 2015 CPP Events (2–6 PM)

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Event Temp.	Daily Max. Temp.
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	(°F)
7/8/2014	Tue	2,165	210.3	202.8	7.5	16.3	3.6%	85.4	95.7
7/14/2014	Mon	2,165	207.2	198.7	8.5	18.5	4.1%	80.6	91.8
7/30/2014	Wed	2,165	218.5	209.3	9.2	19.9	4.2%	88.3	95.4
8/4/2014	Mon	2,165	210.9	197.7	13.2	28.6	6.3%	83.0	89.3
8/22/2014	Fri	2,165	210.7	201.7	8.9	19.3	4.2%	82.2	89.6
8/28/2014	Thu	2,165	228.3	218.5	9.7	21.1	4.3%	90.1	95.6
9/8/2014	Mon	2,165	222.9	210.0	12.9	27.9	5.8%	83.1	86.0
9/11/2014	Thu	2,165	230.7	220.0	10.7	23.2	4.6%	89.4	95.3
9/15/2014	Mon	2,165	244.4	230.5	13.9	30.2	5.7%	96.4	102.5
9/16/2014	Tue	2,165	241.7	230.2	11.4	24.8	4.7%	93.4	102.7
9/22/2014	Mon	2,165	221.4	209.1	12.3	26.6	5.6%	82.2	88.0
9/23/2014	Tue	2,165	224.3	215.4	8.9	19.2	4.0%	85.7	92.5
7/1/2015	Wed	2,165	209.7	193.2	16.6	35.8	7.9%	82.9	94.0
7/2/2015	Thu	2,165	199.9	191.5	8.4	18.2	4.2%	84.9	95.7
7/28/2015	Tue	2,165	210.8	198.1	12.7	27.5	6.0%	85.4	100.4
7/29/2015	Wed	2,165	215.5	203.6	11.9	25.8	5.5%	85.9	102.7
8/3/2015	Mon	2,165	216.4	199.4	17.0	36.8	7.9%	85.0	96.7
8/6/2015	Thu	2,165	214.5	199.8	14.6	31.7	6.8%	83.4	97.3
8/14/2015	Fri	2,165	220.9	207.9	13.0	28.1	5.9%	94.9	107.7
8/17/2015	Mon	2,165	225.3	212.2	13.1	28.4	5.8%	85.2	98.4
8/18/2015	Tue	2,165	221.5	210.4	11.2	24.2	5.0%	83.9	94.9
9/9/2015	Wed	2,165	240.8	225.4	15.5	33.5	6.4%	93.1	107.5
9/10/2015	Thu	2,165	244.1	233.4	10.6	23.0	4.4%	93.5	103.1
9/21/2015	Mon	2,165	220.3	211.3	9.0	19.5	4.1%	80.8	94.8

Figure 7-1 presents the ex post load impact estimates for the persistent customers alongside those for all ex post customers. The persistent customer population is a subset of the 2015 CPP population of all ex post customers. As such, they deliver different load impacts. The impacts are plotted as a function of temperature and the linear fit is displayed for each customer group. Note that the impacts for persistent customers are slightly higher than impacts for all ex post customers, but they exhibit a similar relationship with temperature.

Figure 7-1: Comparison of 2014–2015 CPP Load Impacts for Persistent and All Ex Post Customers vs. Temperature

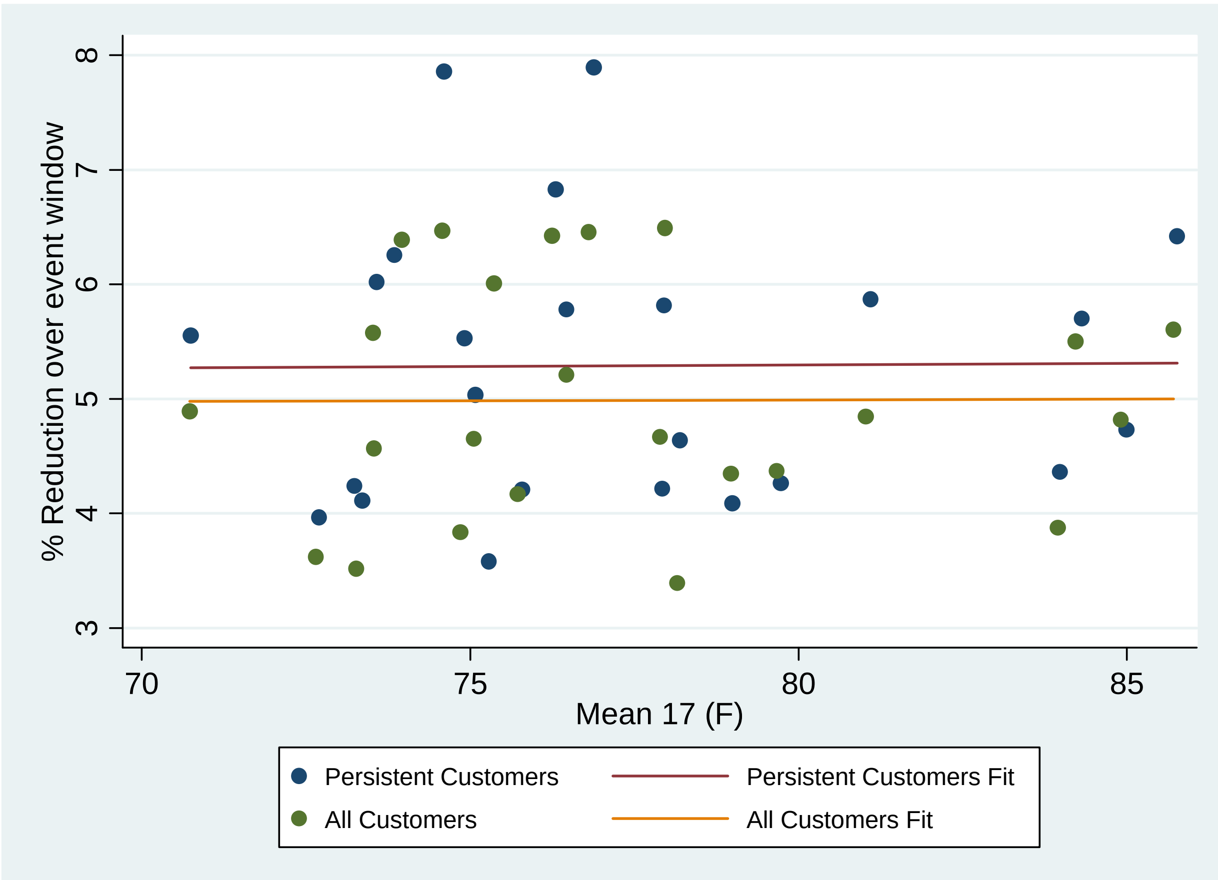


Figure 7-2 illustrates the persistent customer impact temperature relationship from above after it has been applied to the ex ante conditions. It shows the percent demand reductions estimated under 1-in-2 and 1-in-10 year weather conditions (green squares) for the months of May through October based on the SCE weather scenarios. The historical persistent customer percent reductions (blue squares) as a function of temperature for each transmission planning area are also shown. The relationship between percentage load reductions and temperature is generally weak; it is slightly positive for Other, and slightly negative for Orange County and South of Lugo transmission planning areas. This result may be the result of random noise or that load impacts are not related to temperature.

Figure 7-2: Comparison of 2014–2015 CPP Load Impacts and Summer Ex-Ante Load Impacts vs. Temperature by Transmission Planning Area

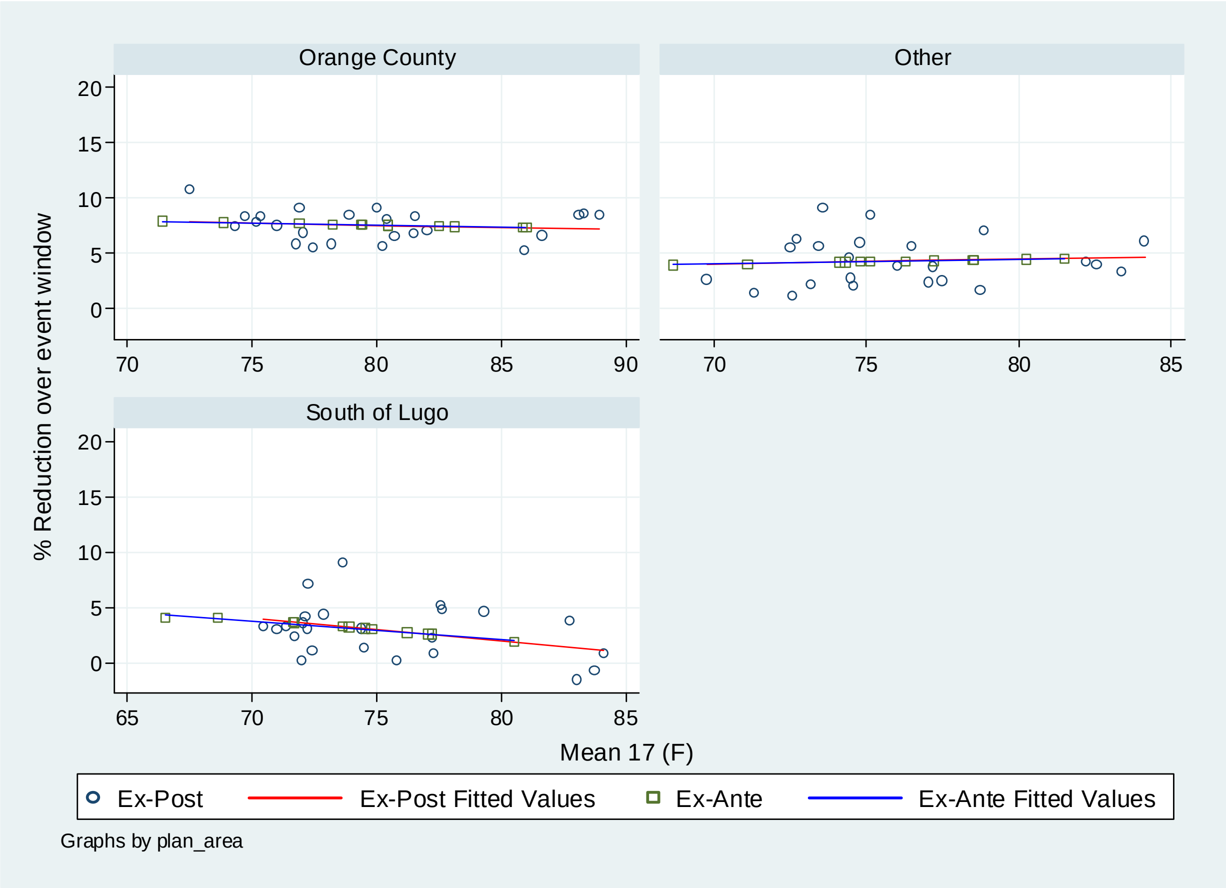


Figure 7-3 examines the sample used to model reference load, and compares loads for large default ex post customers during nonevent days in 2015 to the reference loads for the large customers used to calculate the ex ante reference load. The ex ante customers are the large customers with a full year of interval data identified as enrolled at the end of summer 2015, which are used for reference load modeling to provide an up to date picture of customers enrolled on CPP. The 2,467 customers used for reference load modeling comprised 92% of customers enrolled throughout the summer. The reference loads from nonevent days in May through October are included in the graph (weekends and holidays are excluded). The average reference load of ex ante customers is slightly lower than that of the ex post customers for the same days and weather conditions. The reference loads for ex ante customers show a slightly stronger relationship with temperature than those for all ex post customers, but the difference is negligible.

Figure 7-3: Comparison of Reference Loads of All Large Default Ex Post Customers and Subset of Large Customers Used in Developing the Ex Ante Reference Load

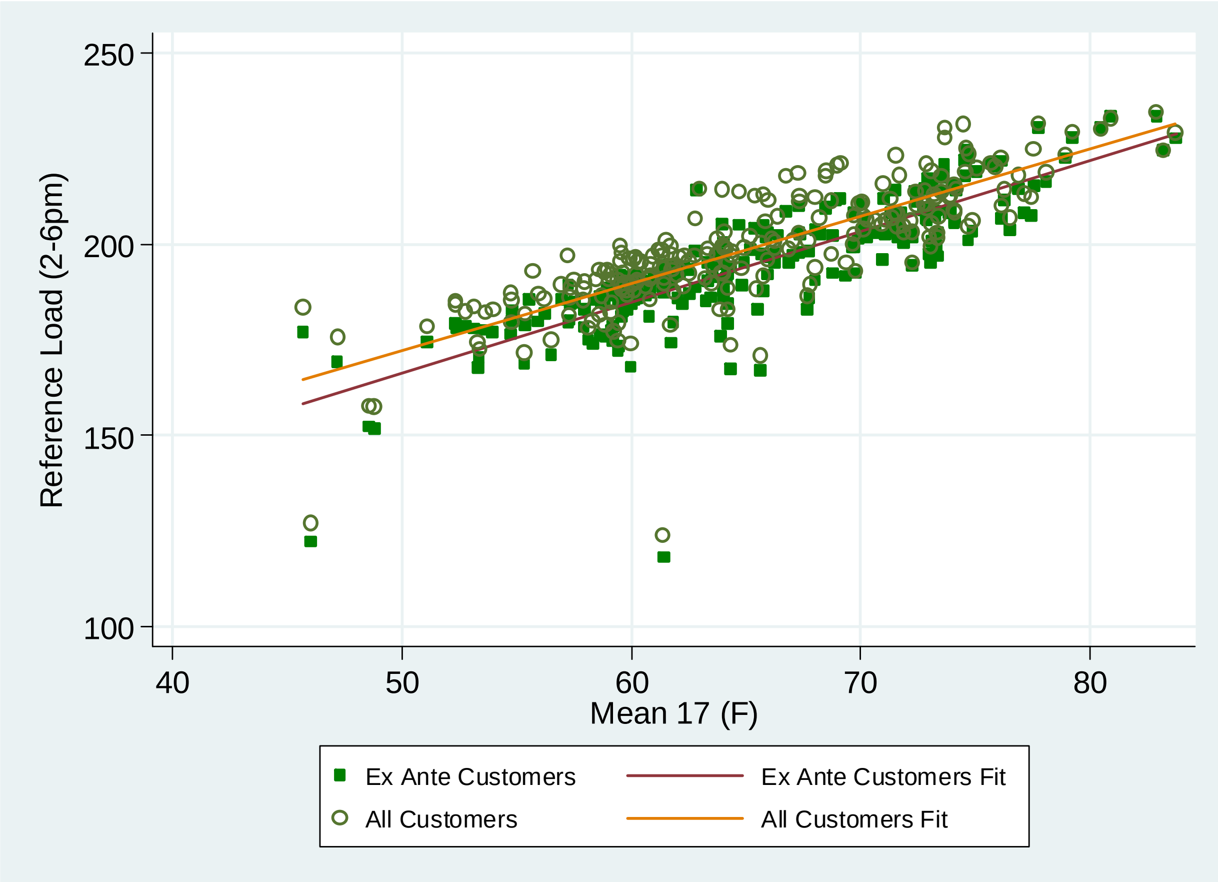


Figure 7-4 illustrates the reference load temperature relationship from the ex ante customers in the figure above after it has been applied to the ex ante conditions. It compares the customer reference loads during nonevent days to the ex ante reference loads. The 1-in-2 and 1-in-10 reference loads from May through October are included in the graph. The ex ante reference loads follow the weather trends observed within each transmission planning area during nonevent days. In assessing the effect on aggregate demand reductions, it is important to factor in both how loads and percent demand reductions vary with weather. For example, in the South of Lugo transmission planning area, loads tend to increase with hotter weather. However, the percent demand reductions tend to decrease with hotter weather and have more influence on the aggregate load reductions.

Figure 7-4: Comparison of Ex Post Loads on Nonevent Days to Ex-Ante Reference Loads for Large C&I

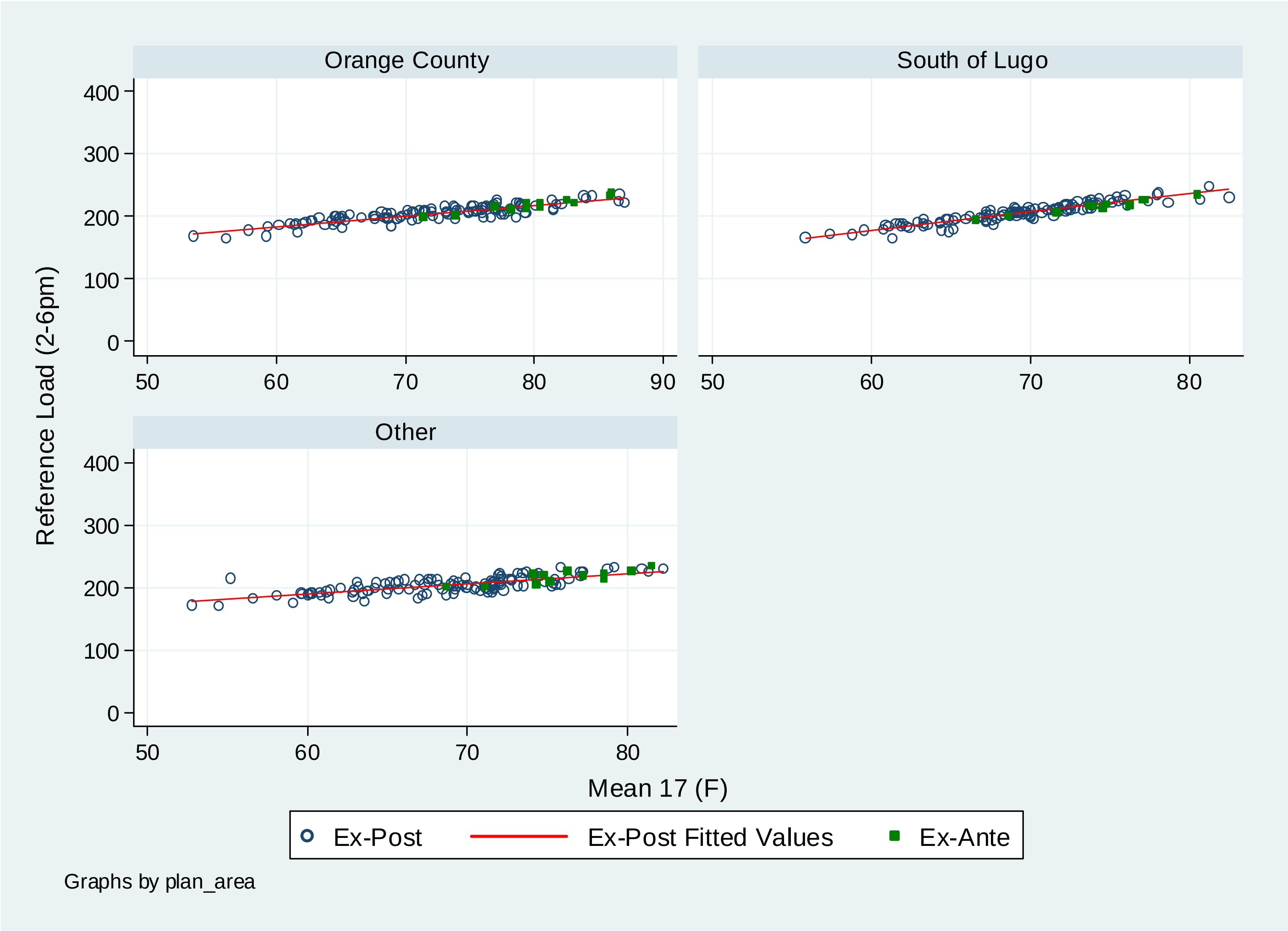


Table 7-2 shows SCE's enrollment projections for large C&I CPP customers through 2026. Impacts for the average customer are scaled up by the enrollments below to yield aggregate impacts. SCE projects that large C&I CPP enrollment will grow by 0.73% per year to approximately 2,813 customers by December 2026.

Table 7-2: SCE Enrollment Projections for Large C&I CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2016	2,718	2,718	2,718	2,718	2,718	2,718	2,718	2,718	2,718	2,718	2,718	2,718
2017	2,738	2,738	2,738	2,738	2,738	2,738	2,738	2,738	2,738	2,738	2,738	2,738
2026	2,813	2,813	2,813	2,813	2,813	2,813	2,813	2,813	2,813	2,813	2,813	2,813

7.1.1 Annual System Peak Day Impacts

Table 7-3 summarizes the aggregate load impact estimates for large C&I customers on SCE's CPP tariff for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios, based on both SCE and CAISO weather scenarios. The table shows the average load reduction across the 1 to 6 PM event period for an August monthly system peak day. Looking first at the aggregate load impacts based on normal, SCE-specific weather, load reductions based on 1-in-2 year SCE weather conditions will grow from 27.7 MW to 28.6 MW between 2016 and 2026. Impacts based on 1-in-10 year SCE weather conditions equal roughly 28 MW in 2016 and will grow to roughly 29 MW by 2026. These estimates equal roughly 4.4% of the aggregate reference load for large C&I customers. Impact estimates based on CAISO weather conditions are marginally lower than the estimates based on SCE weather.

Table 7-3: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I, SCE August System Peak Day (1–6 PM)

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load	Aggregate Estimated Load w/ DR	Aggregate Load Impact	% Load Reduction	Weighted Temp.
				(MW 1-6 PM)	(MW 1-6 PM)	(MW 1-6 PM)	(%)	(°F)
SCE	1-in-10	2016	2,718	637.8	609.5	28.3	4.4%	95.5
		2017	2,738	642.4	613.9	28.5	4.4%	95.5
		2026	2,813	660.0	630.7	29.3	4.4%	95.5
	1-in-2	2016	2,718	623.7	596.0	27.7	4.4%	92.7
		2017	2,738	628.3	600.4	27.9	4.4%	92.7
		2026	2,813	645.4	616.8	28.6	4.4%	92.7
CAISO	1-in-10	2016	2,718	632.0	603.9	28.1	4.4%	93.7
		2017	2,738	636.6	608.3	28.3	4.4%	93.7
		2026	2,813	654.0	624.9	29.1	4.4%	93.7
	1-in-2	2016	2,718	617.5	589.9	27.6	4.5%	92.1
		2017	2,738	622.0	594.2	27.8	4.5%	92.1
		2026	2,813	639.0	610.5	28.5	4.5%	92.1

7.1.2 Ex Ante Load Impact Uncertainty

Table 7-4 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for large C&I customers that are presented in Table 7-3. Ex ante impacts and the uncertainty in those estimates do not reflect uncertainty in the enrollment forecast. At first glance, the uncertainty appears large. For example, in 2016, the projected load impacts for August 1-in-2 year, SCE weather have an 80% confidence interval of 16.5 MW to 38.9 MW. The large confidence intervals in the ex ante forecasts reflect the challenges of accurately estimating small percentage demand reductions and the variability in performance observed across events. It is harder to accurately estimate a smaller percent change from the variation inherent in day to day loads. Put in percentage terms, the uncertainty seems much smaller, with an 80% confidence interval of 2.6% to 6.2%. For this program in particular, small differences in the estimated percent demand reductions can appear to be large changes in the estimate MW reductions, if the uncertainty is not considered.

Table 7-4: Aggregate Default CPP Ex Ante Load Impact Estimates for Large C&I with Uncertainty, SCE August System Peak Day (MW 1–6 PM)

Weather Type	Weather Year	Year	Expected Aggregate Load Impact (MW 1-6 PM)	Impact Uncertainty				
				10th	30th	50th	70th	90th
SCE	1-in-10	2016	28.3	16.7	23.5	28.3	33.1	39.9
		2017	28.5	16.8	23.7	28.5	33.3	40.2
		2026	29.3	17.3	24.4	29.3	34.2	41.3
	1-in-2	2016	27.7	16.5	23.1	27.7	32.3	38.9
		2017	27.9	16.6	23.3	27.9	32.5	39.2
		2026	28.6	17.1	23.9	28.6	33.4	40.2
CAISO	1-in-10	2016	28.1	16.7	23.4	28.1	32.7	39.5
		2017	28.3	16.8	23.6	28.3	33.0	39.8
		2026	29.1	17.3	24.2	29.1	33.9	40.9
	1-in-2	2016	27.6	16.5	23.1	27.6	32.1	38.6
		2017	27.8	16.7	23.2	27.8	32.3	38.9
		2026	28.5	17.1	23.9	28.5	33.2	39.9

7.1.3 Ex Ante Impacts by Geographic Location and Month

Table 7-5 presents aggregate 2016 ex ante impacts for each transmission planning area by month for large C&I customers. Load impacts are shown for the Resource Adequacy hours in effect for each month, which are 1 to 6 PM in the summer months and 4 to 9 PM in the winter months. As a result of the CPP event window ending at 6 PM, impacts are typically between 2 and 3 times larger in the summer months compared with winter months. It should also be noted that estimates for months outside of the June to September time frame should be used with caution as SCE has not called CPP events in shoulder and winter months. As such, there is no real empirical data on how customers will respond in these periods, which vary significantly in terms of weather conditions and event window hours.

In aggregate, the load reductions are largest in the Orange County and Other transmission planning areas. The 2016 enrollment forecast shows 34% of enrollments located in Orange County, and 55% of enrollments located in the Other transmission planning area. Customers classified as Orange County transmission planning area provided 50% of aggregate ex ante impacts for August 1-in-2 year weather conditions despite only accounting for 34% of the total population.

Table 7-5: Aggregate SCE Ex Ante Load Impact Estimates by Transmission Planning Area, Large C&I 2016 Monthly System Peak Days, SCE Weather Scenarios[33]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4-9 pm Resource Adequacy Window				1-6 pm Resource Adequacy Window						4-9 pm	
1-in-10	All	9.1	9.5	10.2	12.0	27.0	26.4	27.1	28.3	28.8	27.8	11.9	9.2
	Orange County	5.6	5.8	6.2	6.3	13.4	13.2	13.4	13.9	14.1	13.8	6.5	5.7
	South of Lugo	1.3	1.4	1.6	1.2	1.5	2.0	1.7	1.5	1.1	1.7	1.2	1.3
	Other	2.2	2.3	2.4	4.5	12.1	11.2	11.9	12.9	13.6	12.3	4.2	2.2
1-in-2	All	9.3	9.6	9.7	10.3	25.2	25.5	26.1	27.7	27.5	27.2	10.4	9.2
	Orange County	5.7	5.8	5.9	6.3	13.0	13.0	13.2	13.8	13.8	13.6	6.4	5.7
	South of Lugo	1.4	1.4	1.5	1.6	2.1	2.2	2.0	1.5	1.8	1.8	1.5	1.3
	Other	2.2	2.3	2.3	2.4	10.0	10.3	10.9	12.4	11.8	11.8	2.5	2.2

7.1.4 Comparison of 2014 and 2015 Ex Ante Estimates

Table 7-6 compares the August ex ante estimates produced for the 2014 evaluation to those presented in this report. Because ex ante impacts take into account changes in utility enrollment forecasts, program design and customer mix as well as additional experience, the forecasts are adjusted each year. In general, forecasts a year out are more reliable while forecasts further into the future are less certain.

Table 7-6 summarizes the comparison between the prior year's ex ante estimates and the current ones. Notable differences are observed in the percent impacts, which are roughly 30% higher than those produced in the 2014 report. The 2014 estimates exhibited a negative relationship with temperature, and so percent impacts under ex ante conditions, which tend to be hotter, were relatively low. Percent impacts in 2015 have a slight positive relationship with temperature, and so percent impacts are more in line with empirical results observed in the ex post analysis. Additionally, the 2015 enrollment forecast is about 6% higher than in 2014. The net effect is that this year's forecast for 2016 is 28.3 MW, which is 38% higher than last year's forecast of 20.5 MW for 1-in-10 weather conditions, and 29% higher than last year's forecast of 21.4 MW for 1-in-2 weather conditions.

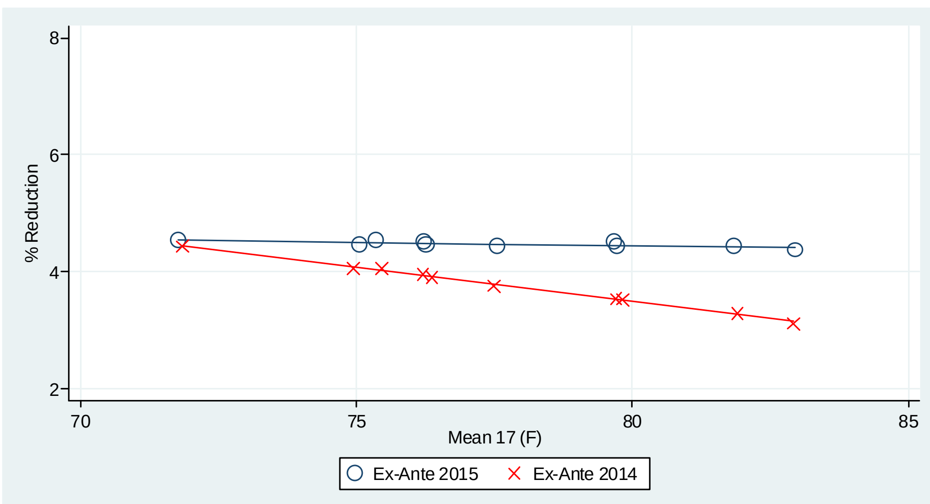
33 Estimates based on CAISO weather scenarios have a similar pattern across months and LCAs. These values can be obtained from the electronic load impact tables that were submitted along with this report.

Table 7-6: Comparison of Large C&I August Ex-ante Estimates to Prior Year Estimates

Weather Year	Year	Accounts		Reference Loads (kW)		Percent Reductions		Aggregate Impacts (MW)	
		2014 Estimates	2015 Estimates	2014 Estimates	2015 Estimates	2014 Estimates	2015 Estimates	2014 Load Impact (MW)	2015 Load Impact (MW)
1-in-10	2016	2,574	2,718	241.8	234.6	3.3%	4.4%	20.5	28.3
	2017	2,657	2,738	241.8	234.6	3.3%	4.4%	21.1	28.5
1-in-2	2016	2,574	2,718	235.2	229.5	3.5%	4.4%	21.4	27.7
	2017	2,657	2,738	235.2	229.5	3.5%	4.4%	22.1	27.9

A graphical comparison between the summer ex ante load impacts for large C&I customers as estimated in the 2014 and 2015 load impact evaluation is shown in Figure 7-5. The 2014 ex ante estimates are lower than those estimated this year, but the main difference in the percentage impacts is the inverse relationship with temperature. At lower temperatures, 2015 impacts are similar to 2014 impacts. Last year's estimates used a different estimating sample (the 2013 and 2014 CPP persistent customers), which produced a different temperature relationship. The 2015 ex ante estimates show a significantly less negative relationship with temperature than the estimates from 2014.

Figure 7-5: Comparison of 2014 Ex Ante Load Impacts to 2015 Ex Ante Large C&I Summer Months Load Impacts vs. Temperature



7.1.5 Relationship between Ex Post and Ex Ante Estimates

The ex post estimates presented in Section 6 and the ex ante estimates presented in this section differ for a number of reasons, including differences in weather, enrollment, event window and estimation methodology. This section discusses the impact of each of these factors on the difference between ex post and ex ante impact estimates.

Table 7-7 summarizes the key factors that lead to differences between ex post and ex ante estimates for CPP and the expected influence that these factors have on the relationship between ex post and ex ante impacts. CPP load impacts at SCE are not particularly sensitive to variation in weather; the temperature relationship was negative and not particularly strong. For the typical event day, ex ante impacts based on 1-in-2 year weather for both SCE and CAISO weather scenarios are very similar to those based on ex post weather. Impacts based on 1-in-10 year weather are about 4% lower.

Table 7-7: Summary of Factors Underlying Differences between Ex Post and Ex Ante Impacts for the Default CPP Customers for the Ex Ante Typical Event Day

Factor	Ex Post	Ex Ante	Expected Impact
Weather	Default CPP customers: 73.5 < event day mean17 < 85.7 Average event day mean17 = 77.9	Program specific mean17 for 1-in-2 typical event day = 75.8 and 77.0 for SCE and CAISO weather, respectively Program specific mean17 for 1-in-10 typical event day = 80.2 and 80.0 for SCE and CAISO weather, respectively	Ex ante estimates are sensitive to variation in mean17, but ex ante conditions are similar to ex post conditions, so ex ante impacts will be similar.
Event window	All events called from 2 to 6 PM	Common ex ante event window is 5 hours, from 1 to 6 PM, and 1 to 2 PM impact is much closer to zero than that from 2 to 3 PM.	Average ex ante impacts will be about 20% lower.
Enrollment	Enrollment remained fairly constant over the 2015 summer	2015 enrollment is higher.	Ex ante estimates will be higher due to changes in enrollment
Methodology	2015 impacts based on combination of matched control groups and individual customer regressions	Impacts: regression of ex post percent impacts against mean17 for each hour using two years' worth of ex post impacts for persistent customers Reference Load: regression of kW against mean17 and date variables for each hour using large ex ante population from January 2016	Pooled impacts from 2014 and 2015 for persistent customers are slightly larger than impacts for all customers (5.3% vs 5.0%). Impacts will be slightly larger.

Table 7-8 shows how aggregate load impacts change for large default CPP customers as a result of differences in the factors underlying ex post and ex ante estimates. Column C uses the 2015 ex post impacts shown in Table 6-1 and the projected enrollment for August 2016 to produce a scaled-up ex post impact estimate. This leads to a slight increase in load reductions of about 1%. The next column, column D, shows what the ex ante model would produce using the same August 2016 enrollment figures and the ex post weather conditions for each event day. The ex ante model over predicts load reductions on average by about 7% compared with the 2015 ex post impacts. As discussed earlier, this is the result of estimating ex ante impacts using percent impacts from the persistent population's 2014 and 2015 ex post values. Column E shows impacts estimated over the RA event window, which includes a 1 to 2 PM impact that is very close to zero, so impacts estimated over the RA event window are about 20% lower than those estimated over the 2 to 6 PM window. The final four columns F-I show how aggregate load reductions vary with the different ex ante weather scenarios. On average across all event days, the impacts derived from the SCE 1-in-2 conditions are most similar to those derived using the 2015 SCE ex post weather conditions, although for an given ex post event day, the impacts can differ significantly. Using the SCE 1-in-2 year conditions increases the average impacts by about 1% compared with the impacts from the ex post weather conditions. The CAISO and SCE 1-in-10 year weather conditions yield impacts about 2% larger than the impacts derived from their respective 1-in-2 year weather conditions.

Table 7-8: Differences in Large C&I Ex Post and Ex Ante Impacts Due to Key Factors

Date	Mean 17	Ex Post Impact	Ex Post Impact with Ex Ante Enrollment	Ex Ante Model Ex Post Weather and Event Window	Ex Ante Model Ex Post Weather RA Event Window	CAISO 1-in-2	SCE 1-in-2	CAISO 1-in-10	SCE 1-in-10
	A	B	C	D	E	F	G	H	I
	(F)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
7/1/2015	76.8	36.3	36.6	31.3	27.0	27.6	27.7	28.1	28.3
7/2/2015	75.7	22.7	23.0	31.2	27.0				
7/28/2015	73.5	25.5	25.9	30.5	26.5				
7/29/2015	74.9	21.8	22.2	30.8	26.7				
8/3/2015	74.6	37.0	37.7	30.8	26.7				
8/6/2015	76.2	36.4	37.1	31.3	27.1				
8/14/2015	81.0	28.0	28.5	32.4	27.9				
8/17/2015	77.9	27.4	27.9	31.7	27.3				
8/18/2015	75.1	26.8	27.3	31.0	26.8				
9/9/2015	85.7	35.6	36.0	33.5	28.8				
9/10/2015	83.9	25.0	25.3	33.0	28.3				
9/21/2015	79.0	25.4	25.8	31.7	27.4				
Avg.	77.9	29.0	29.4	31.6	27.3				

7.2 Medium C&I Ex Ante Impacts

Overall, there is greater uncertainty regarding medium C&I customer impacts under default CPP. To date, PG&E is the only California IOU which has implemented default CPP for medium customers. Nexant used the PG&E default small and medium percent reductions for the expected response of SCE's defaulted small and medium customers. Medium C&I customers at PG&E yielded percent reductions of .9, which translates to a percent reduction of .7% over the RA event hours. These estimates should be interpreted with caution because medium C&I customers who are on the rate at PG&E may not be representative of the medium C&I sector at SCE. The reference loads were developed by using a sample of interval data for medium customers at SCE and estimating reference loads for them within each transmission planning area. We simply applied the percent reductions to the reference loads.

Table 7-9 presents SCE's enrollment projections for medium C&I customers through 2026. In April 2018, medium C&I customers on a TOU rate will be defaulted onto CPP, leading to the increase in enrollment. Of the customers who will default in April 2018, 13,918 medium C&I customers are projected to remain on CPP.

Table 7-9: SCE Enrollment Projections for Medium C&I CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2018	0	0	0	34,795	34,795	34,795	34,795	34,795	34,795	34,795	34,795	34,795
2019	34,795	34,795	34,795	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918
2025	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918

7.2.1 Annual System Peak Day Impacts

Table 7-10 summarizes the aggregate load impact estimates for medium C&I customers on SCE's CPP rate for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios based on both SCE and CAISO weather scenarios. The table shows the average load reduction across the 1 to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on SCE-specific weather, August load reductions are predicted to fall from 8.6 MW in 2018 to 3.4 MW in 2019 under 1-in-10 weather conditions. After default CPP is fully implemented, medium customers are forecasted to reduce 0.7% of their demand under all weather conditions. The estimated percent reductions are constant as enrollment changes. Impact estimates based on CAISO weather 1-in-2 year conditions are very similar to estimates based on SCE weather. The CAISO 1-in-10 weather values also produce a load reduction that is nearly identical to that of the 1-in-10 year SCE estimates.

Table 7-10: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Medium C&I, SCE August System Peak Day (1–6 PM)

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
SCE	1-in-10	2018	34,795	1176.7	1168.1	8.6	0.7%	95.2
		2019	13,918	470.7	467.2	3.4	0.7%	95.2
		2026	13,918	470.7	467.2	3.4	0.7%	95.2
	1-in-2	2018	34,795	1130.8	1122.5	8.3	0.7%	92.1
		2019	13,918	452.3	449.0	3.3	0.7%	92.1
		2026	13,918	452.3	449.0	3.3	0.7%	92.1
CAISO	1-in-10	2018	34,795	1164.9	1156.3	8.5	0.7%	93.6
		2019	13,918	465.9	462.5	3.4	0.7%	93.6
		2026	13,918	465.9	462.5	3.4	0.7%	93.6
	1-in-2	2018	34,795	1123.0	1114.8	8.2	0.7%	91.6
		2019	13,918	449.2	445.9	3.3	0.7%	91.6
		2026	13,918	449.2	445.9	3.3	0.7%	91.6

7.2.2 Ex Ante Impacts by Geographic Location and Month

Table 7-11 summarizes aggregate 2020 ex ante impacts for each transmission planning area by month for medium C&I CPP customers. It shows the per customer impacts for each monthly system peak day under SCE 1-in-2 and 1-in-10 system peaking conditions. As a result of the CPP event window ending at 6 PM, impacts are typically between 3 and 4 times larger in the summer months compared with winter months. Although there is no real empirical data on how customers will respond in winter months, the load impacts in these months reflect the 0.7% impact from 2 to 6 PM that was assumed. Differences in impacts over months occur as a result of differences in reference load as well.

The variation in impact by transmission planning area reflects the weather, size of customers and the industry mix in each of SCE's transmission planning areas, which in turn affect reference load. Impacts for 2020, when default CPP will have been fully implemented across SCE's territory, are shown in the table. Like the large C&I ex ante load impacts by LCA, most of the load impacts will come from the Orange County and Other transmission planning areas. Orange County accounts for 27% of the forecasted 2020 medium C&I enrollment while the Other transmission planning area accounts for 60%.

Table 7-11: Aggregate SCE Ex Ante Load Impact Estimates by Transmission Planning Area
Medium C&I 2020 Monthly System Peak Days (1–6 PM), SCE Weather Scenarios[34]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4-9 pm Resource Adequacy Window				1-6 pm Resource Adequacy Window						4-9 pm	
1-in-10	All	0.9	1.0	1.1	1.3	3.0	3.2	3.4	3.4	3.4	3.0	1.2	0.9
	Orange County	0.2	0.2	0.3	0.3	0.8	0.8	0.9	0.9	0.9	0.8	0.3	0.2
	South of Lugo	0.1	0.1	0.2	0.2	0.4	0.4	0.4	0.4	0.4	0.4	0.2	0.1
	Other	0.6	0.6	0.7	0.8	1.8	1.9	2.1	2.1	2.0	1.8	0.7	0.6
1-in-2	All	0.9	1.0	1.0	1.2	2.7	2.9	3.1	3.3	3.1	2.9	1.1	0.9
	Orange County	0.2	0.3	0.3	0.3	0.7	0.8	0.8	0.9	0.8	0.8	0.3	0.2
	South of Lugo	0.1	0.1	0.1	0.2	0.3	0.4	0.4	0.4	0.4	0.4	0.1	0.1
	Other	0.6	0.6	0.6	0.7	1.6	1.8	1.9	2.0	1.8	1.7	0.7	0.6

7.3 Small C&I Ex Ante Impacts

As was true for medium customers, there are no SCE ex post impacts for small C&I customers upon which to base ex ante estimates. As discussed in the prior section, we apply ex post impacts from small C&I default customers at PG&E, which yielded a 0.5% load reduction. This results in a 0.4% load reduction over RA event hours.

Table 7-12 presents SCE's enrollment projections for small C&I customers through 2026. As with medium C&I customers, small C&I customers with at least 24-months of experience on a TOU rate will be defaulted onto CPP in April 2018. Of the customers who were already defaulted in April 2018, 86,082 small C&I customers are projected to remain on CPP. By April 2026, the small C&I population is expected to reach enrollment of 86,082 accounts.

Table 7-12: SCE Enrollment Projections for Small C&I CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2018	0	0	0	215,205	215,205	215,205	215,205	215,205	215,205	215,205	215,205	215,205
2019	215,205	215,205	215,205	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082
2026	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082

7.3.1 Annual System Peak Day Impacts

Table 7-13 summarizes the aggregate load impact estimates for small C&I customers on SCE's CPP rate for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios, based on both SCE and CAISO weather scenarios. The table shows the average load reduction across the 1 to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on SCE-specific weather, August load reductions fall from 2.0 MW in 2018 to around 0.8 MW in 2019 under 1-in-10 weather

[34] Estimates based on CAISO weather scenarios have a similar pattern across months and transmission planning areas. These values can be obtained from the electronic load impact tables that were submitted along with this report.

conditions. After default CPP is fully implemented, small customers are forecasted to reduce 0.4% of their demand under all weather conditions. The estimated percent reductions are constant as enrollment changes. Impact estimates based on CAISO weather 1-in-2 year conditions are very similar to estimates based on SCE weather. The CAISO 1-in-10 weather values also produce a load reduction that is nearly identical to that of the 1-in-10 year SCE estimates.

Table 7-13: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Small C&I, SCE August System Peak Day (1–6 PM)

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
SCE	1-in-10	2018	215,205	521.1	519.1	2.0	0.4%	95.0
		2019	86,082	208.5	207.6	0.8	0.4%	95.0
		2026	86,082	208.5	207.6	0.8	0.4%	95.0
	1-in-2	2018	215,205	493.1	491.2	1.9	0.4%	92.0
		2019	86,082	197.2	196.5	0.8	0.4%	92.0
		2026	86,082	197.2	196.5	0.8	0.4%	92.0
CAISO	1-in-10	2018	215,205	513.7	511.7	2.0	0.4%	93.4
		2019	86,082	205.5	204.7	0.8	0.4%	93.4
		2026	86,082	205.5	204.7	0.8	0.4%	93.4
	10-in-2	2018	215,205	488.6	486.7	1.9	0.4%	91.4
		2019	86,082	195.5	194.7	0.8	0.4%	91.4
		2026	86,082	195.5	194.7	0.8	0.4%	91.4

7.3.2 Ex Ante Impacts by Geographic Location and Month

Table 7-14 summarizes aggregate 2020 ex ante impacts for each transmission planning area by month for small C&I CPP customers. It shows the per customer impacts for each monthly system peak day under SCE 1-in-2 and 1-in-10 system peaking conditions. As a result of the CPP event window ending at 6 PM, impacts are typically 2 times larger in the summer months compared with winter months. Although there is no real empirical data on how customers will respond in winter months, the load impacts in these months reflect the 0.4% impact from 2 to 6 PM that was assumed. Differences in impacts over months occur as a result of differences in reference load as well.

The variation in impact by transmission planning area reflects the weather, size of customers and the industry mix in each of SCE's transmission planning areas, which in turn affect reference load. Impacts for 2020, when default CPP will have been fully implemented across SCE's territory, are shown in Table 7-14. Like the large C&I ex ante load impacts by transmission planning area, most of the load impacts will come from the Orange County and Other transmission planning areas. Orange County accounts for 24% of the forecasted 2020 medium C&I enrollment while the Other transmission planning area accounts for 64%.

Table 7-14: Aggregate SCE Ex Ante Load Impact Estimates by Transmission Planning Area
Small C&I 2020 Monthly System Peak Days (1–6 PM), SCE Weather Scenarios[35]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4-9 pm Resource Adequacy Window				1-6 pm Resource Adequacy Window						4-9 pm	
1-in-10	All	0.3	0.3	0.3	0.4	0.7	0.7	0.8	0.8	0.8	0.7	0.4	0.3
	Orange County	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1
	South of Lugo	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
	Other	0.2	0.2	0.2	0.2	0.4	0.5	0.5	0.5	0.5	0.4	0.2	0.2
1-in-2	All	0.3	0.3	0.3	0.4	0.6	0.7	0.7	0.8	0.7	0.6	0.3	0.3
	Orange County	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.1	0.1
	South of Lugo	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
	Other	0.2	0.2	0.2	0.2	0.4	0.4	0.5	0.5	0.4	0.4	0.2	0.2

[35] Estimates based on CAISO weather scenarios have a similar pattern across months and LCAs. These values can be obtained from the electronic load impact tables that were submitted along with this report.

8 SDG&E Ex Post Load Impacts

This section summarizes the ex post load impact evaluation for customers on SDG&E's CPP tariff. SDG&E called five CPP events in 2015. The first event occurred on August 27 and the last was held on September 11. On average, there were 1,207 accounts enrolled on SDG&E's tariff in 2015. There was some minor variation in enrollment during the course of the summer largely due to typical customer churn, with the highest enrollment at 1,209 participants and the lowest enrollment at 1,206. The average 2015 CPP customer enrollment of 1,207 represents a 5.7% increase from 2014 enrollment, which was 1,142 customers. Unlike at PG&E and SCE, there is no significant opt-in enrollment on the SDG&E CPP rate. The participant-weighted average temperature during the event period was 90.8°F.

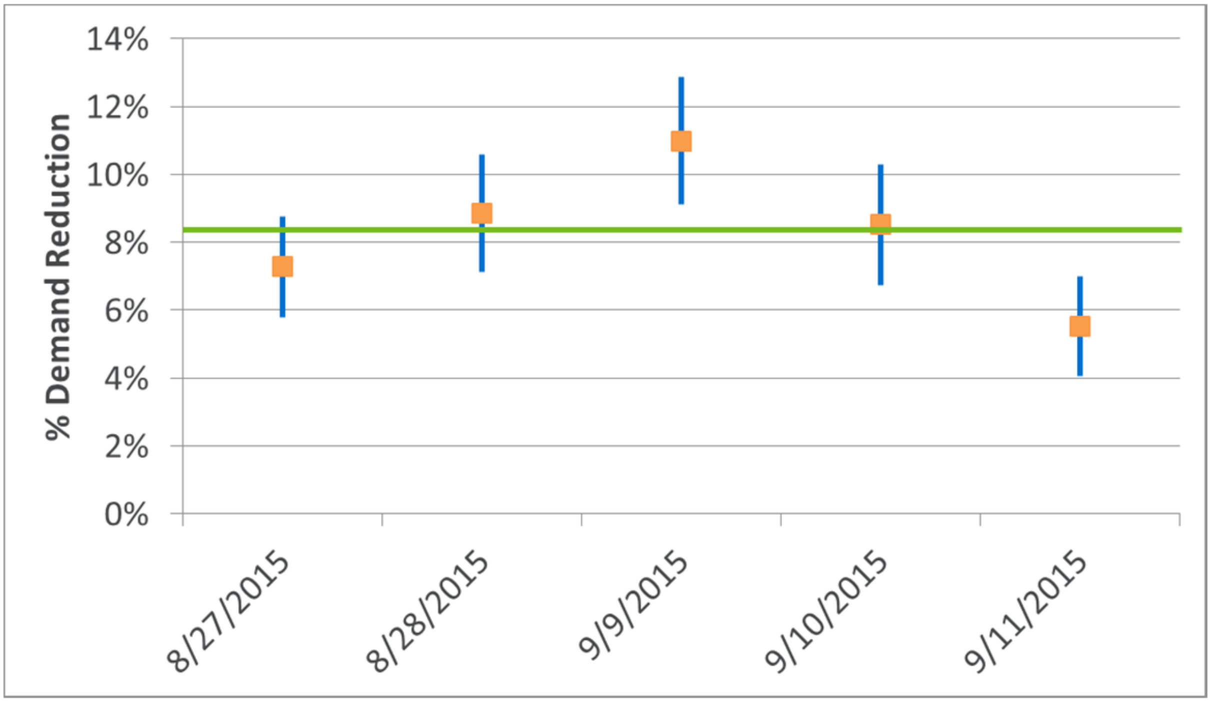
Table 8-1 shows the ex post load impact estimates for each event day and for the average event in 2015. The participant-weighted average temperature during the event period ranged from a low of 87.3°F to a high of 94.6°F. Percent impacts ranged from 5.5% to 11.0%, average impacts ranged from 13.5 kW to 29.7 kW and aggregate impacts across events ranged from 16.4 MW to 35.9 MW. On the average event day, the average participant reduced peak period load by 8.3%, or 21.0 kW. In aggregate, SDG&E's CPP customers reduced load by 25.3 MW on average across the five events in 2015.

Table 8-1: Default CPP Ex Post Load Impact Estimates by Event Day SDG&E 2015 CPP Events (11 AM to 6 PM)

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp.	Daily Maximum Temp.
			(kW)	(kW)	(kW)	(MW)	%	°F	°F
8/27/2015	Thu	1,207	240.6	223.1	17.5	21.1	7.3%	88.5	91.2
8/28/2015	Fri	1,206	240.8	219.5	21.3	25.7	8.8%	91.2	92.2
9/9/2015	Wed	1,209	270.7	241.0	29.7	35.9	11.0%	94.6	95.9
9/10/2015	Thu	1,209	267.4	244.6	22.8	27.5	8.5%	92.6	95.1
9/11/2015	Fri	1,208	245.8	232.2	13.5	16.4	5.5%	87.3	89.7
Avg. Event		**1,207**	**253.1**	**232.1**	**21.0**	**25.3**	**8.3%**	**90.8**	**91.6**

Figure 8-1 presents the ex post load impact estimates for individual 2015 events and the average 2015 event with 90% confidence intervals around each point estimate. All estimates are significantly greater than zero. These individual event day load impact estimates are less precise than the average event estimate due to event-to-event variability among customer load patterns and ability to shift load.

Figure 8-1: Ex Post Load Impact Estimates with 90% Confidence Intervals SDG&E 2015 CPP Events (11 AM to 6 PM)



8.1 Average Event Day Impacts

Figure 8-2 shows the hourly impacts for the average event for all customers across all hours of the day. The CPP event period for SDG&E runs from 11 AM to 6 PM, which is substantially longer than the 2 to 6 PM event periods at SCE and PG&E.

Percent reductions in each hour of SDGE's average 2015 weekday event varied from a high of 9.3% from 4 to 5 PM to a low of 7.4% from 11 to 12 PM, but these differences may not be statistically significant. The highest aggregate impact, 26.9 MW, occurred in the penultimate hour; and the lowest impact, 23.6 MW, occurred in the first hour.

The hourly load impacts for the average 2015 event day are slightly weaker in the earliest hours of the event than in the later hours, which is consistent with SDG&E's 2014 results. The overall magnitude of the hourly load impact across the five days is slightly lower in 2015 (8.3%) compared with 2014 (8.8%). We address this difference in the next section, which compares impacts across industry segments.

Figure 8-2: Aggregate Impact per Customer for the Average Event Day in 2015 Default CPP Ex Post Load Impacts

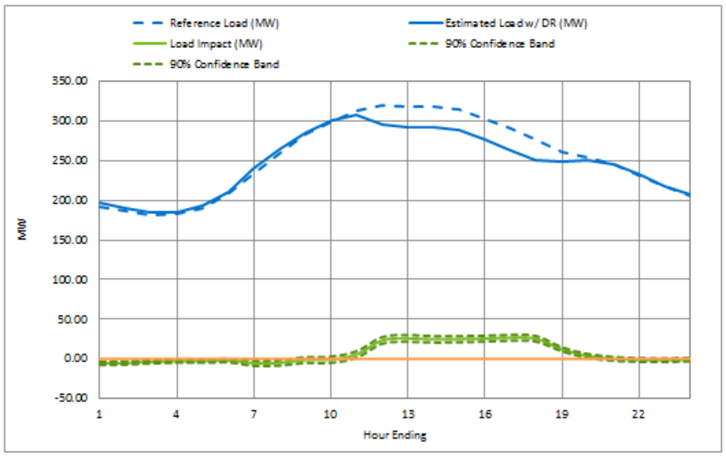
San Diego Gas & Electric
2015 Ex Post Load Impacts - CPP

TABLE 1: Menu options

Type of Results	Aggregate
Customer category	All Customers
Event Date	Avg. Event

TABLE 2: Event Day Information

Event Start	11:00 AM
Event End	6:00 PM
Total Enrolled Accounts	1,207
Avg. Load Reduction for Event Window (MW)	25.3
% Load Reduction for Event Window	8.3%



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1	191.3	196.8	-5.6	-2.9%	78.0	-7.2	-6.2	-5.6	-4.9	-4.0
2	185.7	190.7	-5.0	-2.7%	77.4	-6.6	-5.7	-5.0	-4.4	-3.5
3	182.0	185.6	-3.6	-2.0%	76.6	-5.2	-4.3	-3.6	-3.0	-2.0
4	182.2	184.8	-2.6	-1.4%	76.6	-4.2	-3.3	-2.6	-1.9	-1.0
5	190.0	192.6	-2.6	-1.4%	76.2	-4.2	-3.3	-2.6	-2.0	-1.0
6	209.4	211.4	-1.9	-0.9%	76.2	-3.7	-2.6	-1.9	-1.2	-0.2
7	234.0	239.3	-5.3	-2.3%	76.0	-7.8	-6.3	-5.3	-4.2	-2.7
8	259.2	264.2	-5.0	-1.9%	77.6	-7.6	-6.0	-5.0	-3.9	-2.4
9	283.7	284.9	-1.3	-0.4%	81.3	-4.1	-2.4	-1.3	-0.1	1.6
10	299.6	300.5	-0.9	-0.3%	84.0	-3.9	-2.1	-0.9	0.4	2.2
11	313.4	307.6	5.8	1.8%	87.5	2.5	4.4	5.8	7.1	9.0
12	319.7	296.1	23.6	7.4%	90.1	20.3	22.2	23.6	24.9	26.8
13	318.7	292.7	26.0	8.1%	91.3	22.6	24.6	26.0	27.3	29.3
14	317.4	292.7	24.7	7.8%	91.6	21.5	23.4	24.7	26.1	28.0
15	313.8	288.8	25.0	8.0%	91.4	22.0	23.8	25.0	26.3	28.1
16	302.6	276.9	25.7	8.5%	91.0	22.8	24.5	25.7	26.9	28.6
17	289.6	262.8	26.9	9.3%	90.7	24.0	25.7	26.9	28.0	29.7
18	276.4	251.0	25.4	9.2%	89.7	22.6	24.3	25.4	26.5	28.2
19	261.1	248.9	12.1	4.6%	87.8	10.1	11.3	12.1	12.9	14.1
20	254.2	250.3	3.8	1.5%	85.9	1.8	3.0	3.8	4.6	5.8
21	245.5	245.2	0.3	0.1%	84.0	-1.6	-0.5	0.3	1.0	2.1
22	231.5	232.7	-1.3	-0.5%	81.7	-3.1	-2.0	-1.3	-0.5	0.5
23	216.8	218.4	-1.6	-0.7%	79.8	-3.3	-2.3	-1.6	-0.9	0.1
24	205.8	206.5	-0.7	-0.3%	79.3	-2.4	-1.4	-0.7	0.0	0.9
	Reference Energy Use (MWh)	Estimated Energy Use w/ DR (MWh)	Total Load Impact (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Event	305.5	280.1	25.3	8.3%	320.4	0.2	15.0	25.3	35.6	50.5

Note: A positive value % Daily Load Change indicates the use of less energy for the day.

8.2 Load Impacts by Industry

Table 8-2 compares the reference load, load impact and the number of accounts, in percentage terms, across industry segments. It also shows the share of demand reduced by the average customer within each industry and whether or not the demand reduction was statistically significant with 90% confidence. The industries are presented in rank order based on the aggregate demand reduction.

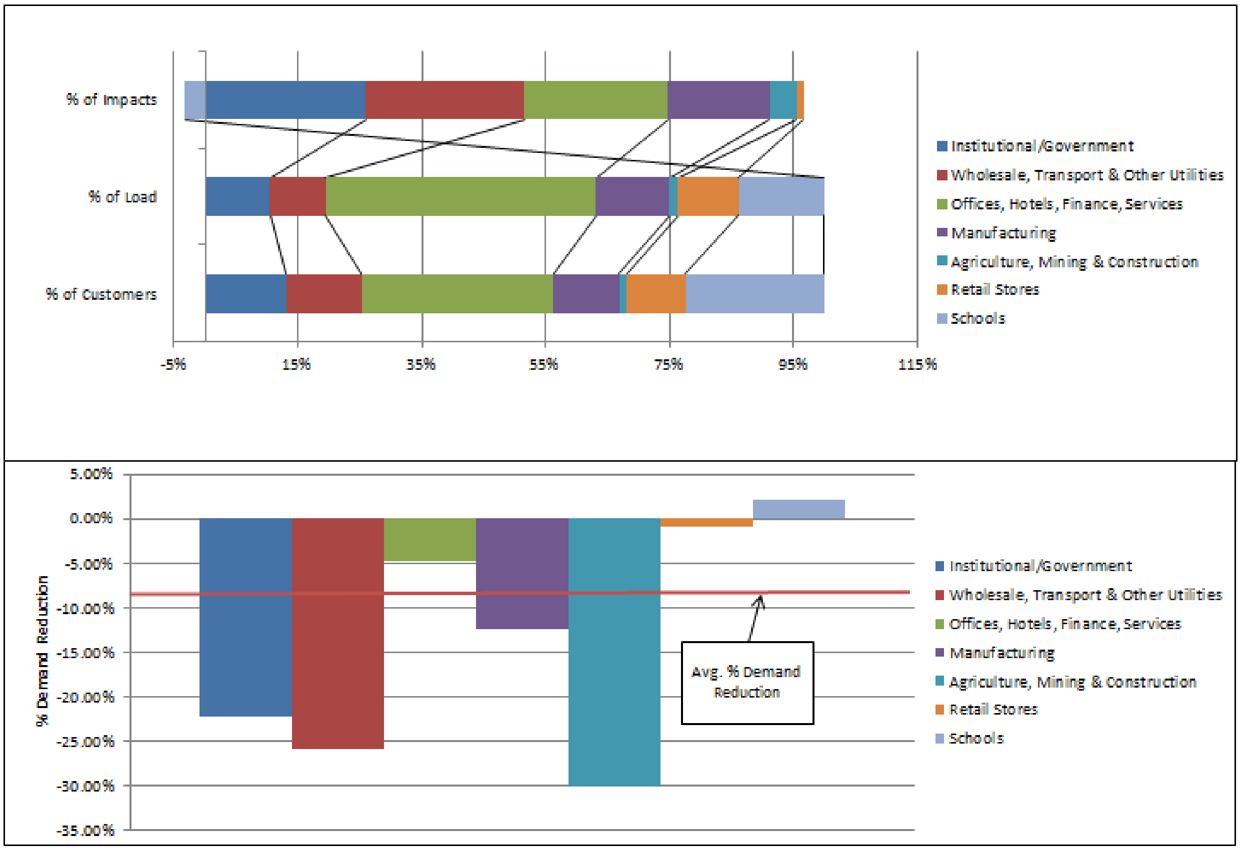
Nearly all of the load reduction, 78.4%, was provided by three sectors with relatively equal shares of the load impact: Institutional/Government, Wholesale, Transport & Other Utilities and Offices, Hotels, Finance, Services. Schools comprise much of the enrollment in the program, but showed highly variable and no significant load impacts.

Table 8-2: Default CPP Ex Post Load Impact Estimates by Industry Average 2015 SDG&E CPP Event (11 AM to 6 PM)

Industry	Accounts		Aggregate Reference Load		Aggregate Impact		Average Customer Impact	% Reduction	Stat. Sig?
	Enrollment	% of Program	MW	% of Program	MW	% of Program	kW		
Institutional/Government	158	13.1%	32.1	10.5%	7.1	27.8%	44.7	22.1%	Yes
Wholesale, Transport & Other Utilities	147	12.2%	27.2	8.9%	7.0	27.5%	47.3	25.7%	Yes
Offices, Hotels, Finance, Services	373	30.9%	133.2	43.7%	6.3	24.7%	17	4.7%	Yes
Manufacturing	129	10.7%	36.1	11.8%	4.5	17.7%	35	12.5%	Yes
Agriculture, Mining & Construction	15	1.2%	4.0	1.3%	1.2	4.7%	78.9	30.0%	Yes
Retail Stores	114	9.5%	29.9	9.8%	0.3	1.2%	2.9	1.0%	No
Schools	270	22.4%	42.2	13.9%	-0.9	-3.5%	-3.3	-2.1%	No

The largest share of the aggregate reference load is concentrated in the Offices, Hotels, Finances & Services sector. These customers are typically at office building premises. They accounted for 44% of the estimated reference load (133.2 MW) and produced 24.7% of the load reduction (6.3 MW). However, this sector also had the most participants and, on average, offices only reduced load by 4.7%. In contrast, the Wholesale, Transport & Other Utilities and Institutional/Government sectors together accounted for 19.4% of the reference load (59.3MW) but produced 55.3% of the impacts (14.1 MW). Figure 8-3 presents the same information visually, but better illustrates the concentration of load impact in specific industries—that much of the CPP load impacts SDG&E are coming from a relatively small amount of enrolled reference load.

Figure 8-3: Default CPP Enrollment, Load, Impact and Percent Demand Reduction by Industry Average 2015 SDG&E CPP Event (11 AM to 6 PM)



8.3 Load Impacts by Customer Size

Table 8-3 shows the estimated ex post load impact by customer size, using two different size categorization methods. First, load impacts are reported for the three demand categories: greater than 200 kW, less than 200 kW and greater than 20 kW, and less than 20 kW. The other size categorization is by usage quintile; all CPP customers were assigned to a usage quintile based on annual consumption. This metric of customer size is more useful than the demand response size categories because it provides estimates for a broad spectrum of customer sizes, where the segments all have sample sizes large enough to support reasonable estimates, which detracts from the value of using the demand response size categories. In fact, the load impact for the < 20 kW size category is insignificant, owing principally to the fact that there are only 23 customers in that category. Table 8-3 shows that customers in the two smallest and the largest usage quintiles have the largest percentage load impacts, while customers in the 4th quintile has the lowest percentage load impacts.

Table 8-3: Default CPP Ex Post Load Impact Estimates by Customer Size Average 2015 SDG&E CPP Event (11 AM to 6 PM)

Categorization	Size Category	Accounts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Average Customer Impact (kW)	Aggregate Impact (MW)	% Reduction (%)	Avg. Temp (°F)	Stat. Sig?
By DMDRCAT	Size: Over 200kW	826	344.2	314.7	29.5	24.4	8.6%	90.8	Yes
	Size: 20 kW to 199.99 kW	358	56.8	53.2	3.7	1.3	6.5%	91.0	Yes
	Size: Under 20 kW	23	75.6	92.7	-17.1	-0.4	-22.6%	91.5	No
By Annual Consumption Quintiles	5th Quintile	247	706.9	626.2	80.7	19.9	11.4%	90.4	Yes
	4th Quintile	240	265.7	256.6	9.1	2.2	3.4%	90.2	Yes
	3rd Quintile	242	163	156.6	6.4	1.5	3.9%	91.3	Yes
	2nd Quintile	241	89.1	83.6	5.5	1.3	6.2%	91.3	Yes
	1st Quintile	236	25.3	23.9	1.5	0.4	5.9%	91.0	Yes

8.4 Load Impacts for Multi-DR Program Participants

Table 8-4 shows load impacts for SDG&E customers who were dually enrolled in other DR programs in 2015. SDG&E's CPP population had dual enrollment with two other demand response programs in 2015: the base interruptible program (BIP) and the capacity bidding program (CBP). BIP estimates are not reported here as only two customers were dually enrolled with CPP. BIP and CBP are implemented at SDG&E the same way as they are at PG&E (see section 4.5 for a description of BIP and CBP).

Despite the fact that the load impact estimate for CPP customers dually enrolled in CBP may be statistically significant, remember that these estimates are developed with data from very few customers. These estimates should only be cited with caution so as not to infer that CBP enrollment causes greater CPP load impacts.

Table 8-4: Default CPP Ex Post Load Impact Estimates for Dually-enrolled Participants Average 2015 SDG&E CPP Event (11 AM to 6 PM)

Dually Enrolled DR	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Temp.	Stat. Sig?
		(kW)	(kW)	(kW)	(MW)	%	°F	
CBP								
Not Dually-enrolled	1,195	252.1	231.4	20.7	24.7	8.2%	90.8	Yes

8.5 TI and AutoDR Load Impacts and Realization Rates

Table 8-5 shows the average weekday event load impacts for customers enrolled in TI and AutoDR. Given the extremely small number of customers on TI and AutoDR, this point impact estimate is surrounded by a significant amount of uncertainty.

As was true for the analysis of TI and AutoDR for PG&E and SCE, analysis of realization rates for SDG&E CPP customers is hampered by the small number of customers who participated in the enabling technology programs. The realization rate estimate contained in Table 8-5 should be cited with caution due to the very small number of customers with the enabling technology.

Table 8-5: Default CPP Ex Post Load Impact Estimates of TI and AutoDR Participants Average 2015 SDG&E CPP Event (11 AM to 6 PM)

AutoDR	Accounts	Average Customer Impact	% Reduction	90% Confidence Interval		Approved kW	Realization Rate
		(kW)	%	Lower	Upper		
AutoDR/TI**	27	3.4	0.9%	-27.6	34.4	169.9	2.0%
TI**							
No AutoDR/TI	1,174	21.4	8.9%	12.5	30.3	-	-

* Does not represent a conclusive finding for this reporting segment due to the small sample size and uncertainty in the estimate.

9 SDG&E Ex Ante Load Impacts

This section presents ex ante load impact estimates for SDG&E's nonresidential CPP tariff. As discussed in Section 3, the main purpose of ex ante load impact estimates is to reflect the load reduction capability of a demand response resource under a standard set of conditions that align with system planning. These estimates are used in assessing alternatives for meeting peak demand, cost-effectiveness comparisons and long-term planning. The ex ante impact estimates for SDG&E are based on ex post load impacts of CPP events that occurred in 2014 and 2015. In total, load impact estimates 11 events were used as input to the ex ante model. All load impact estimates presented here are incremental to the effects of the underlying TOU rates.

This section presents the ex ante load impact projections separately for medium and large customers projected to receive service under SDG&E's default CPP tariff. Load reduction capability is summarized for each segment under annual system peak day conditions for a 1-in-2 and a 1-in-10 weather year for selected years (e.g., 2016, 2017 and 2026).[36] The estimates presented here are at the program level and do not account for dual enrollment of CPP participants in other DR programs. Portfolio-adjusted estimates that net out impacts for other programs if called at the same time are presented in Appendix F. Explanations of how CPP ex ante load impact estimates vary by geographic location and month under standardized ex ante conditions are also included in this section.

In addition to reflecting ex ante weather conditions and a standard event window, ex ante load impacts take into account both utility enrollment forecasts and changes to the design of default CPP ordered or approved by the CPUC. This section details how weather, enrollment and program changes affect any differences between ex post and ex ante impacts. A substantive change is scheduled for SDG&E in the 2016–2026 forecast horizon: SDG&E is scheduled to begin to default medium C&I customers onto CPP rates starting in 2016. These customers can elect to opt out to TOU rates if they do not wish to take a CPP rate.

9.1 Large C&I Ex Ante Load Impacts

As discussed in Section 3, the ex ante load impact estimates for large C&I customers are based on a regression model that relates impacts to weather conditions using the ex post impacts and weather data for 2014 and 2015 to estimate model coefficients. By removing variation in the customer mix from the analysis, we are better able to identify the underlying relationship between temperature and percent impacts. Before reviewing ex ante results, we provide an overview of the ex ante methodology. The steps involved in the analysis are as follows:

1. Identify persistent customers from 2014 and 2015;
2. Re-run 2014 and 2015 ex post analysis for just persistent customers to yield persistent customer ex post impacts;

[36] Enrollment is set to increase gradually between 2016 and 2026, in the same fashion as it does between 2015 and 2016, so the interim years don't provide much additional information of interest. The electronic load impact tables contain estimates for each year over the forecast horizon.

3. Model persistent customer ex post impacts as a function of weather;

4. Apply percent impacts model to ex ante weather conditions;

5. Identify large ex post customers enrolled at the end of the summer in 2015 who are also in the large demand category and have a full panel of data for 2015, and model their reference load as a function of temperature;

6. Apply reference load model to ex ante weather conditions;

7. Combine percent impacts and reference load for each set of ex ante conditions to get kW impacts for the average customer;

8. Multiply average customer impacts by ex ante enrollment.

Table 9-1 shows the ex post load impact estimates for each event day and for the average event day in 2014 and 2015 for large, persistent customers. The participant-weighted average temperature during the event period ranged from a low of 61.3°F to a high of 94.6°F. Percent impacts ranged from 4.9% to 11.6%; average impacts ranged from 8.6 kW to 29.2 kW; and aggregate impacts ranged from 8.7 MW to 29.6 MW[37].

Table 9-1: Default CPP Ex Post Load Impact Estimates for Persistent Customers by Event Day SDG&E 2014, 2015 CPP Events (11 AM to 6 PM)

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Average Customer Impact	Aggregate Impact	% Reduction	Avg. Event Temp.	Mean17
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	(°F)
2/7/2014	Fri	1013	177.1	168.5	8.6	8.7	4.9%	61.3	58.6
5/15/2014	Thu	1013	246.5	221.8	24.8	25.1	10.0%	93.4	84.6
7/31/2014	Thu	1013	251.9	222.7	29.2	29.6	11.6%	79.2	75.5
9/15/2014	Mon	1013	282.5	260.5	22.0	22.3	7.8%	86.2	81.1
9/16/2014	Tue	1013	288.1	265.0	23.1	23.4	8.0%	91.0	84.1
9/17/2014	Wed	1013	282.0	257.2	24.8	25.1	8.8%	82.7	82.2
8/27/2015	Thu	1013	253.9	235.3	18.6	18.8	7.3%	88.4	79.3
8/28/2015	Fri	1013	255.3	232.0	23.2	23.5	9.1%	91.2	81.3
9/9/2015	Wed	1013	281.2	253.7	27.5	27.9	9.8%	94.6	85.8
9/10/2015	Thu	1013	284.4	258.4	26.0	26.4	9.2%	92.7	84.7
9/11/2015	Fri	1013	269.0	245.7	23.4	23.7	8.7%	87.3	82.2

[37] It should be noted the impacts at the low end of the range are from an event in February 2014, and aren't representative of a typical CPP event. However, it does illustrate the temperature sensitivity of impacts and provides an additional data point for ex ante estimation, improving the precision of future ex ante estimates. For these reasons, it was included in the ex ante impact estimation process despite the non-standard (ie winter) timing of the event.

Figure 9-1 presents the ex post load impact estimates for the persistent customers alongside those for all ex post customers. The persistent customer population is a subset of the 2015 CPP population of all ex post customers. As such, they deliver different load impacts. Persistent customers are used for forecasting ex ante performance given they have been on the program for at least two years, and are more representative of customers expected to remain on the program over the longer time horizon. The impacts are plotted as a function of temperature and the linear fit is displayed for each customer group. Persistent customers have a more sensitive response to temperature than the customer population as a whole.

Figure 9-1: Comparison of 2014–2015 CPP Load Impacts for Persistent and All Ex Post Customers vs. Temperature

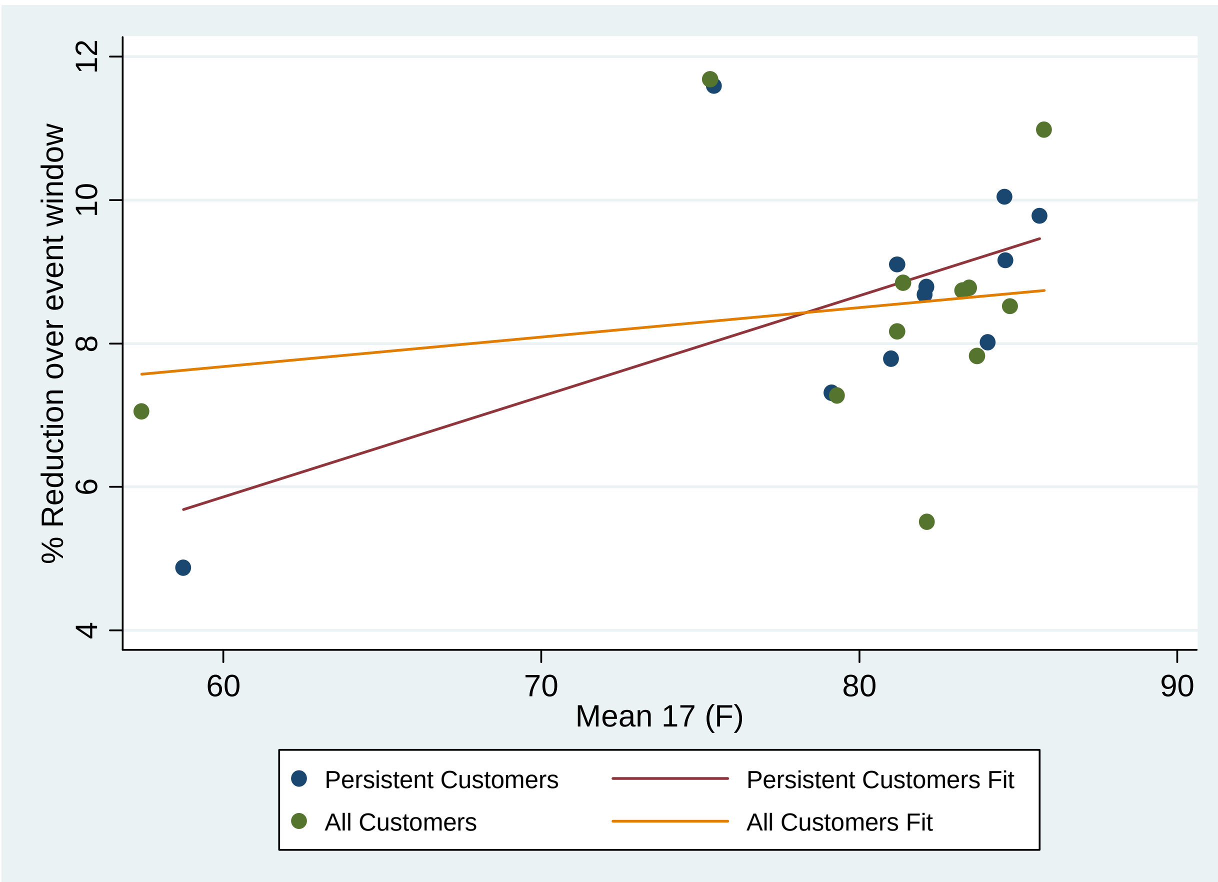


Figure 9-2 illustrates the historical 2014–2015 percent reductions as a function of temperature (blue circles). It also includes the percent demand reductions estimated under 1-in-2 and 1-in-10 year weather conditions (green squares) for the months of May through October based on the SDG&E weather scenarios (not the CAISO weather). Estimates of CPP percentage load impacts, based on the history of load impacts in 2014 and 2015, are shown to increase as temperatures increase. These percent demand reduction estimates for persistent customers were applied to large customer reference loads for all customers enrolled in 2015.

Figure 9-2: Comparison of 2014–2015 CPP Load Impacts and Summer Ex-Ante Load Impacts vs. Temperature

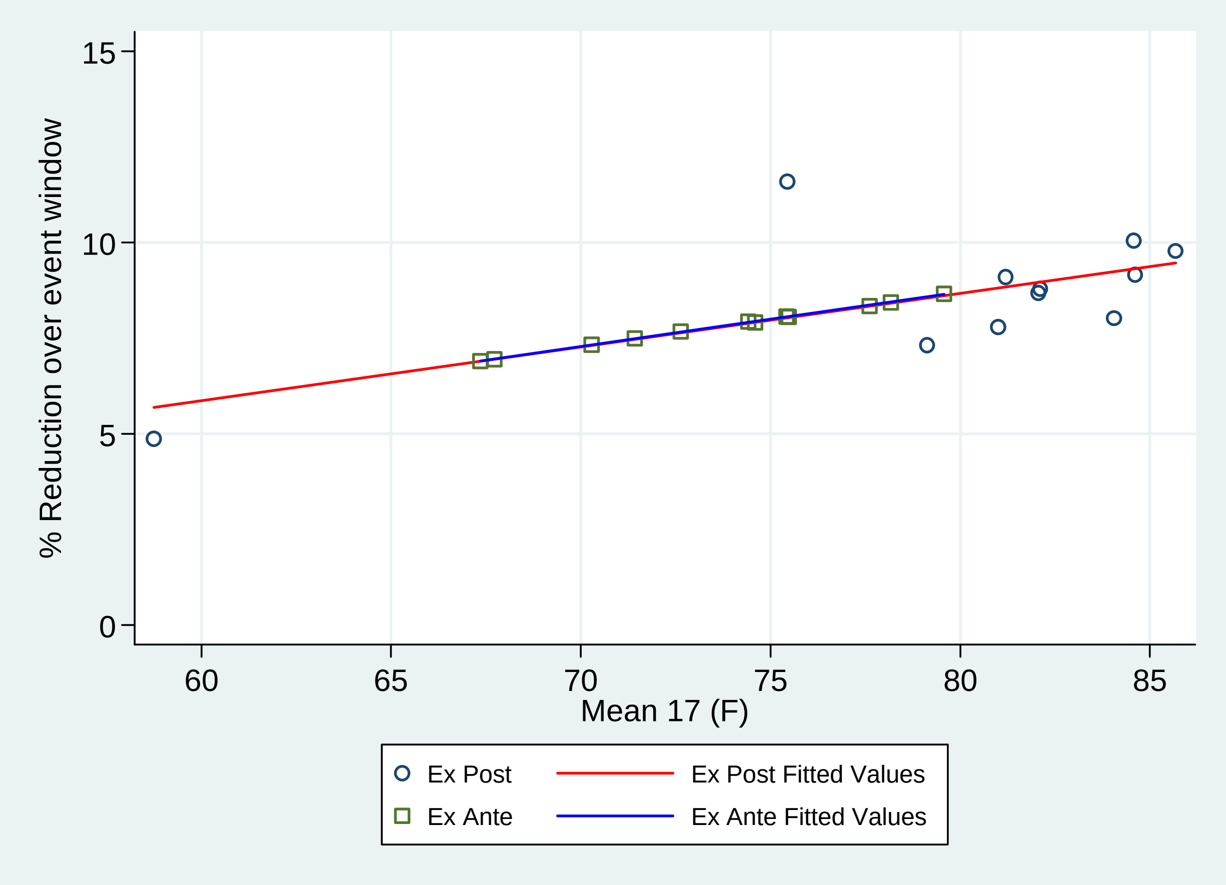


Figure 9-3 examines the sample used to model reference load, and compares loads for large default ex post customers during nonevent days in 2015 to the reference loads for the large customers used to calculate the ex ante reference load. The ex ante customers are the large customers with a full year of interval data identified as enrolled at the end of summer 2015, which are used for reference load modeling to provide an up to date picture of customers enrolled on CPP. The reference loads from nonevent days in May through October are included in the graph (weekends and holidays are excluded). The reference load sensitivity to temperature of persistent customers used to develop the ex ante forecast is nearly identical to that of ex post customers.

Figure 9-3: Comparison of Reference Loads of All Large Default Ex Post Customers and Subset of Large Customers Used in Developing the Ex Ante Reference Load

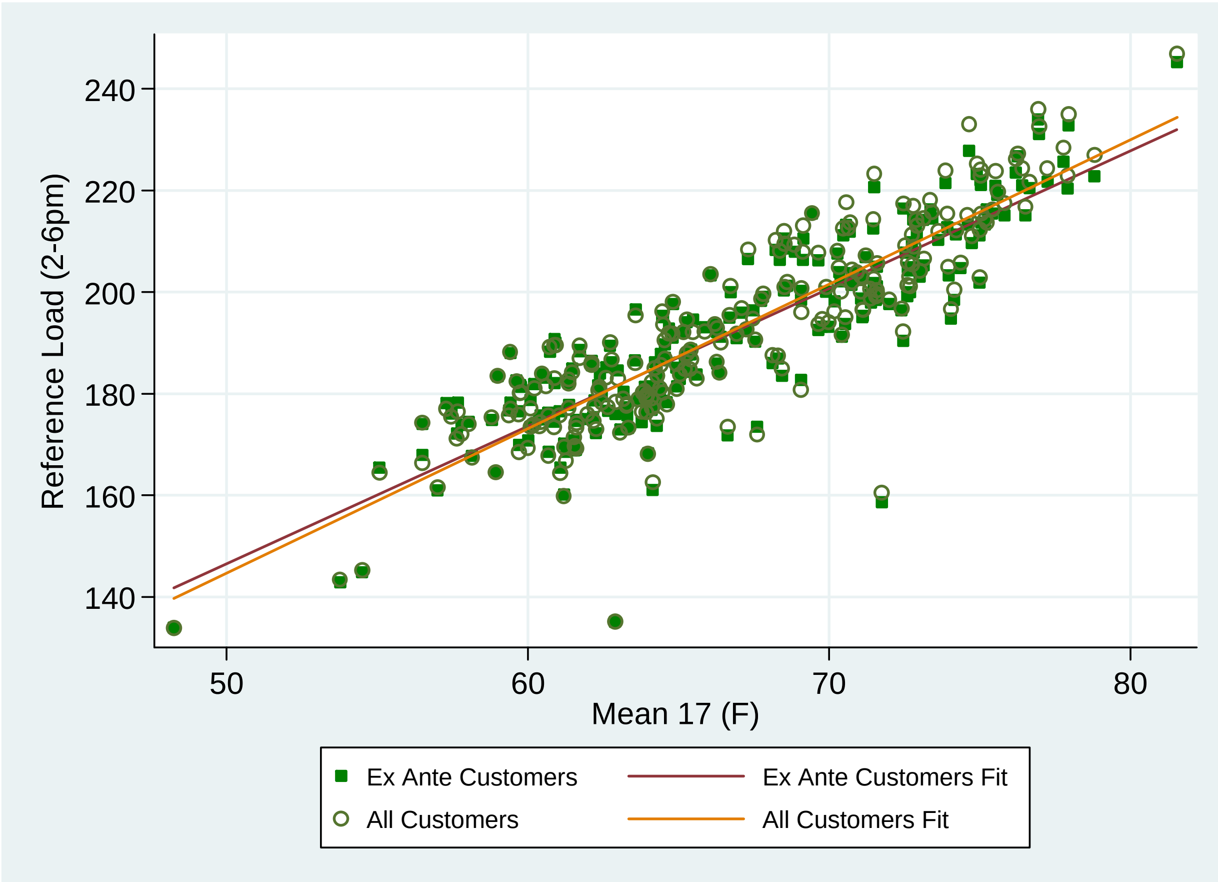


Figure 9-4 illustrates the reference load temperature relationship from the ex ante customers in the figure above after it has been applied to the ex ante conditions. It compares the customer reference loads during nonevent days to the ex ante reference loads. The 1-in-2 and 1-in-10 reference loads from May through October are included in the graph. The ex ante reference loads follow the weather trends observed during nonevent days. In assessing the effect on aggregate demand reductions, it is important to factor in both how loads and percent demand reductions vary with weather. For SDG&E, both percent impacts and reference loads increase with warmer temperatures; leading to larger aggregate impacts.

Figure 9-4: Comparison of Ex post Loads on Nonevent Days to Ex Ante Reference Loads for Large C&I

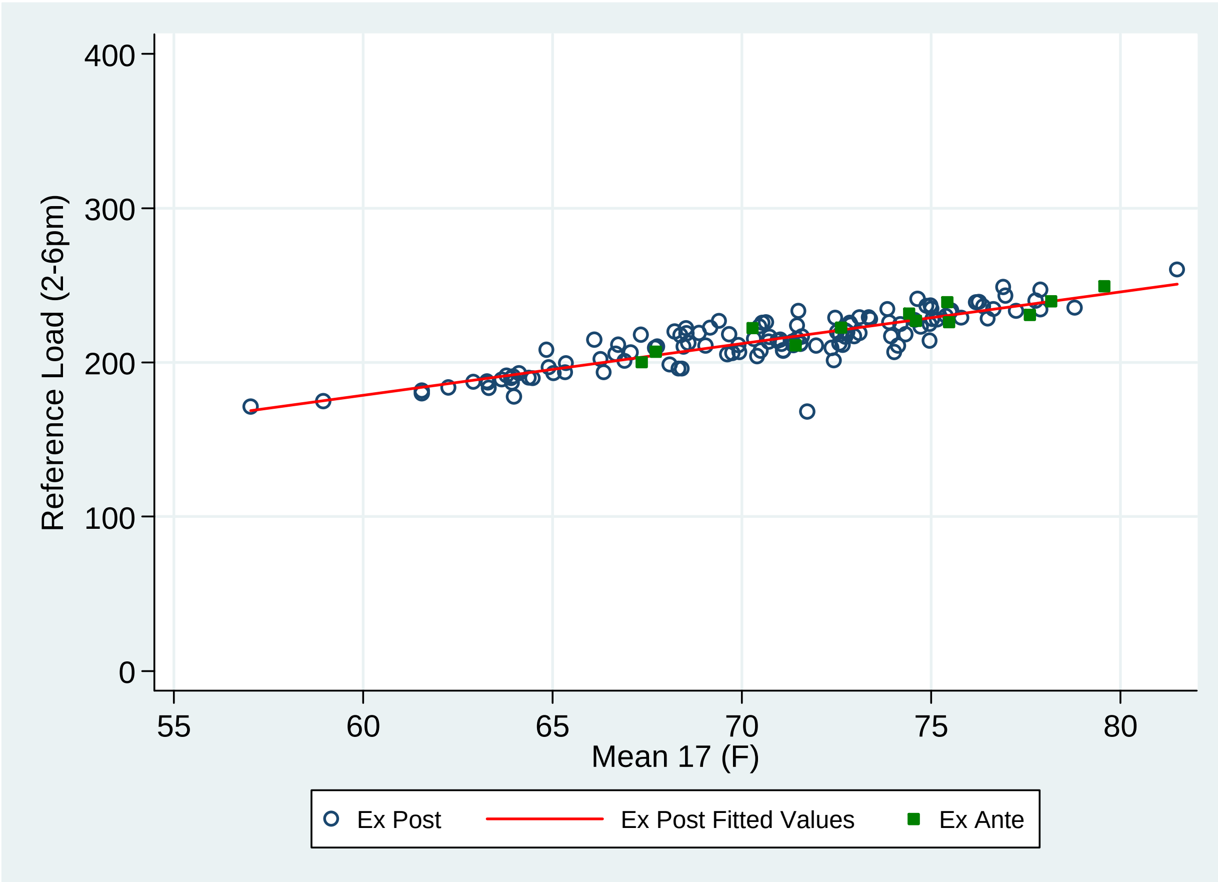


Table 9-2 shows SDG&E's enrollment projections for large C&I CPP customers through 2026. Overall, 1,207 large customers were enrolled in default CPP in 2015.[38] The forecasted year-to-year change in enrollment is a gradual increase which simply reflects the expected growth of SDG&E's large customer population.

38 For ex ante estimation, SDG&E split its existing default CPP population into medium and large customers. In contrast, ex post impacts were reported for all default CPP customers.

Table 9-2: SDG&E Enrollment Projections for Large C&I CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2016	1,263	1,264	1,265	1,266	1,267	1,268	1,270	1,271	1,272	1,273	1,274	1,275
2017	1,276	1,277	1,278	1,278	1,279	1,280	1,281	1,282	1,283	1,283	1,284	1,285
2018	1,286	1,288	1,289	1,290	1,291	1,293	1,294	1,295	1,296	1,298	1,299	1,300
2019	1,301	1,303	1,304	1,305	1,307	1,308	1,310	1,311	1,312	1,314	1,315	1,316
2020	1,318	1,319	1,320	1,321	1,322	1,323	1,324	1,326	1,327	1,328	1,329	1,330
2021	1,331	1,333	1,334	1,335	1,336	1,338	1,339	1,340	1,342	1,343	1,344	1,345
2022	1,347	1,348	1,349	1,351	1,352	1,353	1,354	1,356	1,357	1,358	1,360	1,361
2023	1,362	1,364	1,365	1,366	1,367	1,369	1,370	1,371	1,373	1,374	1,375	1,377
2024	1,378	1,379	1,381	1,382	1,383	1,385	1,386	1,387	1,389	1,390	1,391	1,393
2025	1,394	1,395	1,397	1,398	1,399	1,401	1,402	1,403	1,405	1,406	1,407	1,409
2026	1,410	1,411	1,413	1,414	1,415	1,417	1,418	1,419	1,421	1,422	1,424	1,425

9.1.1 Monthly System Peak Day Impacts

Table 9-3 summarizes the aggregate load impact estimates for large customers on SDG&E's CPP tariff for each forecast year under both 1-in-2 and 1-in-10 year weather conditions based on both SDG&E and CAISO weather scenarios. The table shows the average load reduction across the 1 PM to 6 PM event period for an August monthly system peak day.

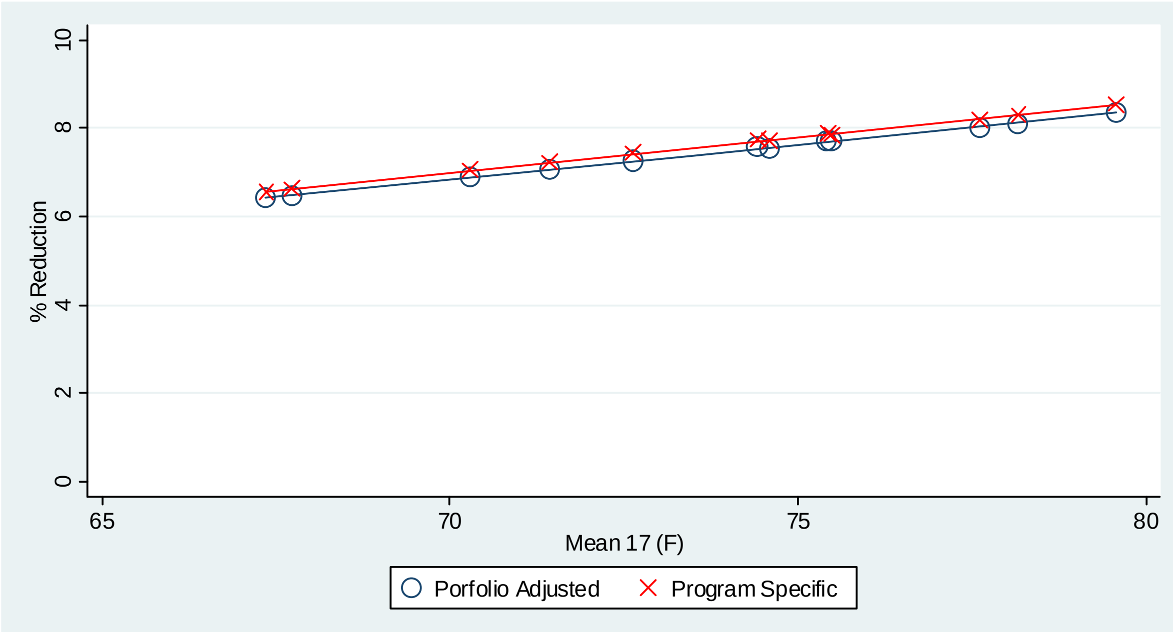
Looking first at the aggregate load impacts based on SDG&E-specific, 1-in-2 year weather conditions, load reductions will grow from roughly 22 MW to 25 MW between 2016 and 2026. Impacts based on 1-in-10 year SDG&E weather conditions equal roughly 25 MW in 2016 and will grow to 28 MW by 2026. These estimates equal roughly 8% of the aggregate reference load for large C&I customers. Impact estimates based on CAISO-specific, 1-in-2 year weather conditions are roughly 5% larger than the estimates based on SDG&E weather. The CAISO 1-in-10 year weather values produce a load reduction that is about 6% less than the 1-in-10 year SDG&E estimates in aggregate terms. These differences were driven by underlying differences in the weather forecast temperatures across the four scenarios that impact both the estimated reference loads as well as impact estimates.

Table 9-3: Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I SDG&E August System Peak Day (1–6 PM)

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1–6 PM)	Aggregate Estimated Load w/ DR (MW 1–6 PM)	Aggregate Load Impact (MW 1–6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
SDG&E	1-in-10	2016	1,271	302.0	276.9	25.1	8.3%	86.6
		2017	1,282	304.6	279.3	25.3	8.3%	86.6
		2026	1,419	337.2	309.2	27.9	8.3%	86.6
	1-in-2	2016	1,271	286.8	264.7	22.1	7.7%	81.2
		2017	1,282	289.3	267.0	22.3	7.7%	81.2
		2026	1,419	320.2	295.6	24.6	7.7%	81.2
CAISO	1-in-10	2016	1,271	293.3	269.9	23.4	8.0%	83.8
		2017	1,282	295.9	272.3	23.6	8.0%	83.8
		2026	1,419	327.5	301.5	26.0	8.0%	83.8
	1-in-2	2016	1,271	291.1	268.1	22.9	7.9%	83.5
		2017	1,282	293.6	270.5	23.1	7.9%	83.5
		2026	1,419	325.0	299.5	25.6	7.9%	83.5

Load impacts presented in Table 9-3 (in addition to the remainder of this section) do not reflect adjustments for dual enrollment in the BIP and CBP programs. Figure 9-5 illustrates the effect of removing dually enrolled customers from the forecast to produce the portfolio-adjusted load impact estimates. The portfolio-adjusted demand reductions are lower than the program-specific results by less than half a percentage point. The portfolio-adjusted estimates are fully documented in the electronic ex ante load impacts table generator, provided under separate cover, and are summarized in Appendix F.

Figure 9-5: Comparison of Portfolio-adjusted to Program-specific Ex Ante Load Impacts May through October Monthly Peaks for Current Participants



9.1.2 Ex Ante Load Impact Uncertainty

Table 9-4 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for large C&I customers. The ex ante impacts and the uncertainty reported in Table 9-4 do not reflect uncertainty in the CPP enrollment forecast. They do, however, reflect the challenge of accurately estimating small percentage demand reductions for individual event days. The uncertainty is relatively large. For example, in 2016, the projected load impacts for August 1-in-2 year, SDG&E weather conditions, are 22.1 ± 6.5 MW, with 80% confidence. But in percentage terms, the uncertainty seems smaller, 7.7%± 2.2%, with 80% confidence. For this program in particular, small differences in the estimated percent demand reductions can appear as large changes in the estimated MW reductions, if the uncertainty is not considered.

Table 9-4: Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I with Uncertainty
SDG&E August System Peak Day (1–6 PM)

Weather Type	Weather Year	Year	Expected Aggregate Load Impact	Impact Uncertainty				
			(MW 1–6 PM)	10th	30th	50th	70th	90th
SDG&E	1-in-10	2016	25.1	18.6	22.4	25.1	27.7	31.6
		2017	25.3	18.7	22.6	25.3	28.0	31.9
		2026	27.9	20.7	25.0	27.9	30.9	35.1
	1-in-2	2016	22.1	15.8	19.5	22.1	24.7	28.4
		2017	22.3	15.9	19.7	22.3	24.9	28.7
		2026	24.6	17.7	21.8	24.6	27.5	31.6
CAISO	1-in-10	2016	23.4	17.0	20.8	23.4	26.0	29.8
		2017	23.6	17.1	20.9	23.6	26.2	30.0
		2026	26.0	19.0	23.2	26.0	28.9	33.1
	1-in-2	2016	22.9	16.6	20.3	22.9	25.5	29.3
		2017	23.1	16.7	20.5	23.1	25.8	29.5
		2026	25.6	18.5	22.7	25.6	28.4	32.6

9.1.3 Comparison of 2014 and 2015 Ex Ante Estimates

Table 9-5 compares the ex ante estimates produced for the 2014 evaluation to those presented earlier in this report. Because ex ante impacts take into account changes in utility enrollment forecasts, program design and customer mix as well as additional experience, the forecasts are adjusted each year. In general, forecasts a year out are more reliable while forecasts further into the future are less certain. The largest changes observed in Table 9-5 are the decreases in predicted reference loads between the 2014 CPP evaluation and this year due to smaller average 2015 reference loads in the persistent customers used to estimate the ex ante reference loads. Percent impacts for both evaluations are roughly the same, with the net effect that this year's forecast for 2016 is 25.1 MW, which is 7% lower than last year's forecast of 27.1MW.

Table 9-5: Comparison of Ex Ante Estimates to Prior Year Estimates

Weather Year	Year	Accounts		Reference Loads (MW)		Percent Reductions		Aggregate Impacts (MW)	
		2014 Estimates	2015 Estimates	2014 Estimates	2015 Estimates	2014 Estimates	2015 Estimates	2014 Estimates	2015 Estimates
1-in-10	2016	1,267	1,271	254.6	237.7	8.4%	8.3%	27.1	25.1
	2017	1,283	1,282	254.6	237.6	8.4%	8.3%	27.5	25.3
	2025	1,405	1,403	254.3	237.6	8.3%	8.3%	29.8	27.6
1-in-2	2016	1,267	1,271	243.5	225.7	7.9%	7.7%	24.5	22.1
	2017	1,283	1,282	243.5	225.7	7.9%	7.7%	24.8	22.3
	2025	1,405	1,403	243.2	225.6	7.9%	7.7%	26.9	24.4

9.1.4 Relationship Between Ex Post and Ex Ante Estimates

The ex post estimates presented in Section 8 and the ex ante estimates presented in this section differ for a number of reasons, including differences in weather, enrollment and estimation methodology. This section discusses the impact of each of these factors on the difference between ex post and ex ante impact estimates.

Table 9-6 summarizes key factors that lead to differences between ex post and ex ante estimates for CPP and the expected influence that these factors have on the relationship between ex post and ex ante impacts. Given that the CPP load impacts are sensitive to variation in weather, even small changes in *mean17* between ex post and ex ante weather conditions can produce differences in load impacts. For the typical event day, ex ante impacts are significantly lower than the ex post values when based on SDG&E ex ante weather and also lower than the ex post values when based on CAISO weather conditions. This is primarily due to the difference in summer season weather observed in the ex post and ex ante results. The average midnight to 5pm (mean17) weather in all four of the ex ante weather scenarios are all lower than the lower end the mean17 weather experienced in 2015 season. This change decreases the ex ante impacts by roughly 20% for the typical event day under 1-in-2 SDG&E weather conditions, compared with the average 2015 event day. Changes in enrollment between the values used for ex post estimation and the 2016 enrollment values increase impact estimates by about 5%. Finally, the fact that the ex ante model is based on ex post impacts from both 2014 and 2015 for persistent customers, which exhibit a stronger relationship with temperature, will result in slightly higher ex ante load impacts at higher temperature values than ex post impacts at similar values.

Table 9-6: Summary of Factors Underlying Differences Between Ex Post and Ex Ante Impacts for the Default CPP Customers for the Ex Ante Typical Event Day

Factor	Ex Post	Ex Ante	Expected Impact
Weather	Default CPP customers: 79.9 < event day mean17 < 86.3 Average event day mean17 = 83.2	Program specific mean17 for 1-in-2 typical event day = 72.5 and 73.2 for SDG&E and CAISO weather, respectively Program specific mean17 for 1-in-10 typical event day = 77.5 and 76.0 for SDG&E and CAISO weather, respectively	Ex ante estimates are sensitive to variation in mean17 – impacts will be lower based on both SDG&E weather and CAISO weather
Enrollment	Enrollment remained fairly constant over the 2015 summer	2016 enrollment is forecast to be about 5% higher	Ex ante estimates will be about 5% higher than ex post
Methodology	2015 impacts based on combination of matched control groups and individual customer regressions	Impacts: regression of ex post percent impacts against mean17 for each hour using two years' worth of ex post impacts for persistent customers Reference Load: regression of kW against mean17 and date variables for each hour using default cpp population	Pooled impacts from 2014 and 2015 for persistent customers exhibit a stronger temperature relationship than those for all customers. Impacts will be higher at higher temperatures and lower or similar at lower temperatures. Reference load of the ex ante population is similar to that of the ex post population.

Table 9-7 shows how aggregate load impacts change for large default CPP customers as a result of differences in the factors underlying ex post and ex ante estimates. The third column uses the 2015 ex post impacts shown in Table 8-1 and the projected enrollment for August of 2016 to produce a scaled-up ex post impact estimate, which is approximately the same as the average ex post impact since enrollment grew very little. The next column shows what the ex ante model would produce using the same August 2016 enrollment figures and the ex post weather conditions for each event day. The ex ante model predicts load reductions fairly accurately on average, but estimates tend to be higher on individual days. As discussed above, this is the result of estimating ex ante impacts using percent impacts from the persistent population's 2014 and 2015 ex post values. The final four columns show how aggregate load reductions vary with the different ex ante weather scenarios. The impacts are similar across SDG&E and CAISO weather scenarios. On average across all event days, the impacts derived from the 1-in-10 conditions are most similar to those derived using the 2015 SDG&E ex post weather conditions, although the impacts are still lower than the average ex post day by about 12%.

Table 9-7: Differences in Large C&I Ex Post and Ex Ante Impacts Due to Key Factors

Date	Mean 17	Ex Post Impact	Ex Post Impact with Ex Ante Enrollment	Ex Ante Model Ex Post Weather	CAISO 1-in-2	SDG&E 1-in-2	CAISO 1-in-10	SDG&E 1-in-10
	(F)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
8/27/2015	79.9	21.1	22.3	25.6	20.8	20.6	21.8	22.4
8/28/2015	82.0	25.7	27.1	27.3				
9/9/2015	86.3	35.9	37.8	30.8				
9/10/2015	85.1	27.5	29.0	29.8				
9/11/2015	82.4	16.4	17.2	27.6				
Avg.	83.2	25.3	26.7	28.2				

9.2 Medium C&I Ex Ante Impacts

Overall, there is greater uncertainty regarding medium C&I customer impacts under default CPP. To date, opt-in CPP rates have been implemented on a very limited basis for medium customers. Medium C&I customers who are on the CPP rate are generally not representative of the medium C&I sector as a whole. In addition, only one year of data is available for default SMB CPP rates for California customers; at PG&E, not SDG&E. While some SDG&E medium customers volunteered onto CPP rates, their mix and demand reductions are not representative of the current and future medium default customer population. 2015 was the first year of PG&E's small and medium business default CPP enrollment, while SDG&E will begin defaulting SMB customers in early 2016 before the typical CPP event season. For this reason, the initial results from PG&E's program are being used to estimate SDG&E's ex ante impacts.

Previous studies of residential customers have shown that customers who enroll on an opt-in basis tend to be more engaged and deliver significantly larger percent reductions than those who enroll on a default basis.[39] To estimate impacts for the larger SMB population, Nexant therefore used the PG&E Medium CPP percent reductions as the estimate for SDG&E defaulted medium customers, yielding percent reductions of 0.9%. The reference loads were developed by using interval data for customers that are eligible to be defaulted in March 2016. Table 9-8 presents SDG&E's enrollment projections for medium C&I customers through 2026. In March 2016, medium C&I customers with at least 24 months of experience on a TOU rate will be defaulted onto CPP, leading to the increase in enrollment. While the number of eligible customers is due to increase over the next ten years due to growth in accounts, higher levels of opt-out to a TOU rate reduce the CPP enrollment forecast over time. Of the customers who were already defaulted in March 2016, 16,260 customers are projected to remain on CPP in March 2026.

Table 9-8: SDG&E Enrollment Projections for Medium C&I CPP Customers by Forecast Year and Month

Year	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
2016	19,308	19,308	19,308	19,308	19,308	19,308	19,308	19,308	19,308	19,308	19,308	19,308
2017	17,276	17,276	17,276	17,276	17,276	17,276	17,276	17,276	17,276	17,276	17,276	17,276
2026	16,260	16,260	16,260	16,260	16,260	16,260	16,260	16,260	16,260	16,260	16,260	16,260

9.2.1 Monthly System Peak Day Impacts

Table 9-9 summarizes the aggregate load impact estimates for medium C&I customers on SDG&E's CPP rate for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios based on both SDG&E and CAISO weather scenarios. The table shows the average load reduction across the 1 PM to 6 PM event period for an August monthly system peak day.

[39] Interim report on Sacramento Municipal Utility District's Smart Pricing Options pilot: https://www.smartgrid.gov/sites/default/files/MASTER_SMUD%20CBS%20Interim%20Evaluation_Final_SUBMITTED%20TO%20TAG%2020131023.pdf

Looking first at the aggregate load impacts based on SDG&E-specific weather, August load reductions decrease from 4.4 MW in 2016 to 3.9 MW in 2017 under 1-in-10 weather conditions, and then increase to 4.8 MW in 2026. Once default CPP is fully implemented, medium customers are forecasted to reduce less than 1% of their demand under all weather conditions. Aggregate impact forecasts are dependent upon the underlying persistent ex post impacts, enrollment forecasts, and awareness factors that capture how likely a customer will be to take action on an event day. Underlying the enrollment of SDG&E customers on to the CPP rate are both the aggregate number of eligible accounts, forecasted to rise over time, and the rate at which they opt out of default CPP on to a TOU rate only. This forecasted opt-out rate is the reason why enrollment declines slowly over the first three years of the forecast, then flattens out in the later years. In the meantime, the awareness factor increases as described above. Together these conflicting influences cause the drop in aggregate impacts in the short to mid term, but then increase in the later years of the forecast period.. Impact estimates based on CAISO weather 1-in-2 year conditions are the same as under SDG&E scenarios. Reference loads under the SDG&E-specific 1-in-10 year weather are higher than CAISO-specific, while CAISO-specific weather yields higher reference loads in the 1-in-2 year weather scenario. In both cases, reference loads do not vary by more than 3% between the two scenarios.

Table 9-9: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Medium C&I, SDG&E August System Peak Day (1 PM to 6 PM)

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load	Aggregate Estimated Load w/ DR	Aggregate Load Impact	% Load Reduction	Weighted Temp.
				(MW 11 AM–6 PM)	(MW 11 AM–6 PM)	(MW 11 AM–6 PM)	(%)	(°F)
SDG&E	1-in-10	2016	19,308	676.2	669.9	6.2	0.92%	91.0
		2017	17,276	605.0	599.4	5.6	0.92%	91.0
		2026	16,260	569.4	564.2	5.2	0.92%	91.0
	1-in-2	2016	19,308	631.6	625.8	5.8	0.92%	83.5
		2017	17,276	565.1	559.9	5.2	0.92%	83.5
		2026	16,260	531.9	527.0	4.9	0.92%	88.5
CAISO	1-in-10	2016	19,308	656.2	650.2	6.0	0.92%	88.5
		2017	17,276	587.2	581.8	5.4	0.92%	88.5
		2026	16,260	552.6	547.5	5.1	0.92%	88.5
	1-in-2	2016	19,308	649.8	643.8	6.0	0.92%	88.1
		2017	17,276	581.4	576.1	5.4	0.92%	88.1
		2026	16,260	547.2	542.2	5.0	0.92%	88.1

10 Recommendations

Program enrollment and the number and timing of events called were similar between 2014 and 2015 for SCE and SDG&E. Consequently, the ex post and ex ante impacts for SCE and SDG&E were generally comparable[40] for the large existing customers in the program as well. PG&E experienced significant changes in the population of customers, and in the number and timing of events being called. This was the first wave of default SMB customers at PG&E, so there isn't another year of impacts available for comparison yet. The trend of poor early season performance and improved performance in the later events appears to be at least partially driven by schools. However, it is possible that some customers were becoming more aware of the program or learning how to better respond later in the season. In the 2016 evaluation it will be useful to compare the performance of the newly defaulted customers from that year to customers defaulted in 2015 to determine if the poor early performance was seasonal, industry related, or perhaps related to learning or awareness.

In addition to the newly defaulted SMB customers; PG&E also increased the number of events from 10 in 2014 to 15 in 2015. The 5 additional events also took place much later in the year than the 2014 events. Generally speaking, the later season events exhibited lower performance. The lower performance is possibly due to a combination of seasonality for certain industries, and event fatigue. Furthermore, the vast majority of events in 2015 were called in sequence on consecutive days. It would be possible to develop an experimental design to vary the number and timing of event dispatches across customers for the 2016 event season to learn more about the effects of seasonality and possible event fatigue. However, varying the event dispatch among program participants may present unforeseen operational challenges and concerns about customer equity. Because of this, careful consideration should be taken to assess the feasibility, benefits, and costs of implementing such an experiment. In the absence of undertaking such an experiment to provide greater clarity around the effect of the number and timing of events, it should be noted there is a possibility that having such a high number of events could be leading to event fatigue, and resulting in real impacts to the program performance.

[40] SCE's ex ante load impacts did increase, however they are now more in-line with the ex post impacts due to a change in the relationship between temperature and load impact magnitude observed over the past 2 years.

Appendix A Candidate Probit Models

Twelve separate probit model specifications were tested in the propensity score matching, in addition to 13 different hard match criteria and six caliper values. The matching analysis dataset consisted of CPP customers and a pool of potential control group customers. Tables A-1 and A-2 show the probit model specifications and variable definitions. Models were selected to describe load on proxy event days and nonevent summer days. Table A-3 lists variables used as hard match criteria, and the following caliper values were used: 0.0005, 0.001, 0.005, 0.01, 0.05 and 0.1.

Table A-1: Candidate Probit Models

Model #	Specification
1	$P(CPP_i) = \Phi\left(a + \sum_{h=12}^{21} b_h * kW_{hi} + e_i\right)$
2	$P(CPP_i) = \Phi\left(a + \sum_{h=12}^{21} b_h * kW_{hi} + c * Avg\ Summer\ Day\ kWh_i + e_i\right)$
3	$P(CPP_i) = \Phi\left(a + \sum_{h=12}^{21} b_h * kW_{hi} + c * Avg\ Proxy\ Day\ kWh_i + e_i\right)$
4	$P(CPP_i) = \Phi\left(a + \sum_{h=12}^{21} b_h * kW_{hi} + c * Avg\ Summer\ Day\ kWh_i + d * Proxy\ Day\ Percent\ Peak\ Usage_i + e_i\right)$
5	$P(CPP_i) = \Phi\left(a + \sum_{h=12}^{21} b_h * kW_{hi} + c * Avg\ Proxy\ Day\ kWh_i + d * Proxy\ Day\ Percent\ Peak\ Usage_i + e_i\right)$
6	$P(CPP_i) = \Phi\left(a + \sum_{h=15}^{18} b_h * kW_{hi} + e_i\right)$
7	$P(CPP_i) = \Phi\left(a + \sum_{h=15}^{18} b_h * kW_{hi} + c * Avg\ Summer\ Day\ kWh_i + e_i\right)$
8	$P(CPP_i) = \Phi\left(a + \sum_{h=15}^{18} b_h * kW_{hi} + c * Avg\ Proxy\ Day\ kWh_i + e_i\right)$

Model #	Specification
9	$P(CPP_i) = \Phi\left(a + \sum_{h=15}^{18} b_h * kW_{hi} + c * Avg\ Summer\ Day\ kWh_i + d * Proxy\ Day\ Percent\ Peak\ Usage_i + e_i\right)$
10	$P(CPP_i) = \Phi\left(a + \sum_{h=15}^{18} b_h * kW_{hi} + c * Avg\ Proxy\ Day\ kWh_i + d * Proxy\ Day\ Percent\ Peak\ Usage_i + e_i\right)$
11	$P(CPP_i) = \Phi(a + b * Avg\ Summer\ Day\ kWh_i + c * Proxy\ Day\ Percent\ Peak\ Usage_i + e_i)$
12	$P(CPP_i) = \Phi(a + b * Avg\ Summer\ Day\ kWh_i + c * Proxy\ Day\ Percent\ Peak\ Usage_i + e_i)$

Table A-2: Description of Probit Model Variables

Variable	Description
kW	Energy usage in each hourly interval h averaged over proxy days
Avg Summer Day kWh	Total energy usage for all hours in a day averaged over nonevent summer days
Avg Proxy Day kWh	Total energy usage for all hours in a day averaged over proxy days
Proxy Day Percent Peak Usage	Percentage of total energy occurring in peak hours averaged over proxy days

Table A-3: Description of Hard Match Variables

Variable	Description
Quintiles of Avg Summer Day kWh	Customers divided into five equal groups according to the distribution of *Avg Summer Day kWh*
Deciles of Avg Summer Day kWh	Customers divided into 10 equal groups according to the distribution of *Avg Summer Day kWh*
15-tiles of Avg Summer Day kWh	Customers divided into 15 equal groups according to the distribution of *Avg Summer Day kWh*
Weather Station	Customers divided into groups according to their weather station
LCA	Customers divided into groups according to their LCA
Industry	Customers divided into groups according to their industry
Avg Summer Day kWh 2-tiles within LCA	Customers in each LCA are divided into two equal groups according to the distribution of *Avg Summer Day kWh*
Avg Summer Day kWh 2-tiles within Industry	Customers in each Industry are divided into two equal groups according to the distribution of *Avg Summer Day kWh*
Quintiles of Avg Proxy Day kWh	Customers divided into five equal groups according to the distribution of *Avg Proxy Day kWh*
Deciles of Avg Proxy Day kWh	Customers divided into 10 equal groups according to the distribution of *Avg Proxy Day kWh*
15-tiles of Avg Proxy Day kWh	Customers divided into 15 equal groups according to the distribution of *Avg Proxy Day kWh*
Avg Proxy Day kWh 2-tiles within LCA	Customers in each LCA are divided into two equal groups according to the distribution of *Avg Proxy Day kWh*
Avg Proxy Day kWh 2-tiles within Industry	Customers in each Industry are divided into two equal groups according to the distribution of *Avg Proxy Day kWh*

Appendix B Matching Model Selection Summary Statistics and Rankings

Tables B-1, B-2 and B-3 show summary statistics and rankings for the candidate probit models described in Appendix A. For purposes of comparison, we present the 50 best performing models of those tested, as well as the single worst performing model at the end of the table. The final chosen model is highlighted in grey, and the worst performing model is highlighted in red. As described in Section 3.1, the ultimate model selection was not performed in a rule-based fashion, but outcomes from the selection procedure were used to inform our decision making. For example, while other model parameters were allowed to vary, Nexant decided to perform a hard match within industry for each IOU's matching model. This decision was made to limit the seasonal variation that was observed in certain industries, such as schools, and on the basis of its intuitive sense. The final model was then selected on the basis of average percent error, taking into account both its absolute value and its deviation across the excluded days, provided that the absolute sum of errors was acceptable relative to other potential models.

Table B-1: PG&E Large Default Matching Model Selection Summary Statistics and Rankings

Hard Match Group	Model Number	Caliper	Percent Matched	Event Hour Absolute Sum of Errors		Event Hours Average Percent Error		Standard Deviation of Event Hours Average Percent Error for Individual Events	
				Value (kWh)	Rank	Value (%)	Rank	Value (%)	Rank
Average Proxy Day kWh 2-tiles within Industry	6	0.05	98.5	6,185,392	89	-0.03%	1	2.65%	24
Average Proxy Day kWh 2-tiles within Industry	12	0.1	99.2	6,139,959	84	0.09%	2	2.89%	40
Industry	11	0.0005	89.0	5,527,967	36	-0.19%	3	4.44%	132
Industry	10	0.005	97.8	5,846,086	58	0.24%	4	2.60%	20
Industry	2	0.005	95.8	7,121,615	136	-0.25%	5	5.36%	148
Average Proxy Day kWh 2-tiles within Industry	3	0.01	94.8	6,250,777	95	-0.30%	6	2.17%	6
Average Proxy Day kWh 2-tiles within Industry	7	0.01	96.7	6,140,575	85	0.33%	7	3.51%	79
Average Proxy Day kWh 2-tiles within Industry	9	0.005	94.2	6,082,935	79	-0.36%	8	3.96%	104
Average Proxy Day kWh 2-tiles within Industry	8	0.005	94.8	6,030,091	75	0.41%	9	4.42%	131
Average Proxy Day kWh 2-tiles within Industry	12	0.05	99.0	6,096,935	80	-0.41%	10	2.73%	26
Average Proxy Day kWh 2-tiles within Industry	2	0.001	85.1	5,887,526	61	-0.52%	11	3.37%	66
Average Proxy Day kWh 2-tiles within Industry	4	0.1	99.7	5,606,551	44	-0.52%	12	3.99%	105
Industry	3	0.001	89.0	6,674,642	122	-0.53%	13	2.75%	27
Average Proxy Day kWh 2-tiles within Industry	9	0.01	95.8	6,224,093	93	0.57%	14	4.31%	123
Average Proxy Day kWh 2-tiles within Industry	10	0.05	99.6	5,428,427	29	0.63%	15	2.72%	25
Industry	12	0.005	96.8	6,457,694	111	0.68%	16	3.93%	102
Average Proxy Day kWh 2-tiles within Industry	5	0.01	97.4	5,886,756	60	-0.70%	17	4.22%	117
Average Proxy Day kWh 2-tiles within Industry	10	0.1	99.8	5,443,043	31	0.80%	18	2.76%	28
Average Proxy Day kWh 2-tiles within Industry	1	0.05	98.1	6,396,631	104	0.83%	19	4.13%	113
Average Proxy Day kWh 2-tiles within Industry	7	0.005	95.2	6,010,966	72	-0.83%	20	2.78%	29
Average Proxy Day kWh 2-tiles within Industry	6	0.1	99.0	6,255,106	96	0.84%	21	2.34%	9
Average Proxy Day kWh 2-tiles within Industry	11	0.1	99.7	5,963,534	68	-0.86%	22	2.85%	36
Industry	1	0.001	90.4	6,688,272	124	0.89%	23	2.99%	48
Industry	11	0.001	92.8	5,822,624	57	0.93%	24	4.99%	143
Industry	10	0.01	98.7	5,988,073	70	0.97%	25	2.84%	35
Industry	5	0.001	92.4	5,901,821	63	-1.02%	26	3.76%	93
Industry	13	0.01	99.1	4,338,124	4	1.02%	27	2.65%	23
Average Proxy Day kWh 2-tiles within Industry	2	0.01	95.2	6,112,337	82	-1.06%	28	3.49%	75
Industry	13	0.0005	96.1	4,047,430	1	1.07%	29	3.19%	58
Average Proxy Day kWh 2-tiles within Industry	9	0.001	86.1	5,739,035	50	-1.07%	30	3.49%	76
Average Proxy Day kWh 2-tiles within Industry	10	0.01	98.6	5,283,342	23	-1.08%	31	2.31%	8
Average Proxy Day kWh 2-tiles within Industry	5	0.005	96.2	5,752,097	53	-1.11%	32	3.51%	78
Industry	8	0.001	90.8	5,989,294	71	-1.12%	33	4.01%	108
Average Proxy Day kWh 2-tiles within Industry	2	0.005	93.6	6,033,187	76	-1.13%	34	3.79%	96
Industry	13	0.005	98.9	4,305,451	3	1.13%	35	2.58%	16
Industry	13	0.05	99.2	4,359,810	5	1.15%	36	2.60%	18
Industry	13	0.1	99.2	4,359,810	5	1.15%	36	2.60%	18
Average Proxy Day kWh 2-tiles within Industry	4	0.05	99.2	5,552,806	39	-1.18%	38	3.88%	101
Average Proxy Day kWh 2-tiles within Industry	3	0.001	84.6	5,889,990	62	-1.19%	39	3.47%	74
Average Proxy Day kWh 2-tiles within Industry	3	0.005	93.3	6,144,058	86	-1.20%	40	2.38%	10
Average Proxy Day kWh 2-tiles within Industry	8	0.01	96.5	6,181,620	88	1.20%	41	4.64%	137
Industry	13	0.001	97.3	4,150,254	2	1.24%	42	3.34%	65
Industry	4	0.1	99.9	6,484,657	115	-1.25%	43	4.49%	134
Industry	4	0.05	99.8	6,452,580	110	-1.31%	44	4.37%	130
Average Proxy Day kWh 2-tiles within Industry	6	0.01	96.8	6,017,546	74	-1.31%	45	2.94%	44
Average Proxy Day kWh 2-tiles within Industry	2	0.05	98.2	6,368,721	98	1.38%	46	2.97%	46
Average Proxy Day kWh 2-tiles within Industry	11	0.05	99.5	5,925,648	66	-1.39%	47	2.92%	43
Average Proxy Day kWh 2-tiles within Industry	2	0.0005	78.2	5,749,687	52	-1.41%	48	4.35%	126
Average Proxy Day kWh 2-tiles within Industry	5	0.05	99.2	6,077,221	78	1.42%	49	3.62%	87
Average Proxy Day kWh 2-tiles within Industry	3	0.0005	77.2	5,757,850	54	-1.49%	50	2.79%	30
Industry	1	0.1	99.7	8,289,094	156	14.22%	156	4.19%	115

Table B-2: SCE Matching Model Selection Summary Statistics and Rankings

Hard Match Group	Model Number	Caliper	Percent Matched	Event Hour Absolute Sum of Errors		Event Hours Average Percent Error		Standard Deviation of Event Hours Average Percent Error for Individual Events	
				Value (kWh)	Rank	Value (%)	Rank	Value (%)	Rank
Average Summer Day kWh 2-tiles within Industry	13	0.01	98.0	3,920,675	255	0.00%	1	2.26%	224
Average Proxy Day kWh 2-tiles within Industry	12	0.0005	81.7	3,518,143	90	-0.01%	2	1.73%	71
Average Proxy Day kWh 2-tiles within Industry	2	0.001	85.4	3,707,053	151	-0.02%	3	1.26%	4
Average Proxy Day kWh 2-tiles within Industry	15	0.005	96.3	3,788,856	191	-0.03%	4	1.54%	39
Average Summer Day kWh 2-tiles within Industry	10	0.0005	79.7	3,716,016	153	-0.05%	5	2.06%	155
Industry	5	0.1	99.4	4,813,461	386	-0.05%	6	3.00%	341
Industry	17	0.001	96.6	3,854,419	226	0.06%	7	2.05%	151
Average Summer Day kWh 2-tiles within Industry	16	0.0005	86.9	2,687,707	1	0.07%	8	1.90%	111
Average Proxy Day kWh 2-tiles within Industry	16	0.0005	86.7	2,786,555	3	-0.07%	9	1.59%	52
Average Proxy Day kWh 2-tiles within Industry	14	0.001	87.6	3,741,843	167	0.08%	10	2.89%	330
Industry	5	0.05	99.3	4,803,050	384	-0.09%	11	2.89%	329
Average Summer Day kWh 2-tiles within Industry	3	0.005	95.0	3,965,819	270	0.09%	12	2.65%	297
Average Proxy Day kWh 2-tiles within Industry	10	0.0005	80.6	3,569,254	102	0.10%	13	2.08%	161
Average Summer Day kWh 2-tiles within Industry	1	0.0005	77.7	3,603,359	115	0.11%	14	1.93%	116
Industry	2	0.001	93.2	4,720,607	376	-0.11%	15	3.18%	355
Industry	13	0.005	98.4	4,255,619	334	0.12%	16	2.26%	225
Industry	17	0.0005	94.2	3,773,854	182	-0.12%	17	2.06%	156
Average Summer Day kWh 2-tiles within Industry	15	0.005	96.4	3,836,945	216	0.13%	18	1.86%	100
Industry	13	0.01	99.1	4,296,959	339	0.15%	19	2.30%	233
Average Proxy Day kWh 2-tiles within Industry	13	0.01	98.1	3,729,251	162	-0.15%	20	2.11%	172
Average Proxy Day kWh 2-tiles within Industry	20	0.0005	81.7	3,473,752	74	0.15%	21	2.40%	249
Average Summer Day kWh 2-tiles within Industry	12	0.0005	81.4	3,659,482	133	-0.16%	22	1.94%	118
Average Summer Day kWh 2-tiles within Industry	16	0.001	92.8	2,738,598	2	0.18%	23	1.56%	44
Industry	4	0.0005	88.8	4,595,917	364	-0.19%	24	1.65%	60
Industry	6	0.001	95.9	3,522,124	93	-0.19%	25	1.77%	81
Average Summer Day kWh 2-tiles within Industry	8	0.001	88.7	3,741,686	166	0.19%	26	1.71%	69
Average Proxy Day kWh 2-tiles within Industry	21	0.0005	87.4	3,292,742	22	-0.19%	27	1.79%	82
Average Proxy Day kWh 2-tiles within Industry	16	0.001	92.5	2,818,514	5	0.19%	28	1.53%	37
Industry	18	0.1	99.9	3,778,944	186	-0.20%	29	1.87%	102
Average Summer Day kWh 2-tiles within Industry	15	0.001	87.9	3,812,998	206	0.20%	30	1.67%	66
Industry	18	0.05	99.9	3,778,689	185	-0.20%	31	1.86%	98
Industry	18	0.01	99.6	3,762,684	178	-0.20%	32	1.80%	84
Average Proxy Day kWh 2-tiles within Industry	13	0.005	96.7	3,701,905	150	-0.20%	33	2.13%	182
Average Summer Day kWh 2-tiles within Industry	15	0.01	97.8	3,860,455	229	0.23%	34	1.52%	34
Industry	16	0.001	96.8	3,453,909	70	0.24%	35	1.65%	62
Industry	8	0.005	98.6	3,760,718	177	0.25%	36	1.48%	26
Industry	15	0.005	98.1	4,491,538	356	0.25%	37	1.45%	19
Average Proxy Day kWh 2-tiles within Industry	12	0.001	88.8	3,597,307	110	0.28%	38	1.76%	78
Average Summer Day kWh 2-tiles within Industry	11	0.001	89.9	3,406,344	47	0.30%	39	2.08%	165
Average Proxy Day kWh 2-tiles within Industry	6	0.001	90.1	3,222,883	17	0.30%	40	2.65%	298
Average Summer Day kWh 2-tiles within Industry	12	0.005	96.8	3,817,450	208	0.31%	41	1.74%	74
Average Summer Day kWh 2-tiles within Industry	18	0.0005	84.0	3,453,091	68	-0.31%	42	3.53%	370
Average Summer Day kWh 2-tiles within Industry	16	0.005	98.7	2,789,273	4	0.32%	43	1.87%	101
Industry	21	0.0005	94.1	3,311,451	26	-0.33%	44	2.44%	259
Average Summer Day kWh 2-tiles within Industry	3	0.01	96.9	4,020,220	284	0.33%	45	2.57%	278
Industry	15	0.01	98.7	4,537,070	360	0.33%	46	1.55%	41
Average Proxy Day kWh 2-tiles within Industry	15	0.01	97.8	3,827,471	212	0.33%	47	1.63%	58
Industry	21	0.001	97.5	3,390,287	42	0.34%	48	2.90%	331
Average Proxy Day kWh 2-tiles within Industry	15	0.001	87.9	3,692,652	145	-0.35%	49	1.39%	11
Average Proxy Day kWh 2-tiles within Industry	5	0.0005	76.3	3,626,856	126	0.35%	50	3.05%	345
Average Proxy Day kWh 2-tiles within Industry	3	0.1	99.2	4,192,355	320	4.45%	396	3.49%	367

Table B-3: SDG&E Matching Model Selection Summary Statistics and Rankings

Hard Match Group	Model Number	Caliper	Numer of Customers Unmatched	Event Hour Absolute Sum of Errors		Event Hours Average Percent Error		Standard Deviation of Event Hours Average Percent Error for Individual Events	
				Value (kWh)	Rank	Value (%)	Rank	Value (%)	Rank
Average Proxy Day kWh 10-tiles	1	0.1	183.5	1,144,747	143	0.01%	1	2.92%	88
Average Proxy Day kWh 5-tiles	12	0.001	279.9	717,202	10	0.01%	2	1.62%	14
Average Proxy Day kWh 10-tiles	2	0.1	189.4	1,122,950	136	0.02%	3	3.73%	150
Average Summer Day kWh 15-tiles	12	0.1	77.8	866,815	29	0.05%	4	2.26%	49
Average Proxy Day kWh 10-tiles	9	0.1	75.6	1,066,483	118	0.05%	5	3.60%	139
Average Proxy Day kWh 10-tiles	12	0.01	78.7	901,571	32	0.06%	6	1.94%	29
Average Summer Day kWh 15-tiles	4	0.05	108.3	1,060,635	115	0.07%	7	2.54%	66
Average Summer Day kWh 5-tiles	12	0.005	81.4	585,637	3	0.07%	8	2.15%	40
Average Proxy Day kWh 5-tiles	11	0.1	30.8	1,004,647	85	0.07%	9	1.62%	12
Average Proxy Day kWh 5-tiles	11	0.05	30.8	1,004,647	85	0.07%	9	1.62%	12
Average Summer Day kWh 15-tiles	12	0.05	80.9	865,504	28	0.08%	11	2.24%	46
Average Summer Day kWh 5-tiles	11	0.01	46.6	738,010	11	0.09%	12	1.59%	9
Average Proxy Day kWh 15-tiles	12	0.005	221.8	711,778	9	0.09%	13	1.94%	26
Average Proxy Day kWh 10-tiles	1	0.05	185.8	1,140,165	140	0.12%	14	2.94%	90
Weather Station	12	0.001	127	1,551,170	201	0.14%	15	3.68%	148
Average Proxy Day kWh 10-tiles	6	0.01	238.8	970,309	68	0.16%	16	5.00%	216
Average Proxy Day kWh 10-tiles	2	0.05	191.3	1,118,076	135	0.17%	17	3.83%	156
Average Summer Day kWh 5-tiles	11	0.05	38	745,291	12	0.20%	18	1.72%	17
Average Summer Day kWh 5-tiles	11	0.1	38	745,291	12	0.20%	18	1.72%	17
Average Summer Day kWh 5-tiles	11	0.005	64.3	696,542	8	0.21%	20	1.90%	22
Average Proxy Day kWh 10-tiles	6	0.1	173.1	1,061,491	116	0.22%	21	4.55%	198
Average Proxy Day kWh 10-tiles	9	0.05	78.7	1,060,119	112	0.24%	22	3.66%	146
Average Summer Day kWh 15-tiles	4	0.1	94.2	1,079,213	123	0.28%	23	2.53%	65
Average Proxy Day kWh 5-tiles	9	0.01	71.9	1,145,069	144	0.28%	24	1.87%	21
Average Proxy Day kWh 15-tiles	6	0.05	159.4	938,645	45	0.30%	25	1.25%	4
Average Proxy Day kWh 10-tiles	6	0.05	175.4	1,051,121	104	0.32%	26	4.49%	194
Average Proxy Day kWh 10-tiles	1	0.01	272.5	973,420	70	0.34%	27	3.34%	123
Average Proxy Day kWh 5-tiles	9	0.005	122.9	1,077,520	121	0.36%	28	1.74%	19
Average Proxy Day kWh 15-tiles	12	0.01	136.5	774,305	16	0.43%	29	2.31%	54
Average Proxy Day kWh 10-tiles	11	0.01	94.6	969,974	67	0.43%	30	2.20%	43
Average Proxy Day kWh 10-tiles	2	0.01	283.8	975,223	73	0.44%	31	3.57%	136
Average Proxy Day kWh 10-tiles	7	0.01	246	973,720	71	0.45%	32	4.03%	174
Average Proxy Day kWh 10-tiles	9	0.005	281.2	862,776	27	0.45%	33	3.32%	122
Average Proxy Day kWh 15-tiles	4	0.05	145.8	917,821	39	0.45%	34	3.20%	116
Average Proxy Day kWh 10-tiles	3	0.01	278.2	981,746	75	0.45%	35	2.40%	60
Average Summer Day kWh 15-tiles	9	0.05	87.6	1,007,949	88	0.46%	36	3.00%	98
Average Summer Day kWh 10-tiles	11	0.01	113.8	1,006,876	87	0.49%	37	2.07%	36
Average Summer Day kWh 15-tiles	12	0.01	179.9	798,932	17	0.49%	38	2.21%	45
Average Summer Day kWh 15-tiles	9	0.01	270.2	838,421	25	0.50%	39	3.48%	129
Average Proxy Day kWh 5-tiles	12	0.005	68.8	857,172	26	0.50%	40	1.22%	3
Average Summer Day kWh 15-tiles	9	0.1	83.9	1,010,580	89	0.51%	41	2.94%	91
Average Proxy Day kWh 5-tiles	11	0.01	43	963,039	59	0.52%	42	1.49%	7
Average Summer Day kWh 10-tiles	11	0.005	177.8	947,622	53	0.52%	43	1.61%	11
Average Summer Day kWh 5-tiles	12	0.001	257.9	469,839	1	0.54%	44	2.40%	61
Average Proxy Day kWh 10-tiles	4	0.05	90.6	1,097,867	130	0.56%	45	3.75%	151
Average Proxy Day kWh 10-tiles	12	0.005	140.2	836,220	24	0.57%	46	2.06%	35
Average Proxy Day kWh 10-tiles	12	0.1	45.6	931,634	43	0.57%	47	1.99%	32
Average Proxy Day kWh 10-tiles	12	0.05	45.8	931,613	42	0.57%	48	1.99%	33
Average Proxy Day kWh 10-tiles	11	0.1	46.3	1,002,575	84	0.57%	49	2.55%	69
Average Proxy Day kWh 15-tiles	3	0.05	201.8	979,655	74	0.58%	50	2.75%	77
Average Summer Day kWh 5-tiles	4	0.005	151.2	1,124,682	137	6.97%	230	4.64%	203

Appendix C Difference-in-differences Regression Models

In the fixed effects regression models that estimate the CPP impact through difference-in-differences, separate models are estimated for each hour. The analysis dataset consisted of the event-like days and actual event days for CPP customers and their matched control group customers. The dependent variable was the hourly consumption over the course of each hour. Nexant elected to use a treatment model rather than a price elasticity model for two reasons. First, for any hour there are only two price points, or at most three, which is insufficient for fitting price elasticity curves. Second, it avoids assumptions such as constant price elasticity inherent in demand models. The model is expressed by the below equations:

Avg. Event Equation:

$$kW_{i,t} = a + b \cdot Treatment_i + c \cdot Event_t + d \cdot (Treatment_i \cdot Event_t) + u_t + v_i + \varepsilon_{i,t} \text{ for } i \in \{1, \dots, n_i\} \text{ and } t \in \{1, \dots, n_t\}$$

Individual Event Equation:

$$kW_{i,t} = a + b \cdot Treatment_i + \sum_{n=1}^{max} c_n \cdot Event_n + \sum_{n=1}^{max} d_n \cdot (Treatment_i \cdot Event_n) + u_t + v_i + \varepsilon_{i,t} \text{ for } i \in \{1, \dots, n_i\} \text{ and } t \in \{1, \dots, n_t\}$$

Variable	Definition
i, t, n	Indicate observations for each individual i, date t and event number n, where the number of events varies by utility and is denoted *max*
a	The model constant
b	Pre-existing difference between treatment and control customers
c	The difference between event and nonevent days common to both CPP participants and control group members[41]
d	The net difference between CPP and control group customers during event days–this parameter represents the difference-in-differences
u	Time effects for each date that control for unobserved factors that are common to all treatment and control customers but unique to the time period
v	Customer fixed effects that control for unobserved factors that are time-invariant and unique to each customer; fixed effects do not control for fixed characteristics such as air conditioning that interact with time varying factors like weather
E	The error for each individual customer and time period
Treatment	A binary indicator or whether or not the customer is part of the treatment (CPP) or control group
Event	A binary indicator of whether an event occurred that day–impacts are only observed if the customer is on CPP (*Treatment* = 1) and it was an event day

[41] In practice, this term is absorbed by the time effects, but it is useful for representing the model logic.

Appendix D Individual Customer Regression Models

Table D-1 summarizes all individual customer regression specifications and Table D-2 describes each of the regression terms. The analysis dataset is at the individual, hour and date level, and each individual has a separate model for every hour. Based on a simple cross-validation, the best model for each customer was chosen and then applied in ex post analysis.

Table D-1: Individual Customer Regression Models

Model #	Specification
1	$kW_{ihd} = a_{ih} + \sum_{j=2}^{12} b_{ihj} * month_{ihdj} + \sum_{k=2}^{5} c_{ihk} * dow_{ihdk} + d_{ih} * cdd_{ihd} + f_{ih} * cddsqr_{ihd} + \sum_{l=1}^{n} g_{ihl} * eventday_{ihdl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
2	$kW_{ihd} = a_{ih} + \sum_{j=2}^{12} b_{ihj} * month_{ihdj} + \sum_{k=2}^{5} c_{ihk} * dow_{ihdk} + d_{ih} * cdd_{ihd} + f_{ih} * cdh_{ihd} + \sum_{l=1}^{n} g_{ihl} * eventday_{ihdl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
3	$kW_{ihd} = a_{ih} + \sum_{j=2}^{12} b_{ihj} * month_{ihdj} + \sum_{k=2}^{5} c_{ihk} * dow_{ihdk} + d_{ih} * cdh_{ihd} + f_{ih} * overnightcdh_{ihd} + \sum_{l=1}^{n} g_{ihl} * eventday_{ihdl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
4	$kW_{ihd} = a_{ih} + \sum_{j=2}^{12} b_{ihj} * month_{ihdj} + \sum_{k=2}^{5} c_{ihk} * dow_{ihdk} + d_{ih} * cdh_{ihd} + f_{ih} * cdhsqr_{ihd} + \sum_{l=1}^{n} g_{ihl} * eventday_{ihdl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
5	$kW_{ihd} = a_{ih} + \sum_{j=2}^{12} b_{ihj} * month_{ihdj} + \sum_{k=2}^{5} c_{ihk} * dow_{ihdk} + \sum_{l=1}^{n} d_{ihl} * eventday_{ihl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
6	$kW_{ihd} = a_{ih} + \sum_{k=2}^{5} b_{ihk} * dow_{ihdk} + c_{ih} * cdd_{ihd} + d_{ih} * cddsqr_{ihd} + \sum_{l=1}^{n} f_{ihl} * eventday_{ihdl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
7	$kW_{ihd} = a_{ih} + \sum_{k=2}^{5} b_{ihk} * dow_{ihdk} + c_{ih} * cdd_{ihd} + d_{ih} * cdh_{ihd} + \sum_{l=1}^{n} f_{ihl} * eventday_{ihdl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
8	$kW_{ihd} = a_{ih} + \sum_{k=2}^{5} b_{ihk} * dow_{ihdk} + c_{ih} * cdh_{ihd} + d_{ih} * overnightcdh_{ihd} + \sum_{l=1}^{n} f_{ihl} * eventday_{ihdl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
9	$kW_{ihd} = a_{ih} + \sum_{k=2}^{5} b_{ihk} * dow_{ihdk} + c_{ih} * cdh_{ihd} + d_{ih} * cdhsqr_{ihd} + \sum_{l=1}^{n} f_{ihl} * eventday_{ihdl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$
10	$kW_{ihd} = a_{ih} + \sum_{k=2}^{5} b_{ihk} * dow_{ihdk} + \sum_{l=1}^{n} c_{ihl} * eventday_{ihl} + e_{ihd}$, for $i \in \{1, \ldots, n_i\}, h \in \{1, 2, 3 \ \ldots \ 24\}$ *and* $d \in \{1, \ldots, n_d\}$

Table D-2: Description of Individual Customer Regression Model Variables

Variable	Description
i, h, d	Index for individual customer, index for hour, and index for event day
kW	Energy usage in each hourly interval h={1,2,3, …, 24} for each date d
month	Binary variable indicating the month of the hourly observation
dow	Binary variable for the day type of the hourly observation
cdh	Cooling Degree Hour – the max of zero and the hourly temperature value less a base value of 60°F
cdhsqr	The square of Cooling Degree Hour
cdd	Cooling Degree Day–the max of zero and the mean temperature of the day of the hourly observation less a base value of 60°F
cddsqr	The square of Cooling Degree Day
overnightcdh	The average of CDH from midnight through 9 AM
eventday	Binary variables indicating each event day, 1, ..., n, where n varies by IOU

Appendix E Portfolio-adjusted Ex Ante Load Impacts

This section summarizes the portfolio-adjusted ex ante load impact estimates, which reflect the load impacts after accounting for other DR programs that take precedence over CPP in the portfolio analysis. Estimates are provided for the utility specific August System Peak Day. Portfolio estimates for all ex ante weather scenarios from 2016 through 2026 are provided in the electronic appendices.

Table E-1: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I, PG&E August System Peak Day (MW 1–6 PM) – Portfolio-adjusted

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load	Aggregate Estimated Load w/ DR	Aggregate Load Impact	% Load Reduction	Weighted Temp.
				(MW 1-6 PM)	(MW 1-6 PM)	(MW 1-6 PM)	(%)	(°F)
PG&E	1-in-10	2016	2,280	665.1	633.1	31.9	4.8%	95.9
		2017	2,808	812.2	772.2	40.0	4.9%	96.1
		2026	2,951	855.9	814.1	41.8	4.9%	96.1
	1-in-2	2016	2,280	639.4	608.5	30.9	4.8%	92.4
		2017	2,808	781.3	742.5	38.7	5.0%	92.7
		2026	2,951	823.2	782.6	40.5	4.9%	92.6
CAISO	1-in-10	2016	2,280	647.4	616.1	31.3	4.8%	92.9
		2017	2,808	791.2	751.9	39.3	5.0%	93.2
		2026	2,951	833.5	792.5	41.1	4.9%	93.1
	1-in-2	2016	2,280	612.0	582.3	29.7	4.9%	89.3
		2017	2,808	748.0	710.8	37.2	5.0%	89.6
		2026	2,951	788.1	749.2	38.9	4.9%	89.5

Table E-2: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Medium C&I, PG&E August System Peak Day (1–6 PM) – Portfolio-adjusted

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
PG&E	1-in-10	2016	33,070	867.1	860.8	6.4	0.7%	95.3
		2017	58,235	1560.1	1548.7	11.4	0.7%	94.9
		2018	64,286	1724.7	1712.1	12.6	0.7%	94.9
		2026	69,426	1863.6	1849.9	13.7	0.7%	94.8
	1-in-2	2016	33,070	813.7	807.7	6.0	0.7%	91.6
		2017	58,235	1464.9	1454.2	10.7	0.7%	91.2
		2018	64,286	1619.5	1607.7	11.9	0.7%	91.1
		2026	69,426	1750.0	1737.1	12.8	0.7%	91.1
CAISO	1-in-10	2016	33,070	832.9	826.8	6.1	0.7%	92.0
		2017	58,235	1497.9	1486.9	11.0	0.7%	91.5
		2018	64,286	1655.7	1643.5	12.1	0.7%	91.5
		2026	69,426	1788.9	1775.8	13.1	0.7%	91.4
	1-in-2	2016	33,070	756.5	751.0	5.6	0.7%	88.4
		2017	58,235	1364.4	1354.4	10.0	0.7%	88.0
		2018	64,286	1508.6	1497.6	11.1	0.7%	88.0
		2026	69,426	1630.3	1618.3	12.0	0.7%	88.0

Table E-3: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Small C&I, PG&E August System Peak Day (1–6 PM) – Portfolio-adjusted

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
PG&E	1-in-10	2016	184,002	453.9	452.1	1.8	0.4%	95.9
		2017	234,307	557.8	555.7	2.2	0.4%	95.9
		2018	260,726	612.0	609.6	2.4	0.4%	95.9
		2026	287,956	668.6	666.0	2.6	0.4%	95.8
	1-in-2	2016	184,002	415.7	414.0	1.6	0.4%	92.3
		2017	234,307	509.7	507.7	2.0	0.4%	92.3
		2018	260,726	558.8	556.6	2.2	0.4%	92.2
		2026	287,956	610.1	607.7	2.4	0.4%	92.2
CAISO	1-in-10	2016	184,002	430.4	428.8	1.7	0.4%	93.0
		2017	234,307	528.1	526.0	2.1	0.4%	93.0
		2018	260,726	579.0	576.7	2.3	0.4%	93.0
		2026	287,956	632.2	629.7	2.5	0.4%	93.0
	1-in-2	2016	184,002	373.2	371.7	1.5	0.4%	88.9
		2017	234,307	456.7	454.9	1.8	0.4%	88.9
		2018	260,726	500.4	498.4	2.0	0.4%	88.8
		2026	287,956	546.0	543.9	2.1	0.4%	88.8

Table E-4: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I, SCE August System Peak Day (MW 1–6 PM) – Portfolio-adjusted

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
SCE	1-in-10	2016	3,624	850.4	827.7	22.6	2.7%	95.5
		2017	3,650	856.6	833.8	22.8	2.7%	95.5
		2026	3,750	880.0	856.5	23.4	2.7%	95.5
	1-in-2	2016	3,624	831.6	809.5	22.1	2.7%	92.7
		2017	3,650	837.7	815.4	22.3	2.7%	92.7
		2026	3,750	860.6	837.7	22.9	2.7%	92.7
CAISO	1-in-10	2016	3,624	842.6	820.2	22.5	2.7%	93.7
		2017	3,650	848.8	826.2	22.6	2.7%	93.7
		2026	3,750	872.0	848.7	23.2	2.7%	93.7
	1-in-2	2016	3,624	823.3	801.3	22.0	2.7%	92.1
		2017	3,650	829.3	807.1	22.2	2.7%	92.1
		2026	3,750	852.0	829.2	22.8	2.7%	92.1

Table E-5: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Medium C&I, SCE August System Peak Day (1–6 PM) – Portfolio-adjusted

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load (MW 1-6 PM)	Aggregate Estimated Load w/ DR (MW 1-6 PM)	Aggregate Load Impact (MW 1-6 PM)	% Load Reduction (%)	Weighted Temp. (°F)
SCE	1-in-10	2018	34,795	1176.7	1168.1	8.6	0.7%	95.2
		2019	13,918	470.7	467.2	3.4	0.7%	95.2
		2026	13,918	470.7	467.2	3.4	0.7%	95.2
	1-in-2	2018	34,795	1130.8	1122.5	8.3	0.7%	92.1
		2019	13,918	452.3	449.0	3.3	0.7%	92.1
		2026	13,918	452.3	449.0	3.3	0.7%	92.1
CAISO	1-in-10	2018	34,795	1164.9	1156.3	8.5	0.7%	93.6
		2019	13,918	465.9	462.5	3.4	0.7%	93.6
		2026	13,918	465.9	462.5	3.4	0.7%	93.6
	1-in-2	2018	34,795	1123.0	1114.8	8.2	0.7%	91.6
		2019	13,918	449.2	445.9	3.3	0.7%	91.6
		2026	13,918	449.2	445.9	3.3	0.7%	91.6

Table E-6: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Small C&I, SCE August System Peak Day (1–6 PM) – Portfolio-adjusted

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load	Aggregate Estimated Load w/ DR	Aggregate Load Impact	% Load Reduction	Weighted Temp.
				(MW 1-6 PM)	(MW 1-6 PM)	(MW 1-6 PM)	(%)	(°F)
SCE	1-in-10	2018	215,205	521.1	519.1	2.0	0.4%	95.0
		2019	86,082	208.5	207.6	0.8	0.4%	95.0
		2026	86,082	208.5	207.6	0.8	0.4%	95.0
	1-in-2	2018	215,205	493.1	491.2	1.9	0.4%	92.0
		2019	86,082	197.2	196.5	0.8	0.4%	92.0
		2026	86,082	197.2	196.5	0.8	0.4%	92.0
CAISO	1-in-10	2018	215,205	513.7	511.7	2.0	0.4%	93.4
		2019	86,082	205.5	204.7	0.8	0.4%	93.4
		2026	86,082	205.5	204.7	0.8	0.4%	93.4
	10-in-2	2018	215,205	488.6	486.7	1.9	0.4%	91.4
		2019	86,082	195.5	194.7	0.8	0.4%	91.4
		2026	86,082	195.5	194.7	0.8	0.4%	91.4

Table E-7: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I, SDG&E August System Peak Day (MW 11 AM to 6 PM) – Portfolio-adjusted

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load	Aggregate Estimated Load w/ DR	Aggregate Load Impact	% Load Reduction	Weighted Temp.
				(MW 1–6 PM)	(MW 1–6 PM)	(MW 1–6 PM)	(%)	(°F)
SDG&E	1-in-10	2016	1,258	297.6	273.4	24.1	8.11%	86.6
		2017	1,269	300.2	275.8	24.4	8.11%	86.6
		2026	1,406	332.8	305.8	27.0	8.11%	86.6
	1-in-2	2016	1,258	282.5	261.2	21.3	7.54%	81.2
		2017	1,269	285.0	263.5	21.5	7.54%	81.2
		2026	1,406	315.9	292.1	23.8	7.54%	81.2
CAISO	1-in-10	2016	1,258	289.0	266.5	22.5	7.79%	83.8
		2017	1,269	291.6	268.9	22.7	7.79%	83.8
		2026	1,406	323.2	298.0	25.2	7.79%	83.8
	1-in-2	2016	1,258	286.8	264.7	22.1	7.70%	83.5
		2017	1,269	289.3	267.0	22.3	7.70%	83.5
		2026	1,406	320.7	296.0	24.7	7.70%	83.5

Table E-8: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Medium C&I, SDG&E August System Peak Day (MW 11 AM-6 PM) – Portfolio-adjusted

Weather Type	Weather Year	Year	Enrolled Accounts	Aggregate Reference Load	Aggregate Estimated Load w/ DR	Aggregate Load Impact	% Load Reduction	Weighted Temp.
				(MW 1-6 PM)	(MW 1-6 PM)	(MW 1-6 PM)	(%)	(°F)
SDG&E	1-in-10	2016	18,743	653.5	647.5	6.0	0.92%	91.0
		2017	16,770	584.7	579.4	5.4	0.92%	91.0
		2026	15,783	550.3	545.3	5.1	0.92%	91.0
	1-in-2	2016	18,743	609.0	603.4	5.6	0.92%	83.5
		2017	16,770	544.9	539.9	5.0	0.92%	83.5
		2026	15,783	512.9	508.2	4.7	0.92%	83.5
CAISO	1-in-10	2016	18,743	633.6	627.7	5.8	0.92%	88.5
		2017	16,770	566.9	561.7	5.2	0.92%	88.5
		2026	15,783	533.5	528.6	4.9	0.92%	88.5
	1-in-2	2016	18,743	627.2	621.4	5.8	0.92%	88.1
		2017	16,770	561.2	556.0	5.2	0.92%	88.1
		2026	15,783	528.1	523.3	4.9	0.92%	88.1

Appendix F Ex Ante Reference Load Regression Specification

This section provides the regression model specification for modeling reference loads. The resulting model is applied to each weather scenario in the 2016 through 2026 ex ante load impact forecast.

$$kW_{lhd} = a_{lh} + \sum_{j=2}^{12} b_{lhj} * month_{lhdj} + \sum_{k=2}^{5} c_{lhk} * dow_{lhdk} + d_{lh} * mean17_{lhd} + f_{lh} * mean17sqr_{lhd} + \sum_{p=1}^{n} g_{lhp} * eventday_{lhdp} + e_{lhd} \text{ for } l \in \{1, \ldots, n_l\}, h \in \{1, 2, 3 \ldots 24\} \text{ and } d \in \{1, \ldots, n_d\}$$

Variable	Description
l, h, d	Index for segment (LCA or industry, depending on utility), index for hour, and index for event day
kW	Energy usage in each hourly interval t={1,2,3, …, 24} for each date d
month	Binary variable indicating the month of the hourly observation
dow	Binary variable for the day type of the hourly observation
mean17	Daily average temperature from midnight to 5 PM, which is used to capture heat buildup in the daylight hours
mean17sqr	The square of *mean17*
eventday	Binary variables indicating each event day in other DR programs, 1, ..., n, where n varies by IOU

Appendix G Ex Ante Percent Load Impact Regression Specification

This section provides the regression model specification for modeling percent load impacts for large CPP customers. The resulting model is applied to each weather scenario in the 2015 through 2025 ex ante load impact forecast.

$$pctimpact_{lhd} = a_l + b_l \times mean17_{lhd} + e_{lhd} \text{ for } l \in \{1, \ldots, n_l\}, h \in \{1, 2, 3 \ \ldots \ 24\} \text{ and } d \in \{1, \ldots, n_d\}$$

Variable	Description
l,h,d	Index for segment (LCA or industry, depending on utility), index for hour and index for event day
$pctimpact$	Per customer ex post load percent impact for each hour of each event day
a	Estimated constant
b	Estimated parameter coefficient
$mean17$	Daily average temperature from midnight to 5 PM, which is used to capture heat buildup in the daylight hours
e	Error term, assumed to be mean zero and uncorrelated with any of the independent variables