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2010 California Statewide Non-Residential Critical Peak Pricing Evaluation

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Freeman, Sullivan & Co.
101 Montgomery St., 15th Floor
San Francisco, CA 94104

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Prepared for:

Kathryn Smith
Electric Load Analysis
San Diego Gas & Electric
8315 Century Park Court
San Diego, CA 92123

Prepared by:

Stephen S. George, PhD
Josh Bode, MPP
Josh Schellenberg, M.A.
Sam Holmberg, B.A.

Freeman, Sullivan & Co.

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1 Executive Summary

This report provides ex post and ex ante load impact estimates for the default Critical Peak Pricing (CPP) tariffs that have been implemented by California's three investor owned utilities, Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE) and San Diego Gas and Electric Company (SDG&E). Although PG&E refers to their tariffs as Peak Day Pricing (PDP), for the sake of clarity, the relevant tariffs from all three utilities are referred to as CPP throughout the report. By the summer of 2010, all three utilities had defaulted large commercial and industrial (C&I) customers (peak demand >200kW) onto a CPP tariff layered over a time-of-use (TOU) rate.[1] In addition, SDG&E had defaulted roughly 600 medium C&I customers[2] onto the tariff and PG&E had migrated small and medium C&I customers on its voluntary critical peak rate, SmartRate, onto the new, default CPP tariff.

This is the first time in the U.S. that critical peak pricing has been used as the default tariff for such a substantial number of large and medium customers. The 2010 California experience provides the largest body of evidence regarding non-residential customer choices and price response on default dynamic pricing. It also provides the only source of data for medium customer price responsiveness under default dynamic pricing.

Under default CPP rates, higher prices on critical peak days are offset by a reduction in off-peak prices, demand charges or both. In addition, for SCE and SDG&E, the introduction of default CPP in 2010 and 2008, respectively, was made in conjunction with changes to the underlying TOU rates. All utilities offered bill protection to customers on CPP for the first year in order to provide an opportunity to test the tariff without risk. This is particularly relevant to the analysis of PG&E and SCE customers because those utilities defaulted customers onto CPP in May 2010 and October 2009, respectively. Given this, bill protection was in effect for all of their participants for all 2010 events. In addition, SDG&E and PG&E customers on the CPP rate were provided with the opportunity to insure against bill volatility by protecting a portion of their load from high energy prices during the peak period on critical event days.

This report contains the ex post and ex ante load impact estimates for all three utilities. Ex post impacts reflect the change in average hourly electricity demand attributable to the CPP tariff for specific 2010 days in which higher priced event days were called. In contrast, ex ante impacts are based on performance and load reduction patterns during historical event days but are standardized for normal and extreme weather year conditions that align with system planning. The most likely system peaking conditions are reflected in the 1-in-2 weather year while the 1-in-10 weather year reflects extreme conditions that drive system peaks and the need for more resources.

1.1 Ex Post Load Impact Summary

Several key differences exist in ex post conditions across all three utilities and comparisons of ex post impacts should be made with caution. Each utility calls event days based on the conditions on their system. Due to the climatic diversity in California, the system load patterns across utilities are not always

[1] Throughout this report, any reference to CPP refers to what is actually the CPP/TOU tariff being implemented by each utility.

[2] Throughout this report the word "customer" is used synonymously with "service account."

coincident, particularly for Northern and Southern California. For example, PG&E's system peaked on August 24th while SCE and SDG&E's peaked on September 27th. As a result, although utilities have several common event days, not all events overlap. Another key difference in ex post results is event duration. System peak day load profiles for SDG&E are generally flatter than those for SCE and PG&E and, as a result, 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. Another key difference is the rate itself. In spite of the common rate design principles and framework provided in the CPUC guidelines, 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, price levels themselves are fairly different.

Table 1-1 summarizes the 2010 event days and impacts for each utility. Enrollment for each utility varies slightly from event to event. On average, PG&E, SCE and SD&GE called on roughly 1,650, 4,100 and 1,350 customers, respectively, to reduce loads on event days. PG&E called 9 critical peak events and obtained an average load reduction of 23.0 MW, or 3.9% of the average reference load on event days. SCE called 12 critical peak events, including an event on September 27th, when the peak temperature in downtown Los Angeles reached 110°F. SCE participants provided an average load reduction of 30.7 MW, or 2.8%. SDG&E called four critical peak events in 2010. Like SCE, one event was called on SDG&E's all-time system peak day, September 27th. The approximately 1,350 accounts enrolled on SDG&E's CPP tariff provided an average load reduction of 18.8 MW, or 5.26% of estimated peak load across all events.

For SCE and SDG&E, the lowest impacts occurred on September 27th when their electric systems each peaked. There are several potential explanations for the lower impacts and it would be inappropriate to automatically conclude that participants provide lower impacts with hotter temperatures. The September 27th event occurred very late in the summer and on a Monday. It is possible that the lower impact was due to the fact that customers are not as likely to notice day-ahead notification on a Monday. However, it must be noted that several other events were called on Mondays and the load impacts were comparable to the impacts on other event days. Another possibility is the lateness of the event, which occurred just a few days before the end of the summer tariff season. The intensity of the heat wave and events themselves were probably unexpected that late in the summer. Another possibility is that the temperature was so far outside the range of other event days, the estimated reference load may be biased downward at those very extreme values. The final possibility is that participants simply “bought through” on that extreme day.

Table 1-1:
Summary of Ex Post Load Statewide Impacts by Event

Date	PG&E			SCE			SDG&E		
	Reference Load 2-6 PM (MW)	Load Impact 2-6 PM (MW)	% Impact	Reference Load 2-6 PM (MW)	Load Impact 2-6 PM (MW)	% Impact	Reference Load 11 AM-6 PM (MW)	Load Impact 11 AM-6 PM (MW)	% Impact
6/30/2010	-	-	-	1,045.7	34.3	3.3%	-	-	-
7/16/2010	512.5	26.9	5.2%	1,063.4	29.0	2.7%	-	-	-
8/6/2010	-	-	-	953.4	33.8	3.5%	-	-	-
8/12/2010	-	-	-	1,005.7	33.7	3.4%	-	-	-
8/16/2010	534.1	28.1	5.3%	1,054.9	31.9	3.0%	-	-	-
8/18/2010	-	-	-	1,121.3	28.6	2.6%	-	-	-
8/23/2010	592.8	20.9	3.5%	1,108.7	29.6	2.7%	-	-	-
8/24/2010	619.4	16.2	2.6%	1,139.6	28.7	2.5%	-	-	-
8/25/2010	614.7	21.9	3.6%	1,129.5	30.1	2.7%	347.9	21.6	6.2%
8/26/2010	-	-	-	-	-	-	340.2	24.6	7.2%
9/1/2010	608.5	22.0	3.6%	-	-	-	-	-	-
9/2/2010	622.0	22.3	3.6%	1,085.0	32.2	3.0%	-	-	-
9/3/2010	563.9	27.3	4.8%	-	-	-	-	-	-
9/20/2010	-	-	-	1,031.8	33.8	3.3%	-	-	-
9/27/2010	-	-	-	1,196.0	22.9	1.9%	373.2	11.3	3.0%
9/28/2010	661.6	21.6	3.3%	-	-	-	365.5	17.3	4.7%
AVERAGE EVENT	**592.3**	**23.0**	**3.9%**	**1,078.0**	**30.7**	**2.8%**	**356.5**	**18.8**	**5.3%**

Statewide, from 2009 to 2010, the number of CPP participants increased from approximately 2,700 to 7,100 customers. With the additional participants, the event day load absent DR – the reference load – increased from 805 MW in 2009 to 2,027 MW in 2010. Despite the increased enrollment, the growth in load impacts was moderate, increasing from 56.4 MW in 2009 to 72.6 MW in 2010. Detailed changes in enrollment, reference load and impacts for each utility are contained later in the report.

In addition to producing estimates for historical event days, the analysis examined the extent to which several factors affected price responsiveness, including industry type, prior participation on voluntary CPP, dual participation in other DR programs and AutoDR or enabling technology. For PG&E and

SDG&E, it was also possible to quantify the effect of the share of load that was insured against high prices. For SDG&E, it was possible to analyze persistence of impacts across multiple years and the effect of bill protection. To date, SDG&E is the only utility where it is possible to analyze the effect of these two important issues. Highlights from the analysis of underlying drivers of price responsiveness include:

- In all three utilities, industrial businesses such as manufacturing and wholesale and transport provided larger load reductions than commercial customers;
- For SCE, customers that had previously voluntarily enrolled in CPP were 4.4 times more price responsive than those that were defaulted onto the tariff;
- Customers dually-enrolled in other demand response programs produced substantially larger load impacts than the average customer. This was particularly true for SDG&E where 6% out of roughly 1,350 accounts were dually-enrolled but accounted for 35% of the aggregate load reduction;
- AutoDR and Technical Incentives (TI) do not lead to statistically significant higher percent impacts. This does not mean AutoDR and TI are ineffective. First, there are very few customers for whom load impacts can be observed both before and after the installation of enabling technology from AutoDR and TI. Second, AutoDR and TI are designed to remove barriers to participation and to help enroll customers that might not otherwise try out enabling technology. If these complementary programs increase enrollment over what it would be otherwise, they might still be effective even if participant impacts are similar to those of customers that did not participate in the TA/TI or AutoDR program;
- For both SDG&E, insuring part of a customer's demand against high prices leads to lower percent load reductions during events. Put another way, the smaller the share of the electricity consumption exposed to higher prices, the lower the percent load reductions. This coefficient variable was statistically significant but small for SD&GE and insignificant for PG&E. SCE did not offer this hedging option;
- Percent impacts for SDG&E customers decreased by half a percentage point for each additional year of participation in the program. In other words, percent load reductions decreased, but by very little. While the results are statistically significant, it is not possible to infer whether the small decay in percent load reductions will continue tor will level out after customers have experienced multiple seasons of CPP events. Given the available data, it is also hard to know for sure whether or not this result is due to exogenous factors that cannot be controlled for in the absence of an external control group; and
- After controlling for other factors, percent impacts with and without bill protection were indistinguishable.

1.2 Ex Ante Load Impact Summary

Within the next 3 years, an additional 220,000 medium and 1,000,000 small non-residential accounts are scheduled to default onto CPP across California. Small C&I and agricultural accounts are not included in the ex ante load impacts because there is no empirical data on customer enrollment and impacts under default CPP. SCE medium C&I impacts are not included in this year's report because they lack data on medium customer price response under default conditions. SCE submitted medium C&I impact estimates under voluntary CPP with their smart meter application and plans to rely on those estimates until empirical data on price response under default conditions become available for their customers.

For customers already enrolled in CPP, the ex ante impacts are reliable as long as there is a sufficiently long history of events under different weather conditions, including extreme ones. The primary source of uncertainty in ex ante impacts arises from program changes. These include growth in program participants, changes in program rules or tariff design and policy shifts.

For large customers, uncertainty in ex ante load impacts is relatively small because most of them have already been defaulted onto CPP. We now know what initial year retention rates were, how much load reduction customers they provided during events and what types of customers are more price responsive. For medium customers there is a growing body of evidence regarding the likelihood they remain on default CPP and their price responsiveness when defaulted. The uncertainty associated with medium customer participation rates and load impacts, however, is larger than it is for the large customer population. SDG&E and PG&E defaulted a small number of medium customers onto CPP by the end of 2010. To obtain a larger and more diverse sample, customers that were slightly above the large-customer threshold were used as a proxy for medium customers. Customers with average hourly demands below 100 kW across the year were combined with medium customers to produce ex ante impacts. The results were weighted to account for differences in industry mix and/or geographic location and scaled for the medium customer population.

Table 1-2 summarizes the statewide ex ante load impacts for the August monthly peak day under normal (1-in-2) weather year conditions for both large and medium C&I customers. For 2011, large customer enrollment statewide is projected to decrease from 7,100 to 5,800 relative to enrollment in 2010. The decrease is due to anticipated attrition when bill protection expires and customers receive a comparison bill for CPP and the alternative TOU rate. Thereafter, enrollment increases both because of general population growth and because PG&E will default additional large customers when they have had interval data available for 12 months. Commensurate with the enrollment growth, the reference load during event days – that is the electricity use absent demand response – is projected to grow from 1,770 MW in 2011 to almost 2,050 MW by 2011. Likewise, load impacts are estimated to grow from 58.4 MW to 74.3 MW for the large C&I accounts.

With the introduction of default CPP in the medium C&I sector, enrollment for PG&E and SDG&E is projected to peak in 2013 at 31,000 accounts, which jointly account for 1,180 MW of demand during normal weather year peak conditions. Once default CPP is fully in place, these customers are projected to deliver roughly 70 MW of demand response. Overall, medium C&I customers are projected to deliver higher percent impacts than large C&I accounts. While large customers produce average load reductions of 3.6%, medium accounts are projected to provide load reductions of 6.5%. There are three primary reasons for the difference. First, the medium C&I values do not include SCE while large C&I estimates do. In 2010, SCE had the lowest percent impacts among the three utilities. Second, for PG&E, large customers with demands less than 100 kW were used as a proxy for medium customers and these were the most price responsive PG&E segment in 2010. They make up roughly 60% of the accounts in Table 1-2. Third, SDG&E is providing technology that automates load response – thermostats with two way communication – to medium customers as part of its transition to default CPP. Roughly 31% of SDG&E medium CPP participants are projected to have automated load response by 2017.

Table 1-2:
Summary of Ex Ante Statewide Load Impact by Forecast Year
August System Peak Day, 1-in-2 Weather Year Conditions, Event Window from 2 to 6 PM

Weather Year	Year	Enrolled Accts (Forecast)[1]	Reference Load MW	Estimated Load with DR MW	Aggregate Load impact MW	% Load Reduction
Large C&I	2011	5,828	1,767.3	1,708.8	58.4	3.30%
	2012	5,989	1,887.9	1,816.6	71.3	3.78%
	2013	6,358	2,010.0	1,936.1	73.8	3.67%
	2014	6,359	2,022.3	1,946.1	76.2	3.77%
	2015	6,377	2,012.3	1,938.0	74.2	3.69%
	2016	6,396	2,028.3	1,954.5	73.9	3.64%
	2017	6,415	2,032.0	1,958.1	74.0	3.64%
	2018	6,435	2,035.9	1,962.0	74.0	3.63%
	2019	6,456	2,040.1	1,966.1	74.1	3.63%
	2020	6,477	2,044.4	1,970.3	74.2	3.63%
	2021	6,499	2,048.9	1,974.8	74.3	3.63%
Medium C&I [1]	2011	147	5.6	5.2	0.4	7.14%
	2012	15,856	599.3	557.5	41.7	6.96%
	2013	31,626	1,181.7	1,111.2	70.5	5.97%
	2014	30,731	1,147.5	1,079.2	68.4	5.96%
	2015	29,012	1,084.2	1,016.5	67.7	6.24%
	2016	28,477	1,064.5	996.8	67.8	6.37%
	2017	27,985	1,046.4	978.5	68.0	6.50%
	2018	28,259	1,056.6	988.0	68.5	6.48%
	2019	28,530	1,066.5	997.4	69.2	6.49%
	2020	28,798	1,076.5	1,006.7	69.8	6.48%
	2021	29,067	1,086.4	1,016.1	70.3	6.47%

[1] Does not include SCE medium accounts

2 Overview of Critical Peak Pricing and Transition Process

By the summer of 2010, the three California Investor Owned Utilities – PG&E, SCE and SDG&E – defaulted approximately 15,000 commercial and industrial (C&I) accounts onto default CPP. Of the customers defaulted onto CPP, roughly 7,100 remained on the CPP tariff by end of 2010 summer and, combined, accounted for approximately 2,000 to 2,200 MW of system coincident peak load.

Within the next three years, approximately 220,000 medium and 1,000,000 small non-residential additional accounts are scheduled to default onto CPP across California. Combined, they account for roughly 8,500 MW during peaking conditions. Although small customers far outnumber medium and large customers, they account for a small share of the overall C&I sector load. Large accounts (200 kW and up) make up less than 2% of C&I customers but they account for over 50% of demand coincident with the system peak. The almost 220,000 medium C&I customers account for roughly 35% of the C&I sector's demand coincident with the system peak. The roughly 1,000,000 small customers with peak demands of less than 20 kW account for less 15% of the total C&I peak demand. While the small customers vastly outnumber medium and large customers, they have less load and by connection, less DR potential than medium or large C&I customers.

2.1 Critical Peak Tariff Design

In 2009, the CPUC produced guidelines for dynamic pricing rate design. The decision (D.08.07.045) provided standard guidelines to investor-owned utilities for several key elements of rate design in California, including:

- Making the default tariff for large, medium and small commercial and industrial customers a dynamic pricing tariff;
- Including a critical peak price during critical peak periods and time-of-use rates during non-critical periods in the default tariff;
- Using a a time-varying rate as the opt-out tariff for large, medium and small commercial and industrial customers;
- Having a critical peak price that represents the cost of capacity used to meet peak energy needs plus the marginal cost of energy – in essence, loading all capacity value on critical peak hours; and
- Offering first year bill protection to customers defaulted onto dynamic pricing rates.

The decision also provided guidance for several other elements of rate design. In spite of the common principles and framework provided in the CPUC guidelines, 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 across the utilities, price levels themselves are fairly different. For example, each utility has a CPP rate with an underlying TOU component as the default rate and an opt-out TOU rate. However, the actual TOU prices vary across utilities. The same is true of CPP event prices, credits and options associated with CPP and many other relevant rules and details.

Implementation timing also varies. Table 2-1 summarizes the timing and rules associated with the default process at each utility, as well as rate features such as rate periods, seasonal timing and other program characteristics. Prices in each period are summarized in Table 2-2.

SDG&E implemented default CPP pricing first on May 1, 2008. SCE began defaulting customers onto the rate 18 months later in October 2009 and PG&E did so in May 2010. SDG&E customers became eligible for default if their demand exceeded 20 kW for 12 consecutive months. PG&E defaulted customers that exceeded 200 kW for three consecutive months in the prior year. In addition, PG&E transitioned nearly 200 small and medium customers voluntarily enrolled on SmartRate, a pure CPP tariff, to CPP with an underlying TOU component. SCE required only that a customer's "monthly Maximum Demand exceeded 200 kW." At all 3 utilities, it is necessary for a customer to have a full 12 months of interval data available before being defaulted. Each utility gave customers a minimum of 45 days notice before the default went into effect. If customers did not opt out during this time period, at SDG&E, they were locked into the rate for the following year. At PG&E and SCE, customers can opt out of the rate at anytime, but they would forfeit any payments that might be made under their bill protection if they do so during the first year.

Table 2-1:
CPP Characteristics Across California Utilities

CPP Characteristic	Utility		
	PG&E	SDG&E	SCE
Date of First CPP Default	May-10	May-08	Oct-09
Demand Criterion for CPP Default	>200 kW	>20 kW	>200 kW
Number of Months Demand Must Exceed Threshold	3 out of 12	12 out of 12	NA
Opt-Out Period	Rolling	Once Annually	Rolling
Event Period Hours	2 pm-6 pm	11 am-6 pm	2 pm-6 pm
Event Season	Year-round	Year-round	Summer M-F
Number of Events	9 (Min) -15 (Max)	Maximum 18	9 (Min) -15 (Max)
Summer TOU Peak Hours	12 pm-6 pm, M-F	11 am-6 pm, M-F	12 pm-6 pm, M-F
Winter TOU Part-Peak Hours	NA	5pm-8pm, M-F	NA
Summer Season Definition	May-Oct	May-Sep	Jun-Sep
Winter Season Definition	Nov-Apr	Oct-Apr	Oct-May
Capacity Reservation Default Level	50%*	50%*	NA
First Year Bill stabilization	Yes	Yes	Yes

*Capacity reservation default level of 50% refers to 50% of the customer's peak demand during the previous summer

SCE and PG&E share the same set of CPP event hours: 2 PM to 6 PM, though some A-10 customers in PG&E's service territory have the option of a 12 PM to 6 PM event window with reduced credits and CPP charges. They also share the same TOU peak period hours: 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 have the right to call events year-round 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 events and a maximum of 15 events each year. SDG&E is committed to a maximum of 18 and no minimum. PG&E attempts to notify customers via phone, email, pager or text message by 2 PM on the day before the event, while SCE and SDG&E attempt to notify customers by 3 PM the day before. SCE and SDG&E

use the same set of notification technologies as PG&E, although SCE does not offer text message notification and SDG&E does not offer phone notification.

Another difference across the three tariffs has to do with the definitions of seasons and rate blocks. For example, SCE defines summer as the period from June through September while SDG&E defines summer as May through September. Also, SCE's CPP event period is from 2:00 PM to 6:00 PM only on non-holiday summer weekdays while SDG&E's CPP event period is from 11:00 AM to 6:00 PM any day of the year.

PG&E has defaulted over 5,000 accounts onto CPP. By September 2010, slightly more than 1,800 accounts remained on the default tariff. SCE has defaulted over 8,000 accounts onto CPP. By the end of the 2010 summer, roughly 4,100 accounts remained. Since 2008, SDG&E has defaulted approximately 2,400 accounts and has retained over 1,500 accounts.

All three utilities offered customers bill comparisons between the default CPP and opt-out TOU tariffs. In addition, SCE compared the CPP and opt-out TOU rates to their historical tariff. By chance, the SCE customers transitioned to default CPP at the same time that a 3.1% rate reduction was being implemented for large customers.

Table 2-2 summarizes the prices that are in effect on the CPP tariff at each utility. The three tariffs share many similarities and some important differences. These differences are particularly important to pay attention to when comparing opt-out and retention rates across the utilities. Although PG&E refers to their tariffs as Peak Day Pricing (PDP), for the sake of clarity, the relevant tariffs from all three utilities are referred to as CPP tariffs througout this report. Comprehensive tables detailing the pre-default rate, CPP rate and otherwise applicable tariff (OAT) for each rate schedule are provided in appendices.

At all three utilities, not only do peak period prices change on critical peak days relative to the pre-CPP tariff, but there are also substantial changes to peak period prices during non-event days that must be factored into the analysis. The effect of those rate reductions is not transparent because the rate reductions took the form of reduced consumption charges, reduced demand charges or both:

- For SDG&E CPP participants, the summer on-peak electricity price is almost 5¢/kWh or 36% lower than the summer on-peak price of the pre-default tariff;
- Compared to the pre-default tariff, SCE's CPP/TOU rate lowers the demand charges by roughly $17 per kW to $11 per kW, depending on the rate. Given the number of hours affected, this is equivalent to a decrease in peak-period prices on non-event days of approximately 8.8¢/kWh, or a 30% ($11.62 per kW / 132 hours of exposure per month = 8.8¢/kWh); and
- PG&E's default CPP rate lowers both on-peak and part-peak summer demand charges relative to pre-default tariffs and also provides a credit for consumption charges during those rate blocks. The discounts from the on-peak period are substantial, effectively translating to on-peak charges 20% lower than with the TOU rate, depending on the rate and service level.

Table 2-2:
Example Default CPP Rates at PG&E, SCE & SDG&E[3]

			Default CPP Rate		
Season	**Type of Charge**	**Period**	**PG& E's E-19**	**SCE's GS-3**	**SDG&E's AL-TOU**
Summer	Energy Rates ($ per kWh)	CPP Event Period	$1.20	$1.36	$1.03
		On-Peak	$0.15	$0.15	$0.11
		Semi-Peak	$0.11	$0.11	$0.09
		Off-Peak	$0.09	$0.07	$0.06
	Summer CPP Energy Credits	On-Peak	($0.004)	NA	NA
	($ per kWh)	Semi-Peak	($0.0007)	NA	NA
	Summer CPP Demand Credit	On-Peak	($6.10)	($11.62)	NA
	($ per kW)	Semi-Peak	($1.30)	NA	NA
	CR Charge ($'s per kW/Month)	Summer	$13.05	NA	$6.25
	Summer Season Time Related Demand Charge	On-Peak	$13.05	$15.09	$7.06
		Semi-Peak	$2.99	$3.59	NA
	($ per kW)	Maximum Demand	$8.58	NA	NA
Winter	Energy Rates ($ per kWh)	CPP Event Period	$1.20	NA	$1.03
		On-Peak	NA	NA	$0.10
		Semi-Peak	$0.09	$0.08	$0.09
		Off-Peak	$0.08	$0.06	$0.07
	CR Charge ($'s per kW/Month)	Winter	$1.12	NA	$6.25
	Winter Season Time Related Demand Charge	On-Peak	NA	NA	$4.69
		Semi-Peak	$1.12	NA	NA
	($ per kW)	Maximum Demand	$8.58	NA	NA

*NA=Not Applicable

The event-period price adder for each utility varies from $0.90/kWh for PG&E A-10 customers to $1.03/kWh for SDG&E customers, to $1.20/kWh for PG&E E-19 and E-20 customers, to $1.36/kWh for SCE customers. The summer peak-time demand credit for CPP customers varies substantially across the tariffs, from $1.54/kW for PG&E A-10 customers, to about $6/kW for PG&E E-19 and E-20 and SDG&E customers, to $12.47/kW for SCE customers on TOU-8. PG&E and SDG&E also have small energy credits for non-event periods. SCE does not have a peak-time energy credit. SDG&E's peak energy and demand credits come in the form of a difference between the energy and demand rates that CPP customers pay and energy and demand rates under the OAT, rather than as credits, per se. The

3 For comparison purposes, Table 2-2 shows the rates for secondary service level 200-500kW customers. In practice, rates vary by service level and customer size.

summer CPP demand credit is essentially $5.81/kW and the energy credits are around 1 cent per kWh. The effect on customer bills is the same as 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] 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 a customer 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. Just as with any insurance policy, a customer will pay the capacity reservation fee whether or not events are called and whether or not they actually reach that level of demand during an event. SDG&E charges $6.25/kW per month for this option and the default level for SDG&E customers is 50% of a customer's peak demand during the previous summer. PG&E also sets the default level to 50% of a customer's peak demand during the previous summer, 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 they normally pay during the hours of a CPP event, based on their TOU rate. This means that the summer price for the capacity reservation level (CRL) is about $13/kW and the winter price is about $1/kW.

2.2 Report Organization

The remainder of this report is organized as follows. Section 3 summarizes the methodology used to produce the ex post impact estimates and the results of the validation tests used to determine the best model specification and approach. Sections 4 through 6 contain the ex post impact estimates for each utility, while Sections 7 through 9 present the ex ante impact estimates for 2011 through 2021. Section 10 provides recommendations. The appendices contain detailed information on the relevant tariffs, greater detail on model validation than is contained in Section 3 and tables summarizing impacts for 2012 resource adequacy. Electronic spread sheet files have been provided containing hourly load impact estimates for each utility for the day types and event conditions required by the CPUC Load Impact Protocols.

[4] PG&E's 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.

3 Methodology

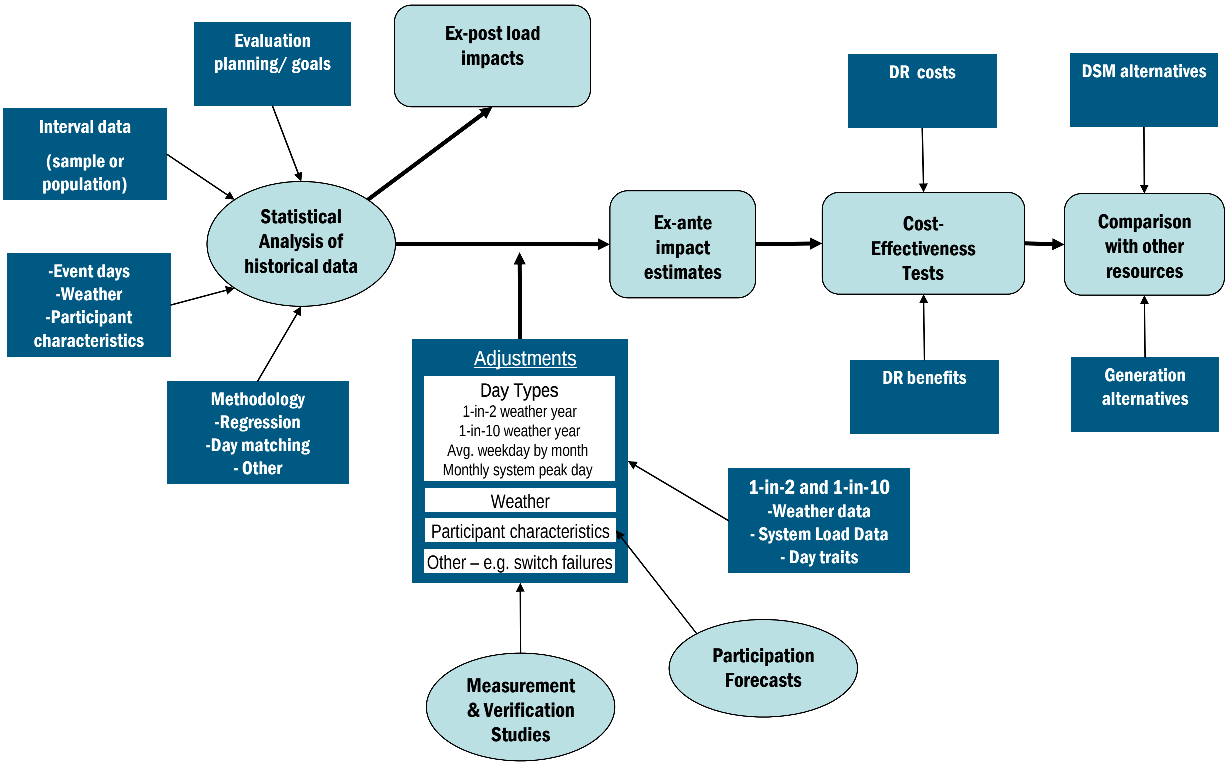
The protocols governing the development of load impacts were designed to help ensure that demand response impact estimates would be directly comparable with other resource alternatives (i.e., other DR resources, energy efficiency, renewables and generation). Ex post impacts measure the change in average hourly electricity demand attributable to the CPP tariff for specific 2010 days in which higher priced event days were called. In contrast, 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.

Historical program impacts do not necessarily reflect the full load reduction capability of DR programs. Demand response load impacts can vary as a function of weather, participant characteristics, changes in the number of program participants and other factors such as the use of enabling technology. For many programs, event impacts are tied to conditions – e.g., weather – and the participants in place when events occur. In any given year, the extreme weather conditions that drive the system peak and need for additional resources may or may not occur. Ex post impacts also may not reflect the full load reduction capability of a program because of dispatch decisions. For example, many programs such as the Baseline Interruptible Tariff and AC load control programs allow for localized dispatch of resources to meet system needs. Impacts during those historical, targeted events do not fully reflect the load reduction capability of those programs.

In contrast, ex ante impacts are based on performance and load reduction patterns during historical event days but are standardized for normal and extreme weather year conditions that align with system planning. The most likely system peaking conditions are reflected in the 1-in-2 weather year while the 1-in-10 weather year reflects extreme conditions that drive extreme system peaks and the need for more resources.

Figure 3-1 shows how ex post and ex ante load impact estimates are linked to each other and, ultimately, to cost-effectiveness analysis and resource planning. As shown, ex ante load impact estimates are based on analysis of historical data whenever the existing data and characteristics of the program allow for it. Analysis of historical program data is then employed to produce ex ante load impact estimates that are subsequently used for resource adequacy, cost-effectiveness assessment and long-term planning.

Figure 3-1:
Summary of Ex Post and Ex Ante Analysis Process and Connections



The remainder of this section:

- Documents the ex post evaluation methodology used to estimate 2010 impacts, including explicit test to ensure results are unbiased and precise;
- Describes how historical load impacts were used to develop large customer ex ante load impact estimates and were eventually combined with utility enrollment projections; and
- Explains how default CPP impacts per customer for medium customers were developed and combined with utility enrollment projections.

3.1 Ex Post Evaluation Methodology

To calculate load reductions for demand response programs, participant's load patterns in the absence of program participation—the counterfactual or reference load—must be estimated. There are a variety of ways of estimating reference loads for DR programs, including using pre-enrollment data, observing behavior during event and non-event days (e.g., within subject designs, or using participants as their own controls), use of an external control group or a mixture of the above. The most rigorous method for impact evaluations is a well-executed experiment with random assignment to control and treatment conditions. Randomized experiments are rarely feasible for actual programs, particularly when equal treatment is required across all customers as is the case with Critical Peak Pricing. The best available method is a function of the program characteristics, available data, the ability to incorporate research design elements and statistical methods.

Based on the program dispatch pattern, CPP naturally produces an alternating or repeated treatment design. The primary intervention – event days with higher critical peak prices – is introduced in some days and not in others, making it possible to observe behavior with and without events under similar conditions. A repeated treatment design enables us to assess whether the outcome – electricity consumption – rises or falls with the presence or absence of the main treatment, a critical peak pricing event. This approach works if the effect of the event dissipates after it is removed. The entire event day is evaluated to estimate both load reductions during event hours and load shifting to non-event hours. The natural variation in CPP allows us to estimate the impact of events relative to non-event days.

However, the effect of these interventions in PG&E, SCE and SDG&E default CPP implementation cannot be accurately quantified by simply including event-day variables. In this instance, the decreases in on-peak demand charges and changes in the opt-out TOU tariff structure due to the implementation of default CPP are too substantial to ignore. As a result, we use pre-default CPP data in order to quantify the effects of the rate changes. There are two reasons why the use of pre-enrollment data is important. First, it is absolutely necessary to quantify the effect of reductions in demand charges and/or changes in the opt-out TOU prices. Second, the use of pre-enrollment data helps ensure that factors correlated with event days are not confounded with CPP impacts. CPP event days tend to coincide with hot temperatures and responses to CPP prices are more easily confounded with weather when pre-enrollment data is *not* employed.

Load impacts are estimated using regression analysis, which has several advantages over alternative methods such as day-matching or baseline that are often used for DR program settlement. First, regression analysis can help identify the key drivers and predictors of load patterns and load reductions. Second, regression results provide more robust estimates of load reductions and are not as sensitive to biases in the reference load. Put differently, impacts are based on coefficients and the accuracy of the impact is related to whether the treatment variables are correlated with the error term. Third, baseline methods typically rely on neighboring days to develop a counterfactual. However, with CPP, neighboring days are potentially affected by rate credits for non-event days. Regressions with pre-enrollment data or a control group can quantify the extent to which the rate credits affect the non-event day load shapes while baseline methods cannot.

We relied on individual customer regressions as our primary source for ex post impacts. There is a substantial amount of variation in non-residential sector electricity use patterns. The size of customers ranges widely and production and occupancy patterns vary substantially by industry and even within industry. In addition, there is wide variation in the climate experienced by customers and their weather sensitivity. Individual customer regressions better explain the variation in individual customer production and/or occupancy patterns, weather sensitivity, price responsiveness, etc., than aggregated models. However, the regressions require a model that explains electricity use patterns. The better regression models explain variation in electricity use patterns, the more unlikely they are to confound unexplained variation – error – with event day effects and changes in the underlying TOU rates.

We strongly considered panel models as the primary regression method. Like individual customer regressions, panel models can make use of pre-enrollment data. In addition, they make use of information from a control group, if it is available. The benefit of a panel is directly related to the quality of the control group and the extent to which it provides information about how CPP customers would have used electricity if they were on the otherwise applicable tariff (OAT). Because non-participants actively chose to stay on or opt out from the CPP tariff, it is necessary to control for selection effects if an external control group is used to estimate impacts. A panel model that uses data from a control group that differs substantially from CPP participants can, in fact, produce worse results than individual customer regressions. A priori, there is no reason to assume that panel models produce more accurate results without random assignment to treatment and control groups. Because there was no confidence that a suitable control group could be obtained, panel models were primarily used to cross-check the individual customer results rather than as the primary analysis method. When both approaches provide similar results, it bolsters the confidence in the findings.

Ultimately, individual customer regressions were selected because they produce deep insight into how impacts vary across customers and key segments such as location, industry type, customer size and rate. They can also be used to better understand whether the demand reductions are concentrated among a small sub-set of customers.

3.1.1 Model Development

For demand response resources that have numerous events, regression analysis can be used to estimate the typical (absolute or percentage) load reduction associated with events as a function of event-day conditions (e.g., weather, day-of-week, etc.). These regression models can then be used to predict either ex ante or ex post impacts as a function of the conditions that occurred on those historical days or that are expected to occur on future days on which program events are most likely to be called.

With DR programs for which there is substantial event history, like CPP, this regression-based method can be used to predict load reductions. For ex post load impact estimation purposes, regression analysis is used to predict the reference load (i.e., the load that would occur in the absence of a program event) for the historical event day and the actual load for that day. The difference between the two is the load impact. For ex ante load impact estimation purposes, the parameters from ex post regression analysis can be used to predict the reference load and the actual load under a variety of weather conditions and day characteristics. The remainder of this section focuses on the ex post model development.

For ex post analysis, the estimated load reduction for CPP is a function of:

- Predicted load in the absence of a DR event (i.e. the reference load); and
- Predicted load in the presence of a DR event (i.e. the estimated load with DR).

The regression model was developed with the primary goal of accurately predicting the counter-factual. To do so, it was necessary to account for variation in customer loads given enrollment in CPP, time-of-day, day-of-week, month, year, temperature and participation in other DR programs. CPP customers experienced a rate change at some point in their interval data history and variables were included to capture the hourly effects from the TOU component of each rate schedule as well as during event days. In specifying the primary models, the CPP impacts were estimated directly through treatment variables rather than use actual prices. Direct estimation of the impacts on electricity use provides the results devoid of any theoretical construct about how customers respond to dynamic pricing. The ex post estimated models are based on hourly load data for each customer including a year of pre-enrollment data and 2010 data. The ex ante models include all historical event data with default CPP. This only affects SDG&E which had default CPP events in both 2009 and 2010.

The dependent variable is the average demand (kW) in each hour for each participant. The regression model contains variables consisting largely of shape and trend variables (and interaction terms) designed to track variation in load across days of the week and hours of the day. Weather, day type and other explanatory variables can interact with occupancy and production schedules. To capture this behavioral component, these variables were interacted with hour of day. Weather variables were tested extensively. In preliminary models, a regression equation was included exactly like the one below except that the weather variables were replaced with a single variable for linear CDH. If the regression equation returned a negative coefficient on CDH, the model was run without weather variables. The difference in results was negligible so it was not deemed necessary to specify the final model in this way. Another experiment was to customize the regressions for specific customers with distinctive operation schedules, but that was also deemed unnecessary. The model below gains credibility in that it is robust for all three utilities. Too often in applied econometrics, variables are added with little true economic intuition behind them to fine-tune a model and boost its predictive power by a trivial amount. Mathematically, the regression model can be expressed as:

$$
\begin{aligned}
kW_t = A &+ \sum_{i=1}^{24} B_i \times Hour_i \times Year2010 + \sum_{i=1}^{24}\sum_{j=1}^{5} C_{ij} \times Hour_i \times DayType_j \\
&+ \sum_{i=1}^{24}\sum_{j=1}^{12} D_{ij} \times Hour_i \times Month_j + \sum_{i=1}^{24} E_i \times Hour_i \times TotalCDH_t \\
&+ \sum_{i=1}^{24} F_i \times Hour_i \times TotalCDHsqr_t + \sum_{i=1}^{24} G_i \times Hour_i \times TotalHDH_t \\
&+ \sum_{i=1}^{24} H_i \times Hour_i \times TotalHDHsqr_t + \sum_{i=1}^{24} I_i \times Hour_i \times SummerCPP_t \\
&+ \sum_{i=1}^{24} J_i \times Hour_i \times WinterCPP_t + \sum_{i=1}^{24} K_i \times Hour_i \times OtherDR_t \\
&+ \sum_{i=1}^{24} L_i \times Hour_i \times Eventday_t + \sum_{i=1}^{24} M_i \times Hour_i \times Eventday_t \times TotalCDH_t + \varepsilon_t
\end{aligned}
$$

Table 3-1:
Variable Definitions and Logic for Inclusion in Evaluation Model

Variable	Definitions and Logic for Inclusion
kW_t	Represents the average hourly demand (kW) for each time period
A	Is the estimated constant term.
B through M	Represent the regression model parameters.
$Hour_i$	Is a series of binary variables for each hour. They account for the basic hourly load shape of the customer after other factors such as weather and prices are accounted for.
$Year_j$	Is a binary variable with a value equal to 1 for 2010. It was included to reflect changes in overall load patterns and economic conditions between the pre- and post-enrollment periods.
$DayType_j$	Is a series of binary variables representing five different day types (Mon, Tues-Thurs, Fri, Sat, Sunday/Holiday).
$Month_j$	Is a series of binary variables for each month designed to reflect seasonality in loads.
$TotalCDH_t$	Is a measure of heat intensity for the day. It is the sum of cooling degree hours (base 65) for the day.
$TotalCDHsqr_t$	Is the square of the above variable;
$TotalHDH_t$	Is the sum of heating degree hours (base 65) for the day;
$TotalHDHsqr_t$	Is the above variable squared;
$SummerCPP_t$	Is a binary variable representing a customer's CPP status (enrolled or not enrolled) on summer weekdays in interval $_t$. By interacting it with the hourly binary variables, the effect of the CPP summer period rate discount is captured
$WinterCPP_t$	Is a binary variable representing a customer's CPP status (enrolled or not enrolled) on winter weekdays in interval $_t$. By interacting it with the hourly binary variables, the effect of the CPP summer period rate discount is captured
$OtherDR_t$	Is a binary variable representing a customer's participation in another DR event in interval t;
$Eventday_t$	Is a binary variable representing a CPP event day in interval t,[5] and;
e_t	Is the error term.

3.1.2 Validation Methods

The validation of the regression models focuses on two issues: lack of bias and precision. An unbiased model produces accurate impact estimates. A model with high precision produces estimates with smaller standard errors and tighter confidence bands. The precision of the estimates are particularly important when percent load reductions are relatively small. Lack of bias and precision are closely related but are not one and the same. We are interested foremost in accuracy or lack of bias of the impact estimates.

Technically, a regression produces unbiased impact estimates as long as the variables of interest – CPP effects – are not correlated with the error term. In other words, the impact estimates are not confounded with omitted factors that explain event-day behavior. In general, the better regressions explain variation in electricity use, the less likely that the error (also known as residuals) is confounded with the variables

[5] SCE had 12 events during the time period included in the estimation, whereas PG&E had 9 events and SDG&E had 4 events.

that capture DR effects. However, explaining variation in electricity use is not a pre-requisite for unbiased estimates. Experiments that use random assignment to control and treatment groups are powerful because they do not depend on a model that explains customer electricity use or behavior. By using random assignment, they ensure that CPP effects are not systematically confounded with other factors.

Estimating the bias, or lack thereof, of the regression models requires knowledge of the actual load in the absence of DR and event impacts. During event days, the load without the critical peak price in effect cannot be directly observed during event days, it must be estimated. However, actual load patterns without DR can be observed for event-like days during both pre-enrollment and post-enrollment periods. These were defined as the five hottest non-event days from the pre-enrollment period or from non-event days after enrollment in CPP.

To ensure that the results are accurate (i.e., unbiased), we:

1. Tested the ability of the regressions to produce accurate out-of-sample estimates for days that in all respect looked like event days;
2. Assessed whether event hours during event-like days were being confounded with error by introducing false event-day coefficients;
3. Cross-checked results using panel regressions and a non-equivalent control group based on stratified matching;
4. Ran multiple specifications with individual customer regressions to asses if the results varied or remained the same;
5. Compared the within–sample, predictive accuracy of the regressions by temperature and across hours for high temperature days when events were not called; and
6. Separately assessed the accuracy of the regression models for high performers – that is customers that provided substantial percent load reductions. This was done to ensure the impacts for high performers were not exaggerated due to systematic errors.

3.1.3 **Accuracy of Regression Models**

This section contains a high-level overview of the validation results and their implications. Appendices E, F, and G show the detailed results of the validity assessment for all three utilities. For each utility, we performed out-of-sample tests by defining groups of days similar to event days, withholding those days from the regression database, predicting out-of-sample for these days and then comparing the predicted load on these days to the actual load.

The event days were sampled from the hottest days in the pre-CPP or non-event day history of each customer. This is our principal method of making sure that the counterfactual, or reference load, is highly accurate.

Table 3-2 summarizes the out-of-sample predictive accuracy of the models during days that in all respects are similar to actual event days. For all three utilities, the regression models produce highly accurate estimates of the actual load during those days. For SCE, PG&E and SDG&E the difference between predicted and actual values across the event window is less than 0.9%, 0.2% and 1.1%, respectively. The high degree of accuracy during out-of-sample event-like days provides added confidence that the regressions produce accurate impact estimates.

Table 3-2:
Out-of-Sample Predictive Accuracy for Proxy Event Days

Hour	SCE			PG&E			SDG&E		
	Actual kW	Predicted kW	% Difference	Actual kW	Predicted kW	% Difference	Actual kW	Predicted kW	% Difference
1	197.0	194.8	-1.1%	222.4	224.5	0.9%	174.2	174.4	0.1%
2	190.7	189.0	-0.9%	217.8	219.3	0.7%	167.6	167.6	0.0%
3	183.0	181.7	-0.7%	215.0	215.1	0.1%	160.2	159.8	-0.2%
4	178.8	178.2	-0.3%	215.6	214.7	-0.4%	158.8	157.9	-0.5%
5	186.2	184.4	-1.0%	226.5	224.2	-1.0%	164.7	164.0	-0.4%
6	209.4	206.5	-1.4%	250.5	249.1	-0.6%	180.2	178.8	-0.8%
7	235.2	232.4	-1.2%	291.0	286.9	-1.4%	200.5	199.0	-0.8%
8	255.9	253.1	-1.1%	325.6	322.0	-1.1%	221.2	218.3	-1.3%
9	273.3	269.4	-1.4%	354.0	352.6	-0.4%	238.8	235.7	-1.3%
10	289.2	284.6	-1.6%	371.6	371.7	0.0%	252.4	248.2	-1.6%
11	303.9	298.7	-1.7%	389.1	389.0	0.0%	263.0	258.7	-1.6%
12	306.4	302.3	-1.3%	394.4	392.0	-0.6%	267.8	263.5	-1.6%
13	305.1	303.1	-0.7%	390.1	387.7	-0.6%	269.4	265.7	-1.4%
14	307.4	305.1	-0.7%	396.6	394.2	-0.6%	269.9	266.6	-1.2%
15	305.1	302.0	-1.0%	392.7	391.4	-0.4%	264.8	262.5	-0.9%
16	298.8	295.7	-1.0%	381.5	381.0	-0.1%	260.9	258.5	-0.9%
17	288.4	285.9	-0.8%	363.9	363.1	-0.2%	256.5	254.0	-1.0%
18	273.0	271.2	-0.7%	332.8	331.9	-0.3%	245.8	243.5	-0.9%
19	255.7	254.0	-0.6%	293.3	296.8	1.2%	226.5	226.5	0.0%
20	249.1	246.8	-0.9%	279.0	277.2	-0.6%	218.7	219.2	0.2%
21	245.5	242.7	-1.1%	268.9	268.6	-0.1%	214.0	214.8	0.3%
22	235.5	232.9	-1.1%	257.1	258.5	0.5%	205.5	206.1	0.3%
23	223.1	220.8	-1.0%	246.1	248.5	1.0%	192.9	194.5	0.8%
24	212.3	209.3	-1.4%	235.4	237.4	0.9%	186.5	187.6	0.6%

In addition to testing out-of-sample predictive accuracy, false event day variables were included during event-like days to determine if error is being confounded with critical peak pricing conditions. The coefficients for false event-day variables should be insignificant and centered around zero because, in fact, there are no events. If the coefficients on these false event-day variables impact actual electricity use by close to 0%, it is reasonable to conclude that error is not being confounded with treatment effects and that the model is specified correctly. If the difference is substantial, the model is incorrectly specified and needs to be improved. In practice, coefficients are sometimes significant due to the large number of observations analyzed,[6] so we looked at the percent by which the false event day coefficients impact actual electricity use.

Table 3-3 illustrates just how little bias exists in the false event-day coefficients during event hours. The default assumption is that the false event day and hour interactions should have close to 0% impact on the dependent variable, otherwise there is evidence that event hours are correlated with the error term. Except for PG&E, all of the coefficients on the false event day and hour interactions are insignificant. For SCE, the coefficients on the estimated false event day and hour interactions bias actual kWh by 0.04%. For SDG&E, the bias is 0.26%. PG&E shows a small degree of bias, 2.32%, although the out-of-sample predictions of the counterfactual are highly accurate.

Table 3-3:
False Event Coefficient Tests

Event hour	SCE		PG&E		SDG&E	
	T-Value	% Bias	T-Value	% Bias	T-Value	% Bias
11 AM to 12 PM	-	-	-	-	0.52	0.06%
12 PM to 1 PM	-	-	-	-	-0.35	-0.04%
1 PM to 2 PM	-	-	-	-	1.83	0.27%
2 PM to 3 PM	0.56	0.18%	13.02	2.43%	0.9	0.14%
3 PM to 4 PM	0.27	0.08%	13.36	2.52%	1.97	0.32%
4PM to 5 PM	-0.47	-0.15%	12.58	2.42%	2.45	0.38%
5 PM to 6 PM	-0.90	-0.30%	9.07	1.86%	5.75	0.73%
TOTAL	-0.27	-0.04%	24.01	2.32%	4.88	0.26%

As noted earlier, Appendices E, F and G show the detailed results of the validity assessment for each of the three utilities.

3.1.4 Summary of Precision and Goodness of Fit

Although the regressions were estimated at the individual customer level, from a policy standpoint, the focus is less on how the regressions perform for individual customers than it is on how the regressions perform for the average participant and for specific customer segments. Overall, individual customers exhibit more variation and less consistent energy use patterns than the aggregate participant population. Likewise, regressions explain better the variation in electricity consumption and load impacts for the average customer (or average customer within a specific segment) than for individual customers. Put differently, it is more difficult to explain fully how a customer from a specific industry behaves on an hourly basis than it is to explain how the average customer in that industry behaves on an hourly basis.

[6] Statistical power is a function of the amount of data. With a large volume of data even small differences are significant. For each customer, almost two years or interval data were used – roughly 16,000 observations. For each utility, tens of millions of observations were used in estimating aggregate impacts.

Because of this, we present measures of the explained variation, as described by the R-squared goodness-of-fit statistic, for the individual regressions for specific customer segments and for the average customer overall.

In order to estimate the average customer R-squared values for each industry, LCA or the program as a whole, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour and for average customers in specific industries. This process produced regression predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value.

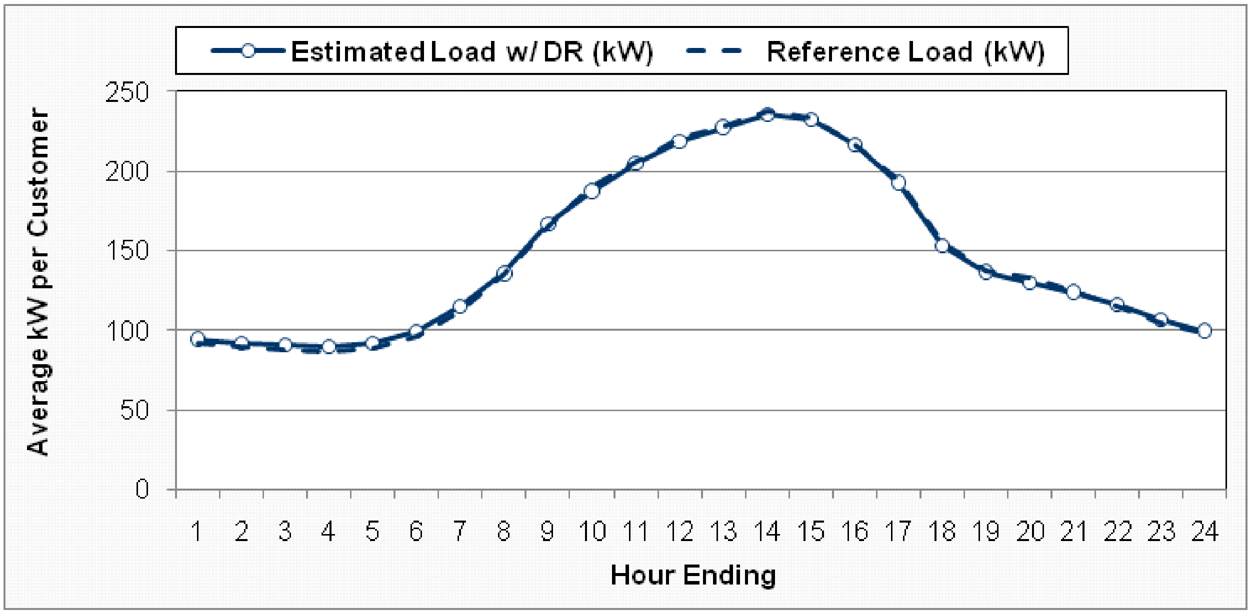
Table 3-4 summarizes the amount of variation explained by the regressions for each industry and for the average customer. Across all three utilities, the regressions explain over 97% of the variation around the mean. In other words, factors not included in the regression account for less than 3% of the variation in average customer behavior and electricity use patterns. The likelihood that CPP effects are confounded with unaccounted factors is minimal. For almost all industries in each utility, well over 90% of the variation in electricity use is explained. The R-squared values are lowest among industries with few customers or a high degree of volatility.

Table 3-4:
R-squared values by Industry for Each Utility

Industry	R-squared		
	PG&E	SDG&E	SCE
Mining & Construction	0.82	0.86	0.92
Manufacturing	0.94	0.94	0.95
Wholesale, Transport, Other utilities	0.87	0.88	0.93
Retail stores	0.99	0.98	0.99
Offices, Hotels, Finance, Services	0.98	0.97	0.98
Schools	0.91	0.93	0.94
Institutional/Government	0.94	0.97	0.90
Other or undefined	0.98	0.95	0.82
All Customers	0.98	0.97	0.97

Schools are zeroed out in the ex post results (i.e., the estimated load with DR and reference load are both set to the actual hourly kW value on each event day). With schools, operating schedules vary greatly between districts and even within districts and idiosyncrasies of usage do not cancel out in the aggregate as they tend to do in other industries. Considerable time was spent testing unique specifications on schools to pick up their load impacts on event days and found that, with a correctly specified model on the average event day, schools showed no load impact. Figure 3-2 shows the estimated load with DR and reference load for schools within SCE's jurisdiction on the average event day as derived from a panel model. Because of the potential for error in predicting school load shapes on individual event days and evidence that schools do not show event impacts, we chose to set the reference load equal to actual load on event days for schools.

Figure 3-2:
Reference Load and Estimated Load with DR for Schools in SCE's Service Territory
Average 2010 SCE CPP
Event



3.2 Ex Ante Impact Estimation Methodology

Whenever possible, ex ante load impacts are grounded on analysis of historical load impact performance. The protocols governing DR evaluations do not require that ex ante impact estimates be based on the same regression models used to estimate the ex post. The best ex post evaluation method is not necessarily the best one for producing ex ante impacts. In this instance, the same regression models were used to estimate both ex post and ex ante impacts except for SDG&E, where there were two differences. First, the regression used for ex ante impacts was based on a year of pre-enrollment data for each customer and 2009 and 2010 data if they were enrolled during that period. By including 2009 events, the ex ante regressions are better able to account for variation in impacts across different weather conditions. Second, an exponential moving average of the primary weather variable, cooling degree hours, was used to ensure that the regression was stable when predicting for 1-in-10 weather year conditions.

For customers already enrolled in CPP, the ex ante impacts are reliable as long as there is a sufficiently long history of events under different weather conditions, including extreme ones. The ex ante estimates implicitly assume that past event performance is indicative of future customer behavior. The primary source of uncertainty in ex ante impacts arises from program changes. These include growth in program participants, changes in program rules or tariff design and policy shifts. Put differently, 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.

For SCE and PG&E some uncertainty remains regarding how customers will react when they come off bill protection. Besides SDG&E, there is no reliable precedent and no guarantee that the experience at SDG&E will be replicated for PG&E and SCE. The response for customers coming off bill protection can be anywhere between greater exit from the program, to significantly more event curtailment, to loss of interest in reducing or shifting loads. The most reliable gauge is actual experience from choices at each utility. Recently defaulted CPP customers do not have a track record of event performance other than behavior under bill protection. This creates enrollment and performance uncertainties in the ex ante forecasts for this group of customers. This uncertainty will be reduced once performance data outside of the bill protection become available within each of the utilities.

For all utilities, load impacts during the winter months of October through May should be used with extreme caution. Recent CPP dynamic pricing events have occurred on hot summer days. In general, there is very limited information available (not just in California but elsewhere as well) concerning what load shifting behavior might be in the winter under dynamic rates.

3.2.1 Large C&I Ex Ante Impact Development

For large customers, the degree of uncertainty for ex ante load impacts has narrowed substantially because they have already been defaulted. We now know how many of these customers tried out default CPP, how much load reduction they provide during events, what types of customers are more responsive and how many remained on CPP at the end of the summer. In addition, while some attrition will occur as customers in the first and second year determine if CPP is the right rate for them, the customer mix for these customers is expected to remain relatively stable.

For the most part, the ex ante load impacts for large customers describe the load reduction capability of existing resources under a standard set of 1-in-2 and 1-in-10 weather conditions. To produce ex ante impacts, for each continuing customer, we:

1. Stored the regression parameters from the ex post regression models. This includes parameters that describe customer hourly load patterns, weather sensitivity, average event load impacts absent weather, and how load impacts vary under different weather conditions;
2. Used the 1-in-2 and 1-in-10 weather year conditions based on the location of each customer. For example, in predicting the 1-in-2 August Peak Day impacts for a customer in the Greater Bay Area, the weather patterns underlying normal July peak system loads were used;
3. Replicated the same variables used in the ex post regression models;
4. Predicted the customer electricity use patterns absent event day response – reference loads – based on the regression coefficients and ex ante event-day conditions; and
5. Predicted the hourly electricity use pattern with event day response - the estimate load with DR – based on the regression coefficients and ex ante event-day conditions.

Impacts were calculated as the difference in loads with and without DR. The reference loads and impacts were then weighted to reflect any changes in enrollment levels and/or mix. Finally, they were aggregated for the program as whole and for each local capacity area. When dually-enrolled customers account for a large share of the program reductions such as in SDG&E, we produced both program specific and portfolio impacts. Portfolio impacts apply attribution rules to ensure dually-enrolled customer impacts are not double-counted in the portfolio. In general, programs with higher degrees of commitment are attributed load impacts. For example, impacts for a customer dually-enrolled in an aggregator program and CPP would be attributed to aggregator program because it involved a contractual commitment to deliver specific amounts of load reduction.

3.2.2 **Medium C&I Ex Ante Impact Development**

For medium customers, the magnitude of ex ante impacts under default dynamic pricing is 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 the 250,000 medium customers have been defaulted onto CPP, but it is necessary to account for differences between them and the far larger population of medium customers scheduled to default onto CPP.

To estimate medium customer impacts, we relied on customers that had already been defaulted onto CPP that were most similar to medium customers. To obtain a larger and more diverse sample, customers with average hourly demand below 100 kW throughout the year were combined with medium customers.[7] In other words, customers that are only slightly above the large customer threshold were used as a proxy for medium customers. This is possible for three reasons. First, across all three utilities medium customer rates (20-200 Max kW) are very similar to the rates to those of customers in the next size category (200 to 500 Max kW). For SDG&E and SCE, the tariffs are nearly identical. Although, the PG&E medium customer tariff lacks a time of use component the CPP prices that drive the load reductions are similar to those of large customers. Second, a substantial number of customers are slightly above the large customer threshold. Third, there is substantial overlap in the electricity use patterns and industry mix between medium and large customers.

To produce ex ante impacts, we applied the same five step process described in Section 3.2.1, but excluded any customer that voluntarily enrolled in CPP prior to the default period. There were two primary differences in producing the final impact estimates. First, the estimating sample was weighted by industry and climate region to reflect the distribution of medium customers. Second, the estimating sample load shapes were rescaled to the size of medium customers. In other words, in producing medium customer ex ante impacts, we accounted for differences in the size, industry mix and geographic distribution between the estimating sample and the larger medium customer population.

For SDG&E it was also necessary to estimate the incremental load impacts of enabling technology – or, more specifically, programmable communicating thermostats (PCTs) – on pricing. After the introduction of default CPP, SDG&E will be actively encouraging medium customer to accept thermostats that automate the response of AC units to price signals and projects that up to 31% of participants will accept it by 2017. In response to price signals, the thermostats typically increase the temperature settings by four or six degrees over the event window, leading to lower AC electricity consumption. The benchmark

[7] 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 100 kW and below may look more like medium customers.

study of small and medium C&I price response under *opt-in dynamic pricing*, the California Statewide Pricing Pilot, concluded that medium customer load responsiveness doubled with enabling technology. To date, empirical data on the incremental effect of thermostats on medium customer price response under default dynamic pricing is unavailable. Because of this, the incremental impacts of thermostats under voluntary pricing from the Statewide Pricing Pilot were applied to the load impacts observed under default pricing. The impact of the thermostat on electricity use is a function of weather, AC use patterns, communication success rates and the magnitude of the temperature setting adjustments made in response to higher prices. In other words, impacts are largely a function of the thermostat device. The main difference in the incremental impacts of thermostats under opt-in and default pricing is the extent to which customers reduce AC use on their own without enabling technology.

3.2.3 Small C&I Ex Ante Impact Development

For small customers, there is less applicable evidence of customer response to default dynamic pricing. Neither opt-out patterns nor impacts under default dynamic pricing have been empirically tested for this segment. The benchmark study of small and medium C&I price response under *opt-in dynamic pricing*, the California Statewide Pricing Pilot, concluded that small C&I customers did not provide load response in the absence of enabling technology. Moreover, while the number of small customers is large, they account for a far smaller share of load coincident with the system peak then either small or medium customers. For all of the above reasons, small customer ex ante load impacts under default CPP are assumed to be zero until empirical data of their response under default CPP is available.

3.2.4 Agricultural Ex Ante Impact Development

While many agricultural customers participated in TOU rates through 2010, none of the three California Investor Owned utilities had a substantial number of customers enrolled in either voluntary or default CPP. PG&E and SCE did not default large customers on agricultural rates onto CPP for the 2010 summer. While SDG&E did default approximately 100 agricultural and pumping accounts onto CPP, a closer examination of these customers revealed they were almost exclusively golf courses and water districts. There was not enough diversity in the SDG&E accounts to provide a basis for inferring agricultural customer impacts for PG&E or SCE. In short, the empirical data available is insufficient for estimating agricultural customer load impacts at this time.

4 PG&E Ex Post Load Impact Results

Table 4-1 below provides the estimated ex post load impacts for each event day and the average event in 2010 for PG&E's CPP tariff. PG&E called nine events in 2010, with four events in both August and September. Load reduction for the average 2010 event is 13.8 kW for the average participant and 23.0 MW for the entire CPP population. Relative to the reference load of 354.9 kW, the average event impact was a 3.9%. The percent load impacts are inversely related to temperature. The impacts are lower with hotter temperatures. For example, the percent load impact for the August 16, 2010 event was 5.3% at an average event temperature of 80.2°F, while the percent load impact for the August 24, 2010 event was 2.6% at an average event temperature of 98.7°F. The CPP price signal is strong, but perhaps not strong enough to deter customers from using energy on extreme weather days. In other words, the opportunity cost of abating usage on higher days is greater than the price that has to be paid under the CPP event charge.

Table 4-1:
Estimated Ex Post Load Impacts by Event Day
2010 PG&E CPP Events

Event Date	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
7/16/2010	1651	310.4	294.1	16.3	5.3%	26.9	85.0
8/16/2010	1646	324.5	307.4	17.1	5.3%	28.1	80.2
8/23/2010	1643	360.8	348.1	12.7	3.5%	20.9	91.8
8/24/2010	1643	377.0	367.2	9.9	2.6%	16.2	98.7
8/25/2010	1645	373.7	360.4	13.3	3.6%	21.9	92.5
9/1/2010	1659	366.8	353.6	13.3	3.6%	22.0	90.5
9/2/2010	1657	375.4	361.9	13.5	3.6%	22.3	91.6
9/3/2010	1656	340.5	324.0	16.5	4.8%	27.3	86.2
9/28/2010	1817[8]	364.1	352.2	11.9	3.3%	21.6	95.3
Average Event	1,669	354.9	341.1	13.8	3.9%	23.0	90.2

In comparison to 2009, the number of large customers enrolled in CPP during 2010 more than doubled; increasing from 642 accounts to 1,669 accounts for the average event. Correspondingly, the event day load absent DR – the reference load – more than doubled; increasing from 256 MW in 2009 to 592 MW in 2010. The increase in load impacts outpaces the growth in customers and reference loads; they increased from 8.4 MW to 23.0 MW. For PG&E, the percent load reductions observed under default CPP in 2010, 3.9%, were comparable to the percent impacts under opt-in CPP in 2009, 3.3%.

[8] There were approximately 450 customers who opted out at some point and then re-enrolled in CPP, many of them around September.

4.1 Average Event Day Impacts

Figure 4-1 shows the hourly impacts for the average event for the average customer. It is a snapshot of the electronic appendix included with this report, which includes hourly load impacts for each ex post event. The impacts increase for event hours, as expected, and are relatively constant throughout the event, ranging from 3.7% to 4.1% load reductions. For the program as a whole, there is very little load shifting to pre-event hours. During the event, overall load levels drop and the reduction is sustained after event hours.

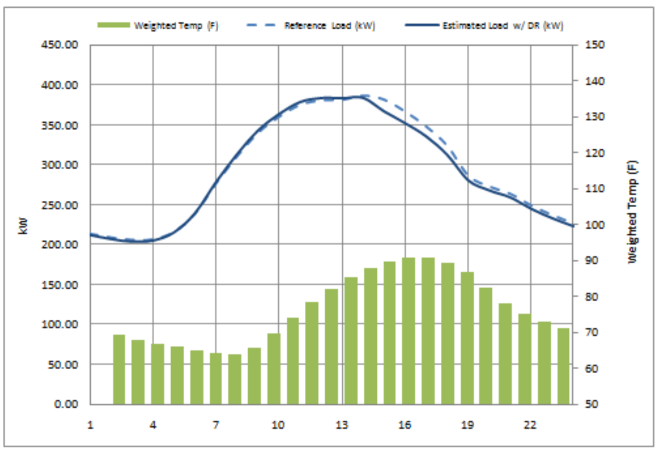
Figure 4-1:
2010 Hourly Ex Post Load Impacts for Average Customer and Average Event

TABLE 1: Menu options

Type of Results	Average Customer
Customer Type	All

TABLE 2: Event Day Information

Event Date	Average Event
Event Start	2:00 PM
Event End	6:00 PM
TOTAL ENROLLED ACCOUNTS	1,669
Avg. Load Reduction for Event Window	13.80
% Load Reduction for Event Window	**3.89%**



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Impact (kW)	%Load Reduction	Weighted Temp (F)
1	213.78	212.28	1.51	0.7%	69.3
2	209.16	207.21	1.95	0.9%	68.0
3	206.16	203.96	2.19	1.1%	66.9
4	206.66	205.29	1.37	0.7%	65.9
5	216.15	215.30	0.84	0.4%	65.0
6	238.58	239.28	-0.70	-0.3%	64.2
7	276.56	278.03	-1.47	-0.5%	63.8
8	310.39	312.61	-2.22	-0.7%	65.5
9	339.80	342.20	-2.40	-0.7%	69.6
10	360.02	362.73	-2.71	-0.8%	73.9
11	374.77	377.61	-2.84	-0.8%	78.4
12	380.49	382.67	-2.18	-0.6%	82.2
13	381.23	382.43	-1.20	-0.3%	85.5
14	386.33	382.88	3.45	0.9%	87.9
15	381.36	366.06	15.29	4.0%	89.8
16	366.53	351.43	15.10	4.1%	90.9
17	347.84	334.90	12.94	3.7%	90.8
18	323.81	311.94	11.87	3.7%	89.4
19	286.62	280.25	6.37	2.2%	86.7
20	272.85	267.70	5.15	1.9%	82.3
21	263.71	258.98	4.73	1.8%	78.1
22	249.09	244.76	4.33	1.7%	75.2
23	237.11	233.06	4.05	1.7%	73.0
24	226.85	223.15	3.70	1.6%	71.2
	Reference Energy Use (kW)	**Estimated Energy Use w/ DR (kW)**	**Total Load Impact (kW)**	**% Daily Load Change**	**Cooling Degree Hours (Base 65)**
Daily	7,055.86	6,976.74	79.12	1.12%	68.3

4.2 Load Impacts by Industry

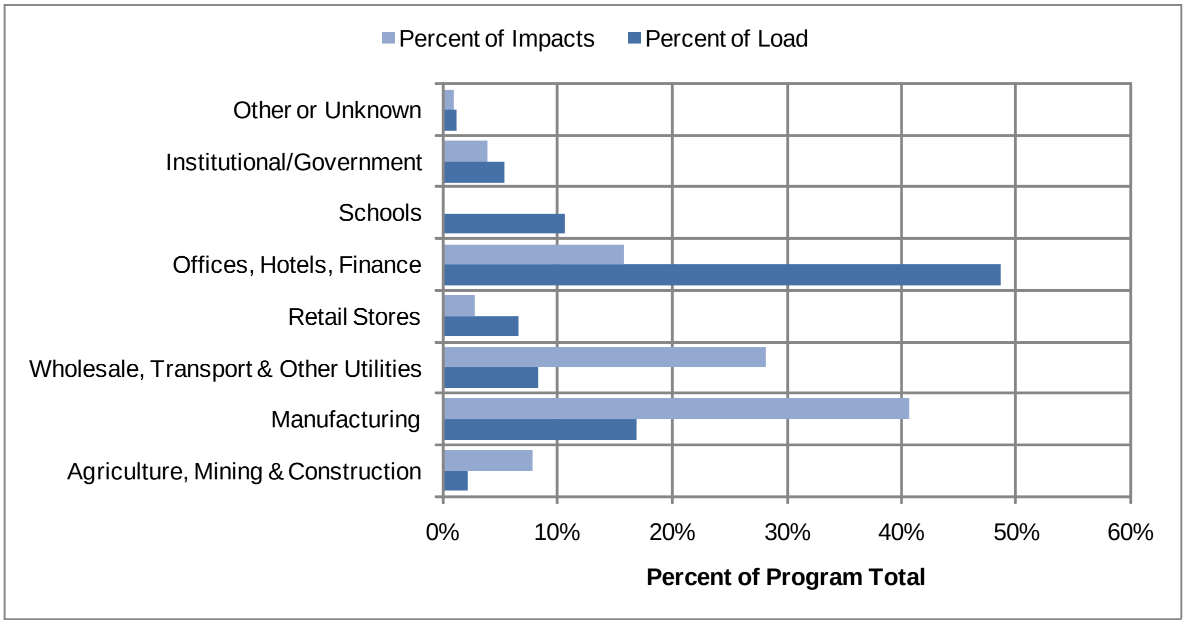
Table 4-2 shows load impacts by industry. The aggregate load impacts take into account the price responsiveness of customers, their average load (or size) and the number of accounts in the segments. For the average 2010 event, customers from the Manufacturing segment provided 9.3 MW of load reduction (9.3%), the largest aggregate load impact across all segments. However, this segment also had the greatest number of customers, and larger participants on average, than other business types. Wholesale, Transport & Other Utilities also shows a large impact with a 6.8 MW reduction (13.5%) during the average event window. Participants in the Agricultural, Mining & Construction sector provided the largest percent load impacts at 14.1%, followed by the Wholesale and Transportation sector, which provided 13.5% load reductions. Retail stores, Offices and Schools had the lowest average demand response on a percentage basis.

Table 4-2:
Estimated Ex Post Load Impacts by Industry
Average 2010 PG&E CPP Event (2-6 pm)

Industry	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
Mining & Construction	45	308.9	265.3	43.6	14.1%	2.0	94.8
Manufacturing	324	310.4	281.6	28.8	9.3%	9.3	90.7
Wholesale, Transport & Other Utilities	197	253.6	219.2	34.3	13.5%	6.8	91.7
Retail Stores	109	354.8	348.9	5.9	1.7%	0.6	90.3
Offices, Hotels, Finance, Services	543	526.5	520.1	6.3	1.2%	3.4	86.7
Schools	296	212.0	212.0	0.0	0.0%	0.0	94.1
Institutional/Government	124	259.9	252.8	7.1	2.7%	0.9	91.1
Other or Unknown	31	244.1	235.9	8.2	3.4%	0.3	90.8
All Customers	1,669	354.9	341.1	13.8	3.9%	23.0	90.2

Figure 4-2 compares the distribution of customer load without DR – as estimated by the regressions – and the impacts by sector.

Figure 4-2:
Distribution of Event Period Reference Load and Impacts by Industry



The majority of the load among the large C&I participants is concentrated among the Office, Hotel and Finance sectors. These are typically office buildings. They accounted for 48% of the estimated load with DR (286 MW) but only produced 15% of the load reduction (3.4 MW). On average, offices reduced load by 1.2%. In contrast, the Manufacturing and Wholesale and Transport sector over performed relative to their load levels. Combined, they accounted for 26% of the reference load (151 MW) but produced 70% of the impacts (16.1 MW).

4.3 Load Impacts by Customer Size

Table 4-3 shows the estimated ex post load impacts by customer size. There is wide variation in the size of CPP participants and many customers resemble medium customers. The impacts from customers that resemble small and medium customers are of particular interest because of the planned default of small and medium customers onto a default CPP tariff with an underlying TOU component.

Based on the summary table, there is no apparent pattern between price responsiveness and customer size. Customers with average usage from 50 kW to 100 kW provide the largest percent load impacts, at 5.9%. The smallest customers, with an average demand under 50 kW, provide similar percent load reduction (3.6%) as customers in the 200-500 kW and in the 500 kW and up ranges.

In aggregate, the load impacts are concentrated among larger customers because they have more load – not because they are more price responsive. The largest customers are responsible for almost 40% of the aggregate load impact for all customers even though they only make up about 10% of the 1,669 participants. They provide 41% of aggregate load impacts (9.4 MW).

Table 4-3:
Estimated Ex Post Load Impacts by Customer Size
Average 2010 PG&E CPP Event

Size	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
Under 50 Average kW	225	51.4	49.6	1.8	3.6%	0.4	95.8
50-100 Average kW	345	135.0	127.0	8.0	5.9%	2.8	91.5
100-200 Average kW	576	222.4	213.3	9.1	4.1%	5.2	89.3
200-500 Average kW	358	462.2	445.9	16.3	3.5%	5.8	88.6
Over 500 Average kW	165	1568.7	1511.4	57.2	3.6%	9.4	86.4
All Customers	1669	354.9	341.1	13.8	3.9%	23.0	90.2

4.4 Load Impacts by Local Capacity Area

Local capacity areas (LCA) are geographic planning zones in the electric grid. They are typically defined by transmission constraints and the location of electric generation. PG&E has seven local capacity areas and a general "Other" category that mostly reflects less interconnected regions. Load impacts by local capacity area useful for resource adequacy planning and for grid operations.

Table 4-4 below shows load impacts by local capacity area. The percent load reduction by LCA range from a low of 2.0% in the Bay Area to 9.7% load reductions by customers in the "Other" LCA, which are primarily located in California's Central Valley. The results reflect both differences in weather and the industry mix. For example, the Bay Area LCA has a substantially higher share of customers in the Offices, Hotels and Finance business category, which as shown earlier are generally the least price responsive.

Participants from the Bay Area make up 52% of the enrolled accounts and 67% of the event day load without DR, as estimated by the regressions. Despite providing the lowest percent load reductions, for the average 2010 event, customers from the Greater Bay Area provided the largest aggregate load impacts, 8.0 MW, or 35% of the aggregate impacts.

Table 4-4:
Estimated Ex Post Load Impacts by Local Capacity Area
Average 2010 PG&E CPP Event

Local Capacity Area	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
Greater Bay Area	867	456.8	447.6	9.3	2.0%	8.0	85.8
Greater Fresno	167	265.2	252.2	13.0	4.9%	2.2	100.6
Kern	116	135.8	125.0	10.8	8.0%	1.3	98.4
Northern Coast	94	249.1	235.0	14.1	5.7%	1.3	92.6
Other	281	277.1	250.3	26.8	9.7%	7.5	90.3
Sierra	75	277.7	255.5	22.1	8.0%	1.7	97.1
Stockton	69	199.4	183.9	15.5	7.8%	1.1	96.5
Total	1,669	354.9	341.1	13.8	3.9%	23.0	90.2

4.5 Load Impacts for Voluntary CPP and Multi-DR Program Participants

Table 4-5 below shows load impacts of customers who are enrolled in other demand response programs and customers who were enrolled in PG&E's historic voluntary CPP rate, E-CPP. Prior Smart Rate customers now on CPP are labeled as voluntary participants because they volunteered onto the CPP-D tariff. Customers dually-enrolled in the Demand Bidding Program (DBP) provide an average impact of 23.9 kW relative to their 505.2 kW reference load, but there are only 24 of them so they do not drive aggregate load impacts by a substantial measure. Customers who were originally on E-CPP and stayed on CPP-D, on the other hand, are responsible for 18% of the total load reduction on the average event day and have slightly higher percent load impacts than those of the average customer (5.4% vs. 3.9%).

Table 4-5:
Estimated Ex Post Load Impacts of Multi-DR & Voluntary CPP Participants
Average 2010 PG&E CPP Event

Dual Enrollees, Volunteers and Prior Participants	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event
Dually-enrolled: DBP	24	505.2	481.3	23.9	4.7%	0.6	90.8
Voluntary Participant: Smart Rate	84	2.1	2.0	0.1	5.2%	0.0	98.4
Pre-Default CPP Participant	190	415.2	392.9	22.3	5.4%	4.2	92.3
Population Totals	1,669	354.9	341.1	13.8	3.9%	23.0	90.2

4.6 Distribution of Participant Price Responsiveness

For customers who show large impacts, it is instructive to look at the distribution of these impacts. Because there is so much variation in size among customers who are enrolled in PG&E's CPP program, it is more practical to consider the distribution of percent load impacts. Figure 4-3 shows the distribution of percent load impacts for the 522 PG&E customers who show load impacts greater than 5% for the average 2010 PG&E CPP event. Over a quarter of these customers show percent load impacts of less than 10%, but the distribution shows that a substantial amount of PG&E customers do indeed show large percent impacts, which drove the overall load impacts.

Figure 4-3:
Distribution of Percent Load Impacts for PG&E Customers
Average 2010 PG&E CPP Event

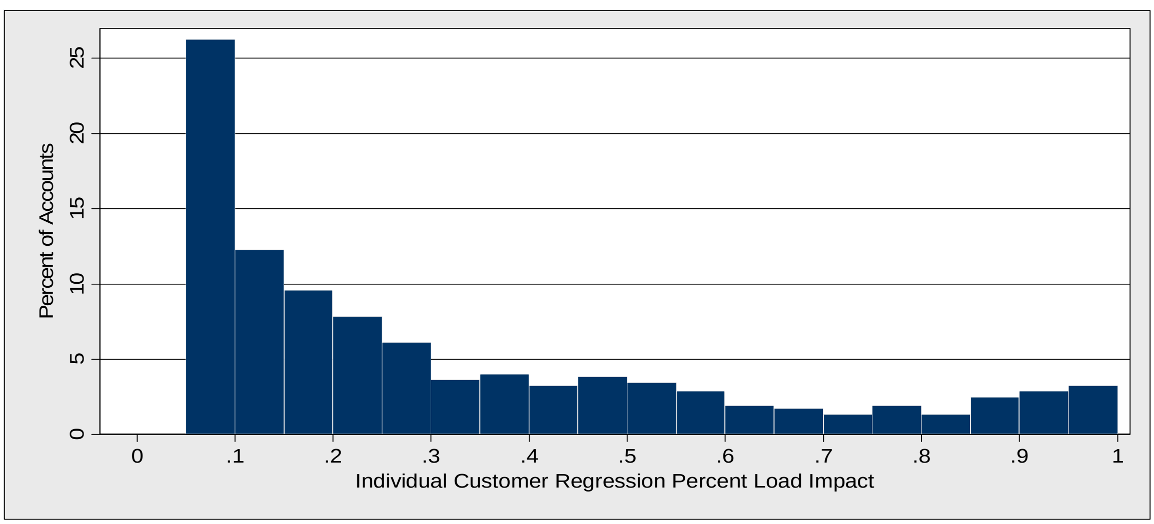
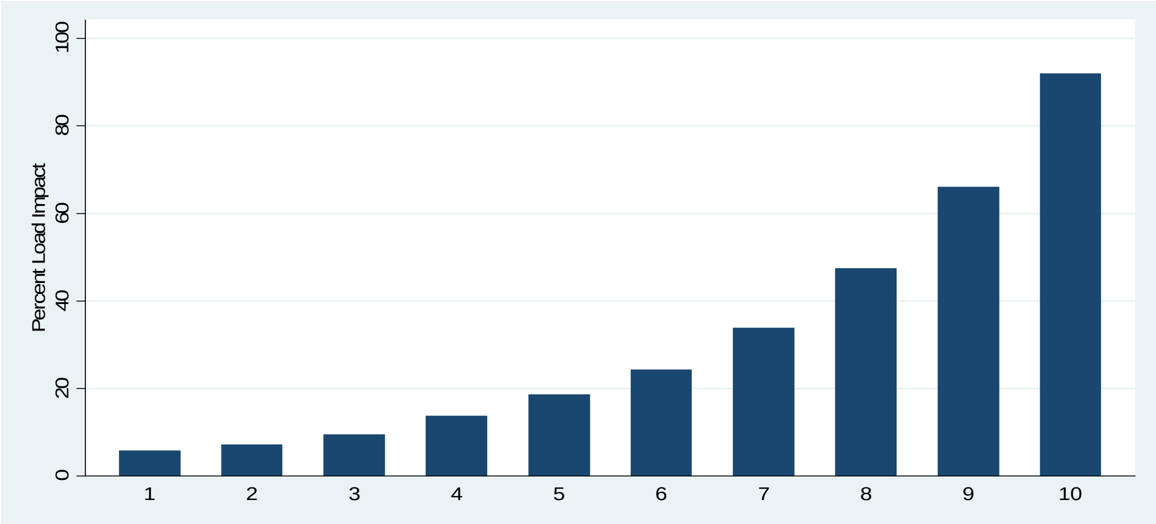


Figure 4-4 shows the percent load reduction for the 522 customers that provided load impacts of 5% or greater by price responsiveness deciles. About 20% of these customers, roughly 100 customers, provided aggregate percent load impacts of more than 60%.

Figure 4-4:
Percent Drops by Customers by Price Responsiveness Deciles
Average 2010 PG&E CPP Event



4.7 Drivers of Price Responsiveness

In order to identify the factors that are correlated with percent load impacts, a regression model was estimated that quantifies percent demand response as a function of customer and event day characteristics. While local capacity area, size, industry and other fixed customer characteristics correlate with load impacts, the primary interest was in the effect of dual enrollment in other DR programs, capacity reservation levels, TI and AutoDR. Table 4-6 documents the variables that were included in the regression model and describes the logic for inclusion.

Capacity reservation levels (CRL) refer to the percent of load that customers choose to insure against high prices on CPP event days. By default, the CRL is set at 50%. Since the percent of load exposed to high CPP prices varied across event days, a variable was created to capture the percent of load that was exposed to CPP prices on each event day for each customer. In theory, the coefficient of this variable is expected to be positive. That is, as more load becomes exposed to CPP prices, percent load impacts should increase.

TI and AutoDR are part of a multi-stage 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. The response is automated, but the customer still decides whether and when to drop load. AutoDR provides an incremental incentive to encourage customers to allow the utility to remotely dispatch the automated load reduction. To estimate the effect of TI and AutoDR on CPP event load reductions, a variable was included in the regression that reflects a customer's approved load reduction plan as a percent of their load on each event day. If the TI or AutoDR load shed is incremental, then its value approaches one. If it is not, its value is near zero.[9]

Based on the data provided, only a single PG&E customer was enrolled in TI during the 2010 event window. As such, a TI variable was not included in the regression, although a realization rate is reported for this customer – that is, how much of their approved load reduction from TI or AutoDR is realized in practice.

Mathematically, the regression model for the ex post analysis of drivers can be expressed as:

$$
\begin{aligned}
PercentImpact_{it} = {} & A + B_i \times LCA_i + C_i \times Industry_i + D_i \times SizeBins_i \\
& + E_i \times VoluntaryCPP2009_i + F_i \times SmartRate_i + G_{it} \times DBP_{it} \\
& + H_{it} \times Temperature_{it} + I_{it} \times AutoDR_{it} + v_{it}
\end{aligned}
$$

Table 4-6:
Definitions and Logic for Inclusion

Variable	Definitions and Logic for Inclusion
$PecentImpact_{it}$	Represents the average percent impact for each individual, $_i$, for each event, $_t$
A	Is a fixed population parameter
B through L	Represent the regression model parameters
LCA_i	Is a binary variable for customer $_i$'s local capacity area. There are 8 LCA's with Greater Bay Area set as the base
$Industry_i$	Is a binary variable for customer $_i$'s industry. There are 8 industries with Schools set as the base
$SizeBins_i$	Is a binary variable for customer $_i$'s size bin (based on average kW). There are 5 size bins with Size: Under 50 kW as the base
$VoluntaryCPP2009_i$	Is a binary variable indicating whether or not customer $_i$ was enrolled in PG&E's voluntary CPP program and experienced CPP events in 2009
$SmartRate_i$	Is a binary variable indicating whether customer $_i$ was previously enrolled in SmartRate and voluntary migrated to CPP
DBP_{it}	Is a binary variable indicating whether customer $_i$ was enrolled in DBP during event $_t$
$Temperature_{it}$	Is the average temperature in customer $_i$'s vicinity for event $_t$
$AutoDR_{it}$	Is the percent of customer $_i$'s reference load that they are supposed to shed during event $_t$ due to AutoDR
V_{it}	Is the usual error term, e_{it} plus the random effect, u_{it}

The model was estimated using a panel regression model with random effects estimation. Panel models with fixed effects are typically used because they control for time-invariant customer characteristics and

[9] In practice, there were few instances where a customer's load response could be observed before and after the installation of technology, making hard to draw conclusive findings on whether TI/AutoDR produces incremental impacts.

make fewer assumptions regarding the error structure.[10] In contrast, a random effects model assumes that customer specific effects are uncorrelated with the error.[11] However, many of the key drivers of interest are, for all intents and purposes, time-invariant and were absorbed into the fixed effects. Given this, the random effects estimation procedure was chosen as the best method.

Table 4-7 shows the coefficient for each variable after random effects regression on percent load impacts. Coefficients for three of the six tested LCA's are significant. The results suggest that, holding all else constant, percent load impacts increase by 3.88 percentage points for customers in Kern, 5.02 percentage points for customers in Other and 10.58 percentage points for customers in Stockton relative to the percent impacts for customers in the Greater Bay Area. All of the coefficients on the industry dummy variables are highly significant. Relative to the percent impacts for schools, which are set to zero, percent load impacts increase by as much as 30.18 percentage points for customers in Mining & Construction and only 5.71 percentage points for customers in Office, Hotels, Finance and Services. Percent impacts for customers in the 50 kW or less size category were very similar to those in the 100 kW to 200 kW and 200 kW to 500 kW categories in the ex post analysis (3.28%, 3.90% and 3.00% respectively). However, percent impacts decrease for customers in the 100 kW to 200 kW and 200 kW to 500 kW categories relative to percent impacts for customers in the 50 kW or less category. In other words, holding all other factors constant, smaller customers were more price responsive on a percentage basis than larger customers, although only by a small amount. Of course, absolute impacts were much less for smaller customers.

Except for temperature, the remaining coefficients are all insignificant. Insignificance does not mean that the results are unimportant. The regression results indicate that prior participation in voluntary CPP or SmartRate and dual enrollment with DBP do not lead to significantly different percent load reductions. This is corroborated by a simple comparison to the ex post results. As expected, the coefficients on the dummy variables identifying these customers are insignificant. The incremental effect of price insurance on load impact is also insignificant. This means that as more of a customer's load becomes exposed to CPP prices, their percent impacts do not necessarily change. A TI variable was omitted because only a single customer was on TI for whom we had data. The AutoDR variable shows up as insignificant, which is not surprising since only 10 customers were enrolled in AutoDR for which data was available.

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10 While fixed effects models control for time-invariant unobserved characteristics, they still have limitations. They can't control for factors that vary across time and customers or fixed characteristics that interact with other factors which vary with time - e.g., the AC unit is fixed at the location but is always interacting with weather and occupancy.

11 The intercept parameters in a random effects model are traditionally specified to consist of a fixed part that represents the population average and random individual differences from the population average. In practice we rearrange the equation by adding the random effect to the usual error term. We ran the random effects model with cluster corrected standard errors based on clusters of each individual, i. In random effects models the errors, vit are correlated over time for a given individual, but are otherwise are assumed to be uncorrelated with the dependent and explanatory variables. Mathematically, this within customer correlation is given by

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}$$

Here the correlation equals the proportion of the variance in the total error term, vit that is attributable to the variance of the individual component, uit. Cluster corrected standard errors allow for any type of heteroskedasticity across individuals and general intercorrelation among the observations on the individual. In other words, they help us control for the noted issues of within customer correlation.

However, the direction of the coefficient for AutoDR is positive as expected. According to this model, percent impacts decrease by 0.09 percentage points for a small increase in temperature. In other words, temperature isn't highly related to impacts for large customers.

Table 4-7:
Regression Coefficients for Load Impact Drivers for PG&E

Variable	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
LCA						
Greater Bay Area (Base)						
Greater Fresno	-0.89	1.47	-0.61	0.54	-3.77	1.98
Kern	3.88	2.32	1.67	0.09	-0.66	8.42
Northern Coast	0.35	1.80	0.19	0.85	-3.18	3.88
Other	5.02	1.39	3.62	0.00	2.30	7.75
Sierra	3.31	2.11	1.57	0.12	-0.83	7.44
Stockton	10.58	2.64	4.01	0.00	5.41	15.75
Industry						
Agriculture, Mining & Construction	30.18	4.63	6.52	0.00	21.11	39.26
Manufacturing	16.70	1.55	10.74	0.00	13.65	19.74
Wholesale, Transport, other utilities	17.94	2.11	8.52	0.00	13.81	22.07
Retail stores	6.81	1.48	4.60	0.00	3.91	9.72
Offices, Hotels, Finance, Services	5.71	1.27	4.49	0.00	3.22	8.20
Schools (Base)						
Institutional/Government	7.76	1.54	5.03	0.00	4.73	10.78
Other or unknown	14.30	3.91	3.66	0.00	6.63	21.96
Size						
50 kW or less (Base)						
50 kW to 100 kW	-0.58	1.99	-0.29	0.77	-4.48	3.32
100 kW to 200 kW	-3.71	2.02	-1.84	0.07	-7.67	0.25
200 kW to 500 kW	-5.56	2.19	-2.54	0.01	-9.85	-1.28
500 kW and up	-3.26	2.58	-1.26	0.21	-8.31	1.79
Voluntary CPP	0.96	1.38	0.70	0.49	-1.75	3.68
SmartRate	0.05	3.64	0.01	0.99	-7.08	7.19
DBP	0.08	3.72	0.02	0.98	-7.22	7.37
Temperature	-0.09	0.02	-5.01	0.00	-0.13	-0.06
CRL	-0.64	1.55	-0.41	0.68	-3.68	2.41
AutoDR	10.00	18.52	0.54	0.59	-26.30	46.29
Constant	6.74	2.63	2.56	0.01	1.57	11.90

Table 4-8 shows the realization rate for both TI and AutoDR. To calculate the realization rate, ratio statistics were used and standard errors were adjusted for clustering by customer. The realization rate for TI indicates that, on average, 18% of the approved TI load shed is actually shed during events by the single customer who received technical incentives. For TI, the realization rate depends on whether the equipment is typically used during event like conditions and whether the customer decides to drop load. The realization rate for AutoDR, at 53%, is higher than for TI, which makes sense since for AutoDR customers, load is automatically shed during each event.

Table 4-8:
Realization Rates

Variable	Accts	Aggregate Approved kW	Realization Rate	Robust Std. Err.	[95% Conf.	Interval]
Technical Incentives (TI)	1	28.8	18.0%	0.0%	.	.
AutoDR	10	585.3	53.0%	19.7%	8.0%	97.0%

Within the dataset results of this analysis have predictive power; the regression on percent load impacts tells which characteristics correlate with percent load impacts. However, the results of this regression can't be interpreted as causal effects. They are merely descriptive, telling us something about the customers in the dataset. For TI and AutoDR especially, there isn't anything close to randomization of treatment. Customers were not assigned randomly to TI and AutoDR, they volunteered. This, coupled with the few data points, makes it difficult to tease out incremental or even discrete impacts with certainty.

5 SCE Ex Post Load Impact Results

Table 5-1 provides the estimated ex post load impacts for each event day and the average event in 2010 for SCE's CPP tariff. Load reduction per participant for the average event was 7.5 kW and aggregate impacts averaged 30.7 MW for the entire CPP population. Relative to the reference load of 263.2 kW, the average participant provided a load reduction of 2.85%. Percent impacts were lowest on the hottest event day, September 27th when they equaled just 1.9%. On that day, temperatures in Downtown LA reached 110°F, producing the highest temperature ever recorded. A detailed review of the load shapes indicate a downward bias for the reference loads of Offices, Institutional and Retail Customers, all of which have weather sensitive electricity use patterns. Simply put, there was no other day like it in the analysis period, making it extremely difficult to accurately estimate event day loads for weather sensitive customers. As a result, the impact estimates for that day are biased downward.

Table 5-1:
Estimated Ex Post Load Impacts by Event Day
2010 SCE CPP Events

Event Date	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
6/30/2010	4198	249.1	241.0	8.2	3.3%	34.3	77.4
7/16/2010	4117	258.3	251.3	7.0	2.7%	29.0	89.4
8/6/2010	4085	233.4	225.2	8.3	3.5%	33.8	76.5
8/12/2010	4085	246.2	238.0	8.2	3.3%	33.7	76.7
8/16/2010	4081	258.5	250.7	7.8	3.0%	31.9	81.7
8/18/2010	4076	275.1	268.1	7.0	2.6%	28.6	87.9
8/23/2010	4076	272.0	264.7	7.3	2.7%	29.6	89.5
8/24/2010	4076	279.6	272.6	7.0	2.5%	28.7	91.1
8/25/2010	4076	277.1	269.7	7.4	2.7%	30.1	88.5
9/2/2010	4076	266.2	258.3	7.9	3.0%	32.2	82.6
9/20/2010	4075	253.2	244.9	8.3	3.3%	33.8	74.9
9/27/2010	4075	293.5	287.9	5.6	1.9%	22.9	100.1
Average Event	4091	263.5	256.0	7.5	2.8%	30.7	84.7

Although the introduction of default CPP increased the number of customers and load absent DR more than eight-fold, it did not lead to a commensurate growth in load reductions. From 2009 to 2010, the number of customers enrolled on CPP for the average event increased from 476 accounts to 4,091 accounts. Likewise, the program event day load absent DR – the reference load – increased from 130 MW in 2009 to 1,078 MW in 2010. In contrast, average event program impacts grew from 24.6 MW in 2009 to 30.7 MW in 2010, while percent load reductions decreased from 18.9% to 2.8%. In essence, customers that had voluntarily enrolled in CPP prior to the implementation of default CPP accounted for the majority of the impacts in 2010. Put differently, customers that experienced CPP for the first time due to the default, on average, provided very small percent load reductions.

There are several potential explanations for the small change in load impacts despite the eight-fold increase in enrollment. In 2009, the percent load reductions from SCE voluntary CPP participants were at least three times larger than that of participants in other California utilities. In other words, with voluntary CPP, SCE had done an excellent job of not only targeting customers that could drop load but also helping to ensure that they did. In addition, the mix of voluntary CPP customers, which is dominated by Manufacturing and Water Districts, is substantially different from those defaulted onto CPP for the first time. Customers defaulted onto CPP may very well be less price responsive.

Another explanation is SCE's strong TOU price signals. They reflect prices customers experience if not on default CPP and, on their own, provide strong incentives to shift or reduce electricity use during peak periods over summer months. Taken alone, the ratio of the summer peak to off-peak period prices, roughly 15¢ and 7¢, do not appear too different. However, SCE has an on peak demand charge that exceeds $15.00 per kW and is concentrated in the 12-6 PM window on weekdays. It provides customers another strong signal to reduce peak load and/or shift to off-peak periods during the summer. To put this in perspective, if the summer on-peak demand charge ($ per max kW) were converted to a consumption charge ($/kWh), the on-peak price would have to increase by a minimum of 11.4¢,[12] likely more. Taken together, the higher on-peak consumption prices and demand charges during the summer already provide a strong time-of-use price signal that gives customers a significant incentive to shift load away from the peak period. In other words, what customers could easily shift to off-peak periods may have already been shifted in response to strong TOU prices, leaving less load potential reduction for CPP.

The final alternative explanation for the low-load response of customers defaulted onto CPP is that many customers may not have a clear idea of what actions would have the largest impact on their demand response and bills under the new tariff. Providing education and information to these customers could help improve the average demand response that is currently being provided by default customers.

5.1 Average Event Hourly Impacts

Figure 5-1 shows the hourly impacts for the average event for the average customer. On average, SCE participants do not begin reducing load until the start of an event. The impacts increase for event hours, as expected, and are relatively constant throughout the event; centering around 3% load reductions.

[12] To calculate this, divide the on-peak charge by the number of at risk hours. That is $15 divided by 6 hours and approximately 22 weekdays ($15.00 / (6*22)=0.114. This provides a lower bound for the price increase. For a customer whose max demand equaled its average demand over the 12-6 PM weekday window, the on-peak price change would be 11.4¢. In practice, the incremental charge would have to be higher.

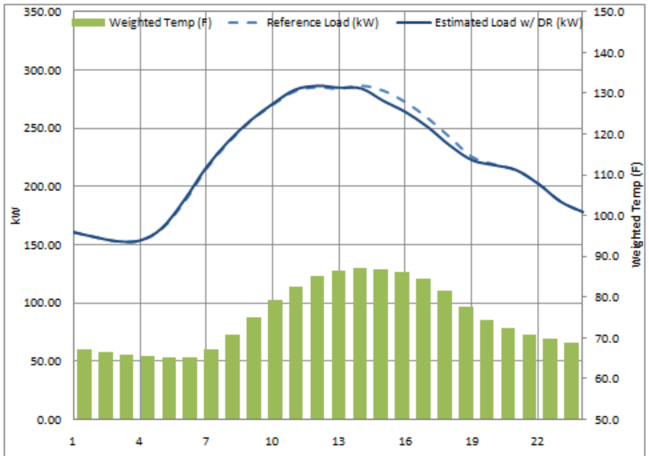
Figure 5-1:
2010 Hourly Ex Post Load Impacts for Average Customer and Average Event

TABLE 1: Menu options

Type of Results	Average Customer
Customer Type	All

TABLE 2: Event Day Information

Event Date	Average Event
Event Start	2:00 PM
Event End	6:00 PM
TOTAL ENROLLED ACCOUNTS	4,091
Avg. Load Reduction for Event Window	7.50
% Load Reduction for Event Window	2.85%



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)
1	160.36	160.40	-0.04	0.0%	67.1
2	155.91	156.06	-0.14	-0.1%	66.4
3	152.34	152.58	-0.24	-0.2%	65.9
4	152.84	153.10	-0.26	-0.2%	65.4
5	163.00	163.85	-0.85	-0.5%	65.0
6	185.76	187.83	-2.07	-1.1%	65.1
7	214.36	216.15	-1.79	-0.8%	67.2
8	237.40	238.78	-1.37	-0.6%	70.8
9	255.74	256.84	-1.10	-0.4%	75.1
10	269.73	271.16	-1.43	-0.5%	79.2
11	281.43	283.33	-1.90	-0.7%	82.5
12	284.96	286.81	-1.85	-0.6%	85.0
13	283.57	285.12	-1.54	-0.5%	86.4
14	286.20	284.50	1.70	0.6%	87.0
15	281.94	273.70	8.24	2.9%	86.9
16	272.05	264.08	7.96	2.9%	86.1
17	258.32	251.13	7.18	2.8%	84.4
18	241.80	235.18	6.63	2.7%	81.4
19	224.94	222.61	2.33	1.0%	77.5
20	218.53	218.27	0.26	0.1%	74.3
21	213.38	213.95	-0.57	-0.3%	72.2
22	201.75	201.97	-0.22	-0.1%	70.8
23	186.56	186.67	-0.11	-0.1%	69.7
24	177.24	177.83	-0.59	-0.3%	68.8
	Reference Energy Use (kW)	Estimated Energy Use w/ DR (kW)	Total Load Impact (kW)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	5,360.12	5,341.89	18.23	0%	29.3

5.2 Load Impacts by Industry

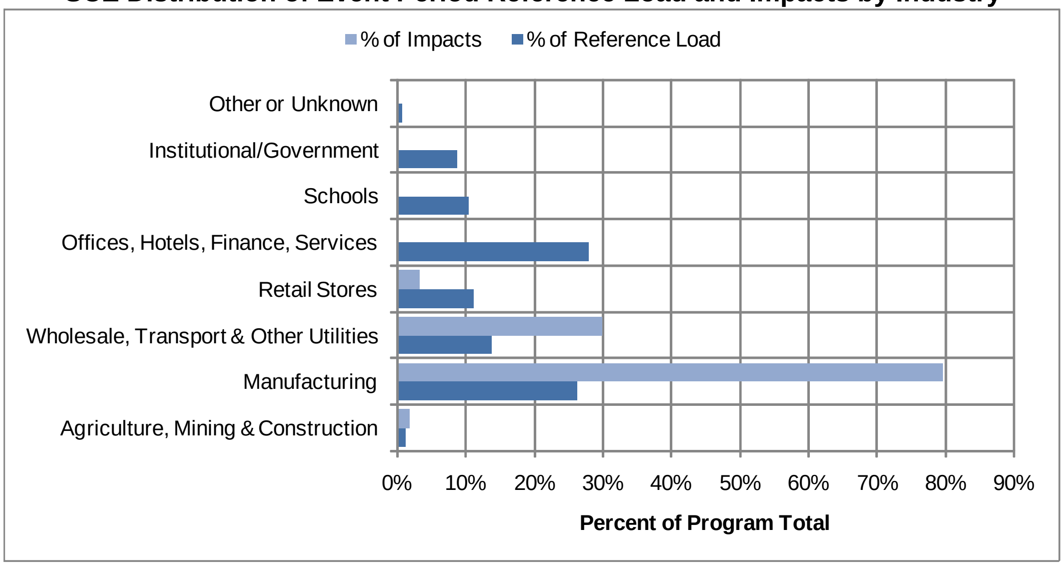
Table 5-2 shows load impacts by industry. For the average 2010 event, customers from the Manufacturing segment provided 23.8 MW of load reduction (8.5%), the largest aggregate load impacts across all industries. However, this segment also has more and larger participants, on average, then other business types. Wholesale, Transport & Other Utilities also showed a large aggregate load impact, with a reduction of 9.0 MW (6.1%) during the average event window. Some industries such as Offices, Hotels, Finance and Services showed negative impacts. As outlined in the model validation section, the predictions of this model are bounded by 1% error during event hours. The -1.0% impact is not statistically different from 0 but these impacts are still factored in with the positive values to produce accurate average predictions.

Figure 5-2 compares the distribution of customer load without DR – as estimated by the regressions – and the impacts by sector. In total, SCE participants would have averaged 1,078 MW of load during the event periods if not for CPP. Instead, they averaged 1,047 MW, a 31 MW reduction. The two largest sectors among enrolled participants are Office, Hotel and Finance and Manufacturing sectors. Offices accounted for 28% of the load (299 MW) but did not produce any load impacts. On the other hand, Manufacturing accounted for 26% of the event period load absent DR (280 MW), but delivered 78% of the impacts (23.8 MW).

Table 5-2:
Estimated Ex Post Load Impacts by Industry
Average 2010 SCE CPP Event

Industry	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
Agriculture, Mining & Construction	87	147.8	140.9	6.9	4.7%	0.6	88.0
Manufacturing	1053	266.8	244.3	22.6	8.5%	23.8	84.7
Wholesale, Transport & Other Utilities	610	240.9	226.1	14.8	6.1%	9.0	85.4
Retail Stores	429	280.3	278.0	2.3	0.8%	1.0	84.8
Offices, Hotels, Finance, Services	1016	294.6	297.5	-2.9	-1.0%	-2.9	82.4
Schools	493	226.9	226.9	0.0	0.0%	0.0	85.7
Institutional/Government	336	281.3	283.0	-1.7	-0.6%	-0.6	86.9
Other or Unknown	67	141.1	147.7	-6.6	-4.7%	-0.4	89.6
All Customers	4091	263.5	256.0	7.5	2.8%	30.7	84.7

Figure 5-2:
SCE Distribution of Event Period Reference Load and Impacts by Industry



5.3 Load Impacts by Customer Size

Table 5-3 shows the estimated ex post load impacts by customer size. There is wide variation in the customer size of SCE 2010 CPP participants and many customers resemble medium customers. As previously discussed, the impacts from customers that resemble small and medium customers are of particular interest because of the planned default of small and medium customers onto a default CPP tariff.

In general, the larger SCE participants are more price-responsive than smaller ones. This may be because a larger share of those customers was previously enrolled on voluntary CPP. Customers with average usage above 500 kW provided the largest percent load impacts, at 5.6%. Participants with average usage under 50 kW and from 50 kW to 100 kW provided the smallest percent load impacts, 0.4% and 1.0% respectively.

On aggregate, the load impacts are concentrated among larger customers because they not only have more load, but are also more price responsive. The largest customers are responsible for almost 24.1% of the aggregate load of all participants even though they only make up about 5.6% of the 4,091 participants. They account for 47% of aggregate load impacts (14.5 MW).

Table 5-3:
Estimated Ex Post Load Impacts by Customer Size
Average 2010 SCE CPP Event

Size	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
Under 50 Average kW	460	52.8	52.6	0.2	0.4%	0.1	86.7
50-100 Average kW	1110	131.2	129.8	1.4	1.0%	1.5	85.5
100-200 Average kW	1443	212.4	209.0	3.4	1.6%	4.9	84.0
200-500 Average kW	851	402.8	391.6	11.2	2.8%	9.5	83.8
Over 500 Average kW	227	1134.4	1070.5	63.9	5.6%	14.5	84.1
All Customers	4091	263.5	256.0	7.5	2.8%	30.7	84.7

5.4 Load Impacts by Local Capacity Area

Table 5-4 below shows load impacts by local capacity area. For the average 2010 event, customers from the LA Basin provided the largest aggregate load impacts (26.5 MW), which is not surprising since they comprised just over 83% of all CPP customers. The greatest percent load impact is also in the LA Basin where the average customer reduces load by 7.8 kW relative to a 262.0 kW reference load for a 3.0% load impact. Outside LA Basin shows the smallest average load impacts for the average customer and for all customers combined, at 4.8 kW (1.9%) and 1.1 MW respectively.

Table 5-4:
Estimated Ex Post Load Impacts by Local Capacity Area
Average 2010 SCE CPP Event

Local Capacity Area	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
LA Basin	3398	262.0	254.2	7.8	3.0%	26.5	84.6
Outside	228	253.7	248.9	4.8	1.9%	1.1	91.7
Ventura	465	279.5	272.9	6.6	2.4%	3.1	81.8
Total	4,091	263.5	256.0	7.5	2.8%	30.7	84.7

5.5 Load Impacts for Voluntary CPP and Multi-DR Program Participants

Figure 5-3 shows load impacts of customers who were previously enrolled in voluntary CPP programs with SCE. As evidenced by the large load impacts of these customers, they drive much of the impact reductions for SCE’s CPP-D program. In fact, these 397 customers are responsible for 65% of the aggregate impact for the average event, which is astounding because they only make up about 10% of SCE’s CPP population.

In order to achieve greater load impacts from all customers, SCE should consider interviewing highly responsive customers to better understand how these customers who were previously on voluntary CPP were able to provide such large load reductions. These lessons could be incorporated into educational materials and shared with other program participants to try and increase average demand response.

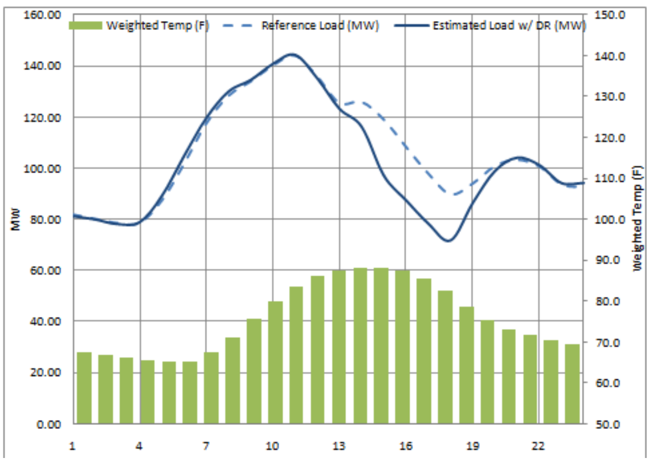
Figure 5-3:
2010 Hourly Ex Post Load Impacts for Average Customer Previously Enrolled in Voluntary CPP on the Average Event Day

TABLE 1: Menu options

Type of Results	Aggregate
Customer Type	Pre-Default CPP

TABLE 2: Event Day Information

Event Date	Average Event
Event Start	2:00 PM
Event End	6:00 PM
TOTAL ENROLLED ACCOUNTS	397
Avg. Load Reduction for Event Window	20.07
% Load Reduction for Event Window	**19.37%**



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)
1	81.76	81.16	0.60	0.7%	67.5
2	80.04	79.83	0.21	0.3%	66.8
3	78.42	78.04	0.39	0.5%	66.2
4	78.53	78.80	-0.27	-0.3%	65.6
5	87.25	89.03	-1.79	-2.0%	65.2
6	101.58	104.73	-3.15	-3.1%	65.2
7	117.35	119.59	-2.24	-1.9%	67.4
8	128.16	130.02	-1.86	-1.4%	71.1
9	133.79	134.55	-0.76	-0.6%	75.6
10	140.00	140.87	-0.87	-0.6%	79.9
11	143.88	144.41	-0.53	-0.4%	83.4
12	135.63	135.16	0.47	0.3%	86.0
13	125.33	123.26	2.07	1.7%	87.5
14	125.77	116.15	9.62	7.7%	88.2
15	118.81	96.99	21.82	18.4%	88.1
16	108.12	87.33	20.79	19.2%	87.3
17	97.76	78.20	19.56	20.0%	85.5
18	89.68	71.58	18.10	20.2%	82.5
19	93.90	86.31	7.59	8.1%	78.5
20	100.71	98.90	1.81	1.8%	75.2
21	103.14	104.06	-0.92	-0.9%	73.0
22	100.56	101.13	-0.58	-0.6%	71.5
23	93.55	94.10	-0.56	-0.6%	70.3
24	92.47	94.17	-1.70	-1.8%	69.3

	Reference Energy Use (MW)	Estimated Energy Use w/ DR (MW)	Total Load Impact (MW)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	2,556.19	2,468.39	87.80	3%	34.1

Table 5-5 shows load impacts for SCE customers who are dually-enrolled in other DR programs. It also shows load impacts for customers who received service under SCE's historic voluntary CPP rate before CPP-D. Dually-enrolled customers in the DBP program provide an average impact of 75.3 kW relative to their 432.6 kW reference load for a 17.4% load reduction on average. Altogether, they drive 16% of the load impact on the average event day (4.6 MW). CPP customers dually-enrolled in the BIP program show large percent load impacts, 52%, but because there are only 6 of them, they only provide a total reduction of 1.3 MW on the average event day.

Table 5-5:
Estimated Ex Post Load Impacts for Multi-DR & Voluntary CPP Participants
Average 2010 SCE CPP Event

Dual Enrollees and Prior Participants	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
Dually-enrolled: BIP	6	406.6	195.1	211.5	52.0%	1.3	87.7
Dually-enrolled: CBP	12	241.3	205.6	35.7	14.8%	0.4	88.5
Dually-enrolled: DBP	65	432.6	357.2	75.3	17.4%	4.9	85.9
Dually-enrolled: SDP	42	156.4	150.6	5.8	3.7%	0.2	90.0
Pre-Default CPP Participant	397	260.9	210.4	50.5	19.4%	20.1	85.9
Population Totals	4,091	263.5	256.0	7.5	2.8%	30.7	84.7

5.6 Distribution of Participant Price Responsiveness

Figure 5-4 shows the distribution of percent load impacts for the 805 SCE customers who show load impacts greater than 5% for the average 2010 SCE CPP event. More than 30% of these customers show percent load impacts of less than 10%. It is interesting that out of nearly 4,100 SCE customers on CPP-D, only 20% show load impacts greater than 5%. Average event impacts are clearly driven by a small subset of the CPP-D population and the small average event impact of 2.85% reflects the fact that 20% of customers drive most of the aggregate load impacts on event days.

Figure 5-4:
Distribution of Percent Load Impacts for SCE Customers
Average 2010 SCE CPP Event

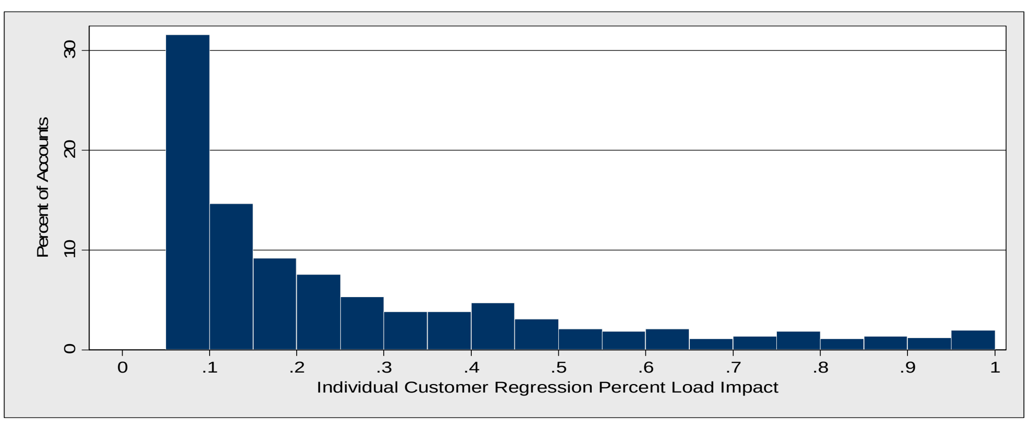
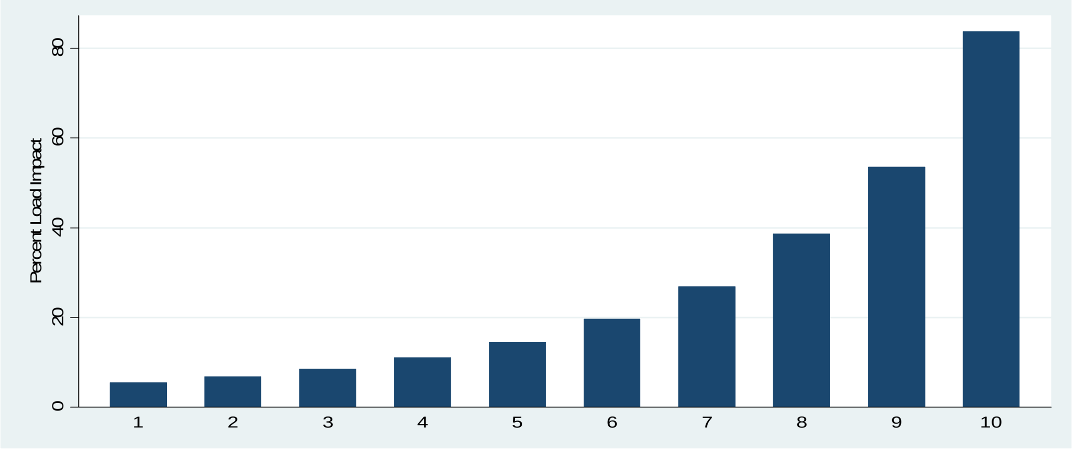


Figure 5-5 shows percent impacts for the 805 customers who provide percent load impacts of 5% or greater by price responsiveness deciles. 20% of these customers, roughly 160 customers, provide aggregate percent load impacts of more than 50%.

Figure 5-5:
Percent Drops by Customers by Price Responsiveness Deciles
Average 2010 SCE CPP Event



5.7 Drivers of Price Responsiveness

For SCE, the incremental effects of TI and AutoDR were assessed along with other factors to determine their correlation with variation in percent load reductions during events. To estimate the effect of TI and AutoDR on CPP load response, a variable was included in the regression that reflects a customer's approved load reduction plan as a percent of the load on each event day. Ratio statistics were also used to arrive at the realization rate – that is, how much of the approved load reduction from TI or AutoDR is realized in practice. Table 5-6 lists all the variables included in the regression along with brief definitions for each variable. The panel regression was estimated with random individual customer effects. The specifics of this method are explained in Section 4.7.

Mathematically, the regression model can be expressed as:

$$
\begin{aligned}
PercentImpact_{it} = A &+ B_i \times LCA_i + C_i \times Industry_i + D_i \times SizeBins_i \\
&+ E_i \times VoluntaryCPP2009_i + F_{it} \times CBP_{it} + G_{it} \times DBP_{it} + H_{it} \times BIP_{it} \\
&+ I_{it} \times SDP_{it} + J_{it} \times Temperature_{it} + K_{it} \times TI_{it} + L \times AutoDR_{it} + v_{it}
\end{aligned}
$$

Table 5-6:
Definitions and Logic for Inclusion

Variable	Definitions and Logic for Inclusion
$PecentImpact_{it}$	Represents the average percent impact for each individual, i, for each event, t;
A	Is a fixed population parameter;
B through L	Represent the regression model parameters;
LCA_i	Is a binary variable for customer i's local capacity area. There are 3 LCA's with LA Basin set as the base;
$Industry_i$	Is a binary variable for customer i's industry. There are 8 industries with Agriculture, Mining, and Construction set as the base;
$SizeBins_i$	Is a binary variable for customer i's size bin (based on average kW). There are 5 size bins with Size: Under 50 kW as the base;
$VoluntaryCPP2009_i$	Is a binary variable indicating whether or not customer i was enrolled in SCE's voluntary CPP program and experienced CPP events in 2009;
CBP_{it}	Is a binary variable indicating whether customer i was enrolled in CBP during event t;
DBP_{it}	Is a binary variable indicating whether customer i was enrolled in DBP during event t;
BIP_{it}	Is a binary variable indicating whether customer i was enrolled in BIP during event t;
SDP_{it}	Is a binary variable indicating whether customer i was enrolled in SDP during event t;
$Temperature_{it}$	Is the average temperature in customer i's vicinity for event t;
TI_{it}	Is the percent of customer i's reference load that they are supposed to shed during event t due to TI;
$AutoDR_{it}$	Is the percent of customer i's reference load that they are supposed to shed during event t due to AutoDR, and;
V_{it}	Is the usual error term, e_{it} plus the random effect, u_{it}.

Table 5-7 shows the coefficient for each variable. All of the coefficients on the industry dummy variables are significant except for the coefficient on Offices, Hotels, Finance and Services. Relative to the percent load impacts for schools, which are set to zero, percent impacts increase by as much as 7.96 percentage points for customers in Manufacturing and only 2.22 percentage points for customers in Institutional/Government. Percent impacts for customers in the 50 kW or less size category were lower than those in the 50 kW to 100 kW and 100 kW to 200 kW categories in the ex post analysis (0.45%, 1.04% and 1.61% respectively). However, percent impacts decrease for customers in the 50 kW to 100 kW and 100 kW to 200 kW categories relative to percent impacts for customers in the 50 kW or less category. We have more than twice as many data points for SCE than we do for PG&E or SDG&E, lending more credibility to these LCA, industry and customer size effects.

The other coefficients are, for the most part, as expected. Percent impacts increase by 9.83 percentage points relative to their mean value for customers who were enrolled on voluntary CPP in 2009. Further, percent impacts increase by 6.46 percentage points for customers dually-enrolled in the DBP program, and 17.91 percentage points for customers dually-enrolled in BIP. The coefficient on TI is insignificant largely due to limited data, but the coefficient on AutoDR is positive and statistically significant. The interpretation of this coefficient is that, as the approved TI/AutoDR reduction increases by 1 percentage point as the share of an individual's reference load, percent load impacts will increase by 1.97 percentage points. While the results are reasonable, they should be interpreted with caution because most customers lack data on impacts before and after TI/AutoDR. Few data points are also a problem when estimating statistical models. And, there were only 4 SCE CPP-D customers enrolled in the TI program and 35 customers enrolled in the AutoDR program during the 2010 event window for which data is available.

Table 5-7: Regression Coefficients for Load Impact Drivers for SCE

Variable	Coef.	Std. Err.	Z	P>z	[95% Conf. Interval]	
LCA						
LA Basin (Base)						
Outside LA	0.19	0.94	0.21	0.84	-1.65	2.03
Ventura/ BC	0.16	0.73	0.22	0.82	-1.28	1.60
Industry						
Agriculture, Mining & Construction	5.66	2.36	2.39	0.02	1.03	10.30
Manufacturing	7.96	0.81	9.79	0.00	6.37	9.55
Wholesale, Transport, other utilities	6.65	0.91	7.31	0.00	4.87	8.43
Retail stores	2.29	0.73	3.12	0.00	0.85	3.72
Offices, Hotels, Finance, Services	0.85	0.68	1.26	0.21	-0.47	2.18
Schools (Base)						
Institutional/Government	2.22	0.78	2.86	0.00	0.70	3.75
Other or unknown	6.99	2.50	2.80	0.01	2.10	11.88
Size						
50 kW or less (Base)						
50 kW to 100 kW	-3.34	0.96	-3.50	0.00	-5.22	-1.47
100 kW to 200 kW	-2.13	0.94	-2.27	0.02	-3.97	-0.29
200 kW to 500 kW	-1.64	1.01	-1.63	0.10	-3.62	0.33
500 kW and up	0.06	1.39	0.04	0.97	-2.66	2.78
Voluntary CPP	9.83	1.36	7.21	0.00	7.15	12.50
CBP	4.81	5.86	0.82	0.41	-6.67	16.29
DBP	6.46	3.23	2.00	0.05	0.13	12.80
BIP	17.91	9.44	1.90	0.06	-0.59	36.42
SDP	-2.73	1.95	-1.40	0.16	-6.55	1.10
Temperature	-0.05	0.01	-4.19	0.00	-0.08	-0.03
TA TI	-23.94	14.85	-1.61	0.11	-53.04	5.16
AutoDR	1.97	0.82	2.41	0.02	0.37	3.57
Constant	4.29	1.43	3.01	0.00	1.49	7.08

Table 5-8 shows the realization rate for both TI and AutoDR. To calculate the realization rate, ratio statistics were used with standard errors adjusted for clustering by customer. The realization rate for TI indicates that on average, 31% of the approved TI load shed is actually shed during events by customers who received technical incentives. For TI, the realization rate is a function of whether the end use is typically in use during event like hours and the customer's decision concerning whether or not to shed load during events. The realization rate for AutoDR, at 37%, is higher than that of TI, mainly because the utility dispatched the automated load reductions for each event. The realization rate cannot be expected to be 100% because the loads that are under automated control are not always operating during events.

Table 5-8:
Realization Rates

Variable	Accts	Aggregate Approved kW	Realization Rate	Robust Std. Err.	[95% Conf.	Interval]
Technical Incentives (TI)	4	511.5	31.0%	12.5%	-9.0%	71.0%
AutoDR	32	8597.3	37.0%	7.6%	22.0%	53.0%

6 SDG&E Ex Post Load Impact Results

Table 6-1 shows the estimated ex post load impacts for each event day and the average event in 2010 for SDG&E's CPP tariff. For the average event, CPP customers provided an average load reduction of 13.7 kW and an aggregate reduction of 18.8 MW. Relative to the reference load of 260.6 kW, the average percent reduction is 5.3%. The lowest impacts occurred on September 27, 2010, the hottest event day and the all-time system peak. For SD&GE, the raw data affirms the percent impacts were low that day rather than simply an artifact of some downward bias in the regression model during extreme weather conditions. There are several potential explanations. The event occurred late in the summer and on a Monday. Given the day-ahead notification, it is possible that the lower impacts reflect a day of week effect since notification procedures differ for Mondays and some customers may not be aware of the event or may simply not have as much lead time to enact steps to reduce loads. Another explanation is the fact that the summer period was essentially over. The final possible explanation is that participants provide lower percent load impacts with hotter weather. Considering that there were four events in 2010, there are few degrees of freedom for modeling how load impacts vary across event days. However, when 2009 events are included in the analysis as was done for ex ante impact estimates, hotter weather conditions correlate with larger percent impacts.

Table 6-1:
Estimated Ex Post Load Impacts by Event Day
2010 SDG&E CPP Events

Event Date	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event
8/25/2010	1,368	254.3	238.6	15.8	6.2%	21.6	78.8
8/26/2010	1,368	248.7	230.7	18.0	7.2%	24.6	76.0
9/27/2010	1,368	272.8	264.5	8.3	3.0%	11.3	89.5
9/28/2010	1,368	267.2	254.5	12.7	4.7%	17.3	81.2
Average Event	1,368	260.6	246.9	13.7	5.3%	18.8	81.3

In comparison to 2009, the number of large customers enrolled in CPP during 2010 dropped by roughly 200 accounts, decreasing from 1,576 to 1,368 for the average event. The decrease is mainly due to the fact that for many customers, bill protection expired by the 2010 summer. Correspondingly, the event day load absent DR – the reference load – decreased proportionately, from 419 MW in 2009 to 357 MW in 2010. The percent load reduction in 2009 and 2010 were essentially equivalent, 5.6% and 5.3%, respectively.

6.1 Average Event Hourly Impacts

Figure 6-1 shows the hourly impacts for the average event for the average customer. The current results show that SDG&E customers on average shifted load to pre-event periods. The SDG&E panel model validation results in Appendix F confirm that not just Manufacturing customers shifted load, as expected, but also customers in the Offices, Hotels, Finance and Service industry. The draft ex post impacts indicate a load reduction of 5.26% that is more or less consistent throughout the event window. Participants also reduced load in the hours immediately after the event as they likely ramp back to normal production levels and operations patterns.

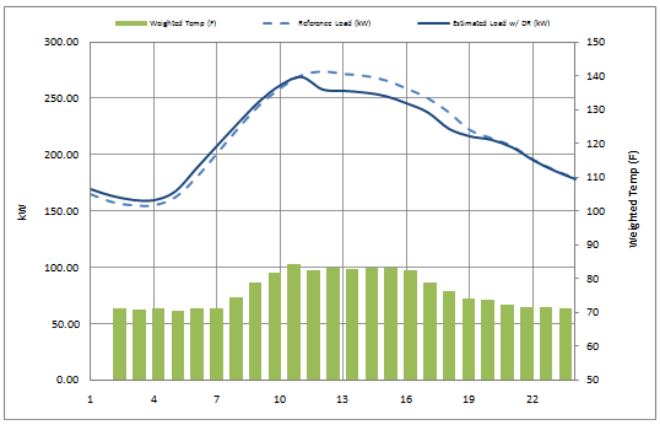
Figure 6-1:
2010 Hourly Ex Post Load Impacts for Average Customer and Average Event

TABLE 1: Menu options

Type of Results	Average Customer
Customer Type	All

TABLE 2: Event Day Information

Event Date	Average Event
Event Start	11:00 AM
Event End	6:00 PM
TOTAL ENROLLED ACCOUNTS	1,368
Avg. Load Reduction for Event Window	13.72
% Load Reduction for Event Window	**5.26%**



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)
1	165.04	169.45	-4.41	-2.7%	70.9
2	158.23	163.53	-5.31	-3.4%	70.9
3	155.30	159.93	-4.64	-3.0%	71.1
4	155.45	159.69	-4.24	-2.7%	70.3
5	162.39	167.42	-5.04	-3.1%	71.2
6	179.74	187.77	-8.03	-4.5%	71.2
7	201.41	208.33	-6.92	-3.4%	74.5
8	223.44	228.44	-5.00	-2.2%	78.7
9	243.60	247.49	-3.89	-1.6%	81.5
10	258.70	261.88	-3.19	-1.2%	84.2
11	270.03	269.06	0.97	0.4%	82.4
12	273.26	257.97	15.29	5.6%	83.2
13	271.22	256.82	14.40	5.3%	82.7
14	269.47	255.24	14.24	5.3%	83.1
15	265.49	252.12	13.37	5.0%	83.2
16	258.17	245.64	12.53	4.9%	82.3
17	249.68	237.53	12.14	4.9%	78.7
18	237.16	223.06	14.09	5.9%	76.1
19	221.61	216.38	5.23	2.4%	74.1
20	214.60	213.38	1.21	0.6%	73.5
21	207.41	206.56	0.86	0.4%	72.1
22	195.55	195.13	0.42	0.2%	71.6
23	186.48	185.89	0.59	0.3%	71.4
24	179.11	178.39	0.72	0.4%	71.0
	Reference Energy Use (kW)	Estimated Energy Use w/ DR (kW)	Total Load Impact (kW)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	5,202.51	5,147.12	55.39	1.06%	12.1

6.2 Load Impacts by Industry

Table 6-2 shows the estimated ex post load impacts by industry. For the average event in 2010, participants in the Offices, Hotels, Finance and Services segment provided 8.2 MW of aggregate load impacts. This segment comprises 44% of the aggregate load impact for all customers. Larger aggregate impacts for this sector were expected because it has more and larger participants, on average, then other business types. Outside of the few participants in the Other or unknown segment, customers in the Wholesale, Transport & Other Utilities provided the largest percent load impact (7.8%). Although this percent load impact is relatively high, load impacts per customer are relatively low because they have a low estimated reference load (160.2 kW).

Table 6-2:
Estimated Ex Post Load Impacts by Industry
Average 2010 SDG&E CPP Event

Industry	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event
Manufacturing	181	294.6	278.5	16.1	5.5%	2.9	81.4
Wholesale, Transport & Other Utilities	247	160.2	147.7	12.5	7.8%	3.1	82.2
Retail Stores	96	295.8	284.0	11.8	4.0%	1.1	81.1
Offices, Hotels, Finance, Services	409	378.1	358.1	20.0	5.3%	8.2	80.5
Schools	238	148.1	148.1	0.0	0.0%	0.0	81.7
Institutional/Government	172	215.2	206.7	8.5	4.0%	1.5	81.8
Other or Unknown	25	306.7	219.1	87.6	28.6%	2.2	81.4
All Customers	1,368	260.6	246.9	13.7	5.3%	18.8	81.3

6.3 Load Impacts by Customer Size

Table 6-3 shows the estimated ex post load impacts by customer size. In this table, size is defined by the average demand across the year, rather than by maximum demand levels. Participants with average usage above 500 kW provided the largest impact per customer, the largest percent reduction and the largest aggregate load impact. These customers comprised 51% of the aggregate load impact for all customers even though they comprised only 6% of the 1,368 participants. Participants with average usage between 100 and 200 kW provide the lowest percent load impact (1.9%). The percent load impact for small customers (under 50 kW) was 3.0%. While the aggregate load impact in this segment is only 0.4 MW, the results are instructive because of the planned default of small and medium customers onto the CPP tariff. To date, SDG&E provides the richest source of information concerning for medium customer price responsiveness under default dynamic pricing.

Table 6-3:
Estimated Ex Post Load Impacts by Customer Size
Average 2010 SDG&E CPP Event

Size	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event
Under 50 Average kW	370	39.7	38.5	1.2	3.0%	0.4	81.8
50-100 Average kW	293	129.9	125.1	4.8	3.7%	1.4	81.9
100-200 Average kW	347	216.3	212.2	4.1	1.9%	1.4	81.0
200-500 Average kW	274	431.7	412.0	19.7	4.6%	5.4	80.7
Over 500 Average kW	84	1224.5	1109.7	114.7	9.4%	9.6	80.9
All Customers	1,368	260.6	246.9	13.7	5.3%	18.8	81.3

6.4 Load Impacts for Voluntary CPP and Multi-program Participants

Figure 6-2 shows load impacts for customers who are dually-enrolled in BIP and CPP. Even though only 6 customers are represented here and they only make up 0.4% of CPP customers, they drive 21% of the aggregate CPP load impacts on the average event day. In order to achieve greater load impacts from all customers, SDG&E should consider evaluating precisely why these customers and other customers dually-enrolled in demand response programs such as CBP and Demand SMART respond with greater load reductions and use this information to develop educational packages to provide to other CPP customers.

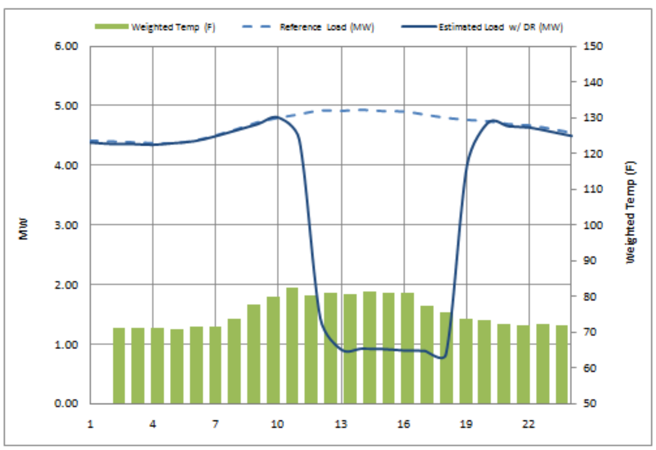
Figure 6-2:
2010 Hourly Ex Post Aggregate Load Impacts for BIP Customers Dually-enrolled in CPP Average Event Day

TABLE 1: Menu options

Type of Results	Aggregate
Customer Type	Dually Enrolled: BIP

TABLE 2: Event Day Information

Event Date	Average Event
Event Start	11:00 AM
Event End	6:00 PM
TOTAL ENROLLED ACCOUNTS	6
Avg. Load Reduction for Event Window	3.94
% Load Reduction for Event Window	**80.35%**



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact	%Load Reduction	Weighted Temp (F)
1	4.41	4.38	0.04	0.9%	71.1
2	4.40	4.35	0.05	1.1%	71.0
3	4.39	4.35	0.03	0.8%	71.2
4	4.37	4.34	0.04	0.8%	70.8
5	4.37	4.36	0.01	0.1%	71.4
6	4.41	4.40	0.02	0.3%	71.4
7	4.50	4.48	0.02	0.5%	73.7
8	4.61	4.58	0.03	0.6%	77.6
9	4.73	4.68	0.05	1.0%	79.9
10	4.80	4.79	0.01	0.2%	82.5
11	4.87	4.42	0.44	9.1%	80.1
12	4.93	1.43	3.50	71.0%	80.8
13	4.92	0.90	4.02	81.7%	80.7
14	4.94	0.92	4.03	81.5%	81.1
15	4.92	0.91	4.01	81.5%	80.9
16	4.91	0.89	4.03	82.0%	80.8
17	4.86	0.88	3.98	81.9%	77.4
18	4.80	0.82	3.98	82.8%	75.4
19	4.77	3.99	0.78	16.4%	73.8
20	4.75	4.70	0.04	0.9%	73.4
21	4.70	4.65	0.05	1.0%	72.2
22	4.67	4.63	0.05	1.1%	72.0
23	4.62	4.56	0.06	1.3%	72.0
24	4.55	4.49	0.06	1.3%	71.7
	Reference Energy Use (MW)	**Estimated Energy Use w/ DR (MW)**	**Total Load Impact (MW)**	**% Daily Load Change**	**Cooling Degree Hours (Base 65)**
Daily	112.21	82.88	29.32	26.13%	8.5

Table 6-4 shows load impacts for SDG&E customers who are dually-enrolled in other DR programs. It also shows load impacts for customers who are defined as medium based on maximum demand. Customers dually-enrolled in the CBP DR program provided an average impact of 30.9 kW relative to their 280.3 kW reference load. In aggregate, they provided 9% of the load impact on the average event day. Medium customers showed small average load impacts, percent load impacts and aggregate load impacts at 1.4 kW, 2.5% and 0.5 MW respectively. However, the medium customers that had been defaulted by 2010 were dominated by Schools and are not representative of the broader medium customer population scheduled to be defaulted onto CPP in the future.

Table 6-4:
Estimated Ex Post Load Impacts for Multi-DR & Voluntary CPP Participants
Average 2010 SDG&E CPP Event

Dual Enrollees and Medium Customers	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event
Dually-enrolled: BIP	6	816.5	160.5	656.0	80.3%	3.9	79.6
Dually-enrolled: CBP	52	280.3	249.4	30.9	11.0%	1.6	83.0
Dually-enrolled: Demand SMART	23	184.3	141.5	42.8	23.2%	1.0	83.3
Medium Customers (20 kW to 200 kW)	381	55.8	54.4	1.4	2.5%	0.5	81.8
Population Totals	1,368	260.6	246.9	13.7	5.3%	18.8	81.3

6.5 Distribution of Participant Price Responsiveness

Figure 6-3 shows the distribution of percent load impacts for the 376 SDG&E customers who showed load impacts greater than 5% for the average 2010 SDG&E CPP event. A little over 30% of these customers showed percent load impacts of less than 10%. At the other extreme, about 4% reduced load by close to 100% relative to their reference load.

Figure 6-3:
Distribution of Percent Load Impacts for SDG&E Customers
Average 2010 SDG&E CPP Event

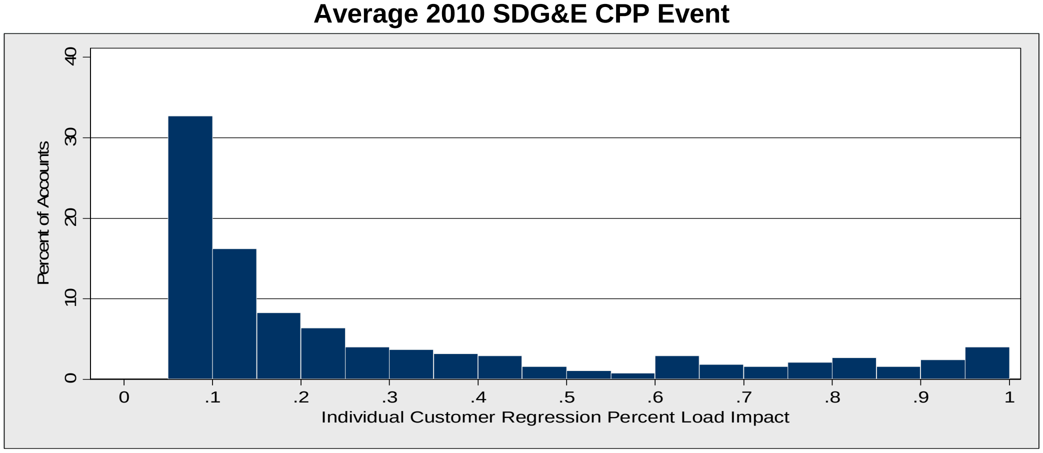
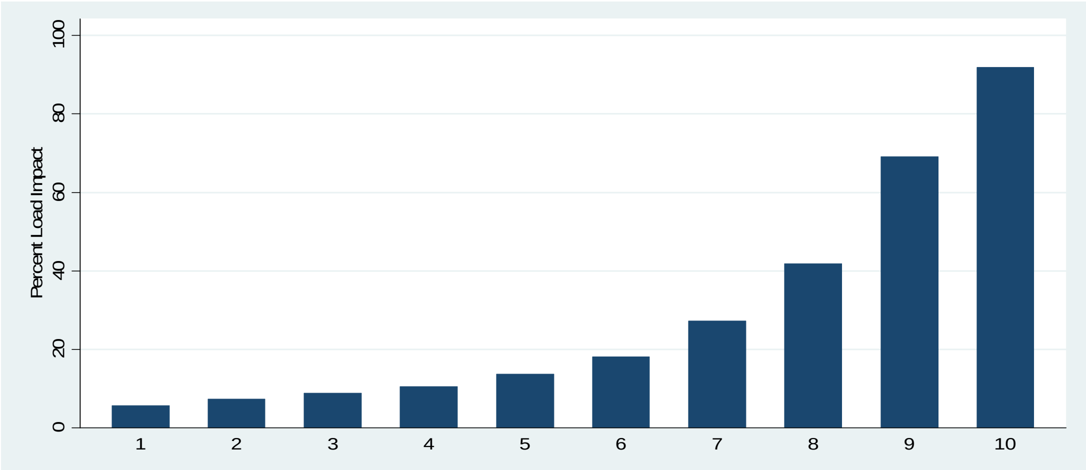


Figure 6-4 shows percent reductions for the 376 customers who provided percent load impacts of 5% or greater by price responsiveness deciles. Roughly 80 customers (20%) provided aggregate percent load impacts of more than 60%.

Figure 6-4:
Percent Drops by Customers by Price Responsiveness Deciles Average 2010 SDG&E CPP Event



6.6 Drivers of Price Responsiveness

For SDG&E, regression analysis was used to correlate variation in percent demand response with variables representing multi-year participation, bill protection, CPP price insurance (capacity reservation levels), TI and AutoDR, and other factors. Each event day experienced by each customer was treated as a separate observation, producing multiple observations per customer. The regression analysis included all 2009 and 2010 event days experienced under default CPP.

In most cases, disentangling the effects of first year bill protection from multi-year participation is difficult because the two are closely related. For SDG&E this was not the case. For most participants, bill protection expired in May, 2009, as initially scheduled. However, halfway through the 2009 summer, the CPUC retroactively extended bill protection for customers that defaulted in 2008 for an additional year. For the first half of 2009, those customers provided price response as if bill protection had expired since the extension of bill protection was not known at the time. For the latter half of the 2009 summer, they provided price response with bill protection. The regulatory change provided a unique opportunity to disentangle the effects of multi-year participation from bill protection.

Capacity reservation levels refer to the percent of load that customers choose to insure against high prices on CPP event days. By default, the CRL is set at 50% of maximum monthly demand averaged across summer months. Importantly, a customer's maximum demand is not necessarily coincident with system peaking conditions. As a result, roughly 20% of customers rarely or never exceed the default CRL. Customers with the same capacity reservation percentage (e.g., 50%) have different amounts of their event day load exposed to CPP prices. This occurs because of how the default CRL is determined and because loads naturally vary across event days. If a customer does not have load exposed to CPP prices, they have no incentive to reduce load. Likewise, if only 30% of a customer's load is exposed to CPP prices and the rest is insured against CPP prices, a customer does not have an economic incentive to reduce loads by more than 30%. Since the percent of load exposed to high CPP prices varied across event days, a variable was created that captured the percent of load on each event day for each customer that was exposed to CPP prices. This variable was based on the counter-factual. In theory, it was expected that the coefficient on this variable would be positive. That is, as more load becomes exposed to CPP prices, percent load impacts should increase.

TI and AutoDR are part of a multi-stage process that begins with technical assistance (TA), an audit of a customer's facilities to determine the potential for installing energy saving technology or processes. A technical incentive (TI) is paid if a customer installs equipment or reconfigures processes and demonstrates that they produce load reductions. With TI, the response is automated, but the customer still decides whether and when to drop load. AutoDR provides an incremental incentive to encourage customers to allow the utility to remotely dispatch the automated load reduction. To estimate the effect of TI and AutoDR on CPP event load reduction, a variable was included in the regression that reflects a customer's approved load reduction plan as a percent of their reference load on each event day. If the TI or AutoDR load shed is incremental, then its value approaches one. If it is not, its value is near zero.[13] SDG&E's TI and AutoDR programs are effectively rolled into one with AutoDR as a subset of TI.Ratio statistics were used to get at the realization rate – that is, how much of the approved load reduction from TI or AutoDR is realized in practice. Table 6-5 lists all variables included in the regression along with brief definitions for each variable.

Mathematically, the regression model is expressed as:

$$\begin{aligned} PercentImpact_{it} = {} & A + B_i \times Industry_i + C_i \times SizeBins_i \\ & + D_i \times MediumCustomer_i + E_{it} \times BIP_{it} + F_{it} \times DemandSMART_{it} \\ & + G_{it} \times CBP_{it} + H_{it} \times Temperature_{it} + I_{it} \times CRL_{it} + J_{it} \times Persistence_{it} \\ & + K_{it} \times BillProtection_{it} + L_{it} \times TI_{it} + M_{it} \times AutoDR_{it} + v_{it} \end{aligned}$$

Table 6-5:
Definitions and Logic for Inclusion

Variable	Definitions and Logic for Inclusion
$PecentImpact_{it}$	Represents the average percent impact for each individual, i, for each event, t;
A	Is a fixed population parameter;
B through M	Represent the regression model parameters;
$Industry_i$	Is a binary variable for customer i's industry. There are 8 industries with Agriculture, Mining, and Construction set as the base;
$SizeBins_i$	Is a binary variable for customer i's size bin (based on average kW). There are 5 size bins with Size: Under 50 kW as the base;
$MediumCustomer_i$	Is a binary variable indicating whether or not customer i is classified as a medium customer under SDG&E's definition (under 200 kW max demand);
BIP_{it}	Is a binary variable indicating whether customer i was enrolled in BIP during event t;

[13] In practice, there were few instances where a customer's load response could be observed before and after the installation of technology, which tempers the ability to draw conclusive findings on whether TI/AutoDR produces incremental impacts.

Variable	Definitions and Logic for Inclusion
$DemandSMART_{it}$	Is a binary variable indicating whether customer i was enrolled in Demand SMART during event t;
CBP_{it}	Is a binary variable indicating whether customer i was enrolled in CBP during event t;
$Temperature_{it}$	Is the average temperature in customer i's vicinity for event t;
CRL_{it}	Is the percent of customer i's reference load exposed to CPP pricing for event t (i.e., the percent of their reference load not insured against CPP pricing);
$Persistence_{it}$	Is a binary variable equal to 1 for 2010 events if customer i also experienced events in 2009. In other words, it captures the impact of second year events on percent load impacts.
$BillProtection_{it}$	Is a binary variable equal to 1 for all events, t, during which customer i was covered by bill protection.
TI_{it}	Is the percent of customer i's reference load that they are supposed to shed during event t due to TI;
$AutoDR_{it}$	Is the percent of customer i's reference load that they are supposed to shed during event t due to AutoDR, and;
V_{it}	Is the usual error term, e_{it} plus the random effect, u_{it}.

Table 6-6 shows the coefficient for each variable after random effects regression on percent load impacts. Customers who experience structural wins under CPP-D give bigger impacts. The logic for applying a random effects rather than fixed effects estimation method for the panel regression is documented in Section 4.7.

We can say with a high degree of certainty that both customers who experience 0% to 1% structural wins and customers who experience greater than 1% structural wins have larger percent impacts than customers who are structural losers. All of the coefficients on the industry dummy variables are significant except for the coefficient on Other. Relative to the percent load impacts for schools, which are set to zero, percent impacts are as much as 34.77 percentage points greater for customers in Agriculture, Mining & Construction and 28.85 percentage points for customers in Wholesale, Transport and other utilities.

Customer size, measured by average demand across the year, was included in the regression. Percent impacts for customers in the 50 kW or less size category were greater than those in the 50 kW to 100 kW and 100 kW to 200 kW categories in the ex post analysis (3.57%, 3.08% and 1.62% respectively). The regression corroborates that percent impacts for customers in the 50 kW to 100 kW and 100 kW to 200 kW categories are smaller than those for customers in the 50 kW or less category. The coefficients imply that smaller customers are more price responsive than larger ones after holding other factors constant. However, this conclusion is tempered by the results for medium customers. Medium customers have typically been defined by maximum demand rather than average demand across the year. SDG&E's medium CPP customers were dominated by schools. Percent load impacts for medium customers are 4.87 percentage points less than the mean value. It is possible that the results for medium customers are confounded with Schools, which provide no load reduction.

Most of the coefficients on the other variables are as expected. Percent impacts are 32.38 percentage points higher for customers dually-enrolled in the BIP program, and 11.10 percentage points higher for customers dually-enrolled in CBP. Unlike for PG&E, the CRL variable is significant and positive, which means that as the percent difference between an individual's reference load and their insured load increases (i.e., as more of the load becomes exposed to CPP prices), the percent load impacts for that individual increase. However, the increase is trivial at .01 percentage points for every 1 percentage point increase in the percent difference between an individual's reference load and their insured load. The dummy variable for persistence of impacts is insignificant, indicating that customers do not behave differently during their second or third year on the CPP program. The marginal effect of the dummy variable for bill protection is insignificant. This is plausible because the period during which customers were under bill protection was their only chance to figure out how the rate will impact them financially without being responsible for their losses. It would be in the interest of most customers to proceed with business as usual while bill protected and determine whether or not CPP pricing was in their best interest. The variables for TI and AutoDR are both insignificant largely due to a limited number of observations, so it's not certain that percent impacts increase incrementally as more of a customer's load is supposed to be shed during CPP periods. Throughout both 2009 and 2010, there were a total of 5 SDG&E CPP–D customers enrolled in the TI program and 10 customers enrolled in the AutoDR program for which data was available.

Table 6-6:
Regression Coefficients for Load Impact Drivers for SDG&E

Variable	Coef.	Std. Err.	Z	P>z	[95% Conf. Interval]	
Structural Wins						
Less than -2%	-0.21	2.31	-0.09	0.93	-4.74	4.32
-2% to -1%	-0.33	1.47	-0.22	0.82	-3.22	2.56
-1% to 0% (Base)						
0% to 1%	2.97	1.61	1.85	0.07	-0.18	6.13
Greater than 1%	7.86	2.12	3.70	0.00	3.70	12.01
Industry						
Agriculture, Mining & Construction	34.77	9.31	3.73	0.00	16.52	53.02
Manufacturing	18.03	2.42	7.45	0.00	13.29	22.78
Wholesale, Transport, other utilities	28.85	2.57	11.20	0.00	23.80	33.90
Retail stores	14.03	2.42	5.79	0.00	9.28	18.78
Offices, Hotels, Finance, Services	12.64	1.49	8.48	0.00	9.72	15.56
Schools (Base)						
Institutional/Government	14.05	1.88	7.49	0.00	10.37	17.73
Other or unknown	16.35	11.42	1.43	0.15	-6.03	38.73
Size						
50 kW or less (Base)						
50 kW to 100 kW	-9.47	2.46	-3.84	0.00	-14.30	-4.64
100 kW to 200 kW	-15.26	2.92	-5.23	0.00	-20.98	-9.54
200 kW to 500 kW	-12.03	3.29	-3.66	0.00	-18.47	-5.59
500 kW and up	-12.61	3.63	-3.48	0.00	-19.72	-5.50
Med. Cust. (20 kW to 200 kW)	-4.87	2.36	-2.07	0.04	-9.49	-0.25
BIP	32.38	17.84	1.81	0.07	-2.59	67.35
DemandSMART	3.20	3.49	0.92	0.36	-3.65	10.05
CBP	11.10	4.86	2.28	0.02	1.57	20.63
Temperature	0.22	0.05	4.24	0.00	0.12	0.33
CRL	0.01	0.01	2.34	0.02	0.00	0.03
Persistence of Impacts	-0.08	6.01	-0.01	0.99	-11.86	11.69
Bill Protection	-1.78	6.01	-0.30	0.77	-13.56	10.00
TI	-0.77	1.33	-0.58	0.56	-3.38	1.84
AutoDR	11.16	21.06	0.53	0.60	-30.12	52.45
Constant	-16.83	7.65	-2.20	0.03	-31.83	-1.83

Table 6-7 shows the realization rate for both TI and AutoDR. To calculate the realization rate ratio statistics were used with standard errors adjusted for clustering by customer. The realization rate for TI indicates that on average, 22% of the approved TI load shed is actually shed during events by customers who receive technical incentives. The realization rate for AutoDR, at 76%, is higher as expected since the AutoDR process is automated. Clearly customers on TI and AutoDR are reducing usage by a significant amount; but there are not enough data points to tease out the incremental impacts.

Table 6-7:
Realization Rates

Variable	Accts	Aggregate Approved kW	Realization Rate	Robust Std. Err.	[95% Conf.	Interval]
Technical Incentives (TI)	5	2900.0	22.0%	16.4%	-24.0%	67.0%
AutoDR	10	1263.5	76.0%	5.5%	64.0%	89.0%

Within the dataset the results of this analysis have predictive power; the regression on percent load impacts tells which characteristics correlate with percent load impacts. However, the results of this regression can't be interpreted as causal effects. They are merely descriptive, telling us something about the customers in the dataset. For TI and AutoDR especially, there isn't anything close to randomization of treatment. Customers were not selected randomly for TI and AutoDR, rather they volunteered. This, coupled with the few data points, makes it difficult to tease out incremental or even discrete impacts with certainty.

7 Ex Ante Load Impact Estimates for PG&E

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 DR 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 remainder of this section separately presents the ex ante load impact projections for medium and large customers projected to receive service under PG&E's CPP tariff. For each segment, the load reduction capability is summarized during annual system peak day conditions for a 1-in-2 and a 1-in-10 weather year for the 2011 to 2021 period. In addition, this section illustrates how impacts per customer vary by geographic location and month under the standardized ex ante conditions.

Small C&I and agricultural customer impacts are not included because, to date, there is almost no empirical data regarding their impacts under default dynamic pricing. The largest California study on small customer load impacts under dynamic pricing, the California Statewide Pricing Pilot, concluded that small customers did not produce statistically significant load reductions in the absence of enabling technology. PG&E's large agricultural customers were defaulted onto CPP in February, 2011 and empirical data on event day impacts is not yet available.

7.1 Large C&I Ex Ante Impacts

In total, approximately 1,670 large customers were enrolled in default CPP in 2010 and experienced 9 events. As a result, we now know initial year retention rates for default CPP, how much load reduction large customer provide during events and what types of customers are more responsive.

Table 7-1 shows The Brattle Group's enrollment projections for large customers through 2021. The development of the enrollment forecast and underlying assumptions are documented in The Brattle Group's "*Executive Summary: 2011-2021 Demand Response Portfolio of Pacific Gas and Electric Company* ." The forecasts show a sizeable increase in CPP enrollment between 2011 and 2012. In August 2011, 1,435 customers are forecast to receive service under the tariff, while in August 2012, 2,260 customers are projected to be served under the CPP rate schedule.

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

Forecast Year	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	1,670	1,686	1,689	1,691	1,486	1,449	1,442	1,435	1,433	1,429	1,454	1,450
2012	1,555	1,626	1,724	1,821	1,926	2,045	2,137	2,260	2,377	2,488	2,536	2,620
2013	2,649	2,661	2,637	2,630	2,601	2,577	2,546	2,530	2,507	2,486	2,451	2,437
2014	2,430	2,420	2,414	2,419	2,415	2,417	2,408	2,417	2,420	2,422	2,405	2,408
2015	2,413	2,410	2,404	2,410	2,407	2,408	2,400	2,408	2,411	2,414	2,396	2,400
2016	2,405	2,402	2,396	2,402	2,398	2,400	2,392	2,400	2,403	2,406	2,388	2,392
2017	2,396	2,394	2,388	2,394	2,390	2,392	2,384	2,392	2,395	2,398	2,380	2,384
2018	2,389	2,386	2,380	2,386	2,383	2,384	2,376	2,384	2,387	2,390	2,373	2,376
2019	2,381	2,378	2,372	2,379	2,375	2,376	2,368	2,377	2,380	2,382	2,365	2,369
2020	2,373	2,371	2,365	2,371	2,367	2,369	2,361	2,369	2,372	2,375	2,358	2,362
2021	2,366	2,363	2,358	2,364	2,360	2,362	2,354	2,362	2,365	2,368	2,351	2,354

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 2 PM to 6 PM historical event period for an August monthly system peak day. The average aggregate load impacts, presented in the sixth column, are similar for 1-in-2 and 1-in-10 weather year conditions. The aggregate impacts change substantially by forecast year in the near term. In 2011, the average aggregate load impact during an August event for the 1-in-10 weather year scenario is 21.7 MW. Largely because of population growth, the forecast impacts grow to 32.3 MW for the same scenario in 2012. An additional 1,200 customers that are large, but mostly on the A10 tariff, are projected to default in 2012 and 2014 after they have had hourly interval data for a full year. These customers largely drive the growth in impacts.

Table 7-2:
Aggregate Ex Ante Annual Peak Day Load Impacts for Large PG&E CPP Customers
(Hourly Average Reduction in MW Over Historic Event Day Period - 2 to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)[1]	Avg. Reference Load (MW 2-6 PM)	Avg. Estimated Load w DR (MW 2-6 PM)	Avg. Load impact (MW 2-6 PM)	% Load Reduction (MW 2-6 PM)	Weighted Temp (°F)
1-in-10 August System Peak Day	2011	1,435	562.5	540.8	21.7	3.9%	94.5
	2012	2,260	809.1	776.8	32.3	4.0%	95.6
	2013	2,530	900.9	865.7	35.2	3.9%	95.6
	2014	2,417	860.7	826.9	33.8	3.9%	95.6
	2015	2,408	857.2	823.5	33.7	3.9%	95.7
	2016	2,400	853.7	820.2	33.5	3.9%	95.7
	2017	2,392	850.3	816.9	33.4	3.9%	95.7
	2018	2,384	847.0	813.7	33.3	3.9%	95.7
	2019	2,377	843.7	810.5	33.2	3.9%	95.7
	2020	2,369	840.5	807.4	33.0	3.9%	95.7
	2021	2,362	837.3	804.4	32.9	3.9%	95.7
1-in-2 August System Peak Day	2011	1,435	554.5	532.8	21.6	3.9%	94.1
	2012	2,260	796.9	764.7	32.3	4.0%	94.3
	2013	2,530	887.7	852.6	35.1	4.0%	94.3
	2014	2,417	848.0	814.3	33.7	4.0%	94.3
	2015	2,408	844.5	810.9	33.6	4.0%	94.3
	2016	2,400	841.1	807.6	33.5	4.0%	94.3
	2017	2,392	837.7	804.4	33.3	4.0%	94.3
	2018	2,384	834.5	801.2	33.2	4.0%	94.3
	2019	2,377	831.2	798.1	33.1	4.0%	94.3
	2020	2,369	828.1	795.1	33.0	4.0%	94.3
	2021	2,362	824.9	792.1	32.9	4.0%	94.3

7.1.2 Ex Ante Load Impact Uncertainty

Underlying the impact estimates summarized above is a significant amount of uncertainty. Table 7-3 summarizes the uncertainty in the ex ante annual system peak load impact estimates for large customers. As can be seen, the uncertainty is large. For example, in 2012, the 80% confidence interval for 1-in-2 impacts ranges from 14.0 MW up to 50.1 MW. The major source of uncertainty is associated with the enrollment projections.

Table 7-3:
Aggregate Ex Ante Annual Peak Day Load Impacts for Large Customers with Uncertainty
(Hourly Average Reduction in MW Over the Historical Event Day Window- 2 to 6 PM)

Weather Year	Year	Expected Avg. Load Impact (MW 2-6 PM)	Impact Uncertainty				
			10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2011	21.7	9.5	17.4	21.7	26.4	33.5
	2012	32.3	14.0	25.9	32.3	39.5	50.1
	2013	35.2	15.4	28.3	35.2	43.0	54.3
	2014	33.8	14.7	27.1	33.8	41.3	52.2
	2015	33.7	14.7	27.0	33.7	41.1	52.0
	2016	33.5	14.6	26.9	33.5	41.0	51.8
	2017	33.4	14.6	26.8	33.4	40.8	51.6
	2018	33.3	14.5	26.7	33.3	40.7	51.4
	2019	33.2	14.5	26.6	33.2	40.5	51.3
	2020	33.0	14.4	26.5	33.0	40.4	51.1
	2021	32.9	14.4	26.4	32.9	40.2	50.9
1-in-2 August System Peak Day	2011	21.6	9.6	17.4	21.6	26.3	33.3
	2012	32.3	14.1	25.9	32.3	39.4	49.8
	2013	35.1	15.5	28.2	35.1	42.7	54.0
	2014	33.7	14.9	27.1	33.7	41.1	51.9
	2015	33.6	14.8	27.0	33.6	40.9	51.7
	2016	33.5	14.8	26.9	33.5	40.8	51.5
	2017	33.3	14.7	26.8	33.3	40.7	51.4
	2018	33.2	14.7	26.7	33.2	40.5	51.2
	2019	33.1	14.6	26.6	33.1	40.4	51.0
	2020	33.0	14.6	26.5	33.0	40.2	50.8
	2021	32.9	14.5	26.5	32.9	40.1	50.7

7.1.3 Ex Ante Impacts by Geographic Location

PG&E is comprised of seven geographic planning zones known as local capacity areas (LCAs). An eighth region, deemed 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 7-4 summarizes the ex ante load reduction capability available for each LCA by month for large customers. It shows the load reduction available for each monthly system peak day under 1-in-2 and 1-in-10 system peaking conditions. In aggregate, the load reductions are largest in the Greater Bay Area and Other. Based on the 2010 ex post analysis, more than 50% of customers are in the Greater Bay Area and about 17% are outside of the primary LCA's and classified as Other. In the ex post analysis, customers in Other provided 33% of aggregate impacts despite only accounting for 17% of the total population. By comparison, customers in the Greater Bay Area accounted for 35% of aggregate impacts despite representing 50% of the accounts. Customers in the Other LCA are larger, on average, than customers in the Greater Bay Area and provide larger per-customer impacts.

Table 7-4:
2014 Aggregate Ex Ante Annual Impacts for Large Customers by Local Capacity Area
(Hourly Average Reduction in MW Over the Event Window - 2 to 6 PM)

Weather Year	Local Capacity Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	Greater Bay Area	18	18	18	14	12	3	9	12	8	14	18	18
	Greater Fresno	3	3	3	4	4	4	4	4	4	4	3	3
	Kern	3	3	3	3	3	3	3	2	3	3	3	3
	Northern Coast	3	3	3	3	2	3	2	2	2	2	3	3
	Other	17	17	17	13	9	8	7	7	10	11	17	17
	Sierra	-2	-2	-2	0	2	2	4	4	2	3	-2	-2
	Stockton	1	1	1	2	2	2	3	2	2	2	1	1
	All Customers	**44**	**44**	**44**	**38**	**34**	**25**	**31**	**34**	**31**	**39**	**44**	**44**
1-in-2	Greater Bay Area	18	18	18	14	17	7	11	10	15	13	18	18
	Greater Fresno	3	3	3	4	4	4	4	4	4	4	3	3
	Kern	3	3	3	3	3	3	3	3	3	3	3	3
	Northern Coast	3	3	3	3	2	3	2	2	2	3	3	3
	Other	17	17	17	14	11	11	8	10	10	13	17	17
	Sierra	-2	-2	-2	0	2	2	3	3	3	0	-2	-2
	Stockton	1	1	1	1	2	2	2	2	2	1	1	1
	All Customers	**44**	**44**	**44**	**39**	**41**	**31**	**34**	**34**	**40**	**37**	**44**	**44**

Load impacts during the winter months of October through May should be used with caution. Recent dynamic pricing events in PG&E's CPP program have occurred on hot summer days. As such, the winter impact estimates are based on average percent reductions from the summer period for the event day with the least cooling degree hours, to reflect load reductions associated with usage that is less related to weather-sensitive load. They are a crude proxy for what load reductions might be during the winter period, when lightning and other factors that do not influence summer load shifting could have an important impact. The willingness of consumers to shift load associated with other end uses may also have a seasonal pattern that is not captured through the approach used here. In general, there is very limited information available (not just in California but elsewhere as well) concerning what load shifting behavior might be in the winter under dynamic rates.

7.2 Medium C&I Ex Ante Impacts

Overall, there is less certainty regarding medium customer impacts under default CPP. To date, relatively few PG&E medium customers have been defaulted onto CPP. Most of the medium accounts that defaulted in 2010 were schools and are not representative of the medium segment. To obtain a larger and more diverse sample, customers from the large category with average hourly demands below 100 kW, were used as a proxy for medium customers. The results were weighted to account for differences in industry mix and/or geographic location.

The ex ante load impact estimates for CPP reflect statistical uncertainty and enrollment uncertainty in estimates of average customer load impacts. Table 7-5 shows PG&E's enrollment projections for medium customers through 2021. There is a large increase in enrollment projected between 2011 and 2012. Starting in November 2011, medium customers that have had hourly interval data collected for at least 12 months will begin defaulting onto CPP, leading to the increase in enrollment. The increase in enrollment is gradual because it is tied to the roll out of smart meters. In August of 2011, 147 medium customers are forecast to receive service under the tariff, most of whom voluntarily enrolled in CPP. In contrast, by August 2012, 15,866 medium customers are projected to be served under the rate schedule.

Table 7-5
PG&E's Enrollment Projections for Medium CPP Customers by Forecast Year and Month

Forecast Year	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	172	172	172	172	151	148	147	147	146	146	4,604	4,840
2012	6,233	7,427	8,759	9,963	11,473	13,020	14,390	15,866	17,308	18,663	18,786	19,749
2013	20,024	20,202	20,022	19,850	19,547	19,232	18,954	18,655	18,357	18,079	17,852	17,645
2014	17,525	17,451	17,454	17,462	17,479	17,494	17,509	17,522	17,534	17,544	17,552	17,561
2015	17,573	17,584	17,599	17,617	17,633	17,648	17,661	17,674	17,685	17,694	17,702	17,711
2016	17,722	17,733	17,747	17,765	17,781	17,796	17,809	17,821	17,832	17,842	17,849	17,857
2017	17,868	17,879	17,893	17,910	17,926	17,940	17,953	17,965	17,976	17,985	17,992	18,000
2018	18,011	18,022	18,036	18,053	18,069	18,083	18,096	18,108	18,118	18,127	18,135	18,142
2019	18,153	18,163	18,176	18,194	18,209	18,223	18,235	18,247	18,257	18,266	18,273	18,280
2020	18,290	18,300	18,313	18,330	18,345	18,358	18,370	18,382	18,392	18,400	18,407	18,414
2021	18,424	18,434	18,447	18,464	18,478	18,491	18,504	18,515	18,524	18,533	18,539	18,546

The remainder of this section presents the ex ante load impact projections for medium customers projected to receive service under PG&E's CPP tariff. The load reduction capability for these customers is summarized on the annual system peak day under 1-in-2 and 1-in-10 weather year conditions for the 2011 to 2021 period. In addition, per customer impacts by geographic location and month are provided under the standardized ex ante conditions.

7.2.1 Annual System Peak Day Impacts

Table 7-6 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 2 PM to 6 PM historical event period for an August monthly system peak day. The average aggregate load impacts, presented in the sixth column, are slightly higher under 1-in-10 conditions as expected. And, impacts increase proportionally with population growth. In 2011, the average aggregate load impact during an August event for the 1-in-10 weather year scenario is 0.4 MW for medium customers. Due to the planned default of PG&E's medium C&I population, the impacts are projected to grow to 37.2 MW for the same scenario in 2012. Impacts for August reach their peak at 43.4 MW in 2013 with 18,655 customers enrolled.

Table 7-6:
Aggregate Ex Ante Annual Peak Day Load Impacts for Medium PG&E CPP Customers
(Hourly Average Reduction in MW Over Historic Event Day Period - 2 to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)[1]	Avg. Reference Load (MW 2-6 PM)	Avg. Estimated Load w DR (MW 2-6 PM)	Avg. Load impact (MW 2-6 PM)	% Load Reduction (2-6 PM)	Weighted Temp (°F)
1-in-10 August System Peak Day	2011	147	5.8	5.3	0.4	7.0%	95.6
	2012	15,866	592.7	555.4	37.2	6.3%	96.2
	2013	18,655	700.6	657.2	43.4	6.2%	95.9
	2014	17,522	657.0	616.2	40.8	6.2%	96.1
	2015	17,674	663.3	622.1	41.2	6.2%	96.1
	2016	17,821	669.3	627.8	41.5	6.2%	96.1
	2017	17,965	675.2	633.3	41.9	6.2%	96.1
	2018	18,108	681.1	638.8	42.3	6.2%	96.1
	2019	18,247	686.8	644.1	42.6	6.2%	96.1
	2020	18,382	692.3	649.3	43.0	6.2%	96.1
	2021	18,515	697.7	654.4	43.3	6.2%	96.1
1-in-2 August System Peak Day	2011	147	5.5	5.1	0.4	7.3%	94.2
	2012	15,866	566.4	529.0	37.4	6.6%	94.5
	2013	18,655	670.3	627.1	43.2	6.4%	94.4
	2014	17,522	628.2	587.6	40.6	6.5%	94.4
	2015	17,674	634.1	593.2	41.0	6.5%	94.4
	2016	17,821	639.9	598.6	41.3	6.5%	94.4
	2017	17,965	645.6	603.9	41.7	6.5%	94.4
	2018	18,108	651.2	609.1	42.1	6.5%	94.4
	2019	18,247	656.6	614.2	42.4	6.5%	94.4
	2020	18,382	661.9	619.1	42.7	6.5%	94.4
	2021	18,515	667.1	624.0	43.1	6.5%	94.4

7.2.2 Ex Ante Load Impact Uncertainty

Underlying the impact estimates summarized above is a significant amount of uncertainty. Table 7-7 summarizes the uncertainty in the ex ante annual system peak load impact estimates for medium customers. For 2012, the 80% confidence interval for 1-in-2 impacts ranges from 10.2 MW up to 63.5 MW, a difference of close to 54 MW. The majority of uncertainty once again is associated with enrollment projections.

Table 7-7:
Aggregate Ex Ante Annual Peak Day Load Impacts for Medium Customers with Uncertainty
(Hourly Average Reduction in MW Over the Historical Event Day Window- 2 to 6 PM)

Weather Year	Year	Expected Avg. Load Impact (MW 2-6 PM)	Impact Uncertainty				
			10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2011	0.4	0.2	0.3	0.4	0.5	0.6
	2012	37.2	10.2	27.8	37.2	47.8	63.5
	2013	43.4	13.2	32.8	43.4	55.2	72.8
	2014	40.8	12.3	30.8	40.8	51.9	68.5
	2015	41.2	12.4	31.1	41.2	52.4	69.1
	2016	41.5	12.5	31.4	41.5	52.9	69.8
	2017	41.9	12.6	31.7	41.9	53.3	70.4
	2018	42.3	12.8	31.9	42.3	53.8	71.0
	2019	42.6	12.9	32.2	42.6	54.2	71.6
	2020	43.0	13.0	32.4	43.0	54.7	72.1
	2021	43.3	13.1	32.7	43.3	55.1	72.7
1-in-2 August System Peak Day	2011	0.4	0.2	0.3	0.4	0.5	0.6
	2012	37.4	12.5	28.7	37.4	47.2	61.7
	2013	43.2	15.3	33.4	43.2	54.1	70.4
	2014	40.6	14.3	31.4	40.6	50.8	66.1
	2015	41.0	14.4	31.7	41.0	51.3	66.7
	2016	41.3	14.6	31.9	41.3	51.8	67.3
	2017	41.7	14.7	32.2	41.7	52.2	67.9
	2018	42.1	14.8	32.5	42.1	52.7	68.5
	2019	42.4	14.9	32.8	42.4	53.1	69.1
	2020	42.7	15.1	33.0	42.7	53.5	69.6
	2021	43.1	15.2	33.3	43.1	53.9	70.2

7.2.1 Ex Ante Impacts by Geographic Location

Table 7-8 summarizes the ex ante load reduction capability available for each LCA by month for medium customers. It shows the load reduction available for each monthly system peak day under 1-in-2 and 1-in-10 system peaking conditions. In aggregate, the load reductions are largest in the Greater Bay Area, Greater Fresno and Other. For an August monthly system peak day under 1-in-2 conditions, the Greater Bay Area provides 8 MW of load reduction, Greater Fresno provides 11 MW and Other provides 13 MW. Impacts in Greater Fresno and Other increase with temperature, going up in summer months. On the other hand, impacts in the Greater Bay Area go down during summer months. As mentioned before, load impacts during the winter months of October through May should be used with extreme caution.

Table 7-8:
2014 Aggregate Ex Ante Annual Impacts for Medium Customers by Local Capacity Area
(Hourly Average Reduction in MW Over the Event window - 2 to 6 PM)

Weather Year	Local Capacity Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	Greater Bay Area	26	26	26	15	7	1	-1	6	5	11	26	26
	Greater Fresno	6	6	6	9	12	12	14	14	11	10	6	6
	Kern	5	5	5	5	5	5	5	5	5	5	5	5
	Northern Coast	6	6	6	4	2	2	0	0	1	2	6	6
	Other	7	7	7	10	13	16	15	14	12	11	7	7
	Sierra	2	2	2	1	1	0	0	0	0	0	2	2
	Stockton	2	2	2	2	2	2	3	2	2	2	2	2
	All Customers	**55**	**54**	**54**	**46**	**41**	**39**	**35**	**41**	**37**	**42**	**55**	**55**
1-in-2	Greater Bay Area	26	26	26	17	19	7	6	8	12	15	26	26
	Greater Fresno	6	6	6	8	11	11	13	11	12	9	6	6
	Kern	5	5	5	5	5	5	5	5	5	5	5	5
	Northern Coast	6	6	6	4	3	2	2	1	1	4	6	6
	Other	7	7	7	10	11	11	14	13	12	11	7	7
	Sierra	2	2	2	2	0	0	0	0	0	1	2	2
	Stockton	2	2	2	2	2	2	2	2	2	2	2	2
	All Customers	**55**	**54**	**54**	**48**	**52**	**39**	**42**	**41**	**44**	**48**	**55**	**55**

8 Ex Ante Load Impact Estimates for SCE

This report section presents ex ante load impact estimates for SCE's CPP tariff. 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. These estimates are used in assessing alternatives for meeting peak demand, cost-effectiveness comparisons and long-term planning.

The ex ante load impact estimates for SCE reflect statistical uncertainty in estimates of average customer load impacts. However, they do not incorporate enrollment uncertainty. Enrollment uncertainty is greatest when substantial program growth is projected. It is relatively small when enrollment and resources are maintained constant – that is when new enrollment simply replaces closed accounts or customers that leave the rate.

The enrollment estimates for SCE assume attrition between the current time period and 2012 as customers who enrolled on CPP for the first time with the October 2009 default determine whether to continue on the rate. The first two years of experience allows the opportunity to assess if the rate fits their electricity use patterns and load reduction capability. Customers that voluntarily enrolled in CPP before it became the default rate are expected to remain on CPP because both actively elected CPP as their tariff and have had prior experience with the tariff. Table 8-1 shows SCE's enrollment projections through 2021. SCE is assuming a high attrition rate from the CPP tariff prior to 2012. On average 4,100 accounts participated in 2010 events. By January 2012 only 2,465 customers are projected to be served under the rate schedule. The decline in enrollment is assumed to occur as bill protection expires for customers that are trying out default CPP for the first time.

Table 8-1:
SCE's Enrollment Projections for the CPP Tariff by Forecast Year and Month

Forecast Year	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011					3386	3299	3213	3127	2995	2862	2730	2597
2012	2465	2472	2479	2487	2494	2501	2508	2516	2523	2530	2538	2545
2013	2552	2560	2567	2574	2582	2589	2596	2604	2611	2618	2626	2633
2014	2641	2648	2655	2663	2670	2677	2685	2692	2692	2692	2692	2692
2015-2021	2692	2692	2692	2692	2692	2692	2692	2692	2692	2692	2692	2692

The remainder of this section contains the ex ante load impact projections for SCE's CPP tariff. The load reduction capability is summarized for the program on the annual system peak day under 1-in-2 and 1-in-10 weather year conditions for the 2011 to 2021 period. In addition, this section contains per customer impacts are provided by geographic location and month under the standardized ex ante conditions.

8.1 Annual System Peak Day Impacts

At the end of 2010, SCE had roughly 4,000 large accounts enrolled in CPP. By 2012, enrollment is projected to drop to roughly 2,500 service accounts, but the decline is only assumed to occur among customers that were trying out default CPP for the first time. The impact estimates assume that the roughly 400 customers that voluntarily enrolled in CPP before it became the default rate do not opt out at the same rate as customers who were defaulted onto the tariff. These customers are larger and account for two thirds (20 out of 30 MW) of the 2010 ex post load impacts.

Table 8-2 summarizes the CPP ex ante impacts for 1-in-2 and 1-in-10 conditions through 2021. It shows the average load reduction across the 2 PM to 6 PM historical event period for an August monthly system peak day. 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 22.8 MW. At the upper end, the forecasted aggregate impacts are 26.8 MW in 2010 under the 1-in-2 weather year scenario. In general, large CPP customers are not highly weather sensitive so their impacts do not change much with higher temperatures. Although SCE is expecting enrollment to decrease by a significant margin, the load drops do not change substantially because it is assumed that customers who voluntarily enrolled and account for most of the impacts will remain on the rate. Put differently, while large C&I CPP enrollment drops, impacts remain relatively constant.

Table 8-2:
Aggregate Ex Ante Annual System Peak Day Load Impacts for SCE's CPP Tariff by Year
(Hourly Average Reduction in MW Over Historic Event Day Period - 2 to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load (MW 2-6 PM)	Avg. Estimated Load w DR (MW 2-6 PM)	Avg. Load impact (MW 2-6 PM)	% Load Reduction (MW 2-6 PM)	Weighted Temp (°F)
1-in-10 August System Peak Day	2011	3,127	890.2	864.0	26.2	2.9%	94.6
	2012	2,516	719.3	694.9	24.3	3.4%	94.6
	2013	2,604	728.1	705.3	22.8	3.1%	94.4
	2014	2,692	773.7	748.8	25.0	3.2%	94.4
	2015-2021	2,692	759.1	735.8	23.4	3.1%	94.6
1-in-2 August System Peak Day	2011	3,127	874.3	847.5	26.8	3.1%	92.9
	2012	2,516	705.0	680.3	24.7	3.5%	93.0
	2013	2,604	715.8	692.8	22.9	3.2%	92.8
	2014	2,692	760.5	734.6	25.9	3.4%	92.8
	2015-2021	2,692	746.6	722.8	23.8	3.2%	93.0

Figures 8-1 and 8-2 show the impacts by hour for the annual peak day based on 1-in-2 year weather conditions for 2011 and 2012. They illustrate how enrollment changes substantially, but aggregate impacts stay relatively constant. The figures are an example of the electronic appendices included with this report, which contain hourly load impact tables for each day type, weather year and forecast year.

As seen in Figure 8-1, in 2011 the aggregate reference load decreases steadily over the 4-hour event period, from roughly 930 MW to 810 MW. Both the load drop (MW) and the percent load drop vary across the hours, with the lowest load drop occurring in the last event hour. Impacts vary with the magnitude of the reference load and range from 23.8 MW to 29.6 MW.

In contrast, the 2012 electricity consumption patterns differ largely in scale, but not significantly in the magnitude of load impacts. In total, 611 customers are projected to opt out from default CPP between August 2011 and August 2012, leading to lower program loads than in 2011. The aggregate reference load is much lower than in 2011, decreasing steadily over the 4-hour event period, from roughly 750 MW to 650 MW. Despite lower program loads, 2012 aggregate impacts are comparable to those in 2011 and range from 22.0 MW to 26.5 MW. In addition, the 2012 percent load impacts are slightly larger than those in 2011; 3.5% versus 3.1%.

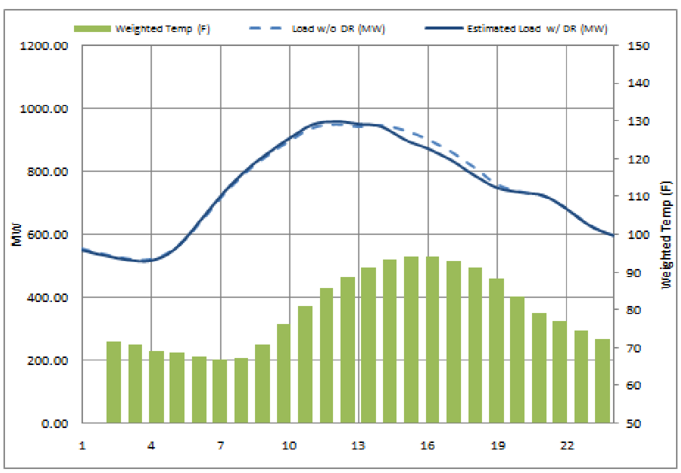
Figure 8-1:
Hourly Aggregate Load Reduction for CPP for an August Monthly System Peak Day
1-in-2 Weather Year Conditions and 2011 Program Enrollment

TABLE 1: Menu options

Type of Results	Aggregate
Local Capacity Area	All Customers
Day type	August Monthly Peak
Weather Year	1-in-2
Forecast Year	2011

TABLE 2: Event Day Information

Event Start	2:00 PM
Event End	6:00 PM
Load Reduction for RA Window	26.78
% Load Reduction for RA Window	3.1%
Forecast Customers Enrolled	3127



Hour Ending	Load w/o DR (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)
1	552.17	550.69	1.48	0.3%	71.5
2	534.27	533.60	0.67	0.1%	70.7
3	520.24	519.97	0.28	0.1%	69.2
4	518.38	517.43	0.96	0.2%	68.7
5	551.29	551.29	0.00	0.0%	67.7
6	623.45	631.34	-7.89	-1.3%	66.9
7	711.94	719.88	-7.94	-1.1%	67.3
8	787.53	794.86	-7.32	-0.9%	70.7
9	846.23	853.71	-7.48	-0.9%	76.4
10	894.42	903.45	-9.03	-1.0%	81.1
11	936.13	946.62	-10.49	-1.1%	85.6
12	947.57	956.60	-9.02	-1.0%	88.6
13	940.26	948.30	-8.04	-0.9%	91.2
14	944.33	939.94	4.39	0.5%	93.5
15	927.98	898.41	29.57	3.2%	93.9
16	898.94	870.62	28.31	3.1%	93.9
17	859.97	834.55	25.42	3.0%	92.8
18	810.26	786.45	23.80	2.9%	91.0
19	756.00	747.06	8.94	1.2%	88.4
20	733.21	732.75	0.46	0.1%	83.6
21	719.40	722.50	-3.10	-0.4%	79.3
22	679.26	680.71	-1.45	-0.2%	76.9
23	626.33	627.33	-1.00	-0.2%	74.6
24	594.66	596.72	-2.06	-0.3%	72.4
	Total Enery Use w/o DR (MW)	Observed Energy Use (MW)	Change in Energy Use (MW)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	17,914.24	17,864.79	49.46	0%	81.1

Note: A positive value % Daily Load Change indicates the use of less energy for the day.
Note: Commercial loads are whole-building loads

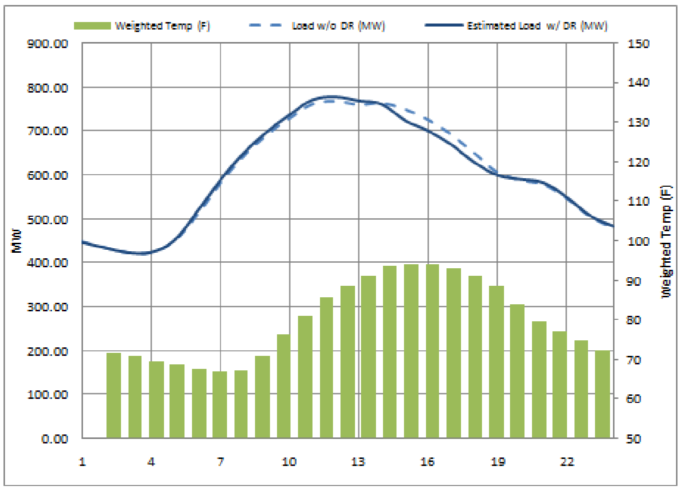
Figure 8-2:
Hourly Aggregate Load Reduction for PDP Tariff for a July Monthly System Peak Day
1-in-2 Weather Year Conditions and 2012 Program Enrollment

TABLE 1: Menu options

Type of Results	Aggregate
Local Capacity Area	All Customers
Day type	August Monthly Peak
Weather Year	1-in-2
Forecast Year	2012

TABLE 2: Event Day Information

Event Start	2:00 PM
Event End	6:00 PM
Load Reduction for RA Window	24.71
% Load Reduction for RA Window	3.5%
Forecast Customers Enrolled	2516



Hour Ending	Load w/o DR (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)
1	448.61	446.16	2.46	0.5%	71.6
2	435.38	433.30	2.08	0.5%	70.8
3	423.89	422.39	1.50	0.4%	69.2
4	423.88	422.73	1.16	0.3%	68.8
5	449.37	449.37	0.00	0.0%	67.8
6	508.65	515.32	-6.68	-1.3%	66.9
7	581.54	587.33	-5.79	-1.0%	67.3
8	642.95	648.74	-5.79	-0.9%	70.7
9	691.24	696.96	-5.73	-0.8%	76.4
10	729.76	736.90	-7.14	-1.0%	81.1
11	762.29	770.70	-8.41	-1.1%	85.6
12	768.67	777.45	-8.78	-1.1%	88.6
13	760.89	768.75	-7.85	-1.0%	91.2
14	764.18	760.83	3.35	0.4%	93.5
15	750.49	724.04	26.46	3.5%	94.0
16	726.42	700.08	26.34	3.6%	94.0
17	692.94	668.91	24.03	3.5%	92.9
18	650.19	628.19	22.00	3.4%	91.1
19	606.35	599.07	7.28	1.2%	88.5
20	588.89	589.79	-0.90	-0.2%	83.7
21	578.72	581.80	-3.08	-0.5%	79.5
22	547.31	548.79	-1.49	-0.3%	77.0
23	505.72	506.75	-1.03	-0.2%	74.7
24	480.79	482.67	-1.88	-0.4%	72.5
	Total Enery Use w/o DR (MW)	Observed Energy Use (MW)	Change in Energy Use (MW)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	14,519.14	14,467.02	52.12	0%	81.7

Note: A positive value % Daily Load Change indicates the use of less energy for the day.
Note: Commercial loads are whole-building loads

8.2 Ex Ante Load Impact Uncertainty

Table 8-3 summarizes the uncertainty in the ex ante annual system peak load impact estimates. The statistical uncertainty of the impact estimates is substantial due to the relatively small percent impacts. For example, for 2012, the 80% confidence interval for 1-in-10 impacts ranges from 18.2 MW up to 30.4 MW - a swing of 11.2 MW.

Table 8-3:
Aggregate Ex Ante Annual System Peak Day Load Impacts with Uncertainty
(Hourly Average Reduction in MW Over the Historical Event Day Window- 2 to 6 PM)

Weather Year	Year	Expected Avg. Load Impact (MW 2-6 PM)	Impact Uncertainty				
			10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2011	26.2	20.1	23.7	26.2	28.7	32.3
	2012	24.3	18.2	21.8	24.3	26.8	30.4
	2013	22.8	18.2	20.9	22.8	24.7	27.4
	2014	25.0	19.0	22.5	25.0	27.4	31.0
	2015-2021	23.4	18.3	21.3	23.4	25.4	28.4
1-in-2 August System Peak Day	2011	26.8	20.9	24.4	26.8	29.2	32.7
	2012	24.7	18.8	22.3	24.7	27.1	30.6
	2013	22.9	18.4	21.1	22.9	24.8	27.5
	2014	25.9	20.0	23.5	25.9	28.2	31.7
	2015-2021	23.8	18.9	21.8	23.8	25.9	28.8

8.3 Ex Ante Impacts by Geographic Location

SCE is comprised of three geographic planning zones known as local capacity areas (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 8-4 summarizes the ex ante load reduction capability available for each LCA by month. It shows the load reduction available for each monthly system peak day under 1-in-2 and 1-in-10 system peaking conditions. In the aggregate, the load reductions are largest in the LA Basin. This is because there are far more participants in the LA Basin than in any other LCA. In fact, the LA Basin accounts for over 87% of the load reduction capability for the August monthly system peak day under 1-in-2 weather conditions. This is simply due to the fact that 83% of SCE's CPP participants are located in the LA Basin.

Table 8-4:
2012 Aggregate Ex Ante Annual Impacts by Local Capacity Area
(Hourly Average Reduction in MW Over the Event window - 2 to 6 PM)

Weather Year	Local Capacity Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	LA Basin	21	23	23	19	24	22	20	21	20	22	16	25
	Outside LA Basin	1	1	1	1	1	1	1	1	1	1	1	1
	Ventura	4	3	3	2	3	3	3	3	3	3	1	4
	All Customers	**26**	**26**	**27**	**22**	**28**	**26**	**23**	**25**	**23**	**27**	**19**	**31**
1-in-2	LA Basin	21	23	24	24	24	24	21	22	21	21	23	25
	Outside LA Basin	1	1	1	1	1	1	1	1	1	1	2	1
	Ventura	4	4	4	4	3	3	3	3	3	3	3	4
	All Customers	**26**	**28**	**29**	**28**	**28**	**28**	**24**	**26**	**24**	**25**	**27**	**31**

8.4 Per Customer Ex Ante Reference Loads and Impacts

It is instructive to look at ex ante per customer estimates of peak reference loads and load reduction independent of enrollment projections. As noted earlier, the biggest source of uncertainty in aggregate ex ante impacts arise from the enrollment projections under default CPP. The per customer impacts can also help inform how results may vary with different enrollment mix, targeting strategies or default CPP policies.

Table 8-5 shows the average reference loads and load reduction over the 2 PM to 6 PM event window for the average customer in 2014 by industry, month and weather year. The Other or Unknown industry category was omitted because there are few customers in this category and the results have little causal validity. Within each industry, the overall load absent DR – the reference loads – vary significantly with weather year and month. Industrial customers such as those in Agriculture, Mining & Construction, Manufacturing and Wholesale, Transport and Other Utilities are not particularly weather sensitive. For example, under 1-in-2 weather conditions, the highest per customer reference load for Wholesale, Transport and Other Utilities occurs in November. Loads for these segments are lower during summer months when SCE peak period prices are higher. On the other hand, the load shapes of commercial customers are positively correlated with temperatures. Retail stores, Offices, Hotels, Finance, Services, Schools and Institutional/Government all reach their highest per customer reference loads in the summer months of July through September under both 1-in-2 and 1-in-10 weather scenarios.

Table 8-5:
2010 Per Customer Reference Loads in 1-in-2 and 1-in-10 Weather Years
(Average Over the Historical Event window - 2 to 6 PM)

Weather Year	Industry	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	Mining & Construction	102	119	127	152	138	109	157	146	154	148	125	156
	Manufacturing	250	280	280	289	291	289	280	294	282	295	284	238
	Wholesale & Transport	231	220	249	258	264	256	251	259	245	270	274	230
	Retail stores	239	252	278	287	311	306	310	324	309	289	295	221
	Offices & Hotels	254	280	298	307	313	329	325	325	335	308	304	228
	Schools	147	175	198	201	208	205	214	221	242	225	224	155
	Institutional/Government	160	235	237	252	284	318	341	312	294	286	275	195
1-in-2	Mining & Construction	108	107	107	153	135	110	157	146	152	150	120	158
	Manufacturing	248	264	258	279	286	282	278	291	282	295	277	237
	Wholesale & Transport	225	207	225	240	259	246	245	256	244	270	260	231
	Retail stores	238	223	233	264	302	291	305	319	306	290	277	224
	Offices & Hotels	249	253	248	280	303	310	319	319	333	310	281	231
	Schools	147	154	160	172	194	184	202	212	233	228	189	156
	Institutional/Government	157	200	186	230	272	300	334	306	290	280	258	206

Table 8-6 shows the average load reduction per customer over the 2 PM to 6 PM event window for each industry, month and weather year. Industrial customers show much larger load impacts. For example, the average load reduction per CPP customer in the Manufacturing industry is between 27 and 29 kW, 9% to 10%, in the June to September months under both 1-in-2 and 1-in-10 conditions. Customers in the Wholesale & Transport sector are also more price responsive than average, delivering load impacts between 6% to 9% during the summer months. Retail stores produce an average impact of 5 kW per CPP customer, a reduction of slightly less than 2%. The impacts for Offices & Hotels, Schools, and Institutional/Government are not statistically significantly different from zero.

Table 8-6:
Average Load Reduction per CPP Customer (kW) During Peak Period by Industry and Month for 2014 (1-in-2 and 1-in-10 Year Weather Conditions)

Weather Year	Industry	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	Mining & Construction	7	17	13	15	5	13	10	9	6	7	12	21
	Manufacturing	23	28	27	22	29	28	28	28	26	28	23	26
	Wholesale & Transport	16	12	19	17	17	19	16	21	20	18	17	17
	Retail stores	6	5	5	4	4	4	5	5	2	5	2	6
	Offices & Hotels	0	-2	-3	-6	-2	-4	-5	-6	-6	-3	-9	1
	Schools	0	0	0	0	0	0	0	0	0	0	0	0
	Institutional/Government	-1	-2	0	1	-1	-2	-3	-3	-5	-1	-3	1
1-in-2	Mining & Construction	7	17	20	16	7	14	13	9	7	12	11	21
	Manufacturing	23	27	25	26	28	28	27	27	27	25	27	26
	Wholesale & Transport	16	13	18	17	17	18	16	20	20	19	15	17
	Retail stores	6	5	4	4	4	4	5	6	3	6	4	6
	Offices & Hotels	0	1	1	-1	-1	-2	-4	-5	-6	-6	-2	1
	Schools	0	0	0	0	0	0	0	0	0	0	0	0
	Institutional/Government	-1	-1	1	2	0	-2	-3	-3	-5	-2	0	1

Load impacts during the winter months of October through May should be used with extreme caution. Recent dynamic pricing events in SCE's CPP program have occurred on hot summer days. In general, there is very limited information available (not just in California but elsewhere as well) concerning what load shifting behavior might be in the winter under dynamic rates.

9 Ex Ante Load Impact Estimates for SDG&E

This section presents ex ante load impact estimates for SDG&E. Load impacts during the winter months of November through March should be used with extreme caution were set at zero due the lack of empirical event data during those months. Recent CPP dynamic pricing events have occurred on hot summer days. In general, there is very limited information available (not just in California but elsewhere as well) concerning what load shifting behavior might be in the winter under dynamic rates.

Table 9-1 shows enrollment projections for large and medium customers through 2021. The large customer forecasts show an increase in CPP enrollment commensurate with expected growth in the population of accounts. In addition, the share of SDG&E customers with enabling technology is projected to grow, particularly for the medium sector.

The approximately 20,000 medium SDG&E customers will default onto CPP starting in 2013. The enrollment number grows gradually rather than suddenly because customers must have at least 12 months of hourly interval data before they are defaulted onto CPP. As a result, the growth is tied to the installation of smart meters among medium customers plus a year. By the end of 2013, all medium C&I customers will have been defaulted onto CPP. Thereafter, the growth is tied to general population growth in the number of medium customer accounts. SDG&E is also providing customers with technology to automate their load response in the form of thermostats with two-way communication. The thermostat installations start in 2013 and by June 2017 include 31.0% of medium C&I participants. As a result, the medium ex ante impacts incorporate the incremental effect of enabling technology.

The remainder of this section separately presents the ex ante load impact estimates for medium and large customers projected to receive service under SDG&E's CPP tariff. Small customer impacts are not included because, to date, there is almost no empirical data regarding small customer impacts or enrollments under default dynamic pricing. In addition, the largest California study on small customer load impacts under dynamic pricing, the California Statewide Pricing Pilot, concluded that small customers did not produce statistically significant load reductions in the absence of enabling technology. For each segment, the load reduction capability is summarized during annual system peak day condition of a 1-in-2 and a 1-in-10 weather year for the 2011 to 2021 period. In addition, this section contains per customer impacts by geographic location and month under the standardized ex ante conditions.

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

Size	Forecast Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Large C&I	2011			1,262	1,260	1,258	1,256	1,254	1,252	1,250	1,248	1,246	1,244
	2012	1,244	1,244	1,246	1,244	1,242	1,240	1,238	1,236	1,234	1,232	1,230	1,228
	2013	1,226	1,224	1,226	1,228	1,230	1,232	1,233	1,235	1,237	1,239	1,241	1,242
	2014	1,244	1,246	1,248	1,249	1,251	1,253	1,254	1,256	1,258	1,260	1,262	1,264
	2015	1,266	1,268	1,271	1,273	1,275	1,277	1,279	1,281	1,283	1,285	1,288	1,290
	2016	1,292	1,294	1,296	1,298	1,301	1,303	1,305	1,307	1,309	1,312	1,314	1,316
	2017	1,318	1,320	1,323	1,325	1,327	1,329	1,331	1,334	1,336	1,338	1,340	1,343
	2018	1,345	1,347	1,349	1,352	1,354	1,356	1,358	1,361	1,363	1,365	1,367	1,370
	2019	1,372	1,374	1,377	1,379	1,381	1,383	1,386	1,388	1,390	1,393	1,395	1,397
	2020	1,400	1,402	1,404	1,407	1,409	1,411	1,414	1,416	1,419	1,421	1,423	1,426
	2021	1,428	1,430	1,433	1,435	1,438	1,440	1,442	1,445	1,447	1,450	1,452	1,455
Medium C&I	2011	-	-	-	-	-	-	-	-	-	-	-	-
	2012	-	-	-	-	-	-	-	-	-	-	-	-
	2013	8,049	8,790	9,533	10,278	11,024	11,771	12,520	13,271	14,024	14,777	15,533	13,785
	2014	13,799	13,814	13,829	13,844	13,859	13,874	13,889	13,904	13,919	13,934	13,949	13,964
	2015	13,979	13,986	13,994	14,009	14,024	14,039	14,054	14,069	14,084	14,100	14,115	14,130
	2016	14,145	14,160	14,176	14,191	14,206	14,222	14,237	14,252	14,268	14,283	14,298	14,314
	2017	14,329	14,345	14,375	14,391	14,406	14,422	14,438	14,453	14,469	14,484	14,500	14,515
	2018	14,531	14,547	14,562	14,578	14,594	14,609	14,625	14,641	14,657	14,672	14,688	14,704
	2019	14,720	14,736	14,752	14,768	14,783	14,799	14,815	14,831	14,847	14,863	14,879	14,895
	2020	14,911	14,927	14,943	14,960	14,976	14,992	15,008	15,024	15,040	15,056	15,073	15,089
	2021	15,105	15,121	15,138	15,154	15,170	15,187	15,203	15,219	15,236	15,252	15,269	15,285

9.1 Large C&I Ex Ante Impacts

Most of SDG&E's large customers were defaulted onto CPP in 2008 and experienced events in multiple years. As a result, the uncertainty associated with the ex ante load impacts is primarily statistical uncertainty. We now know how many of these customers tried out default CPP, how much load reduction they provided during events, what types of customers are more responsive and how many remained on CPP after bill protection expired.

9.1.1 **Annual System Peak Day Impacts**

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. In order to allow comparison with PG&E and SCE, the table shows the average load reduction across the 2 PM to 6 PM event window for an August monthly system peak day. In practice, the actual tariff event window at SDG&E is from 11 AM to 6 PM. The average aggregate load impacts, presented in the sixth column, are higher in a 1-in-10 weather year than in 1-in-2 weather year. In general, both overall load in the absence of DR and load impacts are projected to grow over the forecast horizon. Impacts grow from 11.8 MW in 2011 to 15.7 MW at the end of the forecast horizon. While the growth is fueled by increases in the large customer population, the percent load impacts also increase as the share of customers with enabling technology grows.

The ex ante impacts are lower than the program impacts for 2010. In 2011, the ex ante percent impact, 3.4%, is roughly two thirds of the 5.3% impact observed for the average 2010 event. However, as noted in Section 5.5, roughly a third of the 2010 impact was from dually-enrolled participants, particularly those dually-enrolled in BIP. The ex ante load impacts reflect the portfolio rules and avoid double counting of impacts from dually-enrolled customers.

Table 9-2:
Aggregate Portfolio Ex Ante Annual Peak Day Load Impacts for Large SDG&E CPP Customers
(Hourly Average Reduction in MW Over 2 to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)[1]	Avg. Reference Load (MW 2-6 PM)	Avg. Estimated Load w DR (MW 2-6 PM)	Avg. Load impact (MW 2-6 PM)	% Load Reduction (MW 2-6 PM)	Weighted Temp (°F)
1-in-10 August System Peak Day	2011	1,268	349.3	337.5	11.8	3.4%	83.3
	2012	1,254	347.3	335.2	12.1	3.5%	83.3
	2013	1,256	351.5	338.7	12.9	3.7%	83.3
	2014	1,282	363.9	349.8	14.1	3.9%	83.3
	2015	1,308	371.3	356.9	14.4	3.9%	83.3
	2016	1,334	378.3	363.7	14.6	3.9%	83.3
	2017	1,361	385.4	370.6	14.8	3.8%	83.3
	2018	1,388	392.6	377.6	15.0	3.8%	83.3
	2019	1,416	400.0	384.8	15.2	3.8%	83.3
	2020	1,444	407.6	392.1	15.5	3.8%	83.3
	2021	1,473	415.3	399.6	15.7	3.8%	83.3
1-in-2 August System Peak Day	2011	1,268	332.9	323.3	9.5	2.9%	78.7
	2012	1,254	331.1	321.3	9.8	3.0%	78.7
	2013	1,256	335.1	324.7	10.4	3.1%	78.7
	2014	1,282	346.9	335.4	11.5	3.3%	78.7
	2015	1,308	354.0	342.2	11.7	3.3%	78.7
	2016	1,334	360.6	348.7	11.9	3.3%	78.7
	2017	1,361	367.4	355.3	12.1	3.3%	78.7
	2018	1,388	374.3	362.1	12.2	3.3%	78.7
	2019	1,416	381.4	369.0	12.4	3.3%	78.7
	2020	1,444	388.6	376.0	12.6	3.2%	78.7
	2021	1,473	395.9	383.2	12.8	3.2%	78.7

9.1.2 Ex Ante Load Impact Uncertainty

Table 9-3 summarizes the uncertainty in the ex ante annual system peak load impact estimates for large customers. As can be seen, the uncertainty is non-trivial, although all of the impact estimates are statistically significant. For example, for 2011, the 80% confidence interval for 1-in-2 impacts ranges from 6.4 MW up to 12.2 MW. The impact uncertainty bands do not incorporate uncertainty in the enrollment forecast. For SDG&E's large CPP customers, that uncertainty is relatively small since the participant mix is not expected to change substantially and only grows as a function of population growth for the segment.

Table 9-3:
Aggregate Ex Ante Annual Peak Day Load Impacts for Large Customers with Uncertainty
(Hourly Average Reduction in MW Over 2 to 6 PM)

Weather Year	Year	Avg. Load Impact (MW 2-6 PM)	Impact Uncertainty Percentiles				
			10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2011	12	6.4	8.1	9.3	10.5	12.2
	2012	12	6.8	8.5	9.7	10.9	12.6
	2013	13	7.3	9.0	10.2	11.4	13.1
	2014	14	8.1	9.8	11.0	12.2	13.9
	2015	14	8.1	9.8	11.0	12.2	13.9
	2016	15	8.1	9.8	10.9	12.1	13.8
	2017	15	8.1	9.7	10.9	12.0	13.7
	2018	15	8.0	9.7	10.8	12.0	13.6
	2019	15	8.0	9.6	10.8	11.9	13.5
	2020	15	8.0	9.6	10.7	11.8	13.4
	2021	16	8.0	9.5	10.6	11.8	13.3
1-in-2 August System Peak Day	2011	10	4.5	6.3	7.5	8.7	10.5
	2012	10	4.8	6.6	7.8	9.1	10.8
	2013	10	5.3	7.1	8.3	9.5	11.3
	2014	11	6.0	7.7	9.0	10.2	12.0
	2015	12	6.0	7.8	9.0	10.2	11.9
	2016	12	6.0	7.7	8.9	10.1	11.9
	2017	12	6.0	7.7	8.9	10.1	11.8
	2018	12	5.9	7.6	8.8	10.0	11.7
	2019	12	5.9	7.6	8.8	9.9	11.6
	2020	13	5.9	7.6	8.7	9.9	11.5
	2021	13	5.9	7.5	8.7	9.8	11.5

9.1.3 Per Customer Reference Loads and Impacts by Industry

It is instructive to examine ex ante per customer estimates of peak reference loads and load reduction independent of enrollment projections. The impacts per customer can also help inform how results vary with different enrollment mix, targeting strategies or default CPP policies.

Table 9-4 shows the average reference loads and load reduction over the 2 PM to 6 PM event window for the average customer in 2012 by industry, month and weather year. Except for Schools, the overall load absent DR – the reference loads – increase during the summer months, reflecting weather sensitivity. School loads are generally lower during the summer because many schools close down or operate at partial capacity during the June to September period. For the average customer, loads are roughly 35% higher in the July to September period than in December through February. The reference loads are also marginally higher in a 1-in-10 weather year than they are under 1-in-2 weather year conditions.

Table 9-4:
2012 Per Customer Reference Loads in 1-in-2 and 1-in-10 Weather Years
(Average Over 2 to 6 PM)

Weather Year	Industry	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	Mining & Construction	253.3	299.5	353.8	356.9	352.4	325.1	367.9	359.3	342.9	382.7	264.1	219.9
	Manufacturing	239.5	269.4	292.5	301.9	305.1	290.0	313.5	314.3	309.6	313.5	244.9	223.0
	Wholesale & Transport	135.4	144.8	156.2	163.8	174.3	164.6	180.7	181.7	185.5	161.7	131.0	118.4
	Retail stores	230.6	252.9	283.9	291.7	303.4	280.2	330.9	335.6	339.7	319.7	245.6	232.8
	Offices & Hotels	287.8	316.6	351.3	361.5	373.9	337.8	395.9	401.5	401.0	387.0	289.6	274.8
	Schools	128.6	132.7	142.4	130.8	150.2	141.2	129.9	126.2	147.3	169.1	131.5	111.7
	Institutional/ Government	174.3	193.6	216.7	233.2	244.4	230.4	260.0	268.1	268.3	242.1	179.0	174.4
	Other or unknown	135.7	160.6	169.2	192.6	191.6	192.2	235.8	351.5	252.8	232.5	165.1	124.8
	All Customers	205.1	224.4	247.1	253.2	265.0	245.3	274.1	277.0	280.5	272.4	207.7	192.3
1-in-2	Mining & Construction	228.1	285.7	276.4	315.8	318.7	325.7	368.8	359.9	351.9	386.7	302.9	233.7
	Manufacturing	225.6	248.1	247.8	283.3	287.6	291.3	309.0	308.6	297.7	307.2	269.4	229.0
	Wholesale & Transport	137.4	139.6	139.8	152.3	164.5	165.4	175.6	172.3	168.3	157.7	139.3	121.4
	Retail stores	221.2	230.5	230.1	266.8	280.1	281.8	320.7	307.8	311.6	313.1	276.2	240.2
	Offices & Hotels	284.5	291.5	290.9	331.9	340.9	340.0	386.9	374.7	370.1	379.8	318.3	276.7
	Schools	107.9	133.8	132.2	123.3	150.2	140.3	134.4	136.5	160.2	172.9	138.6	115.9
	Institutional/ Government	176.3	174.8	178.9	210.9	224.1	230.9	252.4	251.2	257.6	236.8	204.8	174.7
	Other or unknown	136.3	146.4	138.2	174.7	172.2	197.2	231.9	239.5	226.0	221.9	176.4	124.7
	All Customers	198.2	209.5	209.4	233.6	246.6	246.3	269.1	264.1	265.9	268.4	227.9	195.7

Table 9-5 shows the average portfolio load reduction per customer over the 2 PM to 6 PM event window for each industry, month and weather year. The percent impacts can be calculated by comparing impacts with reference loads in Table 9-4. The largest impacts are from Mining & Construction customers, although they are relatively customers. Customers in the Wholesale & Transport, Manufacturing and Retail sectors are also more responsive than average. On a percentage basis, their impacts in July through September range from 4% to 7% in a 1-in-2 weather year. On the other hand, customers in the Offices & Hotels and Schools sectors are not very price responsive and deliver percent impacts of less than 2%.

Table 9-5:
Average Load Reduction per CPP Customer (kW) During Peak Period by Industry and Month for 2014 (1-in-2 and 1-in-10 Year Weather Conditions)

Weather Year	Industry	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	Mining & Construction	94.9	94.8	76.9	80.1	74.6	99.1	84.8	68.2	37.3	61.8	89.5	96.1
	Manufacturing	26.5	24.5	17.5	15.9	14.4	22.0	13.7	13.6	9.4	15.2	26.5	27.0
	Wholesale & Transport	2.3	3.5	9.5	16.1	15.3	4.2	13.9	16.1	23.6	19.3	1.9	2.0
	Retail stores	12.5	12.4	12.4	14.8	14.1	12.8	13.8	15.0	16.5	17.0	15.5	15.7
	Offices & Hotels	6.8	6.1	5.8	6.9	6.1	6.5	5.8	6.6	6.9	6.5	7.5	7.4
	Schools	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Institutional/ Government	10.7	9.5	7.9	11.3	9.3	8.7	8.6	10.5	11.4	11.0	10.6	10.3
	Other or unknown	-0.3	1.0	2.4	6.8	6.0	0.7	4.8	19.0	11.0	9.1	0.8	0.7
	All Customers	**7.3**	**7.5**	**8.2**	**9.6**	**9.0**	**8.3**	**8.6**	**9.7**	**10.5**	**10.7**	**7.7**	**7.7**
1-in-2	Mining & Construction	101.5	104.7	87.6	94.6	102.0	103.6	91.0	97.4	66.8	83.1	89.4	93.6
	Manufacturing	26.4	26.7	26.4	19.4	26.1	24.4	15.8	17.2	12.0	14.5	25.0	26.5
	Wholesale & Transport	2.2	2.2	2.0	9.0	2.0	2.5	9.6	7.9	10.4	10.7	2.3	2.2
	Retail stores	12.1	12.9	12.9	12.8	13.4	13.4	13.1	12.9	12.4	13.8	15.1	15.7
	Offices & Hotels	6.4	7.1	6.9	5.1	6.9	6.4	5.6	5.5	4.4	5.1	6.9	7.6
	Schools	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Institutional/ Government	10.6	10.6	10.6	8.5	10.7	9.9	7.6	7.4	5.5	6.7	9.9	10.3
	Other or unknown	0.5	-0.1	0.8	5.6	3.2	3.4	1.8	2.2	1.4	2.4	1.2	0.6
	All Customers	**7.2**	**7.4**	**7.3**	**8.3**	**7.4**	**7.3**	**8.0**	**7.8**	**7.0**	**7.6**	**7.6**	**7.7**

Load impacts during the winter months of October through May should be used with extreme caution. Recent dynamic pricing events in SDG&E's CPP program have occurred on hot summer days. In general, there is very limited information available (not just in California but elsewhere as well) concerning what load shifting behavior might be in the winter under dynamic rates.

9.2 Medium C&I Ex Ante Impacts

For SDG&E medium C&I customers, price responsiveness is relatively well defined. First, medium accounts are on the same rate, AL-TOU, as large accounts. In addition, between 2008 and 2010, SDG&E defaulted roughly 400 medium customer accounts onto CPP. However, these medium customers that were defaulted early are not representative of the general medium C&I population. To obtain a larger and more diverse sample of customers for the medium customer price-responsiveness analysis, customers with average hourly demand below 100 kW were also included along with medium customers.[14] In other words, customers that are slightly above the large customer threshold were used as a proxy for medium customers. All of the 2009 and 2010 event data available under default conditions was also used as the basis for ex ante impacts. Section 3.2.2. provides a detailed explanation of the ex ante impact estimation. For SDG&E, there is a substantial amount of data available on how much load reduction medium customers provide during default CPP events and what types of customers are more responsive. In addition, their retention rates for default CPP are better understood than in other utilities.

9.2.1 **Annual System Peak Day Impacts**

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 2 PM to 6 PM for an August monthly system peak day to allow comparison with the other utilities. In practice, the SDG&E event window is longer than PG&E's or SCE's, lasting from 11 AM to 6 PM. The average aggregate load impacts are substantially higher in a 1-in-10 weather year than in 1-in-2 weather year when compared to the ex post impacts for large customers. The difference arises from three reasons. First, the medium customer mix is dominated by Offices and Retail customers, which are generally more weather sensitive. Second, medium customers are projected to receive enabling technology in future years – as a result, the percent load impacts increase from 2013 to 2017. Third, the difference between AC use in 1-in-10 and 1-in-2 weather years is substantial. Although event period temperatures are higher under 1-in-10 weather, the main difference is overnight temperature and associated heat build-up. Under 1-in-2 conditions, throughout 2012 to 2021, August monthly peak program impacts range from a low of 20.4 MW to a high of 21.4 MW.

[14] Customers are classified as small, medium and large based on maximum demand levels rather than average demand levels. As a result, customers with average demand of 100 kW include many customers that would normally be classified as large.

Table 9-6:
Aggregate Portfolio Ex Ante Annual Peak Day Load Impacts for Medium SDG&E CPP Customers
(Hourly Average Reduction in MW Over 2 to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)[1]	Avg. Reference Load (MW 2-6 PM)	Avg. Estimated Load w DR (MW 2-6 PM)	Avg. Load impact (MW 2-6 PM)	% Load Reduction (MW 2-6 PM)	Weighted Temp (°F)
1-in-10 August Monthly Peak	2013	12,979	496.7	456.1	40.7	8.2%	84.0
	2014	13,217	505.3	463.8	41.6	8.2%	84.0
	2015	11,346	430.6	393.6	37.0	8.6%	84.0
	2016	10,663	403.1	367.8	35.3	8.8%	84.0
	2017	10,028	377.6	343.7	33.9	9.0%	84.1
	2018	10,159	382.5	348.2	34.3	9.0%	84.1
	2019	10,291	387.4	352.7	34.8	9.0%	84.1
	2020	10,424	392.5	357.3	35.2	9.0%	84.1
	2021	10,560	397.6	361.9	35.7	9.0%	84.1
1-in-2 August Monthly Peak	2013	12,979	463.0	441.7	21.3	4.6%	80.4
	2014	13,217	471.1	449.3	21.9	4.6%	80.4
	2015	11,346	401.9	381.1	20.8	5.2%	80.4
	2016	10,663	376.5	356.0	20.6	5.5%	80.5
	2017	10,028	352.9	332.5	20.4	5.8%	80.5
	2018	10,159	357.5	336.9	20.6	5.8%	80.5
	2019	10,291	362.1	341.2	20.9	5.8%	80.5
	2020	10,424	366.8	345.7	21.2	5.8%	80.5
	2021	10,560	371.6	350.2	21.4	5.8%	80.5

9.2.2 Ex Ante Load Impact Uncertainty

Table 9-7 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for medium customers. As can be seen, the uncertainty is non-trivial, although all of the impact estimates are statistically significant. For example, in 2013, the 80% confidence interval for 1-in-2 impacts range from 19.4 MW up to 23.2 MW. In practice, the impact uncertainty bands may be slightly larger because they do not incorporate uncertainty in the enrollment forecast or in the share of customers that will accept enabling technology. The 1-in-10 year impacts are substantially higher. The 12 default CPP events to date enable us to examine impacts across different conditions. However, there is still relatively limited data about impacts under the more extreme 1-in-10 conditions. As the history of events grows, the 1-in-10 impact estimates will grow more reliable.

Table 9-7:
Aggregate Ex Ante Annual Peak Day Load Impacts for Medium Customers with Uncertainty
(Hourly Average Reduction in MW Over 2 to 6 PM)

Weather Year	Year	Avg. Load Impact (MW 2-6 PM)	Impact Uncertainty Percentiles				
			10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2013	41	38.8	39.9	40.7	41.4	42.5
	2014	42	39.7	40.8	41.6	42.3	43.4
	2015	37	35.2	36.3	37.0	37.7	38.7
	2016	35	33.7	34.7	35.3	36.0	37.0
	2017	34	32.2	33.2	33.9	34.5	35.5
	2018	34	32.7	33.6	34.3	35.0	35.9
	2019	35	33.1	34.1	34.8	35.4	36.4
	2020	35	33.5	34.5	35.2	35.9	36.9
	2021	36	34.0	35.0	35.7	36.3	37.3
1-in-2 August System Peak Day	2013	21	19.4	20.5	21.3	22.0	23.2
	2014	22	19.9	21.1	21.9	22.6	23.8
	2015	21	19.0	20.1	20.8	21.6	22.6
	2016	21	18.8	19.9	20.6	21.3	22.3
	2017	20	18.7	19.7	20.4	21.0	22.0
	2018	21	18.9	19.9	20.6	21.3	22.3
	2019	21	19.2	20.2	20.9	21.6	22.6
	2020	21	19.4	20.5	21.2	21.9	22.9
	2021	21	19.7	20.7	21.4	22.1	23.2

10 Recommendations

California is the first State in the Nation that has defaulted such a substantial number of large and medium customers onto a critical peak pricing tariff. The 2010 empirical data from PG&E, SCE and SDG&E's critical peak pricing programs has produced practical insights that instruct both short-term and long-term policies regarding the implementation of dynamic pricing default tariffs. The evaluation has also helped inform several key rate design questions such as how structural wins, bill protection and insurance against higher CPP prices affect percent load reductions. However, in light of the upcoming transition of over 1,000,000 non-residential accounts onto default CPP, there is still much that can be learned to reduce uncertainty and improve performance among participants.

Our recommendations are divided into three main categories:

- Research to improve load responsiveness among customers already defaulted onto CPP;
- Research to reduce uncertainty of impacts from small and medium C&I customers scheduled to be defaulted onto CPP; and
- Development of price responsiveness estimates for the Agricultural sector.

Although we recommend 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 real world implementation and resource constraints.

10.1 Research to Improve Price Responsiveness

For all three California utilities, on average, percent load reductions were relatively low -- 3.9%. In all three programs, a small subset of customers was highly price responsive, while the remaining customers provided very small or no load reductions. Several explanations for the low percent load reductions are detailed in the report, including:

- Utilities may have already targeted and enrolled highly price responsive customers onto CPP on a voluntary basis. As a result, the default may have included less responsive customers.
- Customers who migrated from a TOU rate with strong on-peak price signals to CPP may have limited incremental load reduction capacity. On its own, the TOU rate provided strong incentives to shift or reduce electricity use during peak period in summer months. In other words, what customers could easily shift to off-peak periods may have already been shifted in response to strong TOU prices, reducing the CPP load reduction potential.
- A substantial amount of effort in 2010 was devoted to migrating customers onto default CPP and ensuring they had the information necessary to decide whether to stay on default CPP or opt out to a TOU tariff. More effort may need to be devoted to helping customers understand how they can shift or reduce loads. There are "search costs" associated with understanding what loads are discretionary and how they can be reduced without affecting essential operations. Targeted education can help reduce those search costs.
- Without enabling technology, some customers are not price responsive.

It is important to understand why some customers respond to CPP price signals and others do not so that concrete steps to improve load reductions can be identified and tested. The 2010 evaluation addressed the extent to which rate design elements - e.g., bill protection, insurance against CPP prices, etc - and customer characteristics were linked to load responsiveness. While useful, this is different than explicitly testing how specific interventions affect price responsiveness.   Overall, we recommend:

- Conducting a survey or structured interviews of CPP participants;
- Standardized tracking of event awareness and notification success rates; and
- Explicit tests of how assistance and enabling technology affect price responsiveness.

The survey or structured interviews should include both customers that provided substantial percent load reductions in 2010 and those that did not. Because of the individual customer regressions, high responders and non-responders can be easily identified. Given the limited large customer population, the survey or structured interview may be qualitative out of necessity, though ideally it would include over 100 customers and incentives to ensure higher response rates. The survey could help answer key questions such as:

- Did the correct person receive the event notification?
- Was he or she in a position to initiate load reductions or shifting?
- Did they have a plan in place for reducing electricity use on CPP event days?
- What is their perception of their ability to reduce loads?
- Did they know what they could do to reduce loads? What discretionary loads had they identified on their own?
- How likely are they to accept a review of their facilities to identify discretionary loads that can be shed or reduced?
- What assistance do they need to engage in load reductions?
- Were they aware of the most recent summer event dates?
- How well did they understand the CPP tariff structures?

Our second recommendation is to standardize tracking of notification success rates. Logically, event awareness is closely linked to event day response. If a customer is not aware of the event, response is less likely.   The notification success rates should be tracked for each event and type of notification (e.g., phone, email, text, voice message attempted). The data collected should distinguish between successful delivery and actual communication of the event to the person identified for event day contact.

Our third recommendation is to explicitly test and track the effect of customer education and enabling technology.   The existing Technical Assistance (TA), Technology Incentives (TI) and AutoDR program already incorporates those elements and should be tested alongside education efforts by account representatives.   To date, most TA/TI and AutoDR applications have occurred in conjunction with voluntary enrollment in DR programs. It has rarely been possible to observe customer load reductions before and after they received technical assistance or installed enabling technology. Because large CPP customers were all defaulted at the same time, there is a unique opportunity to more accurately assess incremental impacts of education, TA/TI and AutoDR.   For these customers, it will be possible to asses impacts with an without enabling technology. Specifically, we recommend random assignment to three groups: one that received targeted education on how to respond during CPP events from account representatives, one that is offered an audit to design a load response plan, and one that receives proactive offers for TA/TI and AutoDR.

10.2 Reduce Uncertainty Among Small and Medium C&I Customers

Despite the experience with defaulting large customers onto CPP, substantial uncertainty remains for the future transition of small and/or medium C&I customers.   From a utility perspective, there is uncertainty in the CPP opt-out rates, retention rates, load impacts under default conditions and regulatory decisions. The uncertainty affects both short term implementation plans and long term resource planning. The degree of uncertainty is largest for small C&I customers. To date, there is very limited factual data on what works and what doesn't in helping SMB customers migrate to default dynamic pricing simply because there is very little precedent for such a shift among these customers. There is no empirical data on the share of customers that will try out CPP if defaulted, how customers will react and the extent to which they will reduce load under default CPP or opt out TOU. We recommend conducting early staged deployment tests so the uncertainty related to the transition can be reduced and the default process can be tested.

With such a tests, it will be possible to directly observe opt-out rates, retention rates and load response of small customers; thereby reducing uncertainty associated with migrating roughly 1,000,000 accounts onto default CPP.   The test would also inform the default process and help improve it. Ensuring the use or random samples representative of the population in the tests is critical for maximizing the knowledge gained from them.

10.3 Develop Estimates of Load Impacts Among Agricultural Customers

Load impacts for customers on agricultural rates were not developed as part of the 2010 evaluation because empirical data was not available. Neither PG&E nor SCE had defaulted large customers on agricultural rates onto CPP.   SDG&E did default large customers on its agricultural and pumping tariffs onto CPP and had approximately 100 active accounts on CPP during 2010.   However, a closer examination of these customers revealed they were almost exclusively golf courses and water districts. In short, there was not enough diversity in the SDG&E accounts to provide a basis for inferring Agricultural customer impacts for PG&E and SDG&E.

For 2011, it will be possible to develop load impacts for customers on agricultural tariffs. In February 2011, PG&E defaulted all large agricultural accounts onto CPP and defaulted it small and medium customers onto TOU rates. The transition will provide a rich set of data concerning how rate transitions affect price responsiveness. In order to apply them outside of PG&E territory, it will be necessary adjust for differences in the peak prices, off peak prices and event day CPP charges.

APPENDIX A PG&E Tariff Comparison

Table A-1:
E19 Rate Comparison

Season	Type of Charge	Period	Pre-Default TOU Rate	Default CPP	Opt-out TOU
Summer (Jun-Sep)	Energy Rates ($ per kWh)	PDP Event Period	NA	$1.20	$1.20
		On-Peak	$0.16	$0.15	$0.15
		Semi-Peak	$0.11	$0.11	$0.11
		Off-Peak	$0.09	$0.09	$0.09
	Summer PDP Energy Credits ($ per kWh)	On-Peak	NA	($0.004)	NA
		Semi-Peak	NA	($0.0007)	NA
		Off-Peak	NA	NA	NA
	Summer PDP Demand Credit ($ per kW)	On-Peak	NA	($6.10)	NA
		Semi-Peak	NA	($1.30)	NA
	Customer Charge ($'s/Meter/Day)	Daily Charge	$4.12	$4.12	$4.12
	Summer Season Time Related Demand Charge ($ per kW)	On-Peak	$13.17	$13.05	$13.05
		Semi-Peak	$3.02	$2.99	$2.99
		Maximum Demand	$9.02	$8.58	$8.58
Winter (Oct-May)	Energy Rates ($ per kWh)	PDP Event Period	NA	$1.20	NA
		On-Peak	NA	NA	NA
		Semi-Peak	$0.10	$0.09	$0.09
		Off-Peak	$0.09	$0.08	$0.08
	Customer Charge ($'s/Meter/Day)	Daily Charge	$4.12	$4.12	$4.12
	Winter Season Time Related Demand Charge	On-Peak	NA	NA	NA
		Semi-Peak	$1.15	$1.12	$1.12
	($ per kW)	Maximum Demand	$9.02	$8.58	$8.58

Table A-2:
E20 Rate Comparison

Season	Type of Charge	Period	Pre-Default Rate	Default CPP	Opt-out TOU
Summer (Jun-Sep)	Energy Rates ($ per kWh)	PDP Event Period	NA	$1.20	$1.20
		On-Peak	$0.15	$0.15	$0.15
		Semi-Peak	$0.10	$0.10	$0.10
		Off-Peak	$0.09	$0.08	$0.08
	Summer PDP Energy Credits ($ per kWh)	On-Peak	NA	($0.002)	NA
		Semi-Peak	NA	($0.0004)	NA
		Off-Peak	NA	NA	NA
	Summer PDP Demand Credit ($ per kW)	On-Peak	NA	($5.83)	NA
		Semi-Peak	NA	($1.19)	NA
	Customer Charge ($'s/Meter/Day)	Daily Charge	$24.64	$24.64	$24.64
	Summer Season Time Related Demand Charge	On-Peak	$12.78	$12.67	$12.67
		Semi-Peak	$2.84	$2.81	$2.81
	($ per kW)	Maximum Demand	$9.00	$8.56	$8.56
Winter (Oct-May)	Energy Rates ($ per kWh)	PDP Event Period	NA	$1.20	NA
		On-Peak	NA	NA	NA
		Semi-Peak	$0.09	$0.09	$0.09
		Off-Peak	$0.08	$0.08	$0.08
	Customer Charge ($'s/Meter/Day)	Daily Charge	$24.64	$24.64	$24.64
	Winter Season Time Related Demand Charge	On-Peak	NA	NA	NA
		Semi-Peak	$1.15	$1.12	$1.12
	($ per kW)	Maximum Demand	$9.00	$8.56	$8.56

Table A-3:
A10 Rate Comparison

Season	Type of Charge	Period	Pre-Default Rate	Default CPP	Opt-out TOU
Summer (Jun-Sep)	Energy Rates ($ per kWh)	PDP Event Period	NA	$0.90	NA
		On-Peak	$0.17	$0.16	$0.16
		Semi-Peak	$1.14	$0.14	$0.14
		Off-Peak	$0.13	$0.13	$0.13
	Summer PDP Energy Credits ($ per kWh)	On-Peak	NA	($0.01)	NA
		Semi-Peak	NA	($0.01)	NA
		Off-Peak	NA	($0.01)	NA
	Summer PDP Demand Credit ($ per kW)	On-Peak	NA	($1.54)	NA
	Customer Charge ($'s/Meter/Day)	Daily Charge	$3.94	$3.94	$3.94
	Summer Season Time Related Demand Charge ($ per kW)	Summer	$11.32	$10.88	$10.68
Winter (Oct-May)	Energy Rates ($ per kWh)	PDP Event Period	NA	$0.90	NA
		On-Peak	NA	NA	NA
		Semi-Peak	$0.12	$0.11	$0.11
		Off-Peak	$0.10	$0.10	$0.10
	Customer Charge ($'s/Meter/Day)	Daily Charge	$3.94	$3.94	$3.94
	Winter Season Time Related Demand Charge ($ per kW)	NA	$6.91	$6.52	$6.32

APPENDIX B SCE Tariff Comparison

Table B-1:
GS3 Rate Comparison

Season	Type of Charge	Period	Pre-default Rate	Default CPP	Opt out TOU
Summer (Jun-Sep)	Energy Rates ($ per kWh)	CPP Event Period	NA	$1.36	$1.36
		On-Peak	$0.13	$0.15	$0.15
		Semi-Peak	$0.10	$0.11	$0.11
		Off-Peak	$0.06	$0.07	$0.07
	Summer CPP Credit ($ per kW)	On-Peak	NA	($11.62)	NA
	Customer Charge ($'s/Meter/Month)	Monthly charge	$415.58	$434.00	$434.00
	Facilities Related Demand Charge ($ per kW)	NA	$11.78	$11.63	$11.63
	Summer Season Time Related Demand Charge	On-Peak	$16.33	$15.09	$15.09
	($ per kW)	Mid-Peak	$5.60	$3.59	$3.59
Winter (Oct-May)	Energy Rates ($ per kWh)	CPP Event Period	NA	NA	NA
		On-Peak	NA	NA	NA
		Semi-Peak	$0.10	$0.08	$0.08
		Off-Peak	$0.07	$0.06	$0.06
	Customer Charge ($'s/Meter/Month)	Monthly charge	$415.58	$434.00	$434.00
	Facilities Related Demand Charge ($ per kW)	NA	$11.78	$11.02	$11.02

Table B-2:
TOU-8 Rate Comparison

Season	Type of Charge	Period	Pre-default Rate	Default CPP	Opt out TOU
Summer (Jun-Sep)	Energy Rates ($ per kWh)	CPP Event Period	NA	$1.36	$1.36
		On-Peak	$0.12	$0.16	$0.16
		Semi-Peak	$0.09	$0.10	$0.10
		Off-Peak	$0.06	$0.06	$0.06
	Summer CPP Credit ($ per kW)	On-Peak	NA	($12.47)	NA
	Customer Charge ($'s/Meter/Month)	Monthly charge	$518.64	$530.25	$530.25
	Facilities Related Demand Charge ($ per kW)	NA	$13.00	$11.02	$11.02
	Summer Season Time Related Demand Charge ($ per kW)	On-Peak	$15.21	$18.75	$18.75
		Mid-Peak	$5.13	$5.28	$5.28
Winter (Oct-May)	Energy Rates ($ per kWh)	CPP Event Period	NA	NA	NA
		On-Peak	NA	NA	NA
		Semi-Peak	$0.09	$0.09	$0.09
		Off-Peak	$0.06	$0.06	$0.06
	Customer Charge ($'s/Meter/Month)	Monthly charge	$518.64	$530.25	$530.25
	Facilities Related Demand Charge ($ per kW)	NA	$13.00	$11.02	$11.02

APPENDIX C SDG&E Tariff Comparison

**Table C-1:
AL-TOU Rate Comparison
(Includes Commodity and Delivery Charges)**

Season	Type of Charge	Period	Pre-default Rate	Default CPP	Opt out TOU
Summer (Apr-Oct)	Energy Rates ($ per kWh)	CPP Event Period	NA	$1.03	NA
		On-Peak	$0.15	$0.11	$0.11
		Semi-Peak	$0.09	$0.09	$0.09
		Off-Peak	$0.07	$0.06	$0.07
	On-Peak Demand Charge ($ per kW)	On-Peak	$7.06	$7.06	12.87
	Capacity Reservation Charge ($'s per kW/Month)	Monthly charge	NA	$6.25	NA
	NC Demand Charge ($ per kW)	NA	$13.06	$13.06	$13.06
Winter (Nov-Apr)	Energy Rates ($ per kWh)	CPP Event Period	NA	$1.03	NA
		On-Peak	0.15	$0.10	$0.11
		Semi-Peak	$0.09	$0.09	$0.10
		Off-Peak	$0.07	$0.07	$0.07
	On-Peak Demand Charge ($ per kW)	On-Peak	$4.69	$4.69	4.88
	Capacity Reservation Charge ($'s per kW/Month)	Monthly charge	NA	$6.25	NA
	NC Demand Charge ($ per kW)	NA	$13.06	$13.06	$13.06

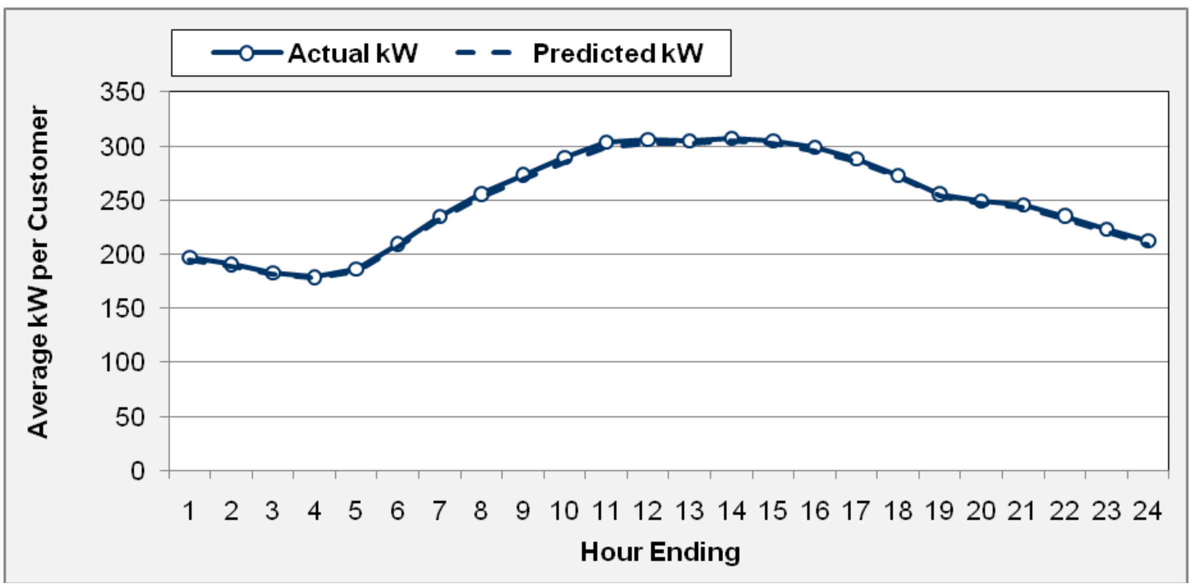
APPENDIX D SCE Detailed Validity assessment

Although regressions were run for each individual customer in SCE's CPP program for which data was provided, what matters most is that the reference loads for all customers combined, or for selected groups of customers (e.g., industry types, LCA) are accurate. Given that load impacts are calculated as the difference between the reference load and our predictions of the observed load, any error in the estimated reference load or observed load would cause an error in the estimated load impact.

D.1. Out-of-Sample and False Event Coefficient Tests

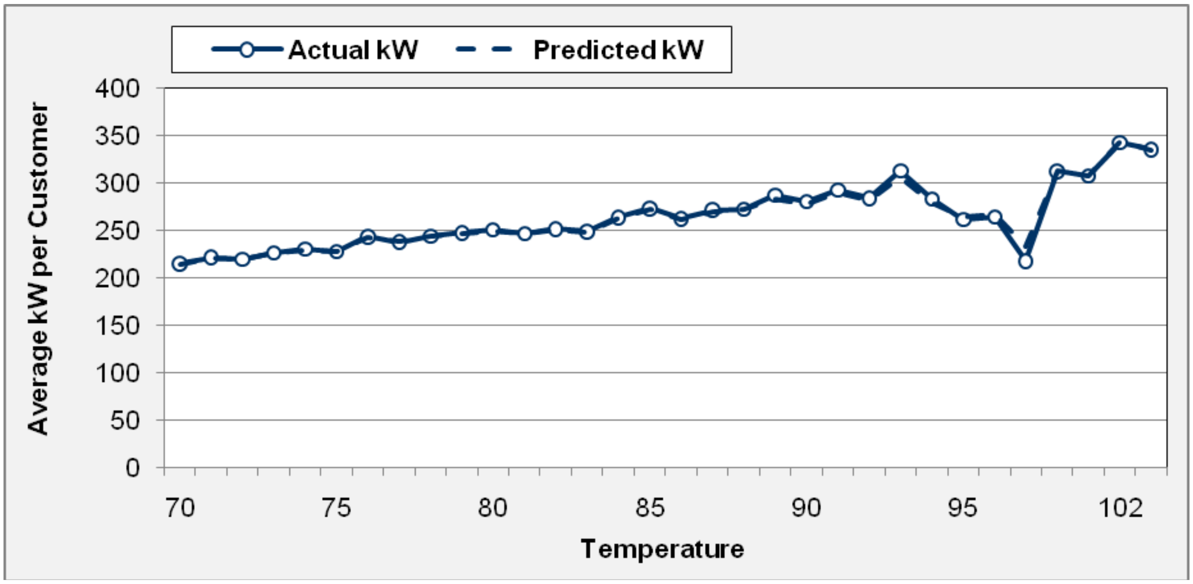
The out-of-sample and false event coefficient test results for SCE are encouraging and show just how little bias exists in the reference load predictions on days similar to event days. Figure D-1 compares the actual and predicted load for each hour on false event days among a sample of currently enrolled SCE CPP customers. As seen in the figure, the model does a very good job of predicting load on false event days, though it under predicts slightly in the late morning hours. The percentage error is low – the difference between actual and predicted load did not exceed 1% between the event hours of 2 PM and 6 PM or 2% during any hour.

Figure D-1:
Actual v. Predicted Average Load by Hour for SCE CPP Customers
False Event Days



Although many CPP customers are not highly weather sensitive, it is still useful to assess how well the model predicts in-sample under different temperature conditions. As seen in Figure D-2, the model also predicts well across various temperatures, with the average error for temperatures between 70 to 103°F equal to 0.16%. The model is only off between 96 and 99°F, where it over predicts by 7.2%, otherwise the percent error is at or below 1%. The dip in load at high temperatures reflects the fact that nearly all of these temperatures occur in the afternoon, when peak-period prices are in effect. That is, the high temperatures are correlated with high prices that depress demand below what it would be at the same temperature with off-peak prices in effect.

Figure D-2:
Actual v. Predicted Average Load by Temperature for SCE CPP Customers



The final check for these false event day tests is to make sure that the false event days are, in fact, like actual event days. Table D-1 below illustrates just how little bias exists in the false event day coefficients during event hours. All of the coefficients on the false event day and hour interactions are insignificant. Further, the coefficients on the estimated false event day and hour interactions bias actual kWh by 0.30% or less. Dividing the actual sum of kWh by the sum of the beta coefficients on the false event day and hour interactions gives us the percent by which the estimated coefficients impact actual kWh. The default assumption is that the false event day and hour interactions should have close to 0% impact on the dependent variable, otherwise this is evidence that the betas are correlated with the error term.

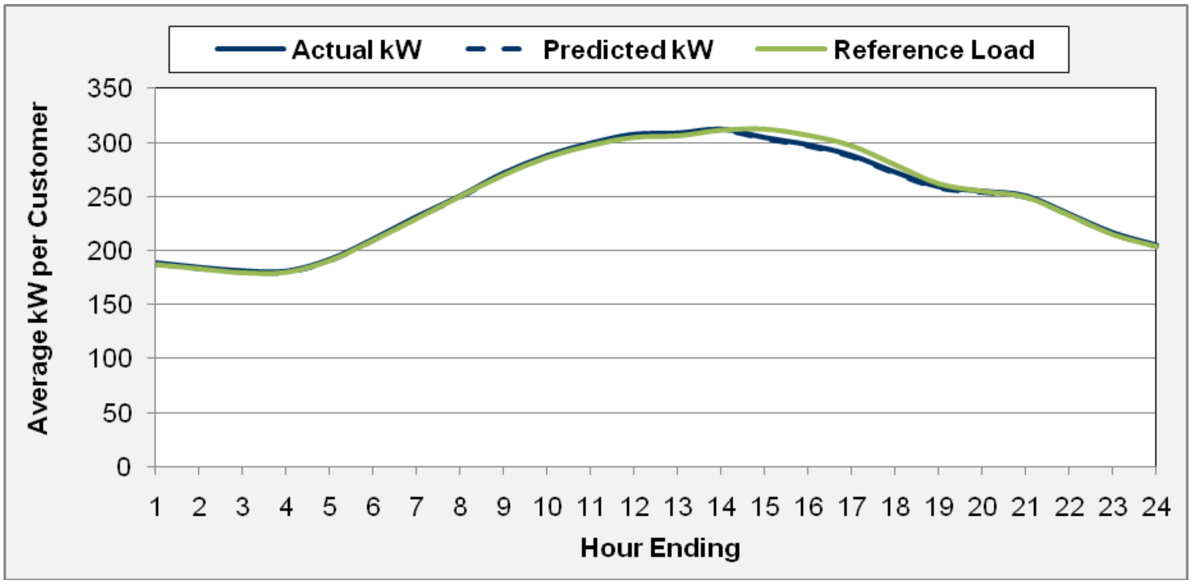
Table D-1:
Results from False Event Coefficient Tests

Hour	Sum of kWh	Sum of Betas	Sum of the Variance	T-Value	% Bias
15	1528983	2678.74	2.29E+07	0.56	0.18%
16	1504239	1275.22	2.29E+07	0.27	0.08%
17	1470589	-2272.41	2.29E+07	-0.47	-0.15%
18	1418733	-4297.72	2.29E+07	-0.90	-0.30%
Total	5922544	-2616.17	9.16E+07	-0.27	-0.04%

D.2. Panel Model Checks

Panel models allow us to tackle issues of unobserved heterogeneity bias in a way that is not possible with individual customer regressions since we can eliminate the biases caused by unobserved variables that are consistent across cross-sectional units. Figure D-3 shows the average event day impact from the panel model across all customers in the stratified SCE sample. During the event hours of 2 PM to 6 PM, the panel model with treatment variables specified as described in the introduction to this section predicts an average load reduction of 3.01%. On the average event day, individual customer regressions predict an average load impact of 2.85%. The similarity in impacts across the different regression methods and with different treatment variables specified provides additional confidence in the individual customer regression results.

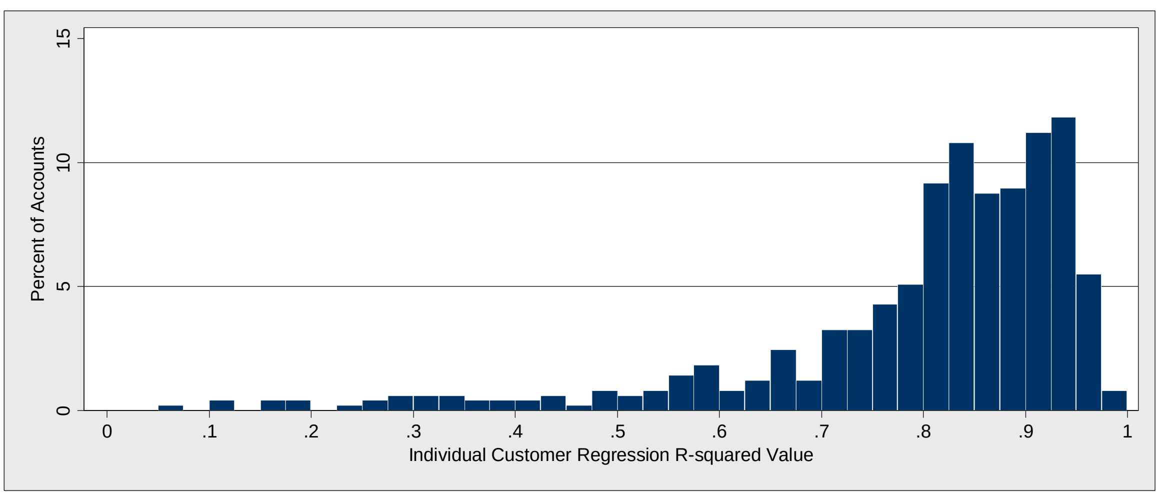
Figure D-3:
SCE Aggregate Panel Model Results



D.3. Goodness of Fit Measures

Figure D-4 shows the distribution of R-squared values from the individual customer regressions. 25% of customers have R-squared values exceeding 0.90, while the mean R-squared value is just about 0.80.

Figure D-4:
Distribution of R-squared Values from Individual Regressions



In order to estimate the average customer R-squared values for each industry, LCA or the program as a whole, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour. This process produced regression predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value. The R-squared values for the average participant and for the average customer by segment were estimated using the following formula:[15]

$$\mathbf{R^2} = 1 - \frac{\sum_t (\hat{y}_t - y_t)^2}{\sum_t (\hat{y}_t - \bar{y})^2}$$

Table D-2:
Variable Definitions

Variable	Definition
y_t	actual energy use at time $_t$
$\hat{y}_t$	regression predicted energy use at time $_t$
$\bar{y}$	actual mean energy use across all time periods

Table D-3 summarizes the amount of variation explained by the regression model for the average customer in specific segments. In aggregate, the model explained 97% of the variation in energy use. The explained variation varied from 36 to 96% across industries and local capacity areas. Only one of the industries or local capacity areas has an R-squared value below 0.90 – Other or undefined (0.82).

[15] Technically, the R-squared value needs to be adjusted based on the number of parameters and observations from each regression. Given that the number of observations per regression was typically over 8,000, the effects of the adjustment were anticipated to be minimal. As a result, the unadjusted R-squared is presented in order to avoid the complication of tracking the number of observations and parameters from each individual regression.

Table D-3:
R-squared Values for the Average Customer by Segment

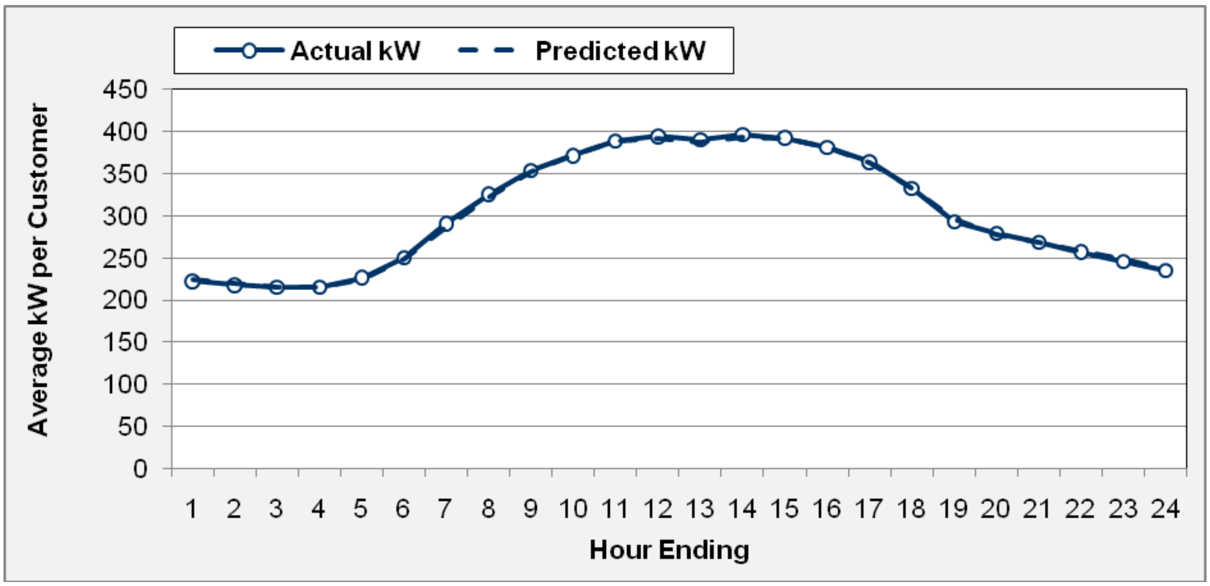
Customer Segment	R-squared
All Customers	0.97
Industry	
Agriculture, Mining & Construction	0.92
Manufacturing	0.95
Wholesale, Transport, other utilities	0.93
Retail stores	0.99
Offices, Hotels, Finance, Services	0.98
Schools	0.94
Institutional/Government	0.90
Other or undefined	0.82
Local Capacity Area	
LA Basin	0.97
Outside LA Basin	0.95
Ventura	0.97

APPENDIX E PG&E Detailed Validity Assessment

E.1. Out-of-Sample and False Event Coefficient Tests

The out-of-sample and false event coefficient test results for PG&E, while not quite as robust as those for SCE, still indicate that the regression coefficients extend well out-of-sample for event-like dayst. Figure E-1 below compares the actual and predicted load for each hour for the three groups of five false event days over which the regression specification was tested. As seen in the figure, the model does a very good job of predicting load out-of-sample. Remarkably, we observe 0.4% bias or less during the event hours of 2 PM to 6 PM and 1.0% bias or less during nearly all other hours of the day.

Figure E-1:
Actual v. Predicted Aggregate Load by Hour for PG&E CPP Customers
False Event Days



As seen in Figure E-2, the aggregate model also predicts well across various temperatures, with the average error in the temperature range between 70 and 99°F equal to 0.5%. The model slightly under predicts at higher temperatures. At 95°F and above, the average error was 2%.

Figure E-2:
Actual v. Predicted Aggregate Load by Temperature for PG&E CPP Customers

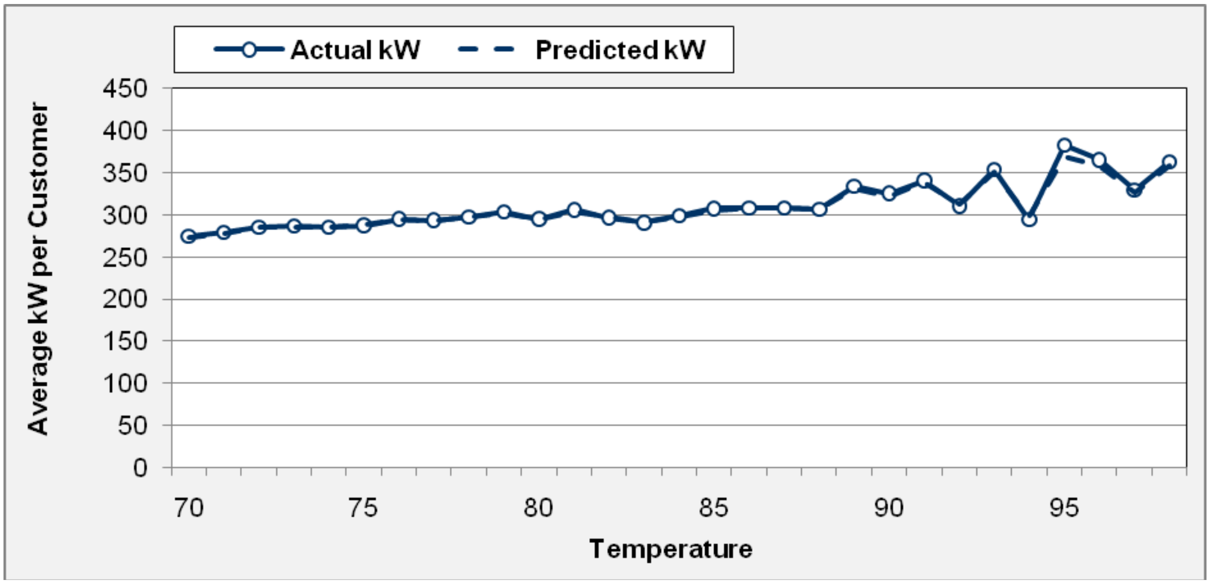


Table E-1 below gives reasonable assurance to trust the out-of-sample testing method employed. Even though coefficients on the false event and hour variables are significant, the coefficients still do not bias actual kWh by a large amount. As mentioned before, dividing the actual sum of kWh by the sum of the beta coefficients on the false event day and hour interactions provides the percent by which the estimated coefficients impact actual kWh. The default assumption is that the false event day and hour interactions should have close to 0% impact on the dependent variable. As a whole, the coefficients on the estimated false event day and hour interactions for PG&E bias actual kWh by 2.52% or less, a trivial amount when we consider the spot-on out-of-sample reference load predictions is considered.

Table E-1:
Results from False Event Coefficient Tests

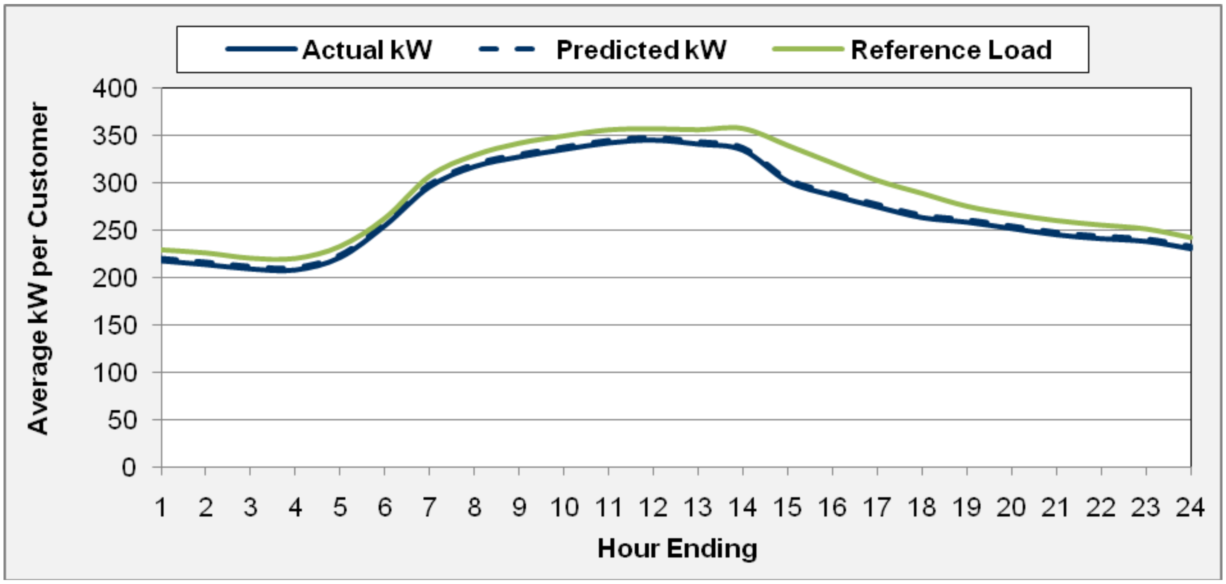
Hour	Sum of kWh	Sum of Betas	Sum of the Variance	T-Value	% Bias
15	2134677	51917.19	1.59E+07	13.020	2.43%
16	2113957	53267.31	1.59E+07	13.359	2.52%
17	2071469	50142.41	1.59E+07	12.575	2.42%
18	1943894	36173.76	1.59E+07	9.072	1.86%
Total	8263997	191500.7	6.36E+07	24.013	2.32%

E.2. Panel Model Checks

Figure E-3 shows the average event day impact for the Manufacturing industry, which is one of the largest industry groups in PG&E's territory and a major driver of load impacts on CPP event days. During the event hours of 2 PM to 6 PM, the panel model with treatment variables specified as described in the introduction to this section predicts an average load reduction of 9.12%. On the average event day, individual customer regressions predict an average load impact of 9.27% for the Manufacturing Industry.

The agreement in results between these two methods gives us additional confidence in the robustness of the individual customer regression results.

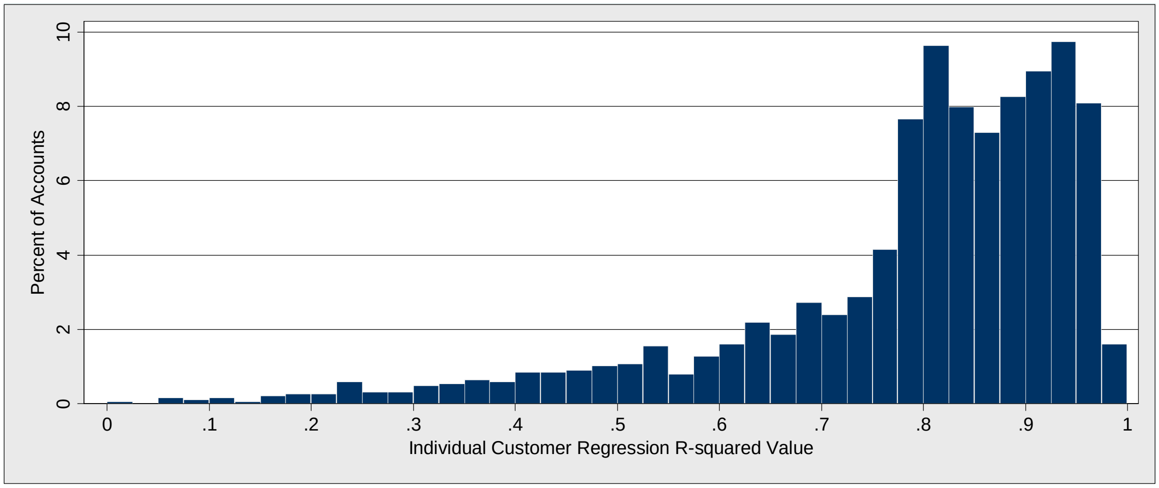
Figure E-3:
PG&E Manufacturing Industry Panel Model Results



E.3. Goodness of Fit Measures

Figure E-4 shows the distribution of R-squared values from the individual customer regressions for PG&E. About three quarters of the individual customer regressions have R-squared values above 0.73, while the mean R-squared value from the individual customer regressions is nearly 0.80.

Figure E-4:
Distribution of R-squared Values from Individual Regressions



In spite of the low R-squared values of some customers at the individual customer level, the explained variation is quite high for the average customer overall, by industry segment and by LCA. In fact, in aggregate, the model explains nearly 98% of the variation in energy use.

Table E-2 summarizes the amount of variation explained by the regression model for the average customer in specific segments. Overall, depending on the specific group assessed, between 82 and 99% of the variation is explained. Customers in the Agriculture, Mining & Construction industry have the lowest R-squared value AT 0.82. Barring Wholesale, Transport, other utilities, in the other industries and LCAs, 90% or more of the variation in hourly energy use is explained.

Table E-2:
R-squared Values for the Average Customer by Segment

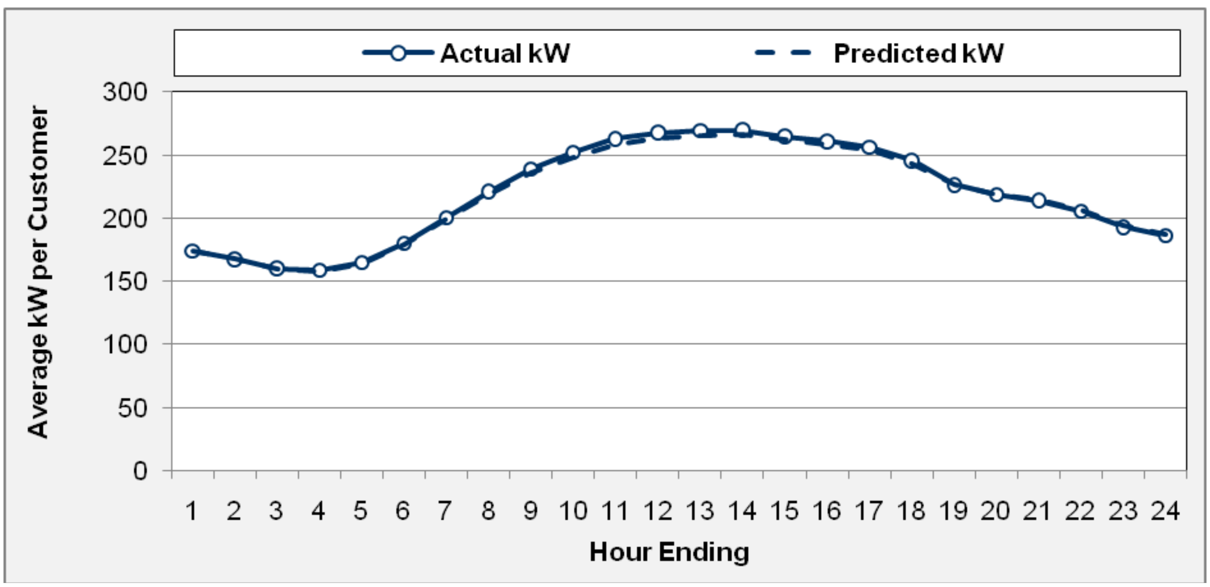
Customer Segment	R-squared
All Customers	0.98
Industry	
Agriculture, Mining & Construction	0.82
Manufacturing	0.94
Wholesale, Transport, other utilities	0.87
Retail stores	0.99
Offices, Hotels, Finance, Services	0.98
Schools	0.91
Institutional/Government	0.94
Other or undefined	0.98
Local Capacity Area	
Greater Bay Area	0.98
Greater Fresno	0.94
Kern	0.98
Northern Coast	0.95
Sierra	0.86
Stockton	0.95
Other	0.91

APPENDIX F SDG&E Detailed Validity Assessment

F.1. Out-of-Sample and False Event Coefficient Tests

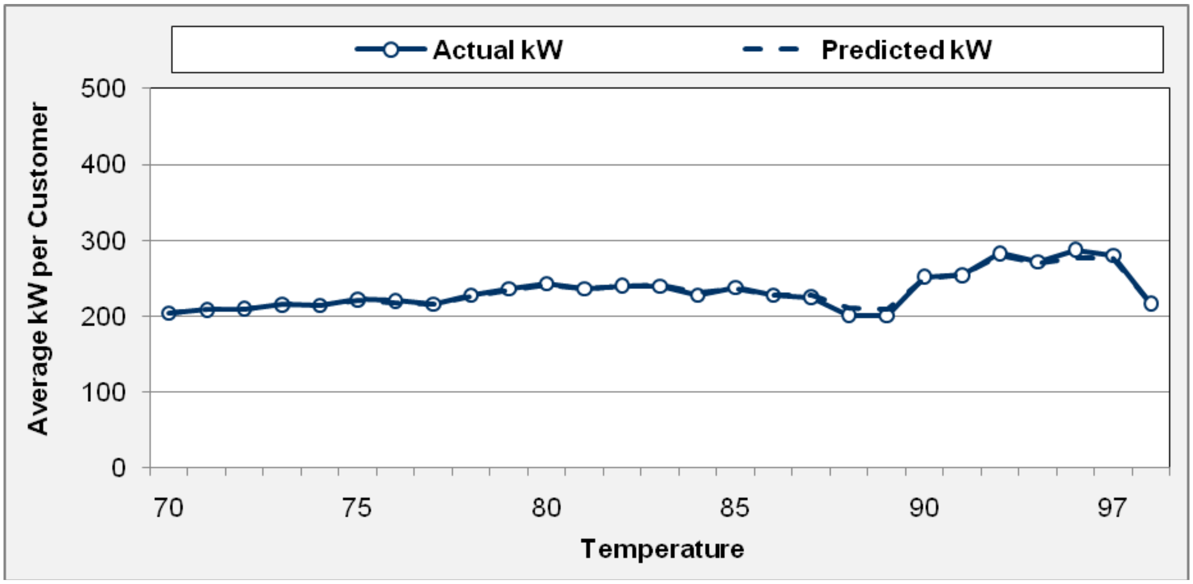
The out-of-sample and false event coefficient test results for SDG&E are similar to those from SCE and also show just how little bias exists in the reference load predictions on days similar to event days. Figure F-1 compares the actual and predicted load for each hour for the three groups of five false event days over which the regression specification was tested. On average, there is 1.1% bias during event hours and never more than 2% bias at any point in the day. As was the case with SCE, the model slightly under predicts in the late morning hours, which is slightly more of a problem since the SDG&E event window begins at 11:00 AM. Still, a model that predicts out-of-sample with less than 2% bias at any point for all three utilities is remarkably robust.

Figure F-1:
Actual v. Predicted Aggregate Load by Hour for SDG&E CPP Customers
False Event Days



As seen in Figure F-2, the aggregate model also predicts well across various temperatures, with the average error from 70 to 97°F equal to 0.15%. However, between 87 and 90°F, the average error is 4.7%. And also, between 93 and 97°F, the average error is about 4%.

Figure F-2:
Actual v. Predicted Aggregate Load by Temperature for SDG&E CPP Customers



Again, to make sure that the false event days are in fact like actual event days, false event variables were tested. Table F-1 shows just how little bias exists in the false event day coefficients during event hours for SDG&E. Most coefficients on the false event day and hour interactions are insignificant, though in the later event hours the coefficients are marginally significant. But more importantly, the coefficients on the estimated false event day and hour interactions bias actual kWh by 0.73% or less across all seven event hours. Since the false event day and hour interactions have close to 0% impact on the dependent variable, there is confidence that the groups of false event days chosen are reasonably similar to actual event days.

Table F-1:
Results from False Event Coefficient Tests

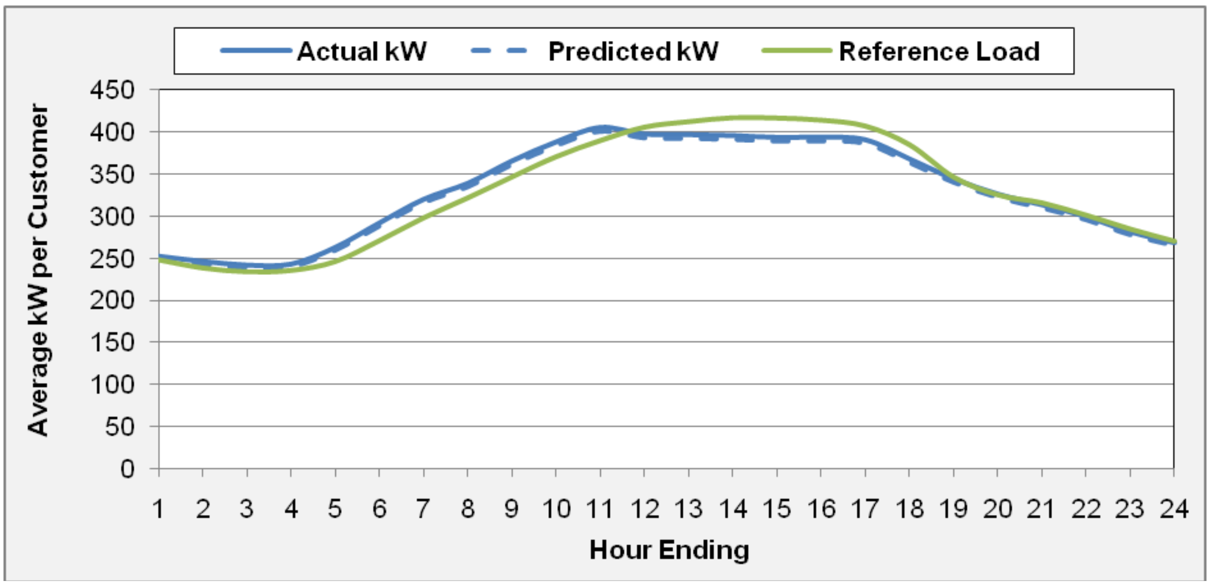
Hour	Sum of kWh	Sum of Betas	Sum of the Variance	T-Value	% Bias
12	1341871	738.0754	2.00E+06	0.52	0.06%
13	1346222	-565.1599	2.56E+06	-0.35	-0.04%
14	1350264	3583.859	3.84E+06	1.83	0.27%
15	1330266	1865.46	4.30E+06	0.90	0.14%
16	1314052	4142.49	4.44E+06	1.97	0.32%
17	1292215	4922.025	4.02E+06	2.45	0.38%
18	1236585	9084.645	2.49E+06	5.75	0.73%
Total	9211475	23771.39	2.37E+07	4.88	0.26%

F.2. Panel Model Checks

Figure F-3 shows the average event day impact for the Offices, Hotels, Finance, Services industry, by far the largest industry in terms of CPP enrollment in SDG&E's territory. During the event hours of 11 AM to

6 PM, the panel model with treatment variables specified as described in the introduction to this section predicts an average load reduction of 5.48%. On the average event day, individual customer regressions predict an average load impact of 5.28% for the same industry. Further, the panel regression definitively answers an initial question with the individual customer regression analysis – that is, the question of pre-event load shifting. As you can see in the figure, the panel model with control group drawn through stratified matching shows the prevalence of pre-event load shifting. When results from two different regression methods agree across differently specified treatment variables, there is added confidence that the results are robust.

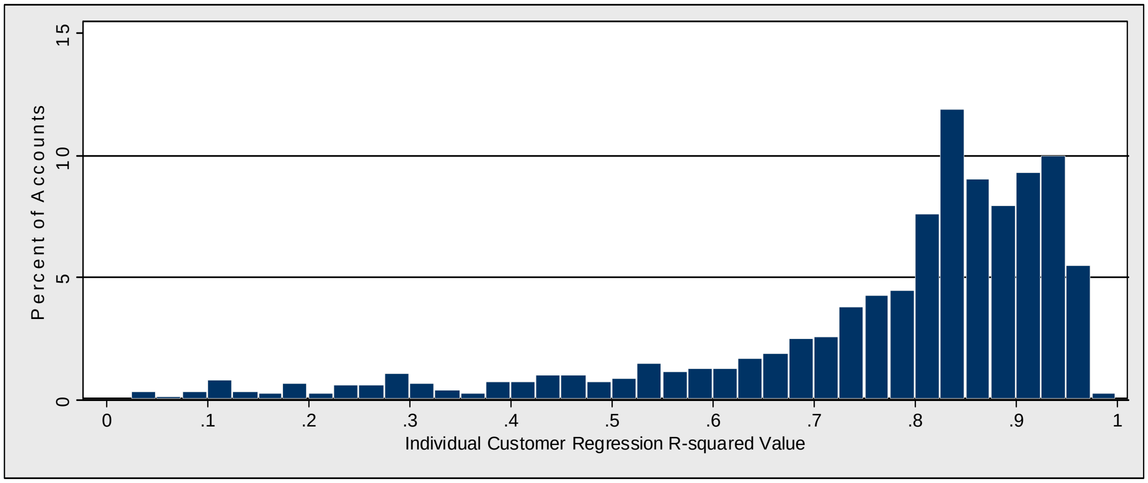
Figure F-3:
SDG&E Offices, Hotels, Finance, Services Industry Panel Model Results



F.3. Goodness of Fit Measures

Figure F-4 shows the distribution of R-squared values from the individual customer regressions for SDG&E's 1364 CPP participants for whom we had data. The individual regressions do a good job of explaining variation in customer load, with 50% having R-squared statistics exceeding 0.83. There are some low R-squared values in the tail, but the mean R-squared value is a respectable 0.77, which is similar to the SCE and PG&E models.

Figure F-4:
Distribution of R-squared Values from Individual Regressions



In spite of some low R-squared values at the individual customer level, the explained variation is quite high for the average customer overall, by industry segment and by LCA. In fact, in aggregate, the model explains nearly 97% of the variation in energy use.

Table F-2 summarizes the amount of variation explained by the regression model for the average customer in specific segments. Overall, depending on the specific group assessed, between 86 and 98% of the variation is explained. Customers in the Agriculture, Mining & Construction industry and the Wholesale, Transport and other utilities industry have the lowest R-squared values. In the other industries, 93% or more of the variation in hourly energy use is explained.

Table F-2:
R-squared Values for the Average Customer by Segment

Customer Segment	R-squared
All Customers	0.97
Industry	
Agriculture, Mining & Construction	0.86
Manufacturing	0.94
Wholesale, Transport, other utilities	0.88
Retail stores	0.98
Offices, Hotels, Finance, Services	0.97
Schools	0.93
Institutional/Government	0.97
Other or Undefined	0.95

APPENDIX G PG&E LARGE AND MEDIUM C&I EX ANTE LOAD IMPACTS

Table G-1:
1-in-2 Year Weather Conditions Program Specific PG&E CPP Load Impacts

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	2 PM - 6 PM											
2011					28.0	20.5	22.4	22.1	25.9	24.5	44.4	45.1
2012	50.7	55.4	61.2	58.9	68.0	57.2	66.3	69.8	83.0	90.5	104.0	108.1
2013	110.2	111.2	110.2	96.3	101.9	75.3	80.6	78.4	86.9	87.6	100.4	99.5
2014	99.0	98.5	98.4	86.6	92.8	69.7	75.5	74.3	83.6	85.4	98.6	98.6
2015	98.8	98.8	98.7	86.9	93.1	70.0	75.8	74.6	83.9	85.7	98.9	99.0
2016	99.1	99.2	99.1	87.3	93.4	70.2	76.1	74.8	84.1	86.0	99.3	99.3
2017	99.5	99.5	99.4	87.6	93.7	70.5	76.3	75.1	84.4	86.3	99.6	99.7
2018	99.8	99.8	99.8	87.8	94.1	70.7	76.6	75.3	84.6	86.6	99.9	100.0
2019	100.2	100.2	100.1	88.1	94.4	71.0	76.8	75.6	84.9	86.9	100.3	100.3
2020	100.5	100.5	100.4	88.4	94.7	71.2	77.0	75.8	85.1	87.2	100.6	100.6
2021	100.8	100.8	100.7	88.7	95.0	71.4	77.3	76.0	85.3	87.5	100.9	100.9

Table G-2:
1-in-10 Year Weather Conditions Program Specific PG&E CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	2 PM - 6 PM											
2011					22.8	16.6	20.2	22.1	20.2	25.6	44.4	45.2
2012	50.8	55.4	61.3	57.5	56.3	53.0	58.1	69.6	68.2	86.0	104.0	108.3
2013	110.3	111.1	110.3	93.3	81.9	69.2	70.1	78.6	70.2	83.5	100.4	99.6
2014	99.1	98.5	98.5	84.0	74.7	63.9	65.7	74.6	67.7	81.4	98.6	98.8
2015	98.9	98.7	98.8	84.3	75.0	64.2	65.9	74.9	68.0	81.7	98.9	99.1
2016	99.2	99.1	99.1	84.6	75.3	64.4	66.1	75.1	68.2	81.9	99.3	99.5
2017	99.6	99.4	99.5	84.9	75.5	64.7	66.3	75.4	68.4	82.2	99.6	99.8
2018	99.9	99.8	99.8	85.2	75.8	65.0	66.5	75.6	68.6	82.4	99.9	100.1
2019	100.3	100.1	100.1	85.4	76.0	65.2	66.7	75.8	68.9	82.6	100.3	100.5
2020	100.6	100.4	100.5	85.7	76.2	65.5	66.9	76.1	69.1	82.9	100.6	100.8
2021	100.9	100.7	100.8	86.0	76.5	65.7	67.1	76.3	69.3	83.1	100.9	101.1

Table G-3:
1-in-2 Year Weather Conditions Portfolio PG&E CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	2 PM - 6 PM											
2011					28.0	20.4	22.3	22.0	25.8	24.4	44.4	45.1
2012	50.7	55.4	61.2	58.9	67.9	57.1	66.2	69.7	83.0	90.4	104.0	108.1
2013	110.2	111.2	110.2	96.3	101.9	75.2	80.6	78.3	86.9	87.5	100.4	99.5
2014	99.0	98.5	98.4	86.6	92.7	69.7	75.5	74.3	83.5	85.3	98.6	98.6
2015	98.8	98.8	98.7	86.9	93.0	69.9	75.8	74.5	83.8	85.6	98.9	99.0
2016	99.1	99.2	99.1	87.3	93.4	70.2	76.0	74.8	84.1	86.0	99.3	99.3
2017	99.5	99.5	99.4	87.6	93.7	70.4	76.3	75.0	84.3	86.3	99.6	99.7
2018	99.8	99.8	99.8	87.8	94.0	70.7	76.5	75.3	84.6	86.6	99.9	100.0
2019	100.2	100.2	100.1	88.1	94.3	70.9	76.8	75.5	84.8	86.8	100.3	100.3
2020	100.5	100.5	100.4	88.4	94.6	71.1	77.0	75.7	85.0	87.1	100.6	100.6
2021	100.8	100.8	100.7	88.7	94.9	71.3	77.2	76.0	85.3	87.4	100.9	100.9

Table A-4:
1-in-10 Year Weather Conditions Portfolio PG&E CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	2 PM - 6 PM											
2011					22.7	16.6	20.2	22.1	20.2	25.5	44.4	45.2
2012	50.8	55.4	61.3	57.5	56.3	53.0	58.1	69.6	68.2	86.0	104.0	108.3
2013	110.3	111.1	110.3	93.3	81.9	69.1	70.0	78.6	70.1	83.4	100.4	99.6
2014	99.1	98.5	98.5	84.0	74.7	63.9	65.7	74.6	67.7	81.4	98.6	98.8
2015	98.9	98.7	98.8	84.3	75.0	64.1	65.9	74.8	67.9	81.6	98.9	99.1
2016	99.2	99.1	99.1	84.6	75.2	64.4	66.1	75.1	68.1	81.9	99.3	99.5
2017	99.6	99.4	99.5	84.9	75.5	64.7	66.3	75.3	68.4	82.1	99.6	99.8
2018	99.9	99.8	99.8	85.2	75.7	64.9	66.5	75.6	68.6	82.3	99.9	100.1
2019	100.3	100.1	100.1	85.4	76.0	65.2	66.7	75.8	68.8	82.6	100.3	100.5
2020	100.6	100.4	100.5	85.7	76.2	65.4	66.9	76.0	69.0	82.8	100.6	100.8
2021	100.9	100.7	100.8	86.0	76.4	65.7	67.1	76.2	69.2	83.0	100.9	101.1

APPENDIX H SCE LARGE C&I MONTHLY EX ANTE LOAD IMPACTS

Table H-1:
1-in-2 Year Weather Conditions Program Specific SCE CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	2 PM - 6 PM											
2011					28.6	30.9	24.6	26.8	27.4	24.1	25.0	31.6
2012	26.0	30.5	29.6	29.4	25.1	27.4	27.1	24.7	23.3	24.1	30.5	30.3
2013	28.2	30.2	27.4	28.0	27.9	26.0	27.4	22.9	26.3	24.1	29.5	29.9
2014	26.0	28.4	29.0	28.4	27.6	27.6	24.2	25.9	24.0	24.9	27.4	30.8
2015-2021	30.9	29.2	32.6	28.0	27.4	27.4	24.5	23.8	24.3	25.1	26.8	31.6

Table H-2:
1-in-10 Year Weather Conditions Program Specific SCE CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	2 PM - 6 PM											
2011					28.1	27.8	23.5	26.2	27.1	26.7	18.7	31.6
2012	26.0	28.4	26.9	24.4	24.7	26.7	26.9	24.3	23.1	26.2	23.3	30.3
2013	28.2	28.8	25.2	24.1	27.6	24.2	26.3	22.8	26.1	26.0	22.4	29.9
2014	26.0	26.5	27.1	22.5	27.6	25.5	23.4	25.0	23.4	26.8	19.4	30.8
2015-2021	30.9	27.0	29.8	24.0	26.9	25.8	23.7	23.4	24.0	27.5	20.1	31.6

Table H-3:
1-in-2 Year Weather Conditions Portfolio SCE CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	2 PM - 6 PM											
2011					28.6	30.9	24.6	26.8	27.4	24.1	25.0	31.6
2012	26.0	30.5	29.6	29.4	25.1	27.4	27.1	24.7	23.3	24.1	30.5	30.3
2013	28.2	30.2	27.4	28.0	27.9	26.0	27.4	22.9	26.3	24.1	29.5	29.9
2014	26.0	28.4	29.0	28.4	27.6	27.6	24.2	25.9	24.0	24.9	27.4	30.8
2015-2021	30.9	29.2	32.6	28.0	27.4	27.4	24.5	23.8	24.3	25.1	26.8	31.6

Table H-4:
1-in-10 Year Weather Conditions Portfolio SCE CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	2 PM - 6 PM											
2011					28.1	27.8	23.5	26.2	27.1	26.7	18.7	31.6
2012	26.0	28.4	26.9	24.4	24.7	26.7	26.9	24.3	23.1	26.2	23.3	30.3
2013	28.2	28.8	25.2	24.1	27.6	24.2	26.3	22.8	26.1	26.0	22.4	29.9
2014	26.0	26.5	27.1	22.5	27.6	25.5	23.4	25.0	23.4	26.8	19.4	30.8
2015-21	30.9	27.0	29.8	24.0	26.9	25.8	23.7	23.4	24.0	27.5	20.1	31.6

APPENDIX I SDG&E MEDIUM AND LARGE C&I EX ANTE LOAD IMPACTS

Table I-1:
1-in-2 Year Weather Conditions Program Specific SDG&E CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	4 PM - 9 PM			1 PM - 6 PM							4 PM - 9 PM	
2011					16.6	16.3	18.3	16.1	15.2	17.7	7.7	7.7
2012	7.1	7.4	8.0	20.0	16.2	15.9	17.9	15.8	14.9	17.3	7.5	7.6
2013	4.2	2.9	4.6	49.5	41.9	41.8	44.9	41.3	38.1	45.0	0.2	1.8
2014	2.4	0.6	3.3	59.3	48.2	46.0	47.6	42.3	37.8	43.2	1.3	2.2
2015	2.8	0.7	3.7	60.1	47.2	45.1	45.8	41.4	36.5	41.6	3.1	3.8
2016	4.4	3.0	5.3	57.9	47.3	45.2	45.5	41.4	36.3	41.3	3.9	4.6
2017	5.1	3.8	6.0	57.6	48.1	45.3	45.3	41.5	36.2	41.1	4.7	5.3
2018	5.8	4.6	6.7	57.2	48.2	46.0	46.1	42.2	36.8	41.7	4.8	5.5
2019	5.9	4.8	6.9	58.1	49.0	46.8	46.8	42.8	37.4	42.4	4.9	5.6
2020	6.1	4.9	7.0	59.1	49.8	47.5	47.6	43.5	38.0	43.1	5.1	5.7
2021	6.2	5.0	7.2	60.0	50.6	48.3	48.3	44.2	38.6	43.8	5.2	5.9

Table I-2:
1-in-10 Year Weather Conditions Program Specific SDG&E CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	4 PM - 9 PM			1 PM - 6 PM							4 PM - 9 PM	
2011					23.3	15.5	20.9	22.1	25.7	26.4	7.6	7.6
2012	7.5	7.8	10.1	25.2	22.9	15.1	20.6	21.7	25.3	26.0	7.4	7.5
2013	4.1	3.6	12.3	61.3	57.6	38.7	54.7	63.9	79.7	81.5	0.3	1.9
2014	1.9	1.6	13.5	73.4	66.1	42.7	58.0	65.3	78.3	77.4	1.4	2.3
2015	2.3	1.7	13.7	74.5	62.2	42.1	55.0	61.3	72.5	71.8	3.2	4.0
2016	4.0	3.8	14.0	69.9	61.2	42.3	54.3	60.3	70.7	70.2	4.0	4.7
2017	4.8	4.7	14.2	68.7	62.2	42.5	53.7	59.4	69.2	68.8	4.8	5.4
2018	5.5	5.5	14.5	67.6	61.3	43.2	54.6	60.3	70.3	69.9	4.9	5.6
2019	5.6	5.6	14.7	68.7	62.3	43.9	55.5	61.3	71.4	71.0	5.0	5.7
2020	5.8	5.7	15.0	69.8	63.3	44.6	56.3	62.2	72.5	72.2	5.1	5.8
2021	5.9	5.9	15.3	70.9	64.3	45.3	57.3	63.2	73.7	73.3	5.3	6.0

Table I-3:
1-in-2 Year Weather Conditions Portfolio SDG&E CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	4 PM - 9 PM			1 PM - 6 PM							4 PM - 9 PM	
2011					12.5	12.2	14.8	12.6	12.2	14.4	6.0	6.0
2012	5.8	6.1	6.5	16.1	12.1	11.9	14.5	12.3	12.0	14.2	5.9	5.9
2013	3.0	1.6	3.1	45.6	37.9	37.9	41.6	37.9	35.2	41.8	-1.5	0.1
2014	1.2	-0.7	1.8	55.5	44.2	42.1	44.3	38.9	34.9	40.1	-0.3	0.5
2015	1.6	-0.6	2.2	56.3	43.2	41.2	42.4	37.9	33.5	38.3	1.4	2.1
2016	3.1	1.6	3.7	53.9	43.2	41.1	42.1	37.9	33.3	38.0	2.2	2.8
2017	3.8	2.4	4.4	53.5	43.9	41.2	41.8	37.9	33.1	37.7	2.9	3.5
2018	4.5	3.2	5.1	53.1	43.9	41.8	42.5	38.5	33.7	38.3	3.0	3.6
2019	4.6	3.3	5.2	53.9	44.6	42.5	43.1	39.1	34.2	38.9	3.1	3.7
2020	4.7	3.4	5.4	54.8	45.3	43.1	43.8	39.7	34.7	39.6	3.2	3.8
2021	4.8	3.5	5.5	55.6	45.9	43.8	44.5	40.3	35.3	40.2	3.3	3.9

Table I-4:
1-in-10 Year Weather Conditions Portfolio SDG&E CPP Load Impacts

Forecast Year	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	4 PM - 9 PM			1 PM - 6 PM							4 PM - 9 PM	
2011					19.8	11.5	17.5	18.7	22.6	22.9	5.8	5.9
2012	6.0	6.5	8.7	21.5	19.5	11.2	17.3	18.4	22.3	22.6	5.7	5.8
2013	2.7	2.3	11.0	57.7	54.2	34.8	51.5	60.7	76.7	78.1	-1.4	0.3
2014	0.6	0.2	12.2	69.8	62.7	38.8	54.8	62.0	75.3	74.0	-0.3	0.7
2015	0.9	0.3	12.4	70.8	58.7	38.2	51.7	58.0	69.4	68.4	1.5	2.3
2016	2.6	2.5	12.6	66.2	57.7	38.3	50.9	56.9	67.6	66.7	2.2	3.0
2017	3.3	3.3	12.8	64.9	58.6	38.4	50.3	55.9	66.0	65.2	3.0	3.7
2018	4.0	4.0	13.0	63.7	57.6	39.0	51.1	56.8	67.0	66.2	3.0	3.8
2019	4.1	4.1	13.3	64.7	58.5	39.6	51.9	57.7	68.1	67.3	3.1	3.9
2020	4.2	4.2	13.5	65.7	59.4	40.2	52.7	58.6	69.1	68.3	3.2	4.0
2021	4.3	4.3	13.8	66.7	60.4	40.8	53.5	59.5	70.2	69.4	3.3	4.1