FREEMAN, SULLIVAN & CO.

A MEMBER OF THE FSC GROUP

2012 California Statewide Non-residential Critical Peak Pricing Evaluation

Prepared for:
Pacific Gas and Electric Co. (PG&E)
Southern California Edison (SCE)
San Diego Gas and Electric Co. (SDG&E)

CALMAC ID SDG0264

April 1, 2013

Prepared by:
Josh L. Bode, M.P.P.
Candice A. Churchwell, M.S.
Stephen S. George, Ph.D.
Freeman, Sullivan & Co.

Freeman, Sullivan & Co.
101 Montgomery St., 15th Fl.
San Francisco, CA 94104
fscgroup.com

The FSC Group

Table of Contents

1 Executive Summary

This report presents the 2012 ex post load impact estimates for the Non-residential Critical Peak Pricing (CPP) tariffs that have been 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 2013 through 2023 are also presented, including a base year 2012 ex ante estimate.

Critical Peak Pricing 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. 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 that faced CPP rates in California in 2012 were large 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 2012, all three IOUs also offered CPP rates to small and medium businesses (SMB) on a voluntary basis. Results from SMB voluntary enrollments are not included in this evaluation. At SDG&E and PG&E, 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 2012 activation events (ex post 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?
- 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?

Table 1-1 summarizes the 2012 program year results for PG&E, SCE and SDG&E and compares them with the 2011 program year impacts.

Table 1-1: Summary of 2011 and 2012 Statewide CPP Impacts
Average Event Day

Utility	Year	Number of Events Called	Approximate Customer Count	Temperature (°F)	Reference Load (MW)	Load Impact (MW)	Percent Impact (%)
PG&E	2011	9	1,750	88.1	473	28	5.9%
	2012	9	1,627	86.5	437	30	6.9%
SCE	2011	12	3,000	84.7	615	35	5.7%
	2012	12	2,508	87.3	554	33	5.9%
SDG&E[1]	2011	2	1,300	86.2	359	19	5.2%
	2012	7	1,117	80.4	268	16	6.0%
Total	2011	–	6,050	–	1,448	81	5.6%
	2012	–	5,252	–	1,259	79	6.3%

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 9, 12 and 7 CPP events, respectively. However, CPP event prices were in effect at all three utilities simultaneously only on August 9, 2012, because system conditions and weather patterns vary across all three utilities. In addition, SDG&E has a longer critical peak period – 11 PM to 6 PM – than PG&E or SCE and also dispatches CPP on Saturdays, due to its system load patterns.

Enrollment by non-residential customers defaulted onto CPP rates was lower in 2012 than in 2011 by approximately 10% across PG&E, SCE and SDG&E.[2] The lower enrollment is reflected in the lower overall program loads without DR in place, referred to as reference loads. Overall, approximately 5,200 customers were enrolled on default CPP for the 2012 summer. Despite the lower enrollment, the aggregate program impacts were similar to 2011 because customers remaining on the rate delivered higher percent demand reductions.

Between 2011 and 2012, enrollment in voluntary SMB rates at PG&E grew from 79 service accounts to nearly 4,000 service accounts and remained constant for SCE at approximately 300 service accounts. However, over 95% of SMB accounts at both PG&E and SCE are linked to a single entity, with service accounts across both territories. The results are not representative of future demand response expected when SMB customers are defaulted onto CPP.

[1] SDG&E dispatched two CPP events in 2011 and seven events in 2012. The 2012 SDG&E value reported in Table 1-1 represents the average weekday load impact across the five weekday events called in 2012. The 2011 SDG&E value represents the load impacts from the single weekday event dispatched on September 7, 2011.

[2] All customers who were defaulted onto the program or would have been defaulted onto CPP due to their size are classified as *Default CPP*.

Table 1-2 summarizes PG&E, SCE and SDG&E ex ante load impacts for forecast years 2013 and 2023 under 1-in-2 weather conditions. Enrollments, and consequently reference load, are forecast to increase substantially in the next 10 years as default CPP is introduced to medium C&I customers. The magnitude of ex ante impacts from medium customers under default dynamic pricing is far less certain than it is for large customers. With the exception of few hundred customers at SDG&E, no utility in the U.S. has defaulted medium customers onto dynamic pricing tariffs. Due to the limited empirical data, medium ex ante impact estimates should be interpreted with caution.

Table 1-2: Summary of 2013 and 2023 Ex Ante Load Impacts
1-in-2 Weather Conditions for August System Peak Day

Utility	Demand Size	Year	Enrollment Forecast	Reference Load (MW)	Load Impact (MW)	Percent Impact (%)
PG&E (1–6 PM)	Large	2013	1,401	519	40.4	7.8%
		2023	1,825	632	50.5	8.0%
	Medium	2013	228	23	0.9	4.0%
		2023	29,576	1,058	64.2	6.1%
SCE (1–6 PM)	Large	2013	3,068	683	31.2	4.6%
		2023	3,141	699	32.0	4.6%
	Medium	2013	–	–	–	–
		2023	–	–	–	–
SDG&E (11 AM – 6 PM)	Large	2013	1,083	282	16.7	5.9%
		2023	1,242	323	19.1	5.9%
	Medium	2013	–	–	–	–
		2023	7,456	392	19.9	5.1%
Total	Large	2013	5,552	1,484	88.3	6.0%
		2023	6,208	1,654	101.6	6.1%
	Medium	2013	228	23	0.9	3.9%
		2023	37,032	1,450	84.1	5.8%

Key findings for PG&E include the following:

- *In aggregate, participants reduced demand by 6.9% across the 2 to 6 PM event window for the average event day, delivering 30.2 MW of demand reduction.*
- *The differences between individual 2012 event day results and average event day results are not statistically significant*. Estimated demand reductions vary from 21.0 MW to 41.2 MW for individual events. On a percentage basis, demand reduction estimates vary from 4.7% to 9.4%. The confidence bands for individual event days are wide and reflect the challenge of detecting relatively 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 are concentrated in specific industry segments – Manufacturing and Wholesale, Transport & Other Utilities, and Agriculture*. For PG&E, these customers make up 41% of program enrollment, 41% of program load and over 85% of the estimated demand reductions. Manufacturing, Wholesale & Transport, and Agriculture customers reduce a larger share of their demand than the average CPP customer, delivering reductions of 11.6%, 20.8% and 13.7%, 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 the regions. The Greater Bay Area accounts for 47% of CPP customers, 56% of program load and 36% of estimated demand reductions. The regions in the Central Valley – Greater Fresno, Stockton, Kern and Other – combined account for 46% of default CPP customers, 35% of program load, and 55% of estimated demand reductions.
- *Ex ante load impact for large customers are expected to grow marginally from 40 MW in 2013 to 51 MW in 2023,* in part because PG&E expects additional large customers to default onto CPP in November 2014.
- *Default CPP load impacts for medium C&I customers are highly uncertain.* The initial estimate developed by using the customers currently on CPP that most resemble medium customers indicate they will deliver approximately 60 MW.

Key findings for SCE include the following:

- *In aggregate, participants reduced demand by 6.0% across the 2 to 6 PM event window for the average event day, delivering 32.9 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 22.6 MW to 45.6 MW for individual events. On a percentage basis, demand reduction estimates vary from 4.4% to 8.7%. The difference between the average event load reduction of 32.9 MW and the demand reduction of 45.6 MW on July 12 is statistically significant. As with PG&E, while day-to-day performance can vary, much of the variation across days is explained by statistical uncertainty.
- *Demand reductions are highly concentrated in specific industry segments – Manufacturing, and Wholesale, Transport & Other Utilities.* These customers make up 45% of program enrollment and 44% of program load at SCE, but contribute 87% of the estimated demand reductions. Manufacturing and Wholesale & Transport customers reduce a larger share of their demand than the average CPP customer, delivering reductions of 13.8% and 9.4%, respectively.
- *Average load reductions are lower in the areas affected by the SONGS outage*. Power flow to the southern Orange County area has been impacted by the outage of two out of three generating units at the San Onofre Nuclear Generating Station (SONGS). 44% of SCE's CPP participants are located in the South of Lugo or South Orange County transmission regions. These 1,082 CPP customers delivered 17.8 MW of demand response, representing a 3.7% load reduction. The lower load impacts in Orange County relative to the rest of the service territory reflect differences in the customer mix.
- *The share of CPP load impacts due to dually enrolled customers has tripled since 2011*. In 2011, 4.0 MW of CPP load impacts (11% of the total CPP load impact) were delivered by dually enrolled customers. The contribution of this group to total program impacts tripled between 2011 and 2012 to 33% (10.7 MW).
- *Under SCE's current enrollment projections, the load reduction capabilities of the large customer default CPP is expected to remain nearly constant*. 2013 aggregate load impacts at SCE during an August event for the 1-in-2 weather year scenario is estimated to be 31.0 MW.

Key findings for SDG&E include the following:

- *SDG&E called many more events in 2012 than in 2011.* Seven events were called in 2012 versus two in 2011. Two of the events in 2012 were called on Saturdays. SDG&E was the only IOU to call Saturday events in 2012.
- *In aggregate, participants reduced demand by 6.0% across the 11 to 6 PM event window for the average weekday event, delivering 18.1 MW of demand reduction.*

- *CPP participants reduced demand by 6.3% across the event window during the average weekend event.* While reference loads were lower during these weekend events, demand response on a percentage basis was similar to responsiveness on weekday events.
- *The differences between individual event day results and average event day results are not statistically significant*. Estimated demand reductions vary from 14.5 MW to 25.9 MW for individual events. On a percentage basis, estimated demand reductions vary from 5.4% to 8.4%. As with the other utility results, day-to-day performance can vary, but most of the variation is explained by statistical uncertainty.
- *Unlike with PG&E and SCE, there was more balance across industry segments in terms of the share of overall aggregate demand reduction, load and enrollment.* The largest SDG&E industry sector was comprised of offices, hotels, finance and services, which accounted for 31.5% of enrollment. This sector also produced 31.6% of the program's load impacts. On a percentage basis, the highest-performing industry was wholesale, transport and other utilities, with average load reductions of 12.0%. These customers accounted for 14% of enrollment and 8.7% of the program's reference load.
- *Ex ante impacts for SDG&E's large customers are relatively constant from year to year.* The aggregate 1-in-2 weather year demand reductions forecasted for 2013, 16.7 MW, do not differ substantially from the 2023 forecast, 19.2 MW. On a percentage basis, the demand reductions are identical to those observed in 2012 for the average event, 5.9%, for all forecast years and weather year conditions.
- *All SDG&E's medium customers are expected to be defaulted onto CPP in 2014*, with forecasted enrollment decreases immediately after the initial default year followed by an increase thereafter. However, the drop in enrollment is not accompanied by a corresponding decrease in forecasted impacts. In fact, the demand reductions under 1-in-2 weather conditions for 2015, 16.9 MW, are very similar to the 2014 forecast, 17.6 MW.

2 Introduction

The 2012 statewide evaluation of California's non-residential 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 2012 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 might occur in the future. Ex ante load impacts, however, 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 2012 activation events (ex post 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?
- 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?

This report draft only addresses the first four questions.

2.1 Non-residential CPP Programs at California IOUs

Critical Peak Pricing 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. 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. For all three IOUs, CPP rates were also available for small commercial and medium C&I customers on an opt-in basis, but most customers taking electric service under CPP rates in 2012 were large C&I customers that were defaulted onto CPP. Most of these customers were previously on TOU rates that already provided incentives to shift or reduce electricity usage during peak periods.[3]

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 commercial and industrial 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 still 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 in October 2009, 18 months later 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 3 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/TOU tariff. SCE required only that a customer's monthly maximum demand exceed 200 kW.
- 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 anytime at PG&E and SCE. However, at these utilities, customers must forgo bill protection if they leave the CPP rate during the first year when bill protection is in effect.
- SCE and PG&E share the same event hours, 2 PM to 6 PM, although a small number of customers in PG&E's service territory have elected a 12 PM to 6 PM event window with reduced credits and CPP charges. SCE and PG&E also share the same TOU peak period hours,

[3] 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 annual 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.

12 PM to 6 PM, Monday through Friday. For SDG&E, both the CPP event period hours and TOU peak period hours are from 11 AM to 6 PM.

- 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 summer weekdays. PG&E and SCE are committed to a minimum of 9 and a maximum of 15 events each year. SDG&E is committed to a maximum of 18 events with no minimum.
- PG&E attempts to notify customers via phone, email, pager or text by 2 PM on the day before an event, while SCE and SDG&E attempt to notify customers by 3 PM the day before.
- PG&E and SDG&E offer customers the ability to hedge part or all of their demand against higher CPP prices – a feature known as a Capacity Reservation – while SCE has not yet implemented this feature.

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 2012 enrollment averaged 1,587 customers. At SCE, most of the 8,000 eligible accounts were placed on default CPP in the fall of 2009, but nearly half of them opted out to TOU before the first summer period. By the end of summer 2011, roughly 3,000 accounts remained on default CPP, and by the end of 2012, 2,508 customers were still on the CPP rate. By the end of 2011, SDG&E had almost 1,300 accounts – or roughly 60% of eligible customers – on CPP and by the end of 2012, SDG&E's CPP rate enrollment stood at 1,136. 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 offered customers bill comparisons between the CPP and opt-out TOU tariffs. In addition, SCE compared the CPP and opt-out TOU rates to each customer's historical tariff. Notably, SCE customers transitioned to default CPP at the same time that a 3.1% rate reduction was being implemented for large customers.

When assessing the impacts that are presented in subsequent chapters, 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 and SCE's system peaked on August 13, 2012 while SDG&E's system peaked on September 14, 2012. 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 PM 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.

Table 2-1 provides 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. Table 2-1 illustrates 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 $1.06/kWh for SDG&E AL-TOU to a high of $1.36/kWh for SCE TOU-GS-3 customers. The CPP credits take the form of reduced demand charges ($/kW), reduced consumption charges ($/kWh), or both. Customers on CPP experience on-peak demand credits that also vary substantially across utilities, ranging from $5.21/kW for SDG&E AL-TOU customers, to $6.35/kW for PG&E E-19 customers, and $11.62/kW for SCE customers on TOU-GS-3. SDG&E and PG&E also have small energy credits for non-event periods, but SCE does not. 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 otherwise applicable tariff (OAT), rather than as explicit credits. The summer on-peak demand credit is $5.21/kW and the energy credits are under $0.01/kWh. The impact on customer bills is the same as that of an explicit credit.

SDG&E offers capacity reservation (CR) to all CPP customers and PG&E offers it to CPP customers whose underlying TOU rate is E-19 or E-20.[4] SCE does not currently offer the CR option. Capacity reservation is a type of insurance contract in which a customer pays a fee (measured 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 during an event. SDG&E charges $6.42/kW per month for this option and the default level for SDG&E customers is 50% of a customer's average of their monthly maximum demands during the previous summer. PG&E also sets the default level to 50% of the same metric, but the capacity reservation structure is different. For PG&E, E-19 and E-20 customers pay capacity reservation charges according to the peak (during summer) and part-peak (during winter) demand charges that they normally pay during the hours of a CPP event. This means that the summer price for capacity reservation is $14.70/kW and the winter price is about $0.21/kW. Because CPP events in PG&E's territory are much more likely to be called in the summer, it is sensible to charge more for insuring against events during the summer.

[4] A-10 customers are not eligible for CR, but they are offered other risk-shifting options to compensate: the every-other-event option and the six-hour-event-period option.

Table 2-1: Example 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	$0.13476	$0.12448	$0.13990
			Semi-peak	$0.09579	$0.09086	$0.12062
			Off-peak	$0.07028	$0.06543	$0.10025
		Demand Charges (per kW)	On-peak	$14.70	$12.96	$12.86
			Semi-peak	$3.43	$3.08	NA
			Maximum	$11.85	$13.30	$13.57
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.20	$1.36229	$1.06282
			On-peak	$0.00	NA	$(0.006460)
			Semi-peak	$0.00	NA	$(0.06380)
			Off-peak	NA	NA	$(0.005910)
		Demand Credits (per kW)	On-peak	$(6.35)	$(11.62)	$(5.21)
			Semi-peak	$(1.37)	NA	NA
		Capacity Reservation Charge (per kW per month)	Summer	$13.05	NA	$6.42
Winter	TOU Component	Energy Charges (per kWh)	On-peak	NA	NA	$0.13403
			Semi-peak	$0.09063	$0.06987	$0.12574
			Off-peak	$0.07320	$0.05412	$0.10558
		Demand Charges (per kW)	On-peak	NA	–	$4.92
			Semi-peak	$0.21	–	NA
			Maximum	$11.85	$13.30	$13.57
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.20	NA	$1.06282
			On-peak	NA	NA	$(0.00593)
			Semi-peak	NA	NA	$(0.00593)
			Off-peak	NA	NA	$(0.00592)
		Demand Credits (per kW)	On-peak	NA	NA	$(0.17)
			Semi-peak	NA	NA	NA
		Capacity Reservation Charge (per kW per month)	Winter	$1.12	NA	$6.42

2.2 Report Organization

The remainder of this document is separated into four sections and two appendices. Section 3 discusses the methodology employed to estimate ex post load impacts. PG&E's ex post results are presented in Section 4, SCE's in Section 5 and SDG&E's in Section 6. Sections 7, 8 and 9 present ex ante load impact forecasts for PG&E, SCE and SDG&E, respectively. Appendix A contains the

[5] Table 2-1 does not include all CPP rates at each utility and the rates shown are presented for illustrative purposes only. Rates may vary over the course of the program year, by customer size and service voltage level. The rates shown are for customers at the secondary service voltage level. E-19 is mandatory for PG&E customers who fail to meet the requirements of E-20, but have monthly maximum billing demand above 499 kW and is voluntary for PG&E customers with maximum billing demand greater than 200 kW and less than 500 kW; TOU-GS-3 is mandatory for SCE customers with maximum demand greater than 200 kW and less than 500 kW; and AL-TOU applies to all SDG&E customers whose monthly maximum demand equals, exceeds, or is expected to equal or exceed 20 kW. This example PG&E E-19 rate was effective March 1, 2012; the SCE TOU-GS-3 rate was effective January 1, 2012; the SDG&E AL-TOU demand charges were effective March 1, 2012 and the energy charges were effective January 1, 2012; the SDG&E EECC AL-TOU and EECC-CPP-D commodity rates were effective January 1, 2012. Please consult each utility's website to obtain the CPP rates that were in effect for specific time periods.

difference-in-differences regression model specifications. Appendix B presents the results of the false experiment testing used for selecting proxy CPP event days. Appendix C provides an overview of the individual regression models. Portfolio-adjusted ex ante load impact forecasts are given in Appendix D. Electronic ex post and ex ante tables that provide hourly load impacts for individual event days and across customer segments are included with this report.

3 Methodology

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. For all three utilities, the rate discount for large and medium customers[6] has been implemented primarily in the form of a reduction in summer on-peak demand charges.

The impacts estimated for 2012 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 other rate periods are not estimated for three reasons: prior analyses in 2010 and 2011 did not find statistically significant impacts due to the rate discount; the pre-enrollment data needed to quantify the effect of the rate discount is too distant (four or five years prior); and any changes are by now embedded in system load forecasts (and not incremental).

The remainder of this section:

- Describes the ex post evaluation method selected;
- Compares the CPP and control group customer characteristics for all three utilities;
- Describes the primary regression models and estimating sample used for ex post evaluation;
- Presents the results from validation tests used to assess the accuracy of the methods; and
- Explains the methodology used to develop ex ante load impacts.

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 event day higher 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.

2012 load impacts were estimated using two methods:

- Difference-in-differences panel regressions – this method makes use of both an external control group and non-event day data; and
- Individual customer regressions – this approach relies on electricity usage patterns for individual customers on non-event days to estimate the reference load for event days. Individual customer regressions are used primarily for comparative purposes in the ex post estimation setting, but as the primary estimation method in the ex ante setting.

[6] Throughout this methodology summary, we use the word *customer* synonymously with service account.

Although the estimated load impacts for the average event day are quite similar for both approaches for all three utilities, the primary ex post impacts reported here rely on the difference-in-differences panel regressions. The difference-in-differences approach produces more accurate results for individual CPP days when tested side-by-side with individual customer regressions. In other words, the difference-in-differences method produces individual event day results that are less noisy, but the average impacts across all days are quite similar for the two methods.

In addition to improved accuracy and precision, there are other reasons to use the difference-in-differences method. A control group provides information about how program participants would have used electricity if they were not exposed to CPP event prices and notification. The control groups developed for the 2012 evaluation are nearly identical to CPP participants across observable characteristics and mirror their usage during hot non-event days. Moreover, the difference-in-differences method makes use of both hot non-event days and a control group.

In addition, the difference-in-differences calculation is simpler, transparent and does not require predicting out of sample using models that may suffer from specification error. Put another way, the difference-in-differences method still works when events are called on nearly all hot days, whereas individual customer regressions have lower accuracy when most or all hot days are event days. This approach also performed well in validation tests, as explained in Section 3.3.

3.1.1 Comparison of Control Groups and CPP Population

Propensity score matching 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[7] and it explicitly addresses self-selection onto CPP tariffs based on *observable* differences between CPP participants and non-participants. The control group was selected from customers who were not on CPP rates but were on the otherwise applicable TOU tariff. It included customers who were defaulted onto CPP and opted out as well as customers enrolled in DR aggregator contracts or on the Baseline Interruptible Program.[8]

With propensity score matching, customer characteristics are weighted based on the degree to which they predict program participation and are used to produce a propensity score. For each CPP customer, the control group candidate with the closest propensity score was selected.[9] CPP participants are matched within industry groups; that is, matched control customers were required to be in the same industry group as CPP participants.[10] Weather conditions (cooling degree days from June through September) were also factored into the match, in addition to location, consumption levels during hot non-event days and the share of their power consumption that occurred during the

[7] 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.

[8] Participants in the latter two programs were included because they were not dispatched at the same time as CPP rates in 2012 and are typically dispatched once or twice per year, mainly for testing.

[9] Matches were restricted to a tight range: if customers within a very similar propensity score (<0.02 difference) could not be found, those CPP customers went unmatched. For each utility, over 90% of CPP participants and load was matched.

[10] Industry groups for SCE and PG&E were defined based on the first two digits of NAICS codes. All categories with less than 150 customers were placed into other groups. Additional weight was given to control group candidates if they had a NAICS code with the same first digit.

peak period. 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, they were selected twice.

Table 3-1 compares control group and CPP participant characteristics for each utility. As seen, control group customers are nearly identical to CPP customers across all variables, indicating a well-matched control group. Control and participant customers are very similar in terms of industry type, location, weather conditions and hourly demand patterns during hot days (prior to any adjustments or modeling). Any observed differences are negligible and typically are not statistically significant.[11]

[11] Based on typical standards for statistical significance, even in fully randomized control trials, 1 in 20 variables will reflect statistically significant differences due to chance.

Table 3-1: Comparison of Matched CPP and Control Group Customers by Utility

Category	Variable	PG&E				SCE				SDG&E			
		CPP (n=1,588)	Control Group (n=869)	t	p>t	CPP (n= 2,279)	Control Group (n=1,458)	t	p>t	CPP (n=1,039)	Control Group (n=446)	t	p>t
Location and Weather[12]	Total CDD June-Sept	1,202.3	1,183.2	-0.32	0.75	1,589.3	1,601.5	-0.70	0.49	151.8	152.5	-0.95	0.34
	Region 1	20.7%	20.7%	-0.34	0.73	14.8%	15.5%	-0.61	0.54	8.4%	9.3%	-0.76	0.45
	Region 2	22.4%	18.5%	-0.36	0.72	27.8%	29.7%	-1.46	0.14	32.3%	32.2%	0.03	0.98
	Region 3	21.1%	19.1%	-0.70	0.48	23.3%	20.7%	2.09	0.04	53.2%	53.8%	-0.26	0.79
	Region 4	35.8%	41.8%	1.22	0.22	25.0%	21.7%	2.68	0.01	6.1%	4.6%	1.47	0.14
Industry Mix	Ag, Mining & Construction	7.7%	9.4%	0.00	1.00	3.2%	3.1%	0.34	0.74	0.0%	0.0%	–	–
	Manufacturing	16.7%	16.7%	0.00	1.00	28.3%	28.3%	0.00	1.00	13.5%	13.5%	0.00	1.00
	Wholesale & Transport	14.7%	15.1%	0.97	0.33	16.1%	15.8%	0.28	0.78	14.2%	14.2%	0.00	1.00
	Retail Stores	4.1%	4.1%	0.00	1.00	6.1%	6.1%	0.00	1.00	9.6%	9.6%	0.00	1.00
	Offices, Hotels, Finance, Services	28.3%	27.1%	0.18	0.86	21.1%	20.9%	0.14	0.89	31.4%	31.4%	0.00	1.00
	Schools	16.1%	16.1%	0.00	1.00	15.8%	15.8%	0.00	1.00	20.2%	20.2%	0.00	1.00
	Institutional/Government	8.3%	9.7%	-0.86	0.39	9.3%	10.0%	-0.75	0.46	11.1%	11.1%	0.00	1.00
	Other or Unknown	4.1%	1.9%	-1.15	0.25	0.0%	0.0%	0.00	1.00	–	–	–	–
Consumption Patterns on Event-Like Days	Peak kWh on hot days (2 PM - 6 PM)	1,402.9	1,400.9	0.34	0.73	1,136.0	1,147.2	-0.31	0.76	1,826.1	1,852.9	-0.25	0.80
	Total Daily KWh on Hot Days	5,672.9	5,686.3	0.33	0.75	4,611.3	4,633.4	-0.13	0.90	5,275.4	5,246.2	0.09	0.93
	% of Consumption During Peak Hours	25.4%	25.4%	-0.14	0.89	25.6%	25.8%	-1.09	0.27	36.3%	36.3%	-0.03	0.97
	Hour ending 1:00 AM	182.6	184.6	0.23	0.82	141.4	139.7	0.23	0.82	176.9	167.7	0.75	0.45
	Hour ending 2:00 AM	177.8	179.8	0.11	0.91	137.0	135.8	0.17	0.86	172.4	163.8	0.71	0.48
	Hour ending 3:00 AM	174.7	176.4	-0.03	0.98	133.3	132.6	0.10	0.92	169.1	160.8	0.69	0.49
	Hour ending 4:00 AM	175.7	177.2	0.10	0.92	131.9	134.9	-0.43	0.67	168.8	161.1	0.65	0.52
	Hour ending 5:00 AM	182.7	182.8	0.42	0.68	140.9	143.8	-0.41	0.68	173.3	166.9	0.54	0.59
	Hour ending 6:00 AM	200.1	197.1	0.59	0.56	163.9	163.4	0.07	0.95	186.1	180.8	0.44	0.66
	Hour ending 7:00 AM	221.6	221.1	0.59	0.55	190.0	191.3	-0.18	0.86	202.0	201.7	0.02	0.99
	Hour ending 8:00 AM	244.3	244.6	0.20	0.85	211.0	212.6	-0.22	0.82	222.2	224.9	-0.20	0.84
	Hour ending 9:00 AM	261.8	262.6	0.33	0.74	226.0	227.7	-0.23	0.82	240.7	242.9	-0.16	0.88
	Hour ending 10:00 AM	275.9	276.3	0.38	0.71	236.2	238.6	-0.32	0.75	254.9	257.6	-0.18	0.85
	Hour ending 11:00 AM	287.1	287.0	0.44	0.66	245.6	247.2	-0.20	0.84	265.6	268.4	-0.19	0.85
	Hour ending 12:00 PM	293.2	292.3	0.48	0.63	248.3	251.3	-0.39	0.70	269.8	273.1	-0.22	0.83
	Hour ending 1:00 PM	292.8	290.0	0.61	0.54	246.4	250.7	-0.56	0.57	271.1	275.2	-0.27	0.79
	Hour ending 2:00 PM	296.8	295.8	0.41	0.68	248.7	252.2	-0.45	0.65	270.7	274.9	-0.27	0.78
	Hour ending 3:00 PM	294.1	293.1	0.31	0.76	243.1	245.6	-0.33	0.74	267.7	271.1	-0.22	0.82
	Hour ending 4:00 PM	284.9	284.9	0.34	0.73	230.3	231.5	-0.15	0.88	260.0	264.0	-0.26	0.79
	Hour ending 5:00 PM	272.5	271.3	0.35	0.73	214.5	216.2	-0.24	0.81	250.5	253.4	-0.19	0.85
	Hour ending 6:00 PM	254.5	255.9	0.30	0.77	199.4	201.7	-0.32	0.75	236.4	241.2	-0.33	0.74
	Hour ending 7:00 PM	235.9	237.3	0.21	0.83	186.7	186.1	0.08	0.93	220.9	218.6	0.17	0.87
	Hour ending 8:00 PM	225.2	228.7	0.20	0.84	183.7	181.5	0.30	0.77	214.4	210.7	0.27	0.79
	Hour ending 9:00 PM	219.9	222.7	0.34	0.74	179.1	177.3	0.23	0.82	208.4	205.8	0.20	0.84
	Hour ending 10:00 PM	213.4	216.5	0.13	0.90	168.8	168.2	0.09	0.93	197.8	195.9	0.14	0.89
	Hour ending 11:00 PM	206.6	208.5	0.24	0.81	156.5	156.1	0.07	0.95	191.3	187.8	0.27	0.79
	Hour ending 12:00 AM	198.5	199.9	0.20	0.84	148.7	147.7	0.14	0.89	184.3	178.2	0.48	0.63

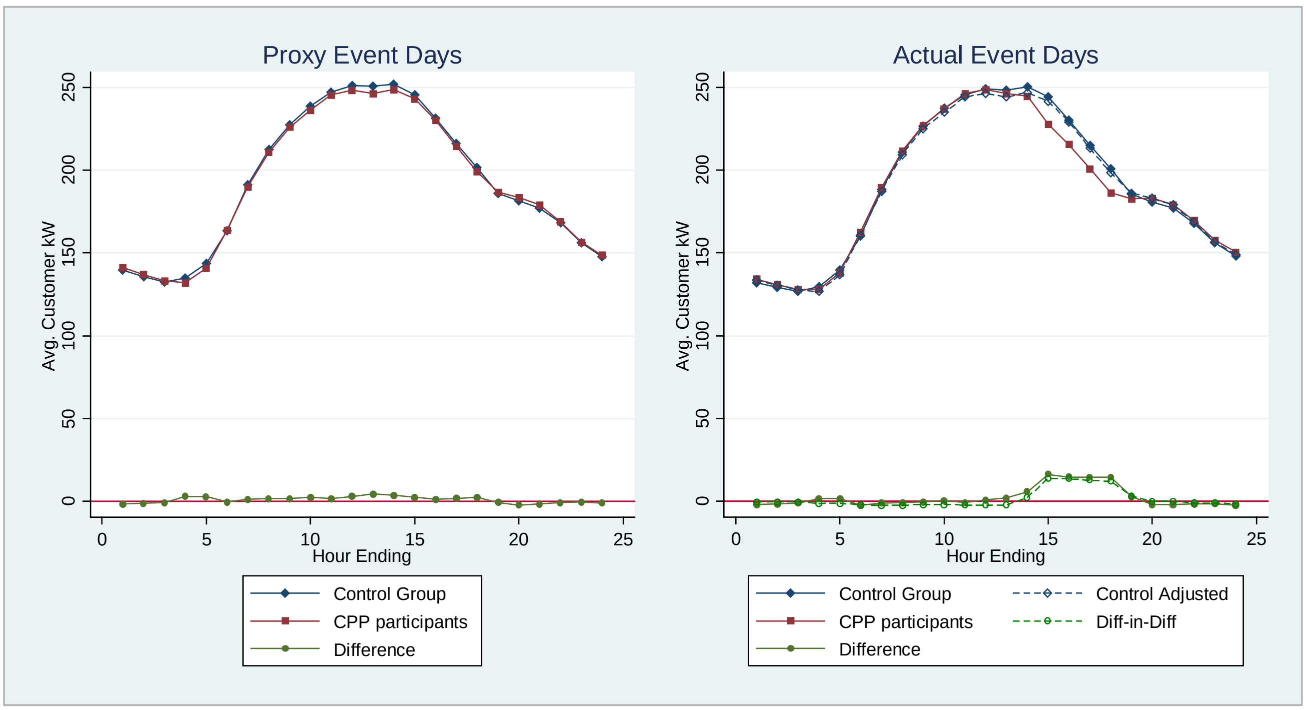
[12] Definition of regions varies across utilities. PG&E's regions reflect Very Hot (e.g., Fresno and Bakersfield), Hot (e.g., Sacramento and Fairfield), Warm (e.g., San Jose and Concord) and Coastal (e.g., San Francisco and Oakland). For SCE, they were based on grouping similar climate zones defined by the California Energy Commission. For SDG&E, they reflect Southeast (e.g., Chula Vista, La Mesa and Alpine), Northeast (e.g., Oceanside, Fallbrook, Ramona and Borrego Springs), Central (e.g., San Diego and San Ysidro) and North (e.g., Mission Viejo).

3.1.2 Regression Models and Estimating Sample

2012 ex post CPP load impacts were estimated using difference-in-differences. Figure 3-1 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 allows us to estimate CPP participant's hourly electricity consumption patterns in the absence of CPP event day prices.

The right side of Figure 3-1 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.

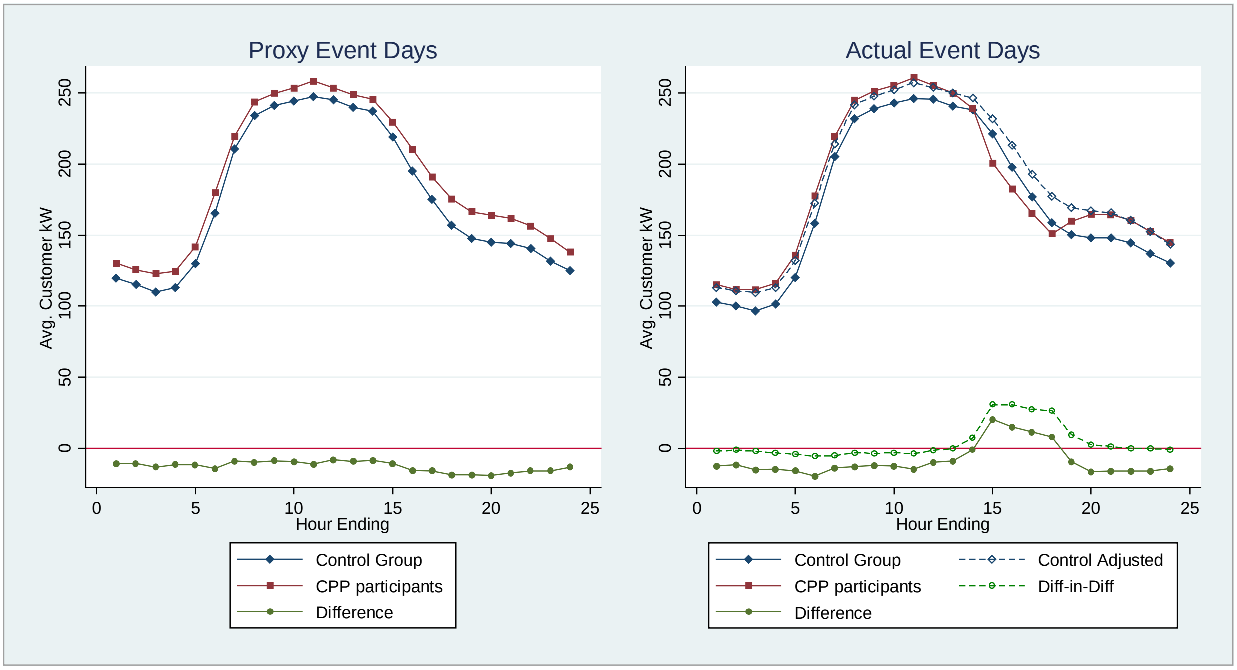
Figure 3-1: Example of Difference-in-differences Calculation (SCE)



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 side of Figure 3-1. 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.

Figure 3-2 illustrates an example for a specific industry, manufacturing, where the adjustment plays a larger role. During proxy event days, the CPP and control group loads closely mirror each other, but there is a noticeable scale difference across all hours. Differences are more common for specific segments because sample sizes are smaller and because loads are often concentrated among a few large customers. The right side of Figure 3-2 illustrates the influence the difference-in-differences adjustment has on estimated impacts. While control groups simplify analysis and make it more transparent, they do not work as well when results are disaggregated too much.[13] As a result, validation tests are important.

Figure 3-2: Example of Difference-in-differences Calculation for Segment (SCE Manufacturing Customers)



While load impact estimates using difference-in-differences calculations can be done arithmetically, that is, by simply 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 simply 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 available 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.[14] 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 experience the CPP event day

[13] This is also true for individual customer regressions.

[14] 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.

prices.[15] Appendix A describes the mathematical representation of the model. It also includes the hourly regression coefficients, standard errors and R-square values for the average event day regressions for each of the utilities.

3.1.3 Validation and Accuracy of Models

Validation tests are essential to load impact evaluation. Determining how well models or methods predict for circumstances where the correct answer is given is a well-known and excellent approach to validation testing. Assessing the accuracy of reference loads is particularly important when load impact estimates are small (e.g., less than 10%), as any small error in reference loads can lead to much larger percent errors in estimated load impacts. For example, if the actual load impact is only 5%, a 1% upward bias in the reference load means the model will predict a load impact of 6%, which is a 20% error in the impact estimate. On the other hand, if the expected load impact is 20%, the same 1% error in the reference load will lead to only a 5% error in the estimated impact.

The accuracy of the difference-in-differences method is assessed using a method known as false experiment testing. False experiments are instances where the *true* answers are known and different approaches or models are systematically tested for accurate results. The first step in this analysis is to select proxy event days. Then, load impacts are estimated for those proxy days using models that include proxy day (or pseudo-event) variables. The models and process used to estimate the pseudo-impacts during proxy event days are identical to those used in the actual estimation of ex post impacts. If a method is accurate, the estimated impacts should center on zero and be statistically insignificant because, in fact, there is no event. If the analysis indicates an impact, the method is producing erroneous results.

Three key questions are addressed in assessing model accuracy:

- *Do proxy event days reflect event conditions?* The value of validation tests diminishes if the tests do not reflect event-like conditions.
- *Does the model produce unbiased estimates at the program level?* The main metric used to assess bias is the program mean percent error, which can be interpreted as the percentage by which a method tends to over or under predict. To illustrate, a bias statistic of 5% indicates that the approach tends to overestimate demand reductions by 5%. Average hourly load impacts during proxy event days are used to assess bias.
- *How closely do program level estimates for individual event hours and days match actual demand reductions (goodness-of-fit)?* An evaluation method can be accurate on average but perform poorly for individual event hours. This occurs when errors cancel each other out.

Proxy event days are selected by matching historical events to non-event days based on system loads, temperature conditions and day of week.[16] CPP event days tend to differ from typical days. System

---

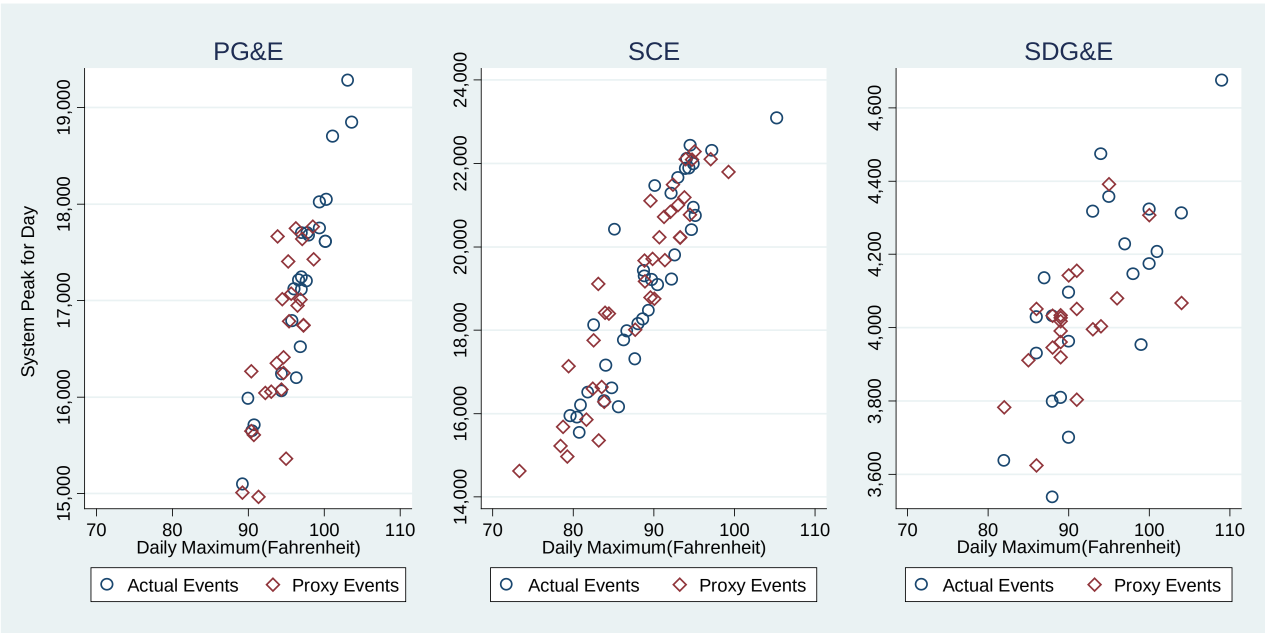
[15] A second model was tested that included weather to assess if it affected the precision of the standard errors or changed the results. The second model produced results that were nearly identical to the first, indicating that the control group and the difference-in-differences adjustment provided nearly all the explanatory power.

[16] 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.

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 proxy event day. In selecting proxy event days, all historical default CPP event days were allowed to be matched. Additional weight was accorded to candidate days that occurred in the same year as actual events. The proxy days match actual event days relatively well. The sole exception is PG&E, where the proxy days tend to have lower temperatures and loads.

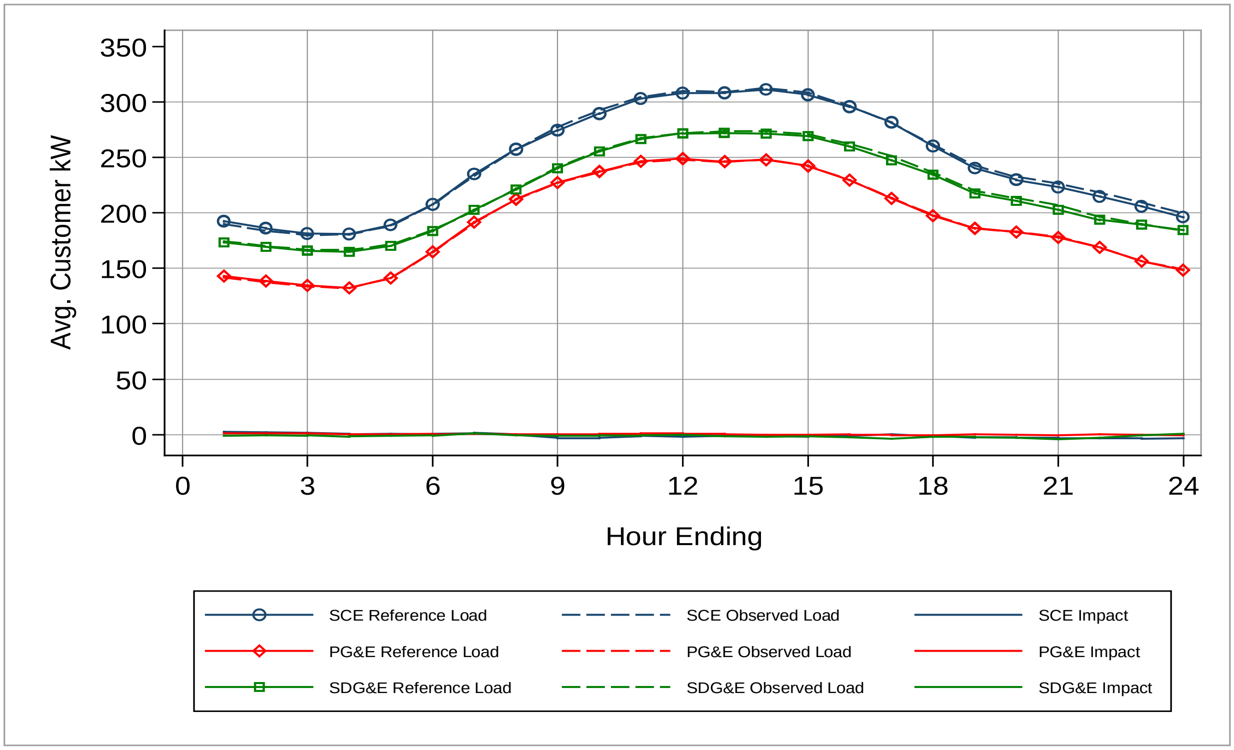
Figure 3-3: Comparison of Actual and Proxy Event Days by Utility



Impacts were estimated for the proxy event days, using the same models and process used for the ex post evaluation.[17] As noted earlier, if a method is accurate, it produces impact estimates for the average event that center on zero and are insignificant because, in fact, there is no event. Figure 3-4 summarizes the results of the validation tests for the average event day for all three utilities. It shows the estimated reference load, the actual loads observed for CPP participants and the estimated impacts for the proxy events. As expected, the impacts when CPP event day prices were *not* in effect are near zero and the reference loads estimated via the control group match the CPP participant loads.

[17] With the difference-in-differences calculation, we calculate the difference between CPP and control groups during proxy event days and net it out of differences observed during actual events. Since the false experiment is designed to replicate the models and process for days when the answer is known, a second set of proxy or control days was selected to match the pseudo-events. These are presented in Appendix B. In the false experiment, we estimated impacts for the pseudo or proxy event days. The second set of proxy days was used to calculate the difference between CPP and control groups, which was then netted out of differences observed during the pseudo-events.

Figure 3-4: False Experiment Results for PG&E, SCE and SDG&E



There are small, but subtle differences. For PG&E, SCE and SDG&E, impacts were estimated to be -0.3%, -0.2% and -0.7%, respectively, during the event hours of the average proxy event. These differences are negligible and are not statistically significant.

There is inherently more volatility and estimation error for individual event days than for the average event day. The results for the average event day are always more accurate and more precise than they are for individual days. An evaluation method can be accurate on average but perform poorly for individual event days. The final check involved assessing how well estimates for individual event days match the actual demand reduction, zero, during the proxy event days.

Table 3-2 summarizes the magnitude of errors for individual days from the false experiments. In percentage terms, the errors are relatively small. The mean absolute percentage error (MAPE) reflects the typical magnitude of the errors for individual events on a percentage basis, with lower values indicating less error. While the typical errors are small, it is critical to remember that the load impact estimates historically have been relatively small (e.g., 6%). A small error, such as 1.5%, can lead to substantive differences in the estimated impacts. For example, if the true demand reduction is 6%, an error of -1.5% in the reference loads will indicate impacts of 4.5%, understating the true demand reductions by 25%. Individual day results should be interpreted with caution, since they are less precise and more volatile than average event day results.

Table 3-2: False Experiment Results for PG&E, SCE and SDG&E

Proxy Event No.	PG&E			SCE			SDG&E		
	Proxy Event Date	Error (kW)	% Error	Proxy Event Date	Error (kW)	% Error	Proxy Event Date	Error (kW)	% Error
1	5/31/2012	-5.7	-2.0%	8/2/2012	-2.4	-1.1%	8/16/2012	-0.9	-0.3%
2	6/1/2012	0.9	0.3%	8/3/2012	-3.6	-1.8%	8/20/2012	-8.7	-3.3%
3	6/11/2012	-2.7	-0.9%	8/6/2012	-1.1	-0.5%	8/28/2012	-5.4	-2.2%
4	6/20/2012	-1.2	-0.4%	8/8/2012	2.1	0.9%	8/29/2012	-5.2	-2.0%
5	7/23/2012	-8.2	-3.0%	8/10/2012	-0.3	-0.1%	8/31/2012	-4.0	-1.6%
6	7/30/2012	-1.1	-0.4%	8/16/2012	0.0	0.0%	9/4/2012	2.6	1.0%
7	7/31/2012	2.7	0.9%	8/17/2012	3.5	1.5%	9/5/2012	-0.3	-0.1%
8	8/1/2012	2.4	0.8%	8/22/2012	2.1	0.9%	9/12/2012	2.0	0.7%
9	–	–	–	8/28/2012	0.3	0.1%	10/1/2012	2.6	1.0%
10	–	–	–	9/14/2012	-3.9	-1.6%	–	–	–
11	–	–	–	9/17/2012	1.5	0.6%	–	–	–
12	–	–	–	9/19/2012	-3.3	-1.4%	–	–	–
13	–	–	–	9/21/2012	0.0	0.0%	–	–	–
Bias	Avg. Event	-1.6	-0.6%	Avg. Event	-0.4	-0.2%	Avg. Event	-2.0	-0.7%
Mean Absolute Percentage Error (MAPE)		1.1%		0.8%			1.4%		
Normalized RMSE (CV RMSE)		1.3%		1.0%			1.6%		

3.2 Ex Ante Impact Estimation Methodology

The main purpose of ex ante load impact estimates is to reflect the load reduction capability of a DR resource under a standard set of conditions that align with system planning. Ex ante impact estimates factor in projected changes in enrollment, known policy decisions such as the implementation of default CPP for medium customers, and approved program changes.

Whenever possible, ex ante load impacts are based on analysis of historical load impact performance. It is preferable to base ex ante impacts on numerous ex post events over multiple years. 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 draw inferences about factors that affect performance.

Two primary steps are required to produce ex ante estimates. First, reference loads need to be estimated for monthly peak days with 1-in-2 and 1-in-10 weather year conditions. By necessity, the development of reference loads relies on modeling electricity use and subsequently predicting electricity use for 1-in-2 and 1-in-10 weather year conditions. For all three utilities, we relied on individual customer regression to produce estimates of the reference loads. Appendix C details the models used to develop reference loads. The second and more important step is to analyze variation and weather trends in load impacts, if any, observed over historical events. In other words, a secondary analysis of historical event impacts is conducted. The analysis of historical event performance can be challenging because different customers experience different events. Some customers have a long history of event performance while other customers have a shorter history based on when they enrolled. The secondary analysis of historical events can be done in one of two ways.

One option is to analyze ex post load impacts developed using the same set of customers and events and a common technique across the historical period. This approach ensures changes in demand reductions are not the artifact of changes in the customer mix over time or the artifact of changes in methodology. It also permits multi-year ex post event impact estimates to rely on techniques such as difference-in-differences that make use of control groups and do not require extrapolating from cooler non-event days to hotter event days. The main drawback to this approach is the fact that only a subset of customers has experienced numerous events over multiple years. These customers may not be representative of the full participant population. Typically, including more historical event performance data leads to bigger differences between the estimating sample and the full participant population. A less than optimal fix is to base ex ante impacts on the analysis of fewer historical events.

A second option is to analyze the event performance history unique to each customer. If a single customer has experienced 27 events over 3 years and a second customer has experienced 5 events during a single year of enrollment, the performance and weather trend for each of these customers is assessed separately. Under this option, ex ante estimates are produced individually and then aggregated. This individualized approach must rely on individual customer regressions. It cannot be done with control groups or aggregate results. The primary benefit of this approach is that it uses all the event history unique to each participant and includes nearly all participants. There are several drawbacks, however. Individual customer results are typically noisy and unreliable for individual customers but can provide accurate results in aggregate. Results from individual customer regressions also are highly dependent on accurately modeling electricity under different weather conditions. These models cannot capture the numerous idiosyncrasies for specific days (e.g., the Monday after a holiday weekend or the first day of school). The individualized approach can produce spurious results that are an artifact of the model selected (e.g., whether a linear, log, or quadratic relationship is assumed) or the inability to model all factors that affect electricity use.

For each utility, a detailed assessment of tradeoffs between the two options was conducted. In specific, we:

- Assessed what share of customers could be included in multi-year analysis that relied on the same set of customers and events;

- Determined if the results from a difference-in-differences approach and individual customer regressions produced the same answer. The comparison was made using the same set of customers and events. It included a comparison of average event impacts and of the weather trends implicit in the ex post results; and
- Conducted validation tests to assess if weather trends implied by individual customer regressions were accurate or an artifact of the underlying models.

Across all three utilities, only 50 to 70% of current CPP customers both had a complete multi-year history of participation on default CPP and a matched control group candidate. For PG&E and SCE, the secondary analysis yielded the same similar percent demand reductions and weather trends regardless of whether ex post impacts were estimated using the difference-in-differences approach or individual customer regressions. While the average impacts were similar, individual customer regressions were less precise and had more estimation error for individual events. The key benefit of relying on individual customer regressions is that a larger number of historical events can be used and ex ante impacts can be developed for nearly all current participants. Both PG&E's and SCE's ex ante impacts are based on ex post results for 2010, 2011 and 2012 events produced with individual customer regressions. Ex ante impacts were based on up to 27 events for PG&E customers; and up to 36 events for SCE customers.

For SDG&E, the secondary analysis produced different answers depending on whether we analyzed historical event impacts produced with difference-in-differences or individual customer regressions. The multi-year individual customer regressions indicated percent demand reductions were highly sensitive to weather. In contrast, the multi-year difference-in-differences load impacts indicated percent demand reductions were weather insensitive. Upon further scrutiny, the high degree of weather sensitivity apparent in multi-year individual regression ex post results proved to be an artifact. The same degree of weather sensitivity was present on proxy event days when higher CPP prices were not in effect. In other words, individual regressions produced inaccurate ex ante impacts for SDG&E: the estimates were too high at hotter temperatures and too low for cooler temperatures. As a result, the demand reductions used to inform ex ante impacts are based on 2012 results produced using the difference-in-differences method.

Besides the estimated demand reductions, a key driver of ex ante impacts is forecasted enrollment growth. Future enrollments are highly uncertain. It is much easier to estimate load impacts under a standard set of conditions for existing customers than it is to do so for a new set of customers, particularly if they differ substantially from existing ones.

The magnitude of ex ante impacts from medium customers under default dynamic pricing is far less certain than it is for large customers. Outside of California, no utility in the U.S. has defaulted medium customers onto dynamic pricing tariffs. Within California, several hundred of 250,000 existing medium customers have been defaulted onto CPP, mostly in SDG&E, but it is necessary to account for substantial differences between them and the far larger population of medium customers scheduled to default onto CPP. In contrast, large customers already have been defaulted and had multiple opportunities to opt-out of default CPP rates. We know how many of these customers tried out default CPP, how much load reduction they provided during historical events, what types of customers are price responsive and their retention rates. In addition, the large customer population is forecasted to remain relatively stable over the 10-year forecast horizon.

Out of necessity, ex ante impacts for medium customers rely on large customers already defaulted onto CPP that are most similar to medium customers. To obtain a larger and more diverse sample, all CPP customers with average hourly demand below 200 kW throughout the year (1,750 MWh or less) were combined with medium customers defaulted onto the CPP rate.[18] In other words, customers that are slightly above the large customer threshold were used as a proxy for medium customers. Across all three utilities medium customer rates (20-200 Max kW) are very similar to the rates of customers in the next size category (200 to 500 Max kW). For SDG&E, the tariffs are identical. In addition, there is substantial overlap in the electricity use patterns and industry mix between medium and large customers. For each utility, we adjusted for differences in the industry mix between proxy medium customers and actual medium customers.

The main, untested assumption is that medium customers will deliver similar percent demand reductions by industry as the estimating sample of medium proxy customers. Actual results could be substantially lower or higher than the point estimates. Medium customers may deliver smaller percent demand reductions due to lower awareness rates and less familiarity with electric rates. They could also deliver larger demand reductions. Not all large customers were defaulted onto CPP rates. Nearly half of the large customer loads at PG&E and SCE were not default because they were already enrolled in DR programs such as aggregator programs and BIP. Arguably, the most demand responsive customers were not defaulted onto CPP. In contrast, relatively few medium customers have enrolled in other DR programs and, as a consequence, utilities are unlikely to exclude the most price responsive customers from defaulting onto CPP.

[18] Customers are classified as small, medium and large based on maximum demand levels rather than average demand levels. As a result, many customers with average demand of 200 kW and below may look more like medium customers. In addition, some customers that met the definition of large customers, at the time, were defaulted onto CPP, but no longer meet the definition of large customers. Many of these customers remain on CPP rates.

4 PG&E Ex Post Load Impacts

This section summarizes the ex post load impact evaluation for customers on PG&E's CPP tariff. PG&E called nine CPP events in 2012. The first event occurred on July 9 and the last was held on August 13. The average number of customers participating in the 9 PG&E CPP events was 1,627. There is event-to-event variation in the number of participating customers due to customer churn; some customers departed and others enrolled in CPP during summer 2012. The highest 2012 enrollment, 1,630 customers, occurred on the August 8 event. The lowest enrollment, 1,623 customers, occurred on the first 4 events in July.

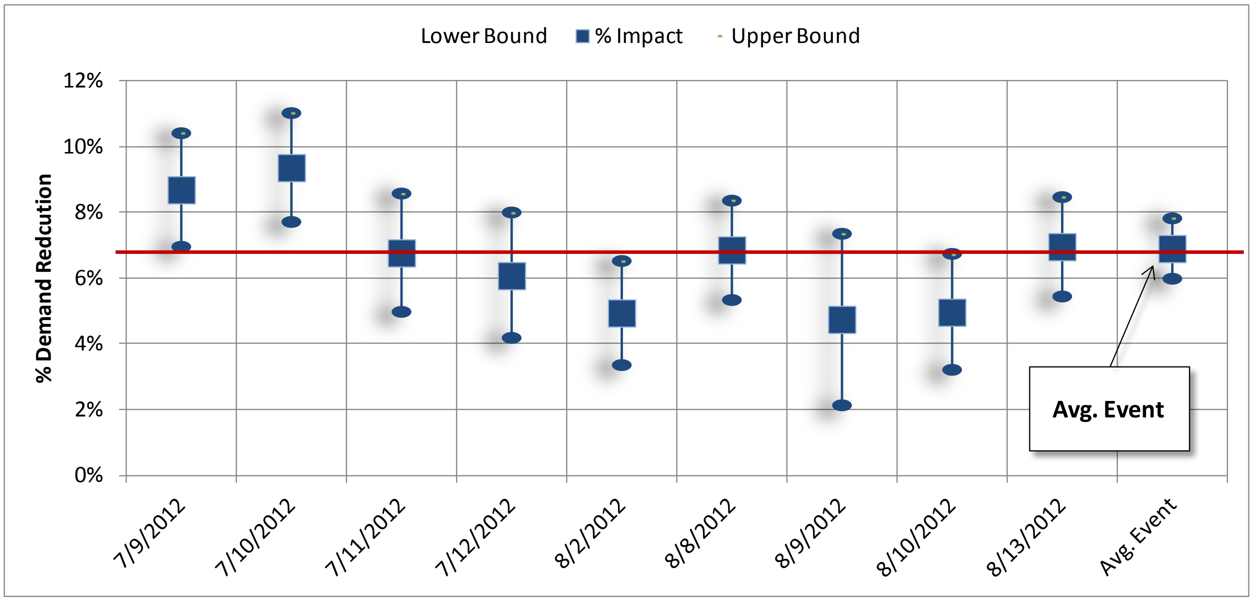
Table 4-1 shows the estimated ex post load impacts for each event day and for the average event day in 2012. The participant-weighted average temperature during the event period ranged from a low of 81.4°F to a high of 90.2°F. Percent impacts range from 4.7% to 9.4%, average impacts range from 12.9 kW to 25.4kW and aggregate impacts range from 21.0 MW to 41.2 MW. On the average event day, the average participant reduced peak period load by 6.9%, or 18.5 kW. In aggregate, PG&E's CPP customers reduced load by 29.3 MW on average across the nine event days in 2012.

Table 4-1: Estimated Ex Post Load Impacts by Event Day
2012 PG&E CPP Events

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
7/9/2012	Mon	1,623	255.0	232.8	22.2	36.0	8.7%	81.4	96.3
7/10/2012	Tue	1,623	271.1	245.8	25.4	41.2	9.4%	88.6	99.9
7/11/2012	Wed	1,623	268.9	250.7	18.2	29.5	6.8%	90.2	103.0
7/12/2012	Thu	1,623	265.1	249.0	16.1	26.1	6.1%	86.0	102.3
8/2/2012	Thu	1,629	260.6	247.7	12.9	21.0	4.9%	85.7	99.8
8/8/2012	Wed	1,630	276.2	257.2	18.9	30.9	6.9%	87.9	98.8
8/9/2012	Thu	1,630	271.8	258.9	12.9	21.0	4.7%	90.2	101.8
8/10/2012	Fri	1,630	261.7	248.7	13.0	21.2	5.0%	88.5	104.3
8/13/2012	Mon	1,630	281.2	261.6	19.6	31.9	7.0%	89.7	103.9
Avg. Event		**1,627**	**268.8**	**250.3**	**18.5**	**30.2**	**6.9%**	**86.5**	**102.8**

Figure 4-1 also presents the estimated load impacts for CPP event days and the average event day in 2012 but here the point estimates are included with 90% confidence intervals. The wider confidence bands around the individual event day estimates, relative to the average event day, illustrate the noise inherent in measuring load impacts for individual event days – the average event day load impact estimate is more precise. The individual event day results are less precise because the percent demand reductions are relatively small and harder to distinguish from the inherent day-to-day variation in loads. A large amount of the variation in load impact estimates across event days is unexplained noise. This is likely a function of CPP customers' differing day-to-day load patterns and ability to shift loads. However, load impacts of individual event days are not significantly different from the average event.

Figure 4-1: Estimated Ex Post Load Impacts with Confidence Intervals 2012 PG&E CPP Events



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. It is a snapshot of the electronic table generator to be 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 7.2% in the third hour to a low of 6.6% in the first hour. Statistically, these differences are probably not significant. Reference loads and load impacts vary more than percentage impacts. The highest aggregate impact, 31.3 MW, occurs in the second hour and the lowest impact, 27.9 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 indicating when many manufacturing plants and other businesses begin shutting down at the end of the work day.

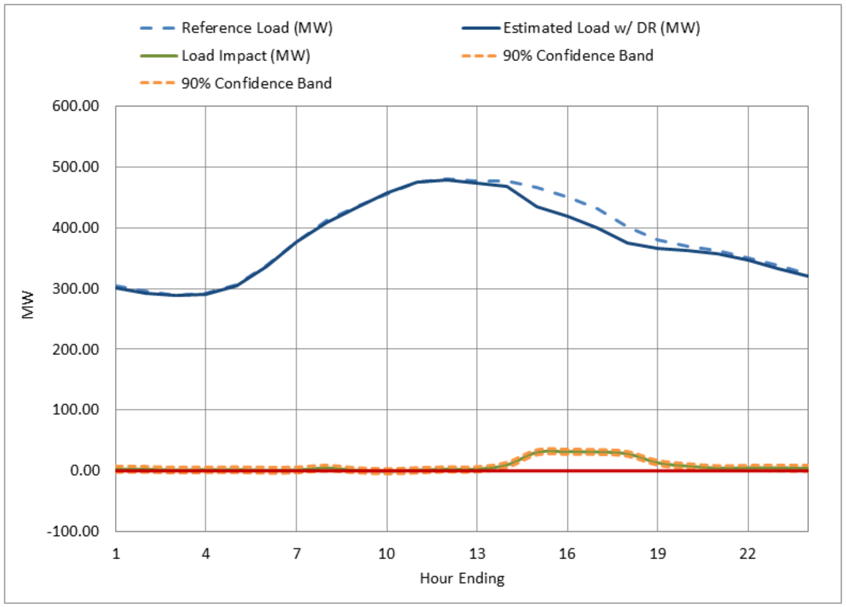
Figure 4-2: Estimated Hourly Impacts for the Average Event Day
2012 PG&E CPP Events

TABLE 1: Menu options

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

TABLE 2: Event Day Information

Event Start	2:00 PM
Event End	6:00 PM
Total Enrolled Acoounts	1,627
Avg. Load Reduction for Event Window (MW)	30.2
% Load Reduction for Event Window	**6.9%**



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	304.5	301.8	2.8	0.9%	66.4	-1.0	1.2	2.8	4.3	6.5
2	295.1	292.7	2.5	0.8%	65.3	-1.2	1.0	2.5	4.0	6.1
3	289.5	288.3	1.2	0.4%	64.2	-2.3	-0.2	1.2	2.7	4.8
4	292.4	290.9	1.5	0.5%	63.2	-2.0	0.1	1.5	2.9	5.0
5	306.4	304.7	1.7	0.6%	62.3	-1.9	0.3	1.7	3.2	5.3
6	337.5	336.5	0.9	0.3%	61.7	-2.9	-0.6	0.9	2.5	4.7
7	377.2	375.8	1.4	0.4%	61.6	-2.3	-0.1	1.4	2.9	5.1
8	412.5	408.1	4.4	1.1%	63.4	0.7	2.9	4.4	5.9	8.1
9	434.6	433.8	0.8	0.2%	66.8	-2.4	-0.5	0.8	2.2	4.1
10	456.1	456.8	-0.7	-0.2%	70.6	-3.9	-2.0	-0.7	0.6	2.5
11	475.8	475.0	0.9	0.2%	74.3	-2.5	-0.5	0.9	2.2	4.2
12	480.6	478.2	2.4	0.5%	77.7	-0.9	1.1	2.4	3.8	5.7
13	476.4	474.0	2.4	0.5%	81.1	-0.8	1.1	2.4	3.8	5.7
14	477.7	467.9	9.8	2.1%	83.8	6.5	8.5	9.8	11.2	13.1
15	465.7	435.1	30.6	6.6%	85.9	27.3	29.2	30.6	31.9	33.9
16	450.4	419.0	31.3	7.0%	87.1	28.1	30.0	31.3	32.6	34.5
17	431.2	400.3	30.9	7.2%	87.2	27.8	29.6	30.9	32.2	34.0
18	402.1	374.2	27.9	6.9%	86.0	24.9	26.7	27.9	29.1	30.9
19	379.5	366.4	13.1	3.5%	83.8	10.0	11.8	13.1	14.4	16.2
20	369.9	362.2	7.6	2.1%	79.9	4.5	6.4	7.6	8.9	10.8
21	362.3	358.0	4.3	1.2%	75.6	1.1	3.0	4.3	5.6	7.4
22	350.7	346.0	4.8	1.4%	72.6	1.6	3.5	4.8	6.1	8.0
23	338.0	333.4	4.6	1.4%	70.4	0.8	3.1	4.6	6.1	8.3
24	324.1	319.8	4.2	1.3%	67.8	0.4	2.7	4.2	5.8	8.1
	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	9,290.1	9,098.7	191.4	2.1%	212.1	174.7	184.6	191.4	198.3	208.2

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, for each industry segment. About 41% of the accounts came from three industry segments: Manufacturing; Wholesale, Transport & Other Utilities; and Agriculture, Mining & Construction. These three industries had the highest percent impact and highest average impact per customer. Combined, they accounted for 40% of the reference load (177.3 MW) but produced over 80% of the impacts. CPP participants in the Manufacturing sector provided 11.4 MW of aggregate load reduction on the average event day, while the Wholesale, Transport & Other Utilities segment provided 10.6 MW of aggregate load impact, reducing loads by 11.6% and 20.8, respectively.

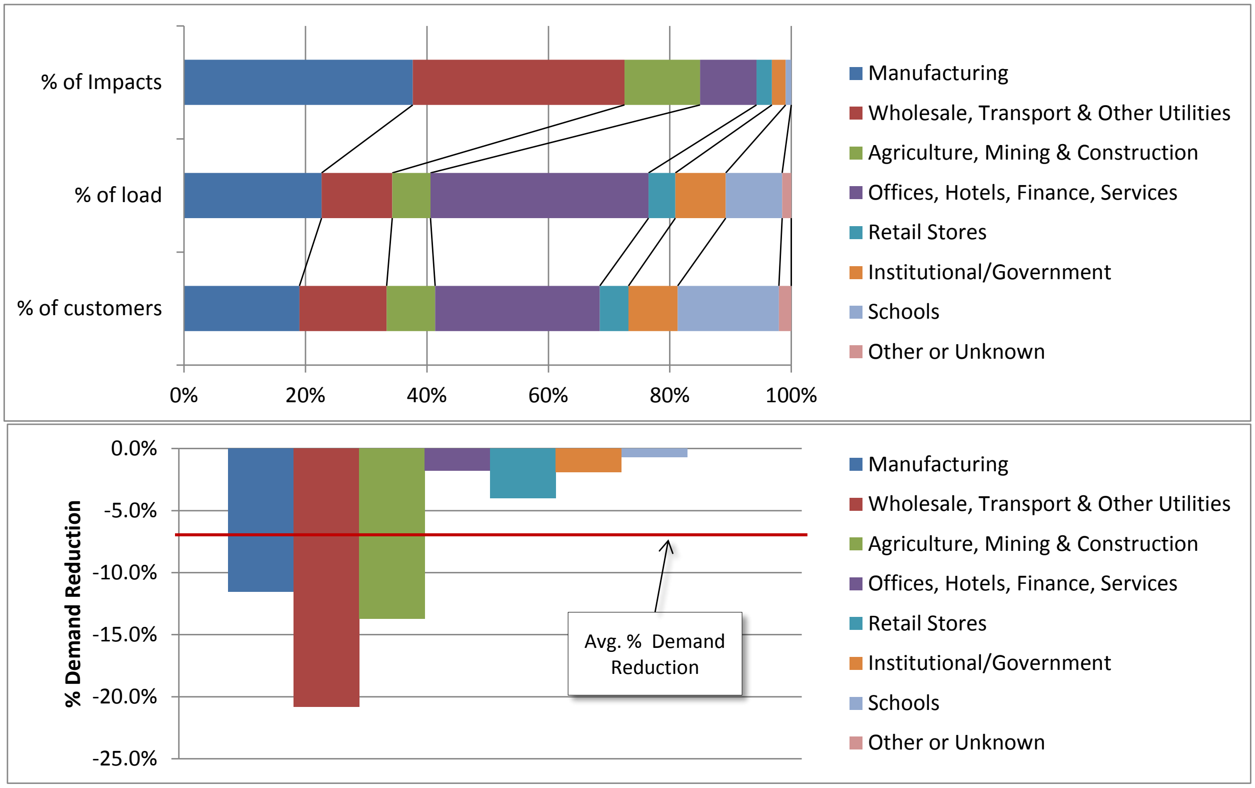
Load impacts for Schools are small, even though schools comprise 17% of the number of participating accounts. The variation in school occupancy and resulting loads across the summer period make it very difficult to estimate load impacts for this segment. It may be that some schools provided meaningful load reductions, but on average, there were no statistically significant impacts for this relatively large participant population. The Offices, Hotels, Finances & Services sector has the most accounts enrolled, but also has very small load reductions on both a percentage and absolute basis. However, load patterns for this segment are much more easily estimated. 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 only produced about 10% of the load reduction (2.8 MW). On average, offices reduced load by 1.8%.

Figure 4-3 presents the same information as Table 4-2, but in graphical form. The benefit of Figure 4-3 is that it readily shows what 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 relatively little to the program's total load impacts.

Table 4-2: Estimated Ex Post Load Impacts by Industry
Average 2012 PG&E CPP Event

Industry	Accounts	% of Program	Aggregate Reference Load (MW)	% of Program	Aggregate Impact (kW)	% of Program	% Reduction	Stat. Significant?
Manufacturing	309	19.0%	98.9	22.6%	11.4	38.6%	11.6%	Yes
Wholesale, Transport & Other Utilities	234	14.4%	50.8	11.6%	10.6	35.7%	20.8%	Yes
Agriculture, Mining & Construction	130	8.0%	27.6	6.3%	3.8	12.8%	13.7%	Yes
Offices, Hotels, Finance, Services	441	27.1%	156.8	35.9%	2.8	9.5%	1.8%	Yes
Retail Stores	77	4.7%	19.2	4.4%	0.8	2.6%	4.0%	Yes
Institutional/Government	132	8.1%	36.3	8.3%	0.7	2.3%	1.9%	Yes
Schools	271	16.7%	40.6	9.3%	0.3	1.0%	0.7%	No
Other or Unknown	33	2.1%	6.5	1.5%	-	-2.4%	-10.8%	No

Figure 4-3: Estimated Enrollment, Load Impacts and Percent Load Reduction by Industry Average 2012 PG&E CPP Event



4.3 Load Impacts by Local Capacity Area

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

Table 4-3 presents the estimated ex post load impacts by local capacity area (LCA). Participants in the Greater Bay Area provided 10.7 MW of aggregate load impact during the average event day, while customers in the Other LCA category provided 6.8 MW of aggregate load reduction. Combined, these LCAs comprise approximately 65% of the enrolled population and 59% of aggregate load impact. Customers in the Greater Bay Area had the highest average reference load of any LCA, at 323.1 kW, while customers in the Kern LCA had the lowest average reference load (150.6 kW). These large differences across LCAs are almost certainly due to differences in the underlying distribution of customers across industry segments and size strata.

Table 4-3: Estimated Ex Post Load Impacts by LCA
Average 2012 PG&E CPP EventLoad Impacts by Customer Size

Local Capacity Area	Accounts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. significant?
		(kW)	(kW)	(kW)	(MW)	%	°F	
Greater Bay Area	760	323.1	309.0	14.1	10.7	4.4%	78.8	Yes
Greater Fresno	190	235.0	216.7	18.3	3.5	7.8%	101.8	Yes
Humboldt	13	212.7	169.4	43.3	0.6	20.4%	61.6	Yes
Kern	104	150.6	121.0	29.6	3.1	19.6%	99.8	Yes
Other	295	234.6	211.4	23.2	6.8	9.9%	87.4	Yes
Northern Coast	84	222.3	210.9	11.4	1.0	5.1%	88.2	Yes
Sierra	77	203.0	186.9	16.1	1.2	7.9%	97.1	Yes
Stockton	105	239.6	210.6	29.0	3.0	12.1%	96.2	Yes

Table 4-4 shows the estimated ex post load impact by customer size, for five customer segments determined by average hourly consumption.[19] Participants with average usage above 500 kWh/hr provided the largest absolute average impact per customer (113.0 kW) and aggregate load impact (12.0 MW). But the smallest customers, with usage under 50 kWh/hr, provided the greatest percent reduction, 21%. The largest customers comprised 38.5% of the aggregate load impact even though they represented only 6.6% of the enrolled population. Participants with average usage between 50 and 100 kWh/hr provided the lowest percent load impact (2.8%).

Table 4-4: Estimated Ex Post Load Impacts by Customer Size
Average 2012 PG&E CPP Event

Consumption Size Category	Accts	Avg. Customer Reference Load	Avg. Customer Load w/ DR	Impact	Aggregate Impact	% Reduction	Avg. Temp	Stat. significant?
(Annual kWh/hr)		(kW)	(kW)	(kW)	(MW)	%	°F	
Over 500 kWh/hr	107	1,210.6	1,097.6	113.0	12.0	9.3%	81.9	Yes
200–500 kWh/hr	360	404.7	374.5	30.2	10.9	7.5%	83.3	Yes
100–200 kWh/hr	555	205.6	196.2	9.5	5.2	4.6%	85.0	Yes
50–100 kWh/hr	387	103.6	100.6	2.9	1.1	2.8%	89.4	No
Under 50 kWh/hr	215	43.0	34.0	9.0	1.9	21.0%	94.2	Yes

[19] Calculated as average kWh per hour, calculated by dividing all Oct 2011-September 2012 consumption by the total hours in that time period.

4.4 Load Impacts for Multi-DR Program Participants

PG&E CPP participants are allowed to 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:

- **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.
- **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.
- **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 twenty customers enrolled in both CPP and CBP. Even the largest dual enrollment category, CPP and AMP, only has 70 customers. 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 CBP are more than twice as price responsive compared with customers dually enrolled in CPP and AMP because the CBP program somehow supports CPP demand response better than the AMP program. Said another way, while dual enrollment in CPP and CBP 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: Estimated CPP Ex Post Load Impacts for Dual Enrollment Participants Average 2012 PG&E CPP Event

Dually Enrolled DR	Accts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	Reduction %	Avg. Temp. °F	Stat. significant ?
AMP	70	323.2	281.1	42.1	2.9	13.0%	88.3	Yes
BIP	24	332.9	209.6	123.3	2.9	37.0%	91.1	Yes
CBP	20	572.4	376.7	195.7	4.0	34.2%	88.1	Yes

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 (TI) 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 significantly 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. Customers with TI showed smaller than average percent impacts of 4.5%, while AutoDR customers produced much larger than average impacts of 50.9%. However, given the extremely small number of customers on TI and AutoDR, the point impact estimates are surrounded by a significant amount of uncertainty. The 90% confidence band is also presented; the wide band around the TI percent reduction statistic reflects the fact that there are only four PG&E CPP customers who have received TI – impact estimates are liable to be extremely inaccurate at such a granular level of analysis. The AutoDR confidence interval is not nearly as wide as the interval for TI, but a significant amount of variation still occurs between the 10^{th} to 90^{th} percentiles.

Table 4-6: Estimated Ex Post Load Impacts of TI & AutoDR Participants Average 2012 PG&E CPP Event

Enabling Technology	Accounts	Load Impact (kW)	% Reduction	90% Confidence Interval		Approved kW	Realization Rate
				Lower	Upper		
TI	4	26.2	4.5%	-2.2%	11.3%	309.0	8%
AutoDR	9	245.6	50.9%	44.2%	57.7%	526.9	47%

Table 4-6 also presents realization rates for TI and AutoDR. Because of the very small sample sizes, these estimates for realization rates must also be used with extreme caution. 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 event-like conditions and whether customers decide to drop load on CPP event days. The average TI realization rate is 8%, while the average AutoDR realization rate is 47%.

4.6 Default CPP Persistence and Weather Sensitivity

Whether default CPP load impacts grow, decrease or remain constant has important implications for long term resource planning and policy. So does the weather sensitivity of demand reductions. A program that provides larger demand reduction when temperatures are hotter and resources are in short supply is more valuable than one that provides constant or decreasing demand reductions as temperatures increase. Persistence analysis is, by necessity, a multi-year analysis. Taking a broader perspective allows for better assessment of overall performance and volatility in demand reductions. It also can help determine whether factors such as weather affect performance. Too few data points weaken the ability to produce reliable estimates and to draw inferences about factors that affect performance.

It is not enough to simply compare the 2010, 2011 and 2012 results. Differences in program impacts can arise because of changes in customer mix, weather, day of week and other idiosyncrasies. To analyze persistence and weather sensitivity, we:

- Narrowed the analysis to customers that were enrolled on CPP rates for each of the 25 events;
- Selected matched control groups from customers that were present over the same time span but were not enrolled on CPP;
- Calculated the demand reduction for each historical event using the same method employed for the 2012 evaluation – a difference-in-differences panel regression; and
- Compared the demand reductions estimated for event days in each year, controlling for temperature.

The results from the persistence analysis need to be interpreted with caution. They reflect the patterns observed for a subset of customers, not those of the entire program. Not all customers on default CPP have a three-year history of CPP participation. Additional customers are gained by restricting the analysis to 2011 and 2012, but the subset remains narrow: of the 1,640 PG&E customers on CPP at the end of 2012, 1,180 (72%) were enrolled in both 2011 and 2012. However, not all of those customers could be matched and certain customer segments such as Agriculture (a price-responsive sector for PG&E) particularly lack multi-year participation history.

Figure 4-4: PG&E CPP Persistence 2011–2012

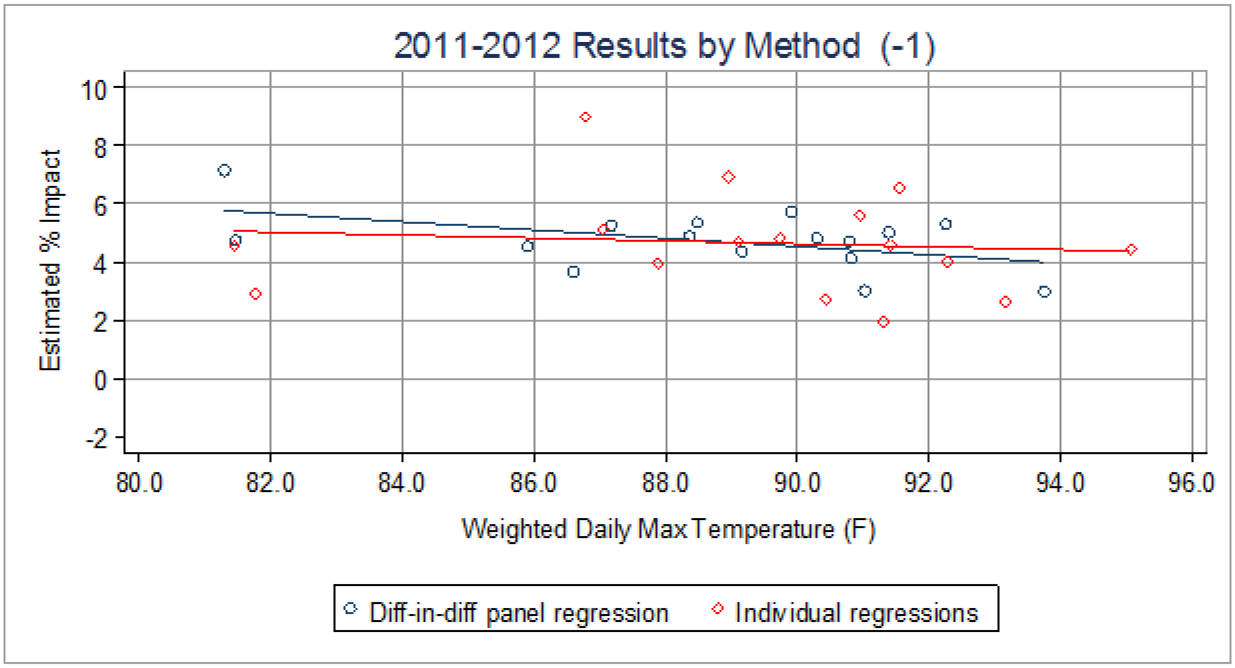


Figure 4-4 shows load impacts for customers who experienced all events in 2011 and 2012, using two analysis methods, difference-in-differences and individual customer regressions, plotted as a function of temperature.[20] Visually, a modest weather trend is observed, but there is a good deal of noise around the average. A linear regression controlling for day-of-week and weather effects, however, does not show the weather trend to be significant, owing largely to the estimation error and relatively few events to analyze.

20 A single observation of negative load impacts with a large amount of leverage in both the difference-in-differences and individual regression datasets has been removed for this graphic.

5 SCE Ex Post Load Impacts

SCE called 12 CPP events in 2012, with the first occurring on June 29 and the last on September 28. The results presented in this discussion focus on customers defaulted onto CPP rates because they account for nearly all of the program's load and all of the aggregate demand reductions.

Table 5-1 shows the estimated ex post load impacts for each event day and for the average event day in 2012. On average, 2,470 accounts were enrolled on the default CPP tariff in summer 2012, although there was some variation in the number of customers enrolled during each event. This variation reflects normal CPP program churn that occurs throughout the summer period, with some customers departing the program and others enrolling between events. The participant-weighted average temperature during the peak period on event days ranged from a low of 80°F to a high of 91°F. Daily maximum temperatures were generally higher, ranging from a low of 87°F to a high of almost 100°F.

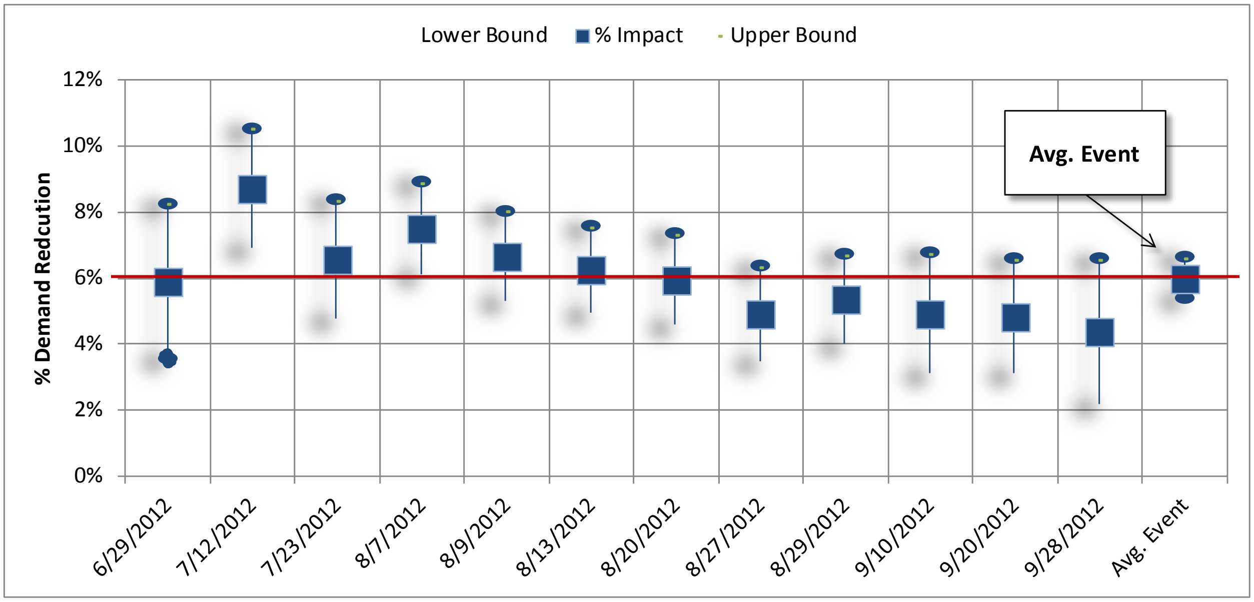
Table 5-1: Estimated Default CPP Ex Post Load Impacts by Event Day
2012 SCE CPP Events (2–6 PM)

Event Date	Day of Week	Accts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	Reduction %	Event Period Temp. °F	Daily Maximum Temp. °F
6/29/2012	Mon	2,464	194.1	182.7	11.4	28.2	5.9%	82.5	86.7
7/12/2012	Tue	2,458	213.0	194.5	18.5	45.6	8.7%	80.3	90.9
7/23/2012	Wed	2,456	207.0	193.5	13.6	33.3	6.5%	80.3	90.6
8/7/2012	Thu	2,473	227.8	210.7	17.0	42.1	7.5%	89.9	96.5
8/9/2012	Thu	2,474	228.8	213.6	15.2	37.7	6.7%	90.5	97.5
8/13/2012	Wed	2,469	232.7	218.2	14.5	35.8	6.2%	90.9	99.5
8/20/2012	Thu	2,475	230.1	216.4	13.7	33.9	6.0%	87.3	93.0
8/27/2012	Fri	2,476	218.8	208.1	10.7	26.5	4.9%	89.4	93.0
8/29/2012	Mon	2,477	238.1	225.3	12.7	31.6	5.4%	89.2	94.0
9/10/2012	Mon	2,468	231.5	220.1	11.4	28.1	4.9%	84.4	88.6
9/20/2012	Thu	2,474	232.0	220.9	11.2	27.7	4.8%	89.0	93.4
9/28/2012	Fri	2,474	208.2	199.0	9.1	22.6	4.4%	84.3	90.3
Avg. Event		**2,470**	**221.9**	**208.6**	**13.3**	**32.9**	**6.0%**	**87.3**	**95.8**

The percent, average and aggregate impacts are similar across events and are not highly correlated with weather. Percent impacts ranged from 4.4% to 8.7%, average customer impacts ranged from 9.1 kW to 18.5 kW and aggregate impacts ranged from 22.6 MW to 43.6 MW. On the average event day, the average participant reduced peak period load by 5.9% or 13.1 kW. SCE called an event on the day their system load peaked, August 13, 2012. CPP participants reduced demand by an estimated 6.2% and delivered 35.8 MW of demand reduction on that day. In aggregate, SCE's CPP customers reduced load by 32.9 MW, or 6.0%, on average across the 12 event days in 2012.

Figure 5-1 shows the estimated load impacts for 2012 CPP event days and the average event day. The figure includes both the estimated percent demand reduction (i.e., the point estimate) and the 90% confidence intervals. The wide confidence bands around the individual event day estimates illustrates the noise inherent in measuring load impacts for individual event days. In contrast, the average event day load impact estimate is more precise. The individual event day results are less precise because the percent demand reductions are relatively small and harder to detect from the inherent day-to-day variation in loads – background noise. A large amount of the event-to-event variation in load impacts is unexplained noise. In fact, it is inaccurate to conclude that individual day percent reductions are different than the average event for 11 out of the 12 events.[21]

Figure 5-1: SCE Percent Load Impact with Confidence Bands by Event Day (2–6 PM)



5.1 Average Event Day Impacts

Figure 5-2 shows the aggregate hourly impact for CPP customers for the average event in 2012. Percent reductions were essentially the same in each hour. Demand reductions varied between 31.1 MW and 34.6 MW, depending on the event hour; however, differences between event hours were not statistically significant. Figure 5-2 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.

[21] The single day where percent demand reductions appear to be different than the average event may also be random noise. Since impacts were estimated with 90% confidence bands, there is a 10% chance that the difference is random.

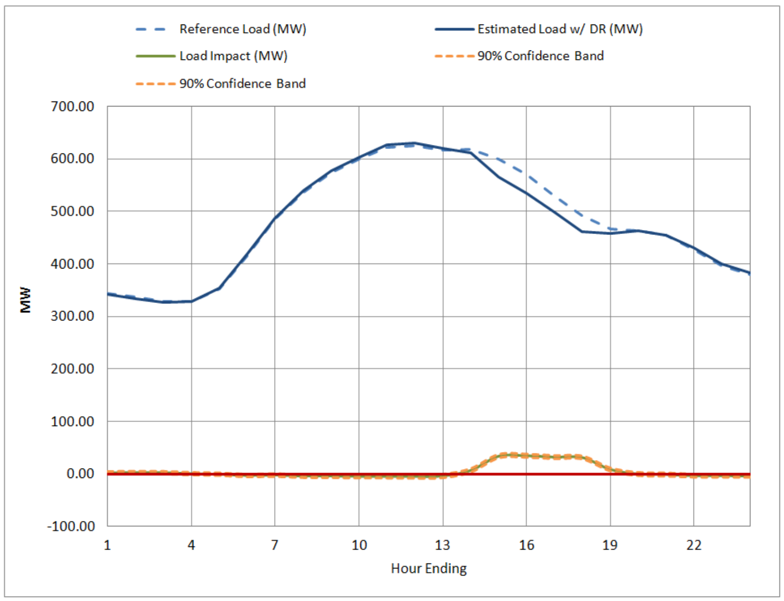
Figure 5-2: Estimated Hourly Impacts for the Average 2012 SCE Event Day

TABLE 1: Menu options

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

TABLE 2: Event Day Information

Event Start	2:00 PM
Event End	6:00 PM
Total Enrolled Accounts	2,471
Avg. Load Reduction for Event Window (MW)	32.9
% Load Reduction for Event Window	**6.0%**



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	344.3	341.9	2.4	0.7%	70.9	0.0	1.4	2.4	3.3	4.7
2	337.1	334.4	2.8	0.8%	70.1	0.4	1.8	2.8	3.7	5.1
3	329.4	326.8	2.5	0.8%	69.4	0.2	1.6	2.5	3.5	4.8
4	328.7	328.0	0.7	0.2%	68.8	-1.5	-0.2	0.7	1.6	2.9
5	353.3	353.6	-0.3	-0.1%	68.2	-2.6	-1.3	-0.3	0.6	1.9
6	416.4	419.2	-2.8	-0.7%	67.8	-5.1	-3.7	-2.8	-1.8	-0.5
7	484.8	486.7	-1.9	-0.4%	67.8	-4.4	-2.9	-1.9	-0.9	0.5
8	536.7	540.6	-3.9	-0.7%	69.7	-6.4	-4.9	-3.9	-2.8	-1.3
9	574.4	578.1	-3.7	-0.6%	73.5	-6.4	-4.8	-3.7	-2.6	-1.0
10	598.9	603.3	-4.4	-0.7%	77.7	-7.2	-5.5	-4.4	-3.3	-1.6
11	622.2	626.5	-4.3	-0.7%	81.7	-7.2	-5.5	-4.3	-3.1	-1.4
12	625.0	629.5	-4.5	-0.7%	84.7	-7.5	-5.7	-4.5	-3.3	-1.6
13	615.9	619.6	-3.7	-0.6%	86.7	-6.6	-4.9	-3.7	-2.5	-0.7
14	619.1	612.2	6.9	1.1%	87.9	3.9	5.7	6.9	8.1	9.8
15	600.2	566.4	33.8	5.6%	88.2	30.9	32.6	33.8	35.0	36.8
16	569.9	535.3	34.6	6.1%	88.1	31.8	33.4	34.6	35.7	37.3
17	530.2	498.2	32.0	6.0%	87.3	29.3	30.9	32.0	33.0	34.6
18	492.7	461.6	31.1	6.3%	85.6	28.6	30.1	31.1	32.2	33.7
19	467.1	458.6	8.5	1.8%	82.7	5.9	7.4	8.5	9.6	11.2
20	463.5	463.4	0.1	0.0%	79.3	-2.6	-1.0	0.1	1.2	2.8
21	454.0	454.9	-0.9	-0.2%	76.6	-3.6	-2.0	-0.9	0.2	1.8
22	427.9	431.0	-3.2	-0.7%	75.0	-5.7	-4.2	-3.2	-2.1	-0.7
23	396.7	399.9	-3.2	-0.8%	73.7	-5.5	-4.1	-3.2	-2.2	-0.8
24	379.6	383.5	-3.9	-1.0%	72.7	-6.1	-4.8	-3.9	-2.9	-1.6
	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	11567.9	11453.2	114.7	1.0%	294.3	102.3	109.6	114.7	119.8	127.1

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

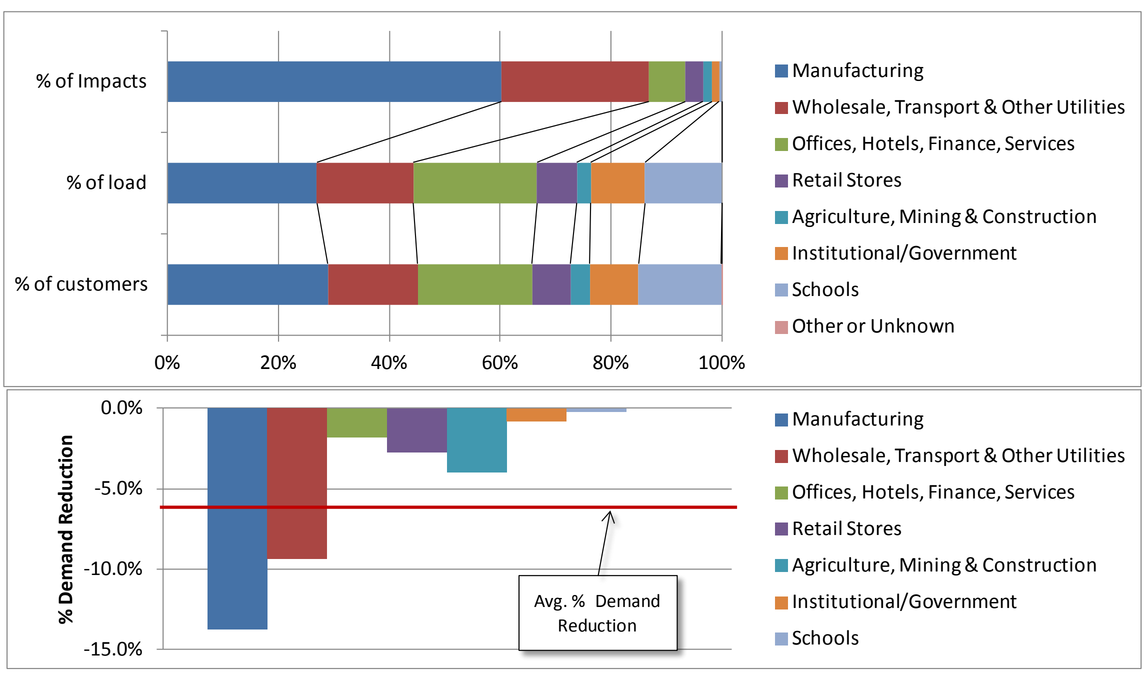
5.2 Load Impacts by Industry

Table 5-2 shows the concentration of accounts, program load and demand reductions across industries. It also shows the share of demand the average customer within each industry reduced 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 5-3 illustrates similar information visually, but better illustrates the concentration across specific industries.

Table 5-2: Estimated Ex Post Load Impacts by Industry
Average 2012 CPP Event (2–6 PM)

Industry	Accts	% of Program	Aggregate Reference Load (MW)	% of Program	Aggregate Impact (MW)	% of Program	% Reduction	Stat. Significant ?
Manufacturing	716	29.0%	147.8	26.9%	20.4	60.3%	13.8%	Yes
Wholesale, Transport & Other Utilities	399	16.2%	95.6	17.4%	9.0	26.6%	9.4%	Yes
Offices, Hotels, Finance & Services	509	20.6%	122.4	22.3%	2.2	6.5%	1.8%	Yes
Retail Stores	172	7.0%	39.7	7.2%	1.1	3.2%	2.7%	Yes
Agriculture, Mining & Construction	87	3.5%	13.5	2.5%	0.5	1.6%	4.0%	No
Institutional/Government	217	8.8%	53.7	9.8%	0.4	1.3%	0.8%	No
Schools	369	14.9%	76.1	13.9%	0.2	0.5%	0.2%	No
Other or Unknown	2	0.1%	0.0	0.0%	0.0	0.0%	0.0%	No

Figure 5-3: Estimated Ex Post Load Impacts by Industry
Average 2012 SCE CPP Event (2–6 PM)



The estimated load impacts for the first four industries presented in Table 4-2 are statistically significant. Except for Agriculture, Mining & Construction, where results are not statistically significant, the estimated demand reduction is less than 1% and therefore hard to distinguish from zero. Two sectors with a large number of CPP enrollees – Institutional/Government and Schools – do not deliver meaningful load reductions. Demand reduction for customers in the Agriculture, Mining & Construction sector was 4.0%. However, the reductions are not statistically significant, likely because of the smaller number of customers, 87, and the inherently variable loads among customers in this segment. Both of these factors affect the amount of background noise – or inherent variability – making it more difficult to detect small percentage demand reductions.

The program demand reductions 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 nearly two thirds of the aggregate load reduction on the average event day, while comprising only 28% of program enrollment. When combined with Wholesale, Transport & Other Utilities, the two segments accounted for 43% of enrollment but more than 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. The Manufacturing segment had the highest percentage demand response, equal to 13%, followed by Wholesale, Transport & Other Utilities customers, who reduced load by 9.4%.

Similar to PG&E's CPP tariff, schools accounted for a relatively large percent of program participants, 15%, but did not produce statistically significant load reductions. Other customer segments also accounted for a large share of enrollment but a small share of the load impacts. The Offices, Hotels, Finance & Services sector showed a small but statistically significant decrease in energy use on the average event day, and the Institutional/Government segment showed statistically insignificant results. Combined, these three sectors accounted for over 40% of the program load but delivered less than 5% of program demand reduction.

5.3 Load Impacts by Local Capacity Area and Transmission Region

Table 5-2 shows the estimated ex post load impacts by local capacity area (LCA). The table also includes results for two transmission constrained areas: South Orange County and South of Lugo. The South Orange County power flow has been affected by the outage of two out of three nuclear generation units at San Onofre.[22]

In total, 84% of enrolled customers and 86% of aggregate load reduction came from the Los Angeles Basin. The customer size and percent demand reductions did not vary substantially across local capacity areas.

Overall, 44% of SCE's CPP participants are located in the South of Lugo or South Orange County transmission regions. These 1,082 CPP customers reduced demand by 17.8 MW for the average event day; they delivered 2.0 MW in South Orange County and 16.8 MW in South of Lugo. At 3.7%, the

[22] San Onofre Nuclear Generating Station (SONGS) reactor units 2 and 3 have been shut down since January 2012 and are still offline as of the writing of this report.

average percentage demand reduction in South Orange County was less than the program average, 6.0%. The difference is likely due to the industry mix in South Orange County.

Table 5-3: Estimated Ex Post Load Impacts by Area
Average 2012 SCE CPP Event (2–6 PM)

Type of Category	Area	Accts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	Reduction %	Avg. Temp °F	Stat. significant?
Local Capacity Area	Outside	141	225.7	211.9	13.8	1.9	6.1%	91.5	Yes
	Ventura	255	230.6	218.5	12.1	3.1	5.2%	83.9	Yes
	LA Basin	2,075	220.9	207.2	13.8	28.6	6.2%	87.4	Yes
Transmission Area	S. Orange County	241	226.2	217.7	8.4	2.0	3.7%	81.3	Yes
	South of Lugo	841	220.8	202.0	18.8	15.8	8.5%	91.3	Yes
	Other	1,389	222.2	211.0	11.1	15.5	5.0%	86.0	Yes

5.4 Load Impacts by Customer Size

Table 5-4 shows the estimated ex post load impact for five customer size categories, determined by average hourly consumption.[23] As expected, the program load is concentrated among customers in the larger size categories. However, these customers not only have larger loads, they also reduce a larger share of their demand than smaller customers. Figure 5-4 shows the trend visually.

Table 5-4: Estimated Ex Post Load Impacts by Customer Size
Average 2012 SCE CPP Event (2–6 PM)

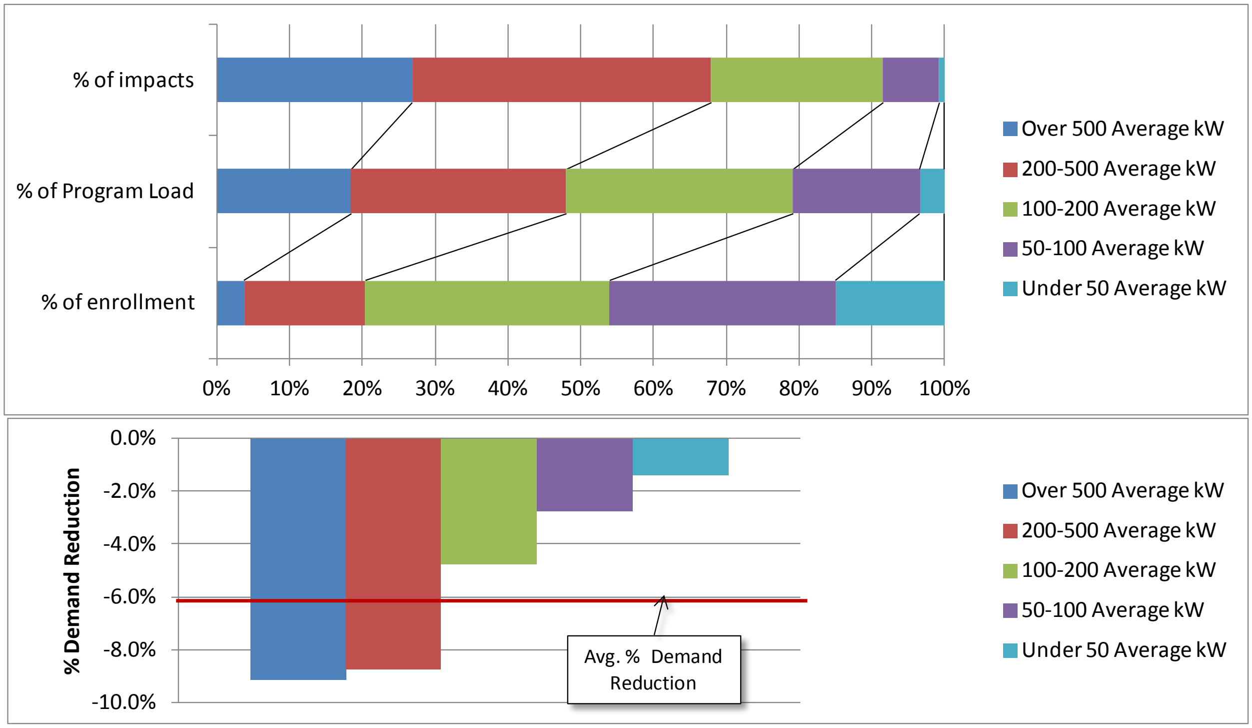
Size Categories (Annual kWh/hr)	Accts.	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	Reduction %	Avg. Temp °F	Stat. Significant?
Over 500 kWh/hr	90	1,098.8	998.6	100.2	9.0	9.1%	88.5	Yes
200–500 kWh/hr	393	400.7	365.7	35.0	13.7	8.7%	86.9	Yes
100–200 kWh/hr	796	207.9	198.0	9.9	7.9	4.8%	86.8	Yes
50–100 kWh/hr	735	126.3	122.8	3.5	2.6	2.8%	87.5	Yes
Under 50 kWh/hr	354	51.3	50.6	0.7	0.3	1.4%	88.5	No

Customers with average hourly usage exceeding 500 kWh/hr accounted for less than 4% of enrollment but delivered 27% of aggregate demand reduction across 2012 events. They reduced their demand by 9.1%. Small customers (below 100 kWh/hr), on the other hand, provided little or no demand response. This group makes up 45% of program enrollment and 21% of aggregate load, but

[23] Calculated as average kWh per hour, calculated as all 2012 consumption over all 2012 hours.

delivers only 8.5% of aggregate load reduction. The estimated impacts for customers in the smallest size category – those with average usage below 50 kWh/h – are not statistically significant.

Figure 5-4: Program Concentration across Customer Size Categories Average 2012 SCE CPP Event (2–6 PM)



5.5 Load Impacts for Multi-DR Program Participants

At SCE, CPP customers can also enroll in several other DR programs, including the Baseline Interruptible Program, Demand Response Resource Contracts (DRRC) and the Capacity Bidding Program (CBP). In 2011, dually enrolled customers accounted for 11% of program impacts. In 2012, they accounted for a third of program impacts. The dramatic increase in dually enrolled load impacts is due, in part, to customers who were previously only enrolled on CPP and dually enrolled in aggregator programs (DRRC or CBP) in 2012. There were also many new dually enrolled CPP customers who were not only new to aggregator programs in 2012 but also new to CPP.

In 2012, nearly 150 accounts were dually enrolled in one of two DR programs: BIP and DRRC. Dual enrollment in BIP grew from 19 to 31 customers from 2011 to 2012. Dual enrollment in aggregator programs grew from 39 to 118 customers from 2011 to 2012. Load impacts from these dually enrolled customers grew commensurately in 2012: dual enrollment load impacts comprised 11% of total CPP impacts in 2011 and have increased to 33% of CPP load impacts in 2012. Table 5-5 shows the estimated load impacts for dual participation customers in SCE's CPP and DR programs. Customers who enrolled in other programs deliver 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 18%. These differences should not be interpreted as implying that dual participation increases 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 events.

Table 5-5: Estimated Ex Post Load Impacts of Multi-DR Participants Average 2012 SCE CPP Event

Dual Enrollment	Accts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	Reduction %	Event Avg. Temp °F	Stat. Significant?
Baseline Interruptible Program	31	248.2	144.8	103.4	3.2	41.7%	87.5	Yes
Aggregator Contracts (DRRC)	118	348.8	285.1	63.7	7.5	18.3%	90.0	Yes
Not Dually Enrolled	2,318	214.6	205.7	8.9	20.6	4.1%	87.2	Yes

5.6 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 technical assistance (TA), which consists of an audit to determine the potential for installing energy saving technology or processes at a particular premise. A technical incentive (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 automate the demand reduction to utility signals. However, over time, many of these customers have exited the CPP program. At the start of 2012, three customers enrolled in CPP had AutoDR. By the end of summer 2012, there were no AutoDR participants enrolled on CPP. Given the drop in AutoDR enrollments, AutoDR impacts or realization rates are not reported for 2012.

5.7 Default CPP Persistence and Weather Sensitivity

Persistence and weather sensitivity of CPP load impacts at SCE were analyzed using the same analysis approach described in section 4.7. Here as well as at PG&E, persistence analysis results must be viewed with caution: they reflect the patterns observed for a subset of customers, not those of the entire program.

Like PG&E, not all SCE customers on default CPP have a three-year history of CPP participation. Approximately 2,500 (excluding voluntary SMB enrollment) SCE customers were participating in CPP at the end of 2012, but only 1,630 (65%) have three years experience on CPP. Further, not all these customers could be matched.

Figure 5-5: SCE CPP Persistence 2010–2012

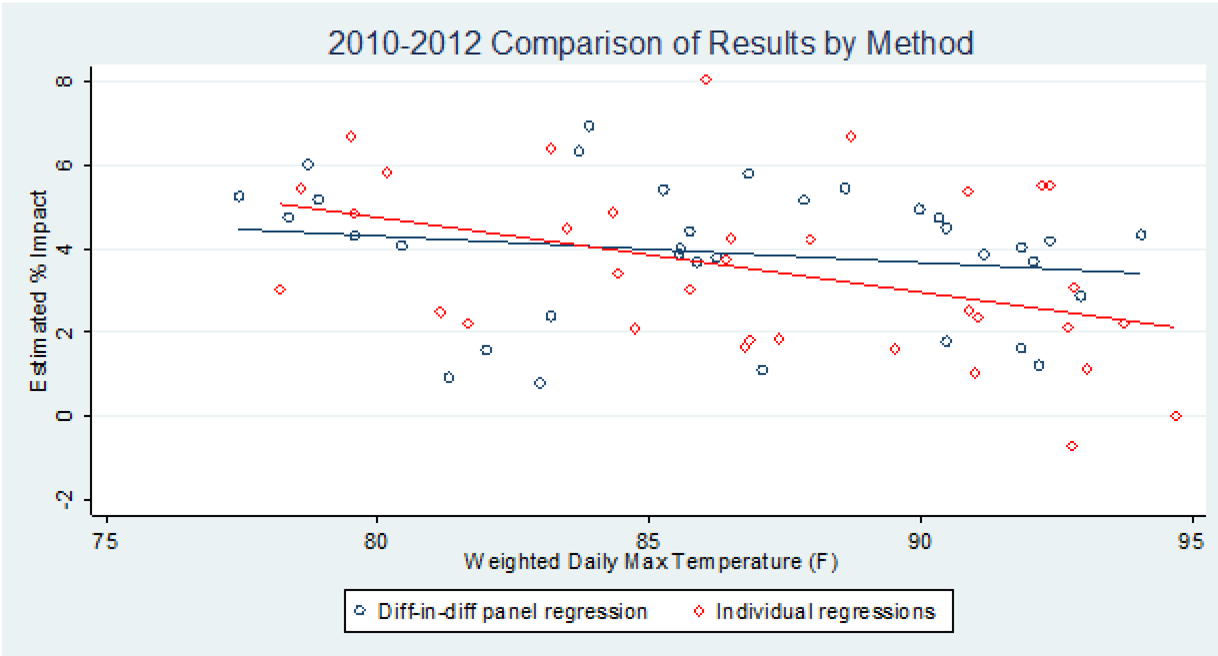


Figure 5-5 presents load impacts for those customers who experienced all events in 2010 through 2012, using both analysis methods, difference-in-differences and individual customer regressions, plotted as a function of temperature. There are many more analysis days available at SCE, 34, than at PG&E, but the relationship between load impacts and temperature is much noisier for both individual regression modeling and the difference-in-differences panel regression. This noise, around already small load impacts, leads to a statistically insignificant difference in weather trends between these two methods.

6 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 seven CPP events in 2012, two of which occurred on Saturdays. The first event occurred on August 9 and the last was held on October 2. On average, there were 1,117 accounts enrolled on SDG&E's tariff in 2012. There was some variation in enrollment during the course of the summer largely due to typical customer churn, with the highest enrollment at 1,138 participants and the lowest enrollment at 1,103. Unlike at PG&E and SCE, there is no significant voluntary enrollment on the SDG&E CPP rate. The participant-weighted average temperature during the event period was 80°F for the weekday events and 87°F for the weekend event.

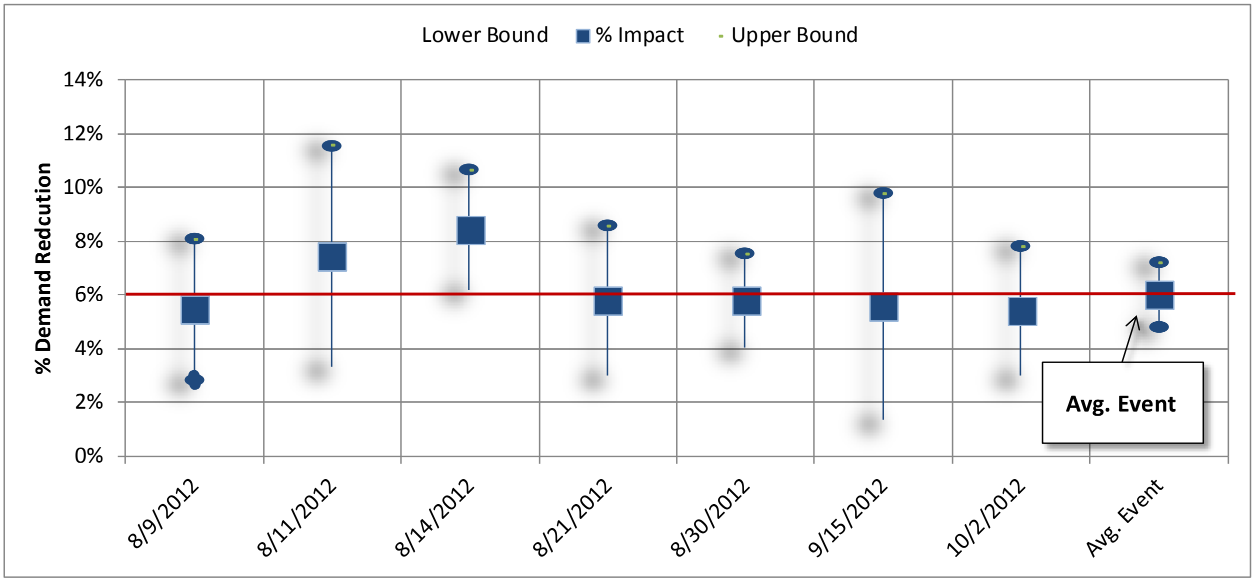
Table 6-1 shows the estimated ex post load impacts for each event day and for average weekday and weekend events in 2012. The participant-weighted average temperature during the event period ranged from a low of 76°F to a high of 95°F. Percent impacts range from 5.4% to 8.4%, average impacts range from 12.7 kW to 23.5 kW and aggregate impacts range from 14.5 MW to 25.9 MW. On the average weekday event day, the average participant reduced peak period load by 6.0%, or 16.2 kW. In aggregate, SDG&E's CPP customers reduced load by 18.1 MW on average across the seven weekday events in 2012. On the average weekend event, the average participant reduced load by 6.3%, or 13.9 kW, and the aggregate impact averaged 15.8 MW. As expected for a group of large C&I customers, weekend reference load is lower than weekday reference load. Notably, despite the lower weekend reference load, SDG&E's CPP customers produced similar percent load reductions on average for weekdays and weekends.

Table 6-1: Estimated Ex Post Load Impacts by Event Day
2012 SDG&E CPP Events

Event Date	Day of Week	Accounts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	Reduction %	Avg. Temp. °F	Daily Maximum Temp. °F
8/9/2012	Thu	1,103	263.4	249.0	14.4	15.9	5.5%	79.8	81.5
8/11/2012	Sat	1,135	217.3	201.0	16.2	18.4	7.5%	82.1	84.1
8/14/2012	Tue	1,103	278.0	254.6	23.5	25.9	8.4%	80.9	83.2
8/21/2012	Tue	1,135	262.0	246.8	15.2	17.2	5.8%	75.7	78.3
8/30/2012	Thu	1,135	270.7	255.0	15.7	17.8	5.8%	80.6	82.7
9/15/2012	Sat	1,138	226.9	214.2	12.7	14.5	5.6%	95.1	100.0
10/2/2012	Tue	1,109	273.8	259.0	14.9	16.5	5.4%	84.5	90.5
Avg. Weekday Event		**1,117**	**269.1**	**252.9**	**16.2**	**18.1**	**6.0%**	**80.4**	**82.9**
Avg. Weekend Event		**1,137**	**221.5**	**207.6**	**13.9**	**15.8**	**6.3%**	**87.1**	**90.3**

Figure 6-1 presents the estimated load impacts for individual 2012 events and the average event with 90% confidence intervals around each point estimate. Notable variance, event-to-event, is evident in the precision of the impact estimates. All estimates are significantly greater than zero, however some events show very little variation in customer demand response, while others, specifically the weekend events on August 11 and September 15, have very wide confidence bands. These individual event day load impact estimates have a noisy quality due to the small, harder-to-detect load impacts and event-to-event variability among customer load patterns and ability to shift load. The highly variable Saturday responses are particularly likely to be a function of ability to shift load: perhaps decision makers or facility managers may not be onsite to take demand response actions on a Saturday. In contrast, the average event day load impact estimate is more precise, but note that the average event day load impact estimate shown in Figure 6-1 is for weekday events only.

Figure 6-1: Estimated Ex Post Load Impacts with Confidence Intervals 2012 SDG&E CPP Events



6.1 Average Event Day Impacts

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

Percent reductions in each hour of SDGE's average 2012 weekday event varied from a high of 6.7% in the second hour to a low of 5.3% in the last hour, but these differences are probably not statistically significant. The highest aggregate impact, 21.0 MW, occurred in the second hour and the lowest impact, 14.4 MW, occurred in the last hour. The reduction in the reference load in the late afternoon is typical for this large C&I population and is reflected in reductions in aggregate load impacts towards the end of the event.

Figure 6-3 presents the same information for the average weekend event day; SDG&E called two events on Saturdays in 2012: August 11 and September 15. The percent reductions during the average weekend event varied from a high of 6.9% in the first hour to a low of 5.3% in the last hour, but again these differences are probably not significant. The highest aggregate impact, 17.7 MW, occurred in the first hour and the lowest impact, 12.8 MW, occurred in the last hour, again in tune with typical large C&I reference load patterns.

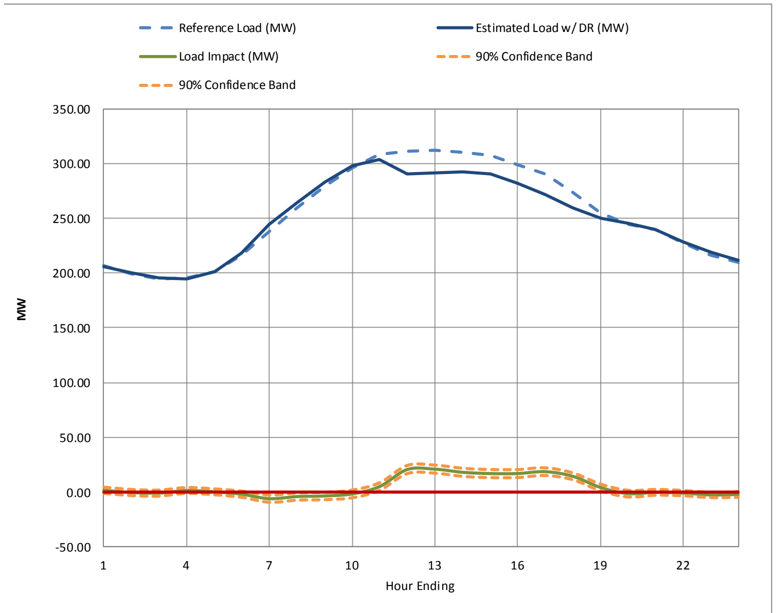
Figure 6-2: Estimated Hourly Impacts for the Average Weekday Event Day 2012 SDG&E CPP Events

TABLE 1: Menu options

Type of Results	Aggregate
Program	Default CPP
Customer category	All Customers
Event Date	Avg. Weekday Event

TABLE 2: Event Day Information

Event Start	11:00 AM
Event End	6:00 PM
Total Enrolled Acoounts	1,117
Avg. Load Reduction for Event Window (MW)	18.1
% Load Reduction for Event Window	**6.0%**



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	207.2	205.5	1.7	0.8%	69.3	-0.5	0.8	1.7	2.6	3.9
2	199.7	200.1	-0.4	-0.2%	68.9	-2.5	-1.3	-0.4	0.5	1.8
3	194.4	195.3	-0.9	-0.5%	68.5	-3.0	-1.8	-0.9	0.0	1.2
4	195.8	194.3	1.5	0.8%	68.1	-0.6	0.6	1.5	2.3	3.5
5	201.3	201.0	0.3	0.1%	68.1	-1.8	-0.6	0.3	1.1	2.3
6	216.6	218.5	-1.9	-0.9%	68.3	-4.1	-2.8	-1.9	-1.0	0.3
7	238.0	244.1	-6.0	-2.5%	71.2	-8.6	-7.1	-6.0	-5.0	-3.5
8	259.7	263.8	-4.1	-1.6%	75.3	-6.7	-5.1	-4.1	-3.0	-1.5
9	279.1	282.6	-3.5	-1.3%	79.2	-6.2	-4.6	-3.5	-2.4	-0.8
10	296.3	297.9	-1.7	-0.6%	81.7	-4.4	-2.8	-1.7	-0.6	1.1
11	308.4	303.2	5.1	1.7%	82.5	2.4	4.0	5.1	6.2	7.8
12	310.8	290.2	20.6	6.6%	82.9	17.7	19.5	20.6	21.8	23.6
13	312.3	291.3	21.0	6.7%	82.5	18.1	19.8	21.0	22.1	23.8
14	310.5	292.4	18.1	5.8%	82.1	15.2	16.9	18.1	19.3	21.0
15	307.1	290.2	16.9	5.5%	81.4	14.0	15.7	16.9	18.1	19.8
16	299.2	282.3	16.9	5.7%	80.4	14.1	15.8	16.9	18.1	19.8
17	290.4	271.7	18.6	6.4%	78.2	15.9	17.5	18.6	19.8	21.4
18	273.4	259.0	14.4	5.3%	75.4	12.0	13.4	14.4	15.4	16.8
19	254.4	250.1	4.2	1.7%	73.5	1.8	3.3	4.2	5.2	6.6
20	244.1	245.5	-1.4	-0.6%	72.5	-3.7	-2.3	-1.4	-0.4	1.0
21	239.3	239.5	-0.2	-0.1%	71.6	-2.3	-1.1	-0.2	0.6	1.8
22	227.6	228.5	-0.9	-0.4%	71.0	-2.8	-1.7	-0.9	-0.1	1.0
23	216.5	219.1	-2.6	-1.2%	70.4	-4.5	-3.4	-2.6	-1.8	-0.7
24	209.2	211.4	-2.1	-1.0%	69.8	-4.2	-3.0	-2.1	-1.3	-0.1

	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	6,091.3	5,977.6	113.6	1.9%	232.5	101.7	108.7	113.6	118.5	125.6

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

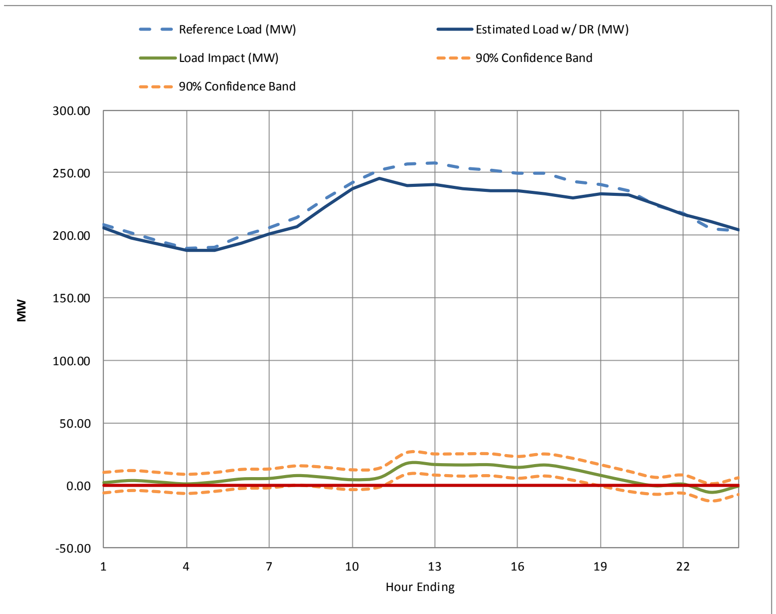
Figure 6-3: Estimated Hourly Impacts for the Average Weekend Event Day
2012 SDG&E CPP Events

TABLE 1: Menu options

Type of Results	Aggregate
Program	Default CPP
Customer category	All Customers
Event Date	Avg. Weekend Event

TABLE 2: Event Day Information

Event Start	11:00 AM
Event End	6:00 PM
Total Enrolled Acoounts	1,137
Avg. Load Reduction for Event Window (MW)	15.8
% Load Reduction for Event Window	**6.3%**



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1	208.4	206.2	2.2	1.1%	71.9	-4.2	-0.4	2.2	4.8	8.6
2	202.0	198.1	3.9	1.9%	71.5	-2.3	1.3	3.9	6.4	10.1
3	195.3	192.7	2.6	1.3%	71.3	-3.4	0.2	2.6	5.1	8.6
4	189.2	188.0	1.2	0.6%	70.5	-4.8	-1.2	1.2	3.6	7.2
5	190.6	187.9	2.7	1.4%	70.3	-3.2	0.3	2.7	5.1	8.6
6	199.0	193.9	5.2	2.6%	70.9	-0.8	2.7	5.2	7.6	11.1
7	206.4	200.8	5.6	2.7%	75.6	-0.3	3.1	5.6	8.0	11.4
8	214.6	206.7	7.8	3.7%	81.4	1.8	5.4	7.8	10.3	13.9
9	228.8	222.3	6.4	2.8%	85.6	0.2	3.9	6.4	9.0	12.7
10	241.8	237.3	4.5	1.9%	88.9	-1.6	2.0	4.5	7.1	10.7
11	251.9	245.7	6.3	2.5%	89.3	0.4	3.9	6.3	8.7	12.2
12	257.2	239.5	17.7	6.9%	90.3	11.0	14.9	17.7	20.5	24.5
13	257.4	240.8	16.7	6.5%	89.5	10.1	14.0	16.7	19.4	23.3
14	253.4	237.1	16.3	6.4%	89.0	9.4	13.5	16.3	19.2	23.3
15	252.2	235.7	16.5	6.5%	87.6	9.7	13.7	16.5	19.3	23.3
16	249.6	235.2	14.4	5.8%	87.1	7.6	11.6	14.4	17.2	21.2
17	249.6	233.3	16.3	6.5%	84.6	9.4	13.5	16.3	19.1	23.1
18	243.0	230.2	12.8	5.3%	81.6	6.0	10.1	12.8	15.6	19.7
19	240.8	232.8	8.0	3.3%	77.3	1.4	5.3	8.0	10.7	14.6
20	236.0	232.6	3.3	1.4%	75.1	-3.0	0.7	3.3	5.9	9.6
21	224.5	224.8	-0.4	-0.2%	73.7	-5.6	-2.5	-0.4	1.8	4.9
22	217.8	216.9	1.0	0.4%	72.2	-4.7	-1.3	1.0	3.3	6.6
23	205.3	210.9	-5.6	-2.7%	71.5	-11.0	-7.8	-5.6	-3.4	-0.2
24	203.6	204.3	-0.6	-0.3%	71.1	-5.8	-2.8	-0.6	1.5	4.6

	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	5,418.5	5,253.6	164.9	3.0%	337.8	134.2	152.3	164.9	177.4	195.5

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

6.2 Load Impacts by Industry

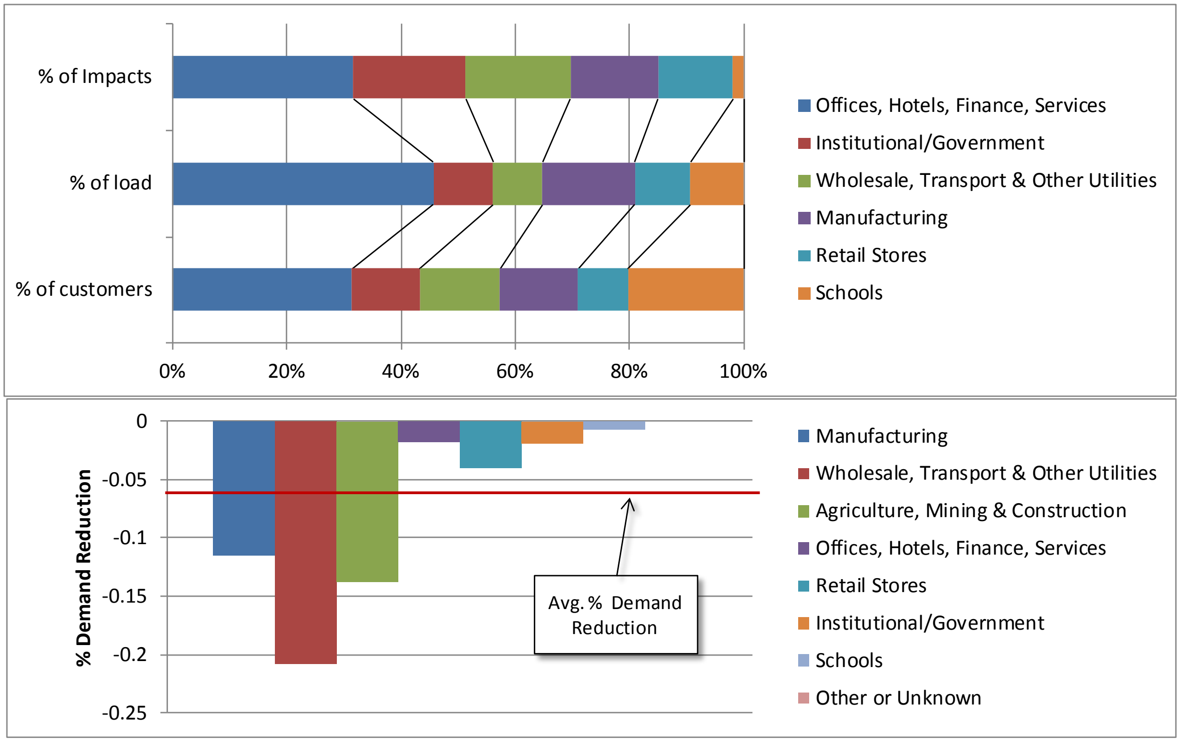
Figure 6-3 compares the distribution of customer reference loads, load impacts and customers by industry sector. The distribution of CPP impacts across industry segments at SDG&E is not as highly concentrated as it is for PG&E and SCE. Large aggregate impacts were provided by customers in Wholesale, Transport & Other Utilities and Manufacturing. The Offices, Hotels, Finances & Services segment performed better than the same segment at PG&E and SCE. Although these customers provided modest per customer impacts of 5.3 kW (3.9%), their average loads were relatively large and this segment had more accounts enrolled than any other segment. As was observed for both SCE and PG&E, estimated CPP impacts for schools at SDG&E were negligible, even though Schools comprised roughly 20% of the number of participating accounts.

Table 6-2: Estimated Ex Post Load Impacts by Industry
Average 2012 Weekday SDG&E CPP Event

Industry	Accounts	% of Program	Aggregate Reference Load (MW)	% of Program	Aggregate Impact (kW)	% of Program	% Reduction	Stat. Significant?
Offices, Hotels, Finance & Services	345	31.5%	134.9	45.7%	5.3	31.6%	3.9%	Yes
Institutional/Government	130	11.8%	30.7	10.4%	3.3	19.7%	10.7%	Yes
Wholesale, Transport & Other Utilities	154	14.0%	25.6	8.7%	3.1	18.4%	12.0%	Yes
Manufacturing	150	13.7%	47.7	16.2%	2.6	15.3%	5.4%	Yes
Retail Stores	96	8.8%	28.9	9.8%	2.2	13.1%	7.6%	Yes
Schools	222	20.2%	27.3	9.3%	0.3	1.9%	1.1%	No

The majority of the load was concentrated in the Offices, Hotels, Finances & Services sector. These are typically office buildings. They accounted for 46% of the estimated reference load (134.9 MW) and produced 32% of the load reduction (5.3 MW). However, this sector also had the most participants, and on average offices only reduced load by 4%. In contrast, the Manufacturing and Wholesale, Transport & Other Utilities sectors together accounted for 25% of the reference load (73.3MW) but produced 34% of the impacts (5.7 MW).

Figure 6-4: Estimated Enrollment, Load Impacts and Percent Load Reduction by Industry Average 2012 SDG&E CPP Event



6.3 Load Impacts by Customer Size

Table 6-3 shows the estimated ex post load impact by customer size, for five customer segments determined by average hourly consumption.[24] Participants with average usage over 500 kW provided the largest reference load (1,251 kW) and absolute average impact per customer (60.2 kW). However, the greatest aggregate impact, 6.4 MW, came from the 200–500 kW group. The largest percent reductions, 8.0%, were delivered by the 50–100 kW customers. The 100–200 kW customers produced the least percentage impacts (3.8%).

[24] Calculated as average kWh per hour, calculated as all 2012 consumption over all 2012 hours.

Table 6-3: Estimated Ex Post Load Impacts by Customer Size Average 2012 Weekday SDG&E CPP Event

Consumption Size Category (Annual kWh/hr)	Accts.	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	% Reduction %	Avg. Temp. °F	Stat. significant?
Over 500 kWh/hr	79	1,251.4	1,191.2	60.2	4.8	4.8%	80.9	Yes
200–500 kWh/hr	221	431.7	402.9	28.9	6.4	6.7%	80.0	Yes
100–200 kWh/hr	270	226.4	217.8	8.7	2.3	3.8%	80.2	Yes
50–100 kWh/hr	245	134.5	123.8	10.7	2.6	8.0%	81.2	Yes
Under 50 kWh/hr	302	34.7	32.6	2.1	0.6	6.1%	80.1	Yes

6.4 Load Impacts for Multi-DR Program Participants

Table 6-4 shows load impacts for SDG&E customers who were dually enrolled in other DR programs in 2012. SDG&E's CPP population has dual enrollment with three other demand response programs in 2012: BIP, CBP and the Clean Generation Program (CGP). 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). SDG&E's CGP consists of a capacity contract with EnerNOC, Inc. The contract provides for the aggregation of large C&I customer standby generators to be called to support the SDG&E grid during times of peak demand. Backup generators controlled by this program have been fitted with California Air Resources Board-approved diesel particulate filters and have been specially permitted by the San Diego County Air Pollution Control District. However, since the program relies on customer generation, it is not considered a demand response program.

Despite the fact that some of these load impact estimates 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 some DR programs generally produce more CPP load impacts than others, or that dually enrolled customers generally produce more load impacts than non-dually enrolled customers. There simply isn't enough data to support those conclusions.

Table 6-4: Estimated Ex Post Load Impacts CPP Participants Enrolled in Other DR Programs Average 2012 PG&E CPP Event

Dually enrolled DR Program	Accounts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	Reduc-tion %	Avg. Temp °F	Stat. significant ?
BIP	3	182.4	180.9	1.5	0.0	0.8%	77.8	No
CBP	13	269.5	194.4	75.1	1.0	27.9%	78.4	Yes
CGP	1	276.8	199.6	77.2	0.1	27.9%	76.9	Yes

6.5 TI and AutoDR Load Impacts and Realization Rates

Table 6-5 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 6-5 should be cited with caution.

Table 6-5: Estimated Ex Post Load Impacts of TI & AutoDR Participants Average 2012 Weekday SDG&E CPP Event

Enabling Technology	Accounts	Load Impact (kW)	% Reduction (%)	90% Confidence Interval		Approved Load Shed (kW)	Realization Rate (%)
				Lower	Upper		
AutoDR	30	21.5	4.4%	3.1%	5.7%	88.0	24.5%
No TI or AutoDR	1,105	10.7	4.2%	3.9%	4.5%	NA	NA

6.6 Critical Peak Pricing – Emergency

Prior to defaulting large C&I customers to CPP-D in 2008, SDG&E offered a voluntary non-residential CPP tariff called Critical Peak Pricing – Emergency (CPP-E). Upon defaulting large customers to CPP-D, SDG&E did not close the legacy CPP-E tariff. However, due to dwindling customer participation, SDG&E proposed closing the rate in its application to the CPUC for 2012–2014 demand response programs and budgets. Later, in light of the protracted SONGS outage particularly affecting southern California, SDG&E proposed in Advice Letter 2373-E to retain the CPP-E rate through December 31, 2012. The proposal to close CPP-E at the end of 2012 was approved.

Two CPP-E events were called in 2012, both on weekdays. While technically not a part of the CPP-D program at SDG&E, estimated 2012 load impacts for CPP-E customers are shown in Table 6-6 for completeness. Due to the very small number of customers taking this rate, these load impacts were estimated using individual customer regressions.

Table 6-6: Estimated Ex Post Load Impacts by Event Day SDG&E 2012 CPP-E Events

CPP-E Event	Day of Week	Accounts	Avg. Customer Reference Load (kW)	Avg. Customer Load w/ DR (kW)	Impact (kW)	Aggregate Impact (MW)	Reduction %	Avg. Temp °F	Stat. significant?
8/13/2012	Mon	5	377.5	143.9	233.6	1.2	61.9%	80.7	Yes
9/14/2012	Fri	5	324.6	147.6	177.0	0.9	54.5%	88.2	Yes
Avg. Event		5	351.1	145.8	205.3	1.0	58.5%	84.4	Yes

7 PG&E Ex Ante Load Impacts

This section presents ex ante load impact estimates for PG&E's non-residential CPP tariff. 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 all historical event information since the implementation of default CPP in 2010. In total, load impact estimates for up to 27 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. As discussed in Section 3.4, the impacts are based on individual customer regressions, not the difference-in-differences output used to estimate ex post impacts.

This section presents the ex ante load impact projections separately for medium and large customers projected to receive service under PG&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 the 2012 to 2023 period. The estimates presented here are not derated 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 contained in Appendix D. In addition, this section illustrates how impacts per customer vary by geographic location and month under standardized ex ante conditions.

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. Two substantive changes are scheduled for PG&E in the 2013–2023 forecast horizon. Starting in 2013, PG&E is scheduled to change the CPP event window, the current period from 2 to 6 PM, to the period from 1 to 6 PM. Starting in November 2014, PG&E will default medium customers that have been on TOU for a minimum of two years onto CPP rates. Those customers can elect to opt out to TOU rates if they do not wish to be on CPP rates.

In order to estimate load reductions for the hour from 1 to 2 PM, the percentage reduction in the hour from 2 to 3 pm was applied to the estimated reference load from 1 to 2 PM. Because the reference load is typically higher from 1 to 2 PM, the absolute ex ante load impact in this hour is typically higher. As a cross check on this assumption, the percent reduction for the 1 to 2 PM hour for SDG&E, which has an event window from 11 AM to 6 PM, was compared with the average reduction from 2 to 6 PM, and was found to be higher. As such, assuming the same percent reduction from 1 to 2 PM and 2 to 3 PM is likely to be conservative.

7.1 Large C&I Ex Ante Impacts

In total, approximately 1,400 large customers were enrolled in default CPP in 2012.[25] The majority of these customers (nearly 70%) have been enrolled in default CPP since 2010 and have experienced nine events each year. As a result, there is ample data on the magnitude of demand response

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

provided by these customers, the types of customers that are more responsive and the extent to which demand response varies with weather conditions.

Table 7-1 shows PG&E's enrollment projections for large customers through 2023. The development of the enrollment forecast and underlying assumptions are documented in PG&E's "*Executive Summary: 2013–2023 Demand Response Portfolio of Pacific Gas and Electric Company*."

Table 7-1: PG&E Enrollment Projections for Large CPP Customers by Forecast Year and Month

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	1,401	1,401	1,401	1,401	1,401	1,401	1,401	1,401	1,401	1,401	1,401	1,401
2013	1,493	1,493	1,493	1,493	1,493	1,493	1,493	1,493	1,493	1,493	1,765	1,765
2014	1,765	1,765	1,807	1,807	1,807	1,807	1,807	1,807	1,807	1,807	1,819	1,819
2015	1,819	1,819	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825
2016	1,825	1,825	1,825	1,825	1,825	1,825	1,826	1,826	1,825	1,825	1,825	1,825
2017	1,825	1,824	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825
2018	1,825	1,824	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825
2019	1,824	1,824	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825
2020	1,824	1,824	1,824	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825
2021	1,824	1,824	1,824	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,824
2022	1,824	1,824	1,824	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,824
2023	1,824	1,824	1,824	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,825	1,824

7.1.1 Annual System Peak Day Impacts

Table 7-2 summarizes the aggregate load impact estimates for large customers on PG&E's CPP tariff for each forecast year under both 1-in-2 and 1-in-10 weather year scenarios. The table shows the average load reduction across the 1 PM to 6 PM event period for an August monthly system peak day. As mentioned earlier, the results do not reflect adjustments for dual enrollment on other DR programs and assume that the 1 to 2 PM demand reductions are equivalent to the 2 to 6 PM demand reductions on a percentage basis. The portfolio adjusted estimates are summarized in Appendix C.

Differences in demand reductions from year to year are a direct result of changes in enrollment and customer mix. In addition to minimal population growth, PG&E projects a substantial increase in enrollments in November 2013 because, at that time, it will default additional large customers who had interval meters recently installed.[26] Most of these customers are in outlying areas of PG&E's service territory and are disproportionately agricultural customers that are more price responsive.

[26] Customers are not defaulted onto CPP until they have had interval data available for at least 12 months.

Table 7-2: PG&E August Peak Day CPP Program Load Impacts for Large Customers (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

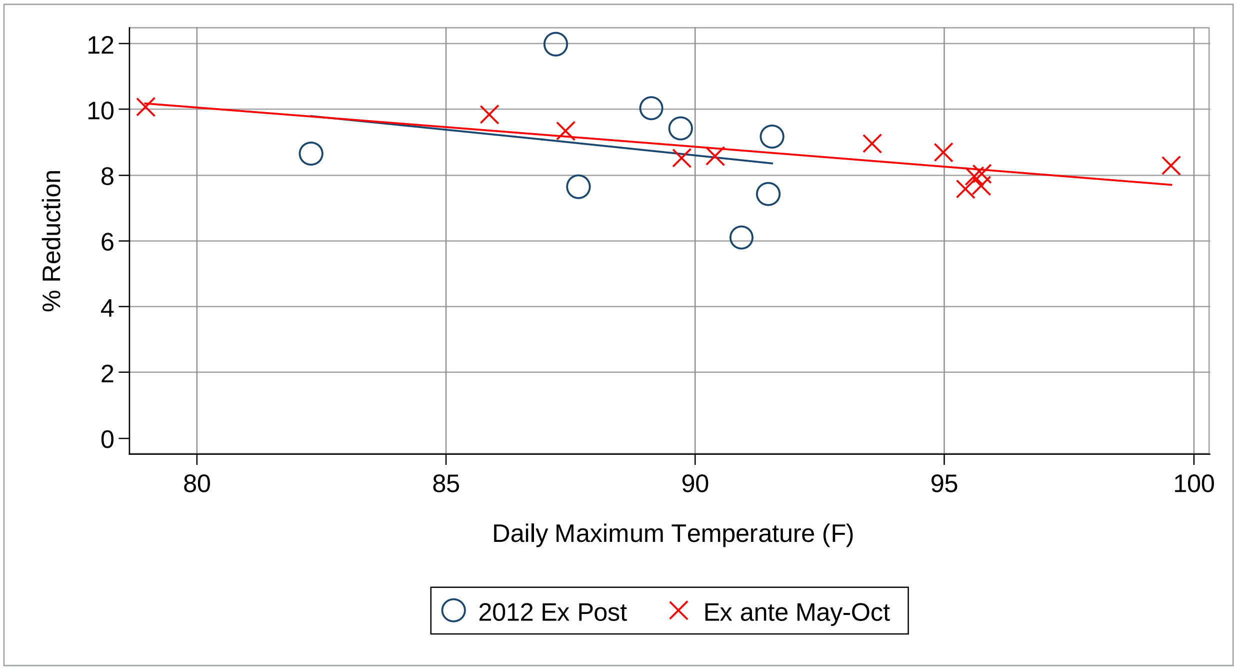
Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	(°F)
1-in-10 August System Peak Day	2012	1,401	471.6	438.2	33.4	7.1%	94.5
	2013	1,483	500.1	464.3	35.7	7.1%	94.4
	2014	1,796	603.6	559.5	44.1	7.3%	94.7
	2015	1,815	609.7	565.2	44.6	7.3%	94.8
	2016	1,815	609.9	565.3	44.6	7.3%	94.8
	2017	1,815	609.9	565.3	44.6	7.3%	94.8
	2018	1,815	609.9	565.3	44.6	7.3%	94.8
	2019	1,815	609.9	565.3	44.6	7.3%	94.8
	2020	1,815	609.8	565.3	44.6	7.3%	94.8
	2021	1,815	609.8	565.2	44.6	7.3%	94.8
	2022	1,815	609.8	565.2	44.6	7.3%	94.8
	2023	1,815	609.8	565.2	44.6	7.3%	94.8
1-in-2 August System Peak Day	2012	1,401	486.6	448.7	37.9	7.8%	93.4
	2013	1,483	516.0	475.9	40.1	7.8%	93.4
	2014	1,796	622.6	572.9	49.7	8.0%	93.5
	2015	1,815	628.9	578.7	50.2	8.0%	93.5
	2016	1,815	629.0	578.8	50.2	8.0%	93.5
	2017	1,815	629.0	578.8	50.2	8.0%	93.5
	2018	1,815	629.0	578.8	50.2	8.0%	93.5
	2019	1,815	629.0	578.8	50.2	8.0%	93.5
	2020	1,815	628.9	578.7	50.2	8.0%	93.5
	2021	1,815	628.9	578.7	50.2	8.0%	93.5
	2022	1,815	628.9	578.7	50.2	8.0%	93.5
	2023	1,815	628.9	578.7	50.2	8.0%	93.5

In 2013, the average aggregate load impact during an August event for the 1-in-2 weather year scenario is estimated to be 40.1 MW. By 2014, the load reduction capability under the same set of conditions is expected to grow to 49.7 MW. Depending on the forecast year and weather conditions, large customers in the CPP program are expected to reduce between 7.1% and 8.0% of load under peaking conditions. The reductions match well to the percent reductions observed for ex post events in 2012, which were around 7% on average. The small differences are due to differences in the weather conditions and because the ex ante impacts are based on ex post results for event days in 2010 and 2011 as well as 2012. In addition, the large population is a subset of the broader default CPP population.

As a reference point, the load reduction capability for the 1,401 large customers enrolled in default CPP at the end of the 2012 summer are included.[27] Any difference between historical ex post demand reductions and ex ante load impacts estimates for these customers is exclusively due to adjustments for standardized weather conditions and the assumption about impacts for the 1–2 PM period. As noted earlier, business loads tend to be higher during that specific hour than they are for the 2–6 PM period.

Figure 7-1 compares the 2012 ex post load impacts based on individual customer regressions and ex ante load impacts for the months of May through October. Both estimates in Figure 7-1 use the historical 2–6 PM event window. Both the magnitude of the demand reductions, between 7% and 12%, and the weather sensitivity of the demand reductions are similar. The ex ante load impacts simply reflect historical event patterns.

Figure 7-1: Comparison of Ex Post and Ex Ante Load Impacts for 2012 Large Participants (2–6 PM)[28]

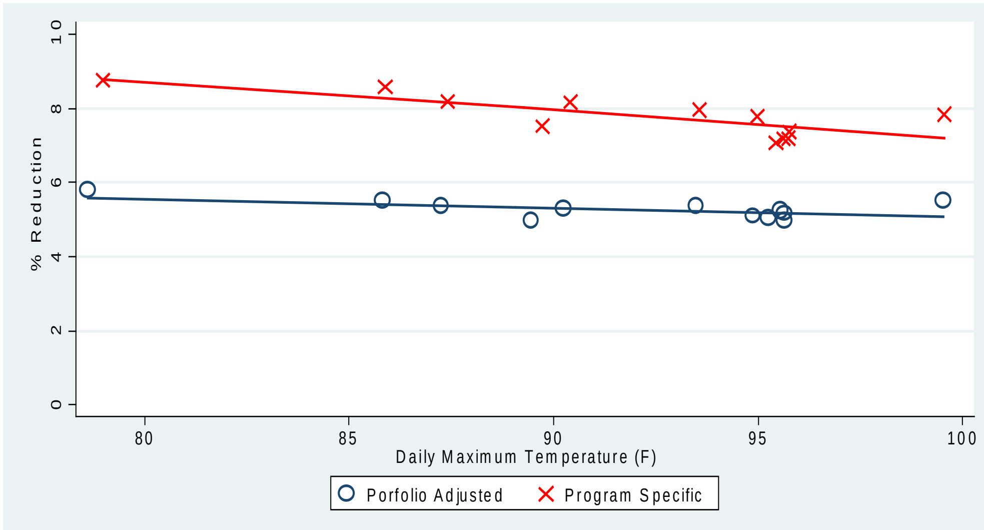


Portfolio-adjusted load impacts exclude customers dually enrolled in BIP or aggregator programs, which are among the most responsive participants. Figure 7-2 illustrates the effect of removing dually enrolled customers. The comparison is made with participants enrolled at the end of summer 2012. The portfolio-adjusted demand reductions are 2 to 3 percentage points lower than the program specific results. For 1-in-2 weather year conditions, the program-specific reduction is 7.8% while the portfolio-adjusted reduction is 5.1% for the August monthly peak.

27 This excludes some customers who were initially enrolled onto CPP on a default basis, but have since been reclassified to medium customers due to changes in their overall non-coincident peak loads.

28 Ex ante load impacts in figure reflect calculation before zeroing out impacts from schools.

Figure 7-2: Comparison of Portfolio-adjusted to Program-specific Ex Ante Load Impacts May to October Monthly Peaks for Current Participants



7.1.2 Ex Ante Load Impact Uncertainty

Table 7-3 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for large customers. The ex ante impacts do not reflect uncertainty in enrollment. At first glance, the uncertainty appears large. For example, in 2013, the projected load impacts for 1-in-2 weather conditions are 40.1 ±5.1 MW, with 80% confidence. The uncertainty reflects both the challenge of accurately estimating small percentage demand reductions and the variability in performance observed across events.

Table 7-3: PG&E Program Annual Peak Day Load Impacts for Large Customers with Uncertainty (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Expected Avg. Load Impact	Impact Uncertainty				
		MW 1–6 PM	10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2012	33.4	29.0	31.6	33.4	35.2	37.8
	2013	35.7	31.0	33.8	35.7	37.7	40.5
	2014	44.1	38.1	41.7	44.1	46.6	50.2
	2015	44.6	38.4	42.1	44.6	47.1	50.7
	2016	44.6	38.4	42.1	44.6	47.1	50.7
	2017	44.6	38.4	42.1	44.6	47.1	50.7
	2018	44.6	38.4	42.1	44.6	47.1	50.7
	2019	44.6	38.4	42.1	44.6	47.1	50.7
	2020	44.6	38.4	42.1	44.6	47.1	50.7
	2021	44.6	38.4	42.1	44.6	47.1	50.7
	2022	44.6	38.4	42.1	44.6	47.1	50.7
	2023	44.6	38.4	42.1	44.6	47.1	50.7
1-in-2 August System Peak Day	2012	37.9	33.1	35.9	37.9	39.9	42.7
	2013	40.1	35.0	38.0	40.1	42.2	45.2
	2014	49.7	43.1	47.0	49.7	52.3	56.2
	2015	50.2	43.6	47.5	50.2	52.9	56.8
	2016	50.2	43.6	47.5	50.2	52.9	56.8
	2017	50.2	43.6	47.5	50.2	52.9	56.8
	2018	50.2	43.6	47.5	50.2	52.9	56.8
	2019	50.2	43.6	47.5	50.2	52.9	56.8
	2020	50.2	43.6	47.5	50.2	52.9	56.8
	2021	50.2	43.6	47.5	50.2	52.9	56.8
	2022	50.2	43.6	47.5	50.2	52.9	56.8
	2023	50.2	43.6	47.5	50.2	52.9	56.8

7.1.3 Ex Ante Impacts by Geographic Location

Table 7-4 summarizes per customer ex ante impacts for each LCA by month for large customers, based on current participants. It shows the per customer impacts for each monthly system peak day under 1-in-2 and 1-in-10 system peaking conditions.

Table 7-4: 2013 Per Customer Ex Ante Impacts for Large Customers by Local Capacity Area (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Local Capacity Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	All Customers	27.9	27.9	26.6	27.7	27.2	25.5	23.8	24.1	25.8	26.8	29.4	27.1
	Greater Bay Area	21.1	21.0	21.0	20.4	20.9	21.3	20.6	20.9	18.1	19.8	21.2	21.3
	Greater Fresno	27.8	27.8	27.9	28.3	30.7	16.5	11.9	12.1	26.6	27.4	38.9	27.9
	Humboldt	62.6	61.3	58.7	60.1	59.0	61.8	58.2	61.7	64.0	62.6	58.9	58.7
	Kern	72.1	72.1	75.6	72.7	69.9	69.2	65.6	64.9	71.2	71.3	77.2	75.6
	Northern Coast	19.0	19.1	18.4	20.9	25.0	29.4	25.0	23.4	25.1	23.7	18.4	18.6
	Other	28.1	28.5	21.0	27.8	29.9	28.6	30.5	31.5	31.6	26.7	25.9	21.3
	Sierra	34.1	34.1	34.0	34.9	29.5	26.3	11.4	11.6	21.5	35.6	34.1	34.0
	Stockton	53.2	53.2	55.5	53.6	28.8	28.1	26.8	26.5	35.5	45.2	58.2	55.2
1-in-2	All Customers	28.2	26.6	27.2	26.5	27.3	26.0	24.6	27.1	25.6	27.9	26.3	27.8
	Greater Bay Area	21.9	20.9	19.7	21.6	20.7	18.1	21.1	21.2	20.5	22.5	20.7	20.8
	Greater Fresno	28.7	27.9	27.8	27.2	24.6	27.1	13.4	28.8	21.4	27.9	15.7	27.8
	Humboldt	60.2	58.5	63.8	63.3	60.6	60.1	60.9	58.8	60.0	57.8	59.1	65.7
	Kern	72.5	75.6	72.1	73.4	71.7	70.9	67.6	72.1	70.8	74.7	72.6	72.1
	Northern Coast	18.3	18.5	19.0	20.3	17.7	25.4	25.8	23.8	17.5	22.5	18.3	19.1
	Other	25.9	21.2	28.3	24.6	29.5	26.1	28.8	25.8	26.1	22.9	26.6	27.2
	Sierra	34.6	34.0	34.1	34.2	31.5	30.8	16.2	29.2	29.0	35.0	34.4	34.1
	Stockton	58.2	55.2	53.5	35.0	52.2	52.4	31.9	43.1	45.5	53.9	54.8	53.2

In aggregate, the load reductions are largest in the Greater Bay Area and Other LCAs. Based on the 2012 ex post analysis, almost 50% of customers are in the Greater Bay Area and about 20% are outside of the primary LCAs and classified as Other. Customers classified as Other provided 31% of aggregate ex post impacts despite only accounting for 20% of the total population. By comparison, customers in the Greater Bay Area accounted for 35% of aggregate impacts despite representing almost 50% of the accounts. Customers classified as Other are also larger, on average, than customers in the Greater Bay Area and provide larger per customer impacts.

7.2 Medium C&I Ex Ante Impacts

Overall, there is greater uncertainty regarding medium customer impacts under default CPP. To date, relatively few PG&E medium customers are enrolled on CPP and because only customers with maximum demand over 200 kW are defaulted, the voluntary medium customers are not necessarily representative of the medium customer population segment as a whole. To obtain a larger and more diverse sample, customers from the large category with average hourly demands below 200 kW, were used as a proxy for medium customers. The results were weighted to account for differences in industry mix and/or geographic location and scaled based on usage. Table 7-5 gives an overview of the weighting process. It shows the percent of the sample and population by industry segment and region. The table also shows the population average kW divided by the sample average kW by strata. Actual medium customers from the PG&E population are substantially smaller than the proxy medium customers. There are also non-trivial differences in the share of customers by industry and region between the sample and population.

Table 7-5: Development of Weights for Proxy Medium Customers

Category	Industry	Medium Proxy Accts	%	Medium Population	%	Medium Proxy % Reductions
						Aug. 1-in-2
Industrial	Agriculture, Mining & Construction	103	8.4%	1,608	2.28%	21.9%
	Manufacturing	206	16.7%	4,859	6.90%	13.3%
	Wholesale, Transport & Other Utilities	165	13.4%	7,168	10.18%	14.4%
	Other or Unknown	46	3.7%	5,287	7.51%	16.4%
Commercial	Retail Stores	58	4.7%	11,256	15.98%	5.0%
	Offices, Hotels, Finance & Services	316	25.6%	27,283	38.74%	2.5%
	Schools	245	19.9%	4,217	5.99%	0.0%
	Institutional/Government	93	7.5%	8,754	12.43%	3.2%

Table 7-6 shows PG&E's enrollment projections for medium customers through 2023. There is a large increase in enrollment projected between 2014 and 2015. Starting in November 2014, medium customers with at least 24 months of experience on a TOU rate will start to be defaulted onto CPP, leading to the increase in enrollment. The enrollment increase is gradual because it is tied to the rollout of smart meters. In August 2013, 228 medium customers are forecast to receive service under the tariff, most of whom voluntarily enrolled on CPP. In contrast, by August 2015, 11,727 medium customers are projected to be served under the rate schedule. And by November 2016, the medium customer population is expected to stabilize at around 30,000 accounts. The enrollment forecast is similar to that from last year.

Table 7-6: PG&E's Enrollment Projections for Medium CPP Customers by Forecast Year and Month

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	210	210	210	210	210	210	210	210	210	210	210	210
2013	227	227	227	227	227	227	227	227	227	227	227	227
2014	227	227	227	227	227	227	227	227	227	227	11,697	11,697
2015	11,697	11,697	11,727	11,727	11,727	11,727	11,727	11,727	11,727	11,727	16,758	16,779
2016	16,802	16,826	16,875	16,909	16,938	16,965	16,991	17,017	17,041	17,063	29,354	29,375
2017	29,398	29,422	30,520	30,552	30,581	30,607	30,633	30,658	30,681	30,702	28,191	28,211
2018	28,233	28,255	28,279	28,310	28,336	28,361	28,385	28,408	28,430	28,450	28,425	28,444
2019	28,464	28,484	28,508	28,537	28,561	28,584	28,606	28,627	28,647	28,665	28,681	28,698
2020	28,717	28,736	28,758	28,785	28,808	28,830	28,851	28,872	28,891	28,908	28,924	28,940
2021	28,959	28,978	29,000	29,027	29,051	29,073	29,094	29,114	29,133	29,150	29,165	29,181
2022	29,199	29,218	29,239	29,266	29,289	29,310	29,330	29,350	29,368	29,384	29,399	29,414
2023	29,431	29,449	29,469	29,495	29,517	29,537	29,557	29,575	29,593	29,608	29,622	29,637

7.2.1 Annual System Peak Day Impacts

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

Due to the planned default of PG&E's medium C&I population starting in November 2014, the impacts are projected to grow from 1.2 MW to a peak of 67 MW in 2017. The growth reflects the gradual implementation of default CPP over three years, as more medium customers meet default criteria. Once default CPP is fully implemented, medium customers are forecasted to reduce approximately 6% of their demand.

Table 7-7: Program Annual Peak Day Load Impacts for Medium PG&E CPP Customers (Hourly Average Reduction in MW Over Event Day Period – 1–6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	(°F)
1-in-10 August System Peak Day	2012	210	19.7	18.6	1.1	5.5%	96.9
	2013	227	21.1	19.9	1.2	5.5%	97.0
	2014	227	21.1	19.9	1.2	5.5%	97.0
	2015	11,727	395.5	372.6	22.9	5.8%	98.1
	2016	17,017	577.5	543.4	34.0	5.9%	97.4
	2017	30,658	1,085.9	1,020.1	65.8	6.1%	96.4
	2018	28,408	1,002.0	941.5	60.5	6.0%	96.6
	2019	28,627	1,009.7	948.7	61.0	6.0%	96.6
	2020	28,872	1,018.3	956.8	61.5	6.0%	96.6
	2021	29,114	1,026.8	964.8	62.0	6.0%	96.6
	2022	29,350	1,035.0	972.5	62.5	6.0%	96.6
	2023	29,575	1,043.0	980.0	63.0	6.0%	96.6
1-in-2 August System Peak Day	2012	210	21.2	20.4	0.8	4.0%	94.8
	2013	227	22.7	21.8	0.9	4.0%	94.9
	2014	227	22.7	21.8	0.9	4.0%	94.9
	2015	11,727	400.0	376.2	23.8	6.0%	94.5
	2016	17,017	585.2	550.3	34.9	6.0%	94.3
	2017	30,658	1,101.6	1,034.6	67.0	6.1%	94.0
	2018	28,408	1,016.2	954.4	61.7	6.1%	94.0
	2019	28,627	1,024.0	961.8	62.2	6.1%	94.0
	2020	28,872	1,032.7	969.9	62.7	6.1%	94.0
	2021	29,114	1,041.3	978.1	63.2	6.1%	94.0
	2022	29,350	1,049.7	986.0	63.7	6.1%	94.0
	2023	29,575	1,057.7	993.5	64.2	6.1%	94.0

7.2.2 Ex Ante Load Impact Uncertainty

Underlying the impact estimates summarized above is a significant amount of uncertainty. Table 7-8 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for medium customers. It does not, however, reflect the largest sources of uncertainty: enrollment uncertainty and the assumption that we can infer medium customers' price responsiveness based on current participants, after adjusting for differences in the industry mix.

Very few medium customers are currently enrolled in CPP. Enrollments are projected to remain around 200 customers until November 2014 when medium customers will begin to be defaulted onto CPP. For 2017, the 80% confidence interval for 1-in-2 impacts ranges from 61 MW up to 73 MW.

Table 7-8: Program Annual Peak Day Load Impacts for Medium Customers with Uncertainty (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Expected Avg. Load Impact	Impact Uncertainty				
		MW 1–6 PM	10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2012	1.1	0.5	0.9	1.1	1.3	1.6
	2013	1.2	0.6	0.9	1.2	1.4	1.7
	2014	1.2	0.6	0.9	1.2	1.4	1.7
	2015	22.9	18.8	21.2	22.9	24.5	26.9
	2016	34.0	28.3	31.7	34.0	36.4	39.7
	2017	65.8	55.0	61.4	65.8	70.2	76.6
	2018	60.5	50.5	56.4	60.5	64.6	70.5
	2019	61.0	50.9	56.9	61.0	65.1	71.0
	2020	61.5	51.4	57.3	61.5	65.6	71.6
	2021	62.0	51.8	57.8	62.0	66.2	72.2
	2022	62.5	52.2	58.3	62.5	66.7	72.8
	2023	63.0	52.6	58.7	63.0	67.2	73.3
1-in-2 August System Peak Day	2012	0.8	0.3	0.6	0.8	1.1	1.4
	2013	0.9	0.3	0.7	0.9	1.2	1.5
	2014	0.9	0.3	0.7	0.9	1.2	1.5
	2015	23.8	19.6	22.1	23.8	25.5	28.0
	2016	34.9	29.0	32.5	34.9	37.4	40.9
	2017	67.0	55.8	62.4	67.0	71.6	78.2
	2018	61.7	51.4	57.5	61.7	66.0	72.1
	2019	62.2	51.8	57.9	62.2	66.5	72.6
	2020	62.7	52.2	58.4	62.7	67.0	73.2
	2021	63.2	52.6	58.9	63.2	67.6	73.8
	2022	63.7	53.1	59.4	63.7	68.1	74.4
	2023	64.2	53.5	59.8	64.2	68.6	75.0

7.2.3 Ex Ante Impacts by Geographic Location

Table 7-9 summarizes the per customer ex ante impacts for each LCA by month for medium customers. It shows the per customer impacts for each monthly system peak day under 1-in-2 and 1-in-10 system peaking conditions. The variation reflects the weather, size of customers and the industry mix in each of PG&E's LCAs. Impacts are shown for 2017 because default CPP will have been fully implemented across PG&E's territory by then.

Table 7-9: 2017 Per Customer Ex Ante Impacts for Medium Customers by Local Capacity Area (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Local Capacity Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	All Customers	2.0	2.0	2.0	2.2	2.3	2.2	2.2	2.1	2.2	2.0	2.5	2.0
	Greater Bay Area	1.0	1.0	1.0	1.1	1.2	1.3	1.3	1.2	1.3	1.1	1.1	1.1
	Greater Fresno	2.2	2.2	2.1	2.1	2.7	1.4	1.2	1.3	2.2	2.1	5.2	2.1
	Humboldt	11.6	11.2	10.4	10.5	10.5	11.0	10.3	9.7	10.3	9.7	10.5	10.4
	Kern	1.4	1.4	1.5	1.3	1.4	1.4	1.5	1.5	1.4	1.4	1.5	1.5
	Northern Coast	3.6	3.6	3.5	3.6	3.6	4.0	3.5	3.4	3.6	3.6	3.9	3.6
	Other	2.3	2.4	1.8	3.1	3.3	3.6	3.8	3.8	3.2	2.7	2.2	1.9
	Sierra	3.1	3.1	3.2	3.2	2.9	2.9	2.5	2.5	2.7	2.9	3.2	3.2
	Stockton	2.4	2.4	3.6	2.4	0.8	1.1	0.9	1.0	1.3	1.9	3.5	3.5
1-in-2	All Customers	2.1	2.0	2.0	1.8	2.0	2.2	2.1	2.2	2.0	2.2	2.0	2.0
	Greater Bay Area	1.3	1.0	1.0	1.2	1.0	1.2	1.2	1.1	1.1	1.3	1.0	1.0
	Greater Fresno	2.2	2.1	2.2	2.1	2.1	2.1	1.3	2.1	1.8	2.1	2.1	2.2
	Humboldt	10.6	10.4	11.9	11.8	11.0	10.8	10.4	10.5	10.8	10.2	10.5	12.4
	Kern	1.3	1.5	1.4	1.4	1.4	1.4	1.5	1.5	1.4	1.4	1.4	1.4
	Northern Coast	3.5	3.5	3.6	3.6	3.5	3.7	3.5	3.4	3.0	3.7	3.6	3.6
	Other	2.4	1.9	2.4	2.1	2.6	2.8	3.6	3.4	3.1	2.5	2.2	2.3
	Sierra	3.1	3.2	3.1	3.1	3.0	3.1	2.6	2.7	2.7	3.2	3.2	3.1
	Stockton	2.8	3.5	2.5	2.1	2.1	2.1	1.3	1.6	1.9	2.4	2.2	2.4

8 SCE Ex Ante Load Impacts

This section presents ex ante load impact estimates for SCE's non-residential CPP tariff. 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 are based on all historical event information since the implementation of default CPP in 2009. In total, estimated demand reductions from up to 36 events were analyzed to estimate default CPP demand reductions and uncertainty across various weather conditions. All demand reduction estimates presented in this chapter are incremental to the effects of the underlying TOU rates. Section 3.4 provides additional details about how the ex ante impacts were developed.

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. One important change scheduled for SCE in the 2013–2023 forecast horizon is that, starting in 2013, the CPP event window at SCE will move from 2–6 PM to 1–6 PM.

SCE has no default CPP historical experience with demand reductions for the hour of 1–2 PM. That is not to say there is no such experience – SDG&E's default CPP rate has a much longer event window, lasting from 11 AM to 6 PM, and demand reductions from 1–2 PM tend to be larger than those from 2–6 PM. The historical data also shows that, on average, business loads are higher from 1–2 PM than they are for 2–6 PM. However, by necessity, the ex ante demand reductions from 1–2 PM presented here are based on the assumption that demand reductions from 1–2 PM are equivalent to historical demand reduction from 2–3 PM on a percentage basis.

The enrollment estimates for SCE assume future enrollments similar to that of 2012, since many default CPP-eligible customers have had three years of experience on the rate, allowing customers ample opportunity to assess if the rate fits their electricity use patterns and load reduction capabilities. However, SCE does project a slight increase in enrollment on the CPP tariff in 2013 through 2015, reflecting the mostly flat enrollment trends but with some increased retention due to the anticipated offering of a CPP customer reference level, not currently offered to SCE CPP customers. Other factors contributing to the CPP enrollment forecast are general population and load growth.

On average, 3,006 accounts participated in 2012 events. Note that the main ex post results presented in section 5 are for default CPP customers only. The analysis basis here in the ex ante section of the report changes because SCE provides enrollment forecasts on a total basis, rather than segregated by opt-in and default. These voluntary customers are low CPP responders and so the ex ante results presented here will tend to be lower due to the inclusion of these customers in the analysis.

By January 2013, 3,051 customers are projected to be served under the rate schedule and by December 2015, 3,141 customers are forecast to be enrolled. Table 8-1 shows SCE's enrollment projections through 2023.

Table 8-1: SCE Enrollment Projections for CPP Customers by Forecast Year and Month

Forecast Year	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	3,047	3,047	3,047	3,047	3,047	3,047	3,047	3,047	3,047	3,047	3,047	3,047
2013	3,051	3,053	3,056	3,058	3,061	3,063	3,066	3,068	3,071	3,074	3,076	3,079
2014	3,081	3,084	3,086	3,089	3,092	3,094	3,097	3,099	3,102	3,104	3,107	3,110
2015	3,112	3,115	3,117	3,120	3,123	3,125	3,128	3,130	3,133	3,136	3,138	3,141
2016–2023	3,141	3,141	3,141	3,141	3,141	3,141	3,141	3,141	3,141	3,141	3,141	3,141

8.1 Annual System Peak Day Impacts

Table 8-2 summarizes the aggregate load impact estimates for customers taking SCE's CPP tariff for each forecast year, through 2023, under both 1-in-2 and 1-in-10 weather year scenarios. The table shows the average load reduction across the 1–6 PM event period for an August monthly system peak day. As mentioned earlier, the results do not reflect adjustments for dual enrollment on other DR programs and assume the 1–2 PM demand reduction are equivalent to the 2–6 PM demand reductions on a percentage basis. The portfolio adjusted estimates are summarized in Appendix D.

Differences in aggregate demand reductions from year to year are a direct result of changes in enrollment and the customer mix. The aggregate load impacts, in the sixth column, stay relatively constant across forecast years and both 1-in-2 and 1-in-10 weather year conditions. On the low end, aggregate impacts in 2013 under the 1-in-10 weather scenario are forecast to be 27.1 MW. At the upper end, the forecasted aggregate impacts are 28.6 MW in the 2016–2023 period under the 1-in-2 weather year scenario. In general, large CPP customers are not highly weather sensitive so their impacts do not change significantly between 1-in-2 and 1-in-10 weather years. Although SCE is expecting enrollment to increase slightly, the reference loads and impacts remain constant and linearly related to the number of customers enrolled because customers currently on CPP are assumed to be fully representative of the small number of customers who will join the program in the future. While large C&I CPP enrollment increases, percent impacts are assumed to remain constant.

Table 8-2: SCE August Peak Day CPP Program Load Impacts
(Hourly Average Reduction in MW over Event Day Period 1–6 PM)

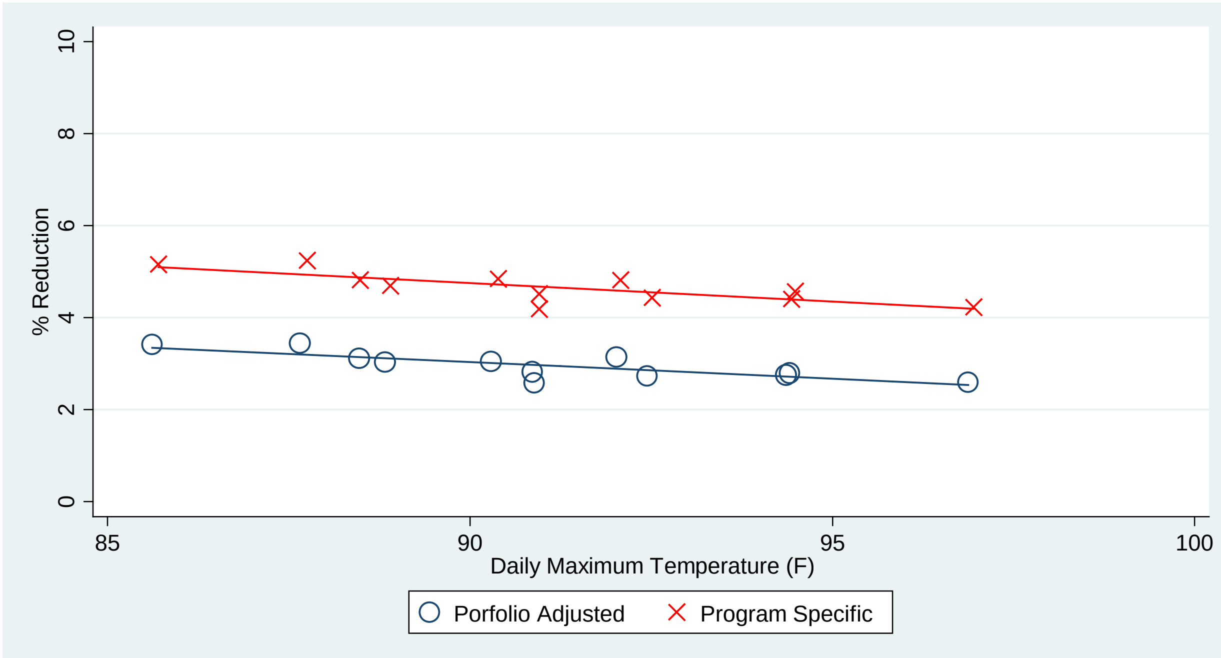
Weather Year	Year	Forecasted Enrolled Accounts	Avg. Reference Load	Avg. Estimated Load with DR	Avg. Load Impact	% Load Reduction	Weighted Temp
			MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	(°F)
1-in-10 August System Peak Day	2012	3,046	691.4	662.1	29.3	4.23%	95.5
	2013	3,068	696.5	667.0	29.5	4.23%	95.5
	2014	3,099	703.5	673.7	29.8	4.23%	95.5
	2015	3,130	710.5	680.4	30.1	4.23%	95.5
	2016–2023	3,141	712.9	682.7	30.2	4.23%	95.5
1-in-2 August System Peak Day	2012	3,046	677.5	646.5	31.0	4.58%	93.6
	2013	3,068	682.5	651.3	31.2	4.58%	93.6
	2014	3,099	689.3	657.8	31.5	4.58%	93.6
	2015	3,130	696.3	664.4	31.9	4.58%	93.6
	2016–2023	3,141	698.6	666.6	32.0	4.58%	93.6

In 2013, the average aggregate load impact during an August event for the 1-in-2 weather year scenario is estimated to be 31.0 MW. Under SCE's current enrollment projections, the load reduction capabilities of the CPP program is not expected to grow. Changes to the population of SCE customers eligible to default to CPP would significantly change this outlook.

Depending on the forecast year and weather conditions, CPP customers are expected to reduce between 4.2% and 4.6% of demand under peaking conditions. Recall that these estimates reflect low-performing SMB customers who opt in to the CPP rate.

The portfolio-adjusted load impacts exclude customers dually enrolled in BIP or aggregator programs, which are among the most responsive participants. Figure 8-1 illustrates the effect of removing dually enrolled customers. The comparison is made with participants enrolled at the end of summer 2012. The portfolio-adjusted demand reductions are 2 to 3 percentage points lower than the program specific results. For 1-in-2 weather year conditions, the program-specific reductions are 4.6% while the portfolio-adjusted reduction is 2.8% for the August monthly peak.

Figure 8-1: Comparison of Portfolio-adjusted to Program-specific Ex Ante Load Impacts May to October Monthly Peaks for Current Participants



8.2 Ex Ante Load Impact Uncertainty

Table 8-3 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for CPP customers. The ex ante impacts do not reflect uncertainty in enrollment. At first glance, the uncertainty appears large. For example, in 2013, the projected load impacts for 1-in-2 weather conditions are 31.2 ±9.2 MW, with 80% confidence. The uncertainty reflects both the challenge of accurately estimating small percentage demand reductions and the variability in performance observed across events.

Table 8-3: SCE Program Ex Ante Annual System Peak Day Load Impacts with Uncertainty (Hourly Average Reduction in MW Over the Event Day Window 1–6 PM)

Weather Year	Year	Expected Avg. Load Impact	Impact Uncertainty (Percentiles)				
		MW 1–6 PM	10^{th}	30^{th}	50^{th}	70^{th}	90^{th}
1-in-10 August System Peak Day	2012	29.3	20.6	25.7	29.3	32.8	37.9
	2013	29.5	20.8	25.9	29.5	33.1	38.2
	2014	29.8	21.0	26.2	29.8	33.4	38.6
	2015	30.1	21.2	26.4	30.1	33.7	39.0
	2016–2023	30.2	21.3	26.5	30.2	33.8	39.1
1-in-2 August System Peak Day	2012	31.0	21.9	27.3	31.0	34.7	40.1
	2013	31.2	22.0	27.5	31.2	35.0	40.4
	2014	31.5	22.3	27.7	31.5	35.3	40.8
	2015	31.9	22.5	28.0	31.9	35.7	41.2
	2016–2023	32.0	22.6	28.1	32.0	35.8	41.4

8.3 Ex Ante Impacts by Geographic Location

It is instructive to look at per customer ex ante estimates of peak reference loads and load reduction independent of enrollment projections. The biggest sources of uncertainty in aggregate ex ante impacts arise from the enrollment projections under default CPP. Table 8-4 shows the average reference loads and load reduction over the 1–6 PM event window for the average customer in 2012 by month, weather year and transmission area. Overall load absent demand response – the reference loads – vary significantly with weather year and month. Table 8-5 follows with per-customer ex ante load reductions by month and weather year. It shows average participant load reduction for each monthly system peak day under 1-in-2 and 1-in-10 system peaking conditions. These tables include estimates of reference load and load impacts for non-summer months, even though no CPP events have been called in the winter, to date. The ex ante modeling process included limitations onto how far out of sample the models were permitted to predict, by setting a load impact “floor” based on the coolest SCE CPP events on record, and a load impact “ceiling” based on the hottest SCE CPP events on record.

Table 8-6 provides additional detail for the August Monthly Peaks by transmission area. On an individual customer basis, the load reductions are largest in the South of Lugo region and lowest in South Orange County. However, the reference loads are largest for those customers classified as Other – located in transmission planning regions other than South of Lugo or South Orange County. South of Lugo has a disproportionate share of Manufacturing and Wholesale, Transport & Other Utilities customers, which are more price responsive, than other areas.

Table 8-4: SCE Average Customer Reference Load (kW) by Month and Transmission Area

Weather Year	Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	South of Lugo	179	204	209	214	226	224	224	235	238	228	214	175
	S. Orange County	189	211	231	246	243	244	246	258	261	251	258	184
	Other	168	183	191	199	211	207	205	218	221	211	198	165
	All Customers	**173**	**192**	**200**	**208**	**219**	**216**	**215**	**227**	**230**	**220**	**208**	**170**
1-in-2	South of Lugo	179	183	183	201	219	215	219	233	235	225	203	175
	S. Orange County	189	191	194	210	236	224	236	253	258	258	218	184
	Other	168	172	171	186	205	197	200	212	219	210	185	165
	All Customers	**173**	**177**	**177**	**193**	**212**	**205**	**209**	**222**	**228**	**219**	**194**	**170**

Table 8-5: SCE Average Customer Load Impacts (kW) by Month and Transmission Area

Weather Year	Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	South of Lugo	15.7	15.7	15.5	15.7	15.1	15.5	15.4	15.5	15.4	15.5	15.1	15.7
	S. Orange County	6.2	5.6	6.1	5.7	5.7	5.8	5.7	5.8	5.8	5.8	6.2	6.3
	Other	11.1	10.2	10.2	9.2	8.5	7.4	7.1	7.2	7.3	8.9	8.9	11.1
	All Customers	**12.0**	**11.4**	**11.4**	**10.9**	**10.3**	**9.7**	**9.5**	**9.6**	**9.6**	**10.6**	**10.6**	**12.1**
1-in-2	South of Lugo	15.7	15.5	15.7	14.2	15.5	15.4	15.6	15.5	15.5	15.5	15.7	15.7
	S. Orange County	6.2	6.2	6.3	5.6	6.0	6.0	5.8	5.7	5.7	5.7	6.1	6.3
	Other	11.1	10.6	11.0	10.7	9.4	9.1	8.0	8.1	7.9	8.8	10.5	11.1
	All Customers	**12.0**	**11.7**	**12.0**	**11.3**	**10.9**	**10.7**	**10.1**	**10.2**	**10.0**	**10.6**	**11.7**	**12.1**

Table 8-6: SCE August System Peak Day Aggregate Impacts by Transmission Area

Weather Year	Area	Forecasted Enrolled Accounts	Reference Load	Estimated Load with DR	Load Impact	% Load Reduction	Weighted Temp
			MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	(°F)
1-in-10 August System Peak Day	South of Lugo	955	224.7	209.8	14.8	6.60%	99.3
	S. Orange County	298	77.1	75.4	1.7	2.24%	88.6
	Other	1,869	407.0	393.5	13.5	3.31%	94.7
	All Customers	3,123	708.7	678.7	30.0	4.23%	95.5
1-in-2 August System Peak Day	South of Lugo	955	222.1	207.3	14.8	6.68%	98.4
	S. Orange County	298	75.6	73.9	1.7	2.26%	87.5
	Other	1,869	396.8	381.6	15.2	3.84%	92.2
	All Customers	3,123	694.5	662.7	31.8	4.58%	93.6

9 SDG&E Ex Ante Load Impacts

This section presents ex ante load impact estimates for SDG&E's non-residential CPP tariff. These estimates are based on the ex post estimates for 2012 developed using the difference-in-differences approach. Typically, a multi-year analysis is preferable as it helps better define variation in performance across events and the relationship between demand reductions and weather. However, a multi-year analysis with a control group was not representative because only 50% of current CPP customers were both matched and had complete multi-year history of participation on default CPP. In addition, SDG&E experienced cooler weather and called few weekday events in 2010 and 2011 and as a result the loss of information by developing ex ante estimates based on 2012 ex post results alone was minimal. While individual regressions are flexible and can be customized to analyze the event history unique to each customer, they produced extremely weather sensitive results which, under further scrutiny, proved to be an artifact. Individual regressions produced inaccurate ex ante impacts for SDG&E: the estimates were too high at hotter temperatures and too low for cooler temperatures. This was not true for PG&E and SCE, where the individual customer regressions and control group methods produced similar results and weather sensitivity.

Two primary steps were required to produce SDG&E's ex ante estimates. First, reference loads were estimated based on the weather observed in 1-in-2 and 1-in-10 weather year conditions for each month. Next, we applied the average percent demand reduction, by industry, observed in 2012. The averages were used because the 2012 ex post percent reductions using the difference-in-differences method showed little weather sensitivity. Reference loads varied based on temperature and industry mix, while the percent demand reductions were constant across temperature but varied by industry.

The remainder of this section separately presents the ex ante load impact projections for medium and large customers projected to receive service under SDG&E's default CPP tariff. For simplicity, all current participants are referred to as large, although some currently do not meet the official definition. 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 the 2012 to 2023 period. This section presents program level impacts – that is, demand reduction capability is not adjusted for dual enrollment of CPP participants in other DR programs. Appendix D presents tables with the portfolio adjusted demand reductions, which are calculated to avoid double counting of load impacts associated with customers enrolled in more than one program.

9.1 Large C&I Ex Ante Impacts

Overall, 1,144 large customers were enrolled in default CPP in 2012. In total, 76% of current participants have been enrolled on default CPP since 2008 and have experienced 17 weekday events since enrolling.

Table 9-1 shows SDG&E's enrollment projections for large customers through 2023. The forecasted year-to-year change in enrollment is minimal and simply reflects the expected growth of SDG&E's large customer population.

Table 9-1: SDG&E Enrollment Projections for Large CPP Customers by Forecast Year and Month

Forecast Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2013	0	0	0	1,143	1,079	1,080	1,083	1,083	1,084	1,085	1,086	1,086
2014	1,090	1,091	1,091	1,092	1,095	1,096	1,096	1,097	1,100	1,102	1,103	1,104
2015	1,104	1,107	1,107	1,109	1,110	1,110	1,113	1,114	1,114	1,117	1,117	1,118
2016	1,119	1,120	1,122	1,123	1,124	1,126	1,127	1,128	1,129	1,131	1,132	1,133
2017	1,135	1,136	1,137	1,138	1,140	1,141	1,142	1,144	1,145	1,146	1,148	1,149
2018	1,150	1,152	1,153	1,154	1,155	1,157	1,158	1,159	1,161	1,162	1,163	1,165
2019	1,166	1,167	1,169	1,170	1,171	1,173	1,174	1,175	1,177	1,178	1,179	1,181
2020	1,182	1,184	1,185	1,186	1,188	1,189	1,190	1,192	1,193	1,194	1,196	1,197
2021	1,198	1,200	1,201	1,203	1,204	1,205	1,207	1,208	1,209	1,211	1,212	1,214
2022	1,215	1,216	1,218	1,219	1,221	1,222	1,223	1,225	1,226	1,228	1,229	1,230
2023	1,232	1,233	1,235	1,236	1,237	1,239	1,240	1,242	1,243	1,244	1,246	1,247
2023	1,232	1,233	1,235	1,236	1,237	1,239	1,240	1,242	1,243	1,244	1,246	1,247

Table 9-2 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 weather year scenarios. The table shows the average load reduction across the 11 AM to 6 PM event period for an August monthly system peak day. As mentioned earlier, the results do not reflect adjustments for dual enrollment on other DR programs. The portfolio-adjusted estimates are summarized in Appendix C.

Differences in demand reductions from year to year are minimal and are the direct result of expected growth of SDG&E's large customer population. The aggregate 1-in-2 weather year demand reductions forecasted for 2013, 16.7 MW, do not differ substantially from the 2023 forecast, 19.2 MW. On a percentage basis, the demand reductions are nearly identical to those observed in 2012 for the average event, 5.9%, for all forecast years and weather year conditions. The percent demand reduction does not change across forecast years because the industry mix is expected to remain stable. It does not change across weather years because percent demand reductions did not vary with weather for ex post events. The aggregate impact does vary, however, because it reflects higher reference loads under 1-in-10 and 1-in-2 weather year conditions. The differences are minimal. For example, the 2013 1-in-2 weather year impact is forecasted to be 16.7 MW versus 17.2 MW for 1-in-10 weather year conditions.

The portfolio-adjusted load impacts exclude customers dually enrolled in BIP or aggregator programs, which are among the most responsive participants. However, the difference between program and portfolio adjusted impacts for SDG&E is very small, less than 0.1 MWs, due to the small number of dually enrolled customers. In 2012, only 6 of SDG&E's 1,117 default CPP participants were dually enrolled.

Table 9-2: SDG&E August Peak Day CPP Program Load Impacts for Large Customers (Hourly Average Reduction in MW Over Event Day Period 11 AM to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			MW 11 AM – 6 PM	MW 11 AM – 6 PM	MW 11 AM – 6 PM	MW 11 AM – 6 PM	MW 11 AM – 6 PM
1-in-10 August System Peak Day	2012	1,117	300.9	283.2	17.7	5.9%	84.4
	2013	1,083	291.8	274.6	17.2		
	2014	1,097	295.5	278.1	17.4		
	2015	1,114	300.0	282.3	17.7		
	2016	1,128	303.9	286.0	17.9		
	2017	1,144	308.1	289.9	18.1		
	2018	1,159	312.3	293.9	18.4		
	2019	1,175	316.6	298.0	18.6		
	2020	1,192	321.0	302.1	18.9		
	2021	1,208	325.4	306.2	19.2		
	2022	1,225	329.9	310.4	19.4		
	2023	1,242	334.4	314.7	19.7		
1-in-2 August System Peak Day	2012	1,117	291.0	273.8	17.2	5.9%	82.0
	2013	1,083	282.2	265.5	16.7		
	2014	1,097	285.7	268.8	16.9		
	2015	1,114	290.1	272.9	17.2		
	2016	1,128	293.8	276.4	17.4		
	2017	1,144	297.9	280.3	17.6		
	2018	1,159	302.0	284.1	17.9		
	2019	1,175	306.1	288.0	18.1		
	2020	1,192	310.4	292.0	18.4		
	2021	1,208	314.6	296.0	18.6		
	2022	1,225	319.0	300.1	18.9		
	2023	1,242	323.4	304.2	19.1		

Table 9-3 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for large customers. The ex ante impacts do not reflect uncertainty in enrollment. 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 2013, the projected load impacts for 1-in-2 weather conditions are 17.2 ±4.9 MW, with 80% confidence.

Table 9-3: SDG&E Program Annual Peak Day Load Impacts for Large Customers with Uncertainty (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Avg. Load impact	Impact Uncertainty Percentiles				
		MW 11 am - 6 pm	10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2013	17.2	12.3	15.2	17.2	19.2	22.1
	2014	17.4	12.5	15.4	17.4	19.4	22.3
	2015	17.7	12.7	15.6	17.7	19.7	22.7
	2016	17.9	12.9	15.8	17.9	20.0	22.9
	2017	18.1	13.0	16.1	18.1	20.2	23.3
	2018	18.4	13.2	16.3	18.4	20.5	23.6
	2019	18.6	13.4	16.5	18.6	20.8	23.9
	2020	18.9	13.6	16.7	18.9	21.1	24.3
	2021	19.2	13.7	16.9	19.2	21.4	24.6
	2022	19.4	13.9	17.2	19.4	21.7	24.9
	2023	19.7	14.1	17.4	19.7	22.0	25.3
1-in-2 August System Peak Day	2013	16.7	11.9	14.7	16.7	18.6	21.4
	2014	16.9	12.1	14.9	16.9	18.9	21.7
	2015	17.2	12.3	15.2	17.2	19.1	22.0
	2016	17.4	12.5	15.4	17.4	19.4	22.3
	2017	17.6	12.6	15.6	17.6	19.7	22.6
	2018	17.9	12.8	15.8	17.9	19.9	22.9
	2019	18.1	13.0	16.0	18.1	20.2	23.2
	2020	18.4	13.2	16.2	18.4	20.5	23.6
	2021	18.6	13.3	16.5	18.6	20.8	23.9
	2022	18.9	13.5	16.7	18.9	21.1	24.2
	2023	19.1	13.7	16.9	19.1	21.3	24.6

9.2 Medium C&I Ex Ante Impacts

For SDG&E, there is more data available on how much load reduction medium customers provide during default CPP events than there is for other utilities. In addition, SDG&E's expected retention rates for default CPP are better understood than for the other utilities. Medium customers are on the same rate, AL-TOU, as large ones. In addition, SDG&E defaulted roughly 600 medium customer accounts onto CPP between 2008 and 2012, and approximately 400 remained on the rate.

Although SDG&E has more information about medium customer price responsiveness for default CPP, overall, there remains a high degree of uncertainty for both enrollment and demand reductions. The medium customers that were defaulted early are not representative of the general medium C&I population. Medium customers defaulted onto CPP were among the largest medium sized customers and had a disproportionate number of schools. To obtain a larger and more diverse sample of customers for the medium customer price-responsiveness analysis, customers with average annual hourly demand below 200 kW were also included along with medium customers.[29] In other words, customers that are slightly above the large customer threshold were used as a proxy for medium customers. As with large customers, the ex ante impacts were developed solely using 2012 events analyzed using difference-in-differences.

Table 9-4 compares the industry mix of the estimating sample to the industry mix expected to remain on default CPP. It also summarizes the percent demand reductions, by industry, for the estimating sample. The ex ante impacts adjust for differences in industry mix between the estimating sample and medium customers.

Table 9-4: SDG&E Industry Distribution for Estimating Sample and Medium Population

Industry	Medium Proxy Accts	%	Medium Population	%	% Demand Reductions (Medium Proxy Accts)
Agriculture, Mining & Construction *	–	–	390	3.4%	–
Manufacturing	97	12.8%	832	7.2%	9.3%
Wholesale, Transport & Other Utilities	113	14.9%	733	6.3%	15.9%
Retail Stores	65	8.6%	1,905	16.5%	11.4%
Offices, Hotels, Finance &Services	188	24.8%	5,334	46.1%	2.8%
Schools	204	26.9%	604	5.2%	1.6%
Institutional/Government	92	12.1%	1,781	15.4%	3.9%

* Control group matches could not be found for agricultural pumps because nearly all of them opted to remain on CPP or enrolled in other DR programs.

The medium customer ex ante impacts include one additional adjustments. The impacts were adjusted down to reflect expected lower awareness rates among the medium population relative to large customers. While large customers have an assigned account representative, many medium customers do not. As a result, some customers may not be aware they were defaulted onto CPP or understand the rate. The ex ante impacts assume that awareness is low (relative to large customers) immediately after the default, 70%, and gradually increases to 90%. Depending on the year, the impacts are 70% to 90% of those observed among default CPP participants that are closest to medium customers.

[29] Customers are classified as small, medium and large based on maximum demand levels rather than average demand levels. The size categorization used is based on consumption. As a result, customers with average annual hourly demand of 200 kW include many customers that are classified as large, based on maximum demand levels.

Table 9-5 shows SDG&E's enrollment projections for medium customers through 2023. All SDG&E's medium customers are expected to be defaulted onto CPP in 2014. SDG&E forecasted retention rates to vary by industry in a similar manner as they varied for large customers. Notice that enrollment decreases immediately after the initial default year and increases thereafter. This pattern reflects the fact that some customers who try out default CPP during the initial bill protection period opt-out once they have experienced the rate. Enrollment growth from 2016–2023 reflects the expected growth of SDG&E's medium customer population.

Table 9-5: SDG&E's Enrollment Projections for Medium CPP Customers by Forecast Year and Month

Forecast Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2013	0	0	0	0	0	0	0	0	0	0	0	0
2014	0	0	0	0	8,678	8,688	8,697	8,707	8,717	8,727	8,737	8,747
2015	8,757	8,767	8,777	8,787	7,095	7,103	7,111	7,119	7,128	7,136	7,144	7,152
2016	7,160	7,168	7,176	7,185	6,752	6,760	6,768	6,775	6,783	6,791	6,799	6,806
2017	6,814	6,818	6,822	6,830	6,837	6,845	6,853	6,861	6,869	6,877	6,884	6,892
2018	6,900	6,908	6,916	6,924	6,932	6,940	6,947	6,955	6,963	6,971	6,979	6,987
2019	6,995	7,003	7,019	7,027	7,035	7,043	7,051	7,059	7,067	7,075	7,083	7,092
2020	7,100	7,108	7,116	7,124	7,132	7,140	7,148	7,157	7,165	7,173	7,181	7,189
2021	7,197	7,206	7,214	7,222	7,230	7,239	7,247	7,255	7,263	7,272	7,280	7,288
2022	7,297	7,305	7,313	7,322	7,330	7,338	7,347	7,355	7,363	7,372	7,380	7,389
2023	7,397	7,406	7,414	7,422	7,431	7,439	7,448	7,456	7,465	7,473	7,482	7,490

Table 9-6 summarizes the aggregate load impact estimates for medium customers on SDG&E's CPP tariff for each forecast year under both 1-in-2 and 1-in-10 weather year scenarios. The table shows the average load reduction across the 11 AM to 6 PM event period for an August monthly system peak day.

Table 9-6: Program Annual Peak Day Load Impacts for Medium SDG&E CPP Customers (Hourly Average Reduction in MW Over Event Day Period 11 AM to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			MW 11 am–6 pm	MW 11 am–6 pm	MW 11 am–6 pm	MW 11 am–6 pm	MW 11 am–6 pm
1-in-10 August System Peak Day	2013	-	-	-	-	-	-
	2014	8,707	478.5	460.3	18.2	3.8%	84.4
	2015	7,119	388.9	371.4	17.4	4.5%	84.4
	2016	6,775	370.1	351.4	18.7	5.0%	84.4
	2017	6,861	374.8	355.8	18.9	5.0%	84.4
	2018	6,955	379.9	360.8	19.2	5.0%	84.4
	2019	7,059	385.6	366.1	19.5	5.0%	84.4
	2020	7,157	390.9	371.2	19.7	5.0%	84.4
	2021	7,255	396.3	376.3	20.0	5.0%	84.4
	2022	7,355	401.7	381.5	20.3	5.0%	84.4
	2023	7,456	407.3	386.7	20.5	5.0%	84.4
1-in-2 August System Peak Day	2013	-	-	-	-	-	-
	2014	8,707	460.5	442.8	17.6	3.8%	81.9
	2015	7,119	374.3	357.4	16.9	4.5%	81.9
	2016	6,775	356.3	338.2	18.1	5.1%	81.9
	2017	6,861	360.8	342.4	18.3	5.1%	81.9
	2018	6,955	365.7	347.2	18.6	5.1%	81.9
	2019	7,059	371.2	352.3	18.8	5.1%	81.9
	2020	7,157	376.3	357.2	19.1	5.1%	81.9
	2021	7,255	381.5	362.1	19.4	5.1%	81.9
	2022	7,355	386.7	367.1	19.6	5.1%	81.9
	2023	7,456	392.1	372.2	19.9	5.1%	81.9

As discussed earlier, there is a noticeable drop in enrollment between 2014 and 2015, from 8,707 to 7,119 customers, which reflects some customers opting-out after testing default CPP during the bill protection period. The drop in enrollment is not accompanied by a corresponding decrease in forecasted impacts. In fact, the demand reductions under 1-in-2 weather conditions for 2015, 17.6 MW, are very similar to the 2014 forecast, 16.9 MW. The estimated impacts do not decrease substantially for a simple reason. Customers that were not aware or did not fully understand the CPP rates are expected to opt-out. Almost by definition, customers that are not aware or understand the rate do not reduce demand. In other words, while enrollments decrease, the decrease is among customers that are not price responsive. The more price-responsive customers are expected to remain on the rate and have a higher awareness of the CPP rate. The forecasted demand reduction capability also increases in 2016, since customers who on the rate then are assumed to have higher awareness rate. This pattern is similar to what has happened with large customers defaulted onto CPP. Overall enrollments have dropped, as customers who initially tried it opted out, but aggregate reductions have not decrease much and in some cases have increased.

Underlying the impact estimates summarized above is a significant amount of uncertainty. Table 9-7 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for medium customers. It does not, however, reflect the largest sources of uncertainty: enrollment uncertainty and the assumption that we can infer medium customers' price responsiveness based on current participants, after adjusting for differences in the industry mix.

Table 9-7: Program Annual Peak Day Load Impacts for Medium Customers with Uncertainty (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Avg. Load impact	Impact Uncertainty Percentiles				
		MW 11 am – 6 pm	10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2013	-	-	-	-	-	-
	2014	18.2	11.2	15.3	18.2	21.1	25.3
	2015	17.4	11.3	14.9	17.4	19.9	23.6
	2016	18.7	12.5	16.1	18.7	21.2	24.9
	2017	18.9	12.6	16.3	18.9	21.5	25.2
	2018	19.2	12.8	16.6	19.2	21.8	25.5
	2019	19.5	13.0	16.8	19.5	22.1	25.9
	2020	19.7	13.2	17.0	19.7	22.4	26.3
	2021	20.0	13.4	17.3	20.0	22.7	26.6
	2022	20.3	13.5	17.5	20.3	23.0	27.0
	2023	20.5	13.7	17.8	20.5	23.3	27.4
1-in-2 August System Peak Day	2013	-	-	-	-	-	-
	2014	17.6	10.9	14.9	17.6	20.4	24.4
	2015	16.9	11.0	14.5	16.9	19.3	22.8
	2016	18.1	12.1	15.6	18.1	20.5	24.1
	2017	18.3	12.3	15.8	18.3	20.8	24.4
	2018	18.6	12.4	16.1	18.6	21.1	24.7
	2019	18.8	12.6	16.3	18.8	21.4	25.1
	2020	19.1	12.8	16.5	19.1	21.7	25.4
	2021	19.4	13.0	16.8	19.4	22.0	25.8
	2022	19.6	13.2	17.0	19.6	22.3	26.1
	2023	19.9	13.3	17.2	19.9	22.6	26.5

10 Recommendations

The empirical data from PG&E, SCE and SDG&E's default critical peak pricing 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 medium customers respond to default CPP rates. In addition, both SCE and PG&E will implement changes to the CPP program design: SCE will provide customers with the ability to partially or fully insure their load against high CPP prices and both PG&E and SCE will adjust event windows from 2–6 PM to 1–6 PM.

These changes provide a unique opportunity to estimate the effect of program changes through well designed tests rather than after-the-fact analysis. Although FSC recommends specific research steps, the 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. The basic idea is to conduct small scale tests as early as possible to avoid making more costly mistakes later in the process. FSC recommends that utilities test default CPP with a smaller, random sub-set of medium 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 customers. Most assumptions about how medium customers will engage and respond are uncertainty because they are based on implementation of default CPP for large customers.
- *Evaluate demand reductions closer to event days by using a control group with a difference-in-differences calculation.* Initial post event estimates of load impacts have typically relied on day-matching baselines and have sometimes differed substantially from evaluation results. Using control groups provides a unique opportunity to better align immediate post event results with the final ex post evaluation results. This faster and more accurate evaluation feedback is particularly useful when major program changes occur, such as the implementation of default CPP for medium customers. Doing so requires developing matched participant and control groups in advance rather than after the fact. In other words, the control group would need to be selected and validated in May or early June of each year. A key benefit of using control groups is that they do not rely exclusively on non-event day weather to estimate demand reductions. Customers in both control and participant groups experience the same weather. As a result, control groups are more valuable for extreme temperature events.
- *Estimate the effect of program changes through research design rather than after-the-fact analysis.* The scheduled program changes at PG&E and SCE 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 expanding the event window lead to lower demand reductions? The ideal approach to answering these questions with scientific accuracy is a phased roll-out 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 Difference-in-differences Regression Models

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. We intentionally elected to use a treatment model rather than a price elasticity model for two reasons. First, for any hour there are only have two price points, or at most three, which is insufficient for fitting price elasticity curves.[30] Second, it avoids assumptions such as constant price elasticity inherent in demand models. The model is expressed by the below equations:

Avg. Event Equation:

$$kW_{i,t} = a + b \cdot Treatment_i + c \cdot Event_t + d \cdot (Treatment_i \cdot Event_t) + u_t + v_i + \varepsilon_{i,t}$$

Individual Event Equation:

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

Variable	Definition
i, t,	Indicate observations for each individual (*i*), date (*t*) and event number (*n*).
a	The model constant.
b	Pre-existing difference between treatment and control customers.[31]
c	The difference between event and non-event days common to both CPP participants and control group members.[32]
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. These control for unobserved factors that are common to all treatment and control customers but unique to the time period.
v	Customer fixed effects. These control for unobserved factors that are time invariant and unique to each customer. It does not control for fixed characteristics such as air conditioning that interact with time varying factors like weather.
ε	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.

Tables A-1 through A-3 present the hourly regression results, including coefficients, standard errors, confidence intervals and R-squared values for the average event day of each utility. All regression models were estimated in STATA using robust standard errors.

30 Given the limited number of price points per hour, price elasticities can be manually estimated based on the percent change in consumption and percent change in prices.

31 In practice, this term is absorbed by the fixed effects, but it is useful for representing the model logic.

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

Table A-1: Simple Difference-in-differences Panel Regression Results
Pacific Gas & Electric 2012 Average Weekday Event

Hour Ending	Impact	Standard Error	T	p. value	95% Confidence Interval		Model R-squared
1:00 AM	1.48	1.631	0.91	0.182	3.44	-0.48	0.916
2:00 AM	2.22	1.624	1.37	0.086	4.18	0.26	0.914
3:00 AM	2.15	1.584	1.36	0.087	4.11	0.19	0.915
4:00 AM	0.89	1.574	0.57	0.286	2.85	-1.07	0.920
5:00 AM	1.47	1.569	0.94	0.174	3.43	-0.49	0.921
6:00 AM	2.22	1.588	1.40	0.081	4.18	0.26	0.922
7:00 AM	2.31	1.601	1.44	0.074	4.27	0.35	0.924
8:00 AM	1.10	1.594	0.69	0.245	3.06	-0.86	0.927
9:00 AM	0.21	1.558	0.14	0.446	2.17	-1.75	0.933
10:00 AM	0.05	1.597	0.03	0.488	2.01	-1.91	0.934
11:00 AM	-0.65	1.639	0.39	0.347	1.32	-2.61	0.935
12:00 PM	-3.22	1.628	1.98	0.024	-1.26	-5.18	0.937
1:00 PM	-3.38	1.558	2.17	0.015	-1.42	-5.34	0.941
2:00 PM	-10.19	1.582	6.44	0.000	-8.23	-12.15	0.938
3:00 PM	-23.66	1.593	14.85	0.000	-21.70	-25.62	0.932
4:00 PM	-24.05	1.508	15.95	0.000	-22.09	-26.01	0.937
5:00 PM	-21.18	1.415	14.97	0.000	-19.22	-23.14	0.943
6:00 PM	-19.52	1.390	14.04	0.000	-17.56	-21.48	0.941
7:00 PM	-9.84	1.445	6.81	0.000	-7.88	-11.80	0.936
8:00 PM	-4.47	1.487	3.01	0.001	-2.51	-6.43	0.934
9:00 PM	-2.60	1.465	1.77	0.038	-0.64	-4.56	0.936
10:00 PM	-2.87	1.472	1.95	0.026	-0.91	-4.83	0.932
11:00 PM	-2.07	1.448	1.43	0.077	-0.11	-4.03	0.934
12:00 AM	-1.63	1.449	1.12	0.131	0.33	-3.59	0.934

Table A-2: Simple Difference-in-differences Panel Regression Results
San Diego Gas & Electric 2012 Average Weekday Event

Hour Ending	Impact	Standard Error	t	p. value	95% Confidence Interval		Model R-squared
1:00 AM	-1.49	1.539	0.97	0.166	0.47	-3.45	0.960
2:00 AM	0.32	1.519	0.21	0.416	2.28	-1.64	0.961
3:00 AM	0.81	1.494	0.54	0.295	2.77	-1.15	0.960
4:00 AM	-1.33	1.442	0.92	0.178	0.63	-3.29	0.961
5:00 AM	-0.23	1.463	0.16	0.438	1.73	-2.19	0.962
6:00 AM	1.73	1.544	1.12	0.131	3.69	-0.23	0.960
7:00 AM	5.40	1.795	3.01	0.001	7.36	3.44	0.955
8:00 AM	3.65	1.801	2.03	0.021	5.61	1.69	0.954
9:00 AM	3.14	1.860	1.69	0.046	5.10	1.18	0.953
10:00 AM	1.50	1.915	0.78	0.216	3.46	-0.46	0.953
11:00 AM	-4.58	1.876	2.44	0.007	-2.62	-6.54	0.954
12:00 PM	-18.49	2.030	9.11	0.000	-16.53	-20.45	0.946
1:00 PM	-18.77	2.001	9.38	0.000	-16.81	-20.73	0.949
2:00 PM	-16.19	2.009	8.06	0.000	-14.23	-18.15	0.950
3:00 PM	-15.15	2.007	7.55	0.000	-13.19	-17.11	0.951
4:00 PM	-15.17	1.987	7.64	0.000	-13.21	-17.13	0.951
5:00 PM	-16.69	1.905	8.76	0.000	-14.73	-18.65	0.953
6:00 PM	-12.89	1.707	7.55	0.000	-10.93	-14.85	0.960
7:00 PM	-3.80	1.677	2.27	0.012	-1.84	-5.76	0.956
8:00 PM	1.24	1.642	0.75	0.225	3.20	-0.72	0.958
9:00 PM	0.21	1.437	0.15	0.442	2.17	-1.75	0.967
10:00 PM	0.81	1.325	0.61	0.271	2.77	-1.15	0.971
11:00 PM	2.32	1.324	1.75	0.040	4.28	0.36	0.969
12:00 AM	1.92	1.433	1.34	0.090	3.88	-0.04	0.964

Table A-3: Simple Difference-in-differences Panel Regression Results
Southern California Edison 2012 Average Weekday Event

Hour Ending	Impact	Standard Error	t	p. value	95% Confidence Interval		Model R-squared
1:00 AM	0.50	0.967	0.52	0.302	2.46	-1.46	0.898
2:00 AM	0.46	1.018	0.45	0.327	2.42	-1.51	0.888
3:00 AM	0.28	1.028	0.27	0.393	2.24	-1.68	0.882
4:00 AM	1.41	1.027	1.38	0.084	3.37	-0.55	0.880
5:00 AM	1.36	1.023	1.33	0.092	3.32	-0.60	0.884
6:00 AM	2.11	1.030	2.05	0.020	4.07	0.15	0.891
7:00 AM	2.40	1.066	2.25	0.012	4.36	0.44	0.887
8:00 AM	2.39	1.072	2.23	0.013	4.35	0.43	0.885
9:00 AM	1.99	1.063	1.87	0.031	3.95	0.03	0.889
10:00 AM	2.10	1.019	2.06	0.020	4.06	0.14	0.903
11:00 AM	2.31	0.983	2.35	0.009	4.27	0.35	0.913
12:00 PM	2.33	0.939	2.48	0.007	4.29	0.37	0.919
1:00 PM	2.32	0.927	2.50	0.006	4.28	0.36	0.921
2:00 PM	-2.39	0.929	2.57	0.005	-0.43	-4.34	0.921
3:00 PM	-13.62	0.940	14.49	0.000	-11.66	-15.58	0.912
4:00 PM	-13.49	0.865	15.59	0.000	-11.53	-15.45	0.921
5:00 PM	-12.57	0.820	15.32	0.000	-10.61	-14.53	0.926
6:00 PM	-12.07	0.809	14.92	0.000	-10.11	-14.03	0.924
7:00 PM	-3.39	0.978	3.47	0.000	-1.43	-5.35	0.898
8:00 PM	-0.05	1.069	0.05	0.482	1.91	-2.01	0.892
9:00 PM	0.16	1.062	0.16	0.439	2.12	-1.80	0.897
10:00 PM	1.09	1.058	1.03	0.151	3.05	-0.87	0.894
11:00 PM	1.01	1.006	1.00	0.158	2.97	-0.95	0.898
12:00 AM	1.57	1.043	1.51	0.066	3.53	-0.39	0.893

Appendix B False Experiment Proxy Event Days

The false experiment proxy days were matched to the pseudo-events using the same matching process employed in the ex post evaluation. In the false experiment, impacts for the pseudo-events are estimated by:

- Estimating the difference between the treatment and control group on the pseudo-event days;
- Estimating the difference between the treatment and control group on the false experiment proxy event days. The proxy days can be thought of as control days used to assess error when the CPP high prices are not in effect; and
- Netting out the error observed on the proxy event days.

The process was implemented using the regression models described in Appendix A. Figure B-1 compares the false experiment proxy days to the pseudo-events.

Figure B-1: Comparison of Proxy Days for False Experiment

Appendix C Individual Customer Regression Models

To calculate load reductions for demand response programs, customers' load patterns in the absence of event day higher 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. Individual customer regressions and day matching baselines are both examples of within-subject methods. An analysis that relies solely on a control groups – that is, one that does not rely on non-event or pre-enrollment data – is an example of a between-subjects method. The primary method employed for ex post estimation, difference-in-differences, makes use of both hot non-event days (within-subjects) and a control group (between-subjects) data. This section presents the secondary method used for ex post analysis: individual customer regressions. In this section, we present the methodology, validation tests and estimated load impacts for 2012.

Individual customer regressions were calculated for three main reasons:

- They serve a cross check for impacts estimated with difference-in-differences;
- They allow readers to understand if differences in estimated demand reductions are due to changing the primary method from individual regressions to difference-in-differences; and
- They facilitate development to ex ante impacts due to their inherent flexibility.

The main conclusions from the analysis are twofold. First, estimated load impacts for the average event day are quite similar for both approaches for PG&E and SCE, but are biased for SDG&E. Second, a side-by-side comparison of validation tests indicates that even when accurate for the average event, individual customer regressions produce noisier results for individual event days.

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. It is also possible to test multiple models for each customer and select the one that is the most accurate based on out-of-sample testing. 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. Because the coefficients are customer specific, they can better explain the variation in individual customer production and/or occupancy patterns, weather sensitivity, enrollment dates and event day dispatch patterns (which vary substantially across customers due to when each customer enrolled). In addition, individual customer regressions can produce insight into how impacts vary across customers and key segments such as location, industry type, customer size and rate.

Individual regressions can work due to the dispatch patterns of CPP programs. The primary intervention – event days when customers face higher peak period prices – is introduced on some days and not on others, making it possible to observe behavior with and without demand response. A repeated intervention design enables us to assess whether the outcome – electricity consumption – rises or falls with the presence or absence of CPP peak hour event day prices. This approach works if the effect of the intervention dissipates after it is removed, meaning the effects do not spill over onto non-event days. It also hinges on whether or not customer behavior during hotter non-event days is similar to event days. CPP programs tend to be dispatched on summer days when system loads are higher and temperatures are hotter. In other words, event days are not random, but rather systematically selected. CPP rates also introduce a secondary intervention – they lower electricity prices during non-event days. As explained in the main report, the effect of this secondary effect was not measured for three reasons: prior analyses in 2010 and 2011 did not find statistically significant impacts due to the rate discount;[33] the pre-enrollment data needed to quantify the effect of the rate discount is too distant (four or five years prior); and any changes are by now likely embedded into system load (and are not incremental).

C.1 Regression Models

Regression models meant to capture the relationship between electricity use, year, day type, season and weather were run for each customer. Ordinary Least Squares regression was used and a separate model was run for each hour, using robust standard errors.[34] In total, 10 models were tested for each customer at each utility. The final results for each customer are based on the model that produces the smallest errors and least bias for that customer. The 10 models vary in how weather variables were defined, if at all, and in the inclusion of monthly or seasonal variables. This tailored approach customizes models based on whether or not customers were weather sensitive or exhibited seasonal patterns. The added level of accuracy and precision using this customized approached is not always large. However, small improvements matter when percent demand reductions are small. If the true effect were 5%, reducing reference load bias from 1.0% to 0.5% is equivalent to reducing impact bias from 20% to 10%.

For each customer, the regression used multiple-years of data. For PG&E, the individual customer regressions were estimated using 2010, 2011 and 2012 non-event weekday data, if it was available for the specific customer. For SDG&E, the regressions were estimated using data from 2009–2012, if available.[35] To the extent possible, the regressions for each customer avoided cooler days, which typically do not provide much information about behavior during hotter non-event days. For example, if the lowest event day maximum temperature a customer experiences was 100°F, only days that exceed 80% of 100°F (or 80°F) were included. Table C-1 summarizes the individual customer regression specifications and Table C-2 describes each of the regressions terms.

33 This does not mean there is no effect; it simply means that the effect, if any, cannot be distinguished from random noise.

34 Running separate models each hour – 24 models – with robust standard errors using OLS produced similar standard errors as time series techniques including Feasible GLS and Newey-West correction for auto-correlation.

35 For SDG&E, regressions for Saturday events were estimated using only Saturday non-event data. No other utility had historical Saturday events.

Table C-1: Individual Customer Regression Models

Model #	Specification
1	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{j=2}^{12} d_j * month_{dtj} + \sum_{k=2}^{5} e_k * daytype_{dtk} + f * cdd_{dt} + g * cddsqr_{dt} + \sum_{l=1}^{n} h_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
2	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{j=2}^{12} d_j * month_{dtj} + \sum_{k=2}^{5} e_k * daytype_{dtk} + f * cdd_{dt} + g * cdh_{dt} + \sum_{l=1}^{n} h_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
3	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{j=2}^{12} d_j * month_{dtj} + \sum_{k=2}^{5} e_k * daytype_{dtk} + f * overnightcdh_{dt} + g * cdh_{dt} + \sum_{l=1}^{n} h_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
4	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{j=2}^{12} d_j * month_{dtj} + \sum_{k=2}^{5} e_k * daytype_{dtk} + f * cdh_{dt} + g * cdhsqr_{dt} + \sum_{l=1}^{n} h_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
5	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{j=2}^{12} d_j * month_{dtj} + \sum_{k=2}^{5} e_k * daytype_{dtk} + \sum_{l=1}^{n} f_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
6	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{k=2}^{5} d_k * daytype_{dtk} + e * cdd_{dt} + f * cddsqr_{dt} + \sum_{l=1}^{n} g_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
7	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{k=2}^{5} d_k * daytype_{dtk} + e * cdd_{dt} + f * cdh_{dt} + \sum_{l=1}^{n} g_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
8	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{k=2}^{5} d_k * daytype_{dtk} + e * overnightcdh_{dt} + f * cdh_{dt} + \sum_{l=1}^{n} g_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
9	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{k=2}^{5} d_k * daytype_{dtk} + e * cdh_{dt} + f * cdhsqr_{dt} + \sum_{l=1}^{n} g_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$
10	$kW_{dt} = a + \sum_{i=2010}^{2012} b_i * year_{dti} + c * season_{dt} + \sum_{k=2}^{5} d_k * daytype_{dtk} + \sum_{l=1}^{n} e_l * eventday_{dtl} + e_{dt},\ t = \{1, 2, 3 \dots 24\}$

Table C-2: Description of Regression Model Variables

Variable	Description
kW	Energy usage in each hourly interval t={1,2,3 …24} for each date, d
Year	Binary variable for year of the hourly observation
Season	Binary variable indicating whether a customer receives CPP rate discount. A value of 1 indicates the hourly observation falls in the summer season and the customer is actively enrolled in CPP and receiving rate discounts.
Month	Binary variable indicating the month of the hourly observation
Daytype	Binary variable for the day type of the hourly observation (Sundays and holidays and Tuesday through Thursday are grouped together
CDH	Cooling Degree Hour – the max of zero and the hourly temperature value less a base value
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
CDDSQR	The square of Cooling Degree Day
OvernightCDH	The average of CDH from 12 AM through 9 AM
eventday1 ...n	Binary variables indicating each event day, 1 ...n.

C.2 Validation Tests

The fact that it is impossible to directly observe what customers would have used in the absence of load control poses a unique challenge for assessing the accuracy of impact estimates. One approach for assessing accuracy is out-of-sample testing. Under this approach, the "true" answers are known and we can systematically test if the regression models produce accurate results. In general, out-of-sample testing helps assess how accurately regressions predict electricity use patterns.

Out-of-sample testing refers to holding back data from event-like days from the model-fitting process in order to test model accuracy. The basic approach involves running regressions using a subset of the available data. Event-like proxy days are excluded from the estimation sample in order to use them to assess accuracy. The regression model is used to predict electricity use on the event-like days that were withheld. Then we directly compare the model's predictions to the actual electricity use observed on those days. If the predictions are close to the true load, then we have confidence that the model can accurately predict load for event-like conditions because the model did not have access to those days when it made its predictions. Once the model specification is chosen using this validation method, the final demand reduction estimates are produced using the most accurate model. This approach helps ensure the predictive accuracy of the models is not the result of over-fitting the data and avoids spurious ex ante predictions. The individual event days were validated on the same days as the difference-in-differences method to allow direct comparison between methods.

In assessing the accuracy of individual regression models, two key questions were addressed:

- *What was the distribution of best models for each utility?*
- *Does the best individual model produce unbiased estimates at the program level?* In other words, does the best model have a tendency to over or under predict program impacts? The main metric used to assess bias is the program mean percent error, which can simply be interpreted as the percentage by which a method tends to over or under predict. To illustrate, a bias statistic of 5% indicates that the approach tends to overestimate demand reductions by 5%.
- *How closely do the program level estimates for individual event hours and days match actual demand reductions (goodness-of-fit)?* An evaluation model can be accurate on average but perform poorly for individual event hours. This occurs when the errors cancel each other out. The goodness-of-fit metrics we typically use – mean absolute percentage error (MAPE) and normalized Root Mean Squared Error (RMSE) – indicate the typical magnitude of the errors for individual curtailment periods on a percentage basis, with lower values indicating less error.

Table C-3 shows the distribution of the best specifications across customers at each utility. Overall, there is a lack of consistency between utilities in terms of the models that were best fitted to their CPP customers. For example, Model 4, which includes CDH and CDHSQR weather variables, was the most frequently chosen model at SDG&E, but the least frequently chosen model at SCE. This can be due to a variety of factors, including nuances of the methods used, but an easily identifiable factor is industry mix. To illustrate the point, consider the models without any weather variables (Models 5 and 10) – models that should be assigned to weather-insensitive customers. These models were quite frequently identified as the best models for customers at both PG&E and SCE, but were not as frequently chosen at SDG&E. This could be because PG&E and SCE have a greater share of customers in weather-insensitive industries as compared to SDG&E. SDG&E's program enrolls many smaller customers as compared to PG&E and SCE, and these customers tend to be more weather sensitive.[36]

Table C-4: Distribution of Best Individual Regression Model by Utility

Regression Model	PG&E	%	SCE	%	SDG&E	%	Total	%
1	212	12.9%	142	4.5%	197	17.2%	551	9.3%
2	132	8.0%	238	7.5%	192	16.8%	562	9.4%
3	166	10.1%	236	7.5%	65	5.7%	467	7.8%
4	161	9.8%	74	2.3%	224	19.6%	459	7.7%
5	294	17.9%	456	14.4%	115	10.1%	865	14.5%
6	151	9.2%	266	8.4%	94	8.2%	511	8.6%
7	116	7.0%	509	16.1%	81	7.1%	706	11.9%
8	120	7.3%	485	15.3%	32	2.8%	637	10.7%
9	106	6.4%	131	4.1%	97	8.5%	334	5.6%
10	188	11.4%	628	19.8%	47	4.1%	863	14.5%
Total	**1,646**	**100%**	**3,165**	**100%**	**1,144**	**100%**	**5,955**	**100%**

Figure C-1 shows actual and predicted load averaged across a group of event-like proxy days for the average customer at each utility. The figure is an example of out-of-sample testing. The parameters

[36] SDG&E's CPP program is open to customers with maximum demand exceeding 20kW, while the minimum threshold at both PG&E and SCE is 200kW.

used to calculate the reference load were derived from a dataset that did not contain the days for which the predictions were made. Percent difference between actual and predicted load ranges by utility. The individual customer regressions at SCE show the least bias (-0.7%) of any of the three utilities at the program level. During the event hours of 2–6 PM, there is no visual difference between actual and predicted loads. For both PG&E and SDG&E, the models show more bias, but the bias is relatively small, -1.2% and -2.0%, for the CPP period. In both cases, actual load is less than predicted load. For SDG&E, this pattern persists more or less throughout the average event-like proxy day, while at SCE the under prediction is most pronounced in the early morning hours and during the afternoon event period of 2–6 PM, though to a lesser extent. Although bias is small for each utility, it is important to understand that small biases translate into large error in the percent demand reductions. For example, a bias -2% in the reference loads would produce impacts estimates of 4.0% if the true reduction were 6%. The small bias in the reference load can have a large effect of estimated demand reductions, particularly when only a small share of the load is reduced.

Figure C-1: Program Level Out-of-sample Test Results – Average Day

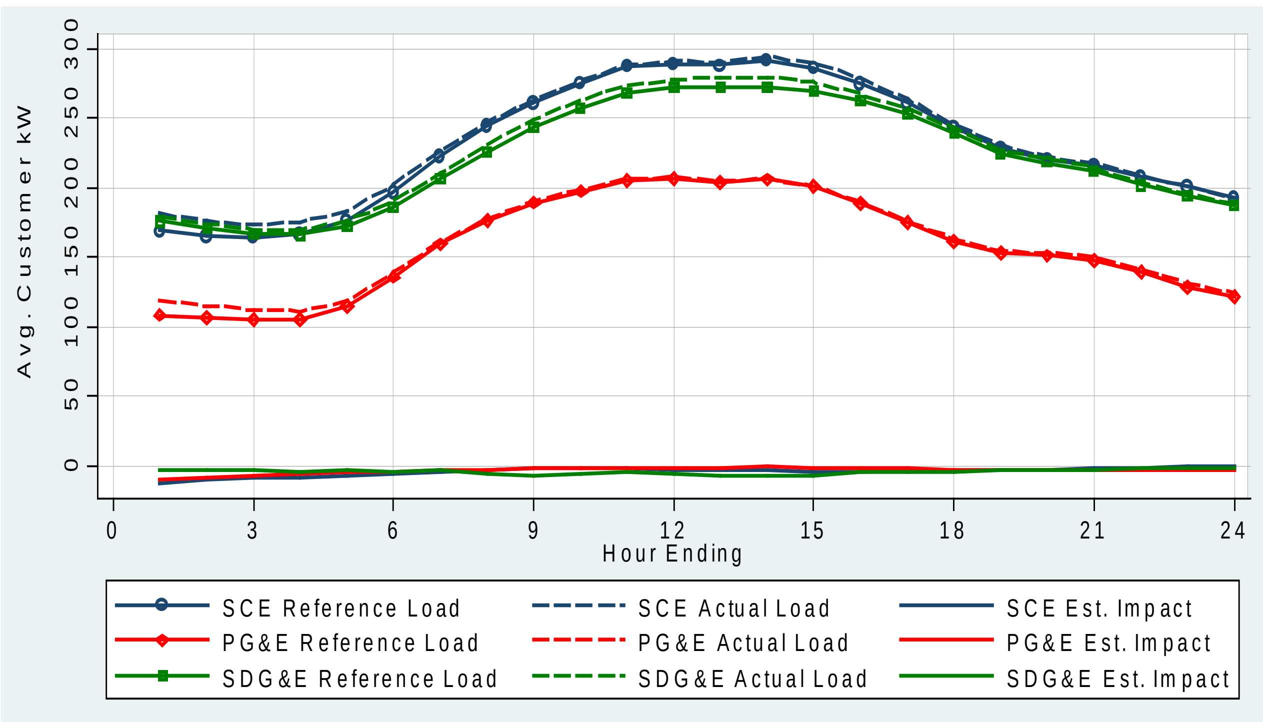


Table C-4 is an extension of the previous figure. It shows the percent difference between predicted and actual loads. However, unlike Figure C-1, it shows the errors by individual proxy day. PG&E has the lowest errors across proxy days, though on average the mean percent error is of greater absolute magnitude than the mean percent error at SCE. At both SCE and SDG&E, the errors on individual event days range widely, by almost 10 percentage points from the greatest negative error to the greatest positive error. Apart from the mean percent error, the other metrics, MAPE and CVRMSE, lend support to the individual day results. PG&E has the least bias across these metrics, followed by SCE and then SDG&E.

Table C-4 result are directly comparable to the false experiment results conducted using difference-in-differences, which are presented in Table 3-2. The difference-in-differences approach categorically showed less bias and more precision for individual event days than individual customer regression; this was true for all three utilities.

Table C-4: Program Level Out-of-sample Test Results – Individual Days

Metric	Proxy Event	PG&E (1-6 PM)	SCE (1-6 PM)	SDG&E (1-6 PM)
Individual Day Percent Error	1	0.6%	3.2%	-2.1%
	2	-1.5%	5.9%	-5.0%
	3	-2.2%	1.8%	-1.5%
	4	2.7%	0.2%	-4.6%
	5	-2.6%	1.4%	-1.8%
	6	-2.2%	-0.9%	-0.2%
	7	-2.9%	-0.7%	4.7%
	8	–	0.4%	-2.9%
	9	–	-3.5%	–
	10	–	-3.2%	–
	11	–	-2.8%	–
	12	–	-2.6%	–
	13	–	-4.1%	–
	14	–	-3.0%	–
Mean Percent Error (Bias)		**-1.2%**	**-0.6%**	**-2.0%**
Mean Absolute Percentage Error (MAPE) Goodness of Fit		**2.1%**	**2.4%**	**3.1%**
Normalized Root Mean Square Error (CVRMSE)		**2.3%**	**2.8%**	**3.6%**

Appendix D Portfolio-adjusted Load Impacts

Table D-1: PG&E August Peak Day CPP Portfolio Load Impacts for Large Customers (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Enrolled Accts. (Forecast)	Avg. Reference Load	Avg. Estimated Load with DR	Avg. Load impact	% Load Reduction	Weighted Temp.
			MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	(°F)
1-in-10 August System Peak Day	2012	1,273	413.2	392.4	20.8	5.0%	94.3
	2013	1,367	444.5	421.7	22.8	5.1%	94.2
	2014	1,681	543.3	514.8	28.5	5.3%	94.6
	2015	1,699	549.2	520.4	28.8	5.2%	94.6
	2016	1,700	549.4	520.5	28.8	5.2%	94.7
	2017	1,699	549.3	520.5	28.8	5.2%	94.7
	2018	1,699	549.3	520.5	28.8	5.2%	94.7
	2019	1,699	549.3	520.5	28.8	5.2%	94.7
	2020	1,699	549.3	520.5	28.8	5.2%	94.7
	2021	1,699	549.3	520.5	28.8	5.2%	94.7
	2022	1,699	549.3	520.5	28.8	5.2%	94.7
	2023	1,699	549.3	520.5	28.8	5.2%	94.7
1-in-2 August System Peak Day	2012	1,273	424.9	403.2	21.7	5.1%	93.3
	2013	1,367	457.0	433.5	23.4	5.1%	93.3
	2014	1,681	558.3	528.9	29.4	5.3%	93.4
	2015	1,699	564.4	534.6	29.7	5.3%	93.4
	2016	1,700	564.5	534.8	29.7	5.3%	93.4
	2017	1,699	564.5	534.8	29.7	5.3%	93.4
	2018	1,699	564.5	534.8	29.7	5.3%	93.4
	2019	1,699	564.5	534.7	29.7	5.3%	93.4
	2020	1,699	564.4	534.7	29.7	5.3%	93.4
	2021	1,699	564.4	534.7	29.7	5.3%	93.4
	2022	1,699	564.4	534.7	29.7	5.3%	93.4
	2023	1,699	564.4	534.7	29.7	5.3%	93.4

Table D-2: PG&E August Peak Day CPP Portfolio Load Impacts for Medium Customers (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			MW 1–6 PM	MW 1–6 PM	MW 1–6 pm	MW 1–6 pm	(°F)
1-in-10 August System Peak Day	2012	196	18.4	17.8	0.6	3.2%	96.4
	2013	218	20.2	19.6	0.7	3.3%	96.6
	2014	218	20.2	19.6	0.7	3.3%	96.6
	2015	11,718	395.7	373.0	22.6	5.7%	98.1
	2016	17,008	577.8	544.1	33.7	5.8%	97.4
	2017	30,649	1,087.1	1,021.8	65.4	6.0%	96.4
	2018	28,399	1,003.1	943.0	60.1	6.0%	96.6
	2019	28,618	1,010.8	950.2	60.6	6.0%	96.6
	2020	28,863	1,019.4	958.3	61.1	6.0%	96.6
	2021	29,105	1,027.9	966.3	61.6	6.0%	96.6
	2022	29,341	1,036.2	974.1	62.1	6.0%	96.6
	2023	29,566	1,044.1	981.6	62.6	6.0%	96.6
1-in-2 August System Peak Day	2012	196	19.9	19.6	0.4	1.9%	94.6
	2013	218	21.9	21.5	0.4	2.0%	94.7
	2014	218	21.9	21.5	0.4	2.0%	94.7
	2015	11,718	400.2	376.7	23.5	5.9%	94.4
	2016	17,008	585.7	551.1	34.6	5.9%	94.3
	2017	30,649	1,103.0	1,036.4	66.6	6.0%	93.9
	2018	28,399	1,017.4	956.1	61.3	6.0%	94.0
	2019	28,618	1,025.2	963.4	61.8	6.0%	94.0
	2020	28,863	1,033.9	971.6	62.3	6.0%	94.0
	2021	29,105	1,042.6	979.8	62.8	6.0%	94.0
	2022	29,341	1,051.0	987.7	63.3	6.0%	94.0
	2023	29,566	1,059.1	995.2	63.8	6.0%	94.0

Table D-3: SCE August Peak Day CPP Portfolio Load Impacts
(Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Forecasted Enrolled Accounts	Avg. Reference Load	Avg. Estimated Load with DR	Avg. Load Impact	% Load Reduction	Weighted Temp
			MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	(°F)
1-in-10 August System Peak Day	2012	2,898	633.4	617.0	16.4	2.60%	95.4
	2013	3,068	670.7	653.3	17.4	2.60%	95.4
	2014	3,099	677.4	659.8	17.6	2.60%	95.4
	2015	3,130	684.2	666.4	17.8	2.60%	95.4
	2016–2023	3,141	686.5	668.7	17.8	2.60%	95.4
1-in-2 August System Peak Day	2012	2,898	620.0	602.7	17.3	2.80%	93.5
	2013	3,068	656.5	638.1	18.4	2.80%	93.5
	2014	3,099	663.1	644.5	18.6	2.80%	93.5
	2015	3,130	669.8	651.0	18.7	2.80%	93.5
	2016–2023	3,141	672.0	653.2	18.8	2.80%	93.5

Table D-4: SDG&E August Peak Day CPP Portfolio Load Impacts for Large Customers (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Forecasted Enrolled Accounts	Avg. Reference Load	Avg. Estimated Load with DR	Avg. Load Impact	% Load Reduction	Weighted Temp
			MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	(°F)
1-in-10 August System Peak Day	2012	1,117	301.7	284.0	17.7	5.9%	84.4
	2013	1,083	292.6	275.4	17.2		
	2014	1,097	296.2	278.8	17.4		
	2015	1,114	300.8	283.1	17.7		
	2016	1,128	304.7	286.8	17.9		
	2017	1,144	308.9	290.7	18.2		
	2018	1,159	313.1	294.7	18.4		
	2019	1,175	317.4	298.8	18.7		
	2020	1,192	321.8	302.9	18.9		
	2021	1,208	326.2	307.1	19.2		
	2022	1,225	330.7	311.3	19.4		
	2023	1,242	335.3	315.6	19.7		
1-in-2 August System Peak Day	2012	1,117	291.6	274.4	17.2	5.9%	82.0
	2013	1,083	282.8	266.1	16.7		
	2014	1,097	286.3	269.4	16.9		
	2015	1,114	290.7	273.6	17.2		
	2016	1,128	294.5	277.1	17.4		
	2017	1,144	298.5	280.9	17.6		
	2018	1,159	302.7	284.8	17.9		
	2019	1,175	306.8	288.7	18.1		
	2020	1,192	311.1	292.7	18.4		
	2021	1,208	315.3	296.7	18.6		
	2022	1,225	319.7	300.8	18.9		
	2023	1,242	324.1	305.0	19.1		

Table D-5: SDG&E August Peak Day CPP Portfolio Load Impacts for Medium Customers (Hourly Average Reduction in MW Over Event Day Period 1–6 PM)

Weather Year	Year	Forecasted Enrolled Accounts	Avg. Reference Load	Avg. Estimated Load with DR	Avg. Load Impact	% Load Reduction	Weighted Temp
			MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	MW 1–6 PM	(°F)
1-in-10 August System Peak Day	2013	0					
	2014	8,707	478.5	460.3	18.2	3.8%	84.4
	2015	7,119	388.9	371.4	17.4	4.5%	84.4
	2016	6,775	370.1	351.4	18.7	5.0%	84.4
	2017	6,861	374.8	355.8	18.9	5.0%	84.4
	2018	6,955	379.9	360.8	19.2	5.0%	84.4
	2019	7,059	385.6	366.1	19.5	5.0%	84.4
	2020	7,157	390.9	371.2	19.7	5.0%	84.4
	2021	7,255	396.3	376.3	20.0	5.0%	84.4
	2022	7,355	401.7	381.5	20.3	5.0%	84.4
	2023	7,456	407.3	386.7	20.5	5.0%	84.4
1-in-2 August System Peak Day	2013	0					
	2014	8,707	460.5	442.8	17.6	3.8%	81.9
	2015	7,119	374.3	357.4	16.9	4.5%	81.9
	2016	6,775	356.3	338.2	18.1	5.1%	81.9
	2017	6,861	360.8	342.4	18.3	5.1%	81.9
	2018	6,955	365.7	347.2	18.6	5.1%	81.9
	2019	7,059	371.2	352.3	18.8	5.1%	81.9
	2020	7,157	376.3	357.2	19.1	5.1%	81.9
	2021	7,255	381.5	362.1	19.4	5.1%	81.9
	2022	7,355	386.7	367.1	19.6	5.1%	81.9
	2023	7,456	392.1	372.2	19.9	5.1%	81.9