REPORT

2014 Load Impact Evaluation of California's Statewide Non-residential Critical Peak Pricing Program

April 1, 2015

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1 Executive Summary

This report presents the 2014 ex post load impact estimates for the non-residential 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 2015 through 2025 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. 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 2014 were large commercial and industrial (C&I) customers that 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. 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:

- What amount of demand did CPP participants reduce at each utility during 2014 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 different industry, 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?

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

Table 1-1 summarizes the 2014 program year default CPP results for PG&E, SCE and SDG&E and compares them with the 2013 program year impacts.

Table 1-1: Summary of 2013 and 2014 Statewide Default CPP Impacts Average Event Hour

Utility	Year	Number of Events Called	Approximate Customer Count	Temperature (°F)	Reference Load (MW)	Load Impact (MW)	Percent Impact (%)
PG&E	2013	8	1,717	90.8	447.5	38.4	8.58%
	2014	10	1,815	88.4	504.6	41.0	8.12%
SCE	2013	10	2,495	87.3	612.6	35.5	5.79%
	2014	12	2,670	86.7	594.4	29.6	4.98%
SDG&E	2013	4	1,095	84.1	292.8	20.2	6.90%
	2014	6	1,142	82.7	290.6	25.4	8.76%
Total	2013	–	5,307	–	1,352.9	94.1	6.95%
	2014	–	5,627	–	1,389.6	96.0	6.91%

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 6 CPP events, respectively. However, there was no single day in 2014 when CPP event prices were in effect at all three utilities because system conditions and weather patterns vary across all three utilities. 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.

Enrollment of non-residential customers defaulted onto CPP rates was higher in 2014 than in 2013 by approximately 6% across PG&E, SCE and SDG&E.[2] This change was driven by a larger number of enrolled customers at all three utilities. Only at PG&E is the higher enrollment reflected in the higher overall program loads without DR in place, referred to as reference loads. Reference loads remained similar to 2013 at SCE and SDG&E. Overall, approximately 5,627 customers were enrolled on default CPP for the 2014 summer.

Between 2013 and 2014, enrollment in opt-in CPP rates at PG&E grew from around 4,000 service accounts to around 7,700; and at SCE enrollment grew from approximately 650 service accounts to approximately 800. However, the majority of opt-in service accounts at PG&E and SCE are linked to a single entity. The results are not representative of future demand response expected when SMB customers are defaulted onto CPP.

[2] 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.

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, which this report refers to as the Early Enrollment Pilot (EEP), yielded an average of 4,760 EEP CPP customers participating in the 10 PG&E CPP events in 2014. Results for these customers are also not representative of future demand response expected when SMB customers are defaulted onto CPP, but are used to inform projected impacts.

Table 1-2 summarizes PG&E, SCE and SDG&E ex ante load impacts for forecast years 2015 and 2025 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.

Table 1-2: Summary of 2015 and 2025 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	Large	2015	2,092	676.9	51.0	7.53%
		2025	2,629	847.7	65.0	7.67%
	Medium	2015	20,267	514.1	6.1	1.19%
		2025	39,677	1,175.0	13.9	1.19%
SCE	Large	2015	2,560	602.1	21.3	3.53%
		2025	3,424	805.2	28.5	3.53%
	Medium	2015	-	-	-	-
		2025	17,375	546.9	6.5	1.19%
SDG&E	Large	2015	1,253	305.2	24.3	7.95%
		2025	1,405	341.7	26.9	7.87%
	Medium	2015	-	-	-	-
		2025	8,577	459.2	10.3	2.20%
Total	Large	2015	5,905	1,584.2	96.6	6.09%
		2025	7,458	1,994.6	120.4	6.04%
	Medium	2015	20,267	514.1	6.1	1.19%
		2025	65,629	2,181.2	30.7	1.41%

Key findings for PG&E include the following:

- **In aggregate, participants reduced demand by 8.1% across the 2 to 6 PM event window for the average event day, delivering 41 MW of demand reduction.**
- **The differences between individual 2014 event day results and average event day results are not statistically significant.** Estimated demand reductions vary from 29.0 MW to 51.3 MW for individual events. On a percentage basis, demand reduction estimates vary from 6.0% to 10.1%. The confidence bands for individual event days are relatively wide and reflect the challenge of detecting small percentage changes in demand from typical load variation. While day-to-day performance can vary, much of the variation across days is due to statistical uncertainty.
- **Demand reductions were concentrated in specific industry segments – Manufacturing, Wholesale, Transport & Other Utilities, and Agriculture.** For PG&E, these customers make up 45% of program enrollment, 44% of program load and 75% of the estimated demand reductions. Manufacturing, Wholesale & Transport, and Agriculture customers reduced a larger share of their demand than the average CPP customer, delivering reductions of 13.4%, 20.4% and 9.5%, respectively.
- **A large share of CPP customers and program load are in the Greater Bay Area, but the majority of demand reductions are delivered by customers in the Central Valley.** This pattern reflects differences in the industry mix between regions. The Greater Bay Area accounts for 45% of CPP customers, 51% of program load and 25% of estimated demand reductions. The regions in the Central Valley—Greater Fresno, Stockton, Kern and Other—combined account for 48% of default CPP customers, 43% of program load and 69% of estimated demand reductions.
- **1-in-2 August ex ante load impacts for large customers are expected to grow from 51 MW in 2015 to 65 MW in 2025***.* This growth is expected partly because PG&E expects additional large customers to default onto CPP.
- **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 early enrollment pilot (EEP) assumes they will deliver approximately 23 MW in 2017.

Key findings for SCE include the following:

- **In aggregate, participants reduced demand by 5.0% across the 2 to 6 PM event window for the average event day, delivering 29.6 MW of demand reduction.**
- **The differences between individual event day results and average event day results are statistically significant for only 1 of 12 event days.** Estimated demand reductions vary from 20.6 MW to 38.4 MW for individual events. On a percentage basis, demand reduction estimates vary from 3.4% to 6.5%. As with PG&E, 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 44% of program enrollment and 42% 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 12.4%.

- **Under SCE's current enrollment projections, the load reduction capability for large default CPP customers is expected to remain nearly constant.** 2015 aggregate load impacts at SCE during an August event for the 1-in-2 weather year scenario is estimated to be 21.3 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 early enrollment pilot (EEP) assumes they will deliver approximately 8.3 MW in 2018.

Key findings for SDG&E include the following:

- **SDG&E called more events in 2014 than in 2013.** Six events were called in 2014 versus four in 2013. One of the events in 2014 was called in February.
- **In aggregate, participants reduced demand by 8.8% across the 11 AM to 6 PM event window for the average event, delivering 25.4 MW of demand reduction.**
- **The differences between individual event day results and average event day results are not statistically significant.** Estimated demand reductions vary from 14.6 MW to 33.7 MW for individual events. On a percentage basis, estimated demand reductions vary from 7.1% to 11.7%. As with the other utility results, day-to-day performance can vary, but most of the variation is explained by statistical uncertainty.
- **Demand reductions were concentrated in wholesale, transport and other utilities and institutional/government sectors.** These customers make up 25% of program enrollment and 19.8% of program reference load, but account for 55.7% of the estimated demand reductions. On a percentage basis, the highest-performing industry was agriculture, mining and construction, with average load reductions of 34.6%; 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 24.3 MW in 2015 to 26.9 MW in 2025.
- **Default CPP load impacts for medium C&I customers are highly uncertain.** The estimate developed by assuming a modest percentage impact forecasts that they will deliver approximately 9.4 MW in 2018.

2 Introduction

The 2014 statewide evaluation of California's non-residential 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 2014 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:

- What amount of demand did CPP participants reduce at each utility during 2014 events (i.e., what are the ex post impacts)?
- How did the estimated demand reductions vary across events and temperature conditions?
- How do the number of accounts, load, demand reductions and performance vary across different industry, 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) year weather conditions (i.e., what are the ex ante load impacts)?
- How do ex ante load impacts vary under normal and extreme weather based on utility-specific and CAISO peak operating conditions?[3]
- 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 and/or the implementation of default CPP for medium businesses?

2.1 Non-residential 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-

[3] This is a new requirement this year and is explained in Section 3.

CPP tariffs, the higher CPP prices are typically offset by reductions in energy prices during non-peak hours, reductions in demand charges or both. For all three IOUs, CPP rates were also available for small and medium business (SMB) customers on an opt-in basis, but most customers taking electric service under CPP rates in 2014 were large C&I customers that were defaulted onto CPP, starting in 2008. Most of these customers were previously on TOU rates that already provided incentives to shift or reduce electricity usage during peak periods.[4]

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 non-event days;
- The opt-out tariff for all non-residential default customers should be a time varying rate—in other words, there should no longer be a flat rate option for non-residential 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 non-residential 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;

[4] 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 day;
- 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; and 1,815 customers in 2014.

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 Pilot (EEP). 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 EEP CPP customers participating in the 10 PG&E CPP events in 2014. A subset of the EEP population was also involved in a pilot 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.

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 and 2,670 customers in 2014.

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 at SDG&E. In 2014, CPP enrollment averaged 1,142 customers. 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). At SDG&E, the result of a 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 June 9, 2014, the SCE system peaked on September 16, 2014 while the SDG&E system peak occurred on September 16, 2014. 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 non-event 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[5]

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	$0.16	$0.13	$0.12
			Semi-peak	$0.11	$0.08	$0.11
			Off-peak	$0.08	$0.06	$0.08
		Demand Charges (per kW)	On-peak	$17.65	$18.83	$19.81
			Semi-peak	$4.07	$5.52	NA
			Maximum	$12.56	$16.14	$21.84
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.20	$1.37	$1.20
			On-peak	$0.00	NA	$0.00
			Semi-peak	$0.00	NA	$0.00
			Off-peak	NA	NA	$0.00
		Demand Credits (per kW)	On-peak	($6.37)	($11.44)	($9.77)
			Semi-peak	($1.38)	NA	NA
		Capacity Reservation Charge (per kW per month)	Summer	$12.94	$11.44	$5.44

[5] 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 May 1, 2014; 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	Rate SCE TOU-GS-3	Rate SDG&E AL-TOU
Winter	TOU Component	Energy Charges (per kWh)	On-peak	NA	NA	$0.11
			Semi-peak	$0.10	$0.07	$0.09
			Off-peak	$0.08	$0.05	$0.08
		Demand Charges (per kW)	On-peak	NA	$0.00	$7.18
			Semi-peak	$0.21	$0.00	NA
			Maximum	$12.56	$16.14	$21.84
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.20	$1.37	$1.20
			On-peak	NA	NA	$0.00
			Semi-peak	NA	NA	$0.00
			Off-peak	NA	NA	$0.00
		Demand Credits (per kW)	On-peak	NA	NA	NA
			Semi-peak	NA	NA	NA
		Capacity Reservation Charge (per kW per month)	Winter	NA	NA	$5.44

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 non-event 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. It also summarizes a new requirement for this year's evaluation, namely the requirement to produce ex ante load impacts based on two sets of weather conditions. 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 non-event 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 2014 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 non-event 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 EEP customers differed slightly. Load impacts for EEP 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

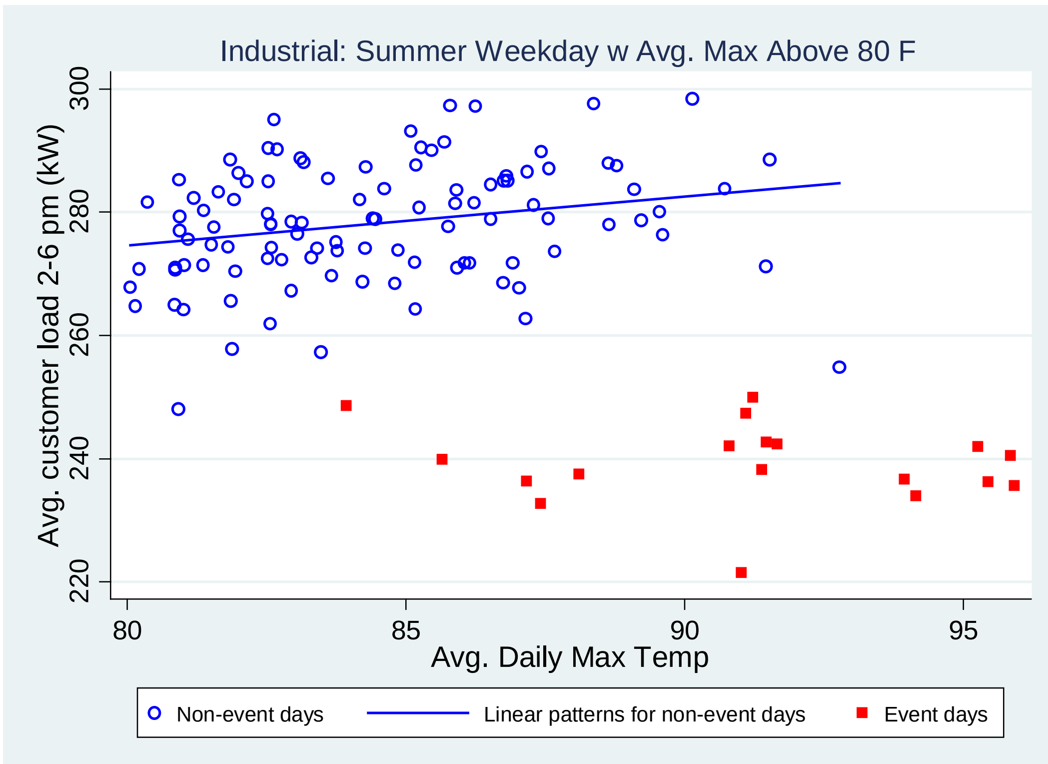
Ex post evaluation is designed to estimate demand reductions on event days when higher CPP prices are in effect. Ex post impacts reflect the enrollment mix, weather, dispatch strategy and program rules in effect at the time of each event and, as a result, may not reflect the full demand reduction capability 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 non-event 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 2014 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 non-event 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 non-event days to estimate reference load for event days. This approach is a refinement of the analysis methodology used in 2013, which estimated impacts using difference-in-differences panel regressions for commercial customers and a within-subjects approach for all industrial customers; which tend to have larger and more idiosyncratic loads than commercial customers. In 2014, the within-subjects method was employed more sparingly, and on a per customer basis, in order to make use of the matched control group method whenever a sufficiently similar control group customer was available.

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 non-event 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 non-event 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 non-event days to predict what load would have been in the absence of CPP on event days, but the non-event 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.

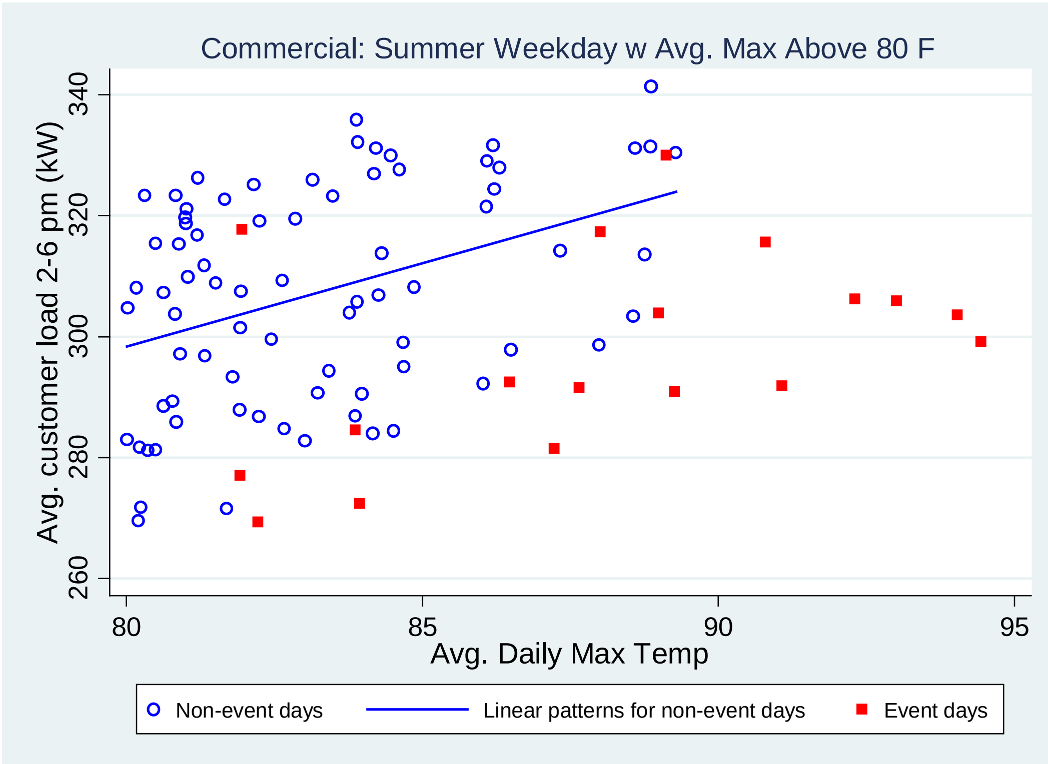
Since PG&E's historically large, defaulted CPP population is still mostly comprised of large C&I customers, it may be hypothesized that CPP load impacts are not weather sensitive. However, the CPP population is comprised of a diverse cross section of industry segments where some segments are known to 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 2013 and 2014. 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 to 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 2013 and 2014. 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 to 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.[6] 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 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 non-event days. The compound result (the difference-in-differences) is a simple and transparent approach that does not suffer from the specification error that can be a problem

[6] 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.

for individual regression modeling. Nonetheless, the matched control group approach rests on the assumption that usage on hot non-event days is an accurate indicator of event day usage for both treatment and control group customers. This assumption is reasonable, but if for whatever reason it does not hold true (e.g., the relationship between event day and non-event day usage is different for treatment customers by virtue of being on CPP), 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 non-event 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 non-event 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[7] 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 non-event days based on system loads, temperature conditions, month and day of week.[8] CPP event days tend to differ from 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 non-event days, however, comparable non-event 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

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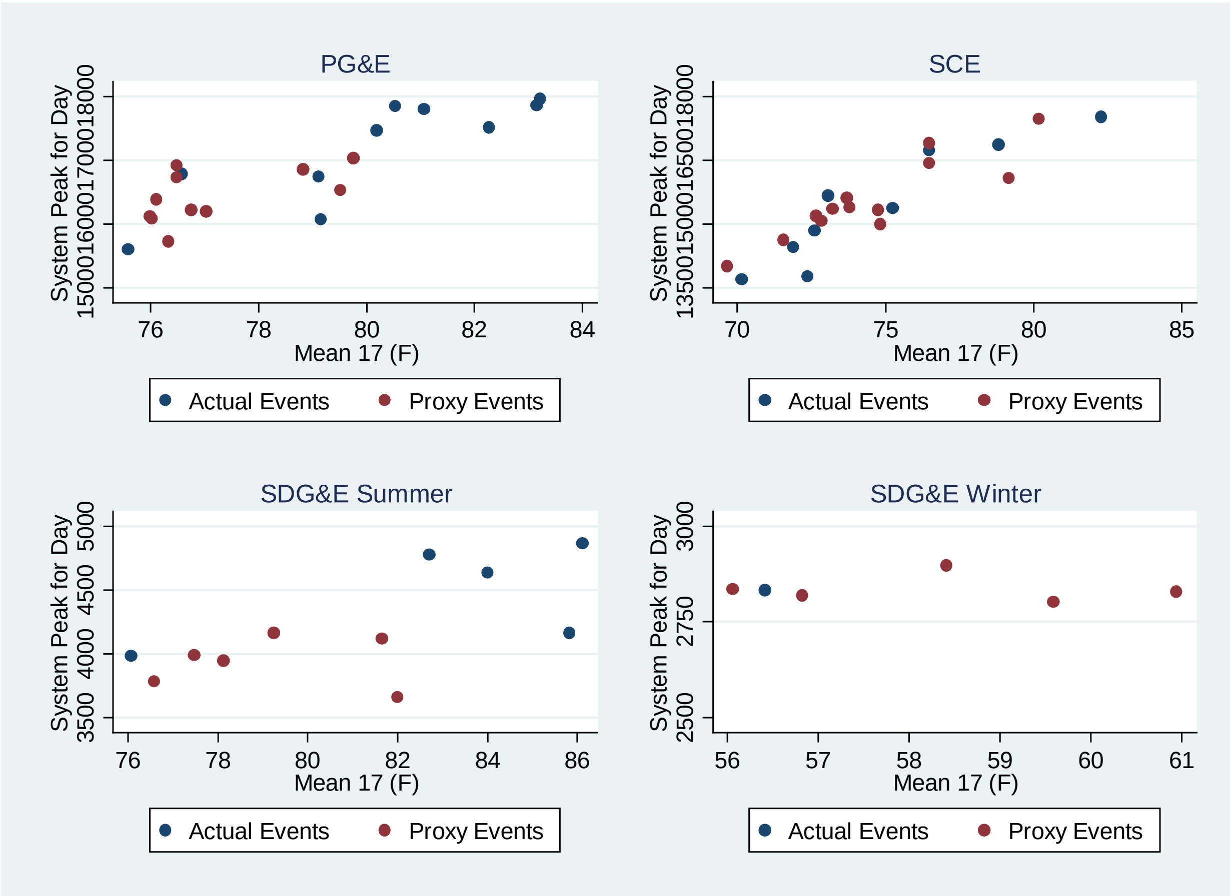
[7] The class of model is the particular type of statistical model used. For example, probit and logistic regression models are two classes of model.

[8] For PG&E, the temperatures were calculated based on the 5-station simple average of the Concord, Fresno, Oakland, 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.

proxy event day. The proxy days match actual event days quite well for SCE but at PG&E and SDG&E, 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 2014[9]



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.[10] The model specification affects both the quality of the match and the number of participants matched given some threshold for the acceptable quality of a match. In the 2014 evaluation, model selection was conducted in a more rigorous and quantitative fashion than in previous years in order to achieve an accurate match for as many CPP customers as possible.

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9 Separate winter and summer graphs are shown for SDG&E. A separate set of proxy days was selected to accompany the winter event that SDG&E called in February, as the impact was estimated separately from the summer events.

10 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.

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 previous years, 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 non-event 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, 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 improves on this approach 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

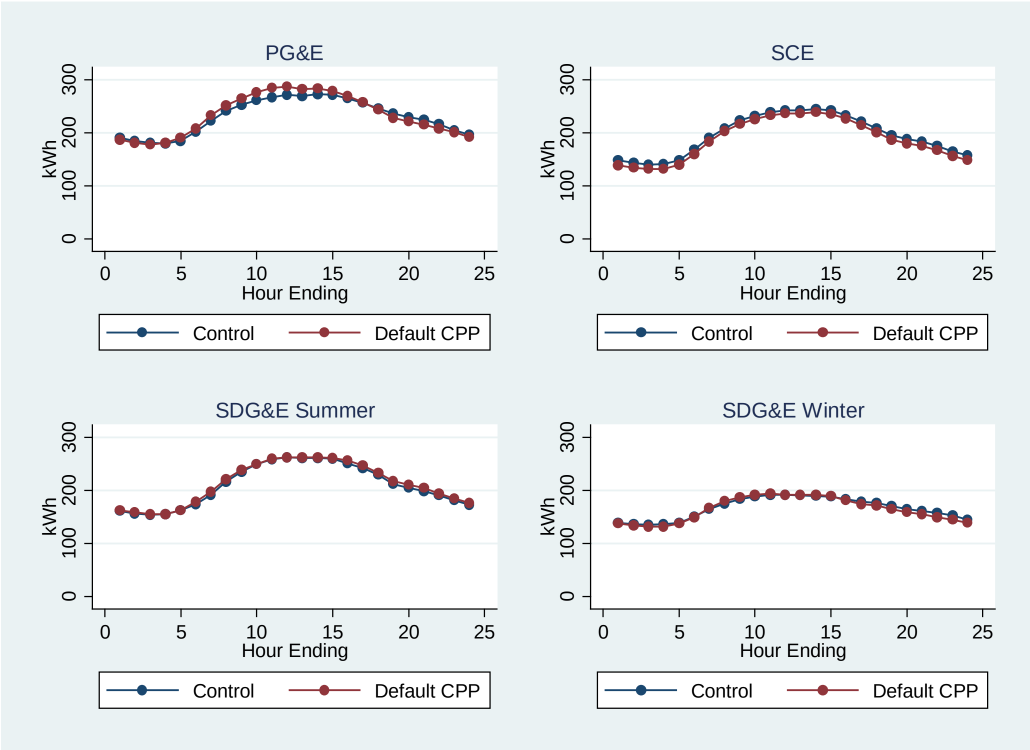
- t - each individual proxy day
- n - total number of proxy days

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.

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. The best performing probit model and caliper were used to select customers from the control pool. The majority of CPP customers were successfully matched: 98% for PG&E; 84% 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, 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

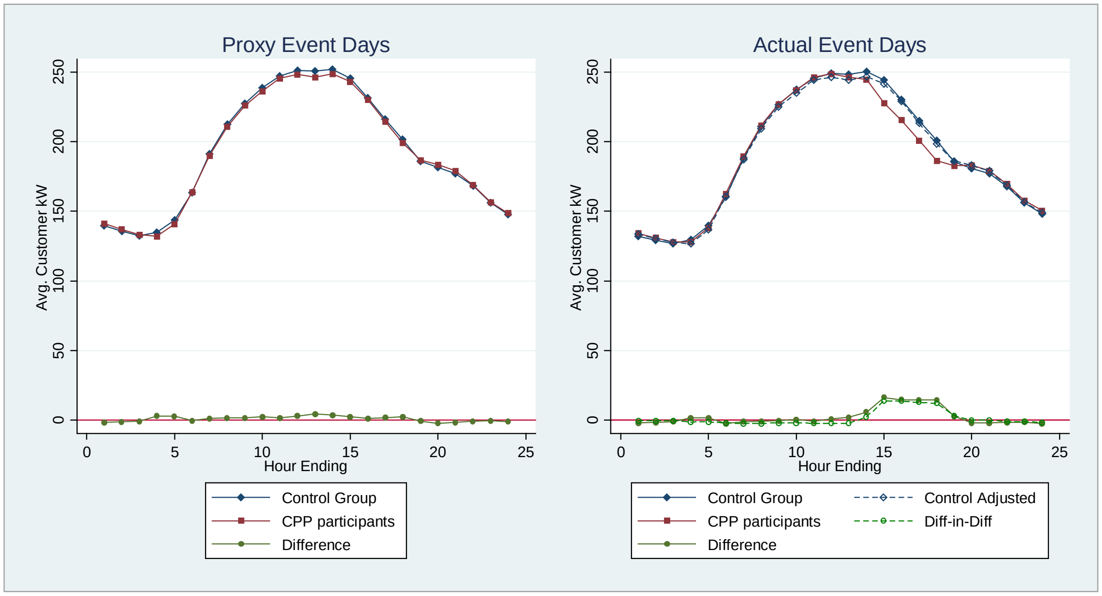


3.1.4 Difference-in-differences

Using the matched control groups, 2014 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.

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 non-event 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 non-event 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 non-event days.

The regression analysis employed a simple model that relies on no explanatory variables other than customer fixed effects and time effects.[11] This model does not rely on modeling the relationship between customers' electricity usage and other factors such as weather; it is informed by control group customers that experience the event day weather, but do not

11 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.

experience the CPP event day prices.[12] 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.[13]

For each customer, we:

- Analyzed hot weekdays from 2014. 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

Ex ante impacts are designed to reflect demand reduction capabilities under a standard set of peak hours, 1 to 6 PM for the summer season, under both 1-in-2 and 1-in-10 weather conditions. As a result, estimating the relationship between weather and demand reductions is critical. It is preferable to base ex ante impacts on numerous ex post events over two to three years (as long as the population of participants is fairly constant over that historical period); a broader perspective allows for a better assessment of overall performance and volatility in demand reductions. It also can help determine whether factors such as weather affect percent demand reductions. Too few data points weaken the ability to produce reliable estimates and to

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[12] 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.

[13] 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 customers regressions were performed for 86 customers. These customers tended to be in the 1st and 4th usage quintiles. SDG&E retail Stores were disproportionately represented as they made up 33% of unmatched customers, but only 10% of the defaulted CPP population. There were no strong trends by industry at PG&E or SCE.

draw inferences about factors that affect performance. For this evaluation, ex ante load impacts are based on ex post load impacts from the 2013 and 2014 program years, given that there was a sufficient number of events in those two years to assess how CPP percent impacts vary with respect to weather conditions.

The remainder of this section is divided into two parts. The first describes the modeling process for ex ante estimation. The second summarizes the approach used to develop ex ante weather estimates under both utility-specific and CAISO peak operating conditions.

3.2.1 Ex Ante Methodology

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). For large customers, the ex ante estimation process began by re-estimating ex post load impacts from 2013 and 2014 for customers enrolled in both years with data for all events (persistent customers), using the same estimation model. Estimates may be sensitive to modeling variation and customer churn, so this re-estimation is necessary to derive impacts that can be used to reliably model a relationship with temperature. Furthermore, estimates for persistent customers are more likely to reflect reductions delivered by customers that remain on CPP in years to come.

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.[14] 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. For small and medium customers at PG&E, an analysis of future enrollees from the remaining population found that they are expected to be larger than SMB customers that are currently enrolled. Therefore, an adjustment factor is applied to the reference load of new small and medium enrollees to be defaulted in the future. Finally, small customer reference loads were not modeled for SDG&E because, as noted below, the future impacts are assumed to be zero until further evidence of small customer CPP impacts is provided.

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 2013 and 2014 for large persistent customers are 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. Appendix G gives details of the regression model used. Given that the large C&I default CPP population has been subject to

[14] 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.

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.

For small and medium customers, we lack robust empirical data about how they respond to default CPP. Around 170,000 SMB customers were defaulted onto CPP in November 2014 at PG&E, but those customers have yet to experience any CPP events. SCE and SDG&E small and medium customers have yet to be defaulted onto CPP. Therefore, default CPP ex post impact estimates are not available. The percent load reductions from the EEP customers at PG&E provide information on how small and medium customers respond to CPP on an opt-in basis. 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.[15] Nexant therefore used the EPP CPP percent reductions as an upper bound for the expected response of defaulted small and medium customers, and adjusted the overall percent reduction downward. For SCE and PG&E, this yielded percent reductions of 2.0% and 1.5%, for small and medium customers respectively, to be applied to SMB customers to be defaulted onto CPP in the future. For SDG&E, the initial percent reduction for medium customers was 2.5%, to which an awareness factor was then applied. The awareness factor increased from 0.7 in 2016 to 0.9 in 2018 onwards, which led to percent impacts of 1.75% in 2016 and 2.25% in 2018 onwards. Small CPP customers were 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 PG&E and SCE 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.

3.2.2 Estimating Ex Ante Weather Conditions

The CPUC Load Impact Protocols[16] 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.

[15] 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

[16] 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 new 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.[17]

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.

[17] 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)

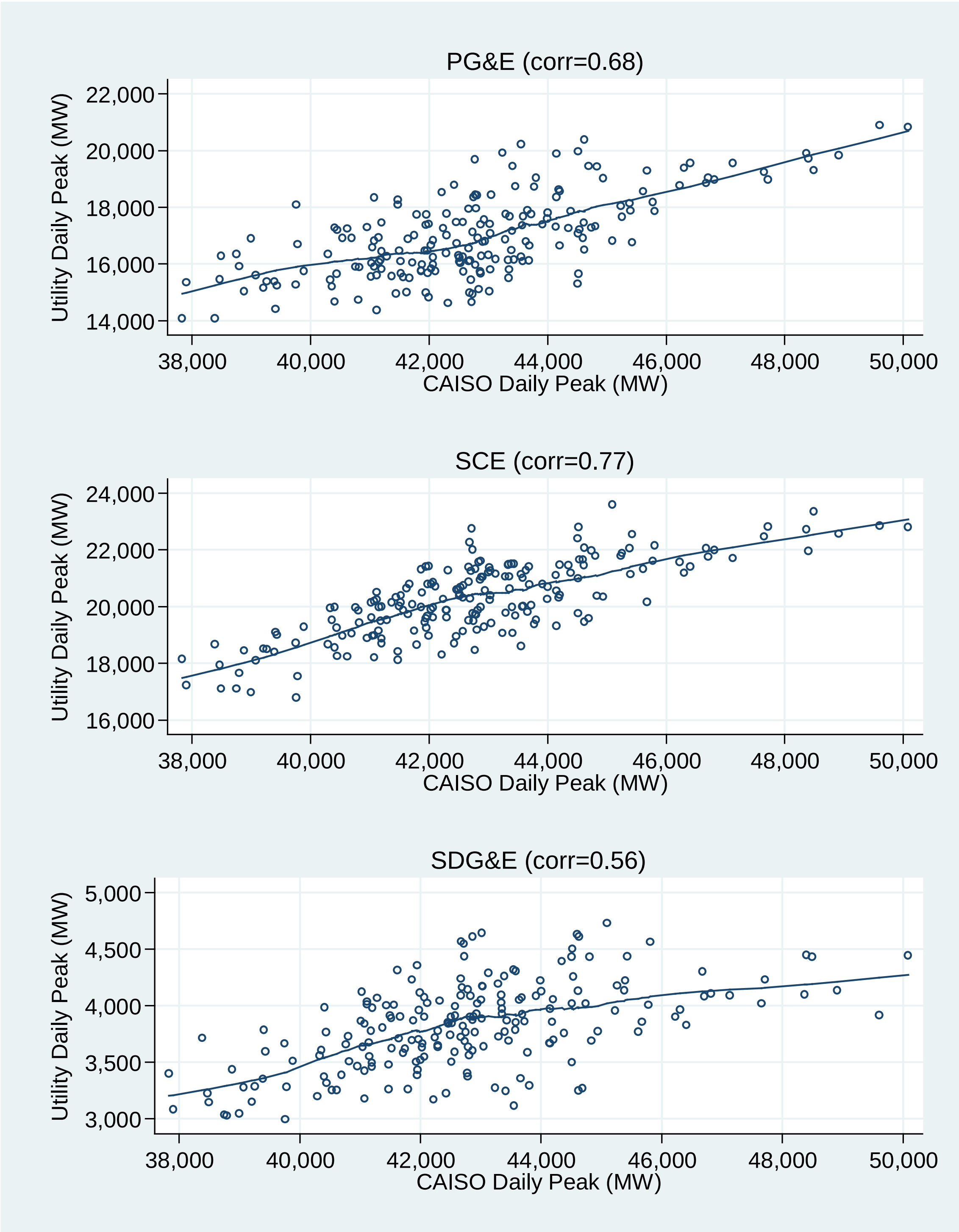


Table 3-2 shows the CPP enrollment-weighted value for *mean17* (the weather variable used in the ex ante model), for the typical event day and the monthly system peak day under the four sets of weather for which load impacts are estimated for each utility. As seen, the differences in weather conditions 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	75.9
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	47.4
February Peak Day	47.0	45.8	49.7	48.7	55.7	53.6	50.7	52.3	53.6	54.1	54.9	55.1
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	74.4	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	72.8
June Peak Day	77.6	82.1	77.3	77.4	71.8	76.4	72.5	76.8	68.1	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	73.6
August Peak Day	77.7	81.2	73.7	78.9	79.7	81.9	78.8	81.1	74.9	78.6	76.0	76.5
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	80.6
October Peak Day	69.5	75.6	69.4	72.9	74.9	77.5	71.0	77.6	70.8	76.0	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 10 CPP events in 2014. The first event occurred on June 9 and the last was held on September 12. The average number of default CPP customers participating in the 10 events was 1,815. There was some very slight variation in the number of default CPP customers participating in each event due to customer churn; some customers departed and others enrolled in CPP during summer 2014. The highest 2014 enrollment, 1,819 customers, occurred on the July 14 event. The lowest enrollment, 1,807 customers, occurred on the first event.

The load impacts described in this report pertain primarily to customers subject to the CPP rate on a default basis, including customers enrolled in the legacy voluntary CPP program prior to the default in 2010 or who were defaulted to CPP and remained on CPP even though their load dropped below 200 kW. This group of customers taking CPP in 2014 is referred to as the default CPP population in this report.

Nexant also estimated ex post load impacts for SMB customers who enrolled in CPP on a voluntary basis through PG&E's EEP. This group of customers is referred to as the EEP CPP population. The EEP targeted SMB customers who were due to be defaulted onto PG&E's CPP tariff in November 2014. 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 EEP CPP customers participating in the 10 PG&E CPP events. About half of the participants were recruited through the first wave, which received a package of in-season support services provided by Gridium, as described in Section 2. Load impacts for EEP CPP customers are presented at the end of this section.

There is also another group of SMB customers who were on the CPP rate in 2014, namely those who enrolled on CPP on a purely voluntary basis. This group of customers is referred to as opt-in CPP customers. In 2014, there were 4,715 opt-in customers and the great majority of these service accounts are associated with a single business entity that did not respond on event days. 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 SMB population that will default onto CPP in coming years. Load impacts for these customers are presented in the PG&E 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.

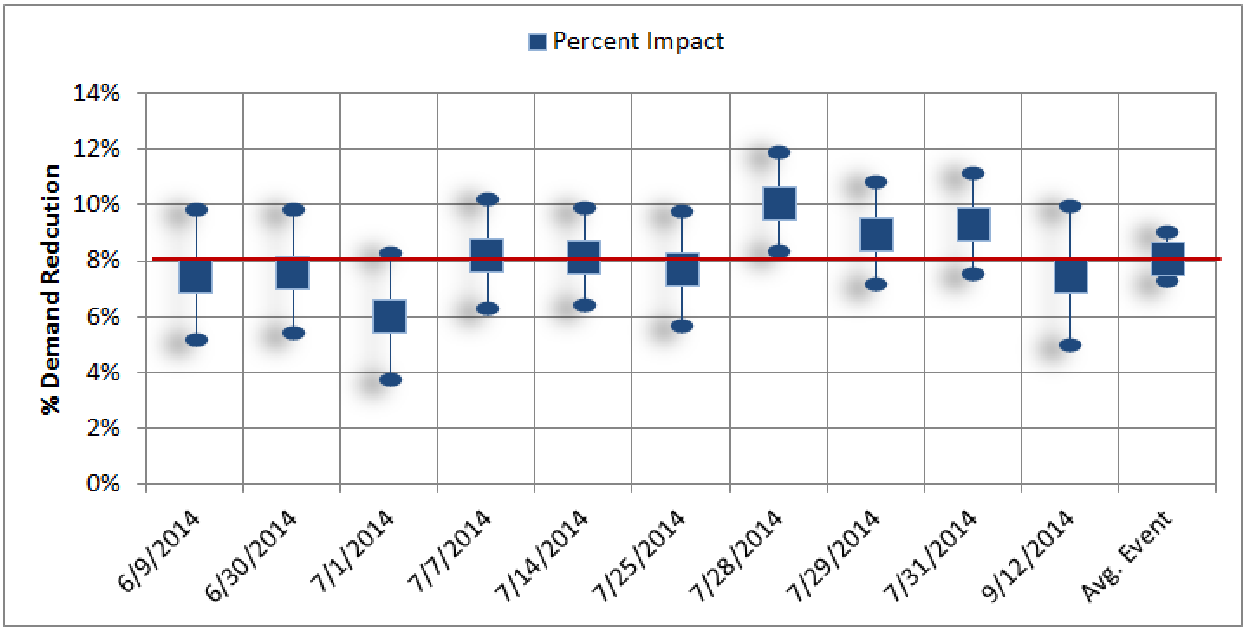
Table 4-1 shows the ex post load impact estimates for each event day and for the average event day in 2014. The participant-weighted average temperature during the event period ranged from a low of 84.0°F to a high of 93.9°F. Percent impacts range from 6.0% to 10.1%; average impacts range from 15.9 kW to 28.2 kW; and aggregate impacts range from 29.0 MW to 51.3 MW. On the average event day, the average participant reduced peak period load by 8.1%. In aggregate, PG&E's CPP customers reduced load by an average of 41.0 MW across the 10 event days in 2014.

Table 4-1: Default CPP Ex Post Load Impact Estimates by Event Day PG&E 2014 CPP Events (2 to 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)
6/9/2014	Mon	1,807	281.9	260.8	21.1	38.2	7.5%	92.1	108.5
6/30/2014	Mon	1,815	275.8	254.8	21.0	38.0	7.6%	90.5	105.0
7/1/2014	Tue	1,817	264.9	249.0	15.9	29.0	6.0%	84.4	106.0
7/7/2014	Mon	1,818	265.5	243.7	21.8	39.7	8.2%	84.0	104.5
7/14/2014	Mon	1,819	275.4	252.9	22.5	40.8	8.2%	86.5	104.5
7/25/2014	Fri	1,817	282.1	260.4	21.7	39.5	7.7%	93.9	102.0
7/28/2014	Mon	1,816	279.0	250.7	28.2	51.3	10.1%	85.5	100.5
7/29/2014	Tue	1,816	281.5	256.2	25.2	45.8	9.0%	89.1	103.0
7/31/2014	Thu	1,817	284.9	258.3	26.6	48.3	9.3%	88.8	106.5
9/12/2014	Fri	1,813	289.4	267.8	21.6	39.1	7.5%	89.4	102.0
Avg. Event		**1,815**	**278.0**	**255.5**	**22.6**	**41.0**	**8.1%**	**88.4**	**102.0**

Figure 4-1 also presents the ex post load impact estimates for the 2014 CPP event days and the average 2014 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: Default CPP Ex Post Load Impact Estimates with 90% Confidence Intervals PG&E 2014 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 not significantly different from the average event.

4.1 Average Event Day Impacts

Figure 4-2 shows the aggregate hourly impacts for all 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 8.5% in the second event hour to a low of 7.7% in the fourth hour. The highest aggregate impact, 44.0 MW, occurs in the second hour and the lowest impact, 36.2 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 non-residential 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 2014 event day are similar in shape to the 2013 hourly load impacts: stronger in the earliest hours of the event and weakest at the end of the event. The average impact (22.6 kW) and percent impact (8.1%) are quite similar to the 2013 estimates (22.4 kW and 8.6%). However, the aggregate impact on the typical event day (41 MW) is larger in 2014 compared with the 2013 value (38.4 MW) because enrollment increased by roughly 100 participants. New additions have been mainly from the agricultural sector.

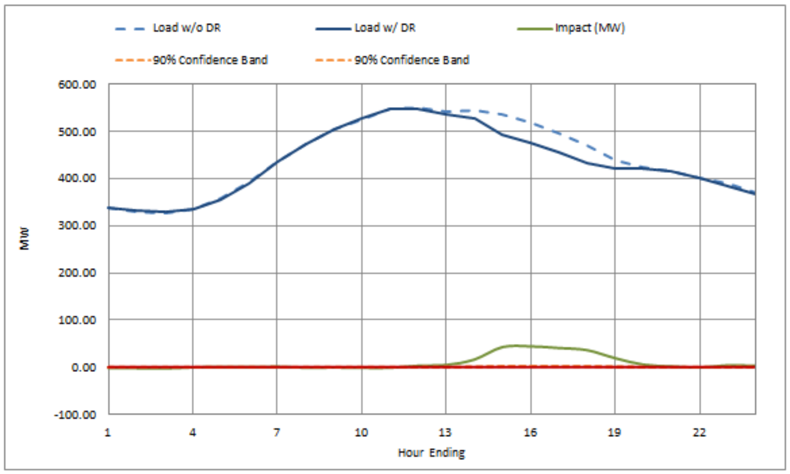
Figure 4-2: Aggregate Impact for the Average Event Day in 2014
Default CPP Ex Post Load Impacts

Menu Options

Result Type	Aggregate
Subprogram Type	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)	88
Aggregate Load Reduction Across Event Window (MW)	41.0
% Load Reduction	8.1%
# of Customers Called for Event	1,815
# of Customers Enrolled in Program	1,815



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	336.6	338.4	-1.8	-0.5%	71.2	-5.4	-3.3	-1.8	-0.4	1.7
2	330.1	332.3	-2.2	-0.7%	70.0	-5.6	-3.6	-2.2	-0.8	1.2
3	325.5	328.2	-2.6	-0.8%	68.9	-5.9	-4.0	-2.6	-1.3	0.6
4	335.6	335.9	-0.3	-0.1%	67.8	-4.0	-1.8	-0.3	1.2	3.3
5	356.9	356.2	0.7	0.2%	66.8	-3.0	-0.8	0.7	2.2	4.4
6	390.9	390.7	0.1	0.0%	66.1	-3.6	-1.4	0.1	1.7	3.9
7	436.7	435.7	1.0	0.2%	66.1	-2.8	-0.6	1.0	2.5	4.8
8	472.7	473.7	-1.0	-0.2%	68.1	-4.9	-2.6	-1.0	0.6	2.8
9	502.8	503.4	-0.6	-0.1%	71.4	-4.5	-2.2	-0.6	1.0	3.4
10	525.3	526.6	-1.3	-0.2%	75.3	-5.4	-3.0	-1.3	0.4	2.9
11	546.1	547.3	-1.2	-0.2%	79.1	-5.5	-3.0	-1.2	0.5	3.0
12	549.3	546.0	3.3	0.6%	82.3	-0.5	1.8	3.3	4.8	7.1
13	540.5	535.6	4.9	0.9%	85.0	1.6	3.5	4.9	6.2	8.2
14	543.7	527.3	16.4	3.0%	87.0	13.1	15.0	16.4	17.7	19.7
15	535.1	492.3	42.9	8.0%	88.2	39.3	41.4	42.9	44.3	46.4
16	518.2	474.2	44.0	8.5%	88.9	40.6	42.6	44.0	45.5	47.5
17	496.0	455.3	40.8	8.2%	88.7	37.4	39.4	40.8	42.1	44.1
18	469.1	433.0	36.2	7.7%	87.9	32.9	34.8	36.2	37.5	39.4
19	438.8	419.7	19.1	4.4%	85.8	15.8	17.8	19.1	20.5	22.5
20	425.2	419.6	5.6	1.3%	82.6	2.2	4.3	5.6	7.0	9.0
21	415.6	414.0	1.5	0.4%	79.1	-1.8	0.2	1.5	2.9	4.9
22	400.5	401.0	-0.5	-0.1%	76.2	-4.0	-1.9	-0.5	0.9	2.9
23	388.3	384.4	3.9	1.0%	74.1	0.2	2.4	3.9	5.4	7.6
24	370.5	367.6	2.8	0.8%	72.6	-0.6	1.4	2.8	4.3	6.3
Avg. Hour in Event Window	504.6	463.7	41.0	8.1%	88.4	37.5	39.6	41.0	42.4	44.4

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

4.2 Load Impacts by Industry

Table 4-2 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 at the 10% significance 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 44% of the reference load (222.8 MW), but produced nearly 75% of the impacts. CPP participants in the Manufacturing sector provided 13.8 MW of aggregate load reduction on the average event day, while the Wholesale, Transport & Other Utilities segment provided 10.1 MW of aggregate load impact, reducing loads by 13.4% and 20.4%, respectively.

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 36% of the estimated reference load, but produced 17.8% of the load reduction (7.3 MW). On average, offices reduced load by 4.0%.

Table 4-2: Default CPP Ex Post Load Impact Estimates by Industry Average 2014 PG&E CPP Event (2-6 PM)*

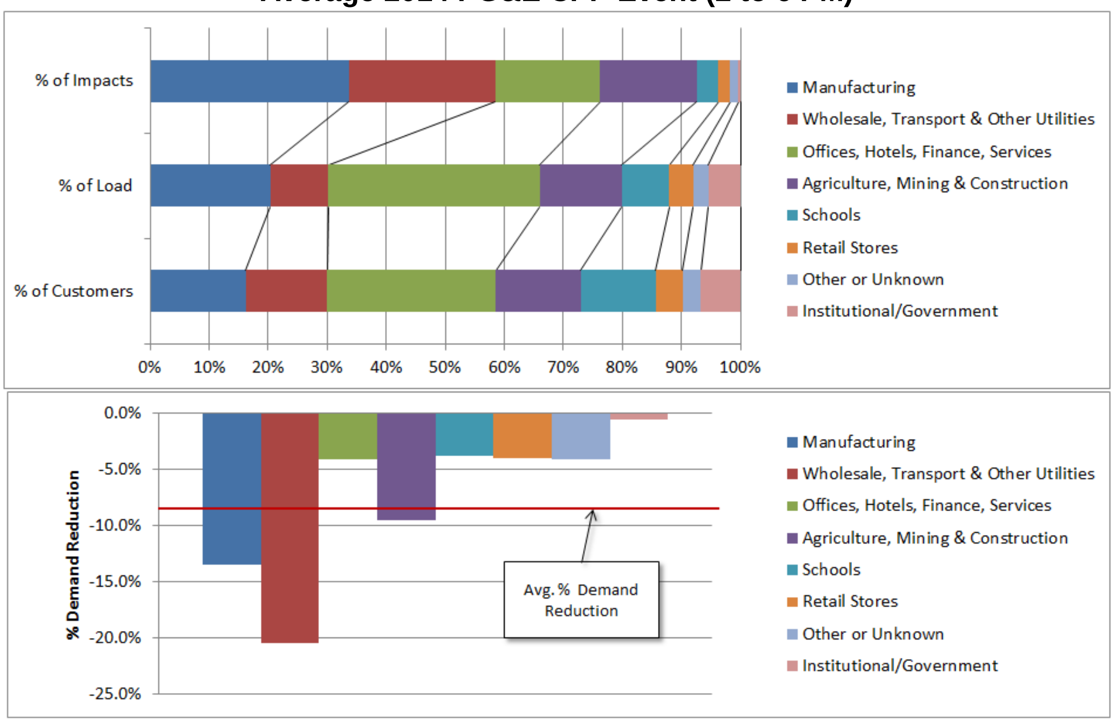
Industry	Accounts		Aggregate Reference Load		Aggregate Impact		Average Impact	% Reduction	Stat. Sig?
	Enrollment	% of Program	MW	% of Program	MW	% of Program	kW		
Manufacturing	294	16.2%	102.8	20.4%	13.8	33.7%	46.9	13.4%	Yes
Wholesale, Transport & Other Utilities	249	13.7%	49.6	9.8%	10.1	24.8%	40.7	20.4%	Yes
Offices, Hotels, Finance, Services	519	28.6%	180.2	35.7%	7.3	17.8%	14.0	4.0%	Yes
Agriculture, Mining & Construction	261	14.4%	70.4	14.0%	6.7	16.3%	25.6	9.5%	Yes
Schools	230	12.7%	40.3	8.0%	1.5	3.7%	6.6	3.8%	Yes
Retail Stores	83	4.6%	20.3	4.0%	0.8	2.0%	9.8	4.0%	Yes
Other or Unknown	56	3.1%	13.0	2.6%	0.5	1.3%	9.5	4.1%	Yes
Institutional/Government	121	6.7%	27.5	5.5%	0.2	0.4%	1.3	0.6%	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 4-3 presents the same information visually, but better illustrates the concentration of load impacts in specific industries. The benefit of Figure 4-3 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.

Four of the eight industry segments decreased their load impacts in 2014 relative to 2013. Before addressing these differences, we note that comparisons across years must be made conservatively, as the matching and modeling across years vary. The matching approach in 2014 differed from that in 2013, so some difference may be an artifact of modeling. Wholesale, Transport & Other Utilities delivered 13.5 MW in 2013 and 10.1 MW in 2014, a 25% reduction. The other industry segments with decreased load impacts, Retail Stores, Institutional/Government and Other, made up only 8% of aggregate impacts in 2013, and now make up 4%. The four industry segments that increased load impacts in 2014 were led by the Agriculture, Mining & Construction segment, which increased aggregate load impacts by 3.0 MW, an 82% increase in the segment's 2013 impact. The increased load impacts delivered by the Agriculture, Mining & Construction sector are the effect of increased enrollment from 155 accounts in 2013 to 261 in 2014, and the larger size of enrolled customers: aggregate reference load in the Agriculture, Mining & Construction sector increased by 150% to 70.4 MW.

Figure 4-3: Default CPP Enrollment, Load, Impact and Percent Demand Reduction by Industry Average 2014 PG&E CPP Event (2 to 6 PM)



4.3 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 4-3 presents the estimated ex post load impacts by LCA. Participants in the Greater Bay Area provided 10.2 MW of aggregate load impact during the average event day, while customers in the Other LCA provided 11.5 MW of aggregate load reduction. The Greater Bay Area had the lowest average impact per customer of 12.5 kW, while customers in the Other LCA provided an average impact of 36.1 kW, which was the second highest. Combined, these LCAs comprise 53% of aggregate load impact. Customers in the Greater Bay Area had the highest average reference load of any LCA, at 316 kW, while customers in the Humboldt LCA had the lowest average reference load (179.3 kW). Figure 4-4 illustrates how large the Bay Area and Other LCAs are on a customer and reference load basis—these two segments comprise 62% of enrolled accounts and 66% of enrolled load.

Table 4-3: Default CPP Ex Post Load Impact Estimates by LCA
Average 2014 PG&E CPP Event (2 to 6 PM)*

Local Capacity Area	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig?
		(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
Greater Bay Area	812	316.2	303.7	12.5	10.2	4.0%	79.8	Yes
Greater Fresno Area	200	250.3	213.9	36.4	7.3	14.6%	101.6	Yes
Humboldt	22	179.3	154.2	25.1	0.6	14.0%	83.4	Yes
Kern	222	284.7	256.8	28.0	6.2	9.8%	102.0	Yes
LCA: Other	318	245.1	209.0	36.1	11.5	14.7%	87.5	Yes
North Coast and North Bay	46	266.0	251.9	14.0	0.6	5.3%	87.8	Yes
Sierra	70	187.5	166.8	20.7	1.5	11.1%	97.2	Yes
Stockton	123	217.5	192.0	25.4	3.1	11.7%	97.4	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 4-4: Default CPP Enrollment, Load and Impact by LCA
Average 2014 PG&E CPP Event (2 to 6 PM)

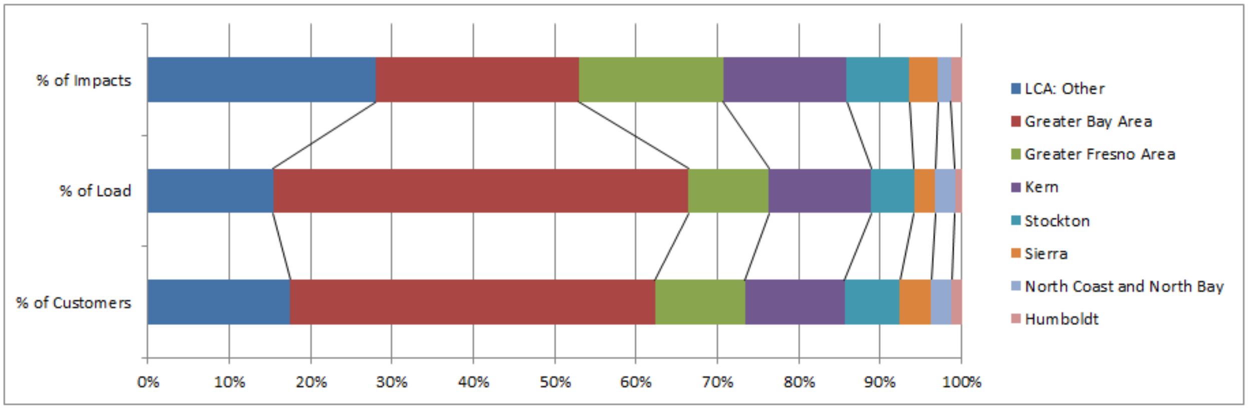


Table 4-4 shows the estimated ex post load impact by customer size, using two different size categorization methods. First, load impacts are reported for the three demand size categories: greater than 200 kW; 20 kW to 200 kW; and less than 20kW. The other size categorization is by usage quintile, in which 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 60 customers in that category. Table 4-4 shows that customers in the smallest and the largest usage quintiles have the largest percentage load impacts while the 4th quintile has the lowest percentage load impacts.

Table 4-4: Default CPP Ex Post Load Impact Estimates by Customer Size Average 2013 PG&E CPP Event (2 to 6 PM)*

Categorization	Size Category	Accounts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	% Reduction (%)	Avg. Temp (°F)	Stat. Sig?
By Demand Response Category	Greater than 200kW	1,602	306.4	281.6	24.7	39.6	8.1%	87.9	Yes
	20 kW to 199.99 kW	149	87.9	81.6	6.3	0.9	7.1%	88.8	Yes
	Less than 20kW	60	1.4	1.1	0.3	0.0	22.4%	102.0	No
By Annual Consumption Quintiles	5th Quintile	375	710.3	645.1	65.2	24.5	9.2%	85.4	Yes
	4th Quintile	354	290.3	274.9	15.4	5.5	5.3%	86.1	Yes
	3rd Quintile	361	194.2	182.8	11.5	4.1	5.9%	87.3	Yes
	2nd Quintile	353	129.0	116.9	12.1	4.3	9.4%	89.5	Yes
	1st Quintile	371	52.4	45.4	7.0	2.6	13.4%	93.6	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.

4.4 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.

Table 4-5 shows CPP load impacts for customers that are dually enrolled in other demand response programs. A word of caution is needed in reviewing Table 4-5. There are relatively few dually enrolled customers in any single DR program. For example, there are only 16 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 4-5 causes CPP customers to respond better.

Table 4-5: Default CPP Ex Post Load Impact Estimates for Dually-enrolled Participants Average 2014 PG&E CPP Event (2 to 6 PM)*

Dually Enrolled DR	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp.	Stat. Sig?
		(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
AMP	114	391.5	288.8	102.8	11.7	26%	86.5	Yes
BIP	40	576.4	290.8	285.7	11.4	50%	92.6	Yes
CBP	16	179.0	158.3	20.6	0.3	12%	88.6	No
Not Dually-enrolled	1,640	263.7	253.5	10.3	16.9	4%	88.4	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.

4.5 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 and AutoDR is hampered by the very small number of customers that participate in these complementary programs. There were only four PG&E accounts on the CPP tariff that received TI payments and nine AutoDR customers. Table 4-6 shows the load impact of the average customer on each of these programs on the average event day. For customers with TI, their response is statistically insignificant—that is, their response, if any, is statistically indistinguishable from zero. AutoDR customers produced much larger than average impacts of 50.5%. However, given the extremely small number of customers on TI and AutoDR, the point impact estimates are surrounded by a large amount of uncertainty.

Table 4-6: Default CPP Ex Post Load 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		
AutoDR**	10	276.4	50.5%	186.8	365.9	1,000.1	27.6%
TI**	4	-7.7	-3.0%	-25.8	10.4	186.9	-4.1%
No TI or AutoDR	1,799	20.9	7.9%	18.5	23.3	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.

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

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.

4.6 Early Enrollment Pilot Ex Post Load Impacts

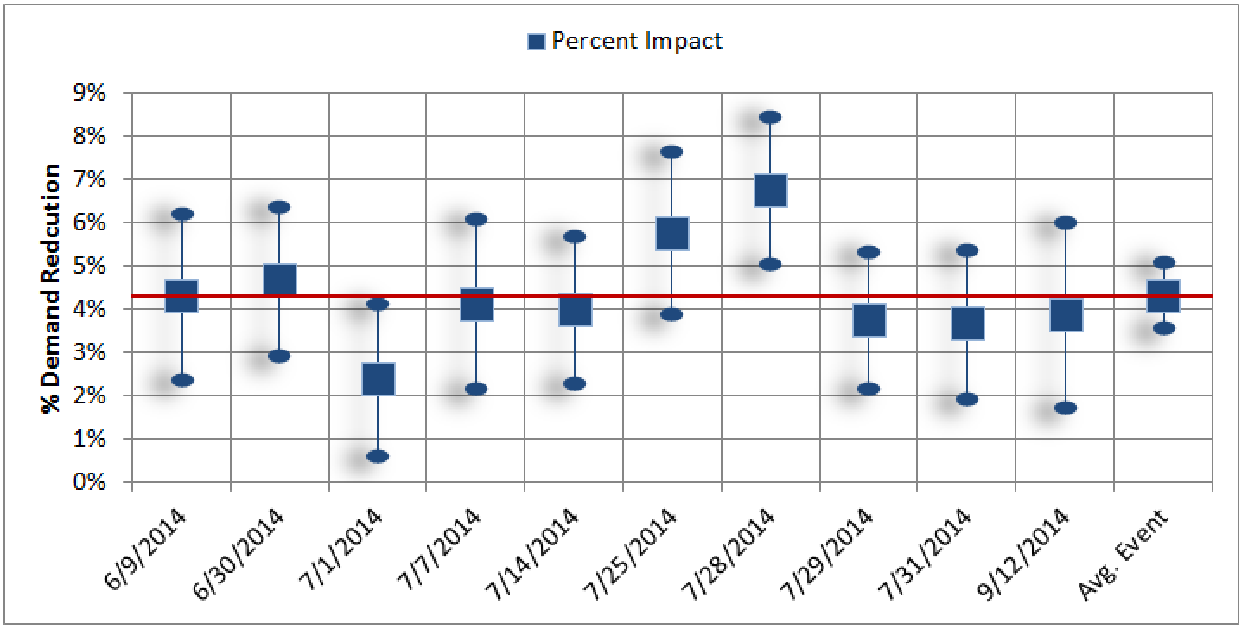
Table 4-7 shows the ex post load impact estimates for the EEP CPP customers for each event day and for the average event day in 2014. The average number of EEP CPP customers who participated in the 10 PG&E CPP events was 4,760. There is event-to-event variation in the number of EEP CPP customers due to customer churn; some customers departed and others enrolled in CPP during summer 2014. The highest 2014 enrollment, 4,823 customers, occurred on the July 14 event. The lowest enrollment, 4,458 customers, occurred on the first event. The participant-weighted average temperature during the event period ranged from a low of 83.2°F to a high of 93.3°F. Percent impacts ranged from 2.4% to 6.8%; average impacts ranged from 0.1 kW to 0.4 kW; and aggregate impacts ranged from 0.6 MW to 1.7 MW. On the average event day, the average participant reduced peak period load by 4.3%. In aggregate, PG&E's EEP CPP customers reduced load by an average of 1.1 MW across the 10 event days in 2014.

Table 4-7: EEP Ex Post Load Impact Estimates by Event Day PG&E 2014 CPP Events (2 to 6 PM)

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp.	Daily Maximum Temp.
			(kW)	(kW)	(kW)	(MW)	%	°F	°F
6/9/2014	Mon	4,458	5.7	5.4	0.2	1.1	4.3%	91.4	92.2
6/30/2014	Mon	4,793	5.6	5.3	0.3	1.2	4.7%	90.2	91.1
7/1/2014	Tue	4,798	5.3	5.2	0.1	0.6	2.4%	83.3	83.7
7/7/2014	Mon	4,813	4.9	4.7	0.2	1.0	4.1%	83.2	83.8
7/14/2014	Mon	4,823	5.3	5.1	0.2	1.0	4.0%	86.7	88.1
7/25/2014	Fri	4,799	5.6	5.3	0.3	1.6	5.8%	93.3	93.9
7/28/2014	Mon	4,794	5.3	5.0	0.4	1.7	6.8%	85.0	85.6
7/29/2014	Tue	4,792	5.6	5.4	0.2	1.0	3.8%	88.5	89.0
7/31/2014	Thu	4,785	5.7	5.5	0.2	1.0	3.7%	88.4	89.1
9/12/2014	Fri	4,747	5.3	5.1	0.2	1.0	3.9%	88.9	89.6
Avg. Event		**4,760**	**5.4**	**5.2**	**0.2**	**1.1**	**4.3%**	**87.9**	**88.4**

Figure 4-5 also presents the PG&E EEP ex post load impact estimates for the 2014 CPP event days and the average 2014 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 4-5: EEP Ex Post Load Impact Estimates with 90% Confidence Intervals PG&E 2014 CPP Events (2 to 6 PM)



5 PG&E Ex Ante Load Impacts

This section presents ex ante load impact estimates for PG&E's non-residential 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 2013 and 2014 for the group of persistent customers that remained on the CPP tariff for both years. In total, load impact estimates for up to 18 events were used as input to the ex ante model.[18] 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., 2015, 2016, 2017 and 2025),[19] 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 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 2013 and 2014 for the group of persistent customers who were enrolled in all 2013 and 2014 event days.

The persistent customer population is a subset of the 2014 CPP population. As such, they deliver different load impacts. Their load impacts are used for ex ante modeling, so in order to demonstrate how ex ante load impacts are derived from ex post impacts, we address the difference in impacts below.

Table 5-1 shows the ex post load impact estimates for each event day and for the average event day in 2013 and 2014 for large, persistent customers. The participant-weighted average temperature during the event period ranged from a low of 82.8°F to a high of 93.3°F. Percent impacts range from 5.5% to 12.5%; average impacts range from 17.1 kW to 38.9 kW; and aggregate impacts range from 20.1 MW to 45.7 MW.

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18 Nexant ran an outlier test, which dropped some days if the impact estimates were well outside the typical range of percent impact estimates.

19 Enrollment is not forecasted to change substantially between 2017 and 2025, 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.

Table 5-1: Default CPP Ex Post Load Impact Estimates for Persistent Customers by Event Day
PG&E 2013, 2014 CPP Events (2 to 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)
6/7/2013	Fri	1,174	290.9	264.8	26.1	30.6	9.0%	88.1	100.5
6/28/2013	Fri	1,174	296.7	273.6	23.1	27.1	7.8%	92.8	102.0
7/1/2013	Mon	1,174	311.1	272.9	38.2	44.8	12.3%	91.4	103.5
7/2/2013	Tue	1,174	312.1	273.2	38.9	45.7	12.5%	91.0	108.0
7/9/2013	Tue	1,174	299.0	267.9	31.1	36.5	10.4%	88.7	103.0
7/19/2013	Fri	1,174	272.8	253.6	19.2	22.5	7.0%	84.1	99.5
9/9/2013	Mon	1,174	309.1	292.0	17.1	20.1	5.5%	88.2	101.0
9/10/2013	Tue	1,174	304.0	285.1	18.9	22.2	6.2%	81.1	99.0
6/9/2014	Mon	1,174	298.6	276.2	22.4	26.3	7.5%	91.0	108.5
6/30/2014	Mon	1,174	290.7	264.3	26.4	31.0	9.1%	89.6	105.0
7/1/2014	Tue	1,174	277.2	257.8	19.3	22.7	7.0%	82.9	106.0
7/7/2014	Mon	1,174	276.4	252.4	24.1	28.2	8.7%	82.8	104.5
7/14/2014	Mon	1,174	293.0	259.7	33.3	39.1	11.4%	85.7	102.5
7/25/2014	Fri	1,174	296.8	269.8	27.0	31.7	9.1%	93.3	102.0
7/28/2014	Mon	1,174	293.2	260.7	32.5	38.2	11.1%	84.6	100.5
7/29/2014	Tue	1,174	296.3	266.5	29.8	35.0	10.1%	88.2	103.0
7/31/2014	Thu	1,174	298.6	269.9	28.7	33.7	9.6%	87.7	106.5
9/12/2014	Fri	1,174	303.2	280.9	22.2	26.1	7.3%	88.6	102.0

Figure 5-1 presents the ex post load impact estimates for the persistent customers alongside those for all ex post customers. 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 generally higher, and also exhibit a stronger relationship with temperature. Due to the relatively high percent impacts of these persistent customers, the estimated percent impacts as estimated from the model have been de-rated by 10% (i.e., multiplied by 0.9). Although it can be argued that persistent customers more closely represent the future program population, this 10% de-rating factor has been applied to adjust for the uncertainty associated with how well these persistent customers represent the future mix of CPP customers.

Figure 5-1: Comparison of 2013–2014 CPP Load Impacts for Persistent and All Ex Post Customers vs. Temperature

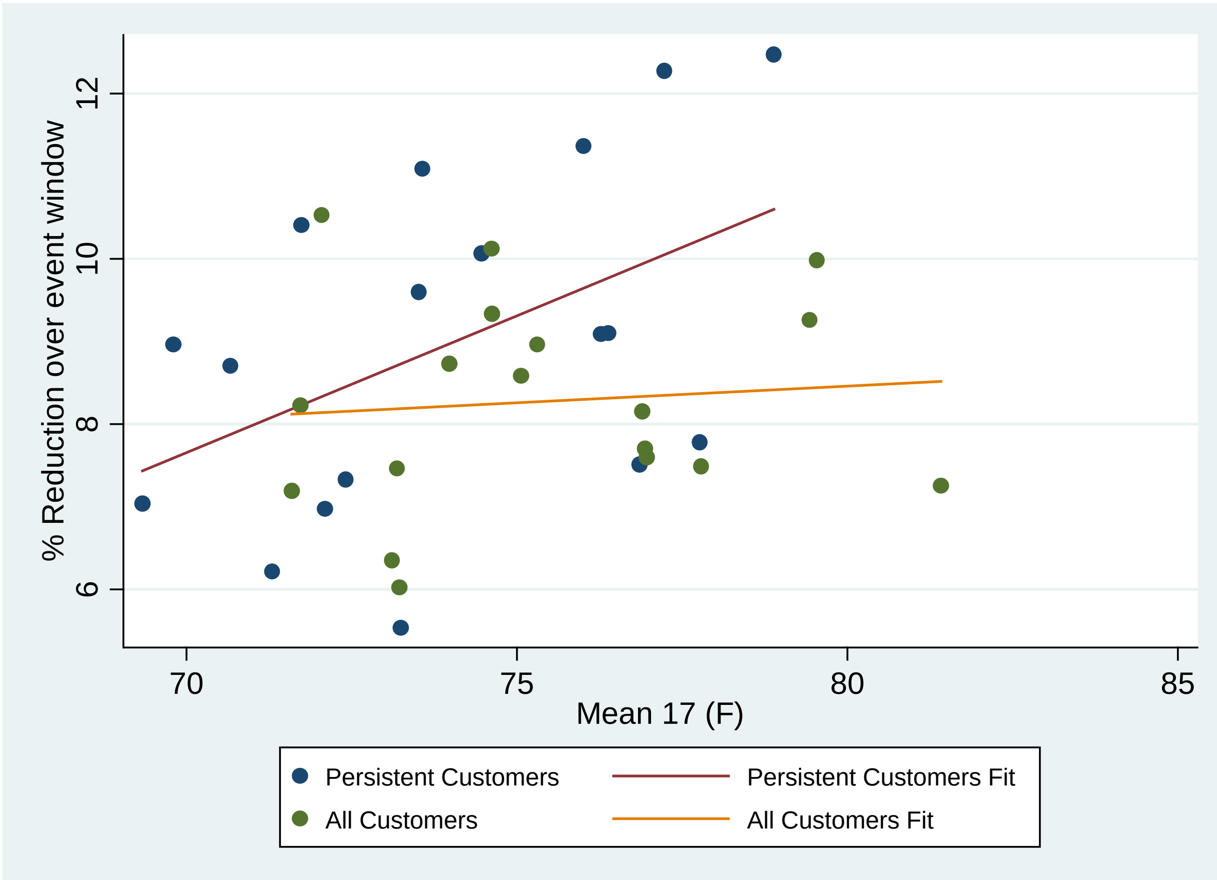


Figure 5-2 compares loads for all ex post customers during non-event days in 2014 to the reference loads for the large ex ante customers. The ex ante customers are the large customers identified using the January 2015 enrollment forecast, which are used for reference load modeling in order to provide the most up to date picture of customers enrolled on CPP. The reference loads from non-event days in May through October are included in the graph (weekends and holidays are also excluded). The average reference load is roughly 30 kW higher for ex ante customers than for the ex post customers for the same days and weather conditions. Furthermore, the reference loads for ex ante customers show a slightly stronger relationship with temperature than those for all ex post customers.

Figure 5-2: Comparison of Reference Loads on Non-event Days for Ex Ante Customers to All Ex Post Customers' Reference Loads

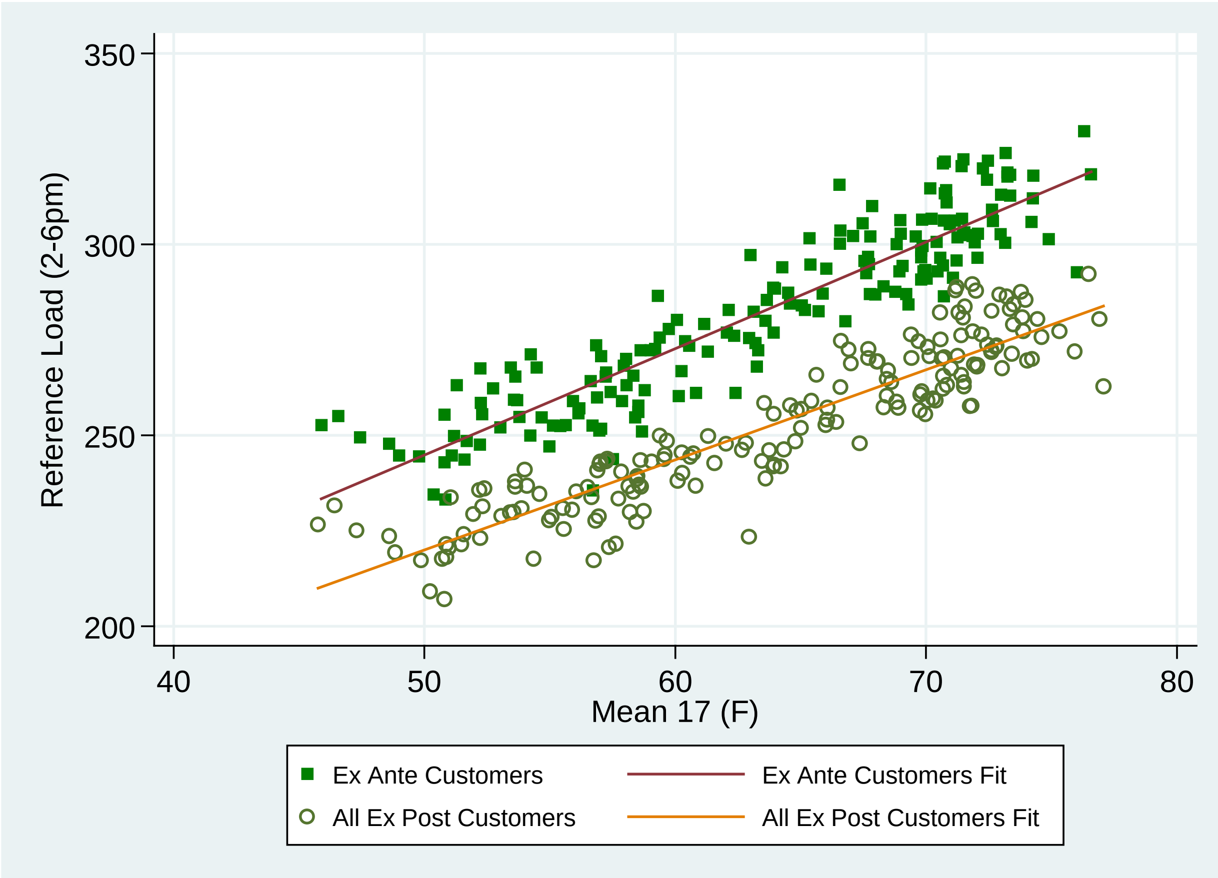


Figure 5-3 illustrates the historical 2013 to 2014 percent reductions (blue squares) as a function of temperature for each LCA. It also includes the percent demand reductions estimated under 1-in-2 and 1-in-10 year weather conditions (green squares) for the months of May to October based on the PG&E weather scenarios (not the CAISO weather). As discussed, the ex ante percent impact estimates are based on the relationship between temperature and percent impacts as estimated in the ex post analysis. However, due to the relatively narrow range of temperatures observed in historical CPP events relative to the temperatures in the ex ante weather conditions, the percent impact model is bounded at *mean17* values that are one degree below the minimum and one degree above the maximum observed *mean17* values in 2013 and 2014 CPP events for each LCA. These bounds ensure that the percent impact model does not produce unreasonable estimates for weather conditions that are far beyond what has been observed in past events. In turn, these percent demand reduction estimates are applied to large customers. For the two LCAs that historically delivered the majority of program impacts—the Greater Bay Area and Other—the relationship between temperature and percentage load reductions is basically flat.

Figure 5-4 compares the customer reference loads during non-event 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 trend observed within each LCA during non-event 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 Northern Coast LCA, loads tend to increase significantly with hotter weather. However, the percent demand reductions tend to decrease with hotter weather and have more influence on the aggregate load reductions.

Figure 5-3: Comparison of 2013–2014 CPP Load Impacts and Summer Ex Ante Load Impacts vs. Temperature by LCA

Figure 5-4: Comparison of Ex Post Reference Loads on Non-event Days to Ex-Ante Reference Loads for Large C&I

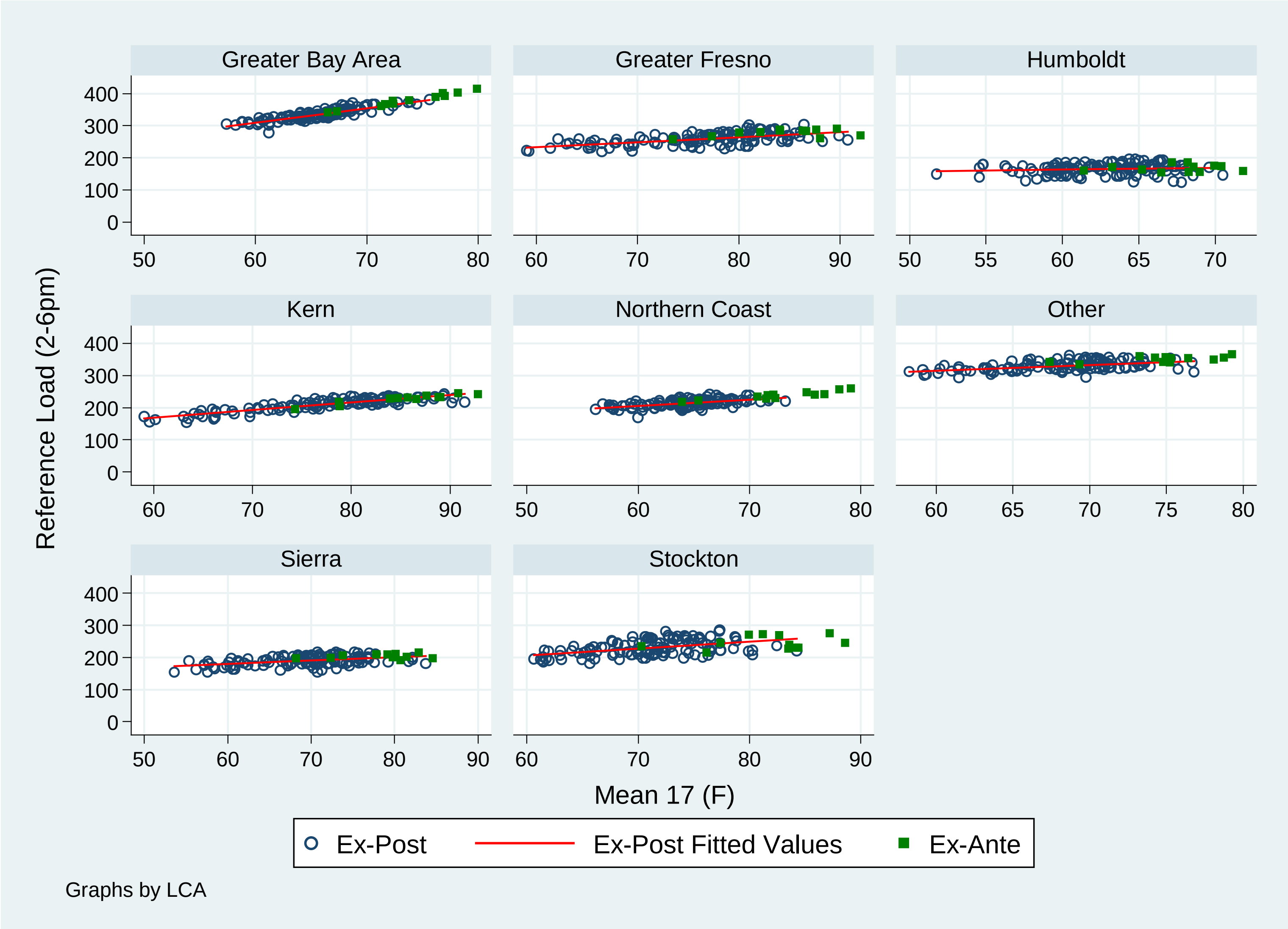


Table 5-2 shows PG&E's enrollment projections for large C&I CPP customers through 2025. PG&E developed the enrollment forecast and underlying assumptions, which are documented in PG&E's *Executive Summary: 2015–2025 Demand Response Portfolio of Pacific Gas and Electric Company*. Due to additional large customers that are scheduled to be defaulted onto CPP, PG&E projects that large C&I CPP enrollment will grow to approximately 2,600 by November 2016 and will then remain essentially flat through 2025.

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.
2015	1,923	1,923	2,092	2,092	2,092	2,092	2,092	2,092	2,092	2,092	2,380	2,380
2016	2,380	2,380	2,594	2,594	2,594	2,594	2,594	2,594	2,594	2,594	2,622	2,622
2025	2,628	2,628	2,629	2,629	2,629	2,629	2,629	2,629	2,629	2,629	2,629	2,629

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 51 MW to almost 65 MW between 2015 and 2025. Impacts based on 1-in-10 year PG&E weather conditions equal roughly 56 MW in 2015 and grow to 72 MW by 2025. These estimates equal roughly 8% of the aggregate reference load for large C&I customers. Impact estimates based on CAISO weather 1-in-2 year conditions are roughly 14% less than the estimates based on PG&E weather. The CAISO 1-in-10 year weather values produce a load reduction that is about 5% 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	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	2015	2,092	704.6	648.4	56.3	8.0%	95.7
		2016	2,594	870.3	799.4	70.9	8.1%	96.0
		2025	2,629	882.0	810.0	72.0	8.2%	96.0
	1-in-2	2015	2,092	676.9	625.9	51.0	7.5%	92.1
		2016	2,594	836.4	772.4	64.0	7.7%	92.4
		2025	2,629	847.7	782.6	65.0	7.7%	92.4
CAISO	1-in-10	2015	2,092	685.2	631.7	53.5	7.8%	92.5
		2016	2,594	846.8	779.4	67.4	8.0%	92.9
		2025	2,629	858.2	789.7	68.4	8.0%	92.9
	1-in-2	2015	2,092	648.3	604.3	44.1	6.8%	89.0
		2016	2,594	801.4	746.3	55.1	6.9%	89.3
		2025	2,629	812.2	756.2	56.0	6.9%	89.3

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 2015, the projected load impacts for August 1-in-2 year, PG&E weather have an 80% confidence interval of 35.0 MW to 66.9 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 5.2% to 9.9%. 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	Impact Uncertainty				
			(MW 1-6 PM)	10th	30th	50th	70th	90th
PG&E	1-in-10	2015	56.3	38.7	49.1	56.3	63.4	73.8
		2016	70.9	49.0	61.9	70.9	79.9	92.8
		2025	72.0	49.8	62.9	72.0	81.1	94.2
	1-in-2	2015	51.0	35.0	44.4	51.0	57.5	66.9
		2016	64.0	44.1	55.9	64.0	72.2	84.0
		2025	65.0	44.8	56.8	65.0	73.3	85.3
CAISO	1-in-10	2015	53.5	37.0	46.7	53.5	60.2	70.0
		2016	67.4	46.7	58.9	67.4	75.8	88.0
		2025	68.4	47.5	59.8	68.4	77.0	89.3
	1-in-2	2015	44.1	29.0	37.9	44.1	50.2	59.1
		2016	55.1	36.2	47.4	55.1	62.8	74.0
		2025	56.0	36.9	48.1	56.0	63.8	75.1

5.1.3 Ex Ante Impacts by Geographic Location and Month

Table 5-5 presents aggregate 2015 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 3 and 4 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 2015 enrollment forecast shows 45% of enrollments located in the Greater Bay Area LCA; and 20% are located outside of the primary LCAs and are classified as Other. Greater Bay Area CPP participants delivered 24% of the program's ex ante load reduction on an average event day while customers classified as Other LCA provided 40% of aggregate ex ante impacts despite only accounting for 20% of the total population. This pattern is similar to that observed in 2014 and 2013 ex post evaluations.

**Table 5-5: Aggregate PG&E Ex Ante Load Impact Estimates by LCA
Large C&I 2015 Monthly System Peak Days, PG&E Weather Scenarios[20]**

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4 to 9 PM Resource Adequacy Window				1 to 6 PM Resource Adequacy Window						4 to 9 PM	
1-in-10	All	15.9	16.1	18.6	28.2	50.4	52.0	57.9	56.3	48.9	44.4	22.9	19.3
	Greater Bay Area	3.6	3.6	3.8	10.0	13.7	14.1	13.4	13.3	13.7	12.9	4.6	3.8
	Greater Fresno	2.3	2.3	2.8	3.4	5.6	6.6	8.2	8.3	4.6	3.5	3.5	2.7
	Humboldt	0.2	0.2	0.3	0.3	1.3	1.0	1.2	1.3	1.1	0.6	0.2	0.2
	Kern	0.2	0.2	0.3	0.5	4.2	4.5	8.3	7.0	3.2	1.5	0.4	0.3
	Northern Coast	0.3	0.3	0.4	0.1	-0.1	-0.1	-0.1	-0.1	-0.1	0.1	0.4	0.4
	Other	7.7	7.7	9.2	11.7	21.1	21.3	21.9	20.9	21.3	21.3	11.6	10.0
	Sierra	0.5	0.5	0.5	0.6	1.3	1.2	1.3	1.4	1.2	1.1	0.6	0.5
	Stockton	1.1	1.1	1.2	1.5	3.3	3.4	3.9	4.2	3.9	3.3	1.6	1.4
1-in-2	All	16.1	16.2	18.2	23.8	40.8	51.1	51.2	51.0	49.2	41.1	22.2	19.8
	Greater Bay Area	3.6	3.7	3.7	5.6	11.1	12.3	12.1	12.4	12.7	11.3	4.4	4.0
	Greater Fresno	2.2	2.2	2.8	3.3	3.6	7.2	6.7	6.7	5.6	3.4	3.4	2.8
	Humboldt	0.2	0.2	0.3	0.3	0.3	0.7	0.9	1.0	0.9	0.3	0.2	0.2
	Kern	0.2	0.2	0.3	0.5	1.7	5.8	5.7	5.2	3.6	1.5	0.4	0.3
	Northern Coast	0.3	0.3	0.4	0.4	0.4	0.1	0.1	0.1	0.1	0.5	0.4	0.4
	Other	7.8	7.7	9.0	11.7	19.7	20.4	21.0	20.3	21.1	20.1	11.3	10.2
	Sierra	0.5	0.5	0.5	0.6	1.1	1.3	1.2	1.3	1.2	1.1	0.6	0.5
	Stockton	1.1	1.2	1.2	1.4	2.9	3.4	3.5	3.9	3.8	3.0	1.5	1.4

5.1.4 Comparison of 2013 and 2014 Ex Ante Estimates

Table 5-6 compares the August ex ante estimates produced for the 2013 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 6% to 21% lower than those produced by PG&E for the 2013 report estimates. This difference is highest in 2015. The adjustment reflects more recent data about the number of customers who will be defaulted onto CPP in the future.

20 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.

Notable differences are also observed in the reference loads, which are roughly 15% higher than those produced in the 2013 report. The percent reductions are similar. The 2014 estimates are driven by percent reductions for persistent default CPP customers that have remained on CPP. These customers deliver larger percent reductions than customers who enroll and then drop off the rate, but are more likely to reflect the percent reductions delivered by customers who persist on the rate into the future (nonetheless, as noted above, these percent impacts do reflect a 10% de-rating factor). However, percent reductions in the hour from 1 to 2 PM are near zero in the 2014 analysis, while in the 2013 analysis this hour's reduction was assumed to be the same as that from 2 to 3 PM. Percent impacts are lower in 2014 using this new approach. The net effect is that this year's forecast for 2015 under 1-in-10 year weather conditions is 56.3 MW, which is 21% lower than last year's forecast of 70.9 MW, with most of the difference due to changes in PG&E's enrollment forecasts, and some due to lower percent impacts over the RA event window. Further into the future, the forecast aggregate impact is greater than that from last year. The aggregate impacts are greater because the differences in enrollment are reduced.

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

Weather Year	Year	Accounts		Reference Loads (MW)		Percent Reductions		Aggregate Impacts (MW)	
		2013 Estimates	2014 Estimates	2014 Estimates	2014 Estimates	2013 Estimates	2014 Estimates	2013 Load Impact (MW)	2014 Load Impact (MW)
1-in-10	2015	2,657	2,092	318.8	336.8	8.4%	8.0%	70.9	56.3
	2016	2,781	2,594	318.7	335.5	8.3%	8.1%	73.7	70.9
	2017-2024	2,783	2,624	318.7	335.7	8.3%	8.1%	73.7	71.8
1-in-2	2015	2,657	2,092	305.2	323.6	7.6%	7.5%	61.3	51.0
	2016	2,781	2,594	305.2	322.4	7.5%	7.7%	63.8	64.0
	2017-2024	2,783	2,624	305.2	322.6	7.5%	7.7%	63.9	64.8

A graphical comparison between the summer ex ante load impacts for large C&I customers as estimated in the 2013 and 2014 load impact evaluation is shown in Figure 5-5. The 2013 ex ante estimates are similar to those estimated this year, but this year's ex ante estimates show a stronger relationship with temperature than the estimates from 2013.

Figure 5-5: Comparison of 2013 Ex Ante Load Impacts to 2014 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 relatively large differences in load impacts. For the typical event day, ex ante impacts are significantly higher when based on PG&E ex ante weather and only slightly higher than ex post values when based on CAISO weather conditions. This change increases the ex ante impacts by roughly 20% for the typical event day under 1-in-2 PG&E weather conditions, as compared to the average 2014 event day. Changes in enrollment between the values used for ex post estimation and the 2015 enrollment values increase impact estimates by about 15%. Finally, the fact that the ex ante model is based on ex post impacts from both 2013 and 2014 for persistent customers, which exhibit a stronger relationship with temperature, will result in higher ex ante load impacts at higher temperature values than ex post impacts at similar values. Furthermore, reference load for the ex ante population enrolled in January 2015, which was used to model reference load for ex ante conditions, is about 30 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: 73 < event day mean17 < 78 Average event day mean17 = 75	Program specific mean17 for 1-in-2 typical event day = 78.1 and 75.6 for PG&E and CAISO weather, respectively Program specific mean17 for 1-in-10 typical event day = 81.7 and 78.8 for PG&E and CAISO weather, respectively	Ex ante estimates are sensitive to variation in mean17 – impacts will be significantly 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 2014 summer	2015 enrollment is forecast to be about 15% higher	Ex ante estimates will be about 15% higher than ex post
Methodology	2014 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 2015	Pooled impacts from 2013 and 2014 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 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. The third column uses the 2014 ex post impacts shown in Table 4-1 and the projected enrollment for August 2015 to produce a scaled-up ex post impact estimate. This leads to an average increase in load reductions of about 15%. The next column shows what the ex ante model would produce using the same August 2015 enrollment figures and the ex post weather conditions for each event day. The ex ante model over predicts load reductions on average by about 12% compared with the 2014 ex post impacts. As discussed earlier, this is the result of estimating ex ante impacts using percent impacts from the persistent population’s 2013 and 2014 ex post values, and the higher reference load of the ex ante population used to predict reference load. The fifth column presents what the ex ante model would produce using the same August 2015 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 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 2014 PG&E ex post weather conditions, 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 7% compared with the impacts from the ex post weather conditions. The CAISO and PG&E 1-in-10 year weather conditions yield impacts of 8% and 5% larger than impacts derived from their respective 1-in-2 year weather conditions.

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

<table>
<tr><th rowspan="2">Date</th><th>Mean 17</th><th>Ex Post Impact</th><th>Ex Post Impact with Ex Ante Enrollment</th><th>Ex Ante Model Ex Post Weather and Event Window</th><th>Ex Ante Model Ex Post Weather RA Event Window</th><th>CAISO 1-in-2</th><th>PG&E 1-in-2</th><th>CAISO 1-in-10</th><th>PG&E 1-in-10</th></tr>
<tr><th>(F)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th><th>(MW)</th></tr>
<tr><td>6/9/2014</td><td>77.8</td><td>38.2</td><td>44.2</td><td>57.3</td><td>50.0</td><td rowspan="11">46.4</td><td rowspan="11">49.7</td><td rowspan="11">50.3</td><td rowspan="11">52.3</td></tr>
<tr><td>6/30/2014</td><td>77.0</td><td>38.0</td><td>43.8</td><td>54.1</td><td>46.8</td></tr>
<tr><td>7/1/2014</td><td>73.2</td><td>29.0</td><td>33.4</td><td>52.9</td><td>46.9</td></tr>
<tr><td>7/7/2014</td><td>71.7</td><td>39.7</td><td>45.7</td><td>49.7</td><td>43.5</td></tr>
<tr><td>7/14/2014</td><td>76.9</td><td>40.8</td><td>47.0</td><td>56.4</td><td>49.2</td></tr>
<tr><td>7/25/2014</td><td>76.9</td><td>39.5</td><td>45.4</td><td>52.5</td><td>45.0</td></tr>
<tr><td>7/28/2014</td><td>74.6</td><td>51.3</td><td>59.1</td><td>54.2</td><td>47.7</td></tr>
<tr><td>7/29/2014</td><td>75.3</td><td>45.8</td><td>52.8</td><td>53.3</td><td>46.5</td></tr>
<tr><td>7/31/2014</td><td>74.6</td><td>48.3</td><td>55.7</td><td>55.4</td><td>49.0</td></tr>
<tr><td>9/12/2014</td><td>73.2</td><td>39.1</td><td>45.2</td><td>48.3</td><td>41.7</td></tr>
<tr><td>Avg.</td><td>75.1</td><td>41.0</td><td>47.2</td><td>53.4</td><td>46.6</td></tr>
</table>

5.2 Medium C&I Ex Ante Impacts

Overall, there is greater uncertainty regarding medium C&I customer impacts under default CPP. To date, default CPP has been implemented on a very limited basis for medium customers and those medium C&I customers who are on the rate are generally not representative of the medium C&I sector as a whole. While some medium customers volunteered onto CPP rates, their mix and demand reductions are not representative of the current and future medium default customer population. The few pilots that tested time varying pricing for small and medium businesses did not do so for default rates, but rather included only customers who volunteered into the pilots. Among such pilots is PG&E's EEP for small and medium CPP customers. In brief, the empirical data on medium customer response is limited.

Previous studies show 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.[21] Nexant therefore used the EPP CPP percent reductions as an upper bound for the expected response of defaulted small and medium customers, and adjusted the overall percent reduction downward by about two-thirds. This yielded percent reductions of 2% and 1.5% for small and medium customers respectively. The reference loads were developed by using a sample of interval data for customers that were defaulted in November 2014 and estimating reference loads for them within each 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 2025. In November 2015 and 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 during those months. Of the customers who were already defaulted in November 2014, 20,267 medium C&I customers are projected to remain on CPP. By November 2015, the medium C&I population is expected to reach enrollment of 27,014 accounts, and 37,579 by November 2016. The enrollment is expected to increase slowly thereafter as a result of growth in accounts. The development and assumptions of PG&E's medium C&I CPP enrollment forecast are documented in PG&E's *Executive Summary: 2015–2025 Demand Response Portfolio of Pacific Gas and Electric Company*.

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.
2015	20,267	20,267	20,267	20,267	20,267	20,267	20,267	20,267	20,267	20,267	27,014	27,014
2016	27,014	27,014	27,014	27,014	27,014	27,014	27,014	27,014	27,014	27,014	37,579	37,579
2017	37,579	37,579	37,579	37,579	37,579	37,579	37,579	37,579	37,579	37,579	38,531	38,531
2025	39,677	39,677	39,677	39,677	39,677	39,677	39,677	39,677	39,677	39,677	39,863	39,863

[21] 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

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 6.5 MW to around 14 MW in 2017 under 1-in-10 weather conditions, and peak at 15 MW in 2025. 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 1.2% 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 8% less than the estimates based on PG&E weather. The CAISO 1-in-10 weather values produce a load reduction that is about 5% 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	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	2015	20,267	550.5	544.0	6.5	1.2%	97.6
		2016	27,014	792.4	783.0	9.4	1.2%	97.0
		2017	37,579	1,182.4	1,168.3	14.0	1.2%	96.6
		2025	39,677	1,261.2	1,246.3	15.0	1.2%	96.5
	1-in-2	2015	20,267	514.1	508.0	6.1	1.2%	93.9
		2016	27,014	739.3	730.5	8.8	1.2%	93.4
		2017	37,579	1,101.8	1,088.7	13.1	1.2%	92.8
		2025	39,677	1,175.0	1,161.1	13.9	1.2%	92.8
CAISO	1-in-10	2015	20,267	528.9	522.6	6.3	1.2%	94.8
		2016	27,014	760.4	751.3	9.0	1.2%	94.1
		2017	37,579	1,132.9	1,119.4	13.4	1.2%	93.5
		2025	39,677	1,208.1	1,193.8	14.3	1.2%	93.4
	1-in-2	2015	20,267	472.6	467.0	5.6	1.2%	90.3
		2016	27,014	678.8	670.7	8.1	1.2%	89.8
		2017	37,579	1,011.0	999.0	12.0	1.2%	89.3
		2025	39,677	1,078.3	1,065.5	12.8	1.2%	89.3

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 1.5% 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 43% 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[22]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4 to 9 PM Resource Adequacy Window				1 to 6 PM Resource Adequacy Window						4 to 9 PM	
1-in-10	All	4.1	3.9	3.9	5.6	13.9	14.6	14.6	14.4	13.8	12.3	4.2	3.9
	Greater Bay Area	2.0	1.9	2.0	2.7	6.4	6.7	6.3	6.2	6.3	5.7	2.0	1.8
	Greater Fresno	0.4	0.3	0.4	0.5	1.3	1.4	1.5	1.5	1.4	1.2	0.4	0.3
	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	0.3	0.3	0.3	0.4	1.1	1.1	1.2	1.2	1.1	0.9	0.3	0.3
	Northern Coast	0.2	0.2	0.2	0.2	0.7	0.7	0.6	0.6	0.7	0.6	0.2	0.2
	Other	0.8	0.7	0.7	1.1	2.8	2.9	3.1	3.0	2.7	2.4	0.8	0.8
	Sierra	0.2	0.2	0.2	0.3	0.7	0.7	0.8	0.8	0.7	0.6	0.2	0.2
	Stockton	0.2	0.2	0.2	0.3	0.8	0.8	0.9	0.9	0.8	0.7	0.2	0.2
1-in-2	All	4.1	3.9	3.9	4.9	11.7	13.4	13.2	13.5	13.2	10.9	4.1	3.9
	Greater Bay Area	2.0	2.0	1.9	2.3	5.2	5.7	5.6	5.8	5.8	5.0	2.0	1.8
	Greater Fresno	0.4	0.3	0.3	0.5	1.3	1.4	1.4	1.5	1.4	1.1	0.4	0.3
	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	0.3	0.3	0.3	0.4	1.0	1.1	1.1	1.1	1.1	0.9	0.3	0.3
	Northern Coast	0.2	0.2	0.2	0.2	0.5	0.6	0.6	0.6	0.6	0.5	0.2	0.2
	Other	0.8	0.7	0.7	1.0	2.4	2.8	2.8	2.8	2.7	2.1	0.8	0.8
	Sierra	0.2	0.2	0.2	0.2	0.6	0.7	0.7	0.7	0.7	0.5	0.2	0.2
	Stockton	0.2	0.2	0.2	0.3	0.7	0.8	0.8	0.8	0.7	0.6	0.2	0.2

22 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, there are no ex post impacts upon which to base ex ante estimates. As discussed in the prior section, a 2% load reduction is assumed to apply to small customers.

Table 5-12 presents PG&E's enrollment projections for small C&I customers through 2025. 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 2015, 2016 and 2017. Of the customers who were already defaulted in November 2014, 151,023 small C&I customers are projected to remain on CPP. By November 2015, the small C&I population is expected to reach enrollment of 185,932 accounts, 203,973 by November 2016, and 240,520 by November 2017. The enrollment is expected to increase slowly thereafter as a result of growth in accounts. The development and assumptions of PG&E's medium C&I CPP enrollment forecast are documented in PG&E's *Executive Summary: 2015–2025 Demand Response Portfolio of Pacific Gas and Electric Company*.

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.
2015	151,023	151,023	151,023	151,023	151,023	151,023	151,023	151,023	151,023	151,023	185,932	185,932
2016	185,932	185,932	185,932	185,932	185,932	185,932	185,932	185,932	185,932	185,932	203,973	203,973
2017	203,973	203,973	203,973	203,973	203,973	203,973	203,973	203,973	203,973	203,973	240,520	240,520
2025	243,264	243,264	243,264	243,264	243,264	243,264	243,264	243,264	243,264	243,264	244,360	244,360

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 7.5 MW to 10.5 MW in 2017 under 1-in-10 weather conditions, and peak at around 13 MW in 2025. 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 2% 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 10% less than the estimates based on PG&E weather. The CAISO 1-in-10 weather values produce a load reduction that is about 5% 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	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	2015	151,023	472.6	465.0	7.5	1.6%	96.4
		2016	185,932	588.5	579.1	9.4	1.6%	95.7
		2017	203,973	656.1	645.7	10.5	1.6%	95.7
		2025	243,264	797.7	785.0	12.7	1.6%	95.6
	1-in-2	2015	151,023	431.4	424.6	6.9	1.6%	92.6
		2016	185,932	537.5	529.0	8.6	1.6%	92.0
		2017	203,973	599.2	589.6	9.5	1.6%	92.0
		2025	243,264	728.4	716.8	11.6	1.6%	91.9
CAISO	1-in-10	2015	151,023	446.6	439.5	7.1	1.6%	93.3
		2016	185,932	556.3	547.5	8.9	1.6%	92.7
		2017	203,973	620.0	610.1	9.9	1.6%	92.7
		2025	243,264	753.6	741.6	12.0	1.6%	92.6
	1-in-2	2015	151,023	387.9	381.7	6.2	1.6%	89.2
		2016	185,932	483.6	475.9	7.7	1.6%	88.7
		2017	203,973	539.2	530.6	8.6	1.6%	88.7
		2025	243,264	655.6	645.2	10.5	1.6%	88.6

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 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 2% 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 18%.

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[23]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4 to 9 PM Resource Adequacy Window				1 to 6 PM Resource Adequacy Window						4 to 9 PM	
1-in-10	All	3.9	3.5	3.3	4.7	12.0	13.0	13.0	12.5	11.8	10.3	3.5	3.8
	Greater Bay Area	2.0	1.9	1.7	2.4	5.9	6.5	6.0	5.8	5.8	5.2	1.8	1.9
	Greater Fresno	0.3	0.2	0.2	0.4	0.9	1.0	1.2	1.1	0.9	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	0.1	0.1	0.2	0.6	0.6	0.7	0.6	0.6	0.5	0.2	0.2
	Northern Coast	0.2	0.2	0.2	0.2	0.7	0.7	0.6	0.6	0.6	0.5	0.2	0.2
	Other	0.8	0.7	0.6	1.0	2.5	2.8	2.9	2.8	2.5	2.2	0.7	0.8
	Sierra	0.2	0.2	0.1	0.2	0.6	0.6	0.7	0.7	0.6	0.5	0.2	0.2
	Stockton	0.2	0.1	0.1	0.2	0.5	0.6	0.7	0.6	0.5	0.5	0.1	0.2
1-in-2	All	3.7	3.5	3.3	4.0	9.4	11.5	11.5	11.5	11.1	8.8	3.4	3.6
	Greater Bay Area	1.9	1.8	1.7	2.0	4.4	5.2	5.2	5.3	5.2	4.4	1.8	1.8
	Greater Fresno	0.3	0.2	0.2	0.3	0.9	1.1	1.1	1.0	1.0	0.7	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	0.1	0.1	0.2	0.5	0.6	0.6	0.6	0.6	0.4	0.2	0.2
	Northern Coast	0.2	0.2	0.2	0.2	0.4	0.6	0.5	0.5	0.5	0.4	0.2	0.2
	Other	0.8	0.7	0.6	0.8	2.1	2.6	2.6	2.6	2.5	1.9	0.7	0.8
	Sierra	0.2	0.2	0.1	0.2	0.5	0.7	0.7	0.6	0.6	0.4	0.2	0.2
	Stockton	0.2	0.1	0.1	0.2	0.4	0.6	0.6	0.6	0.5	0.4	0.1	0.2

[23] 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 2014, with the first occurring on July 8 and the last on September 23. The average number of default CPP customers participating in the 12 SCE CPP events through September was 2,670. 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 in CPP during summer 2014. The highest 2014 enrollment, 2,684 customers, occurred on the September 23 event. The lowest enrollment, 2,658 customers, occurred on the August 28 event.

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 the 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 2014 is referred to as the default CPP population.

There is also another group of customers who were on the CPP rate in 2014: 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 659 opt-in CPP customers at SCE in 2013. In 2014, there were 797 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 may be subject to CPP on a default basis in coming years. 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 2014. The participant-weighted average temperature during the peak period on event days ranged from a low of 80.8°F to a high of 96.4°F. Daily maximum temperatures were higher, ranging from a low of 86.7°F to a high of 102.1°F.

Table 6-1: Default CPP Ex Post Load Impact Estimates by Event Day SCE 2014 CPP Events (2 to 6 PM)

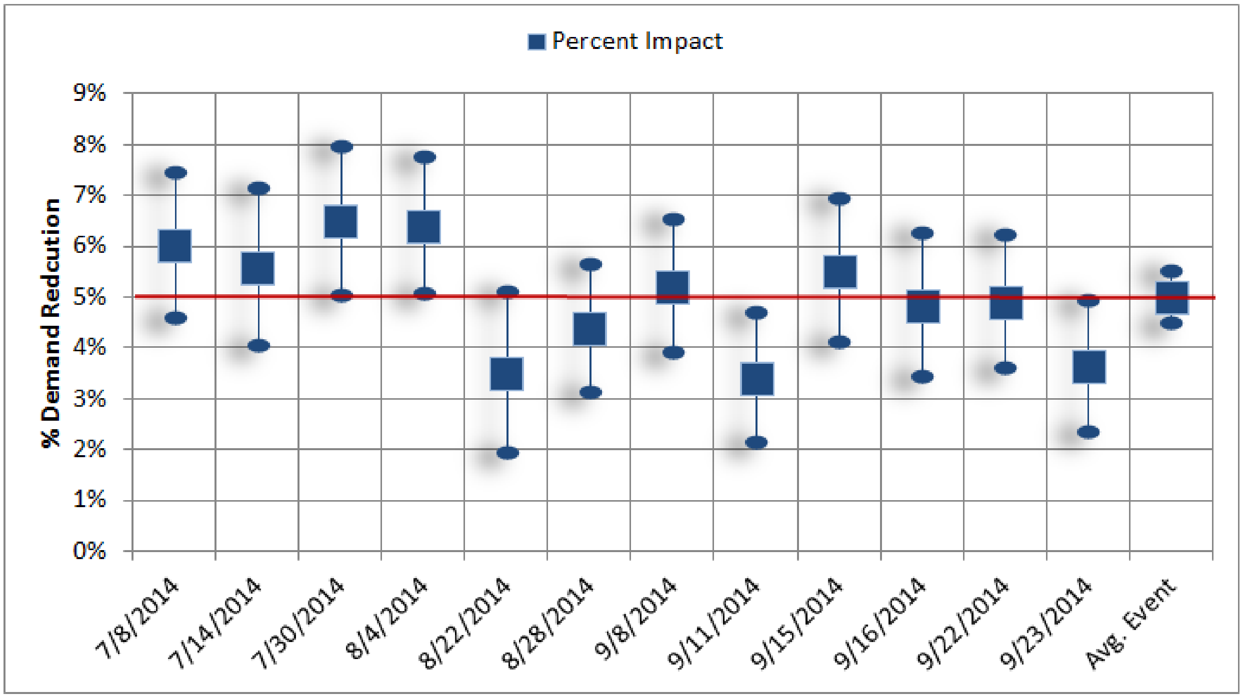
Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp.	Daily Maximum Temp.
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	(°F)
7/8/2014	Tue.	2,672	216.2	203.2	13.0	34.7	6.0%	85.5	95.6
7/14/2014	Mon.	2,663	210.6	198.9	11.7	31.3	5.6%	80.8	91.6
7/30/2014	Wed.	2,662	222.3	207.9	14.4	38.4	6.5%	88.3	95.2
8/4/2014	Mon.	2,660	211.5	198.0	13.5	35.9	6.4%	83.0	89.0
8/22/2014	Fri.	2,660	209.0	201.6	7.4	19.6	3.5%	82.3	89.5
8/28/2014	Thu.	2,658	228.4	218.4	10.0	26.5	4.4%	90.1	95.3
9/8/2014	Mon.	2,674	220.8	209.3	11.5	30.8	5.2%	83.2	86.7
9/11/2014	Thu.	2,676	226.7	219.0	7.7	20.6	3.4%	89.4	95.3
9/15/2014	Mon.	2,678	242.9	229.5	13.4	35.8	5.5%	96.4	102.1
9/16/2014	Tue.	2,677	243.0	231.3	11.7	31.3	4.8%	93.5	101.9
9/22/2014	Mon.	2,683	218.1	207.4	10.7	28.6	4.9%	82.2	88.2
9/23/2014	Tue.	2,684	221.8	213.8	8.0	21.6	3.6%	85.6	91.7
Avg. Event		**2,670**	**222.6**	**211.5**	**11.1**	**29.6**	**5.0%**	**86.7**	**92.2**

Percent impacts ranged from 3.4% to 6.5%, average customer impacts ranged from 7.4 kW to 14.4 kW and aggregate impacts ranged from 19.6 MW to 38.4 MW. On the average event day, the average participant reduced peak period load by 5.0% or 11.1 kW. In aggregate, SCE's CPP customers reduced load by 29.6 MW on average across the 12 event days from July through September 2014.

Figure 6-1 shows the ex post load impact estimates for 2014 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.[24]

[24] 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 2014 CPP Events (2 to 6 PM)



6.1 Average Event Day Impacts

Figure 6-2 shows the aggregate hourly impact for CPP customers for the average event in 2014. Percent reductions are similar across event hours. Demand reductions vary between 26.4 MW and 32.0 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 2014 event day are fairly constant over the hours in the event window, whereas in 2013 the impact was slightly stronger in the early hours of the event. The overall magnitude of the hourly load impacts is slightly lower in 2014: percent impact for the average event day in 2014 and 2013 were 5.0% and 5.9%, yielding 29.6 MW and 35.5 MW, respectively, of load impact. This 17% decrease in CPP load reductions relative to 2013 is addressed in the next section. The decrease in load impact MWs relative to the decrease in percentage load impacts, which decreased by 15%, was enhanced by decreased reference loads overall: the average default CPP customer's reference load was 245.5 kW in 2013 while it was 222.6 kW in 2014.

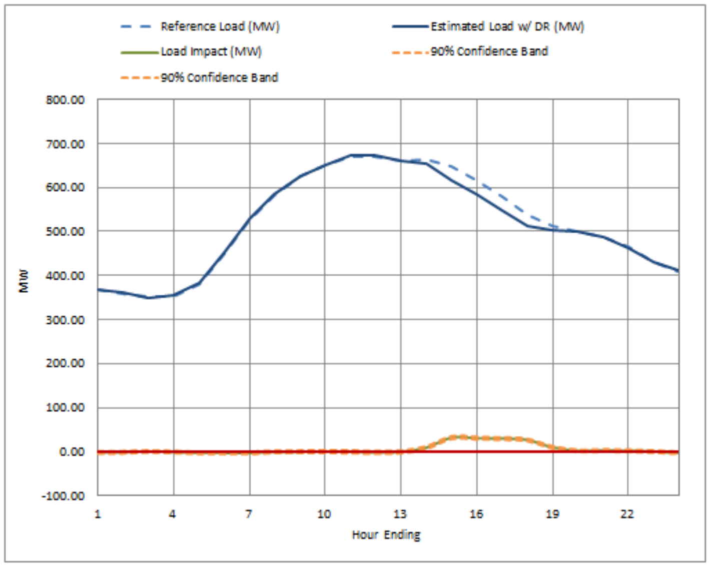
Figure 6-2: Hourly Default CPP Ex Post Load Impacts Average 2014 SCE CPP Event

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	2,670
Avg. Load Reduction for Event Window (MW)	29.6
% 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	366.7	368.8	-2.1	-0.6%	71.4	-4.3	-3.0	-2.1	-1.2	0.1
2	358.5	360.1	-1.5	-0.4%	70.6	-3.7	-2.4	-1.5	-0.7	0.6
3	350.7	350.4	0.3	0.1%	70.0	-1.7	-0.5	0.3	1.2	2.4
4	353.3	354.5	-1.1	-0.3%	69.4	-3.2	-2.0	-1.1	-0.3	0.9
5	381.4	384.3	-2.9	-0.7%	68.7	-4.9	-3.7	-2.9	-2.0	-0.8
6	449.9	452.7	-2.8	-0.6%	68.2	-4.8	-3.6	-2.8	-1.9	-0.7
7	526.3	529.3	-3.0	-0.6%	68.1	-5.1	-3.9	-3.0	-2.1	-0.9
8	582.9	583.5	-0.7	-0.1%	70.1	-2.9	-1.6	-0.7	0.3	1.6
9	625.5	626.0	-0.4	-0.1%	73.7	-2.8	-1.4	-0.4	0.6	2.0
10	650.3	649.9	0.4	0.1%	77.3	-2.1	-0.6	0.4	1.5	3.0
11	671.3	671.7	-0.4	-0.1%	80.6	-3.1	-1.5	-0.4	0.7	2.3
12	671.0	672.8	-1.8	-0.3%	83.1	-4.4	-2.8	-1.8	-0.7	0.8
13	659.4	660.0	-0.6	-0.1%	85.3	-3.1	-1.7	-0.6	0.4	1.9
14	663.2	654.2	9.0	1.4%	86.5	6.5	7.9	9.0	10.0	11.5
15	647.0	615.0	32.0	4.9%	87.2	29.5	31.0	32.0	33.0	34.5
16	615.2	584.7	30.5	5.0%	87.5	28.1	29.5	30.5	31.5	32.9
17	577.4	547.9	29.5	5.1%	86.8	27.3	28.6	29.5	30.5	31.8
18	538.1	511.7	26.4	4.9%	85.2	24.2	25.5	26.4	27.3	28.6
19	511.8	502.3	9.5	1.9%	82.6	7.3	8.6	9.5	10.4	11.7
20	500.8	499.1	1.7	0.3%	79.0	-0.5	0.8	1.7	2.6	3.9
21	488.9	486.3	2.5	0.5%	76.5	0.4	1.6	2.5	3.4	4.7
22	463.9	462.3	1.6	0.3%	74.9	-0.5	0.7	1.6	2.5	3.8
23	430.8	430.7	0.1	0.0%	73.5	-2.0	-0.8	0.1	0.9	2.1
24	408.5	411.1	-2.6	-0.6%	72.4	-4.6	-3.4	-2.6	-1.8	-0.6
	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
Daily	12492.7	12369.0	123.7	1.0%	288.7	112.6	119.1	123.7	128.2	134.8

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 five industries presented in Table 6-2 are statistically significant. The load impact for Institutional/Government and Schools sectors are not statistically significant. The largest industry segment in SCE's default CPP population is Manufacturing, with 729 enrolled accounts. These customers produced the strongest (statistically significant) percentage load impacts of 12.4%.

Table 6-2: Default CPP Ex Post Load Impact Estimates by Industry Average 2013 SCE CPP Event (2 to 6 PM)

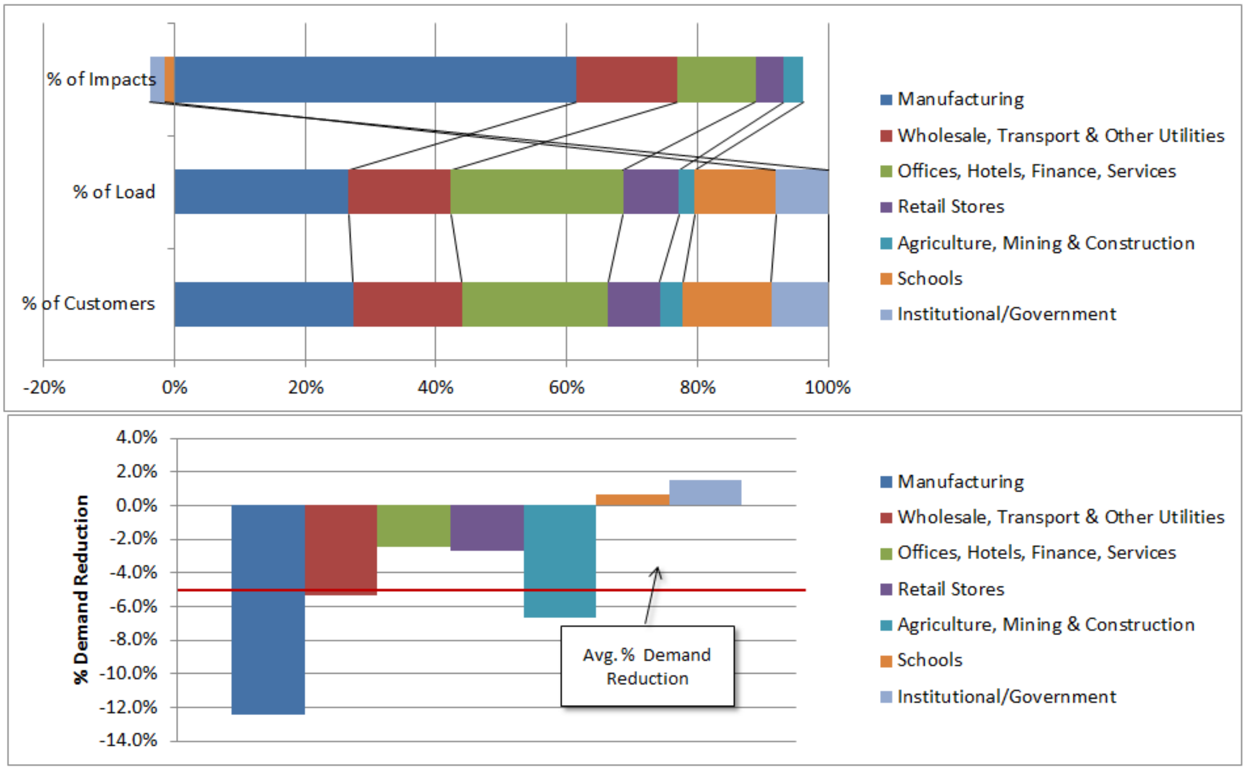
Industry	Accounts		Aggregate Reference Load		Aggregate Impact		Average Impact	% Reduction	Stat. Sig?
	Enrollment	% of Program	MW	% of Program	MW	% of Program	kW		
Manufacturing	729	27.3%	158.1	26.6%	19.6	66.6%	26.9	12.4%	Yes
Wholesale, Transport & Other Utilities	444	16.6%	92.7	15.6%	4.9	16.7%	11.1	5.3%	Yes
Offices, Hotels, Finance, Services	598	22.4%	157.1	26.4%	3.8	12.9%	6.4	2.4%	Yes
Retail Stores	209	7.8%	50.7	8.5%	1.4	4.6%	6.5	2.7%	Yes
Agriculture, Mining & Construction	94	3.5%	14.3	2.4%	1.0	3.2%	10.1	6.7%	Yes
Schools*	362	13.6%	73.6	12.4%	-0.5	-1.7%	-1.4	-0.7%	No
Institutional/Government*	232	8.7%	47.5	8.0%	-0.7	-2.4%	-3.1	-1.5%	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 67% of the aggregate load reduction on the average event day, while comprising only 27% of program enrollment. When combined with Wholesale, Transport & Other Utilities, the two segments account for 44% 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 statistically significant load reductions. The Institutional/Government segment also showed statistically insignificant 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 2014 SCE CPP Event (2 to 6 PM)



Before addressing differences between 2013 and 2014 load impacts, we note that comparisons across years must be made conservatively, as the matching and modeling across years vary. The matching approach in 2014 differed from that in 2013, so some difference may be an artifact of modeling. Relative to 2013, the industry with the most influence on CPP load impacts at SCE, Manufacturing, delivered weaker load impacts: 12.4% in 2014 versus 15.0% in 2013. Enrollment increased in the Retail Stores and Offices, Hotels, Finance, Services sectors by 14% and 21%, respectively. These sectors delivered modest load impacts. Wholesale, Transport and Other Utilities, and Offices, Hotels, Finance, Services were the only sectors in which delivered load impacts increased. Average customer reference load decreased across all sectors, but fell the most in Wholesale, Transport and Other Utilities, where it fell by 29% from 256.8 kW in 2013 to 208.8 kW in 2014.

6.3 Load Impacts by Local Capacity Area

Table 5-3 shows the estimated ex post load impacts by local capacity area (LCA). In total, 83% of enrolled customers and 86% 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	Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. sig?
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
Local Capacity Area	LA Basin	2,210	227.6	216.1	11.5	25.5	5.1%	86.8	Yes
	Outside	164	206.7	195.8	10.9	1.8	5.3%	89.6	Yes
	Ventura	295	194.3	186.3	8.1	2.4	4.2%	83.9	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 increase with customers size at SCE.

Table 6-4: Default CPP Ex Post Load Impact Estimates by Customer Size
Average 2014 SCE CPP Event (2 to 6 PM)

By Annual kWh/h	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig?
		(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
Size: Over 200kW	2,415	239.0	226.8	12.1	29.3	5.1%	86.6	Yes
Size: 20 kW to 199.99 kW*	228	74.7	74.2	0.5	0.1	0.7%	87.5	No
Size: Under 20 kW*	26	-0.4	0.7	-1.1	0.0	277.4%	90.7	No
5th Quintile	518	520.4	486.3	34.1	17.7	6.5%	86.5	Yes
4th Quintile	520	236.8	226.4	10.4	5.4	4.4%	85.8	Yes
3rd Quintile	540	177.4	171.1	6.3	3.4	3.6%	86.3	Yes
2nd Quintile	548	133.5	129.1	4.3	2.4	3.3%	87.0	Yes
1st Quintile	543	60.3	59.0	1.3	0.7	2.1%	87.7	No

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

6.5 Load Impacts for Multi-DR Program Participants

CPP customers can also enroll in several other DR programs at SCE, including the Agricultural Pumping-Interruptible program (API), Base Interruptible Program (BIP), Demand Response Resource Contracts (DRRC) and the Capacity Bidding Program (CBP). 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 2013, they accounted for 52% of program impacts and in 2014, the relatively few dually-enrolled CPP customers still accounted for 49% of CPP load impacts at SCE.

In 2014, 164 accounts were dually enrolled in one of the four DR programs listed above. Dual enrollment in BIP grew from 33 to 34 customers from 2013 to 2014. Dual enrollment in aggregator programs grew from 101 to 125 customers from 2013 to 2014. 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 2014 SCE CPP Event (2 to 6 PM)

Dual Enrollment	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig?
		(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
BIP	34	338.0	196.9	141.1	4.8	41.7%	88.0	Yes
DRC	106	337.6	273.9	63.7	6.8	18.9%	89.0	Yes
DRC CBP	19	410.2	254.4	155.7	3.0	38.0%	87.6	Yes
Other DR: None	2,504	215.1	209.0	6.1	15.2	2.8%	86.6	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 2014 CPP events, there were 59 customers enrolled in CPP with AutoDR, up from 14 in 2013. 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 Average 2014 SCE CPP Event (2 to 6 PM)

Enabling Technology	Accounts	Load Impact	% Reduction	90% Confidence Interval		Approved kW	Realization Rate
		(kW)	(%)	Lower	Upper	(%)	(%)
Auto DR	59	98.3	20.3%	82.1	114.4	264.7	37%
Auto DR/TA&TI: None	2,607	6.5	3.1%	5.4	7.6	NA	NA

7 SCE Ex Ante Load Impacts

This section presents ex ante load impact estimates for SCE's non-residential 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 2013 and 2014 for the group of persistent customers that remained on the CPP tariff for both years. In total, load impact estimates for up to 22 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., 2015, 2016, 2017 and 2025),[25] 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 2013 and 2014 for the group of persistent customers who were enrolled in all 2013 and 2014 event days.

The persistent customer population is a subset of the 2014 CPP population. As such, they deliver different load impacts. Their load impacts are used for ex ante modeling, so in order to demonstrate how ex ante load impacts are derived from ex post impacts, we addressed the difference in impacts below.

Table 7-1 shows the ex post load impact estimates for each event day and for the average event day in 2013 and 2014 for large, persistent customers. The participant-weighted average temperature during the event period ranged from a low of 80.8°F to a high of 96.5°F. Percent impacts ranged from 3.4% to 7.8%; average impacts ranged from 7.7 kW to 17.0 kW; and aggregate impacts ranged from 15.9 MW to 35.3 MW.

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25 Enrollment is not forecasted to change substantially between 2017 and 2025 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.

Table 7-1: Default CPP Ex Post Load Impact Estimates for Persistent Customers by Event Day SCE 2013, 2014 CPP Events (2 to 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)
7/1/2013	Mon	2,076	239.1	231.0	8.0	16.7	3.4%	90.2	100.4
7/3/2013	Wed	2,076	224.5	216.8	7.7	15.9	3.4%	83.2	100.9
8/21/2013	Wed	2,076	247.3	231.9	15.4	31.9	6.2%	86.5	98.4
8/28/2013	Wed	2,076	261.2	245.8	15.4	32.0	5.9%	89.5	97.3
8/30/2013	Fri	2,076	255.4	240.0	15.3	31.9	6.0%	89.3	94.5
9/4/2013	Wed	2,076	267.5	255.7	11.8	24.5	4.4%	91.8	97.9
9/6/2013	Fri	2,076	255.1	241.6	13.6	28.1	5.3%	92.0	97.7
9/13/2013	Fri	2,076	236.4	226.5	9.9	20.5	4.2%	85.0	94.4
9/23/2013	Mon	2,076	244.4	227.4	17.0	35.3	6.9%	87.0	90.5
9/30/2013	Mon	2,076	232.8	216.7	16.1	33.4	6.9%	80.7	87.2
7/8/2014	Tue	2,076	212.5	202.5	10.0	20.8	4.7%	85.5	93.2
7/14/2014	Mon	2,076	206.2	198.5	7.7	15.9	3.7%	80.8	89.4
7/30/2014	Wed	2,076	223.8	207.5	16.3	33.8	7.3%	88.4	94.4
8/4/2014	Mon	2,076	214.9	198.1	16.8	35.0	7.8%	83.0	86.8
8/22/2014	Fri	2,076	212.9	202.1	10.7	22.3	5.0%	82.3	85.9
8/28/2014	Thu	2,076	233.8	222.3	11.6	24.0	4.9%	90.1	95.4
9/8/2014	Mon	2,076	223.9	212.3	11.5	23.9	5.1%	83.2	87.1
9/11/2014	Thu	2,076	233.2	222.8	10.4	21.5	4.4%	89.5	94.7
9/15/2014	Mon	2,076	246.2	234.0	12.2	25.3	5.0%	96.5	102.2
9/16/2014	Tue	2,076	246.5	236.0	10.5	21.9	4.3%	93.5	100.7
9/22/2014	Mon	2,076	222.4	212.5	10.0	20.7	4.5%	82.2	88.1
9/23/2014	Tue	2,076	228.7	219.6	9.1	18.9	4.0%	85.7	91.9

Figure 7-1 presents the ex post load impact estimates for the persistent customers alongside those for all ex post customers. 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 lower, but exhibit a similar relationship with temperature.

Figure 7-1: Comparison of 2013–2014 CPP Load Impacts for Persistent and All Ex Post Customers vs. Temperature

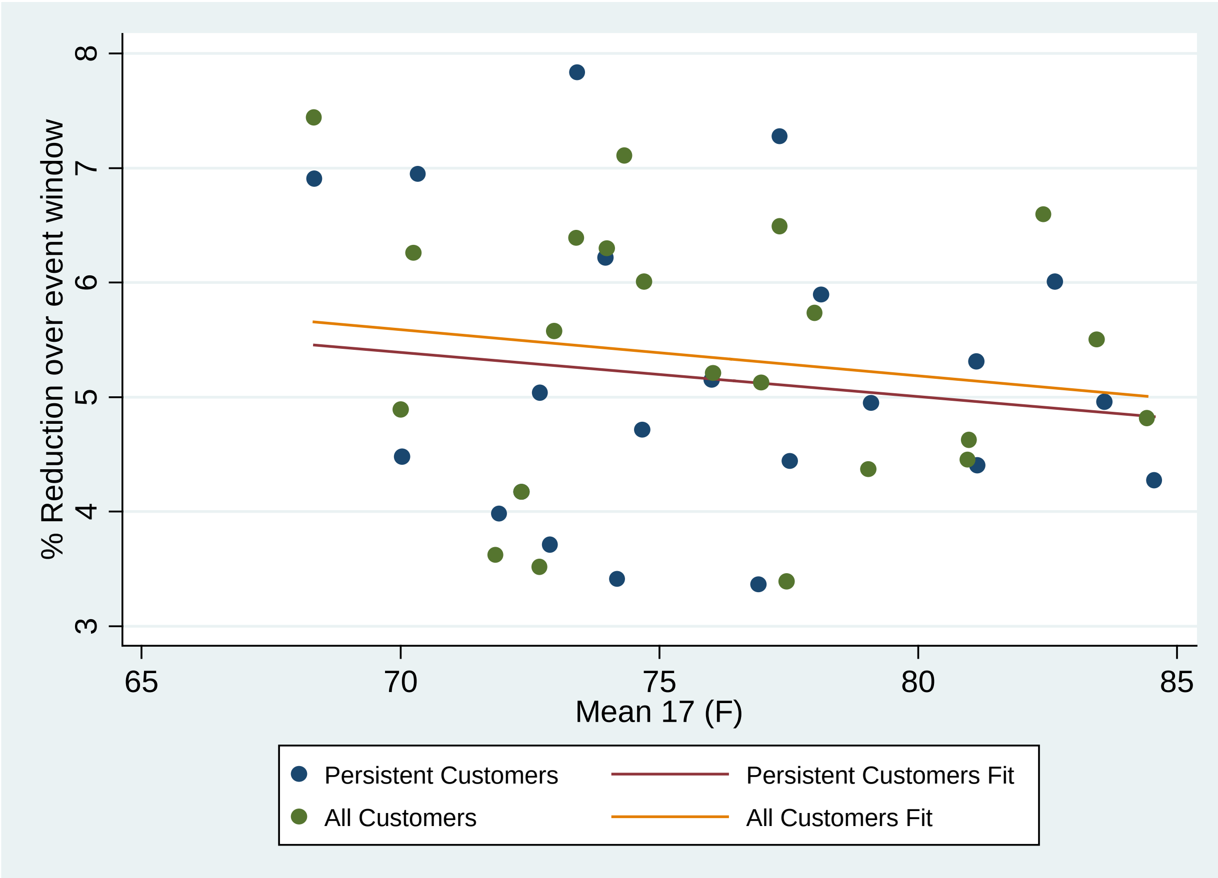


Figure 7-2 compares loads for all ex post customers during non-event days in 2014 to the reference loads for the large ex ante customers. The ex ante customers are the large customers with a full year of interval data identified as enrolled at the end of summer 2014, which are used for reference load modeling to provide an up to date picture of customers enrolled on CPP. The reference loads from non-event days in May through October are included in the graph (weekends and holidays are also excluded). The average reference load of ex ante customers is similar to 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.

Figure 7-2: Comparison of Reference Loads on Non-event Days for Ex Ante Customers to All Ex Post Customers' Reference Loads

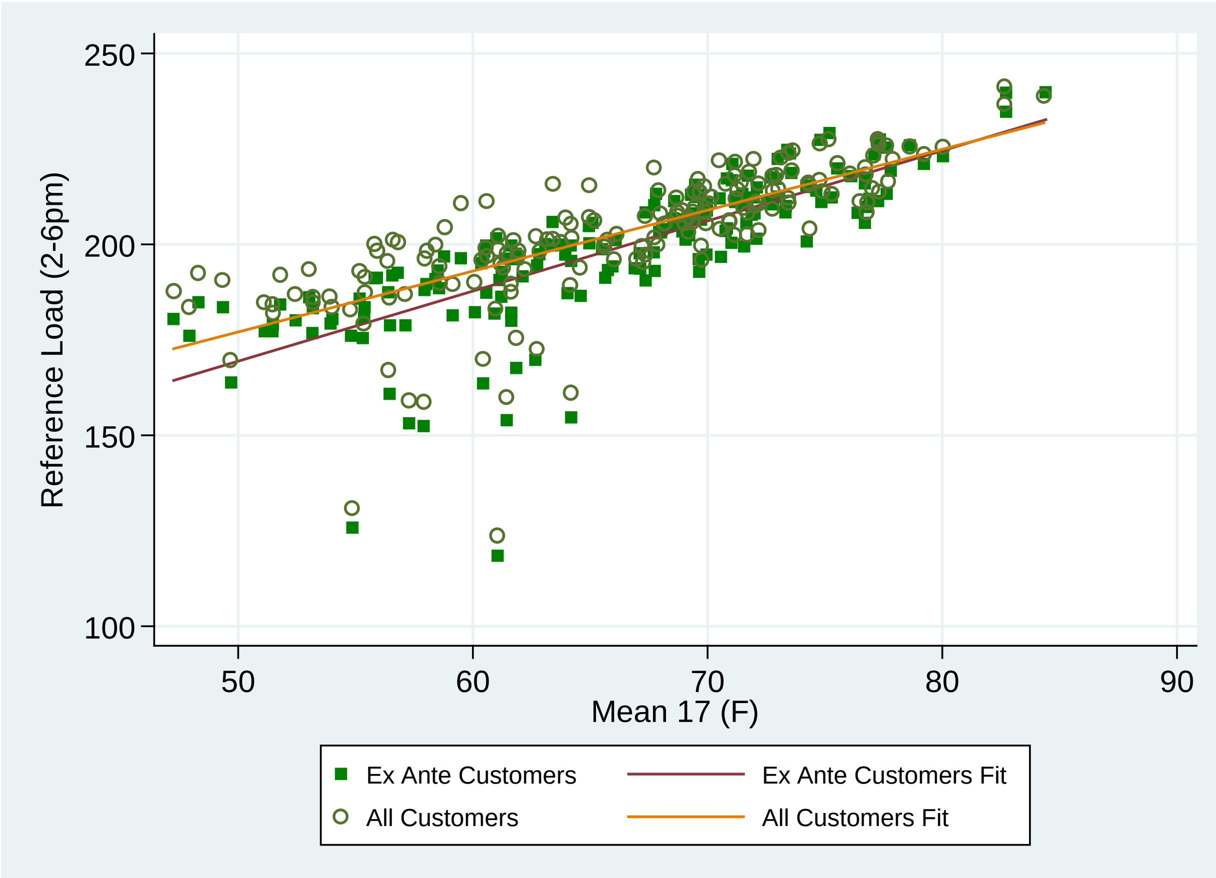


Figure 7-3 illustrates the historical 2013 to 2014 percent reductions (blue squares) as a function of temperature for each transmission planning area. It also includes the percent demand reductions estimated under 1-in-2 and 1-in-10 year weather conditions (green squares) for the months of May through October based on the SCE weather scenarios (not the CAISO weather). These percent demand reduction estimates were applied to large customers. All transmission planning areas deliver slightly lower percentage load reductions with higher temperatures; this result may be the result of random noise or that load impacts are not related to temperature.

Figure 7-4 compares the customer reference loads during non-event 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 non-event 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 Orange County 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 7-3: Comparison of 2013–2014 CPP Load Impacts and Summer Ex-Ante Load Impacts vs. Temperature by LCA

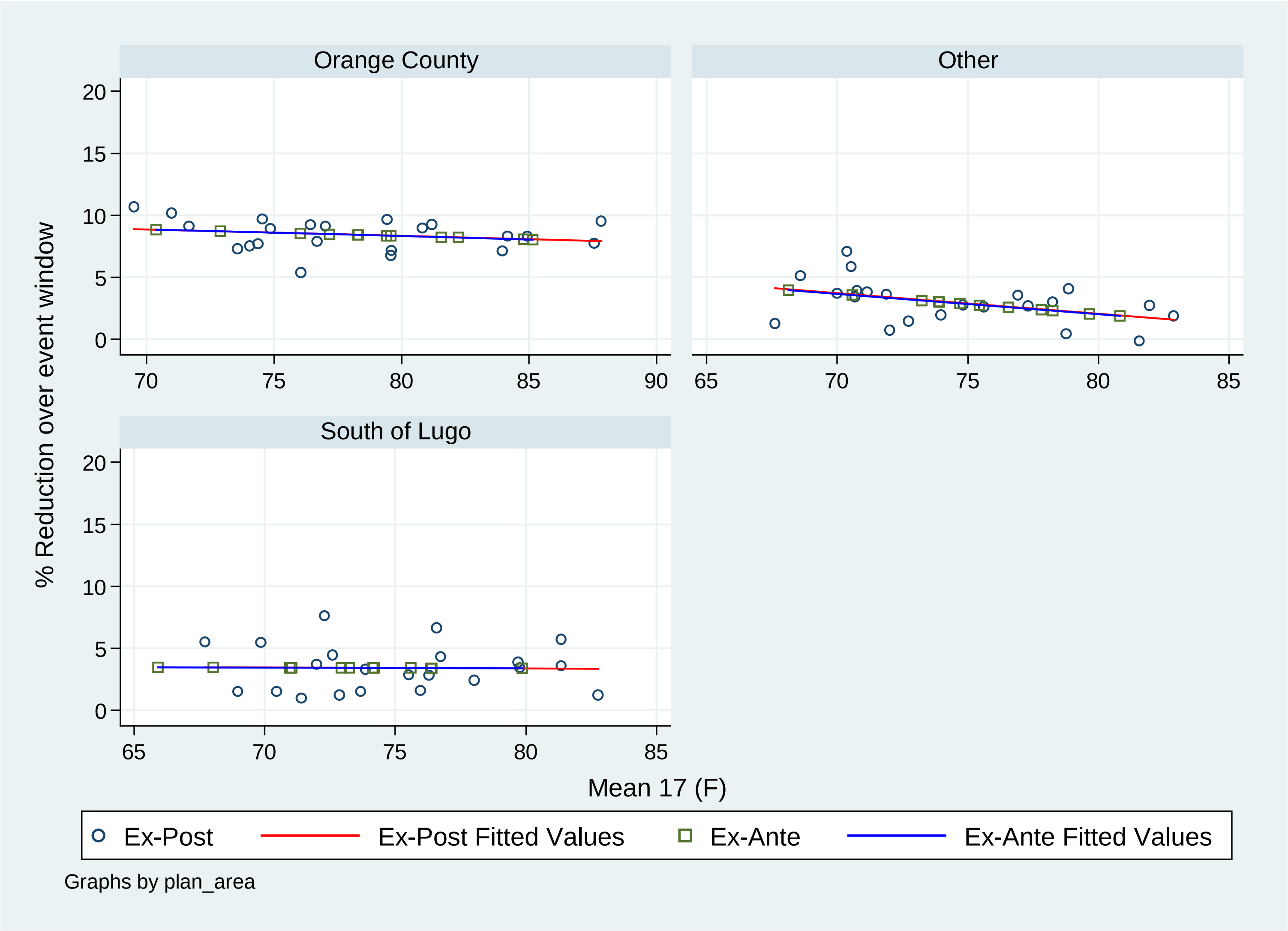


Figure 7-4: Comparison of Ex Post Loads on Non-event Days to Ex-Ante Reference Loads for Large C&I

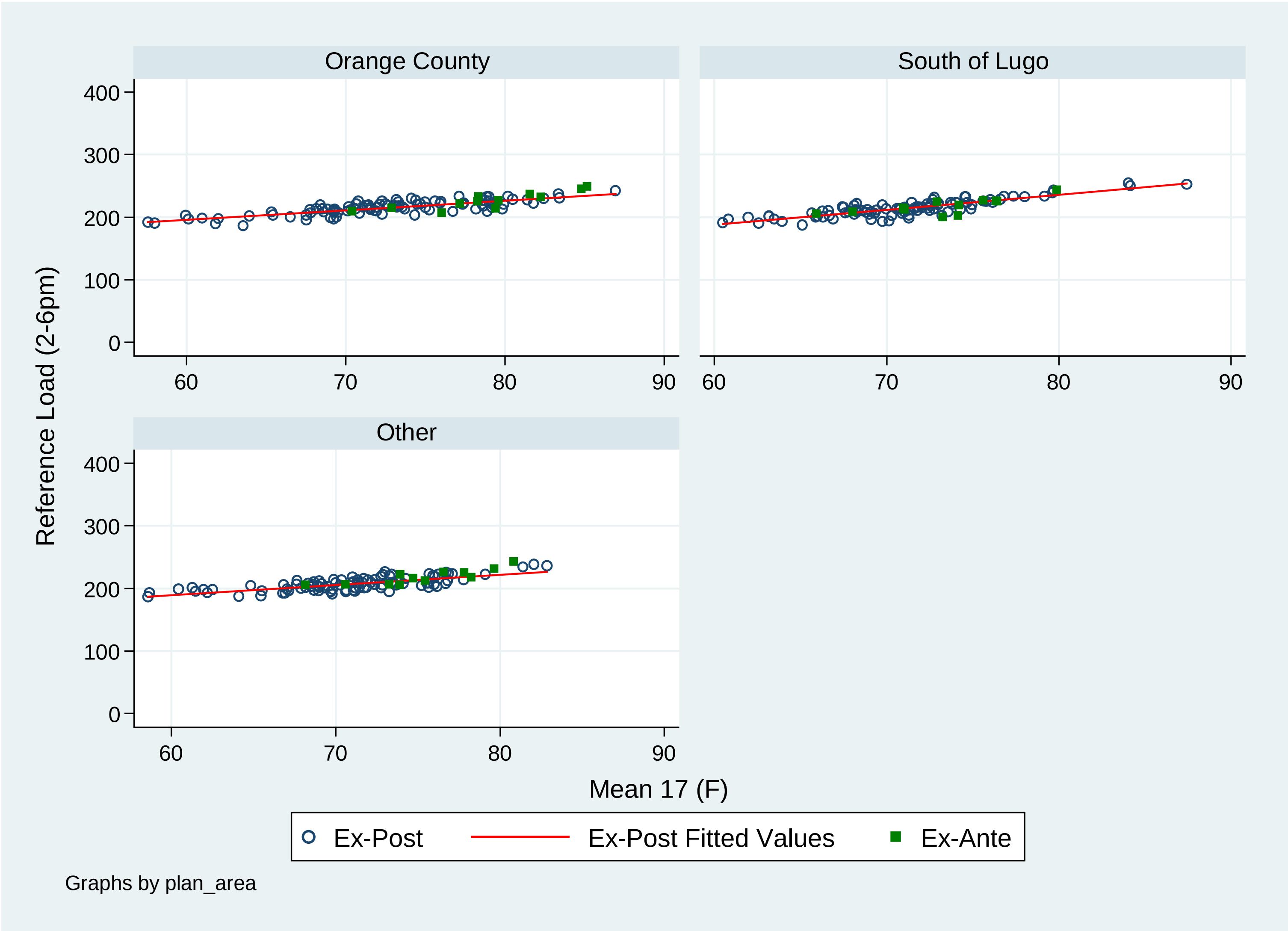


Table 7-2 shows SCE's enrollment projections for large C&I CPP customers through 2025. SCE projects that large C&I CPP enrollment will grow by 3.2% per year to approximately 3,534 customers by December 2025.

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.
2015	2,539	2,539	2,542	2,546	2,549	2,553	2,556	2,560	2,563	2,567	2,570	2,574
2016	2,574	2,574	2,574	2,574	2,574	2,574	2,574	2,574	2,574	2,574	2,574	2,657
2025	3,424	3,424	3,424	3,424	3,424	3,424	3,424	3,424	3,424	3,424	3,424	3,534

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 roughly 21 MW to almost 29 MW between 2015 and 2025. Impacts based on 1-in-10 year SCE weather conditions equal roughly 20 MW in 2015 and will grow to 27 MW by 2025. These estimates equal roughly 3.5% of the aggregate reference load for large C&I customers. Impact estimates based on CAISO weather conditions are roughly 2% higher 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	2015	2,560	619.1	598.7	20.3	3.3%	95.6
		2016	2,574	622.4	602.0	20.5	3.3%	95.6
		2025	3,424	827.9	800.7	27.2	3.3%	95.6
	1-in-2	2015	2,560	602.1	580.8	21.3	3.5%	92.8
		2016	2,574	605.4	584.0	21.4	3.5%	92.8
		2025	3,424	805.2	776.7	28.5	3.5%	92.8
CAISO	1-in-10	2015	2,560	612.3	591.6	20.8	3.4%	93.9
		2016	2,574	615.7	594.8	20.9	3.4%	93.9
		2025	3,424	818.9	791.1	27.8	3.4%	93.9
	1-in-2	2015	2,560	595.4	573.7	21.7	3.7%	92.2
		2016	2,574	598.7	576.8	21.9	3.7%	92.2
		2025	3,424	796.3	767.2	29.1	3.7%	92.2

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 2015, the projected load impacts for August 1-in-2 year, SCE weather have an 80% confidence interval of 11.5 MW to 31.1 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 1.9% to 5.2%. 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 to 6 PM)

Weather Type	Weather Year	Year	Expected Aggregate Load Impact	Impact Uncertainty				
			(MW 1–6 PM)	10th	30th	50th	70th	90th
SCE	1-in-10	2015	20.3	10.1	16.1	20.3	24.5	30.6
		2016	20.5	10.1	16.2	20.5	24.7	30.8
		2025	27.2	13.4	21.6	27.2	32.8	41.0
	1-in-2	2015	21.3	11.5	17.3	21.3	25.3	31.1
		2016	21.4	11.5	17.4	21.4	25.4	31.3
		2025	28.5	15.3	23.1	28.5	33.8	41.6
CAISO	1-in-10	2015	20.8	10.7	16.6	20.8	24.9	30.8
		2016	20.9	10.7	16.7	20.9	25.0	31.0
		2025	27.8	14.3	22.3	27.8	33.3	41.3
	1-in-2	2015	21.7	12.1	17.8	21.7	25.7	31.4
		2016	21.9	12.2	17.9	21.9	25.8	31.6
		2025	29.1	16.2	23.8	29.1	34.4	42.0

7.1.3 Ex Ante Impacts by Geographic Location and Month

Table 7-5 presents aggregate 2015 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 2015 enrollment forecast shows 34% of enrollments located in Orange County, and 56% of enrollments located in the Other transmission planning area. Customers classified as Orange County transmission planning area provided 67% of aggregate ex ante impacts 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 2015 Monthly System Peak Days, SCE Weather Scenarios[26]

Weather Year	Local Capacity Area	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
		4 to 9 PM Resource Adequacy Window				1 to 6 PM Resource Adequacy Window						4 to 9 PM	
1-in-10	All	15.0	14.6	15.3	14.0	21.6	22.4	20.5	20.3	20.2	21.0	14.5	14.2
	Orange County	5.9	5.8	6.2	6.6	13.9	13.9	13.9	14.3	14.5	13.2	6.5	5.6
	South of Lugo	0.3	0.3	0.3	0.4	1.6	1.6	1.6	1.6	1.7	1.5	0.4	0.3
	Other	8.8	8.5	8.7	7.0	6.1	6.8	5.0	4.4	3.9	6.4	7.6	8.3
1-in-2	All	14.6	14.6	15.0	15.6	25.5	24.2	22.4	21.3	23.6	22.0	15.8	14.2
	Orange County	5.8	5.8	6.0	6.3	13.9	13.9	13.8	14.3	14.5	13.1	6.4	5.6
	South of Lugo	0.3	0.3	0.3	0.4	1.5	1.6	1.6	1.6	1.7	1.5	0.3	0.3
	Other	8.5	8.4	8.6	8.9	10.0	8.8	7.0	5.4	7.5	7.4	9.1	8.3

7.1.4 Comparison of 2013 and 2014 Ex Ante Estimates

Table 7-6 compares the August ex ante estimates produced for the 2013 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 40% lower than those produced in the 2013 report. The 2014 estimates are driven by percent reductions for persistent default CPP customers that have remained on CPP. These customers deliver lower percent reductions than the whole 2014 population, but are more likely to reflect the percent reductions delivered by customers who persist on the rate into the future. Additionally, 2014 impact estimates were lower than those in 2012 and 2013, which were used to estimate ex ante load impacts in the 2013 analysis. Finally in the 2014 analysis, estimates for the 1 to 2 PM hour were not estimated using those from the 2 to 3 PM hour, unlike in the 2013 analysis. Thus percent impacts in the RA event window from 1 to 6 PM are about 20% lower than percent impacts in the 2 to 6 PM window. The net effect is that this year's forecast for 2015 is 21.3 MW, which is 40% lower than last year's forecast of 35.5 MW, with most of the difference due to changes in SCE customer response to CPP.

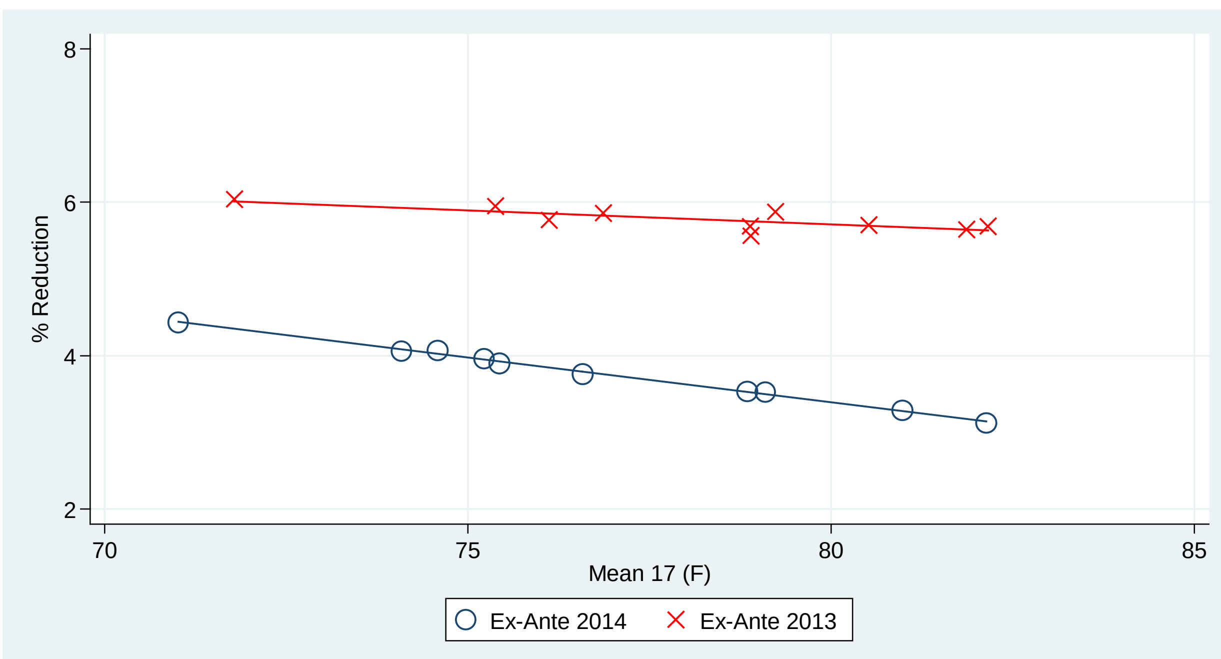
[26] Estimates based on CAISO weather scenarios have a similar pattern across months and LCAs. These values can be obtained from the electronic load impact tables that were submitted along with this report.

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

Weather Year	Year	Accounts		Reference Loads (MW)		Percent Reductions		Aggregate Impacts (MW)	
		2013 Estimates	2014 Estimates	2014 Estimates	2014 Estimates	2013 Estimates	2014 Estimates	2013 Load Impact (MW)	2014 Load Impact (MW)
1-in-10	2015	2,473	2,560	263.8	241.8	5.7%	3.3%	37.1	20.3
	2016	2,473	2,574	263.8	241.8	5.7%	3.3%	37.1	20.5
1-in-2	2015	2,473	2,560	257.6	235.2	5.6%	3.5%	35.5	21.3
	2016	2,473	2,574	257.6	235.2	5.6%	3.5%	35.5	21.4

A graphical comparison between the summer ex ante load impacts for large C&I customers as estimated in the 2013 and 2014 load impact evaluation is shown in Figure 7-5. The 2013 ex ante estimates are higher than those estimated this year. Last year's estimates used a different estimating sample (the 2012 and 2013 CPP persistent customers), which delivered higher percent reductions than the sample of persistent customers used in this year's analysis. The 2014 ex ante estimates also show more negative relationship with temperature than the estimates from 2013.

Figure 7-5: Comparison of 2013 Ex Ante Load Impacts to 2014 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: 70 < event day mean17 < 84 Average event day mean17 = 76	Program specific mean17 for 1-in-2 typical event day = 75.9 and 77.2 for SCE and CAISO weather, respectively Program specific mean17 for 1-in-10 typical event day = 80.3 and 80.1 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 2014 summer	2015 enrollment is similar	Ex ante estimates will not be significantly impacted by changes in enrollment
Methodology	2014 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 2015	Pooled impacts from 2013 and 2014 for persistent customers exhibit a similar temperature relationship to those for all customers, but percent impacts are lower. Impacts will be lower.

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. The third column uses the 2014 ex post impacts shown in Table 6-1 and the projected enrollment for August 2015 to produce a scaled-up ex post impact estimate. This leads to a slight decrease in load reductions of about 4%. The next column shows what the ex ante model would produce using the same August 2015 enrollment figures and the ex post weather conditions for each event day. The ex ante model under predicts load reductions on average by about 3% compared with the 2014 ex post impacts. As discussed earlier, this is the result of estimating ex ante impacts using percent impacts from the persistent population's 2013 and 2014 ex post values. The fifth column 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 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 2014 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 5% smaller 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
	(F)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
7/8/2014	74.7	34.7	33.3	28.7	24.3				
7/14/2014	73.0	31.3	30.1	29.2	24.9				
7/30/2014	77.3	38.4	37.0	28.1	23.5				
8/4/2014	73.4	35.9	34.6	27.3	22.7				
8/22/2014	72.7	19.6	18.8	28.7	24.4				
8/28/2014	79.0	26.5	25.6	26.2	21.2				
9/8/2014	76.0	30.8	29.4	26.7	21.9	22.4	23.0	21.0	21.0
9/11/2014	77.5	20.6	19.7	26.9	22.1				
9/15/2014	83.4	35.8	34.2	25.2	19.6				
9/16/2014	84.4	31.3	30.0	24.8	19.1				
9/22/2014	70.0	28.6	27.3	29.3	25.3				
9/23/2014	71.8	21.6	20.6	29.0	24.8				
Avg.	76.1	29.6	28.4	27.5	22.8				

7.2 Medium C&I Ex Ante Impacts

Overall, there is greater uncertainty regarding medium C&I customer impacts under default CPP. To date, default CPP has been implemented on a very limited basis for medium customers and those medium C&I customers who are on the rate are generally not representative of the medium C&I sector as a whole. While some medium customers volunteered onto CPP rates, their mix and demand reductions are not representative of the current and future medium default customer population. The few pilots that tested time varying pricing for small and medium businesses did not do so for default rates, but rather included only customers who volunteered into the pilots. Among such pilots is PG&E's EEP for small and medium CPP customers. In brief, the empirical data on medium customer response is limited.

Previous studies 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.[27] Nexant therefore used the EPP CPP percent reductions as an upper bound for the expected response of defaulted small and medium customers, and adjusted the overall percent reduction downward by about two-thirds. This yielded percent reductions of 2% and 1.5% for small and medium customers respectively. The reference loads were developed by using a sample of interval data for customers that were defaulted in November 2014 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 2025. In April 2017, 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 2017, 13,918 medium C&I customers are projected to remain on CPP. The enrollment is expected to increase slowly thereafter as a result of growth in accounts.

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.
2017	0	0	0	34,795	34,795	34,795	34,795	34,795	34,795	34,795	34,795	34,795
2018	34,795	34,795	34,795	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918	13,918
2019	13,918	13,918	13,918	14,366	14,366	14,366	14,366	14,366	14,366	14,366	14,366	14,366
2025	16,833	16,833	16,833	17,375	17,375	17,375	17,375	17,375	17,375	17,375	17,375	17,375

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

[27] 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

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 13.6 MW in 2017 to 5.4 MW in 2018 under 1-in-10 weather conditions, and then increase to 6.8 MW in 2025. After default CPP is fully implemented, medium customers are forecasted to reduce 1.2% 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 1% less than the estimates based on SCE weather. The CAISO 1-in-10 weather values produce a load reduction that is also about 1% less than 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	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	2017	34,795	1,143.3	1,129.7	13.6	1.2%	95.3
		2018	13,918	457.3	451.9	5.4	1.2%	95.3
		2019	14,366	472.0	466.4	5.6	1.2%	95.3
		2025	17,375	570.9	564.1	6.8	1.2%	95.3
	1-in-2	2017	34,795	1,095.3	1,082.2	13.0	1.2%	92.3
		2018	13,918	438.1	432.9	5.2	1.2%	92.3
		2019	14,366	452.2	446.8	5.4	1.2%	92.3
		2025	17,375	546.9	540.4	6.5	1.2%	92.3
CAISO	1-in-10	2017	34,795	1,130.5	1,117.0	13.4	1.2%	93.7
		2018	13,918	452.2	446.8	5.4	1.2%	93.7
		2019	14,366	466.7	461.2	5.6	1.2%	93.7
		2025	17,375	564.5	557.8	6.7	1.2%	93.7
	1-in-2	2017	34,795	1,087.8	1,074.8	12.9	1.2%	91.7
		2018	13,918	435.1	429.9	5.2	1.2%	91.7
		2019	14,366	449.1	443.8	5.3	1.2%	91.7
		2025	17,375	543.2	536.7	6.5	1.2%	91.7

7.2.2 Ex Ante Impacts by Geographic Location and Month

Table 7-11 summarizes aggregate 2018 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 1.5% 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 2019, 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 2019 medium C&I enrollment while the Other transmission planning area accounts for 61%.

Table 7-11: Aggregate SCE Ex Ante Load Impact Estimates by LCA Medium C&I 2018 Monthly System Peak Days (1–6 PM), SCE Weather Scenarios[28]

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	1.6	1.6	1.8	2.2	5.0	5.2	5.5	5.6	5.6	4.9	2.1	1.6
	Orange County	0.4	0.4	0.5	0.6	1.4	1.4	1.5	1.6	1.6	1.4	0.6	0.4
	South of Lugo	0.2	0.2	0.3	0.3	0.7	0.7	0.7	0.7	0.8	0.7	0.3	0.2
	Other	0.9	1.0	1.1	1.3	2.9	3.1	3.3	3.3	3.2	2.9	1.2	1.0
1-in-2	All	1.6	1.7	1.7	2.0	4.4	4.8	5.1	5.4	5.0	4.8	1.9	1.6
	Orange County	0.4	0.4	0.4	0.5	1.2	1.3	1.4	1.5	1.4	1.3	0.5	0.4
	South of Lugo	0.2	0.2	0.2	0.3	0.6	0.6	0.7	0.7	0.7	0.7	0.3	0.2
	Other	1.0	1.0	1.0	1.2	2.6	2.9	3.0	3.1	2.9	2.8	1.1	1.0

7.3 Small C&I Ex Ante Impacts

As was true for medium customers, there are no ex post impacts upon which to base ex ante estimates. As discussed in the prior section, a 2% load reduction is assumed to apply to small customers.

Table 7-12 presents SCE's enrollment projections for small C&I customers through 2025. 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 2017. Of the customers who were already defaulted in April 2017, 86,082 small C&I customers are projected to remain on CPP. By April 2025, the small C&I population is expected to reach enrollment of 107,465 accounts as a result of growth in 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.
2017	0	0	0	215,205	215,205	215,205	215,205	215,205	215,205	215,205	215,205	215,205
2018	215,205	215,205	215,205	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082	86,082
2019	86,082	86,082	86,082	88,854	88,854	88,854	88,854	88,854	88,854	88,854	88,854	88,854
2025	104,112	104,112	104,112	107,465	107,465	107,465	107,465	107,465	107,465	107,465	107,465	107,465

28 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.

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 8.1 MW in 2017 to around 3.2 MW in 2018 under 1-in-10 weather conditions, and proceed to increase to 4.0 MW in 2025. After default CPP is fully implemented, small customers are forecasted to reduce 1.6% 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 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	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	2017	215,205	511.6	503.5	8.1	1.6%	95.1
		2018	86,082	204.7	201.4	3.2	1.6%	95.1
		2019	88,854	211.2	207.9	3.3	1.6%	95.1
		2025	107,465	255.5	251.4	4.0	1.6%	95.1
	1-in-2	2017	215,205	482.8	475.2	7.6	1.6%	92.1
		2018	86,082	193.1	190.1	3.1	1.6%	92.1
		2019	88,854	199.3	196.2	3.2	1.6%	92.1
		2025	107,465	241.1	237.3	3.8	1.6%	92.1
CAISO	1-in-10	2017	215,205	504.3	496.3	8.0	1.6%	93.6
		2018	86,082	201.7	198.5	3.2	1.6%	93.6
		2019	88,854	208.2	204.9	3.3	1.6%	93.6
		2025	107,465	251.8	247.9	4.0	1.6%	93.6
	1-in-2	2017	215,205	478.5	470.9	7.6	1.6%	91.5
		2018	86,082	191.4	188.4	3.0	1.6%	91.5
		2019	88,854	197.6	194.4	3.1	1.6%	91.5
		2025	107,465	239.0	235.2	3.8	1.6%	91.5

7.3.2 Ex Ante Impacts by Geographic Location and Month

Table 7-14 summarizes aggregate 2018 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 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 2% 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 2019, 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 2019 medium C&I enrollment while the Other transmission planning area accounts for 65%.

Table 7-14: Aggregate SCE Ex Ante Load Impact Estimates by LCA Small C&I 2018 Monthly System Peak Days (1–6 PM), SCE 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	1.0	0.9	0.9	1.2	2.8	3.0	3.2	3.3	3.3	2.8	1.2	1.0
	Orange County	0.3	0.3	0.3	0.3	0.8	0.8	0.9	1.0	1.0	0.8	0.3	0.3
	South of Lugo	0.1	0.1	0.1	0.1	0.3	0.3	0.3	0.3	0.4	0.3	0.1	0.1
	Other	0.6	0.6	0.6	0.7	1.7	1.9	2.0	2.0	2.0	1.7	0.7	0.6
1-in-2	All	0.9	0.9	0.9	1.1	2.4	2.7	3.0	3.2	2.9	2.7	1.1	1.0
	Orange County	0.3	0.3	0.2	0.3	0.7	0.8	0.8	0.9	0.8	0.8	0.3	0.3
	South of Lugo	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	0.6	0.6	0.5	0.7	1.5	1.7	1.8	1.9	1.7	1.6	0.6	0.6

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.

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 six CPP events in 2014. The first event occurred on February 7 and the last was held on September 17. On average, there were 1,142 accounts enrolled on SDG&E's tariff in 2014. There was some minor variation in enrollment during the course of the summer largely due to typical customer churn, with the highest enrollment at 1,143 participants and the lowest enrollment at 1,141. The average 2014 CPP customer enrollment of 1,142 represents a 7.3% increase from 2013 enrollment, which was 1,064 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 82.7°F.

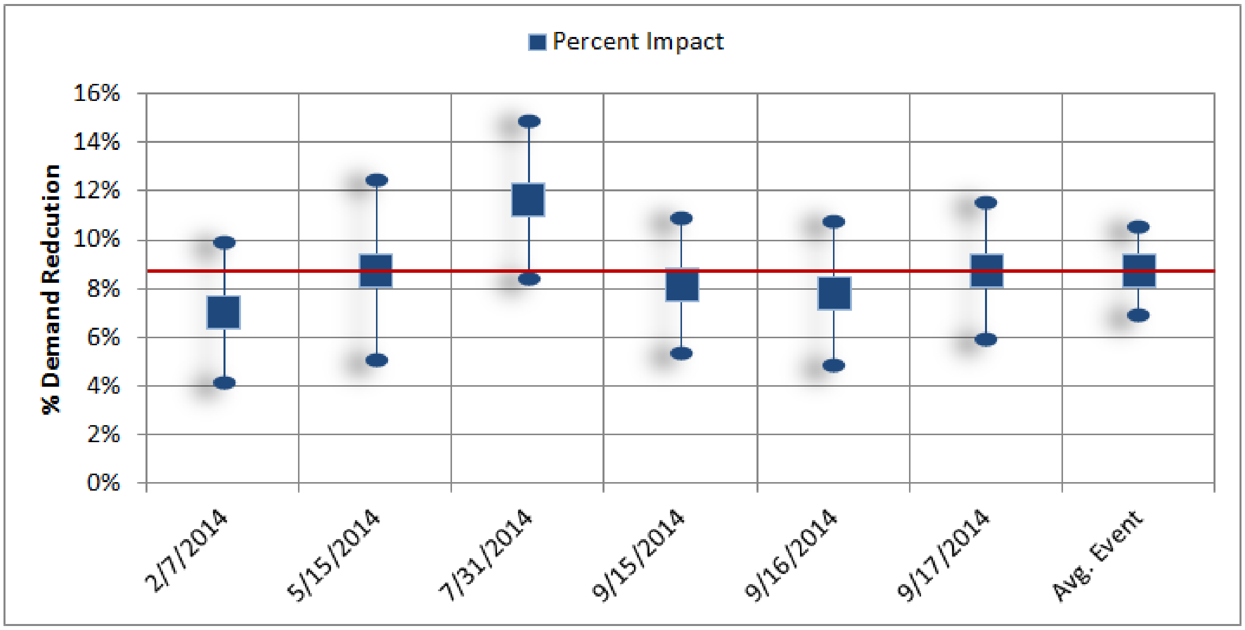
Table 8-1 shows the ex post load impact estimates for each event day and for the average event in 2014. The participant-weighted average temperature during the event period ranged from a low of 60.4°F to a high of 93.8°F. Percent impacts ranged from 7.1% to 11.7%, average impacts ranged from 12.8 kW to 29.5 kW and aggregate impacts ranged from 14.6 MW to 33.7 MW. On the average event day, the average participant reduced peak period load by 8.8%, or 22.3 kW. In aggregate, SDG&E's CPP customers reduced load by 25.4 MW on average across the four events in 2014.

Table 8-1: Default CPP Ex Post Load Impact Estimates by Event Day SDG&E 2014 CPP Events (11 AM to 6 PM)

Event Date	Day of Week	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp.	Daily Maximum Temp.
			(kW)	(kW)	(kW)	(MW)	%	°F	°F
2/7/2014	Fri	1,141	181.8	169.0	12.8	14.6	7.1%	60.4	64.0
5/15/2014	Thu	1,142	242.8	221.5	21.3	24.3	8.8%	93.8	101.5
7/31/2014	Thu	1,143	252.6	223.1	29.5	33.7	11.7%	79.9	88.8
9/15/2014	Mon	1,143	282.1	259.0	23.0	26.3	8.2%	87.2	97.3
9/16/2014	Tue	1,142	285.8	263.5	22.4	25.5	7.8%	91.3	101.6
9/17/2014	Wed	1,141	281.4	256.8	24.6	28.1	8.7%	83.7	96.3
Avg. Event		**1,142**	**254.4**	**232.2**	**22.3**	**25.4**	**8.8%**	**82.7**	**96.4**

Figure 8-1 presents the ex post load impact estimates for individual 2014 events and the average 2014 event with 90% confidence intervals around each point estimate. Although there is some variation in the estimated impacts across days, only one of the differences are statistically significant. 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 2014 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 2014 weekday event varied from a high of 9.5% from 4 to 5 PM to a low of 8.0% from 2 to 3 PM, but these differences may not be statistically significant. The highest aggregate impact, 26.6 MW, occurred in the penultimate hour; and the lowest impact, 23.4 MW, occurred in the fourth hour.

The hourly load impacts for the average 2014 event day are slightly weaker in the earliest hours of the event than in the later hours. This is in contrast with 2013's impacts, which were stronger in the earliest hours of the event and weakest at the end of the event. The overall magnitude of the hourly load impact across the four days is higher in 2014 (8.8%) compared with 2013 (6.9%). We address this difference in the next section, which compares impacts across industry segments.

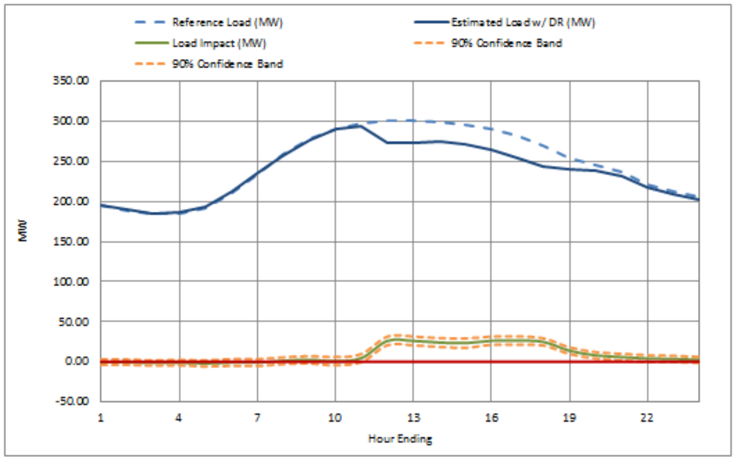
Figure 8-2: Average Impact per Customer for the Average Event Day in 2014 Default CPP Ex Post Load Impacts

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	1,142
Avg. Load Reduction for Event Window (MW)	25.4
% Load Reduction for Event Window	**8.8%**



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	195.0	195.2	-0.2	-0.1%	70.0	-3.0	-1.4	-0.2	1.0	2.6
2	188.7	189.1	-0.4	-0.2%	69.6	-3.0	-1.4	-0.4	0.7	2.3
3	184.1	185.4	-1.3	-0.7%	69.0	-3.9	-2.4	-1.3	-0.2	1.3
4	185.0	185.9	-0.9	-0.5%	68.7	-3.6	-2.0	-0.9	0.2	1.8
5	192.2	194.2	-1.9	-1.0%	68.4	-4.9	-3.1	-1.9	-0.7	1.1
6	211.0	211.7	-0.7	-0.3%	69.5	-4.0	-2.0	-0.7	0.7	2.6
7	233.5	234.3	-0.8	-0.3%	73.4	-4.2	-2.2	-0.8	0.6	2.5
8	258.4	256.8	1.5	0.6%	77.8	-1.8	0.2	1.5	2.9	4.9
9	278.7	276.1	2.6	0.9%	81.9	-1.0	1.1	2.6	4.1	6.3
10	290.7	289.8	1.0	0.3%	84.0	-3.1	-0.7	1.0	2.6	5.0
11	297.8	292.9	4.9	1.6%	85.1	1.0	3.3	4.9	6.5	8.8
12	300.1	273.7	26.3	8.8%	84.9	22.1	24.6	26.3	28.1	30.6
13	300.0	273.8	26.2	8.7%	84.5	21.9	24.4	26.2	27.9	30.5
14	299.5	275.3	24.2	8.1%	84.6	19.9	22.4	24.2	26.0	28.5
15	294.7	271.2	23.4	8.0%	84.3	18.9	21.6	23.4	25.3	28.0
16	290.0	263.6	26.5	9.1%	82.7	22.5	24.8	26.5	28.1	30.5
17	280.9	254.3	26.6	9.5%	80.2	22.5	24.9	26.6	28.3	30.7
18	268.8	243.9	24.9	9.3%	77.8	21.4	23.4	24.9	26.3	28.3
19	254.2	240.3	13.9	5.5%	75.4	10.7	12.6	13.9	15.3	17.2
20	245.9	237.7	8.2	3.3%	73.8	5.0	6.9	8.2	9.5	11.4
21	236.8	230.8	6.0	2.5%	72.1	2.8	4.7	6.0	7.3	9.2
22	221.7	217.5	4.2	1.9%	70.8	1.0	2.9	4.2	5.5	7.4
23	213.3	209.5	3.7	1.7%	70.0	0.7	2.5	3.7	5.0	6.8
24	205.0	202.4	2.6	1.3%	69.5	-0.4	1.4	2.6	3.8	5.5
	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
Daily	5,925.9	5,705.3	220.6	3.7%	267.9	203.4	213.5	220.6	227.6	237.8

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.

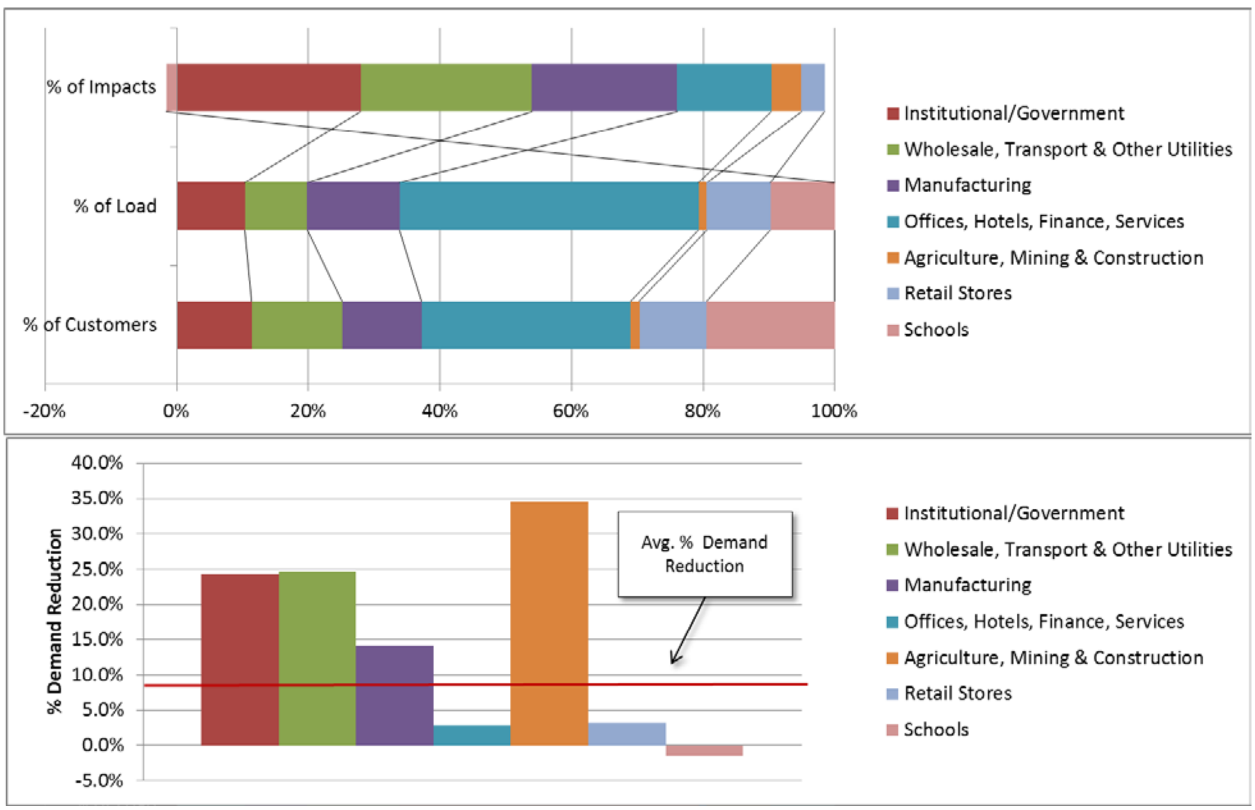
The distribution of CPP impacts across industry segments at SDG&E is not as highly concentrated as it is for PG&E and SCE. Nearly all of the load reduction, 78.4%, was provided by three sectors with relatively equal shares of the load impact: Institutional/Government, Wholesale, Transport & Other Utilities and Manufacturing. 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 2014 SDG&E CPP Event (11 AM to 6 PM)

Industry	Accounts		Aggregate Reference Load		Aggregate Impact		Average Impact	% Reduction	Stat. Sig?
	Enrollment	% of Program	MW	% of Program	MW	% of Program	kW		
Institutional/Government	130	11.4%	30.0	10.3%	7.3	28.8%	56.2	24.4%	Yes
Wholesale, Transport & Other Utilities	157	13.8%	27.5	9.5%	6.8	26.9%	43.4	24.8%	Yes
Manufacturing	137	12.0%	40.8	14.0%	5.8	22.7%	42.1	14.1%	Yes
Offices, Hotels, Finance, Services	363	31.8%	131.9	45.4%	3.8	14.8%	10.3	2.8%	Yes
Agriculture, Mining & Construction	15	1.3%	3.5	1.2%	1.2	4.7%	79.9	34.6%	Yes
Retail Stores	117	10.3%	28.1	9.7%	0.9	3.6%	7.9	3.3%	Yes
Schools	222	19.5%	28.5	9.8%	-0.4	-1.6%	-1.8	-1.4%	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 45% of the estimated reference load (131.9 MW) and produced 14.8% of the load reduction (3.8 MW). However, this sector also had the most participants and, on average, offices only reduced load by 2.8%. In contrast, the Wholesale, Transport & Other Utilities and Institutional/Government sectors together accounted for 19.8% of the reference load (57.5MW) but produced 55.7% 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 2014 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 two 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 60 customers in that category. Table 8-3 shows that customers in the smallest and the largest usage quintiles have the largest percentage load impacts, while customers in the 3th quintile has the lowest percentage load impacts.

Table 8-3: Default CPP Ex Post Load Impact Estimates by Customer Size Average 2014 SDG&E CPP Event (11 AM to 6 PM)

Categorization	Size Category	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. Sig?
			(kW)	(kW)	(kW)	(MW)	(%)	(°F)	
By DMDRCAT	Size: Over 200kW	831	328.0	300.4	27.5	22.9	8.4%	82.7	Yes
	Size: 20 kW to 199.99 kW	300	56.6	48.7	7.8	2.3	13.8%	82.6	Yes
	Size: Under 20 kW	10	76.6	60.8	15.8	0.2	20.6%	85.7	No
By Annual Consumption Quintiles	5th Quintile	232	707.5	637.1	70.4	16.3	9.9%	82.6	Yes
	4th Quintile	233	270.5	253.1	17.4	4.1	6.4%	82.5	Yes
	3rd Quintile	231	159.1	149.4	9.7	2.2	6.1%	82.8	Yes
	2nd Quintile	225	90.1	81.7	8.4	1.9	9.3%	82.9	Yes
	1st Quintile	219	26.2	22.3	4.0	0.9	15.1%	82.7	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 2014. SDG&E's CPP population has dual enrollment with two other demand response programs in 2014: 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 2014 SDG&E CPP Event (11 AM to 6 PM)

Dually Enrolled DR	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp.	Stat. Sig?
		(kW)	(kW)	(kW)	(MW)	%	°F	
CBP	21	416.9	259.7	157.2	3.3	38%	84.0	Yes
Not Dually-enrolled	1,119	251.5	231.7	19.8	22.1	8%	82.7	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 2013 SDG&E CPP Event (11 AM to 6 PM)

AutoDR	Accounts	Impact	% Reduction	90% Confidence Interval		Approved kW	Realization Rate
		(kW)	%	Lower	Upper		
AutoDR/TI**	27	-18.4	-5.0%	-45.0	8.1	164.9	0%
TI**	5	58.3	4.0%	-12.4	129.0	570.6	10.2%
No AutoDR/TI	1,109	23.1	9.4%	18.4	27.9	-	-

* 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 non-residential 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 2013 and 2014. In total, load impact estimates for up to 10 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., 2015, 2016 and 2025).[30] 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 2015–2025 forecast horizon: SDG&E is scheduled to begin to default medium C&I customers onto CPP rates. 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 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 2013 and 2014.

The ex ante percent load reductions for large C&I customers are based on the 2013 and 2014 ex post results for large, persistent customers, which are those that have participated in all events over the past two years. By removing variation in the customer mix from the analysis, we are better able to identify the underlying relationship between temperature and percent impacts. Table 9-1 shows the ex post load impact estimates for each event day and for the average event day in 2013 and 2014 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 93.4°F.

30 Enrollment is set to increase gradually between 2016 and 2025, 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.

Percent impacts ranged from 6.0% to 10.6%; average impacts ranged from 11.8 kW to 27.3 kW; and aggregate impacts ranged from 12.0 MW to 27.8 MW.

Table 9-1: Default CPP Ex Post Load Impact Estimates for Persistent Customers by Event Day SDG&E 2013, 2014 CPP Events (11 AM to 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)
8/29/2013	Thu	1,020	260.6	244.9	15.7	16.0	6.0%	84.0	88.1
9/4/2013	Wed	1,020	278.9	253.5	25.4	26.0	9.1%	83.5	87.7
9/5/2013	Thu	1,020	277.5	251.9	25.6	26.1	9.2%	83.6	86.6
9/6/2013	Fri	1,020	275.4	249.2	26.3	26.8	9.5%	84.8	91.1
2/7/2014	Fri	1,020	185.1	173.3	11.8	12.0	6.4%	61.3	62.9
5/15/2014	Thu	1,020	251.8	228.0	23.8	24.3	9.5%	93.4	98.0
7/31/2014	Thu	1,020	256.5	229.3	27.3	27.8	10.6%	79.2	82.9
9/15/2014	Mon	1,020	291.3	266.6	24.6	25.1	8.5%	86.2	91.3
9/16/2014	Tue	1,020	294.8	271.0	23.9	24.3	8.1%	91.0	95.6
9/17/2014	Wed	1,020	287.0	263.7	23.3	23.8	8.1%	82.7	92.1

Figure 9-1 presents the ex post load impact estimates for the persistent customers alongside those for all ex post customers. The impacts are plotted as a function of temperature and the linear fit is displayed for each customer group.

Figure 9-1: Comparison of 2013–2014 CPP Load Impacts for Persistent and All Ex Post Customers vs. Temperature

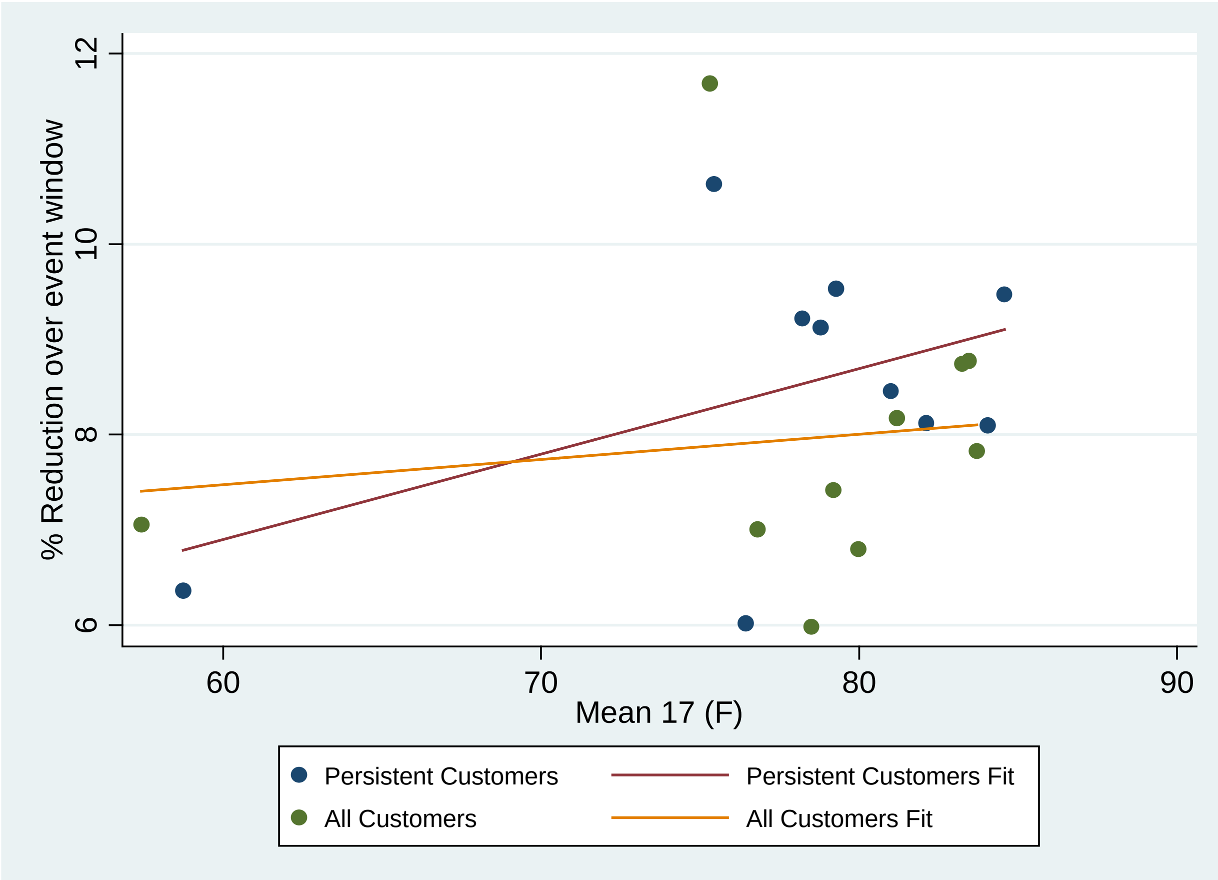


Figure 9-2 compares loads for all ex post customers during non-event days in 2014 to the reference loads for the ex ante customers used for reference load modeling. The ex ante customers used for reference load modeling are simply the ex post customers with the restriction that customers must have a full panel of interval data for the year. The reference loads from non-event days from May through October are included in the graph (weekends and holidays are also excluded). The average reference load is slightly higher for ex ante customers than for the ex post customers for the same days and weather conditions, but the difference is very small.

Figure 9-2: Comparison of Reference Loads on Non-event Days for Ex Ante Customers to All Ex Post Customers' Reference Loads

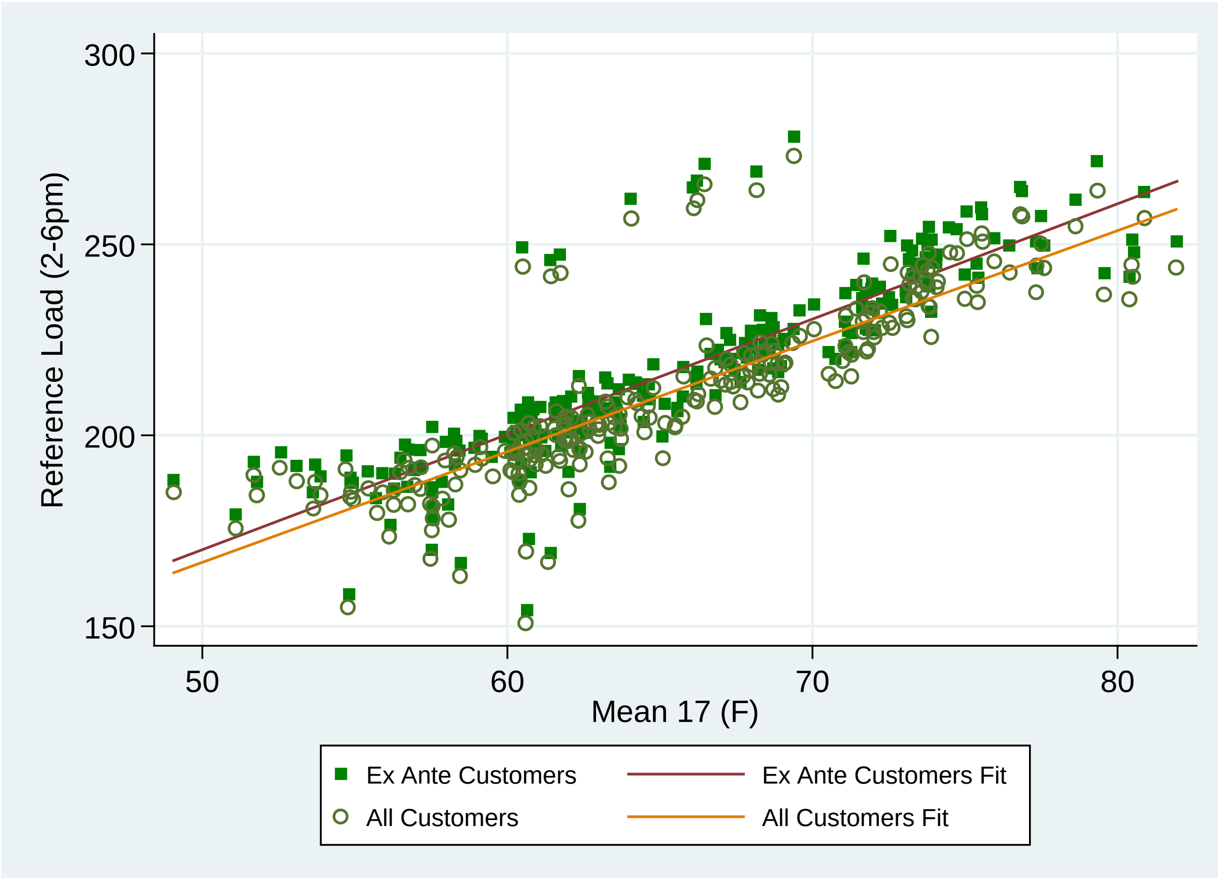


Figure 9-3 illustrates the historical 2013–2014 percent reductions as a function of temperature (blue circles). It also includes the percent demand reductions estimated under 1-in-2 and 1-in-10 year weather conditions (green squares) for the months of May through October based on the SDG&E weather scenarios (not the CAISO weather). Estimates of CPP percentage load impacts, based on the history of load impacts in 2013 and 2014, are shown to increase as temperatures increase. These percent demand reductions estimates were applied to large customers.

Figure 9-4 compares the customer reference loads during non-event days to the ex ante reference loads (blue circles). The 1-in-2 and 1-in-10 reference loads from May through October are included in the graph (green squares). Ex post reference loads are seen to increase with temperature and ex ante reference loads follow the weather trend observed during non-event days.

Figure 9-3: Comparison of 2013–2014 CPP Load Impacts and Summer Ex Ante Load Impacts vs. Temperature by Industry

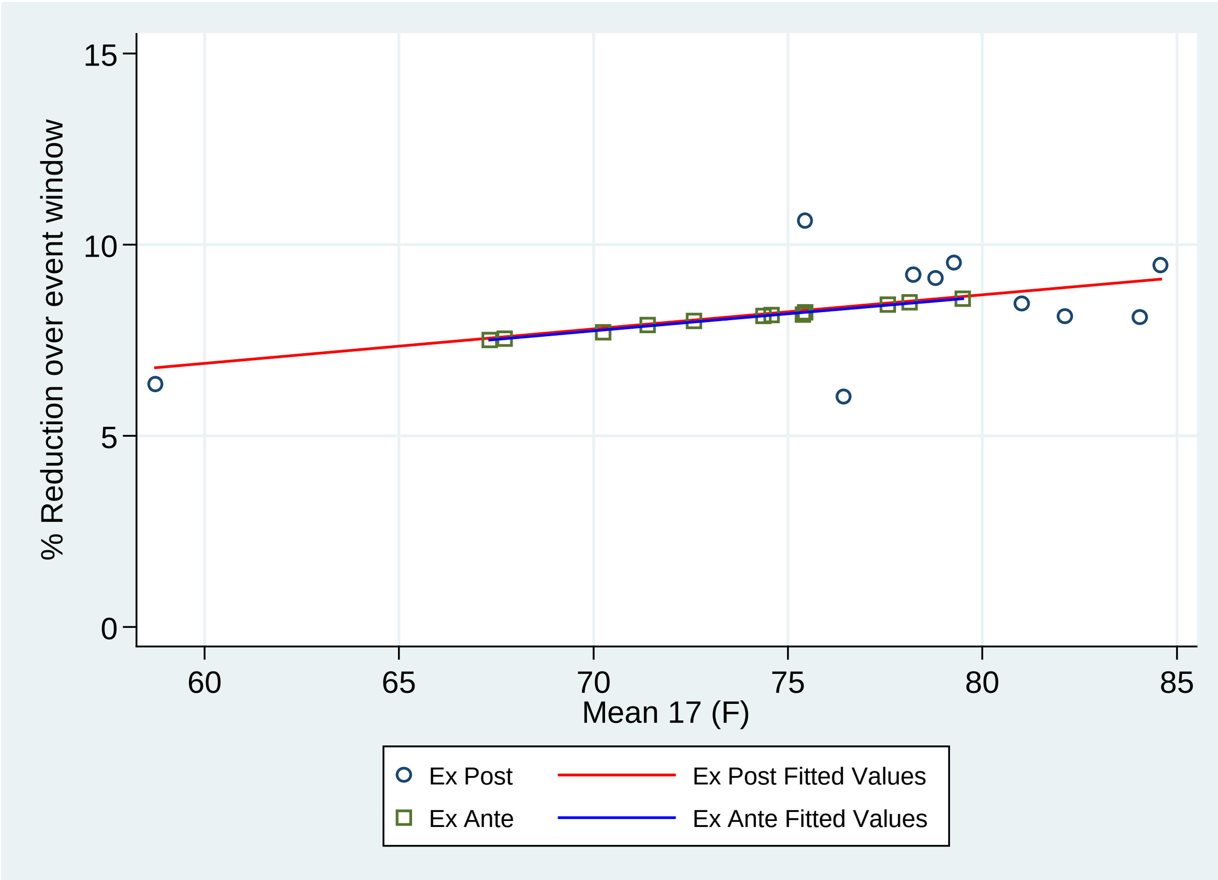


Figure 9-4: Comparison of Ex post Loads on Non-Event Days to Ex Ante Reference Loads for Large C&I

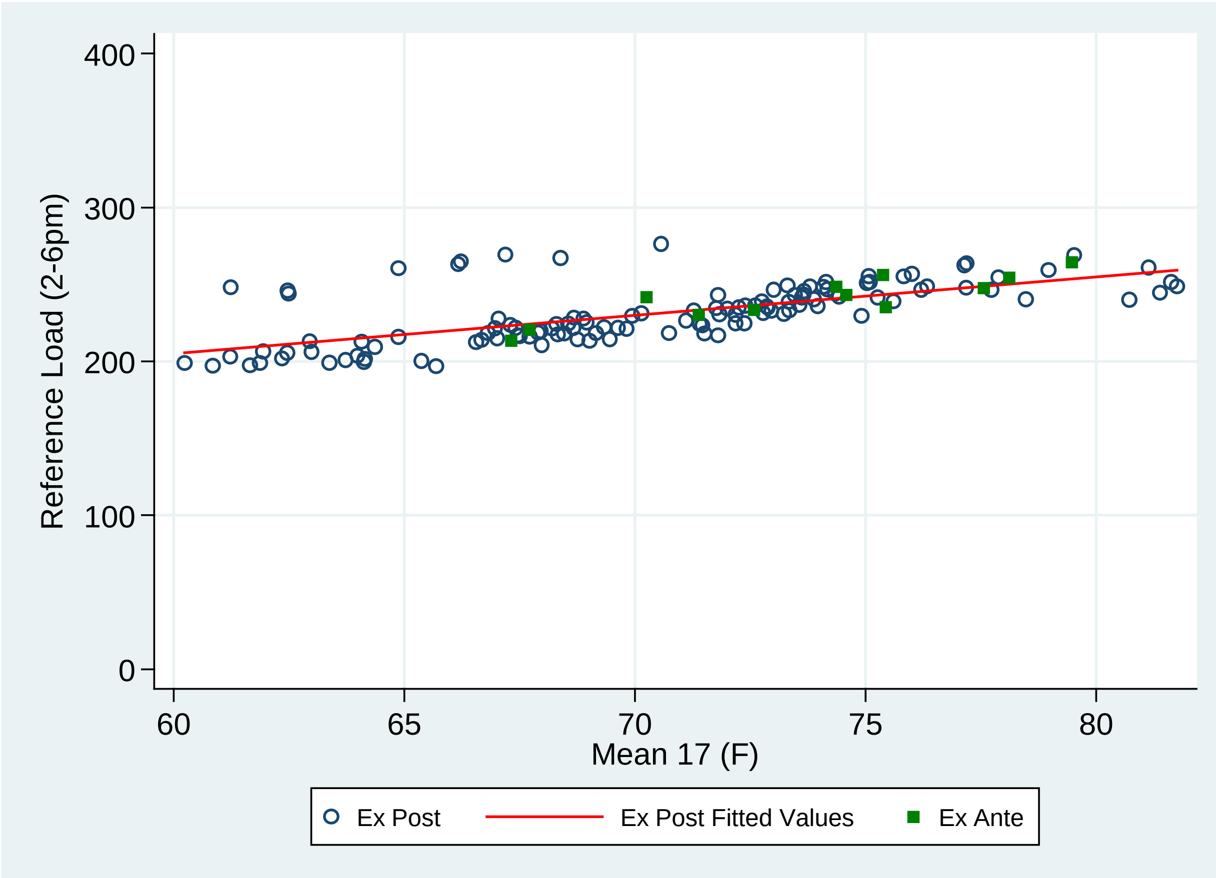


Table 9-2 shows SDG&E's enrollment projections for large C&I CPP customers through 2025. Overall, 1,142 large customers were enrolled in default CPP in 2014.[31] The forecasted year-to-year change in enrollment is minimal and simply reflects the expected growth of SDG&E's large customer population. Years 2017 through 2024 are not shown below as enrollment in these years follows a similar trend to that which occurs throughout 2015 and 2016.

[31] 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.
2015	1,251	1,251	1,252	1,252	1,252	1,253	1,253	1,253	1,254	1,254	1,254	1,255
2016	1,256	1,258	1,259	1,261	1,262	1,264	1,265	1,267	1,268	1,270	1,272	1,273
2025	1,396	1,397	1,398	1,400	1,401	1,402	1,404	1,405	1,406	1,408	1,409	1,410

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 scenarios based on both SDG&E and CAISO weather scenarios. The table shows the average load reduction across the 11 AM to 6 PM event period for an August monthly system peak day.

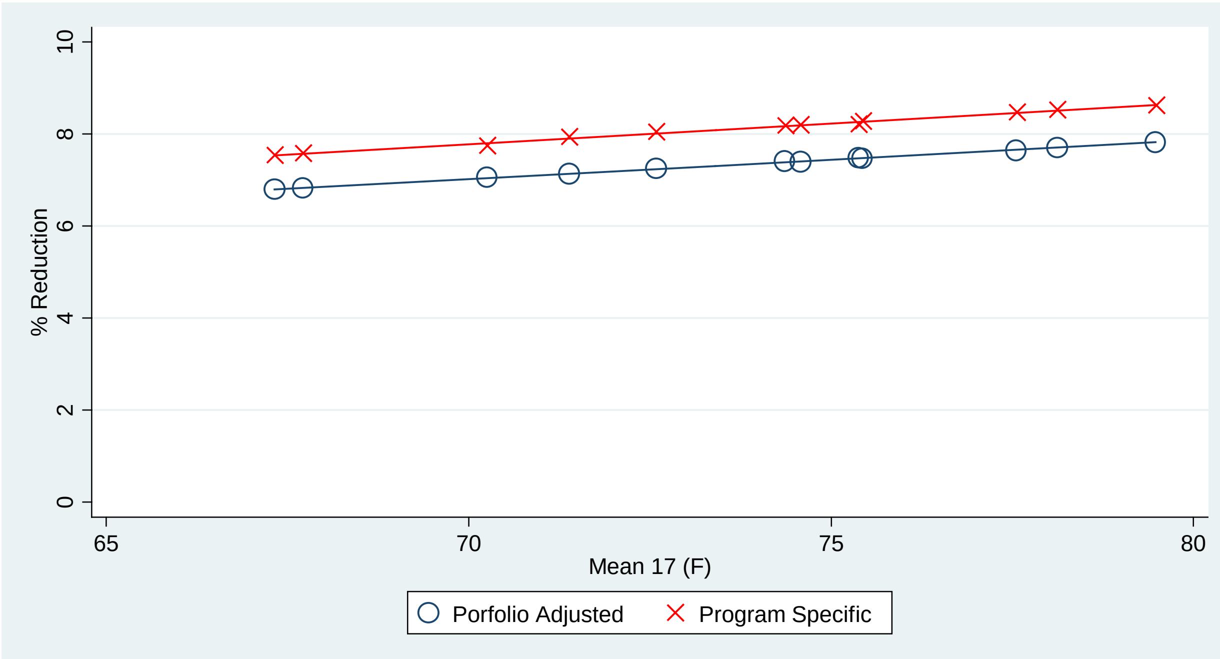
Looking first at the aggregate load impacts based on normal, SDG&E-specific 1-in-2 year weather conditions, load reductions will grow from roughly 25 MW to 28 MW between 2015 and 2025. Impacts based on 1-in-10 year SDG&E weather conditions equal roughly 27 MW in 2015 and will grow to 30 MW by 2025. These estimates equal roughly 8% of the aggregate reference load for large C&I customers. Impacts estimates based on CAISO weather 1-in-2 year weather conditions are roughly 2% larger than the estimates based on SDG&E weather. The CAISO 1-in-10 year weather values produce a load reduction that is about 5% less than the 1-in-10 year SDG&E estimates.

Table 9-3: Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I
SDG&E August System Peak Day (11 AM 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 1–6 PM)	(MW 1–6 PM)	(MW 1–6 PM)	(%)	(°F)
SDG&E	1-in-10	2015	1,253	322.6	295.2	27.4	8.5%	86.6
		2016	1,267	326.0	298.4	27.6	8.5%	86.6
		2025	1,405	361.2	330.9	30.4	8.4%	86.6
	1-in-2	2015	1,253	308.6	283.4	25.2	8.2%	81.0
		2016	1,267	311.9	286.5	25.4	8.2%	81.0
		2025	1,405	345.5	317.6	27.9	8.1%	81.0
CAISO	1-in-10	2015	1,253	314.5	288.4	26.1	8.3%	83.6
		2016	1,267	317.9	291.5	26.4	8.3%	83.6
		2025	1,405	352.2	323.2	29.0	8.2%	83.6
	1-in-2	2015	1,253	312.4	286.6	25.8	8.3%	83.6
		2016	1,267	315.8	289.7	26.0	8.2%	83.6
		2025	1,405	349.8	321.2	28.6	8.2%	83.6

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. Customers dually enrolled in those programs are among the most responsive participants. 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 about 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 broad. For example, in 2015, the projected load impacts for August 1-in-2 year, SDG&E weather, are 25.2±7.0z MW, with 80% confidence. But in percentage terms, the uncertainty seems smaller, 8.2%±2.3%, with 80% confidence. For this program in particular, small differences in the estimated percent demand reductions can appear to be 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 (11 AM to 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	2015	27.4	20.2	24.4	27.4	30.3	34.6
		2016	27.6	20.4	24.7	27.6	30.6	34.9
		2025	30.4	22.4	27.1	30.4	33.6	38.3
	1-in-2	2015	25.2	18.2	22.3	25.2	28.0	32.2
		2016	25.4	18.4	22.5	25.4	28.3	32.5
		2025	27.9	20.2	24.8	27.9	31.1	35.6
CAISO	1-in-10	2015	26.1	19.1	23.2	26.1	29.0	33.2
		2016	26.4	19.3	23.5	26.4	29.3	33.5
		2025	29.0	21.2	25.8	29.0	32.1	36.8
	1-in-2	2015	25.8	18.8	22.9	25.8	28.7	32.8
		2016	26.0	19.0	23.1	26.0	28.9	33.1
		2025	28.6	20.8	25.4	28.6	31.8	36.4

9.1.3 Comparison of 2013 and 2014 Ex Ante Estimates

Table 9-5 compares the ex ante estimates produced for the 2013 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 in the percentage load impact estimates and in the forecasted enrollments. The net effect is that this year's forecast for 2015 is 25.2 MW, which is 35% higher than last year's forecast of 18.8 due primarily to an increased enrollment forecast and higher percentage load impact estimates from this evaluation.

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

Weather Year	Year	Accounts		Reference Loads (MW)		Percent Reductions		Aggregate Impacts (MW)	
		2013 Estimates	2014 Estimates	2014 Estimates	2014 Estimates	2013 Estimates	2014 Estimates	2013 Estimates	2014 Estimates
1-in-10	2015	1,164	1,253	274.3	257.4	6.7%	8.5%	21.4	27.4
	2016	1,193	1,267	274.3	257.4	6.7%	8.5%	22.0	27.6
	2024	1,318	1,389	274.3	257.1	6.7%	8.4%	24.3	30.0
1-in-2	2015	1,164	1,253	261.1	246.2	6.2%	8.2%	18.8	25.2
	2016	1,193	1,267	261.1	246.2	6.2%	8.2%	19.2	25.4
	2024	1,318	1,389	261.1	245.9	6.2%	8.1%	21.2	27.6

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 change decreases the ex ante impacts by roughly 10% for the typical event day under 1-in-2 SDG&E weather conditions, as compared to the average 2014 event day. Changes in enrollment between the values used for ex post estimation and the 2015 enrollment values increase impact estimates by about 10%. Finally, the fact that the ex ante model is based on ex post impacts from both 2013 and 2014 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: 58 < event day mean17 < 84 Average event day mean17 = 78	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 2014 summer	2015 enrollment is forecast to be about 10% higher	Ex ante estimates will be about 10% higher than ex post
Methodology	2014 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 2013 and 2014 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 2014 ex post impacts shown in Table 8-1 and the projected enrollment for August of 2015 to produce a scaled-up ex post impact estimate. This leads to an average increase in load reductions of about 10%. The next column shows what the ex ante model would produce using the same August 2015 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, with the exception of the July 31 event. As discussed above, this is the result of estimating ex ante impacts using percent impacts from the persistent population's 2013 and 2014 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 2014 SDG&E ex post weather conditions, although the impacts are still lower than the average ex post day by about 11%.

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

Date	Mean 17	Enrollment-adjusted 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)
2/7/2014	57.5	14.6	16.1	17.6	24.8	24.8	25.0	25.0
5/15/2014	83.9	24.3	26.7	31.6				
7/31/2014	75.4	33.7	37.0	26.1				
9/15/2014	81.4	26.3	28.9	29.8				
9/16/2014	84.1	25.5	28.0	31.7				
9/17/2014	83.1	28.1	30.8	31.0				
Avg.	77.6	25.4	27.9	28.0				

9.2 Medium C&I Ex Ante Impacts

Overall, there is greater uncertainty regarding medium C&I customer impacts under default CPP. To date, default CPP has been implemented on a very limited basis for medium customers and those medium C&I customers who are on the rate are generally not representative of the medium C&I sector as a whole. While some medium customers volunteered onto CPP rates, their mix and demand reductions are not representative of the current and future medium default customer population. The few pilots that tested time varying pricing for small and medium businesses did not do so for default rates, but rather included only customers who volunteered into the pilots. Among such pilots is PG&E's EEP for small and medium CPP customers. In brief, the empirical data on medium customer response is limited.

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.[32] Nexant therefore used the PG&E EPP CPP percent reductions as an upper bound for the expected response of defaulted small and medium customers, and adjusted the overall percent reduction downward. This yielded percent reductions of 2.5%. The reference loads were developed by using a sample of interval data for customers that are eligible to be defaulted in March 2016. We simply applied the percent reductions to the reference loads, with an awareness factor that increased from 0.7 in 2016 to 0.9 in 2018 onwards.

Table 9-8 presents SDG&E's enrollment projections for medium C&I customers through 2025. 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. Of the customers who were already defaulted in March 2016, 7,670 medium C&I customers are projected to remain on CPP in March 2018. The enrollment is expected to increase slowly thereafter as a result of growth in accounts.

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	0	0	9,572	9,589	9,606	9,623	9,639	8,914	8,929	8,944	8,961	8,976
2017	9,160	9,173	8,412	8,424	8,437	8,449	8,461	8,050	8,062	8,073	8,085	8,097
2018	8,106	8,115	7,662	7,670	7,679	7,687	7,695	7,704	7,712	7,721	7,729	7,738
2025	8,499	8,510	8,521	8,532	8,543	8,555	8,566	8,577	8,588	8,599	8,610	8,621

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

[32] 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

based on both SDG&E and CAISO weather scenarios. The table shows the average load reduction across the 11 AM to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on SDG&E-specific weather, August load reductions increase from 9.0 MW in 2016 to 9.2 MW in 2017 under 1-in-10 weather conditions, and then increase to 11.1 MW in 2025. Once default CPP is fully implemented, medium customers are forecasted to reduce 2.3% of their demand under all weather conditions. The estimated percent reductions increase as more customers become aware of the rate. Impact estimates based on CAISO weather 1-in-2 year conditions are roughly 2% higher than the estimates based on SDG&E weather. The CAISO 1-in-10 weather values produce a load reduction that is also about 3% less than the 1-in-10 year SDG&E estimates.

Table 9-9: Aggregate Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Medium C&I, SDG&E August System Peak Day (11 AM 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	8,914	511.8	502.8	9.0	1.8%	91.3
		2017	8,050	462.2	452.9	9.2	2.0%	91.3
		2018	7,704	442.3	432.4	10.0	2.3%	91.3
		2025	8,577	492.4	481.4	11.1	2.3%	91.3
	1-in-2	2016	8,914	481.3	472.9	8.4	1.8%	83.5
		2017	8,050	434.7	426.0	8.7	2.0%	83.5
		2018	7,704	416.0	406.6	9.4	2.3%	83.5
		2025	8,577	463.1	452.7	10.4	2.3%	83.5
CAISO	1-in-10	2016	8,914	498.0	489.3	8.7	1.8%	88.5
		2017	8,050	449.8	440.8	9.0	2.0%	88.5
		2018	7,704	430.4	420.7	9.7	2.3%	88.5
		2025	8,577	479.2	468.4	10.8	2.3%	88.5
	1-in-2	2016	8,914	493.6	485.0	8.6	1.8%	88.5
		2017	8,050	445.8	436.9	8.9	2.0%	88.5
		2018	7,704	426.6	417.0	9.6	2.3%	88.5
		2025	8,577	475.0	464.3	10.7	2.3%	88.5

10 Recommendations

The empirical data from PG&E, SCE and SDG&E's default CPP programs has produced many practical insights about load impacts from large customer participants on default dynamic pricing rates. However, there remains limited empirical data concerning how SMB customers respond to default CPP rates. Although Nexant recommends specific research steps, additional research can impose additional costs that may not be currently funded. The recommendations presented in this section also may not be feasible at each utility due to the pre-established schedules for implementing default CPP and resource constraints.

Our testing and evaluation recommendations are:

- *Conduct an early test of default CPP for medium customers.* Experimentation and test-and-learn strategies are at the very core of successful innovation. It is a way to learn what works and, more importantly, learn what doesn't work. The basic idea is to conduct small scale tests as early as possible to avoid making more costly mistakes later in the process. Nexant recommends that utilities test default CPP with a smaller, random subset of SMB customers prior to full implementation. This would allow utilities the opportunity to test and evaluate the effectiveness of the default process, reduce uncertainty about enrollments and demand reductions and make appropriate adjustments prior to full implementation. Currently, there is very little precedent for a shift to default dynamic rates among these types of customers. Most assumptions about how SMB customers will engage and respond are uncertain because they are mostly based on the implementation of default CPP for large customers.
- *Estimate the effect of program changes through research design rather than after-the-fact analysis.* Any upcoming program changes provide a unique opportunity to assess the effect, if any, of program changes on load impacts. Specifically, it can help answer two key research questions: Does providing customers the ability to partially or fully insure their load against high CPP prices dampen participant demand reductions? Does changing the event window lead to lower demand reductions? The ideal approach to answering any upcoming key questions like these is a phased rollout of program changes in combination with random assignment. Under this scenario, customers are randomly assigned to one of two groups. In the first year, the program change is implemented for one group, allowing a side-by-side comparison of impacts with and without the program change. By the second year, the program change is implemented across the full population.

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 non-event 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 non-event 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 Matching Model Selection Summary Statistics and Rankings

Hard Match Group	Model Number	Caliper	Event Hours Absolute Sum of Errors		Event Hours Average Percent Error		Standard Deviation of Event Hours Average Percent Error for Individual Events	
			Value (kWh)	Rank	Absolute Value	Rank	Value (%)	Rank
Weather Station	12	0.01	2,798,946	492	0.00%	1	3.93%	546
LCA	12	0.0005	2,109,603	191	0.05%	2	2.15%	125
Average Summer Day kWh 15-tiles	9	0.1	2,258,072	305	0.07%	3	2.83%	345
Average Summer Day kWh 15-tiles	8	0.1	2,227,157	280	0.08%	4	2.21%	141
Average Summer Day kWh 15-tiles	8	0.05	2,222,033	275	0.09%	5	2.24%	146
LCA	10	0.0005	3,332,329	598	0.11%	6	4.74%	642
Average Summer Day kWh 15-tiles	9	0.05	2,252,395	299	0.12%	7	2.81%	338
Weather Station	12	0.005	2,724,966	481	0.13%	8	4.08%	561
Average Summer Day kWh 15-tiles	8	0.001	1,745,781	79	0.16%	9	1.73%	31
Average Proxy Day kWh 2-tiles within Industry	12	0.05	2,002,366	134	0.21%	10	2.90%	363
Average Proxy Day kWh 2-tiles within Industry	12	0.1	2,004,007	135	0.23%	11	2.91%	365
Average Proxy Day kWh 2-tiles within Industry	11	0.005	2,010,851	137	0.28%	12	2.13%	118
Average Proxy Day kWh 2-tiles within Industry	12	0.005	1,968,397	128	0.29%	13	2.87%	353
Average Proxy Day kWh 2-tiles within Industry	12	0.01	1,985,752	129	0.29%	14	2.92%	368
LCA	8	0.01	3,238,207	576	0.30%	15	3.29%	450
Average Summer Day kWh 15-tiles	9	0.01	2,205,316	262	0.32%	16	2.67%	286
Average Summer Day kWh 2-tiles within Indust	10	0.05	3,022,611	524	0.33%	17	1.90%	72
Weather Station	12	0.1	2,833,278	500	0.34%	18	4.27%	587
Average Summer Day kWh 15-tiles	9	0.001	1,852,248	109	0.35%	19	3.34%	464
Weather Station	12	0.05	2,832,156	499	0.37%	20	4.27%	588
Average Proxy Day kWh 2-tiles within Industry	11	0.01	2,029,130	141	0.40%	21	2.15%	126
Average Summer Day kWh 2-tiles within Indust	10	0.1	3,031,453	527	0.40%	22	1.86%	60
LCA	7	0.0005	3,258,150	581	0.42%	23	4.07%	560
Average Proxy Day kWh 2-tiles within Industry	11	0.001	1,856,851	112	0.43%	24	2.18%	131
Average Proxy Day kWh 15-tiles	9	0.001	1,668,390	46	0.43%	25	2.53%	232
Average Summer Day kWh 15-tiles	8	0.01	2,147,617	230	0.45%	26	2.07%	105
Average Proxy Day kWh 2-tiles within Industry	11	0.1	2,043,630	148	0.45%	27	2.06%	103
Average Proxy Day kWh 2-tiles within Industry	11	0.05	2,042,947	147	0.46%	28	2.06%	102
Average Summer Day kWh 15-tiles	7	0.05	2,225,284	278	0.49%	29	3.48%	490
Average Summer Day kWh 15-tiles	7	0.1	2,226,509	279	0.50%	30	3.49%	491
Average Proxy Day kWh 15-tiles	11	0.0005	1,432,050	7	0.50%	31	1.56%	20
Average Proxy Day kWh 5-tiles	11	0.0005	1,547,766	20	0.52%	32	1.93%	83
Weather Station	12	0.001	2,470,654	398	0.53%	33	4.03%	555
Average Summer Day kWh 15-tiles	9	0.005	2,143,506	225	0.55%	34	2.53%	231
Average Summer Day kWh 10-tiles	10	0.0005	1,705,327	64	0.56%	35	2.44%	208
Average Proxy Day kWh 15-tiles	9	0.1	2,125,262	202	0.57%	36	1.99%	93
LCA	11	0.0005	2,253,168	300	0.59%	37	3.40%	472
Average Summer Day kWh 15-tiles	7	0.01	2,180,543	250	0.59%	38	3.50%	494
Average Proxy Day kWh 2-tiles within Industry	12	0.001	1,840,258	108	0.60%	39	2.72%	306
Average Proxy Day kWh 2-tiles within Industry	11	0.0005	1,716,476	73	0.60%	40	2.03%	98
Average Summer Day kWh 15-tiles	10	0.005	2,098,014	185	0.61%	41	2.65%	278
Average Proxy Day kWh 15-tiles	9	0.05	2,118,877	198	0.62%	42	1.98%	92
LCA	8	0.05	3,371,738	605	0.65%	43	3.38%	469
Average Summer Day kWh 15-tiles	10	0.01	2,166,306	241	0.66%	44	2.94%	371
Average Proxy Day kWh 2-tiles within Industry	12	0.0005	1,701,544	61	0.67%	45	2.83%	344
Average Proxy Day kWh 5-tiles	11	0.001	1,578,454	22	0.67%	46	1.93%	82
Average Summer Day kWh 10-tiles	11	0.005	1,762,594	84	0.68%	47	2.30%	170
Average Summer Day kWh 15-tiles	12	0.0005	1,540,085	19	0.68%	48	1.86%	62
LCA	8	0.005	3,167,057	560	0.68%	49	2.96%	378
Average Summer Day kWh 15-tiles	7	0.005	2,131,779	207	0.69%	50	3.51%	497
Weather Station	5	0.05	5,012,990	742	12.15%	743	6.19%	718

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

Hard Match Group	Model Number	Caliper	Event Hours Absolute Sum of Errors		Event Hours Average Percent Error		Standard Deviation of Event Hours Average Percent Error for Individual Events	
			Value (kWh)	Rank	Absolute Value	Rank	Value (%)	Rank
Average Proxy Day kWh 5-tiles	4	0.001	3,508,445	351	0.02%	1	1.86%	417
LCA	8	0.0005	4,076,166	526	0.02%	2	1.81%	371
Average Summer Day kWh 15-tiles	11	0.005	2,789,495	59	0.03%	3	1.59%	200
Average Proxy Day kWh 15-tiles	8	0.0005	2,568,277	22	0.05%	4	1.31%	66
Average Summer Day kWh 10-tiles	7	0.005	3,381,275	289	0.05%	5	1.30%	57
LCA	3	0.0005	4,316,317	581	0.06%	6	1.97%	510
LCA	1	0.005	4,601,583	687	0.06%	7	1.94%	479
Average Summer Day kWh 15-tiles	11	0.0005	2,788,876	58	0.06%	8	1.47%	128
Average Proxy Day kWh 5-tiles	5	0.0005	3,361,088	278	0.06%	9	1.83%	397
Average Proxy Day kWh 10-tiles	9	0.0005	2,922,360	103	0.07%	10	1.38%	99
Average Proxy Day kWh 2-tiles within Industry	1	0.001	4,276,355	572	0.07%	11	1.99%	529
LCA	5	0.0005	4,496,167	643	0.07%	12	2.22%	716
Average Proxy Day kWh 10-tiles	1	0.0005	2,946,190	112	0.07%	13	1.60%	208
Average Proxy Day kWh 2-tiles within Industry	10	0.001	4,163,907	542	0.08%	14	1.41%	105
LCA	2	0.01	4,618,023	693	0.08%	15	2.15%	658
Weather Station	9	0.05	5,305,790	870	0.08%	16	2.39%	814
LCA	2	0.05	4,647,743	708	0.09%	17	2.16%	664
Weather Station	9	0.1	5,322,281	871	0.09%	18	2.37%	805
Average Proxy Day kWh 2-tiles within Industry	8	0.001	4,061,270	524	0.09%	19	1.99%	539
Average Proxy Day kWh 15-tiles	2	0.1	3,056,756	162	0.11%	20	2.42%	824
Average Summer Day kWh 15-tiles	11	0.01	2,801,832	64	0.11%	21	1.56%	181
Average Proxy Day kWh 15-tiles	4	0.05	3,094,378	183	0.11%	22	1.92%	460
Average Proxy Day kWh 15-tiles	5	0.1	3,045,103	154	0.11%	23	1.81%	381
Average Summer Day kWh 15-tiles	11	0.001	2,768,132	53	0.11%	24	1.50%	145
Average Proxy Day kWh 15-tiles	2	0.05	3,056,519	161	0.13%	25	2.43%	826
Average Proxy Day kWh 15-tiles	4	0.1	3,094,811	184	0.13%	26	1.92%	456
LCA	2	0.1	4,651,833	709	0.13%	27	2.18%	672
LCA	5	0.001	4,592,748	682	0.13%	28	2.07%	605
Average Proxy Day kWh 15-tiles	5	0.05	3,043,790	152	0.14%	29	1.85%	408
Average Proxy Day kWh 5-tiles	3	0.0005	3,309,657	261	0.14%	30	1.48%	137
Average Summer Day kWh 15-tiles	11	0.05	2,809,248	69	0.14%	31	1.60%	212
Average Summer Day kWh 15-tiles	11	0.1	2,809,664	70	0.15%	32	1.61%	220
LCA	3	0.001	4,426,405	617	0.16%	33	1.93%	463
Average Proxy Day kWh 15-tiles	6	0.0005	2,393,523	10	0.16%	34	1.52%	155
Average Proxy Day kWh 15-tiles	10	0.0005	2,570,693	23	0.16%	35	1.24%	37
Average Summer Day kWh 2-tiles within Indust	3	0.005	4,575,165	676	0.19%	36	1.98%	524
Average Summer Day kWh 10-tiles	7	0.1	3,484,400	335	0.19%	37	1.45%	117
Average Proxy Day kWh 2-tiles within Industry	1	0.005	4,405,601	607	0.20%	38	2.22%	717
Average Proxy Day kWh 15-tiles	4	0.01	3,030,493	146	0.21%	39	1.87%	422
LCA	1	0.01	4,623,926	697	0.21%	40	1.90%	443
Average Summer Day kWh 10-tiles	7	0.0005	3,211,801	214	0.22%	41	1.48%	134
Average Proxy Day kWh 10-tiles	1	0.1	3,271,783	242	0.22%	42	1.82%	383
Average Summer Day kWh 10-tiles	11	0.0005	2,904,137	96	0.22%	43	1.21%	29
Average Proxy Day kWh 10-tiles	1	0.05	3,272,432	243	0.22%	44	1.83%	390
Average Summer Day kWh 10-tiles	5	0.0005	3,144,313	197	0.23%	45	2.17%	665
Average Summer Day kWh 2-tiles within LCA	11	0.001	3,901,373	489	0.23%	46	1.78%	347
LCA	2	0.005	4,594,077	684	0.24%	47	2.21%	712
Average Proxy Day kWh 10-tiles	7	0.0005	2,798,997	63	0.25%	48	1.69%	282
Average Summer Day kWh 10-tiles	7	0.05	3,480,553	332	0.25%	49	1.45%	118
Average Summer Day kWh 10-tiles	7	0.01	3,439,002	319	0.25%	50	1.28%	46
Industry	3	0.1	5,688,001	899	6.10%	934	1.84%	429

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

Hard Match Group	Model Number	Caliper	Event Hours Absolute Sum of Errors		Event Hours Average Percent Error		Standard Deviation of Event Hours Average Percent Error for Individual Events	
			Value (kWh)	Rank	Absolute Value	Rank	Value (%)	Rank
Average Summer Day kWh 10-tiles	12	0.05	489,653	24	0.00%	1	2.59%	51
Average Summer Day kWh 10-tiles	4	0.01	550,814	68	0.02%	2	2.56%	46
Average Summer Day kWh 10-tiles	12	0.1	490,572	25	0.02%	3	2.62%	55
Average Summer Day kWh 5-tiles	2	0.1	843,937	221	0.04%	4	3.75%	168
Average Summer Day kWh 10-tiles	5	0.01	561,905	75	0.06%	5	5.71%	257
Average Proxy Day kWh 5-tiles	8	0.1	792,553	191	0.06%	6	3.28%	126
Average Proxy Day kWh 10-tiles	10	0.05	594,376	96	0.06%	7	1.80%	6
Average Summer Day kWh 5-tiles	2	0.05	843,517	220	0.06%	8	3.74%	166
Average Summer Day kWh 5-tiles	3	0.05	870,592	235	0.07%	9	3.04%	95
Average Summer Day kWh 5-tiles	3	0.1	870,846	236	0.08%	10	3.03%	92
Average Proxy Day kWh 5-tiles	8	0.05	790,280	188	0.08%	11	3.33%	135
Average Proxy Day kWh 2-tiles within Industry	12	0.05	774,765	176	0.10%	12	2.75%	76
Average Proxy Day kWh 15-tiles	7	0.1	516,179	37	0.15%	13	3.47%	152
Average Summer Day kWh 5-tiles	11	0.1	793,929	193	0.17%	14	2.85%	82
Average Summer Day kWh 5-tiles	12	0.01	820,164	209	0.18%	15	3.83%	173
Average Proxy Day kWh 10-tiles	10	0.1	597,801	100	0.23%	16	1.95%	10
Average Proxy Day kWh 10-tiles	1	0.05	630,744	115	0.25%	17	3.15%	113
Average Summer Day kWh 10-tiles	12	0.01	460,524	17	0.26%	18	2.63%	59
Average Proxy Day kWh 10-tiles	2	0.01	542,804	59	0.27%	19	2.35%	33
Average Proxy Day kWh 10-tiles	6	0.01	533,271	48	0.28%	20	3.40%	146
Average Proxy Day kWh 10-tiles	1	0.1	633,191	119	0.28%	21	3.09%	103
Average Summer Day kWh 10-tiles	4	0.05	632,152	116	0.31%	22	2.49%	40
Average Summer Day kWh 5-tiles	12	0.005	800,894	195	0.31%	23	4.01%	181
Average Summer Day kWh 5-tiles	12	0.05	852,663	226	0.32%	24	3.15%	112
Average Summer Day kWh 10-tiles	4	0.1	632,988	118	0.33%	25	2.53%	42
Average Summer Day kWh 5-tiles	12	0.001	703,757	153	0.33%	26	4.49%	214
Average Proxy Day kWh 15-tiles	7	0.05	512,883	32	0.33%	27	3.46%	150
Average Summer Day kWh 5-tiles	5	0.1	909,187	242	0.34%	28	6.02%	262
Average Proxy Day kWh 15-tiles	8	0.1	492,412	27	0.36%	29	2.08%	19
Average Proxy Day kWh 15-tiles	6	0.05	535,079	51	0.37%	30	4.19%	190
Average Proxy Day kWh 15-tiles	8	0.05	491,885	26	0.37%	31	2.09%	22
Average Proxy Day kWh 15-tiles	6	0.1	536,203	52	0.39%	32	4.26%	195
Average Proxy Day kWh 2-tiles within Industry	12	0.1	791,956	190	0.42%	33	3.03%	93
Average Proxy Day kWh 10-tiles	8	0.01	543,777	62	0.43%	34	2.37%	34
Average Proxy Day kWh 5-tiles	8	0.01	753,919	169	0.45%	35	3.34%	138
Average Summer Day kWh 5-tiles	5	0.05	906,751	241	0.46%	36	6.10%	263
Average Summer Day kWh 5-tiles	12	0.1	855,082	228	0.46%	37	3.31%	131
Average Summer Day kWh 15-tiles	3	0.05	557,284	71	0.47%	38	4.32%	199
Average Summer Day kWh 15-tiles	7	0.01	496,041	29	0.49%	39	3.70%	163
Average Summer Day kWh 15-tiles	8	0.05	571,377	82	0.50%	40	3.10%	105
Average Proxy Day kWh 2-tiles within Industry	12	0.01	708,219	154	0.52%	41	2.56%	47
Average Proxy Day kWh 10-tiles	10	0.01	515,668	36	0.53%	42	3.08%	101
Average Summer Day kWh 15-tiles	8	0.1	574,924	84	0.56%	43	3.12%	108
Average Summer Day kWh 5-tiles	7	0.01	742,497	164	0.57%	44	4.14%	188
Average Proxy Day kWh 10-tiles	4	0.01	524,336	40	0.61%	45	3.20%	117
Average Proxy Day kWh 10-tiles	10	0.005	436,233	9	0.62%	46	2.78%	78
Average Summer Day kWh 10-tiles	12	0.005	415,574	7	0.62%	47	1.44%	1
Average Summer Day kWh 5-tiles	4	0.005	708,757	155	0.63%	48	3.53%	155
Average Proxy Day kWh 15-tiles	1	0.05	534,512	50	0.73%	49	2.74%	72
Average Proxy Day kWh 15-tiles	4	0.05	513,594	34	0.75%	50	3.26%	123
Weather Station	12	0.1	1,477,297	272	10.26%	272	4.37%	208

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 non-event days common to both CPP participants and control group members[33]
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

[33] 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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
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 $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$
10	$kW_{ihd} = a_{ih} + \sum_{k=2}^{5} b_{ihk} * dow_{ihdk} + \sum_{l=1}^{n} c_{ihl} * eventday_{ihl} + e_{ihd}$, for $i \in \{1, \dots, n_i\}, h \in \{1, 2, 3 \ \dots \ 24\}$ *and* $d \in \{1, \dots, n_d\}$

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 2015 through 2025 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	2015	1,927	645.4	594.8	50.5	7.8%	95.7
		2016	2,429	809.3	744.3	65.0	8.0%	95.9
		2025	2,464	820.8	754.7	66.0	8.0%	95.9
	1-in-2	2015	1,927	618.6	573.1	45.6	7.4%	92.0
		2016	2,429	776.2	717.8	58.4	7.5%	92.4
		2025	2,464	787.2	727.9	59.3	7.5%	92.4
CAISO	1-in-10	2015	1,927	626.6	578.7	47.9	7.6%	92.4
		2016	2,429	786.3	724.7	61.6	7.8%	92.8
		2025	2,464	797.4	734.9	62.6	7.8%	92.8
	1-in-2	2015	1,927	591.2	552.1	39.2	6.6%	89.0
		2016	2,429	742.1	692.1	50.0	6.7%	89.3
		2025	2,464	752.7	701.9	50.8	6.8%	89.3

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	2015	20,234	549.5	542.9	6.5	1.2%	97.6
		2016	26,981	791.3	781.9	9.4	1.2%	97.0
		2017	37,546	1181.2	1167.2	14.0	1.2%	96.6
		2025	39,644	1260.0	1245.1	14.9	1.2%	96.5
	1-in-2	2015	20,234	513.1	507.0	6.1	1.2%	93.9
		2016	26,981	738.2	729.4	8.8	1.2%	93.4
		2017	37,546	1100.6	1087.6	13.1	1.2%	92.8
		2025	39,644	1173.9	1160.0	13.9	1.2%	92.8
CAISO	1-in-10	2015	20,234	527.9	521.6	6.3	1.2%	94.8
		2016	26,981	759.3	750.3	9.0	1.2%	94.1
		2017	37,546	1131.7	1118.3	13.4	1.2%	93.5
		2025	39,644	1207.0	1192.7	14.3	1.2%	93.4
	1-in-2	2015	20,234	471.7	466.1	5.6	1.2%	90.3
		2016	26,981	677.8	669.7	8.0	1.2%	89.8
		2017	37,546	1009.9	997.9	12.0	1.2%	89.3
		2025	39,644	1077.2	1064.5	12.8	1.2%	89.3

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	2015	151,008	472.5	465.0	7.5	1.6%	96.4
		2016	185,917	588.5	579.1	9.4	1.6%	95.7
		2017	203,958	656.1	645.6	10.5	1.6%	95.7
		2025	243,249	797.7	785.0	12.7	1.6%	95.6
	1-in-2	2015	151,008	431.4	424.5	6.9	1.6%	92.6
		2016	185,917	537.5	528.9	8.6	1.6%	92.0
		2017	203,958	599.1	589.6	9.5	1.6%	92.0
		2025	243,249	728.4	716.8	11.6	1.6%	91.9
CAISO	1-in-10	2015	151,008	446.6	439.5	7.1	1.6%	93.3
		2016	185,917	556.3	547.4	8.9	1.6%	92.7
		2017	203,958	620.0	610.1	9.9	1.6%	92.7
		2025	243,249	753.6	741.6	12.0	1.6%	92.6
	1-in-2	2015	151,008	387.9	381.7	6.2	1.6%	89.2
		2016	185,917	483.6	475.9	7.7	1.6%	88.7
		2017	203,958	539.1	530.5	8.6	1.6%	88.7
		2025	243,249	655.6	645.1	10.4	1.6%	88.6

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	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	2015	3,657	884.4	868.1	16.3	1.8%	95.6
		2016	3,677	889.2	872.8	16.4	1.8%	95.6
		2025	4,891	1182.7	1161.0	21.8	1.8%	95.6
	1-in-2	2015	3,657	860.1	843.1	17.0	2.0%	92.8
		2016	3,677	864.8	847.7	17.1	2.0%	92.8
		2025	4,891	1150.3	1127.5	22.8	2.0%	92.8
CAISO	1-in-10	2015	3,657	874.8	858.1	16.6	1.9%	93.9
		2016	3,677	879.5	862.8	16.7	1.9%	93.9
		2025	4,891	1169.9	1147.7	22.2	1.9%	93.9
	1-in-2	2015	3,657	850.6	833.2	17.4	2.0%	92.2
		2016	3,677	855.2	837.7	17.5	2.0%	92.2
		2025	4,891	1137.5	1114.3	23.3	2.0%	92.2

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	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	2017	34,795	1143.3	1129.7	13.6	1.2%	95.3
		2018	13,918	457.3	451.9	5.4	1.2%	95.3
		2019	14,366	472.0	466.4	5.6	1.2%	95.3
		2025	17,375	570.9	564.1	6.8	1.2%	95.3
	1-in-2	2017	34,795	1095.3	1082.2	13.0	1.2%	92.3
		2018	13,918	438.1	432.9	5.2	1.2%	92.3
		2019	14,366	452.2	446.8	5.4	1.2%	92.3
		2025	17,375	546.9	540.4	6.5	1.2%	92.3
CAISO	1-in-10	2017	34,795	1130.5	1117.0	13.4	1.2%	93.7
		2018	13,918	452.2	446.8	5.4	1.2%	93.7
		2019	14,366	466.7	461.2	5.6	1.2%	93.7
		2025	17,375	564.5	557.8	6.7	1.2%	93.7
	1-in-2	2017	34,795	1087.8	1074.8	12.9	1.2%	91.7
		2018	13,918	435.1	429.9	5.2	1.2%	91.7
		2019	14,366	449.1	443.8	5.3	1.2%	91.7
		2025	17,375	543.2	536.7	6.5	1.2%	91.7

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 (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	2017	215,205	511.6	503.5	8.1	1.6%	95.1
		2018	86,082	204.7	201.4	3.2	1.6%	95.1
		2019	88,854	211.2	207.9	3.3	1.6%	95.1
		2025	107,465	255.5	251.4	4.0	1.6%	95.1
	1-in-2	2017	215,205	482.8	475.2	7.6	1.6%	92.1
		2018	86,082	193.1	190.1	3.1	1.6%	92.1
		2019	88,854	199.3	196.2	3.2	1.6%	92.1
		2025	107,465	241.1	237.3	3.8	1.6%	92.1
CAISO	1-in-10	2017	215,205	504.3	496.3	8.0	1.6%	93.6
		2018	86,082	201.7	198.5	3.2	1.6%	93.6
		2019	88,854	208.2	204.9	3.3	1.6%	93.6
		2025	107,465	251.8	247.9	4.0	1.6%	93.6
	1-in-2	2017	215,205	478.5	470.9	7.6	1.6%	91.5
		2018	86,082	191.4	188.4	3.0	1.6%	91.5
		2019	88,854	197.6	194.4	3.1	1.6%	91.5
		2025	107,465	239.0	235.2	3.8	1.6%	91.5

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 (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	2015	1,229	314.7	290.5	24.2	7.7%	86.6
		2016	1,243	318.2	293.7	24.5	7.7%	86.6
		2025	1,381	353.6	326.4	27.2	7.7%	86.6
	1-in-2	2015	1,229	299.8	277.6	22.2	7.4%	81.0
		2016	1,243	303.1	280.7	22.4	7.4%	81.0
		2025	1,381	336.8	311.9	24.9	7.4%	81.0
CAISO	1-in-10	2015	1,229	306.1	283.0	23.0	7.5%	83.5
		2016	1,243	309.4	286.2	23.3	7.5%	83.5
		2025	1,381	343.9	318.0	25.9	7.5%	83.5
	1-in-2	2015	1,229	303.9	281.1	22.7	7.5%	83.6
		2016	1,243	307.2	284.2	23.0	7.5%	83.6
		2025	1,381	341.4	315.8	25.5	7.5%	83.6

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	8,137	476.6	468.3	8.3	1.8%	91.3
		2017	7,356	430.9	422.3	8.6	2.0%	91.3
		2018	7,050	413.0	403.7	9.3	2.3%	91.3
		2025	7,923	464.1	453.6	10.4	2.3%	91.3
	1-in-2	2016	8,137	448.1	440.2	7.8	1.8%	83.5
		2017	7,356	405.0	396.9	8.1	2.0%	83.5
		2018	7,050	388.2	379.5	8.7	2.3%	83.5
		2025	7,923	436.3	426.5	9.8	2.3%	83.5
CAISO	1-in-10	2016	8,137	463.7	455.6	8.1	1.8%	88.5
		2017	7,356	419.2	410.8	8.4	2.0%	88.5
		2018	7,050	401.7	392.7	9.0	2.3%	88.5
		2025	7,923	451.5	441.3	10.2	2.3%	88.5
	1-in-2	2016	8,137	459.6	451.5	8.0	1.8%	88.5
		2017	7,356	415.5	407.2	8.3	2.0%	88.5
		2018	7,050	398.2	389.2	9.0	2.3%	88.5
		2025	7,923	447.5	437.4	10.1	2.3%	88.5

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 2015 through 2025 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