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2011 California Statewide Non-residential Critical Peak Pricing Evaluation

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Prepared for:

Pacific Gas and Electric (PG&E)
Southern California Edison (SCE)
San Diego Gas and Electric (SDG&E)

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1 Executive Summary

This report provides the 2011 program year ex post load impact estimates for the Non-Residential Critical Peak Pricing (CPP) tariffs that have been implemented by California's three electric investor owned utilities (IOUs), Pacific Gas and Electric (PG&E), Southern California Edison (SCE) and San Diego Gas and Electric (SDG&E).¹ It also includes ex ante load impact estimates for the CPP program for 2012 through 2022. Ex ante impacts reflect the load reductions capability of the program under a standard set of 1-in-2 and 1-in-10 weather year conditions and factor in expected changes in enrollment.

Critical Peak Pricing is a rate in which the utility charges a higher price for consumption of electricity on a few critical peak days (usually a few hours a day, around 12 days in a year) in exchange for a reduction in non-peak energy charges, demand charges or both. At all three IOUs, CPP is the default rate for large customers.² The CPP rates were also available for small and medium customers on a voluntary basis in 2011. Most customers on CPP rates in 2011 were large customers defaulted onto CPP from pre-existing Time of Use (TOU) rates that already provided incentives to shift or reduce electricity usage during peak periods. SDG&E and PG&E customers on CPP rates 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. In addition, for SCE and SDG&E, the introduction of default CPP in October 2009 and May 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.

By the summer of 2010, all three utilities had defaulted their large commercial and industrial (C&I) customers (peak demand >200kW) onto a CPP tariff layered over a time-of-use (TOU) rate.³ In addition, SDG&E had defaulted roughly 600 medium C&I customers⁴ onto the tariff and PG&E had migrated small and medium C&I customers that had previously enrolled on its voluntary critical peak rate, SmartRate, onto the new, default CPP tariff. Total enrollment on CPP for all three IOUs combined was approximately 6,050 accounts by summer of 2011.

1.1 Ex Post Load Impact Summary

Ex post impacts reflect the change in average hourly electricity demand attributable to the customers enrolled on CPP for days on which CPP events were called. Table 1-1 summarizes the 2011 event days, the estimated reference loads, and the estimated load impacts for each utility.

¹ Although PG&E refers to its tariffs as Peak Day Pricing (PDP), for simplicity, the relevant tariffs from all three utilities are referred to as CPP throughout the report.

² Throughout this report, we use definitions of large, medium and small customers consistent with DR reporting to the CPUC. Accounts with annual peak demand of 200 kW or more are considered large while accounts between 20 kW and 200 kW are referred to as medium. Small businesses include all accounts with annual peak demands under 20 kW. In practice, the PG&E and SCE rate schedules define customers with annual peak demand above 500 kW as large and those between 200 kW to 500 kW as medium or general service customers.

³ Throughout this report, any reference to CPP refers to what is actually the CPP/TOU tariff being implemented by each utility.

⁴ Throughout this report the word "customer" is used synonymously with "service account."

Table 1-1: Summary of Statewide Ex Post CPP 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 11-6 PM (MW)	Load Impact 11-6 PM (MW)	% Impact
6/21/2011	470.4	26.7	5.7%	625.6	33.9	5.4%	-	-	-
7/5/2011	460.1	27.5	6.0%	656.8	36.7	5.6%	-	-	-
7/19/2011	-	-	-	611.9	35.6	5.8%	-	-	-
7/29/2011	424.3	26.2	6.2%	-	-	-	-	-	-
8/1/2011	-	-	-	620.3	36.4	5.9%	-	-	-
8/3/2011	-	-	-	621.7	36.1	5.8%	-	-	-
8/12/2011	-	-	-	571.3	32.7	5.7%	-	-	-
8/16/2011	-	-	-	599.4	33.6	5.6%	-	-	-
8/18/2011	-	-	-	604.5	34.0	5.6%	-	-	-
8/23/2011	487.8	29.0	5.9%	622.5	34.6	5.6%	-	-	-
8/26/2011	-	-	-	614.8	36.6	6.0%	-	-	-
8/27/2011	-	-	-	-	-	-	269.1	16.9	6.3%
8/29/2011	464.9	27.2	5.9%	-	-	-	-	-	-
9/2/2011	465.4	28.8	6.2%	-	-	-	-	-	-
9/6/2011	483.3	27.7	5.7%	664.2	36.6	5.5%	-	-	-
9/7/2011	494.6	28.7	5.8%	-	-	-	358.8	18.6	5.2%
9/20/2011	508.6	28.3	5.6%	-	-	-	-	-	-
9/23/2011	-	-	-	572.3	32.7	5.7%	-	-	-
Average Event	473.4	27.8	5.9%	615.4	35.0	5.7%	-	-	-

Enrollment for each utility varied slightly from event to event and the number of events varied by IOU. On average, PG&E, SCE and SD&GE notified roughly 1,750, 3,000 and 1,300 participants, respectively, of CPP event days. PG&E called 9 critical peak events and obtained an average peak period load reduction⁵ of 27.8 MW, or 5.9% of the average reference load on event days. SCE called 12 critical peak events and obtained an average load reduction of 35.0 MW, or 5.7% of the average reference load. At both utilities, events were only called on summer weekdays. SDG&E called one of two events on a weekday and the other on a weekend. A third event at SDG&E, scheduled for September 8, was cancelled part way through the event period due to a system wide blackout. Because the two event days at SDG&E represent different day types, they have not been averaged. The approximately 1,300 enrolled accounts at SDG&E provided an average of 16.9 MW (6.3%) of load

⁵ The "average event load reduction" is the arithmetic average of all of the individual load reductions for the year.

reduction on August 27, the weekend, and 18.6 MW (5.2%) of load reduction on September 7, the weekday.

Several key differences exist in ex post conditions across all three utilities. As such, cross utility comparisons of load impacts should be made with caution. Each utility calls CPP event days based on their own protocols, which include forecasted conditions on their electrical system. Due to the climatic diversity in California, the electrical system load patterns across utilities are not always coincident, particularly for Northern and Southern California. For example, PG&E's system peaked on June 21, 2011 while SCE's and SDG&E's systems peaked on September 7, 2011. Another key difference in ex post results is event duration. SDG&E uses a longer event window, 11 AM to 6 PM, than PG&E or SCE, which have a 2 PM to 6 PM window. Another key difference is the CPP rate design itself. 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 1-2 compares the average 2010 CPP event with the average 2011 CPP event for each utility. The aggregate load impacts for the average event at PG&E and SCE are larger in 2011 than 2010 by approximately 5 MW at each utility. Further, the percent impacts on the average event day are noticeably larger for PG&E and SCE as well, but not so for SDG&E. In 2010, the percent impacts on the average event day were 3.9% and 2.9% at PG&E and SCE, respectively. In 2011, the percent impacts on the average event day grew to 5.9% and 5.7% at PG&E and SCE, respectively. At SDG&E the percent impacts on the average event day in 2010 (5.3%) closely matched the percent impacts observed for the one weekday event in 2011 (5.2%). The aggregate SDG&E load impacts between the two years differ by a nominal amount, as do the reference loads.

**Table 1-2: Summary of 2010 and 2011 Statewide CPP Impacts
Average Event Day***

	Year	Number of Events Called	Approximate Customer Count	Reference Load (MW)	Load Impact (MW)	Percent Impact (%)	Temperature (°F)
PG&E	2010	9	1,650	592.0	23.0	3.9%	90.2
	2011	9	1,750	473.4	27.8	5.9%	88.1
SCE	2010	12	4,100	1077.2	30.7	2.9%	84.7
	2011	12	3,000	615.4	35.0	5.7%	84.7
SDG&E	2010	4	1,350	356.8	18.8	5.3%	81.3
	2011	2	1,300	358.8	18.6	5.2%	86.2

*For SDG&E the average event day in 2011 is the weekday event on September 7.

Statewide, from 2009 to 2010, the number of CPP participants increased from approximately 2,700 to 7,100 customers. By summer 2011, bill protection expired for PG&E and SCE and statewide enrollment in CPP during the 2011 summer was approximately 6,050 accounts. With fewer participants, the event day load absent DR – the reference load – decreased from 2,027 MW in 2010 to about 1,500 MW in 2011. However, in spite of this drop in enrollment, aggregate statewide CPP load impacts increased from 72.5 MW in 2010 to 81.4 MW in 2011.

Differences in load reductions across years can be due in part to differences in the participant mix. Approximately 1,800 SCE service accounts migrated off CPP between 2010 and 2011. The attrition was somewhat offset by enrollment of an additional 750 accounts, out of which approximately 400 were voluntary small and medium accounts. The customer mix also changed substantially at PG&E, although net enrollment did not change much. While PG&E had approximately 1,650 accounts for the average 2010 event, toward the end of the summer over 1,800 accounts were enrolled in CPP rates. Roughly 480 of those accounts either opted out or closed before the 2011 summer, mostly from the Offices and Schools business sectors. The attrition at PG&E was offset by the addition of approximately 400 customers, the bulk of which came from the Agricultural, Water, Transportation and Manufacturing sectors, which historically have provided larger than average percent reductions.

Load impacts and enrollment at SDG&E remained relatively stable from 2010 to 2011. However, because there was only one weekday event at SDG&E, the cross-year comparison of impacts is weaker. Detailed changes in enrollment, reference load and load impacts for each utility are presented later in the report, as is a more detailed discussion of impact differences between 2010 and 2011.

1.2 Ex Ante Load Impact Summary

Ex ante impacts reflect the load reductions capability of the program under a standard set of 1-in-2 and 1-in-10 weather year conditions and factor in expected changes in enrollment and known upcoming policy or rate changes.

Within the next 2 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 and second year retention rates were, how much load reduction 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. 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. It summarizes the load impacts across the common event period of 2 PM to 6 PM, though in practice each utility has a unique event window. For 2012, large customer enrollment statewide is projected to be 5,800 in 2012. Thereafter, enrollment will increase with 6,600 accounts forecast to be enrolled by 2022. The enrollment increases both because of general population growth and because utilities will default additional large customers when they have had interval data available for 12 months.

**Table 1-2:
Summary of Ex Ante Statewide Load Impacts by Forecast Year (Portfolio)
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	2012	5,832	1,498.4	1,427.4	71.0	4.7%
	2013	6,188	1,608.5	1,530.7	77.9	4.8%
	2014	6,464	1,691.0	1,607.7	83.3	4.9%
	2015	6,513	1,704.5	1,620.3	84.1	4.9%
	2016	6,527	1,708.3	1,624.1	84.2	4.9%
	2017	6,542	1,712.5	1,628.2	84.3	4.9%
	2018	6,557	1,717.0	1,632.6	84.4	4.9%
	2019	6,573	1,721.8	1,637.3	84.5	4.9%
	2020	6,590	1,726.8	1,642.2	84.7	4.9%
	2021	6,607	1,732.1	1,647.3	84.8	4.9%
	2022	6,624	1,737.4	1,652.5	84.9	4.9%
Medium C&I ^[1]	2012	194	7.1	6.5	0.5	7.6%
	2013	196	7.3	6.8	0.5	7.4%
	2014	9,709	332.2	309.9	22.3	6.7%
	2015	19,387	685.8	636.6	49.2	7.2%
	2016	31,254	1153.5	1080.4	73.1	6.3%
	2017	37,029	1387.3	1302.5	84.9	6.1%
	2018	35,828	1338.2	1255.7	82.5	6.2%
	2019	36,166	1350.7	1267.4	83.3	6.2%
	2020	36,506	1363.3	1279.2	84.0	6.2%
	2021	36,839	1375.5	1290.7	84.8	6.2%
	2022	37,161	1387.4	1301.9	85.5	6.2%

1] Does not include SCE medium accounts

Commensurate with the enrollment growth, load impacts are estimated to grow from 71.0 MW in 2012 to 84.9 MW for the large C&I accounts. The large customer ex-ante impacts produced last year for

2012 are nearly identical, 71.3 MW, to this year's projections, 71.0 MW. Despite the similarity, PG&E's and SCE's program underwent non-trivial shifts in their customer mix as first year bill protection expired. The remaining customers were slightly smaller, but delivered larger percent load reductions. Compared to last year's projections, ex-ante aggregate impacts increased by roughly 14% in 2014-2022. The difference reflects the improved performance observed in PG&E and SCE large customers during the second year of CPP participation.

With the introduction of default CPP in the medium C&I sector, enrollment for PG&E and SDG&E is projected to peak in 2022 at approximately 37,200 accounts. Once default CPP is fully in place, these customers are projected to deliver 85.5 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 4.9%, medium accounts are projected to provide load reductions of 6.2% when the programs reach maturity. There are three primary reasons for the difference. First, large customers with demands less than 100 kW were used as a proxy for medium customers and these were one of the most price responsive segments in 2011. Second, 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. Third, many of the best performers among large CPP customers are dually enrolled in other DR programs. To avoid double counting those reductions are attributed to other programs, reducing the CPP portfolio impacts. With medium customers the overlap with other programs is smaller.

1.3 Report Organization

The remainder of this document is separated into nine sections and five appendices. Section 2 summarizes the program details for each tariff. Despite many similarities in design, each utility's default CPP and opt-out TOU rates have different rate blocks, credits and consumption and demand charges. Section 3 discusses the methodology employed to estimate ex post load impacts and develop ex ante impact estimates. PG&E's ex post results are presented in Section 4, SCE's in Section 5 and SDG&E's in Section 6. Section 7 through Section 9 presents the ex ante results for PG&E, SCE and SDG&E, respectively. Appendix A contains a detailed explanation of the validation tests conducted by FSC to ensure reliable results and Appendices B through D contain regression model validations for each utility. Appendix E highlights important issues surrounding limitations of the regression method. Draft electronic ex post tables that provide the hourly load impacts for individual event days and across population segments are included with this report.

2 CPP Program Details

In 2009 the CPUC issued general guidelines for rate design for dynamic pricing (CPUC decision 10-02-032.) The decision standardized several key elements of rate design in California for investor owned utilities:

- The default tariff for large, medium and small commercial and industrial customers is to be a dynamic pricing tariff;
- Default rates will include a high price during peak periods on a limited number of critical event days and time of use rates on non-event days;
- The opt-out tariff for all non-residential default customers should be a time varying rate – in other words, there should no longer be a flat rate option for non-residential customers once the default schedule is completed;
- The critical peak price should represent the cost of capacity used to meet peak energy needs plus the marginal cost of energy – in essence, all capacity value should be allocated to peak period hours on critical event days; and
- The utilities should offer first year bill protection to customers defaulted onto dynamic rates.

The dynamic pricing decision also covered several other elements of rate design. It standardized default tariffs, opt-out tariffs and several components of the default process. It also established a schedule for implementation of dynamic pricing for each utility.

PG&E, SCE and SDG&E have developed CPP tariffs that adhere to the broad principles outlined in the CPUC Decision. However, many details of the CPP tariff vary across the utilities. Among the important differences are:

- The rate design window schedule for each IOU caused the CPP rates to be implemented at different times. SDG&E was the first to default customers onto a CPP tariff, on May 1, 2008. SCE began defaulting customers onto CPP in October 2009, 18 months later and PG&E began defaulting customers in May 2010.
- SDG&E defaulted customers whose maximum demand exceeded 20 kW for the prior 12 consecutive months. PG&E defaulted customers with maximum demand that exceeded 200 kW for 3 consecutive months in the past year. In addition, PG&E transitioned approximately 110 small customers who voluntarily enrolled on SmartRate, a pure CPP tariff, to the new CPP/TOU tariff. SCE required only that a customer's "monthly Maximum Demand exceed 200 kW."
- At SDG&E customers are locked into the CPP rate for a full year if they do not opt out prior to going on the rate, while at PG&E and SCE, customers can opt out at anytime, but they forfeit bill protection if they do so during the first year.
- SCE and PG&E have the same event hours, 2 PM to 6 PM, although a small number of customers in PG&E's service territory have elected a 12 PM to 6 PM event window with reduced credits and CPP charges. SCE and PG&E also share the same TOU peak period hours, 12 PM to 6 PM, Monday through Friday. For SDG&E, both the CPP event period hours and TOU peak period hours are from 11 AM to 6 PM.
- PG&E and SDG&E can call CPP events 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 events with no minimum.

- PG&E attempts to notify customers via phone, email, pager or text by 2 PM on the day before the event, while SCE and SDG&E attempt to notify customers by 3 PM the day before.
- PG&E and SDG&E offer customers the ability to insure part or all of their demand against higher CPP prices – a feature known as a Capacity Reservation Level – while SCE has not yet implemented this feature.

The default enrollment process differed significantly across utilities. At PG&E, more than 5,000 accounts were scheduled to be defaulted onto CPP, but the majority of them migrated to a TOU rate before being placed on the CPP tariff. By the end of the 2011 summer, approximately 1,750 PG&E accounts remained on default CPP. At SCE, most of the 8,000 eligible accounts were placed on default CPP in the fall of 2009, but nearly half of them opted out to TOU before the first summer period. By the end of the 2011 summer, roughly 3,000 accounts remained on default CPP. By the end of 2011 SDG&E had almost 1,300 accounts, or roughly 60% of eligible customers, on CPP. As indicated above, if a customer does not opt out within 45 days of being eligible for default CPP at SDG&E, they must stay on the rate for at least 12 months, whereas at PG&E and SCE customers can opt out at any time.

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

Table 2-1 provides examples of the default CPP and opt-out TOU rates at each utility. There are different versions of CPP rates at each utility, which vary with customer size, service voltage level and time period. The rate components, credits and charges vary significantly across utilities. It should also be noted that seasonal definitions also differ. PG&E defines summer as the period from May through October while SDG&E defines summer as May through September and SCE defines summer as June through September. At all three utilities, peak period energy prices increase on critical peak days relative to the opt-out TOU tariff and there are rate credits during non-event days, which must be considered in the analysis.

The critical peak price is typically an adder, in effect during CPP hours, and varies from a low of \$0.90/kWh for PG&E A-10 customers to \$1.06/kWh for SDG&E customers, to \$1.20/kWh for PG&E E-19 and E-20 customers, to a high of \$1.36/kWh for SCE customers. The CPP credits take the form of reduced demand charges (\$/kW), reduced consumption charges (\$/kWh), or both. At all utilities, customers on CPP experience lower on peak demand credits that vary substantially across tariffs, ranging from \$2.11/kW for PG&E A-10 customers, to about \$5-6/kW for PG&E E-19 and E-20 and SDG&E customers, to \$12.20/kW for SCE customers on TOU-8. PG&E also has a small energy credit for non-event periods as does SDG&E. 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 otherwise applicable tariff (OAT), rather than as explicit credits. The summer on-peak demand credit is \$5.21 and the energy credits are under \$0.01. The impact on customer bills is the same as that of an explicit credit.

Table 2-1: Example Default CPP Rates at PG&E, SCE & SDG&E⁶

Season	TOU/CPP Component	Type of Charge/Credit	Period	Rate		
				PG& E E-19	SCE GS-3	SDG&E AL-TOU
Summer	TOU Component	Energy Rates (\$'s per kWh)	On-Peak	\$0.13476	\$0.12448	\$0.09907
			Semi-Peak	\$0.09579	\$0.09086	\$0.07979
			Off-Peak	\$0.07028	\$0.06543	\$0.05942
		Demand Charges (\$'s per kW)	On-Peak	\$14.70	\$12.96	\$12.86
			Semi-Peak	\$3.43	\$3.08	NA
			Maximum Demand	\$11.85	\$13.30	\$13.57
	CPP Component	Energy Charges and Credits (\$'s per kWh)	CPP Event Adder	\$1.20	\$1.36229	\$1.06282
			On-Peak	\$0.00000	NA	(\$0.00646)
			Semi-Peak	\$0.00000	NA	(\$0.00638)
			Off-Peak	NA	NA	(\$0.00591)
		Demand Credits (\$'s per kW)	On-Peak	(\$6.35)	(\$11.62)	(\$5.21)
			Semi-Peak	(\$1.37)	NA	NA
		Capacity Reservation Charge (\$'s per kW/Month)	Summer	\$13.05	NA	\$6.42
Winter	TOU Component	Energy Rates (\$'s per kWh)	On-Peak	NA	NA	\$0.09320
			Semi-Peak	\$0.09063	\$0.06987	\$0.08491
			Off-Peak	\$0.07320	\$0.05412	\$0.06475
		Demand Charges (\$'s per kW)	On-Peak	NA	\$0.00	\$4.92
			Semi-Peak	\$0.21	\$0.00	NA
			Maximum Demand	\$11.85	\$13.30	\$13.57
	CPP Component	Energy Charges and Credits (\$'s per kWh)	CPP Event Adder	\$1.20	NA	\$1.06
			On-Peak	\$0.00000	NA	(\$0.00646)
			Semi-Peak	\$0.00000	NA	(\$0.00638)
			Off-Peak	NA	NA	(\$0.00591)
		Demand Credits (\$'s per kW)	On-Peak	NA	NA	(\$0.17)
			Semi-Peak	NA	NA	NA
		Capacity Reservation Charge (\$'s per kW/Month)	Winter	\$1.12	NA	NA

*NA=Not Applicable

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-20.⁷ SCE does not have a capacity reservation charge. Capacity reservation is a type of insurance contract in which a customer pays a fee (measured per kW) to set a level of demand below which it will be charged the non-CPP, TOU price during event

⁶ These rates are for illustrative purposes. Rates vary by time, customer size and service voltage level. The rates shown are for customers at the secondary voltage level and assignment of customers varies by utility. E-19 is mandatory for PG&E customers who fail to meet the requirements of E-20, but have monthly maximum billing demand above 499 kW and is voluntary for PG&E customers with maximum billing demand greater than 200 kW and less than 500 kW; TOU-GS-3 is mandatory for SCE customers with maximum demand greater than 200 kW and less than 500 kW; and AL-TOU applies to all SDG&E customers whose monthly maximum demand equals, exceeds, or is expected to equal or exceed 20 kW. The example PG&E E-19 rate was filed February 29, 2012; the SCE TOU-GS-3 rate was filed December 27, 2011; the SDG&E AL-TOU demand charges were filed February 17, 2012 and energy charges were filed December 29, 2011; the SDG&E EECC AL-TOU commodity rates were filed December 29, 2011 and the SDG&E EECC-CPP-D commodity rates were filed December 29, 2011. The table does not include all CPP rates at each utility. Please consult the websites of each utility to obtain the CPP rates that were in effect for specific time periods.

⁷ 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.

periods. Above the set level, a customer will pay the normal CPP price during an event. Customers choosing this option will pay the capacity reservation fee whether or not events are called and whether or not they actually reach their specified level of demand during an event. SDG&E charges \$6.42/kW per month for this option and the default level for SDG&E customers is 50% of a customer's average of their monthly maximum demands during the previous summer. PG&E also sets the default level to 50% of the same metric, but the capacity reservation structure is different. For PG&E, E-19 and E-20 customers pay capacity reservation charges according to the peak (during summer) and part-peak (during winter) demand charges that they normally pay during the hours of a CPP event. This means that the summer price for capacity reservation is \$14.70/kW and the winter price is about \$0.21/kW. Because CPP events in PG&E's territory are much more likely to be called in the summer, it is sensible to charge more for insuring against events during the summer.

3 Methodology

To calculate load reductions for demand response programs, customer's load patterns in the absence of program participation – the reference load – must be estimated. Reference loads can be estimated using pre-enrollment data, by observing differences in behavior during event and non-event days (i.e., a “within subjects” design), by using an external control group or through a combination 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 CPP. In the absence of a controlled experiment, the best available method is a function of program characteristics, available data and the ability to incorporate research design elements into the analysis and statistical modeling. The approach used here is discussed below.

With CPP tariffs, the primary intervention – event days with higher peak period prices – is present on some days and not on others, making it possible to observe behavior with and without events under similar conditions. This type of repeated treatment supports a “within subjects” design in which impacts are determined by comparing differences in peak period energy use on CPP event days and similar days when events are not called. This approach works if a customer's electrical usage on “event-like” days is similar to their usage on event days, absent response to the higher event prices. This underlying assumption can be made with reasonable confidence for weather insensitive customers. However, more caution is required in evaluating impacts from weather sensitive customers. Higher critical peak price days tend to coincide with higher system loads and hotter temperatures. A critical task of the evaluation is to ensure that factors that may correlate with higher prices are not confounded with demand reductions.

Individual customer regressions were the primary source for estimating ex post load impacts.⁸ The analysis consisted of applying regression models separately to each set of customer load data at the hourly level – 24 models for each customer. Running 24 separate models produces coefficients and standard errors that are arithmetically equivalent to the outputs produced by the single model with hourly interactions, but the 24 separate models are easier to interpret and using this approach produces intermediate outputs that can be synthesized more quickly. The regression coefficients are specific to each customer and hour. The fact that each customer is analyzed individually accounts for factors that are constant for each customer such as industry and geographic location. It also better explains the variation in individual customer production and/or occupancy patterns, weather sensitivity, price responsiveness, enrollment dates and event day dispatch patterns (which can vary by customer).

With relatively small percent load impacts, it is particularly important that the models be accurate. Because CPP rates are designed to encourage customers to reduce electricity use during peak hours and to shift it to lower priced hours, it is not possible to know concretely if differences between the reference loads and the event day loads in the pre-event hours are due to downward bias or due to load shifting. As a cross-check to the regression approach, Sections B-3 and D-3 in Appendices B through D contain ex post impact estimates for each of the utilities that were estimated using an

⁸ Individual customer regressions have certain limitations, especially when few events are called. See Appendix E for a detailed discussion of some of these limitations.

external control group method. Overall, impacts from the control group analysis match well with impacts from the individual customer regression approach.

3.1 Regression Models

Regression models meant to capture the relationship between electricity use, year, day type, season and weather were run for each customer. Ordinary Least Squares regression was used and a separate model was run for each hour.⁹ Eight specifications were tested and the final results for each customer are based on the specification that produced the least bias for that customer. The eight models vary in how weather variables were defined, if at all, and in the inclusion of monthly or seasonal variables. This tailored approach customized models based on whether or not customers were weather sensitive or exhibited seasonal patterns.

Mathematically, the models can be expressed as follows for each hour, t :

$$kW_{dt} = a + \sum_{i=2009}^{2011} b_i * year_{dti} + \sum_{j=2}^5 c_j * daytype_{dtj} + d * season_{dt} + e * cooling_{dt} + f * heating_{dt} + g * otherdr_{dt} + h * actcpp_{dt} + i * eventday_{dt} + j * eventdayXtotalcdh_{dt} + e_{dt}, t = \{1, 2, 3 \dots 24\} \quad (1)$$

$$kW_{dt} = a + \sum_{i=2009}^{2011} b_i * year_{dti} + \sum_{j=2}^5 c_j * daytype_{dtj} + \sum_{k=2}^{12} d_k * month_{dtk} + e * cooling_{dt} + f * heating_{dt} + g * otherdr_{dt} + h * actcpp_{dt} + i * eventday_{dt} + j * eventdayXtotalcdh_{dt} + e_{dt}, t = \{1, 2, 3 \dots 24\} \quad (2)$$

For SDG&E, the fact that there were only two events in 2011 and one was on a weekday and the other on a weekend called for a somewhat different treatment specification. In order to identify the weekend, weekday and outage events as distinct, each event day has to be modeled separately with its own coefficients. If the events were not modeled in this way, the reference load predictions from all three days would be blended together, producing nonsensical results. To identify each event day as distinct, a separate event day dummy variable was included for each of the three event days,

$$kW_{dt} = a + \sum_{i=2009}^{2011} b_i * year_{dti} + \sum_{j=2}^5 c_j * daytype_{dtj} + d * season_{dt} + e * cooling_{dt} + f * heating_{dt} + g * otherdr_{dt} + h * actcpp_{dt} + \sum_{l=1}^3 i_l * eventday_{dtl} + e_{dt}, t = \{1, 2, 3 \dots 24\} \quad (1)$$

$$kW_{dt} = a + \sum_{i=2009}^{2011} b_i * year_{dti} + \sum_{j=2}^5 c_j * daytype_{dtj} + \sum_{k=2}^{12} d_k * month_{dtk} + e * cooling_{dt} + f * heating_{dt} + g * otherdr_{dt} + h * actcpp_{dt} + \sum_{l=1}^3 i_l * eventday_{dtl} + e_{dt}, t = \{1, 2, 3 \dots 24\} \quad (2)$$

Table 3-1 defines the variables used in the regression models.

⁹ Running separate models each hour – 24 models – with robust standard errors using OLS produced similar standard errors as time series techniques including Feasible GLS and Newey-West correction for auto-correlation.

Table 3-1: Regression Model Variables

Variable	Description
kW	Energy usage in each hourly interval $t=\{1,2,3 \dots 24\}$ for each date, d
Year	Binary variable for year of the hourly observation
Daytype	Binary variable for the day type of the hourly observation (Sundays and holidays and Tuesday through Thursday are grouped together)
Season	Binary variable indicating whether the hourly observation falls in the summer or winter season
Month	Binary variable indicating the month of the hourly observation
Otherdr	Binary variable indicating the presence of another DR event
Actcpp	Binary variable identifying the pre and post-enrollment periods on CPP as distinct
CDH	Cooling Degree Hour - the max of zero and the hourly temperature value less a base value
HDH	Heating Degree Hour - the inverse of CDH
CDD	Cooling Degree Day - the max of zero and the mean temperature of the day of the hourly observation less a base value
HDD	Heating Degree Day - the inverse of CDD
Totalcdh	The sum of cooling degree hours for the date of the hourly observation
Totalhdh	The sum of heating degree hours for the date of the hourly observation
Eventday	Binary variable indicating whether the day of the hourly observation is an event day
eventdayXtotalcdh	The interaction between whether the day of the hourly observation is an event day and totalcdh
eventdaynum ₁ ... _n	Binary variables indicating each event day, 1 ... _n .

Decisions regarding the weather variables used for each customer as well as the use of a seasonal dummy variable rather than a dummy variable for each month were based on the model that produced the least error for that customer. Only one set of cooling and heating variables was included in each regression (e.g., cdh and hdh, cdd and hdd, or totalcdh and totalhdh). Two models were also run with no cooling or heating variables for weather insensitive customers.

For PG&E and SCE, the treatment variables, “eventday” and “eventdayXtotalcdh,” capture how event impacts across all event days are related to weather. For SDG&E, the treatment variables “eventdaynum₁,” through “eventdaynum₃,” capture the actual load on event days. In both cases the counterfactual is calculated by setting the treatment variables equal to zero and applying the regression-derived coefficients to the model variables. The binary variable indicating the presence of another demand response event was also set to zero for estimation of the reference load so that impacts are not understated due to the presence of other demand response events.

Under the CPP rate schedule there is also a secondary treatment – the rate discounts that CPP customers experience relative to opt-out TOU customers. Estimating the effect of the rate discounts is inherently different and more complex than estimating the effect of CPP event day prices. Once a

customer enrolls on a CPP rate, it is not possible to observe their behavior absent the discount since it is in effect on a daily basis. Simply put, to evaluate the effect of the rate discount, it is critical to have data prior to enrollment on the rates, a control group or both. Ideally, the impacts would be estimated based on an experiment with large, well-matched control and treatment groups.

Evidence from the 2010 and 2011 CPP evaluation control group validity checks indicates that customers do not increase electricity use in response to the summer peak period discounts. In 2010, control groups were selected using pre-enrollment data, when both default CPP and control group customers experienced the same rate. This year, the control group was chosen by selecting statistical look-alikes with similar load shapes during hot days in non-summer months when both CPP and opt-out TOU customers experienced identical or nearly identical prices.¹⁰ In both years, the matched control groups showed very little difference between usage during peak periods on non-event days for CPP customers (who experience discounts relative to opt-out TOU customers) and customers that chose to opt-out to the otherwise available TOU tariff (see Figures B-2 in Section B-3 of Appendix B and D-2 in Section D-3 of Appendix D). This evidence drove our decision not to include a variable designed to capture the effects of TOU rate discount in the individual customer regressions.¹¹

3.2 Overview of Validation Methods

The validation of regression models focuses on lack of bias because an unbiased model produces accurate impact estimates. The accuracy of the estimates is particularly important when percent load reductions are relatively small.

Estimating the bias 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 so it must be estimated. However, actual load patterns without DR can be observed for event-like days (e.g., days with similar conditions on which events are not called).

Model specifications were optimized by checking for accuracy using several validation tests: out-of-sample testing, false experiments and a crosscheck of the results using a control group. In the first two procedures, the “true” answers are known. Out-of-sample testing can help assess how well regressions predict electricity use patterns during event-like days. False experiments test whether the treatment variables are confounding load impacts with other factors under event-like conditions. Ultimately, determining the regression specification is an iterative process that requires paying attention to the ex post results, the ex ante results and the validation assessments.

In summary, to ensure that the results are accurate (i.e., unbiased), we:

- Tested the ability of the regressions to produce accurate out-of-sample estimates for days that are reasonably similar to event days;

¹⁰ The prices that SDG&E CPP customers experience in winter are actually slightly lower than the prices they would experience on the opt-out TOU rate, but the difference in prices is nominal compared with the price differential in the summer season.

¹¹ While the effect of rate discounts can, in theory, be estimated using pre-enrollment data for participating customers – an interrupted time series design – we elected not to do so. In addition to the control group evidence, a key factor in our decision was that the more distant the pre-enrollment data becomes, the harder it becomes to isolate the effect of the rate discount from other factors using an interrupted time series analysis design.

-
- Assessed whether event hours during event-like days were being confounded with error by introducing false event-day variables;
 - Cross-checked results using a matched (but not randomly assigned) control group; and
 - Compared the within-sample, predictive accuracy of the regressions in aggregate, by industry and across hours for high temperature days when events were not called.

3.3 Out-of-sample and False Event Coefficient Tests

This section contains a high-level overview of the validation results and their implications. Appendices B, C and D show the detailed results of the validity assessment for all three utilities.

Out-of-sample testing refers to holding back event-like days from the model-fitting process in order to test model accuracy. The regressions were estimated based on data that excludes five of the seven hottest non-event weekdays. The goal was to withhold event-like days from the model-fitting or, put differently, to simulate the fact that event days are often the hottest days. The regression models were used to predict electricity use on the event-like days that were withheld. Then the model predictions were compared directly to the actual electricity use observed on those days. If the predictions are close to the true load, the model is more likely to predict accurately for event-like conditions. Because different customers have different amounts of data and because the out-of-sample validation tests were run at the individual customer level, different sets of five-days could be selected for each customer.¹²

Table 3-2 summarizes the out-of-sample predictive accuracy of the models during days that are similar to actual event days. For all three utilities, the regression models produce accurate estimates of the actual load during those days. For PG&E, SCE and SDG&E the average differences between predicted and actual values across the event windows are -1.1%, -1.0% and 0.2%, respectively.

¹² Although the term “event-like days” is used throughout this report to refer to the set of days used for the out-of-sample tests, these days are more extreme in temperature than the actual event days observed in a milder year like 2011. Holding back five of the seven hottest days creates a more stringent out-of-sample test than picking days that match the actual event days and more closely simulates the ex ante conditions over which the model will have to predict accurately.

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

Hour	PG&E			SCE			SDG&E		
	Actual kW	Predicted kW	% Difference	Actual kW	Predicted kW	% Difference	Actual kW	Predicted kW	% Difference
1	186.0	183.0	-1.6%	132.5	130.4	-1.6%	165.7	166.6	0.5%
2	181.6	178.8	-1.5%	128.8	126.6	-1.7%	159.9	159.9	0.0%
3	178.9	176.7	-1.2%	125.1	123.0	-1.7%	156.1	156.1	0.0%
4	180.1	176.7	-1.9%	125.1	123.0	-1.7%	155.6	155.7	0.0%
5	190.3	185.3	-2.6%	132.9	130.4	-1.9%	163.1	162.1	-0.6%
6	207.7	201.8	-2.9%	153.0	149.9	-2.0%	179.9	179.7	-0.1%
7	235.7	226.9	-3.7%	180.0	176.1	-2.1%	200.5	199.4	-0.6%
8	261.4	251.2	-3.9%	201.9	198.0	-1.9%	221.7	219.8	-0.8%
9	279.9	272.5	-2.6%	217.0	214.5	-1.2%	241.0	238.5	-1.0%
10	294.8	289.0	-2.0%	228.3	225.9	-1.1%	256.4	255.0	-0.5%
11	307.3	302.5	-1.6%	238.5	235.9	-1.1%	270.0	269.1	-0.3%
12	310.3	306.2	-1.3%	241.4	239.1	-1.0%	275.1	275.9	0.3%
13	309.0	305.6	-1.1%	240.3	238.3	-0.8%	276.8	277.7	0.3%
14	310.8	308.1	-0.9%	242.5	240.7	-0.7%	278.7	278.3	-0.1%
15	306.9	303.8	-1.0%	237.7	236.1	-0.7%	276.3	276.3	0.0%
16	296.1	293.1	-1.0%	226.6	224.5	-0.9%	268.6	269.0	0.2%
17	282.0	279.0	-1.1%	211.5	209.0	-1.2%	259.1	259.8	0.3%
18	265.3	261.8	-1.3%	196.2	193.7	-1.3%	245.1	245.4	0.1%
19	246.3	243.7	-1.1%	183.3	180.8	-1.3%	228.0	227.9	-0.1%
20	237.4	234.5	-1.2%	177.3	175.1	-1.2%	219.0	218.0	-0.4%
21	230.9	226.8	-1.8%	171.4	168.9	-1.5%	210.9	210.8	-0.1%
22	218.8	215.4	-1.6%	162.0	159.5	-1.5%	198.2	197.7	-0.3%
23	207.5	204.3	-1.6%	149.4	147.1	-1.6%	188.2	188.1	-0.1%
24	199.0	195.2	-1.9%	142.1	139.7	-1.7%	181.4	179.4	-1.1%

In addition to testing out-of-sample predictive accuracy, false event day variables were included on 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. If the coefficients on the 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. Coefficients are sometimes significant due to the large number of observations

analyzed,¹³ so it is more reasonable to look at the percent by which the false event day coefficients impact actual electricity use.

Table 3-3 indicates the degree of bias that exists in the false event-day coefficients during event-like 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. For PG&E, the coefficients on the estimated false event day and hour interactions bias actual kWh by 1.3%. For SCE, the bias is 1.8%. SDG&E shows the smallest degree of bias at 0.5%.

Table 3-3: False Event Coefficient Tests

Event hour	PG&E	SCE	SDG&E
	% Bias	% Bias	% Bias
11 AM to 12 PM	-	-	0.5%
12 PM to 1 PM	-	-	0.4%
1 PM to 2 PM	-	-	0.9%
2 PM to 3 PM	1.1%	1.7%	0.8%
3 PM to 4 PM	1.2%	1.9%	0.5%
4 PM to 5 PM	1.3%	2.0%	0.2%
5 PM to 6 PM	1.5%	1.7%	0.3%
Total	1.3%	1.8%	0.5%

3.4 Summary of Control Group Analysis

Another approach to validation is to compare estimates based on individual customer regressions with alternative values developed using a matched control group to develop reference loads. To create the control group load profiles, FSC used propensity score matching to select control group customers and a difference-in-differences calculation to refine the control group load shapes, and net out non-event day differences. PG&E provided interval data for approximately 4,000 opt-out TOU customers, SCE provided interval data for approximately 3,000 opt-out TOU customers and SDG&E provided interval data for approximately 800 opt-out TOU customers.

Propensity score matching is way to identify statistical look-alikes from a pool of candidate control group customers. The approach models different observable factors that explain who participates in the program and reduces a number of observable variables to a single score. Control and treatment group customers are matched based on this score. The difference-in-differences approach was driven by reasonable assumptions concerning how to refine opt-out TOU customer load shapes to better match CPP customer load shapes. In the first step, we estimated the difference in hourly loads between the CPP and TOU groups when both sets of customers faced identical rates (Nov-May). This was done for five different temperature bins, as defined by Cooling Degree Days. In the second step,

¹³ 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 three years of interval data were used – roughly 16,000 observations. For each utility, tens of millions of observations were used in estimating aggregate impacts.

the difference observed between opt-out TOU and CPP load profiles on days with similar temperatures was netted out of the opt-out TOU load profiles on the actual event days at the hourly level.

Table 3-4 compares the aggregate regression and control group results as a cross-check to the individual customer regressions. More detailed comparisons are included in Appendices B, C and D. For the average PG&E event, the control group analysis produces similar results, 27.6 MW (5.8%), compared with those from the individual customer regressions, 27.8 MW (5.9%). For the average SCE event, the control group analysis also produces similar results, 32.9 MW (5.4%), compared with those from the individual customer regressions, 35.0 MW (5.7%). However, at both utilities, the aggregate control group results are more volatile than the aggregate individual customer regression results across individual event days.

For SDG&E, average impacts during the event hours from 11 AM to 6 PM for the control group analysis equal 25.0 kW (6.7%) for the September 7 event. The results from the regression analysis are lower, at 18.6 MW (5.2%). This difference is not terribly surprising since the comparison applies to only a single event day and SDG&E had fewer customers that could be used to develop the control group. As seen in Appendices B and C, underlying the PG&E and SCE comparisons for the average event are differences of similar magnitudes on selected event days.

Table 3-4: Summary of Control Group Cross-check

Event Date	Number of Participants	% Load Impact - Regressions	Aggregate Load Impact - Regressions (MW)	% Load Impact - Control Group	Aggregate Load Impact - Control Group (MW)	Average Temperature During Event (°F)
PG&E	1,750	5.9%	27.8	5.80%	27.6	88.1
SCE	3,006	5.7%	35.0	5.4%	32.9	84.7
SDG&E ^[1]	1,293	5.2%	18.6	6.70%	25.0	86.3

[1] Reflects the weekday event, September 7, 2011

Even though the results from the control group analysis are consistent with the regression results, there were a number of reasons why they were not used in place of the individual customer regression results. Using individual customer regressions ensures consistency in methodology across years. The control group analysis also relies on propensity score matching, which produces control and treatment groups that match in the aggregate, but not necessarily across population segments such as LCA and industry. While it is possible to put together matches for specific segments, given the data constraints, especially at SDG&E, proceeding in this direction would have necessitated potentially tenuous, ad hoc analysis that varied by segment and utility. Finally, with CPP there is the concern that opt-out TOU customers are systemically different from CPP customers in ways that affect energy use since, for some reason, sometimes unobserved, they chose to opt out of CPP.

The control group results generally fall within the uncertainty bands surrounding the individual customer regressions. Confidence in the results of both methods is increased by the relative similarity of results.

3.5 Summary of In-sample Precision and Goodness-of-fit

Although the regressions were estimated at the individual customer level, from a program or process standpoint, the focus should be 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 usage patterns than the aggregate participant population. Likewise, regressions better explain the variation in electricity consumption and load impacts for the average customer (or average customer within a specific segment) than for individual customers.

The R-squared goodness-of-fit statistic is calculated as an indication of the in-sample predictive accuracy of the model across customer segments and in the aggregate. In addition to the R-squared metric, in-sample predictions are plotted across the spectrum of event-like temperatures to determine how well the model predicts for event-like conditions in-sample.

In order to estimate the average customer R-squared values for each industry, LCA or in the aggregate, the regression-predicted and actual electricity usage values were averaged across customers for each date and hour for all customers in a specific segment. This process enabled the calculation of the R-squared value. Table 3-5 summarizes the amount of variation explained by the regressions for each industry and for the average customer.

Table 3-5: R-squared Values by Industry for Each Utility

Industry	R-squared		
	PG&E	SCE	SDG&E
Agriculture, Mining & Construction	0.79	0.85	0.78
Manufacturing	0.93	0.94	0.91
Wholesale, Transport, Other utilities	0.83	0.48 ¹⁴	0.74
Retail stores	0.99	0.98	0.96
Offices, Hotels, Finance, Services	0.98	0.98	0.93
Schools	0.90	0.91	0.89
Institutional/Government	0.98	0.98	0.93
Other or undefined	0.93	0.90	0.92
All Customers	0.96	0.95	0.93

At the utility level, the regressions explain between 93 and 96% of the variation around the mean. For most industries in each utility, well over 90% of the variation in electricity use is explained. The

¹⁴ The R-Squared value of 0.48 for the Wholesale, Transport and Other Utilities industry segment at SCE is unusually low. However, this R-Squared value is calculated based on all of the regression predictions across all of the available data for all customers in this segment. The out-of-sample tests show that the reference load predictions for this segment are biased by - 1.7% on event-like days. Most likely, a single large customer with erratic loads is driving the lower than average overall predictive capability for this segment. The out-of-sample test results indicate the regression produce relatively accurate estimates of the reference loads.

R-squared values are lowest among industries with few customers and low or no weather sensitivity. However, all of the out-of-sample tests for industries with low R-squared values such as Wholesale and Transport at SCE indicate the results for event-like days are unbiased.¹⁵

3.6 Ex Ante Impact Estimation Methodology

Whenever possible, ex ante load impacts are grounded on analysis of historical load impact performance. The ex-ante impacts are based on the similar models used for the ex post analysis but includes all 2010 and 2011 events in order to better inform the event impact coefficients. By including events from prior years, the ex ante regressions are better able to account for variation in impacts across different weather 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 CPP 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 all utilities, load impacts during the winter months are omitted. Recent CPP dynamic pricing events have occurred exclusively on hot summer days and, as a result, 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.

3.6.1 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 and bill protection period has expired for almost all large customers. We now know how many of these customers tried out default CPP, how much load reduction they provided during events, what types of customers were more responsive and how many remained on CPP at the end of the summer. In addition, while some changes in enrollment will occur as newly defaulted customers determine if CPP is the right rate for them, the customer mix for large CPP 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 multi-year 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;

¹⁵ We are looking further into the SCE Wholesale and Transport value. It may be due to a large customer that drives the overall results for the segment.

-
2. Linked the 1-in-2 and 1-in-10 weather year conditions to each customer based on their location. For example, in predicting the 1-in-2 August Peak Day impacts for a customer in the Greater Bay Area and one in Fresno, the ex-ante weather conditions reflected their local conditions.
 3. Replicated the same variables used in the ex post regression models;
 4. Predicted the customer electricity use patterns absent event day response – i.e. the 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.
 6. Accounted for changes in enrollment and customer mix, such as the mandatory default of PG&E's agricultural and SMB customers to PDP.

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. 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 a higher degree of commitment are attributed load impacts. For example, impacts for a customer dually enrolled in an aggregator program and CPP would be attributed to the aggregator program because it involves a contractual commitment to deliver specific amounts of load reduction.

3.6.2 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, mostly in SDG&E, 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.¹⁶ 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 of customers in the next size category (200 to 500 Max kW). For SDG&E, 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.

¹⁶ 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. In addition, some customers that met the definition of large customers, at the time, were defaulted onto CPP, but no longer meet the definition of large customers. Many of these customers remain on CPP rates.

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.

The biggest shifts in ex-ante impacts for medium customer occurred because of updated assumption regarding customer enrollments. PG&E updated their initial and post bill protection expiration opt out rates to reflect what they had observed among the large customer population. Last year, they lacked empirical data about opt out rates after first year bill protection expired for customers. SDG&E updated their enrollment forecast to better reflect the medium customer population that will be defaulted onto CPP. Last year, they assumed all SDG&E customers on AL-TOU, the current standard rate for medium customers, would be defaulted. This year, they included an additional crosscheck to ensure the customers fit the official SDG&E definition of a medium customer. By doing so, the enrollment forecast avoided incorrectly including small customers that had voluntarily enrolled on AL-TOU. In addition, utilities received an extension in the timing of the implementation of default CPP for medium customers.

3.6.3 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 than 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.

4 PG&E Ex Post Load Impact Results

This section summarizes the ex post load impact evaluation for customers on PG&E's CPP tariff. PG&E called nine CPP events in 2011. The first event occurred on June 21 and the last was held on September 20. On average, load impacts were based on the 1,750 accounts that participated in these events, although there was some variation in the number of customers participating in each event, from a low of 1,726 to a high of 1,761. The fluctuation in participation across events was the result of customer churn throughout the summer period, with some customers departing and others enrolling in-between events.

Table 4-1 shows the estimated ex post load impacts for each event day and for the average event day in 2011. The participant weighted average temperature during the peak period on event days ranged from a low of 82°F to a high of 93°F. The percent, average and aggregate impacts are quite similar across all events, suggesting that there is relatively little weather sensitivity for the average PG&E CPP customer. Percent impacts range from 5.6% to 6.2%, average impacts range from 15.0 kW to 16.6 kW and aggregate impacts range from 26.2 MW to 29.0 MW. On the average event day, the average participant reduced peak period load by 5.9%, or 15.9 kW. In aggregate, PG&E's CPP customers reduced load by 27.8 MW on average across the nine event days in 2011.

**Table 4-1: Estimated Ex Post Load Impacts by Event Day
2011 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)
6/21/2011	1,726	272.5	257.1	15.4	5.7%	26.7	92.8
7/5/2011	1,729	266.1	250.2	15.9	6.0%	27.5	90.2
7/29/2011	1,752	242.2	227.2	15.0	6.2%	26.2	82.1
8/23/2011	1,753	278.3	261.7	16.6	5.9%	29.0	90.0
8/29/2011	1,757	264.6	249.1	15.5	5.9%	27.2	82.4
9/2/2011	1,753	265.5	249.0	16.4	6.2%	28.8	86.5
9/6/2011	1,760	274.6	258.9	15.7	5.7%	27.7	87.2
9/7/2011	1,755	281.8	265.4	16.4	5.8%	28.7	91.0
9/20/2011	1,761	288.8	272.7	16.1	5.6%	28.3	91.2
Average Event	1,750	270.5	254.6	15.9	5.9%	27.8	88.1

4.1 Average Event Day Impacts

Figure 4-1 shows the aggregate hourly impacts for all PG&E CPP customers. It is a snapshot of the electronic tables filed with the CPUC along with this evaluation report. Percent reductions in each hour vary little across the four hour event window, ranging from a high of 6.3% in the first hour to a low of 5.6% in the last hour. Statistically, these differences are probably not significant. Reference loads and load impacts vary more than percentage impacts. The highest aggregate impact, 32.5 MW, occurs in the first hour and the lowest impact, 24.0 MW, occurs in the last hour. The decline in

impacts coincides with the decline in the aggregate reference load. This represents a typical pattern for non-residential customers, showing a relatively steep decline in late afternoon and early evening, when many manufacturing plants and many other businesses begin shutting down at the end of the work day.

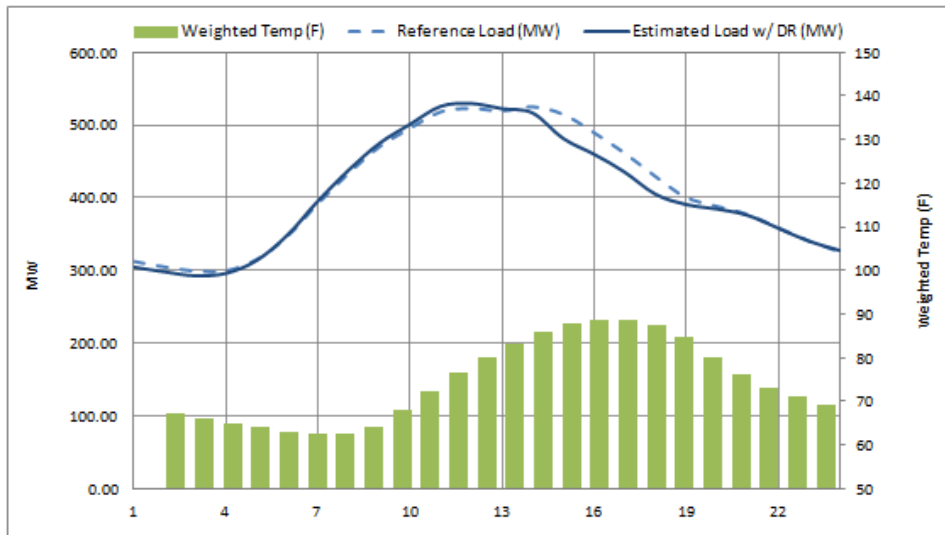
**Figure 4-1: Estimated Hourly Impacts for the Average Event Day
2011 PG&E CPP Events**

TABLE 1: Menu options

Type of Results	Aggregate
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	1,750
Avg. Load Reduction for Event Window	27.8
% Load Reduction for Event Window	5.9%



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)
1	313.3	305.3	8.0	2.5%	67.4
2	305.7	298.9	6.8	2.2%	66.2
3	300.1	293.5	6.6	2.2%	65.1
4	300.6	297.0	3.7	1.2%	64.0
5	315.9	314.6	1.3	0.4%	63.2
6	347.5	349.2	-1.7	-0.5%	62.6
7	392.3	396.1	-3.7	-1.0%	62.4
8	433.7	438.3	-4.6	-1.1%	64.3
9	469.6	474.7	-5.1	-1.1%	68.1
10	495.0	500.9	-6.0	-1.2%	72.3
11	517.5	525.5	-8.0	-1.5%	76.4
12	522.2	529.4	-7.2	-1.4%	80.2
13	518.7	522.3	-3.7	-0.7%	83.3
14	524.3	516.3	7.9	1.5%	86.0
15	514.0	481.4	32.5	6.3%	87.9
16	489.1	460.0	29.0	5.9%	88.7
17	461.1	435.4	25.7	5.6%	88.6
18	429.4	405.4	24.0	5.6%	87.3
19	400.8	391.1	9.7	2.4%	84.6
20	388.6	385.0	3.6	0.9%	80.2
21	377.6	376.5	1.0	0.3%	76.1
22	359.3	358.9	0.4	0.1%	73.2
23	341.5	341.0	0.4	0.1%	71.0
24	326.8	328.4	-1.6	-0.5%	69.2
	Reference Energy Use (MWh)	Estimated Energy Use w/ DR (MWh)	Total Load Impact (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	9,844.4	9,725.3	119.1	1.2%	55.6

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

4.2 Load Impacts by Industry

Table 4-2 shows the estimated ex post load impacts by industry. About 41% of the accounts and 86% of the aggregate load reduction came from three industry segments: Agriculture, Mining & Construction; Manufacturing; and Wholesale, Transport & Other Utilities. These three industries had the highest percent impact and highest average impact per customer. For the average event in 2011, participants in the Manufacturing sector provided 12.1 MW of aggregate load reduction, while the Wholesale, Transport & Other Utilities segment provided 8.3 MW of aggregate load impact. Larger aggregate impacts were expected from these sectors because the number and size of participants, on average, is greater than for other customer segments.

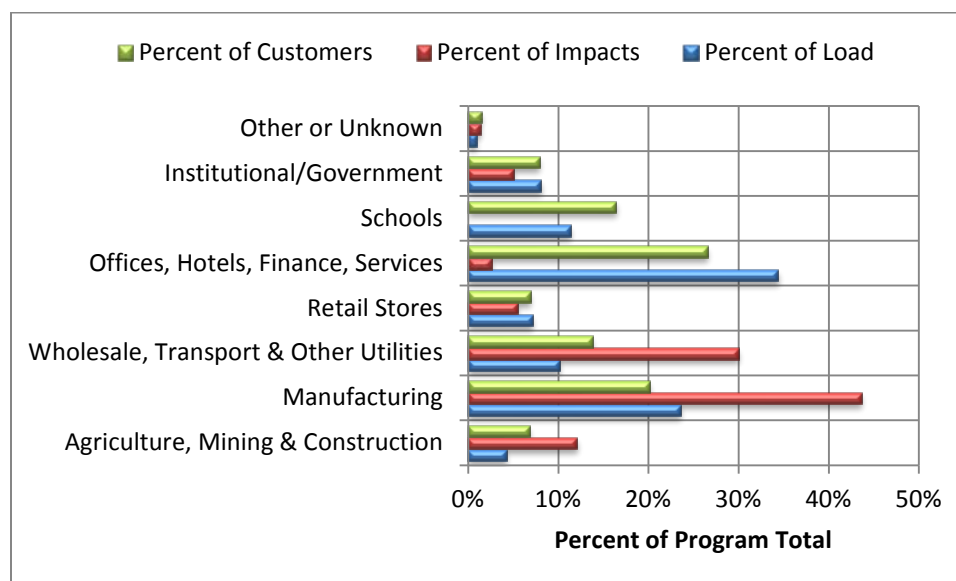
Load impacts for Schools were negligible, even though schools comprised roughly 16% of the number of participating accounts. The variation in school occupancy and resulting loads across the summer period make it very difficult to estimate load impacts for this segment. It may be that some schools provided meaningful load reductions, but on average, there were no statistically significant impacts for this relatively large participant population. The largest participant population, comprised of Offices, Hotels, Finance & Services, had very small load reductions on both a percentage and absolute basis. Load patterns for this segment are much more easily estimated.

**Table 4-2: Estimated Ex Post Load Impacts by Industry
Average 2011 PG&E CPP Events**

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	120	167.4	139.4	28.0	16.7%	3.4	89.7
Manufacturing	352	316.8	282.3	34.5	10.9%	12.1	88.5
Wholesale, Transport & Other Utilities	241	199.7	165.1	34.6	17.3%	8.3	88.8
Retail Stores	121	279.5	266.8	12.7	4.5%	1.5	88.9
Offices, Hotels, Finance, Services	465	350.0	348.4	1.6	0.4%	0.7	84.6
Schools	287	188.2	188.2	0.0	0.0%	0.0	91.9
Institutional/Government	139	275.6	265.7	10.0	3.6%	1.4	88.6
Other or Unknown	25	169.4	154.5	15.0	8.8%	0.4	86.7
All Customers	1,750	270.5	254.6	15.9	5.9%	27.8	88.1

Figure 4-2 compares the reference load, load impact and the number of accounts, in percentage terms for each customer segment.

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



The reference load is concentrated among the Offices, Hotels, Finance and Services sector. These are typically office buildings. They accounted for 34% of the estimated reference load (162.8 MW) but only produced about 3% of the load reduction (0.7 MW). On average, offices reduced load by 0.4%. In contrast, the Manufacturing and Wholesale, Transport and Other Utilities sectors provided much larger load reductions. Combined, they accounted for 34% of the reference load (159.6 MW) but produced 74% of the impacts (20.5 MW).

4.3 Load Impacts by Local Capacity Area

Table 4-3 shows the estimated ex post load impacts by local capacity area. For the average event in 2011, participants in the Greater Bay Area provided 9.7 MW of aggregate load impact, while customers in the Other or Unknown LCA provided 8.5 MW of aggregate load reduction. These LCAs comprised approximately 66% of the enrolled population and aggregate load impact. Customers in the Greater Bay Area had the highest average reference loads of any LCA at 324.3 kW, while customers in the Kern LCA had the lowest average reference loads (102.6 kW). However, customers in the Kern LCA showed the greatest percent load impact of any LCA, at 12.7%. These large differences across LCAs are almost certainly due to differences in the underlying distribution of customers across industry segments and size strata.

**Table 4-3: Estimated Ex Post Load Impacts by LCA
Average 2011 PG&E CPP Events**

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	798	324.3	312.1	12.2	3.8%	9.7	83.1
Greater Fresno	186	258.9	243.2	15.7	6.1%	2.9	98.7
Kern	138	102.6	89.6	13.0	12.7%	1.8	98.1
Northern Coast	99	235.8	219.0	16.8	7.1%	1.7	89.9
Other	350	259.5	235.2	24.3	9.4%	8.5	86.4
Sierra	82	209.8	191.7	18.2	8.7%	1.5	94.4
Stockton	96	214.4	196.7	17.7	8.2%	1.7	94.7
All Customers	1,750	270.5	254.6	15.9	5.9%	27.8	88.1

4.4 Load Impacts by Customer Size

Table 4-4 shows the estimated ex post load impacts for five customer size categories, defined by average usage per hour throughout the year (kWh/hr). Participants with average usage above 500 kWh/hr provided the largest absolute average impact per customer (86.6 kW), percent impact per customer (7.1%) and aggregate load impact (9.3 MW). These customers comprised 34% of the aggregate load impact for all customers even though they represented only 6% of the enrolled population. Participants with average usage between 100 and 200 kWh/hr provided the lowest percent load impact (4.5%). The percent load impact for the smallest customers (Under 50 kWh/hr) was 7.1%, which is similar to the percent load impact that the largest customers provided and greater than the percent impact that customers in any other category provided.

**Table 4-4: Estimated Ex Post Load Impacts by Customer Size
Average 2011 PG&E CPP Events**

Size Category (By Average Annual kWh/hr)	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	264	39.8	37.0	2.8	7.1%	0.7	94.1
50-100 kWh/hr	396	121.0	113.3	7.7	6.4%	3.1	89.2
100-200 kWh/hr	615	210.8	201.2	9.6	4.5%	5.9	86.8
200-500 kWh/hr	368	423.6	399.6	24.1	5.7%	8.9	85.8
Over 500 kWh/hr	108	1211.7	1125.1	86.6	7.1%	9.3	85.4
All Customers	1,750	270.5	254.6	15.9	5.9%	27.8	88.1

4.5 Load Impacts for Multi-DR Program Participants

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

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

Table 4-5 shows CPP load impacts for customers that dually enrolled in other demand response programs and customers who were enrolled in PG&E's historic voluntary CPP rates, SmartRate and voluntary CPP. The latter two table entries are provided for historical perspective and to see if customers that had previously volunteered for a CPP rate responded more or less than customers that were defaulted onto PG&E's CPP rate but had not previously experienced dynamic tariffs. The table also shows the average demand response for all customers not dually enrolled or who had not migrated into the program through the voluntary CPP path.

A word of caution is needed in reviewing Table 4-5. There are relatively few dually enrolled customers in any single DR program, and in most cases, the number of customers is quite small. For example, there are only 5 customers enrolled in both CPP and BIP and 12 in CPP and CBP. Even the largest dual enrollment category, CPP and AMP, only has 41 customers. Given this, the significant variation in average and aggregate load impacts across dual enrollment categories probably has less to do with dual enrollment than it does with fundamental differences in the average characteristics and price responsiveness of the customers who happen to be in each category. The estimates are useful for adjusting portfolio impact estimates under assumptions that both programs are called on the same day, but it is not appropriate to claim that customers dually enrolled in CPP and CBP are 50% more price responsive compared with customers dually enrolled in CPP and AMP because the CBP program somehow supports CPP demand response better than the AMP program. Said another way, while dual enrollment in CPP and CBP appears to correlate with above average load reductions, there is no basis to infer that any combination of dual enrollment listed in Table 4-5 causes CPP customers to respond better.

Table 4-5 also shows the average load impacts for customers that had previously volunteered for opt-in CPP prices and were subsequently defaulted onto the new CPP rate. Customers that had previously volunteered for PG&E's SmartRate tariff are quite small, with average reference loads equal to less

than 1% of the overall CPP participant average. The average load increase shown for these customers is probably not statistically significant and is almost certainly simply the result of random, day-to-day fluctuations in energy use rather than some conscious decision to use more electricity on days when prices are highest. Customers that were previously on PG&E's voluntary CPP tariff are roughly the same size as the average CPP participant and have roughly the same price responsiveness (as measured by % impacts) as the general CPP participant.

**Table 4-5: Estimated Ex Post Load Impacts CPP Participants Enrolled in Other DR Programs
Average 2011 PG&E CPP Event**

Dual and Previous Enrollment	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: AMP	41	307	243	64	21%	3	91
Dually Enrolled: BIP	5	1085	1079	6	1%	0	96
Dually Enrolled: CBP	12	200	146	54	27%	1	92
Previously on SmartRate	79	2	2	0	-3%	0	98
Previously on Voluntary CPP	220	289	269	20	7%	4	90
Not Dually Enrolled	1393	280	265	14	5%	20	87
Population Totals	1750	271	255	16	6%	28	88

4.6 TI and AutoDR Load Impacts and Realization Rates

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

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

A statistically valid assessment of TI and AutoDR is significantly hampered by the very small number of customers that participated in these complementary programs. There were only two PG&E accounts on the CPP tariff that received TI payments and only eight AutoDR customers. Table 4-6 shows the load impact for the average customer on each of these programs on the average event day. Customers on TI and AutoDR showed larger than average percent impacts of 8.6% and 7.0%,

respectively. However, given the extremely small number of customers on TI and AutoDR, the point impact estimates are surrounded by a significant amount of uncertainty.

**Table 4-6: Estimated Ex Post Load Impacts of TI & AutoDR Participants
Average 2011 PG&E CPP Event**

Variable	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)
Technical Incentives (TI)	2	320	298	22	7%	0	89
AutoDR	8	357	326	31	9%	0	82

Table 4-7 shows the distribution of estimated realization rates for both TI and AutoDR. Because of the very small sample sizes, these estimates must be used with extreme caution. The realization rate estimates were developed by taking the average impact for customers who were enrolled in TI or AutoDR and dividing it by the average of the approved TI or AutoDR load shed. Because individual customer impact estimates are highly uncertain, realization rates are also highly uncertain. As such, estimates are presented for the 10th through 90th percentiles of impact uncertainty. The wide range of realization rate values for TI, which includes a number of implausible values, reflects the fact that there are only two PG&E customers enrolled in TI and impact estimates are extremely inaccurate at such a granular level. For TI, the realization rate depends on whether the equipment is typically used during event-like conditions and whether customers decide to drop load.

Realization rates for AutoDR do not vary as drastically across the impact uncertainty percentiles, but still show a significant amount of variation from the 10th to 90th percentiles. At 34.2%, the average realization rate calculated at the 50th percentile of impact uncertainty for AutoDR is larger than for TI

Table 4-7: Realization Rates

Variable	Accts	Aggregate Approved kW	Realization Rate				
			10th Percentile	30th Percentile	50th Percentile	70th Percentile	90th Percentile
Technical Incentives (TI)	2	292	-29%	0%	21%	41%	71%
AutoDR	8	525	12%	25%	34%	43%	56%

4.7 Comparison of 2010 and 2011 Ex Post Results

In 2011, PG&E lost a number of customers due to attrition, but added customers mostly from the agricultural sector, which tends to provide larger percent load reductions. On a net basis, the overall program reference load dropped between 2010 and 2011 but the average demand response increased. In 2010 the percent impacts on the average event day were 3.9%, while in 2011 the average percent impact equaled 5.9%.

Differences in impacts between 2010 and 2011 are almost certainly not due to differences in weather since neither the average nor percent impact is positively correlated with weather. Appendix F shows

a graph relating percent impact to weather, which illustrates that there is a very weak and slightly negative correlation between average temperature and percentage impacts.

At PG&E the difference in load impacts between 2010 and 2011 across size categories reflect the fact that many customers who were not price responsive in 2010 opted out of CPP after bill protection expired and that the new, mostly agricultural enrollees, are more price responsive. The difference in impacts between 2010 and 2011 was most noticeable for customers with average hourly usage above 200 kW. At PG&E the 523 customers with average hourly usage above 200 kW in 2010 provided a 15.2 MW (3.6%) average aggregate load impact on the average event day. By 2011, 476 customers remained in this size category and provided an 18.2 MW (6.4%) average aggregate load impact on the average event day.

5 SCE Ex Post Load Impact Results

SCE called 12 CPP events in 2011, with the first occurring on June 21 and the last on September 23. On average, 3,006 accounts were enrolled on SCE's CPP tariff in the summer of 2011, although there was some variation in the number of customers enrolled during each event, from a low of 2,872 to a high of 3,094. This variation reflects normal CPP program "churn" throughout the summer period, with some customers departing and others enrolling between events.

Table 5-1 shows the estimated ex post load impacts for each event day and for the average event day in 2011. The participant weighted average temperature during the peak period on event days ranged from a low of 78°F to a high of 91°F. The percent, average and aggregate impacts are similar across events, suggesting that there is limited weather sensitivity for the average SCE CPP customer.¹⁷ Percent impacts ranged from 5.4% to 6.0%, average customer impacts ranged from 10.6 kW to 12.4 kW and aggregate impacts ranged from 32.7 MW to 36.7 MW. On the average event day, the average participant reduced peak period load by 5.7% or 11.6 kW. In aggregate, SCE's CPP customers reduced load by 35.0 MW on average across the 12 event days in 2011.

**Table 5-1: Estimated Ex Post Load Impacts by Event Day
2011 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)
6/21/2011	2,935	213.1	201.6	11.6	5.4%	33.9	82.0
7/5/2011	2,953	222.4	210.0	12.4	5.6%	36.7	85.8
7/19/2011	2,872	213.1	200.7	12.4	5.8%	35.6	84.6
8/1/2011	2,992	207.3	195.2	12.2	5.9%	36.4	86.7
8/3/2011	3,015	206.2	194.3	12.0	5.8%	36.1	84.8
8/12/2011	3,094	184.6	174.1	10.6	5.7%	32.7	78.1
8/16/2011	3,014	198.9	187.7	11.1	5.6%	33.6	83.6
8/18/2011	3,014	200.6	189.3	11.3	5.6%	34.0	83.6
8/23/2011	3,024	205.8	194.4	11.4	5.6%	34.6	86.4
8/26/2011	3,038	202.4	190.3	12.1	6.0%	36.6	90.3
9/6/2011	3,077	215.9	204.0	11.9	5.5%	36.6	90.9
9/23/2011	3,047	187.8	177.1	10.7	5.7%	32.7	79.9
Average Event	3,006	204.7	193.1	11.6	5.7%	35.0	84.7

¹⁷ See Appendix F for an illustration of the relationship between temperature and load impacts.

5.1 Average Event Day Impacts

Figure 5-1 shows the aggregate hourly impact for CPP customers for the average event in 2011. Percent reductions were essentially the same in each hour, averaging 5.7%. However, reference loads and load impacts declined by roughly 18% across the four hour event window. The estimated load reduction was 38.0 MW in the first hour and 31.5 MW in the last event hour. For the average customer, the decline in impacts coincided with a decline in the aggregate reference load near the end of the event period.

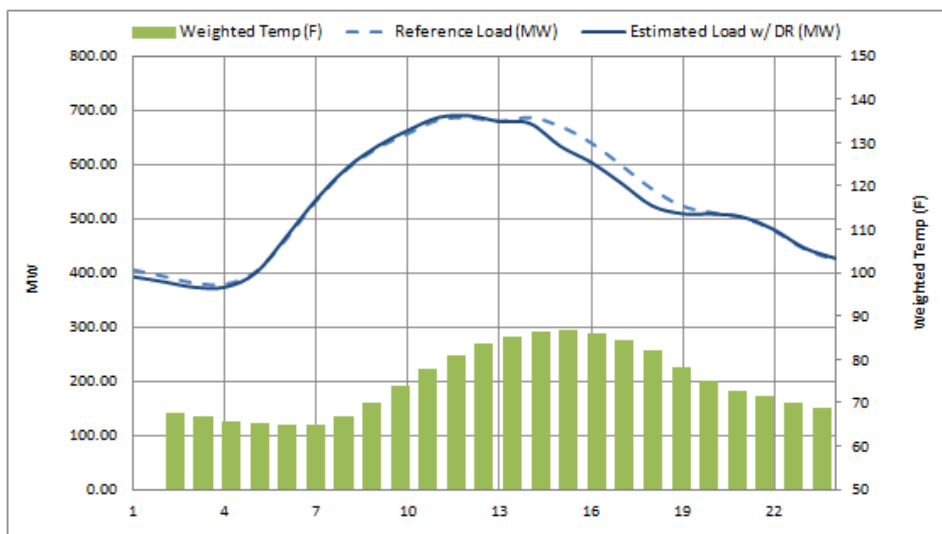
**Figure 5-1: Estimated Hourly Impacts for the Average Event Day
2011 SCE CPP Events**

TABLE 1: Menu options

Type of Results	Aggregate
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	3,006
Avg. Load Reduction for Event Window	35.0
% Load Reduction for Event Window	5.7%



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)
1	403.9	391.0	12.9	3.2%	67.5
2	391.9	381.9	10.1	2.6%	66.6
3	379.8	371.7	8.1	2.1%	65.8
4	377.7	372.3	5.4	1.4%	65.2
5	400.8	398.7	2.1	0.5%	64.7
6	461.4	465.3	-3.9	-0.9%	64.7
7	533.2	535.5	-2.3	-0.4%	66.7
8	591.0	593.0	-2.0	-0.3%	70.0
9	629.9	633.1	-3.2	-0.5%	74.0
10	656.8	662.3	-5.5	-0.8%	77.8
11	682.0	686.0	-4.0	-0.6%	81.1
12	685.9	689.0	-3.1	-0.5%	83.5
13	679.5	678.5	1.0	0.1%	85.4
14	686.4	674.7	11.7	1.7%	86.4
15	670.3	632.3	38.0	5.7%	86.6
16	639.7	603.0	36.7	5.7%	86.0
17	597.6	563.9	33.7	5.6%	84.5
18	554.1	522.6	31.5	5.7%	81.9
19	522.3	507.8	14.5	2.8%	78.2
20	510.1	507.3	2.9	0.6%	74.9
21	500.9	501.2	-0.3	-0.1%	72.8
22	476.7	478.4	-1.7	-0.4%	71.3
23	442.7	444.6	-1.9	-0.4%	70.0
24	422.5	425.7	-3.2	-0.8%	68.8
	Reference Energy Use (MWh)	Estimated Energy Use w/ DR (MWh)	Total Load Impact (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	12,897.2	12,719.8	177.3	1.4%	30.6

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

5.2 Load Impacts by Industry

Table 5-2 shows the estimated ex post load impacts by industry. The distribution of load impacts is even more concentrated for specific industries in SCE's service territory than it was for PG&E. The Manufacturing sector provided two thirds of the aggregate load reduction on the average day, while comprising only 26% of program enrollment. The Manufacturing segment also had the highest percentage demand response, equal to 14.1%. When combined with the Wholesale, Transport & Other Utilities, the two segments accounted for 43% of enrollment but more than 93% of aggregate load reduction.

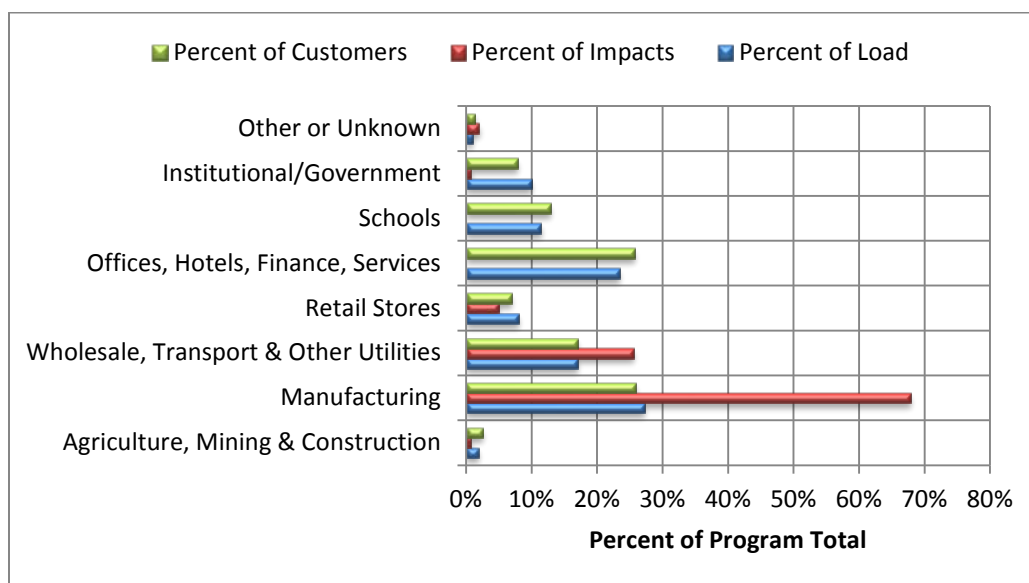
As with PG&E's CPP tariff, Schools accounted for a relatively large percent of program participants, 13%, but did not produce statistically significant load reductions. Several other business segments also accounted for a large share of enrollment but a small share of the load impacts. The Offices, Hotels, Finance and Services sector actually showed a slight increase in energy use on the average event day, and the Institutional/Governmental segment showed small load reductions. In total, 8 of the 10 business segments comprised 57% of enrolled customers but provided only 7% of aggregate ex post load impacts.

**Table 5-2: Estimated Ex Post Load Impacts by Industry
Average 2011 SCE CPP Events**

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	75	159.5	156.1	3.3	2.1%	0.2	87.4
Manufacturing	777	216.0	185.5	30.5	14.1%	23.7	84.2
Wholesale, Transport & Other Utilities	511	204.8	187.3	17.5	8.5%	8.9	84.5
Retail Stores	209	237.1	228.8	8.3	3.5%	1.7	83.2
Offices, Hotels, Finance, Services	772	186.7	187.5	-0.8	-0.4%	-0.6	84.8
Schools	387	182.1	182.1	0.0	0.0%	0.0	85.6
Institutional/Government	235	259.4	258.3	1.1	0.4%	0.3	85.6
Other or Unknown	40	148.6	131.4	17.2	11.6%	0.7	84.0
All Customers	3,006	204.7	193.1	11.6	5.7%	35.0	84.7

Figure 5-2 compares the reference load, load impact and the number of accounts, in percentage terms, for each customer segment.

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



In total, the reference load indicates that SCE participants would have averaged 615.4 MW of load during the event periods if not for CPP. Instead, they averaged 580.5 MW, a 35.0 MW reduction. The two largest sectors among enrolled participants were Office, Hotels, Finance and Services and Manufacturing. Offices accounted for 23% of the reference load (144.2 MW) but did not produce any load impacts. On the other hand, Manufacturing accounted for 27% of the event period reference load (167.8 MW), but delivered 68% of the impacts (23.7 MW).

5.3 Load Impacts by Local Capacity Area

Table 5-3 shows the estimated ex post load impacts by local capacity area. Almost 80% of enrolled customers and 90% of aggregate load reduction came from the LA Basin LCA.

**Table 5-3: Estimated Ex Post Load Impacts by LCA
Average 2011 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	2365	217.5	204.3	13.2	6.1%	31.3	84.0
Outside	168	197.7	191.7	6.0	3.1%	1.0	90.5
Ventura	473	143.4	137.8	5.7	4.0%	2.7	86.3
All Customers	3,006	204.7	193.1	11.6	5.7%	35.0	84.7

5.4 Load Impacts by Customer Size

Table 5-4 shows the estimated ex post load impacts for five customer size categories, defined by average hourly usage throughout the year. Customers with average hourly usage above 200 kW accounted for only 19% of total enrollment but delivered 76% of total demand response on the average event day. Customers with average hourly usage exceeding 500 kW accounted for less than 4% of enrollment but delivered more than a third of total demand reduction on the average event day. Small customers (below 100kWh/hr), on the other hand, provide little or no demand response. The 604 customers with peak demands less than 50kW, which comprise roughly 20% of total enrollment, provide no statistically significant demand reduction. Customers with average usage below 100 kWh/hr comprise more than 50% of total enrollment but collectively deliver less than 5% of total demand response.

**Table 5-4: Estimated Ex Post Load Impacts by Customer Size
Average 2011 SCE CPP Event**

Size Category (By Average Annual KWh/hr)	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	604	34.1	34.1	-0.1	-0.2%	0.0	87.6
50-100 KWh/hr	918	124.3	122.6	1.7	1.4%	1.6	84.5
100-200 kW/hr	918	199.9	192.5	7.5	3.7%	6.8	83.8
200-500 kWh/hr	460	385.5	356.6	28.9	7.5%	13.3	83.6
Over 500 kWh/hr	107	1121.1	996.7	124.4	11.1%	13.3	83.8
All Customers	3,006	204.7	193.1	11.6	5.7%	35.0	84.7

5.5 Load Impacts for Multi-DR Program Participants

At SCE, CPP customers can also enroll in several other DR programs. In 2011, out of the 3,006 accounts enrolled on CPP, 58 were also enrolled on one of three other DR programs: BIP, CBP and DRRC. Table 5-5 shows the estimated load impacts for dual participation customers in SCE's CPP and DR programs. As was discussed in Section 4.5, differences in average and aggregate impacts across

the dual enrollment categories is probably due to variation in customer characteristics in these small samples, not due to any influence of the other DR programs on CPP price response.

**Table 5-5: Estimated Ex Post Load Impacts of Multi-DR Participants
Average 2011 SCE CPP Event**

Dual and Previous Enrollment	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	19	274	172	102	37%	2	86
Dually Enrolled: CBP	7	173	172	0	0%	0	79
Dually Enrolled: DRRC	32	420	357	63	15%	2	87
Legacy Voluntary CPP	325	261	200	61	23%	20	85
Not Dually Enrolled or Legacy	2623	195	190	4	2%	11	85
Population Totals	3,006	205	193	12	6%	35	85

Table 5-5 also shows the average and aggregate load impacts for customers that had been previously enrolled on SCE's voluntary CPP rate. Figure 5-3 shows the average hourly impacts for this group of prior volunteers. These customers accounted for only 11% of participants but more than half of the aggregate load impact for the program. Average usage for these customers is not significantly larger than the average customer on CPP, but their percentage load reduction is an order of magnitude larger than that of the average CPP customer.

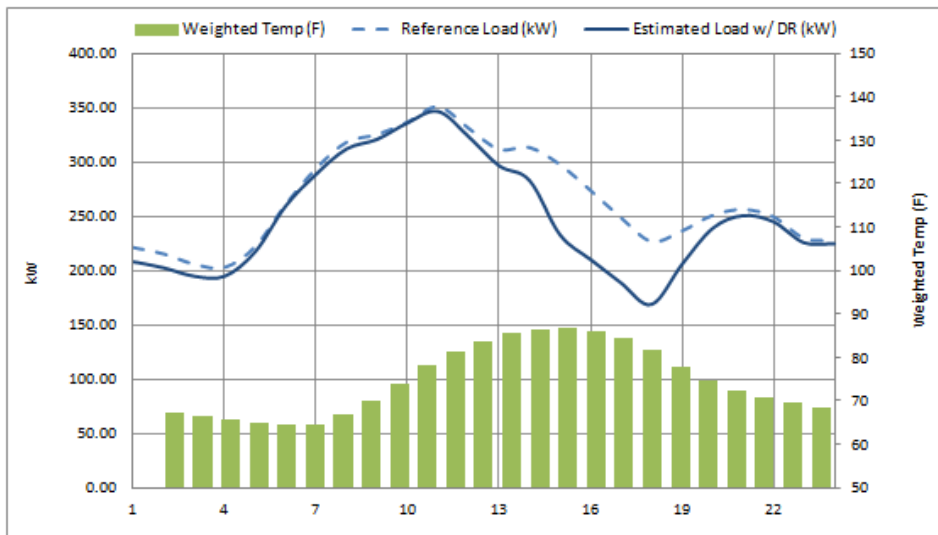
Figure 5-3: 2011 Hourly Ex Post Load Impacts for Average Customer Previously Enrolled in Voluntary CPP on the Average Event Day

TABLE 1: Menu options

Type of Results	Average Customer
Customer Type	Previously on Voluntary CPP

TABLE 2: Event Day Information

Event Date	Average Event
Event Start	2:00 PM
Event End	6:00 PM
Total Enrolled Accounts	325
Avg. Load Reduction for Event Window	60.7
% Load Reduction for Event Window	23.2%



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Load Impact (kW)	% Load Reduction	Weighted Temp (F)
1	220.5	208.4	12.1	5.5%	67.1
2	214.5	202.9	11.6	5.4%	66.3
3	205.1	195.2	9.9	4.8%	65.6
4	202.1	195.2	6.9	3.4%	64.9
5	221.2	217.5	3.7	1.7%	64.5
6	260.3	259.4	0.9	0.4%	64.6
7	293.6	288.5	5.1	1.7%	66.6
8	317.9	311.7	6.3	2.0%	70.0
9	325.0	320.3	4.7	1.4%	74.0
10	336.5	335.4	1.1	0.3%	78.0
11	350.7	345.9	4.8	1.4%	81.2
12	330.8	322.8	8.0	2.4%	83.7
13	311.3	296.2	15.1	4.8%	85.5
14	313.0	282.8	30.2	9.7%	86.5
15	297.1	233.0	64.1	21.6%	86.6
16	273.3	210.5	62.8	23.0%	86.0
17	248.1	189.0	59.0	23.8%	84.3
18	226.2	169.2	56.9	25.2%	81.7
19	235.8	205.9	29.8	12.7%	77.9
20	250.2	238.8	11.4	4.5%	74.5
21	255.7	250.6	5.1	2.0%	72.4
22	248.8	245.0	3.8	1.5%	70.9
23	229.1	225.8	3.3	1.4%	69.6
24	226.8	224.9	1.9	0.8%	68.4
	Reference Energy Use (kWh)	Estimated Energy Use w/ DR (kWh)	Total Load Impact (kWh)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	6,393.4	5,974.9	418.5	6.5%	29.9

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

5.6 TI and AutoDR Load Impacts and Realization Rates – SCE

Table 5-6 shows the load impact for the average CPP customer that took advantage of the complementary TI and AutoDR programs. Customers on TI and AutoDR showed much larger than average percent impacts of 26% and 21%, respectively. The aggregate load impact from these customers accounted for 14% of the total aggregate load impact on the average event day even though the 38 customers enrolled in TI and AutoDR made up just over 1% of the CPP population. However, given the relatively few customers enrolled on TI and AutoDR, the point impact estimates are surrounded by a significant amount of uncertainty.

**Table 5-6: Estimated Ex Post Load Impacts of TI & AutoDR Participants
Average 2011 SCE CPP Event**

Variable	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)
Technical Incentives (TI)	3	755	556	199	26%	1	78
AutoDR	35	500	398	103	21%	4	83

Table 5-7 shows the distribution of realization rates for both TI and AutoDR for SCE customers who took advantage of these program options. The realization rate describes the percent of approved load shed that is met by the estimated impacts on event days. As discussed in Section 4.6, these realization estimates must be viewed with extreme caution because of the small number of customers underlying the estimates. This is particularly true for the TI estimates, which are based on only three customers. The estimates for AutoDR, which are based on 35 customers show less variability.

The realization rate estimates were developed by taking the average impact for customers who were enrolled in TI or AutoDR and dividing it by the average of the approved TI or AutoDR load shed. It assumes that load reductions are due to automated reduction technology and not due to demand reductions from other end-uses. For TI the realization rate depends on whether the equipment is typically in use during event-like conditions and whether the customer decides to drop load. The realization rates for AutoDR do not vary nearly as drastically because there is much more data on AutoDR as compared to TI. From the 10th to 90th percentiles of impact uncertainty, the realization rates for AutoDR vary by about 11 percentage points. The realization rate for AutoDR cannot be expected to be 100% because the loads that are under automated control are not always operating during events.

Table 5-7: Realization Rates

Variable	Accts	Aggregate Approved kW	Realization Rate				
			10th Percentile	30th Percentile	50th Percentile	70th Percentile	90th Percentile
Technical Incentives (TI)	3	474	84%	106%	121%	137%	158%
AutoDR	35	9090	33%	37%	39%	41%	44%

5.7 Comparison of 2010 and 2011 Ex Post Results

SCE experienced the largest shift in program enrollment levels among the three utilities from 2010 to 2011. More than 1,800 customers either moved or left the tariff due to attrition during this time. SCE also added roughly 750 additional accounts, out of which approximately 400 were voluntary enrollments from small and medium accounts. As a result, SCE experienced a net drop of over 1,000 customers. In conjunction with the drop in enrollment, the overall reference load for the program dropped by approximately 460 MW. The average customer enrolled in CPP in 2011 had a lower reference load compared to the average customer enrolled in 2010 (205 kW vs. 264 kW), but participants reduced a larger share of their load in 2011. The results suggest that SCE retained the bulk of the most price responsive customers enrolled in CPP in 2010. As noted in the 2010 evaluation, roughly 400 customers that transitioned from voluntary CPP in 2009 onto default CPP in 2010 accounted for nearly 60% of the load impact on the average event day in 2010. Most of these customers remained on CPP in 2011.

Percent impacts by industry remained relatively constant from 2010 to 2011 at SCE, except for the Retail Stores and Manufacturing segments. With Retail Stores, demand reductions were 0.8% in 2010 and 3.5% in 2011. The change for this sector may be due to the more tailored approach to specifying weather variables.¹⁸ Also of note is that percent impacts from the Manufacturing industry group increased from 8.5% in 2010 to 14.1% in 2011. However, aggregate impacts from this sector remained constant at approximately 24.0 MW although there were approximately 270 fewer customers in 2011. A potential explanation is that price responsive Manufacturing industry customers at SCE may have stayed on CPP while those who were providing small or no demand reductions may have opted out of CPP.

After bill protection expired, customers were provided with shadow bills by SCE that compared how they fared on CPP relative to other rate options. Customers that reduced demands during events in 2010 were more likely to fare better under CPP than those that did not, and may have had a stronger incentive to remain on CPP based on the billing analysis. In addition, SCE proactively engaged CPP customers to prepare for the summer season in 2011. They were reminded that they were losing bill protection and encouraged to have plans in place for CPP events (if they did not already) or consider another DR program if they did not experience savings under CPP. In addition, SCE undertook an

¹⁸ As noted in Section 2, we conducted out-of-sample tests for each customer using eight models that varied in how weather variables were defined (including no weather sensitivity), and the inclusion of monthly or seasonal effect were tested for each customers. The model that produced the most accurate out-of-sample predictions was selected for each customer. In 2010, all customers results were based on the same regression model.

initiative to have their account representatives directly talk to all customers on DR programs before June 1.

As was the case at PG&E, the difference in impacts between 2010 and 2011 was most noticeable for customers with average hourly usage above 200 kWh/hr. At SCE the 1,078 customers with average hourly usage above 200 kWh/hr in 2010 provided a 24.0 MW aggregate load impact (4.0% of reference load) on the average event day. By 2011, 567 customers remained in this size category at SCE and provided a 26.6 MW aggregate load impact (8.9% of reference load) on the average event day.

6 SDG&E Ex Post Load Impact Results

SDG&E only called two CPP events in 2011 and one was on a weekend. The first event occurred on August 27, a Saturday, and the second was held on September 7, a Wednesday. There were 1,291 accounts enrolled during the first event and 1,293 enrolled for the second event. The participant weighted average temperature during the peak period was 80°F for the weekend event and 86°F for the weekday event.

Table 6-1 shows the estimated ex post load impacts for each event day. Not surprisingly, there was a substantial difference in the reference load for the weekday and weekend events. The estimated reference load for the weekday event was 276 MW, nearly 33% higher than for the weekend event. However, the percent load reduction, at 6.3%, was higher on the weekend than the 5.2% estimate for the weekday event. As such, there was only about a 10% difference in the aggregate demand response for the two event days. On the weekend event day, August 27, the aggregate load reduction equaled 16.9 MW, while the September 7 weekday impact equaled 18.6 MW. It should be noted, however, that with only two data points, one on a weekend and the other on a weekday, it is difficult to conclude with certainty that SDG&E CPP customers were more price responsive (on a percentage basis) on the weekend. A more prudent approach would be to assume that the two-day average percentage impact is a better estimate for both days. However, the absolute load reduction is likely to be greater on weekdays because of the significantly higher reference load.

**Table 6-1: Estimated Ex Post Load Impacts by Event Day
2011 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 (°F)
8/27/2011	1,291	208.4	195.3	13.1	6.3%	16.9	79.5
9/7/2011	1,293	277.5	263.1	14.4	5.2%	18.6	86.3

6.1 Average Event Day Impacts

Figures 6-1 and 6-2 show the hourly impacts for each event for all customers. Recall from Section 2 that the CPP event period for SDG&E runs from 11 AM to 6 PM, which is substantially longer than the 2 PM to 6 PM event period employed by SCE and PG&E. Not surprisingly, the estimated load impacts in both absolute and percentage terms varied more over the event period than they did for PG&E and SCE. On both the weekday and weekend, event impacts in absolute and percentage terms were smallest in the first three event hours, even though the reference load was highest in these hours.

For the August 27 event, percent reductions in each hour during the seven hour event window varied from a high of 7.8% in the fifth hour to a low of 4.3% in the first hour. The highest aggregate impact, 21.2 MW, occurred in the fifth hour and the lowest impact, 11.7 MW, occurred in the first hour. For the September 7 weekday event, percent reductions in each hour during the seven hour event window varied from a high of 7.0% in the last hour to a low of 3.8% in the third hour. The highest aggregate impact, 23.3 MW, occurred in the sixth hour and the lowest impact, 14.0, MW occurred in the third hour. In both cases, load impacts grew across the event period. The results show that on the

weekday event (September 7), customers shifted loads to pre-event periods. Similar pre-event shifting was observed for the weekend event (August 27).

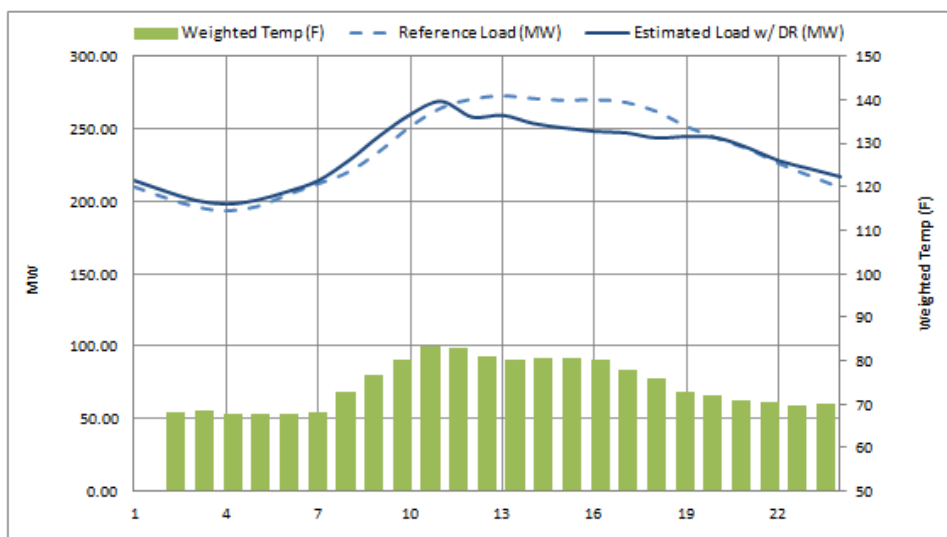
**Figure 6-1: Estimated Hourly Impacts
SDG&E's August 27, 2011 Event**

TABLE 1: Menu options

Type of Results	Aggregate
Customer Type	All

TABLE 2: Event Day Information

Event Date	8/27/2011
Event Start	11:00 AM
Event End	6:00 PM
Total Enrolled Accounts	1,291
Avg. Load Reduction for Event Window	16.9
% Load Reduction for Event Window	6.3%



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	% Load Reduction	Weighted Temp (F)
1	209.6	214.9	-5.3	-2.5%	68.2
2	202.2	207.6	-5.4	-2.7%	68.4
3	195.7	201.1	-5.4	-2.8%	67.8
4	193.0	198.6	-5.6	-2.9%	67.8
5	195.9	201.4	-5.4	-2.8%	67.7
6	204.2	207.3	-3.1	-1.5%	68.3
7	211.9	214.9	-3.0	-1.4%	72.7
8	220.1	228.8	-8.7	-4.0%	76.5
9	234.5	245.8	-11.4	-4.8%	80.3
10	251.5	260.5	-9.0	-3.6%	83.5
11	264.3	269.6	-5.3	-2.0%	82.8
12	270.4	258.7	11.7	4.3%	81.0
13	272.6	259.9	12.7	4.7%	80.1
14	270.8	254.2	16.5	6.1%	80.6
15	269.6	251.2	18.4	6.8%	80.5
16	269.9	248.8	21.2	7.8%	80.0
17	268.1	247.8	20.3	7.6%	77.9
18	261.9	244.3	17.7	6.7%	75.8
19	251.2	245.3	5.9	2.4%	73.0
20	243.2	244.2	-1.1	-0.4%	72.1
21	235.8	237.3	-1.5	-0.6%	70.8
22	225.7	228.5	-2.8	-1.2%	70.3
23	217.3	223.0	-5.7	-2.6%	69.6
24	209.0	217.5	-8.4	-4.0%	69.9
	Reference Energy Use (MWh)	Estimated Energy Use w/ DR (MWh)	Total Load Impact (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	5,648.5	5,611.2	37.3	0.7%	8.7

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

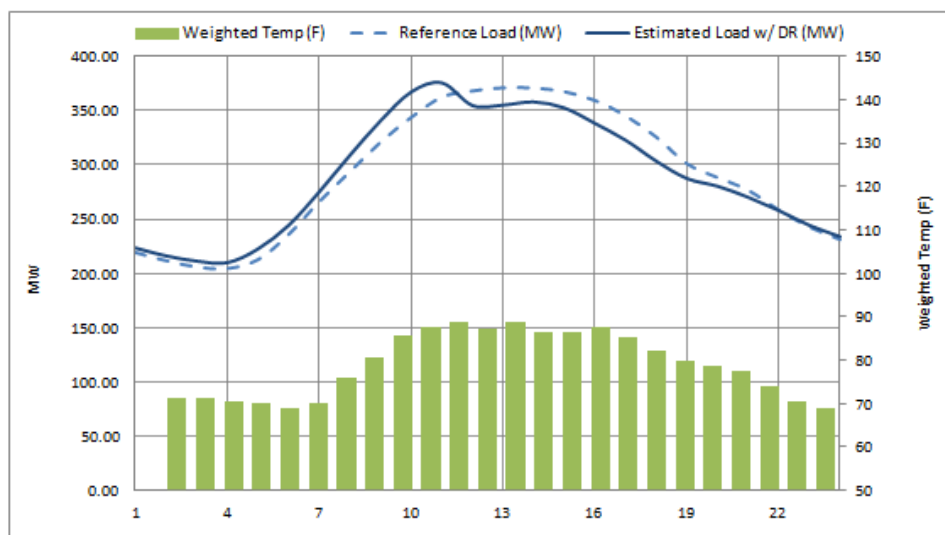
**Figure 6-2: Estimated Hourly Impacts
SDG&E's September 7, 2011 Event**

TABLE 1: Menu options

Type of Results	Aggregate
Customer Type	All

TABLE 2: Event Day Information

Event Date	9/7/2011
Event Start	11:00 AM
Event End	6:00 PM
Total Enrolled Accounts	1,293
Avg. Load Reduction for Event Window	18.6
% Load Reduction for Event Window	5.2%



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)
1	219.3	223.6	-4.3	-2.0%	71.3
2	211.7	216.5	-4.7	-2.2%	71.1
3	205.9	211.6	-5.7	-2.8%	70.3
4	204.5	210.1	-5.7	-2.8%	70.0
5	212.6	222.7	-10.1	-4.8%	69.1
6	235.9	244.3	-8.4	-3.6%	70.1
7	266.2	275.0	-8.8	-3.3%	75.8
8	294.0	308.4	-14.5	-4.9%	80.4
9	321.2	340.1	-18.9	-5.9%	85.8
10	344.1	366.5	-22.4	-6.5%	87.6
11	362.9	375.0	-12.0	-3.3%	88.9
12	368.7	354.2	14.5	3.9%	87.2
13	371.6	354.5	17.1	4.6%	88.6
14	371.4	357.4	14.0	3.8%	86.4
15	368.0	351.9	16.0	4.4%	86.4
16	359.9	337.7	22.2	6.2%	87.4
17	345.7	322.4	23.3	6.8%	85.3
18	326.0	303.2	22.8	7.0%	82.0
19	301.4	287.3	14.1	4.7%	79.9
20	288.6	280.3	8.3	2.9%	78.6
21	276.8	270.0	6.7	2.4%	77.4
22	258.5	258.0	0.6	0.2%	73.9
23	242.8	244.4	-1.6	-0.6%	70.7
24	231.3	234.0	-2.7	-1.1%	68.9
	Reference Energy Use (MWh)	Estimated Energy Use w/ DR (MWh)	Total Load Impact (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	6,989.1	6,949.2	39.9	0.6%	40.5

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

6.2 Load Impacts by Industry

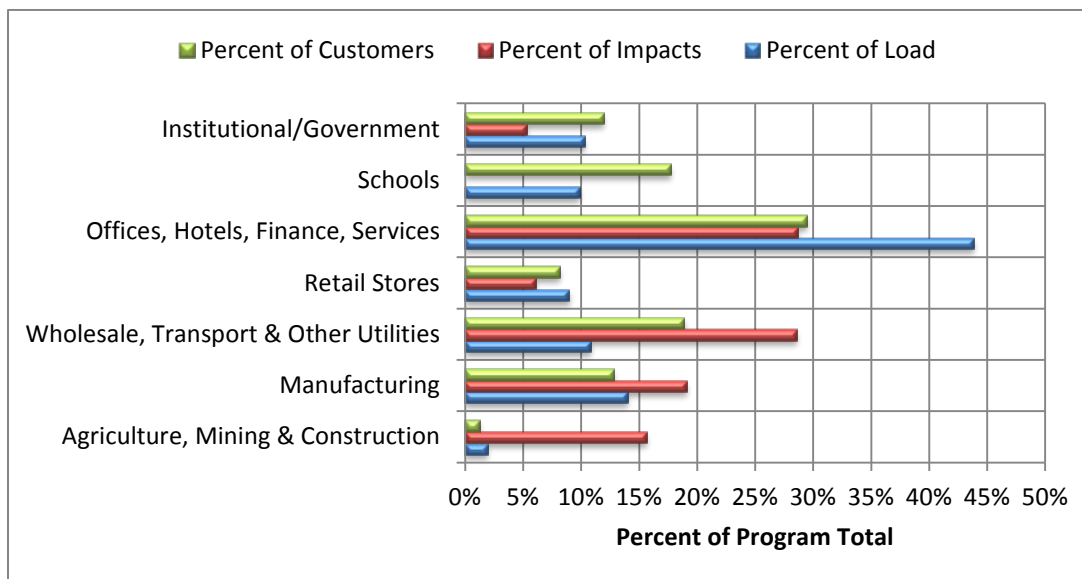
Table 6-2 shows the estimated ex post load impacts by industry. The distribution of impacts across industry segments is not as highly concentrated as is for PG&E and SCE. There are four industry segments that provided large aggregate load impacts. The 16 customers in the Agricultural, Mining & Construction segment provided an average impact of 181.4 kW, a percent impact of 41.5% and an aggregate impact of 2.9 MW. Although there were very few customers in this segment, they are large and are able to shift almost half of their load during CPP events. Large aggregate impacts were also provided by customers in Manufacturing and Wholesale, Transport & Other Utilities. Contrary to what was observed at PG&E and SCE, statistically significant impacts were provided by customers in the Offices, Hotels, Finance & Services segment. Although these customers provided modest per customer impacts of 14.0 kW (3.4%), they were relatively large and there were a lot of them. Customers in the Manufacturing segment and customers in the Offices, Hotels, Finance & Services segment both provided average aggregate impacts of 5.3 MW. As was observed for both SCE and PG&E, estimated impacts for schools were negligible, even though schools comprised roughly 18% of the number of participating accounts.

**Table 6-2: Estimated Ex Post Load Impacts by Industry
September 7, 2011 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 (°F)
Agriculture, Mining & Construction	16	437.4	256.0	181.4	41.5%	2.9	87.6
Manufacturing	165	304.7	283.3	21.5	7.0%	3.5	86.7
Wholesale, Transport & Other Utilities	244	159.6	137.8	21.7	13.6%	5.3	87.5
Retail Stores	105	306.3	295.7	10.7	3.5%	1.1	86.3
Offices, Hotels, Finance, Services	380	413.6	399.6	14.0	3.4%	5.3	85.2
Schools	229	154.7	154.7	0.0	0.0%	0.0	86.0
Institutional/Government	154	239.2	232.8	6.4	2.7%	1.0	86.9
All Customers	1,293	277.5	263.1	14.4	5.2%	18.6	86.3

Figure 6-3 compares the distribution of customer reference loads, load impacts and customers by sector.

Figure 6-3: SDG&E Distribution of Event Period Reference Load and Impacts by Industry



The majority of the load was concentrated in the Offices, Hotels, Finance and Services sector. These are typically office buildings. They accounted for 44% of the estimated reference load (157.2 MW) and produced 29% of the load reduction (5.3 MW). However, this sector also had the most participants, and on average offices only reduced load by 3.4%. In contrast, the Manufacturing and Wholesale, Transport and Other Utilities sectors together accounted for 25% of the reference load (89.2 MW) but produced 48% of the impacts (8.8 MW).

6.3 Load Impacts by Customer Size

Table 6-3 shows the estimated ex post load impacts by customer size. Participants with average usage over 500 kW provided the largest absolute average impact per customer (100.8 kW), percent impact per customer (8.0%) and aggregate load impact (9.0 MW). These customers comprised 48% of the aggregate load impact for all customers even though they were only 7% of the 1,293 participants. Participants with average usage between 100 and 200 kW provided the lowest percent load impact (1.8%). The percent load impact for the smallest customers (under 50 Average kW) was 2.4%, which is substantially less than the larger customers above 200 kW provide, but comparable to what smaller customers between 50 and 200 kW provide.

**Table 6-3: Estimated Ex Post Load Impacts by Customer Size
September 7, 2011 SDG&E CPP Event**

Size Category	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	320	46.7	45.6	1.1	2.4%	0.4	86.3
50-100 Average kW	264	139.7	135.2	4.5	3.2%	1.2	87.2
100-200 Average kW	348	225.6	221.5	4.0	1.8%	1.4	85.9
200-500 Average kW	272	434.7	409.8	24.9	5.7%	6.8	85.8
Over 500 Average kW	89	1267.4	1166.6	100.8	8.0%	9.0	86.3
All Customers	1,293	277.5	263.1	14.4	5.2%	18.6	86.3

6.4 Load Impacts for Multi-DR Program Participants

Table 6-4 shows load impacts for SDG&E customers who were dually enrolled in other DR programs or were previously enrolled in SDG&E's voluntary CPP tariff. Keep in mind that these impacts represent just a single weekday event. As with the other utilities, the small sample sizes suggest caution. However, it should be noted that CPP customers that were also enrolled in the BIP program provided about 11% of the aggregate demand reduction under the CPP program on September 7, even though they accounted for less than 0.5% of CPP accounts. Figure 6-4 shows the hourly load impacts for these customers.

Table 6-4 also shows the aggregate load impact for CPP participants that had previously enrolled in SDG&E's voluntary CPP program. These previous volunteers accounted for roughly 6% of the participants but nearly 20% of the aggregate load reduction on September 7.

**Table 6-4: Estimated Ex Post Load Impacts of Multi-DR Participants
September 7, 2011 SDG&E CPP Event**

Dual and Previous Enrollment	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	442	183	259	59%	2	83
Dually Enrolled: CBP	6	281	242	40	14%	0	85
Previously on Voluntary CPP	76	353	305	48	14%	4	90
Not Dually Enrolled	1205	272	261	11	4%	13	86
Population Totals	1,293	277	263	14	5%	19	86

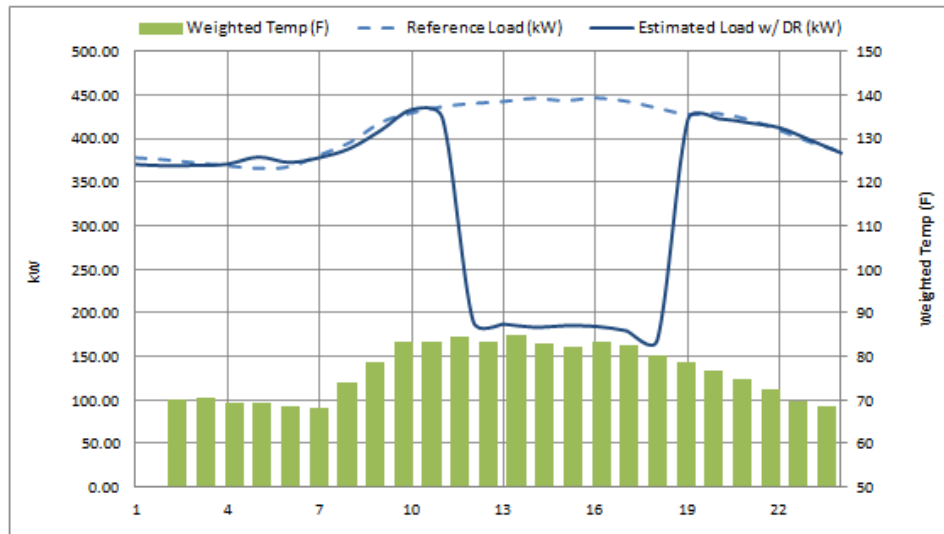
Figure 6-4:
2011 Hourly Ex Post Aggregate Load Impacts for BIP Customers Dually-enrolled in CPP
September 7, 2011 Weekday Event

TABLE 1: Menu options

Type of Results	Average Customer
Customer Type	Dually Enrolled: BIP

TABLE 2: Event Day Information

Event Date	9/7/2011
Event Start	11:00 AM
Event End	6:00 PM
Total Enrolled Accounts	6
Avg. Load Reduction for Event Window	258.9
% Load Reduction for Event Window	58.6%



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Load Impact (kW)	% Load Reduction	Weighted Temp (F)
1	378.5	370.9	7.6	2.0%	70.2
2	376.0	369.3	6.7	1.8%	70.3
3	372.6	369.8	2.8	0.7%	69.2
4	369.3	371.3	-2.0	-0.5%	69.2
5	366.4	379.5	-13.0	-3.6%	68.5
6	368.3	373.2	-4.9	-1.3%	68.3
7	381.7	378.7	2.9	0.8%	73.8
8	396.0	389.7	6.3	1.6%	78.8
9	418.6	410.3	8.3	2.0%	83.5
10	429.3	433.9	-4.6	-1.1%	83.5
11	436.2	424.1	12.1	2.8%	84.3
12	439.9	190.8	249.1	56.6%	83.3
13	442.1	187.6	254.5	57.6%	85.0
14	445.7	184.0	261.8	58.7%	83.0
15	443.1	185.7	257.3	58.1%	82.3
16	446.2	184.9	261.4	58.6%	83.5
17	442.3	179.9	262.5	59.3%	82.5
18	434.7	169.2	265.5	61.1%	80.2
19	427.5	422.3	5.2	1.2%	78.5
20	428.3	423.4	4.9	1.1%	76.8
21	421.5	418.6	2.9	0.7%	74.8
22	409.4	412.8	-3.4	-0.8%	72.5
23	395.9	398.7	-2.8	-0.7%	69.8
24	385.3	384.0	1.3	0.3%	68.5
	Reference Energy Use (kWh)	Estimated Energy Use w/ DR (kWh)	Total Load Impact (kWh)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	9,854.9	8,012.5	1,842.4	18.7%	26.5

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

6.5 TI and AutoDR Load Impacts and Realization Rates

Table 6-5 shows the September 7, 2011 weekday event load impacts for customers enrolled in TI and AutoDR. Customers on TI and AutoDR show larger than average percent impacts of 10.0% and 8.6%, respectively. However, given the extremely small number of customers on TI and AutoDR, the point impact estimates are surrounded by a significant amount of uncertainty. And while the average per customer load impact for TI customers is almost three times greater than that provided by AutoDR customers, the aggregate load impacts from these customers are similar (0.8 MW vs. 1.0 MW). This is because there are almost four times as many customers on AutoDR as there are on TI.

As was true for the analysis of TI and AutoDR for PG&E and SCE, analysis of realization rates for SDG&E CPP customers is severely hampered by the small number of customers that participated in the two complementary programs. At SDG&E, there were 6 TI participants and 22 AutoDR participants. As such, the realization rate estimates contained in Table 6-5 should be used with caution. The same pattern of wide uncertainty bands that was seen for PG&E and SCE is also seen in Table 6-6. Although there are 22 AutoDR customers, the range of uncertainty for these customers is greater than the range of uncertainty for the 6 TI customers. This is probably because the model had less predictive capability for AutoDR customers than for TI customers due to irregular load profiles and/or other factors.

**Table 6-5: Estimated Ex Post Load Impacts of TI & AutoDR Participants
September 7, 2011 SDG&E CPP Event**

Variable	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)
Technical Incentives (TI)	6	1276	1148	128	10%	1	85
AutoDR	22	514	470	44	9%	1	84

Table 6-6: Realization Rates

Variable	Accts	Aggregate Approved kW	Realization Rate				
			10th Percentile	30th Percentile	50th Percentile	70th Percentile	90th Percentile
Technical Incentives (TI)	6	3354	-3%	12%	23%	33%	49%
AutoDR	22	4179	-26%	3%	23%	43%	73%

6.6 Comparison of 2010 and 2011 Ex Post Results

Although enrollment in SDG&E's CPP program was much more stable than for PG&E and SCE between 2010 and 2011, any comparison of load impacts across the two years is questionable since there was only one weekday CPP event day in 2011. The average aggregate impact for 2010 was 18.8 MW which was nearly identical to the aggregate impact on the September 7, 2011 weekday event, which equaled 18.6 MW. September 7 was about 5°F hotter during the event period than the average of the

four 2010 events. While the reductions were nearly identical on a percentage basis, customer loads were higher that day, leading to equivalent aggregate load reductions despite the small decrease in net enrollment. Given the very limited number of observations, these comparisons are not very meaningful and provide limited information about customer weather sensitivity.

Keeping in mind the caution advised above, the most significant differences in impacts between 2010 and 2011 were for the Wholesale Transport & Other Utilities and Offices, Hotels, Finance & Services industry segments. In 2010, Manufacturing customers provided an average aggregate load reduction of 3.1 MW (7.8%) on the average event day, while in 2011 this same industry group provided an average aggregate load reduction of 5.3 MW (13.6%) on the one weekday event. Since the number of customers in this industry remained constant at approximately 245 customers, it's likely that the increase in impacts is either due to differences in event conditions or due to outreach to improve customer price responsiveness. In the Offices, Hotels, Finance & Services industry segment, average aggregate impacts for the average event day were 8.2 MW (5.3%) in 2010 and 5.3 MW (3.4%) for the one weekday event in 2011. In this industry, enrollment decreased from 409 to 380 accounts between 2010 and 2011. The difference in impacts may be due to the change in enrollment or due to the differences in event day weather conditions between 2010 and 2011.

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 2012 to 2022 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 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.

Per Decision 11-06-022 (p. 60), the operating period for Non-Res CPP for 2013 is required to be from 1 PM to 6 PM. PG&E has submitted a proposal to change the CPP rates and event window to the CPUC in its 2012 Rate Design Window application, but an official decision has not yet been issued. In order to provide ex ante impact estimates that reflect the longer 1 PM to 6 PM window, FSC applied the observed percent impact from 2 PM to 3 PM to the 1 PM to 2 PM window for the 2014 forecast onward.

7.1 Large C&I Ex Ante Impacts

In total, approximately 1,750 large customers were enrolled in default CPP in 2011 and experienced 9 events. As a result, we now know second year retention rates for default CPP, how much load reduction large customers 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 2022. The development of the enrollment forecast and underlying assumptions are documented in The Brattle Group's *"Executive Summary: 2012-2022 Demand Response Portfolio of Pacific Gas and Electric Company."* The forecasts show a sizeable increase in CPP enrollment between 2012 and 2014. In August 2012, 1,384 customers are forecast to receive service under the tariff, while in August 2014, 1,849 customers are projected to be served under the CPP rate schedule. The overall enrollment forecasts are very similar to those produced last year – differences for each forecast year are less than 3%.

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

Forecast Year	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	1,445	1,445	1,445	1,445	1,384	1,384	1,384	1,384	1,384	1,384	1,675	1,675
2013	1,704	1,703	1,721	1,721	1,659	1,659	1,658	1,658	1,657	1,657	1,882	1,882
2014	1,882	1,881	1,912	1,912	1,850	1,850	1,850	1,849	1,849	1,849	1,922	1,922
2015	1,921	1,921	1,922	1,922	1,861	1,861	1,860	1,860	1,860	1,859	1,920	1,919
2016	1,919	1,918	1,918	1,919	1,858	1,857	1,857	1,857	1,857	1,856	1,917	1,916
2017	1,916	1,916	1,916	1,916	1,855	1,855	1,855	1,855	1,854	1,854	1,915	1,914
2018	1,914	1,914	1,914	1,914	1,853	1,853	1,853	1,853	1,853	1,852	1,913	1,913
2019	1,912	1,912	1,912	1,912	1,852	1,852	1,851	1,851	1,851	1,851	1,912	1,911
2020	1,911	1,911	1,911	1,911	1,850	1,850	1,850	1,850	1,850	1,850	1,910	1,910
2021	1,910	1,910	1,910	1,910	1,849	1,849	1,849	1,849	1,849	1,849	1,910	1,909
2022	1,909	1,909	1,909	1,909	1,849	1,849	1,849	1,849	1,848	1,848	1,909	1,909

7.1.1 Annual System Peak Day Impacts

Table 7-2 summarizes the aggregate load impact estimates for large customers on PG&E's CPP tariff for each forecast year under both 1-in-2 and 1-in-10 weather year scenarios. The table shows the average load reduction across the 1 PM to 6 PM event period for an August monthly system peak day. Importantly, the event window is from 2 PM to 6 PM for both the 2012 and 2013 forecast, as mentioned previously. The table summarizes the load impacts for portfolio analysis and excludes customers dually enrolled in DR programs that require firm commitments such as BIP or the aggregator programs to avoid double counting them in the portfolio. The program specific estimates are summarized in Appendix H.

Differences in average temperature from year to year are a direct result of changes in enrollment and the customer mix by weather station. 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. The enrollment increases both because of general population growth and because utilities will default additional large customers when they have had interval data available for 12 months.

In 2012, the average aggregate load impact during an August event for the 1-in-10 weather year scenario is estimated to be 28.9 MW. By 2014, the load reduction capability under the same set of conditions is expected to grow to 40.9 MW. Depending on the forecast year and weather conditions, large customers in the CPP program are expected to reduce between 6.2% and 6.7% of demand under peaking conditions. The reductions match relatively well to the average percent reduction, 5.9%, observed for ex post events in 2011. The small differences are due to differences in the weather conditions and because the ex ante impacts incorporate information about current participant performance in both 2010 and 2011.

The ex ante impacts are also comparable to those produced last year under the 2 PM to 6 PM event window. Last year, 32.3 MW were estimated to be available for 2012. This year, we estimate 27.6 MW under 1-in-2 conditions. The difference is due to better information about the enrollment and customer mix after the expiration of first year bill protection. It also reflects the fact that, in this past year, not as many additional large customers were defaulted onto CPP as initially projected due to timing of the installation of hourly meters for the large customers that lacked such meters (mainly agricultural). Going forward, however, this year's ex-ante projections factor in the changes in the customer mix observed after the first year of CPP participation and reflect the higher percent demand reductions observed. These changes are detailed in Section 4.7. Overall, this leads to larger ex ante impacts for 2014 to 2021 than were reported last year. The difference is between 14% and 19%, depending on the forecast year.

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

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 1-6 pm)	(MW 1-6 pm)	(MW 1-6 pm)	(1-6 pm)	(°F)
1-in-10 August System Peak Day	2012	1,384	449.3	420.4	28.9	6.4%	94.8
	2013	1,658	539.1	504.5	34.7	6.4%	94.9
	2014	1,849	612.0	571.1	40.9	6.7%	94.6
	2015	1,860	614.9	573.7	41.2	6.7%	94.6
	2016	1,857	613.4	572.2	41.2	6.7%	94.6
	2017	1,855	612.2	571.0	41.1	6.7%	94.6
	2018	1,853	611.3	570.1	41.1	6.7%	94.6
	2019	1,851	610.5	569.4	41.1	6.7%	94.6
	2020	1,850	609.9	568.9	41.1	6.7%	94.6
	2021	1,849	609.5	568.4	41.1	6.7%	94.6
	2022	1,849	609.1	568.1	41.1	6.7%	94.6
1-in-2 August System Peak Day	2012	1,384	446.7	419.1	27.6	6.2%	94.1
	2013	1,658	535.7	502.5	33.2	6.2%	94.1
	2014	1,849	608.2	569.2	39.0	6.4%	93.6
	2015	1,860	611.1	571.9	39.3	6.4%	93.6
	2016	1,857	609.6	570.4	39.2	6.4%	93.6
	2017	1,855	608.5	569.3	39.2	6.4%	93.6
	2018	1,853	607.6	568.4	39.2	6.4%	93.6
	2019	1,851	606.9	567.7	39.2	6.5%	93.6
	2020	1,850	606.3	567.2	39.2	6.5%	93.6
	2021	1,849	605.9	566.7	39.1	6.5%	93.6
	2022	1,849	605.5	566.4	39.1	6.5%	93.6

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

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 16.0 MW up to 39.2 MW.

Table 7-3:
Portfolio Annual Peak Day Load Impacts for Large Customers with Uncertainty
(Hourly Average Reduction in MW Over the Historical Event Day Window- 1 PM to 6 PM)

Weather Year	Year	Expected Avg. Load Impact	Impact Uncertainty				
		(MW 1-6 pm)	10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2012	28.9	17.1	24.1	28.9	33.7	40.7
	2013	34.7	19.5	28.4	34.7	40.8	49.8
	2014	40.9	23.4	33.7	40.9	48.1	58.4
	2015	41.2	23.5	33.9	41.2	48.4	58.9
	2016	41.2	23.4	33.9	41.2	48.4	58.9
	2017	41.1	23.4	33.9	41.1	48.4	58.9
	2018	41.1	23.4	33.8	41.1	48.3	58.8
	2019	41.1	23.4	33.8	41.1	48.3	58.8
	2020	41.1	23.4	33.8	41.1	48.3	58.8
	2021	41.1	23.4	33.8	41.1	48.3	58.7
	2022	41.1	24.4	34.2	41.1	47.9	57.7
1-in-2 August System Peak Day	2012	27.6	16.0	22.9	27.6	32.4	39.2
	2013	33.2	18.3	27.1	33.2	39.2	48.0
	2014	39.0	21.8	32.0	39.0	46.0	56.2
	2015	39.3	21.9	32.1	39.3	46.4	56.6
	2016	39.2	21.8	32.1	39.2	46.3	56.6
	2017	39.2	21.8	32.1	39.2	46.3	56.6
	2018	39.2	21.8	32.0	39.2	46.3	56.6
	2019	39.2	21.8	32.0	39.2	46.2	56.5
	2020	39.2	21.8	32.0	39.2	46.2	56.5
	2021	39.1	21.8	32.0	39.1	46.2	56.5
	2022	39.1	22.8	32.4	39.1	45.8	55.5

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

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 per customer ex ante impacts for each LCA by month for large customers. It shows the per customer impacts 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 2011 ex post analysis, almost 50% of customers are in the Greater Bay Area and about 20% are outside of the primary LCA's and classified as Other. In the ex post analysis, customers in Other provided 31% of aggregate impacts despite only accounting for 20% of the total population. By comparison, customers in the Greater Bay Area accounted for 35% of aggregate impacts despite representing almost 50% of the accounts. Customers in the Other LCA are larger, on average, than customers in the Greater Bay Area and provide larger per-customer impacts.

Table 7-4:
2012 Per Customer Ex Ante Impacts for Large Customers by Local Capacity Area
(Hourly Average Reduction in kW Over the Historic Event Window – 2 PM 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	-	-	-	-	15	17	16	15	16	14	-	-
	Greater Fresno	-	-	-	-	22	21	20	20	22	23	-	-
	Kern	-	-	-	-	34	34	36	39	32	29	-	-
	Northern Coast	-	-	-	-	19	23	18	15	18	17	-	-
	Other	-	-	-	-	29	26	32	32	35	34	-	-
	Sierra	-	-	-	-	22	24	25	24	24	23	-	-
	Stockton	-	-	-	-	32	34	39	37	31	29	-	-
	All Customers	-	-	-	-	20	21	22	21	22	21	-	-
1-in-2	Greater Bay Area	-	-	-	-	12	15	15	15	14	14	-	-
	Greater Fresno	-	-	-	-	22	23	21	22	22	24	-	-
	Kern	-	-	-	-	31	29	35	32	30	24	-	-
	Northern Coast	-	-	-	-	14	20	21	19	14	19	-	-
	Other	-	-	-	-	30	29	28	28	28	25	-	-
	Sierra	-	-	-	-	23	23	22	23	22	21	-	-
	Stockton	-	-	-	-	26	27	32	30	29	22	-	-
	All Customers	-	-	-	-	19	20	20	20	19	18	-	-

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 are enrolled on CPP and because only customers with

maximum demand over 200 kW are defaulted, the voluntary medium customers are not necessarily representative of the medium customer population segment as a whole. To obtain a larger and more diverse sample, customers from the large category with average hourly demands below 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 2022. There is a large increase in enrollment projected between 2014 and 2015. Starting in November 2014 medium customers that have had at least 24 months of experience on a TOU rate 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 2012, 194 medium customers are forecast to receive service under the tariff, most of whom voluntarily enrolled in CPP. In contrast, by August 2015, 12,291 medium customers are projected to be served under the rate schedule. And by November 2016, the medium customer population is expected to stabilize at around 30,000 accounts.

The enrollment forecast differ from last year, which projected enrollments that reached a peak of almost 19,000 customers. The new enrollment forecast factors in actual empirical data about customer opt out rates after first year bill protection expired. Last year, PG&E did not have experience with opt out rates after first year bill protection expired and used a conservative assumptions. The other substantive difference is that medium customers are now scheduled to default to CPP in 2015, two years after they have been placed on mandatory TOU. This change was made so customers would not confound bill changes due to the TOU with bill changes associated with CPP rates.

**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
2012	198	198	198	198	194	194	194	194	194	194	198	198
2013	201	201	201	201	197	197	196	196	196	196	200	200
2014	200	200	200	200	196	196	196	196	196	196	11,991	12,013
2015	12,036	12,060	12,150	12,185	12,210	12,238	12,265	12,291	12,316	12,339	23,975	23,997
2016	24,021	24,045	24,799	24,833	24,858	24,885	24,912	24,937	24,961	24,982	30,010	30,030
2017	30,052	30,075	30,497	30,529	30,553	30,578	30,603	30,626	30,648	30,668	29,131	29,151
2018	29,171	29,192	29,216	29,246	29,267	29,291	29,313	29,335	29,355	29,373	29,394	29,411
2019	29,430	29,449	29,472	29,500	29,520	29,542	29,564	29,585	29,604	29,621	29,642	29,658
2020	29,677	29,697	29,719	29,748	29,768	29,790	29,812	29,832	29,852	29,869	29,889	29,905
2021	29,923	29,942	29,964	29,992	30,011	30,033	30,054	30,074	30,092	30,108	30,128	30,143
2022	30,161	30,179	30,200	30,226	30,245	30,266	30,286	30,305	30,322	30,338	30,356	30,371

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 2012 to 2022 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 1 PM to 6 PM event period for an August monthly system peak day. Importantly, the event window is from 2 PM to 6 PM for both the 2012 and 2013 forecast, as mentioned previously.

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

Weather Year	Year	Enrolled Accts (Forecast) ^[1]	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 1-6 pm)	(MW 1-6 pm)	(MW 1-6 pm)	(1-6 pm)	(°F)
1-in-10 August System Peak Day	2012	194	7.2	6.4	0.8	10.6%	97.8
	2013	196	7.4	6.6	0.8	10.4%	97.8
	2014	196	7.6	6.8	0.8	10.7%	97.3
	2015	12,291	465.0	412.4	52.6	11.3%	98.1
	2016	24,937	982.0	894.3	87.7	8.9%	96.1
	2017	30,626	1,221.2	1,117.2	104.0	8.5%	95.7
	2018	29,335	1,167.2	1,066.7	100.5	8.6%	95.8
	2019	29,585	1,177.1	1,075.8	101.4	8.6%	95.8
	2020	29,832	1,187.0	1,084.8	102.2	8.6%	95.8
	2021	30,074	1,196.5	1,093.5	103.0	8.6%	95.8
	2022	30,305	1,205.7	1,101.9	103.8	8.6%	95.8
1-in-2 August System Peak Day	2012	194	6.8	6.3	0.5	7.4%	94.9
	2013	196	7.1	6.6	0.5	7.2%	94.9
	2014	196	7.3	6.7	0.5	7.4%	94.3
	2015	12,291	442.1	407.1	35.0	7.9%	94.6
	2016	24,937	936.9	876.4	60.5	6.5%	94.1
	2017	30,626	1,167.7	1,095.7	72.1	6.2%	94.0
	2018	29,335	1,115.5	1,046.0	69.5	6.2%	94.0
	2019	29,585	1,125.0	1,054.9	70.1	6.2%	94.0
	2020	29,832	1,134.4	1,063.7	70.7	6.2%	94.0
	2021	30,074	1,143.6	1,072.3	71.3	6.2%	94.0
	2022	30,305	1,152.3	1,080.5	71.8	6.2%	94.0

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

Differences in average temperature from year to year are a direct result of changes in enrollment and the customer mix by weather station. The average aggregate load impacts, presented in the sixth column, are higher under 1-in-10 conditions as expected. And, impacts increase proportionally with population growth. In 2012, the average aggregate load impact during an August event for the 1-in-10 weather year scenario is 0.8 MW for medium customers. Due to the planned default of PG&E's medium C&I population, the impacts are projected to grow to 52.6 MW for the same scenario in 2015. Impacts for August reach their peak at 104.0 MW in 2017 with 30,626 customers enrolled.

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 2015, the 80% confidence interval for 1-in-2 impacts ranges from 11.8 MW up to 58.1 MW, a difference of close to 50 MW. The majority of uncertainty once again is associated with enrollment projections.

Table 7-7:
Portfolio Annual Peak Day Load Impacts for Medium Customers with Uncertainty
(Hourly Average Reduction in MW Over the Historical Event Day Window- 1 PM to 6 PM)

Weather Year	Year	Expected Avg. Load Impact	Impact Uncertainty				
		(MW 1-6 pm)	10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2012	0.8	0.4	0.6	0.8	0.9	1.1
	2013	0.8	0.4	0.6	0.8	0.9	1.1
	2014	0.8	0.4	0.6	0.8	1.0	1.2
	2015	52.6	26.8	42.1	52.6	63.2	78.4
	2016	87.7	37.6	67.2	87.7	108.3	137.9
	2017	104.0	46.0	80.3	104.0	127.7	161.9
	2018	100.5	44.4	77.6	100.5	123.5	156.6
	2019	101.4	44.8	78.2	101.4	124.5	158.0
	2020	102.2	45.2	78.9	102.2	125.5	159.3
	2021	103.0	45.5	79.5	103.0	126.5	160.5
	2022	103.8	45.9	80.1	103.8	127.5	161.7
1-in-2 August System Peak Day	2012	0.5	0.2	0.4	0.5	0.6	0.8
	2013	0.5	0.2	0.4	0.5	0.7	0.9
	2014	0.5	0.2	0.4	0.5	0.7	0.9
	2015	35.0	11.8	25.5	35.0	44.4	58.1
	2016	60.5	14.7	41.8	60.5	79.2	106.3
	2017	72.1	19.1	50.4	72.1	93.7	125.0
	2018	69.5	18.3	48.6	69.5	90.5	120.8
	2019	70.1	18.5	49.0	70.1	91.3	121.8
	2020	70.7	18.6	49.4	70.7	92.0	122.8
	2021	71.3	18.8	49.8	71.3	92.8	123.8
	2022	71.8	18.9	50.2	71.8	93.5	124.7

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

7.2.1 Ex Ante Impacts by Geographic Location

Table 7-8 summarizes the per customer ex ante impacts for each LCA by month for medium customers. It shows the per customer impacts for each monthly system peak day under 1-in-2 and 1-in-10 system peaking conditions. Impacts are shown for 2015 because the distribution of enrolled medium customers across LCAs will be more stable in 2015 once more medium customers have been defaulted.

Table 7-8:
2015 Per Customer Ex Ante Impacts for Medium Customers by Local Capacity Area
(Hourly Average Reduction in kW Over the Event window – 1 PM 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	-	-	-	-	2	3	3	2	2	1	-	-
	Greater Fresno	-	-	-	-	4	4	5	6	4	3	-	-
	Kern	-	-	-	-	7	7	8	9	6	5	-	-
	Northern Coast	-	-	-	-	1	1	1	1	1	1	-	-
	Other	-	-	-	-	3	5	5	5	3	2	-	-
	Sierra	-	-	-	-	0	1	4	4	0	0	-	-
	Stockton	-	-	-	-	0	1	1	1	0	0	-	-
	All Customers	-	-	-	-	3	4	4	4	3	2	-	-
1-in-2	Greater Bay Area	-	-	-	-	1	2	2	2	1	1	-	-
	Greater Fresno	-	-	-	-	4	3	5	4	4	2	-	-
	Kern	-	-	-	-	6	5	7	6	5	2	-	-
	Northern Coast	-	-	-	-	1	1	1	1	1	2	-	-
	Other	-	-	-	-	2	2	4	3	2	0	-	-
	Sierra	-	-	-	-	-1	-1	3	1	2	-4	-	-
	Stockton	-	-	-	-	-1	0	0	0	0	-1	-	-
	All Customers	-	-	-	-	2	2	4	3	3	1	-	-

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 relatively stable enrollment. The first two years of experience allows customers the opportunity to assess if the rate fits their electricity use patterns and load reduction capability. Table 8-1 shows SCE's enrollment projections through 2022. SCE is assuming a slight increase in enrollment on the CPP tariff in 2012 and a more substantial increase by the end of the forecast period in December 2022. On average 3,006 accounts participated in 2011 events. The changes are simply associated with population growth and the transition of some medium customers into the large customer category. By January 2012 3,247 customers are projected to be served under the rate schedule and by December 2014, 3,452 customers are forecast to be enrolled.

The enrollment forecast differ from last year, which projected large customer enrollment to be between 2,500 and 2,900. The new enrollment forecast factors in actual empirical data about customer opt out rates after first year bill protection expired. For the most part, they reflect customers that are currently enrolled in CPP and have remained on the rate after first year bill protection expired. Last year, SCE did not have experience with opt out rates after first year bill protection expired and used a conservative assumptions.

**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
2012	3271	3261	3267	3272	3278	3283	3289	3294	3300	3305	3311	3316
2013	3322	3328	3333	3339	3344	3350	3355	3361	3367	3372	3378	3384
2014	3389	3395	3400	3406	3412	3418	3423	3429	3435	3440	3446	3452
2015-2022	3452	3452	3452	3452	3452	3452	3452	3452	3452	3452	3452	3452

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 2012 to 2022 period. In addition 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 the 2011 summer, SCE had roughly 3,050 large accounts enrolled in CPP. By 2012, enrollment is projected to increase to roughly 3,300 service accounts. The currently enrolled service accounts are assumed to be fully representative of the service accounts that will enroll. Table 8-2 summarizes the CPP ex ante impacts for 1-in-2 and 1-in-10 conditions through 2022. It shows the average load reduction across the 1 PM to 6 PM 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 2012 under the 1-in-10 weather scenario are forecast to be 28.6 MW. At the upper end, the forecasted aggregate impacts are 34.5 MW in 2015-2022 under the 1-in-2 weather year scenario. In general, large CPP customers are not highly weather sensitive so their impacts do not change significantly between 1-in-2 and 1-in-10 weather years. Although SCE is expecting enrollment to increase slightly, the reference loads and impacts remain constant and linearly related to the number of customer enrolled because customers currently on CPP are assumed to be fully representative of the small number of customers who will join the program in the future. Put differently, while large C&I CPP enrollment increases, percent impacts are assumed to remain constant.

Table 8-2:
Portfolio Annual System Peak Day Load Impacts for SCE's CPP Tariff by Year
(Hourly Average Reduction in MW Over Event Day Period - 1 to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load (MW 1-6 PM)	Avg. Estimated Load w DR (MW 1-6 PM)	Avg. Load impact (MW 1-6 PM)	% Load Reduction (MW 1-6 PM)	Weighted Temp (°F)
1-in-10 August System Peak Day	2012	3,294	710.3	683.8	26.5	3.74%	96.0
	2013	3,361	724.8	697.7	27.1	3.74%	96.0
	2014	3,429	739.4	711.8	27.6	3.74%	96.0
	2015-2022	3,452	744.4	716.6	27.8	3.74%	96.0
1-in-2 August System Peak Day	2012	3,294	695.6	668.2	27.3	3.93%	93.5
	2013	3,361	709.7	681.8	27.9	3.93%	93.5
	2014	3,429	724.1	695.6	28.4	3.93%	93.5
	2015-2022	3,452	728.9	700.3	28.6	3.93%	93.5

Depending on the forecast year and weather conditions, large customers in the CPP program are expected to reduce between 3.7% and 3.9 % of demand under peaking conditions. The reductions are lower than percent reductions observed for ex post events in 2011, which ranged from 5.4% to 5.9%. The difference is explained by three factors. First, the RA window has been extended to include the event window from 1 to 2 PM. Impacts of close to zero are included for this hour in the 1 to 6 PM average event window. This makes sense for ex ante reporting purposes because the price signal will be lowered by approximately 20% to compensate for the longer event window. On another note, customers dually enrolled in other DR programs, are excluded from the portfolio impacts to avoid double counting. Since these customers generally reduce a larger share of their demand, excluding them lower the demand reductions by roughly 12%. The remaining difference is explained

by fact that the ex ante impacts incorporate information about current participant performance in 2010 and 2011.

As mentioned previously, the ex ante impacts in Table 8-2 reflect a 1 to 6 PM window with what is essentially an assumed 20% reduction in impacts. To compare the ex ante impacts produced last year with those produced this year, FSC uses the 2 to 6 PM window in both years. Under the 2 to 6 PM window, the ex ante impacts are higher than those produced last year by roughly one third. Last year, 24.5 MW were estimated to be available for 2012 under 1-in-2 peaking conditions. This year, we estimate 33.0 MW will be available. The difference is due to changes in enrollment forecast and improved performance. Despite a reduction in the number of customers from 4,000 to 3,100 customers between 2010 and 2011, average ex post demand reduction increased from 30.7 MW in 2010 to 35 MW in 2011. As detailed in Section 5.7, the results suggest that SCE retained the bulk of the most price responsive customers enrolled in CPP. The project ex-ante demand reductions are well within the range of reductions observed in 2011.

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 2012 and 2022. They illustrate how enrollment changes slightly and aggregate impacts stay basically constant from the beginning to the end of the forecast period. 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 2012 the aggregate reference load decreases steadily over the 4-hour event period, from roughly 740 MW to 610 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 about 30 MW to 35 MW. The 2022 electricity consumption patterns do not differ significantly. In total, 158 customers are projected to enroll in CPP between August 2012 and August 2022, leading to very little change in aggregate program impacts. Figure 8-2 makes clear that the reference load, observed load, load impacts and percent load impacts are almost the same in August 2012 as August 2015-2022 under SCE's enrollment assumptions.

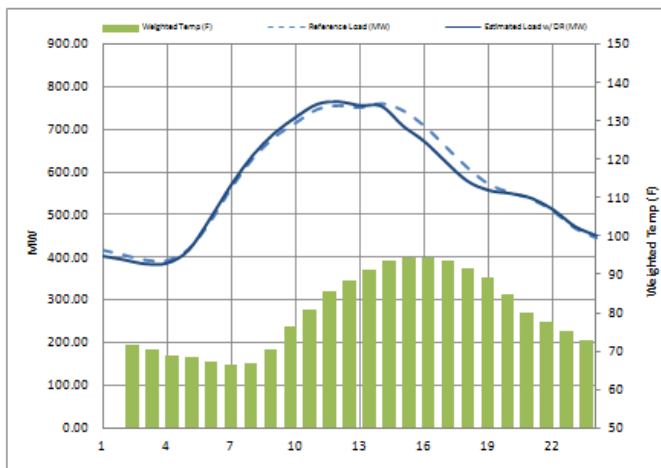
Figure 8-1:
Hourly Aggregate Load Reduction for CPP for an August Monthly System Peak Day
Portfolio Impacts, 1-in-2 Weather Year Conditions and 2012 Program Enrollment

TABLE 1: Menu options

Type of Results	Aggregate
Type of Impacts	Portfolio
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	32.95
% Load Reduction for RA Window	4.8%
Forecast Customers Enrolled	3294



Hour Ending	Reference Load (MW)	Estimated Load w/	Load Impact	% Load Reduction	Weighted Temp (F)
1	415.81	404.59	11.22	2.7%	71.5
2	404.69	395.87	8.82	2.2%	70.5
3	392.63	386.12	6.51	1.7%	69.0
4	391.67	388.07	3.60	0.9%	68.4
5	418.11	418.11	0.00	0.0%	67.2
6	481.30	491.56	-10.26	-2.1%	66.3
7	561.94	571.96	-10.02	-1.8%	66.6
8	630.62	640.71	-10.09	-1.6%	70.3
9	680.87	692.02	-11.15	-1.6%	76.2
10	714.82	729.70	-14.88	-2.1%	80.9
11	746.48	760.12	-13.64	-1.8%	85.5
12	755.16	765.88	-10.72	-1.4%	88.5
13	750.41	757.14	-6.73	-0.9%	91.3
14	759.93	755.20	4.73	0.6%	93.7
15	743.41	709.18	34.23	4.6%	94.4
16	706.98	672.41	34.56	4.9%	94.4
17	657.97	624.41	33.56	5.1%	93.4
18	609.47	580.02	29.45	4.8%	91.7
19	570.52	558.36	12.16	2.1%	89.2
20	551.09	551.18	-0.09	0.0%	84.6
21	535.56	539.64	-4.08	-0.8%	80.1
22	506.59	512.82	-6.23	-1.2%	77.6
23	467.62	473.88	-6.25	-1.3%	75.2
24	444.57	452.50	-7.93	-1.8%	72.8
	Reference Energy Use (MW)	Estimated Energy Use w/ DR (MW)	Change in Energy Use (MW)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	13,898.21	13,831.43	66.78	0%	86.3

Note: A positive value % Daily Load Change indicates the use of less energy for
Note: Medium customer enrollment forecast begins in 2013

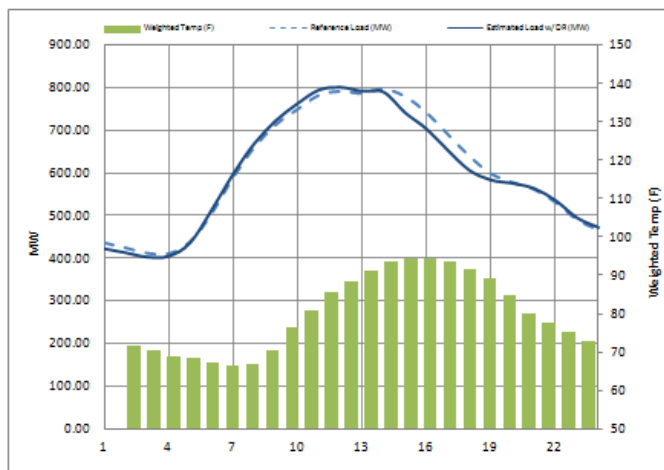
Figure 8-2:
Hourly Aggregate Load Reduction for CPP Tariff for a August Monthly System Peak Day
Portfolio Impacts, 1-in-2 Weather Year Conditions and 2015-2022 Program Enrollment

TABLE 1: Menu options

Type of Results	Aggregate
Type of Impacts	Portfolio
Day type	August Monthly Peak
Weather Year	1-in-2
Forecast Year	2015

TABLE 2: Event Day Information

Event Start	2:00 PM
Event End	6:00 PM
Load Reduction for RA Window	34.53
% Load Reduction for RA Window	4.8%
Forecast Customers Enrolled	3452



Hour Ending	Reference Load (MW)	Estimated Load w/	Load Impact	% Load Reduction	Weighted Temp (F)
1	435.75	424.00	11.76	2.7%	71.5
2	424.10	414.86	9.24	2.2%	70.5
3	411.47	404.64	6.82	1.7%	69.0
4	410.46	406.68	3.78	0.9%	68.4
5	438.17	438.17	0.00	0.0%	67.2
6	504.39	515.14	-10.75	-2.1%	66.3
7	588.89	599.39	-10.50	-1.8%	66.6
8	660.87	671.45	-10.58	-1.6%	70.3
9	713.53	725.21	-11.69	-1.6%	76.2
10	749.11	764.70	-15.59	-2.1%	80.9
11	782.28	796.58	-14.29	-1.8%	85.5
12	791.38	802.62	-11.23	-1.4%	88.5
13	786.40	793.45	-7.05	-0.9%	91.3
14	796.38	791.42	4.96	0.6%	93.7
15	779.07	743.20	35.87	4.6%	94.4
16	740.89	704.66	36.22	4.9%	94.4
17	689.53	654.36	35.17	5.1%	93.4
18	638.70	607.84	30.86	4.8%	91.7
19	597.88	585.14	12.74	2.1%	89.2
20	577.52	577.62	-0.09	0.0%	84.6
21	561.25	565.52	-4.27	-0.8%	80.1
22	530.89	537.42	-6.53	-1.2%	77.6
23	490.05	496.61	-6.55	-1.3%	75.2
24	465.89	474.21	-8.31	-1.8%	72.8
	Reference Energy Use (MW)	Estimated Energy Use w/ DR (MW)	Change in Energy Use (MW)	% Daily Load Change	Cooling Degree Hours (Base 65)
Daily	14,564.85	14,494.87	69.98	0%	86.3

Note: A positive value % Daily Load Change indicates the use of less energy for
Note: Medium customer enrollment forecast begins in 2013

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 20.7 MW up to 32.4 MW - a swing of 11.7 MW.

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

Weather Year	Year	Expected Avg. Load Impact (MW 1-6 PM)	Impact Uncertainty				
			10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2012	26.5	20.7	24.1	26.5	28.9	32.4
	2013	27.1	21.1	24.6	27.1	29.5	33.0
	2014	27.6	21.5	25.1	27.6	30.1	33.7
	2015-2022	27.8	21.7	25.3	27.8	30.3	33.9
1-in-2 August System Peak Day	2012	27.3	21.6	25.0	27.3	29.6	33.0
	2013	27.9	22.0	25.5	27.9	30.2	33.7
	2014	28.4	22.5	26.0	28.4	30.9	34.4
	2015-2022	28.6	22.6	26.2	28.6	31.1	34.6

8.3 Per Customer Ex Ante Reference Loads and Impacts by Geographic Location

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

SCE is comprised of three geographic planning zones known as local capacity areas (LCAs). The per-customer ex ante load impacts differ by geographic location due to differences industry mix and to a lesser extent, climate. Table 8-4 shows the average reference loads and load reduction over the 1 PM to 6 PM event window for the average customer in 2012 by LCA, month and weather year. Within each LCA, the overall load absent DR – the reference loads – vary significantly with weather year and month. Table 8-5 summarizes the per-customer ex ante load reductions for each LCA by month. It shows the average participant load reduction for each monthly system peak day under 1-in-2 and 1-in-10 system peaking conditions. Reference load and impacts are not provided for non-summer months because SCE has never called a CPP event during non-summer months and there is no data to inform plausible load impact estimates. On an individual customer basis, the load reductions are largest in the LA Basin as are the reference loads. Most of SCE's CPP customers are located in the LA Basin including many Industrial customers.

Table 8-4:
Average Reference Load per CPP Customer (kW) During Peak Period
by LCA and Month for 2012
(1-in-2 and 1-in-10 Year Weather Conditions)

Weather Year	Local Capacity Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	LA Basin	-	-	-	-	-	225	229	237	238	-	-	-
	Outside LA Basin	-	-	-	-	-	217	211	227	228	-	-	-
	Ventura	-	-	-	-	-	123	120	126	123	-	-	-
	All Customers	-	-	-	-	-	206	208	216	216	-	-	-
1-in-2	LA Basin	-	-	-	-	-	216	223	233	238	-	-	-
	Outside LA Basin	-	-	-	-	-	197	204	217	217	-	-	-
	Ventura	-	-	-	-	-	117	119	121	124	-	-	-
	All Customers	-	-	-	-	-	196	202	211	215	-	-	-

Table 8-5:
Average Load Reduction per CPP Customer (kW) During Peak Period
by LCA and Month for 2012
(1-in-2 and 1-in-10 Year Weather Conditions)

Weather Year	Local Capacity Area	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-10	LA Basin	-	-	-	-	-	10	9	9	9	-	-	-
	Outside LA Basin	-	-	-	-	-	7	7	7	7	-	-	-
	Ventura	-	-	-	-	-	5	5	5	5	-	-	-
	All Customers	-	-	-	-	-	8	8	8	8	-	-	-
1-in-2	LA Basin	-	-	-	-	-	10	9	9	9	-	-	-
	Outside LA Basin	-	-	-	-	-	5	7	6	6	-	-	-
	Ventura	-	-	-	-	-	5	5	5	6	-	-	-
	All Customers	-	-	-	-	-	9	8	8	8	-	-	-

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 October through March 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 2022. 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 2014. Retention rates are initially assumed to be around 50% with approximately 25% of the remaining customers opting out after they experience CPP for one year. SDG&E is also providing customers with technology to automate their load response in the form of thermostats with two-way communication. 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 conditions of a 1-in-2 and a 1-in-10 weather year for the 2012 to 2022 period. In addition, this section contains per customer impacts by geographic industry 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	2012	-	-	-	1212.71	1151	1151	1153	1154	1156	1157	1158	1159
	2013	1161	1161	1162	1163	1164	1166	1169	1170	1170	1171	1173	1174
	2014	1175	1176	1179	1180	1180	1181	1185	1185	1186	1187	1189	1190
	2015	1191	1193	1194	1195	1197	1198	1199	1201	1202	1204	1205	1207
	2016	1208	1209	1211	1212	1214	1215	1216	1218	1219	1221	1222	1223
	2017	1225	1226	1228	1229	1231	1232	1233	1235	1236	1238	1239	1241
	2018	1242	1243	1245	1246	1248	1249	1251	1252	1254	1255	1256	1258
	2019	1259	1261	1262	1264	1265	1267	1268	1270	1271	1273	1274	1276
	2020	1277	1279	1280	1281	1283	1284	1286	1287	1289	1290	1292	1293
	2021	1295	1296	1298	1299	1301	1302	1304	1305	1307	1309	1310	1312
	2022	1313	1315	1316	1318	1319	1321	1322	1324	1325	1327	1328	1330
Medium C&I	2012	-	-	-	-	-	-	-	-	-	-	-	-
	2013	-	-	-	-	-	-	-	-	-	-	-	-
	2014	-	-	-	-	9480	9491	9500	9513	9524	9534	9545	9555
	2015	9565	9579	9588	9598	7073	7080	7086	7096	7104	7111	7121	7127
	2016	7136	7144	7153	7160	6294	6304	6310	6317	6324	6333	6338	6346
	2017	6351	6361	6368	6375	6381	6390	6397	6403	6411	6419	6426	6433
	2018	6441	6449	6457	6461	6470	6478	6485	6493	6500	6508	6514	6520
	2019	6530	6538	6544	6551	6559	6566	6574	6581	6590	6597	6604	6613
	2020	6619	6627	6634	6643	6649	6657	6663	6674	6680	6688	6695	6703
	2021	6712	6718	6726	6733	6742	6747	6757	6765	6772	6780	6787	6795
	2022	6803	6811	6819	6826	6834	6842	6850	6856	6865	6872	6881	6889

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. The 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 11.4 MW in 2012 to 14.1 MW at the end of the forecast horizon under 1-in-2 conditions and from 17.4

MW in 2012 to 21.1 MW at the end of the forecast horizon under 1-in-10 conditions. The growth is fueled by increases in the large customer population.

Forecast impacts for large C&I customers under ex ante weather conditions are generally lower than the impacts observed ex post. For portfolio level results this is intuitive because in the portfolio analysis, the impacts from dually enrolled customers are excluded from CPP and attributed to the programs that require a firm commitment. Because the ex ante forecast accounts for the transfer off CPP of a number of dually enrolled customers who provided significant load shed, the overall ex ante load impact estimates are lower than ex post for both program specific and portfolio level results. Roughly 12% percent of the 2011 ex post program impacts of large C&I customers¹⁹ came from customers that were dually enrolled in CPP and programs such as BIP and CBP (1.8 MW). These customers typically reduced a substantially higher share of their load, 60% (BIP) and 14% (CBP) than customers who were not dually enrolled. With a number of these customers transferring off CPP, it is not surprising that the ex ante impact estimates are lower than the impacts observed ex post. Further, the percent impacts provided by large customers ex post were actually slightly lower than the percent impacts provided by CPP participants as a whole (4.9% vs. 5.2%).

The range of weather for ex-ante forecasts is broader than the weather variation observed during actual events and SDG&E results are highly sensitive to weather. In specific, the weather conditions for the May and June peaks in a 1-in-2 weather year are substantially milder than those seen during actual events. The percent reductions during these ex ante conditions were effectively capped to avoid extrapolating outside of the observed range. Appendix G provides a brief description of the observed weather sensitivity from SDG&E weather and how the percent reductions were capped for those day types.

¹⁹ A customer is defined as large if their summer max demand equals or exceeds 200 kW.

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

Weather Year	Year	Enrolled Accts (Forecast) ^[1]	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 11 am-6 pm)	(MW 11 am-6 pm)	(MW 11 am-6 pm)	(MW 11 am-6 pm)	(MW 11 am-6 pm)
1-in-10 August System Peak Day	2012	1154	393.9	376.5	17.4	4.4%	84.3
	2013	1170	401.6	383.3	18.2	4.5%	84.3
	2014	1185	409.2	390.2	19.0	4.6%	84.3
	2015	1201	415.5	396.0	19.5	4.7%	84.3
	2016	1218	421.1	401.4	19.7	4.7%	84.3
	2017	1235	426.8	406.8	19.9	4.7%	84.3
	2018	1252	432.5	412.3	20.2	4.7%	84.3
	2019	1270	438.3	417.9	20.4	4.7%	84.3
	2020	1287	444.2	423.6	20.6	4.6%	84.3
	2021	1305	450.2	429.3	20.9	4.6%	84.3
	2022	1324	456.3	435.2	21.1	4.6%	84.3
1-in-2 August System Peak Day	2012	1154	380.7	369.3	11.4	3.0%	78.7
	2013	1170	388.2	376.1	12.1	3.1%	78.7
	2014	1185	395.6	382.9	12.7	3.2%	78.7
	2015	1201	401.6	388.6	13.0	3.2%	78.7
	2016	1218	407.0	393.8	13.2	3.2%	78.7
	2017	1235	412.5	399.2	13.3	3.2%	78.7
	2018	1252	418.0	404.6	13.5	3.2%	78.7
	2019	1270	423.7	410.1	13.6	3.2%	78.7
	2020	1287	429.4	415.6	13.8	3.2%	78.7
	2021	1305	435.2	421.3	13.9	3.2%	78.7
	2022	1324	441.0	427.0	14.1	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 2012, the 80% confidence interval for 1-in-2 impacts ranges from 7 MW up to 16 MW. While the impact uncertainty bands do not incorporate uncertainty in

enrollment, for SDG&E's large CPP customers, that uncertainty is relatively small since all customers have already been defaulted onto CPP and the participant mix is not expected to change substantially.

Table 9-3:
Aggregate Portfolio Annual Peak Day Load Impacts for Large Customers with Uncertainty
(Hourly Average Reduction in MW Over 11 AM to 6 PM)

Weather Year	Year	Avg. Load impact	Impact Uncertainty Percentiles				
		(MW 11 am-6 pm)	10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2012	17	13	15	17	19	22
	2013	18	13	16	18	20	23
	2014	19	14	17	19	21	24
	2015	19	15	17	19	21	24
	2016	20	15	18	20	22	25
	2017	20	15	18	20	22	25
	2018	20	15	18	20	22	25
	2019	20	15	18	20	22	25
	2020	21	16	19	21	23	26
	2021	21	16	19	21	23	26
	2022	21	16	19	21	23	26
1-in-2 August System Peak Day	2012	11	7	9	11	13	16
	2013	12	7	10	12	14	17
	2014	13	8	11	13	15	18
	2015	13	8	11	13	15	18
	2016	13	8	11	13	15	18
	2017	13	8	11	13	15	18
	2018	13	8	11	13	16	19
	2019	14	9	12	14	16	19
	2020	14	9	12	14	16	19
	2021	14	9	12	14	16	19
	2022	14	9	12	14	16	19

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 2011, SDG&E defaulted roughly 600 medium customer accounts onto CPP and approximately 400 remained

on the rate. 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.²⁰ In other words, customers that are slightly above the large customer threshold were used as a proxy for medium customers. All of the 2009 through 2011 event data available under default conditions was also used as the basis for ex ante impacts. Section 3.6 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 11 AM to 6 PM for an August monthly system peak day. 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. 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.

The ex ante impacts are lower than those produced last year by roughly 35%. For example, last year, 21 MW were estimated to be available for 2015 under 1-in-2 peaking conditions (after the default). This year, we estimate 14 MW will be available. The difference is mainly due to changes in enrollment forecast. SDG&E updated their enrollment forecast to better reflect the medium customer population that will be defaulted onto CPP. Last year, they assumed all SDG&E customers on AL-TOU, the current standard rate for medium customers, would be defaulted. This year, they included an additional crosscheck to ensure the customers fit the official SDG&E definition of a medium customer. By doing so, the enrollment forecast avoided incorrectly including small customers that had voluntarily enrolled on AL-TOU.

²⁰ 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 11 AM to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast) ^[1]	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 11 am-6 pm)	(MW 11 am-6 pm)	(MW 11 am-6 pm)	(MW 11 am-6 pm)	(MW 11 am-6 pm)
1-in-10 August System Peak Day	2012	-	-	-	-	-	-
	2013	-	-	-	-	-	-
	2014	9513	353	322	32	8.9%	85.0
	2015	7096	265	244	21	8.0%	84.9
	2016	6317	235	217	19	8.0%	84.9
	2017	6403	239	219	19	8.0%	84.9
	2018	6493	242	223	19	8.0%	84.9
	2019	6581	245	226	20	8.0%	84.9
	2020	6674	249	229	20	8.0%	84.9
	2021	6765	252	232	20	8.0%	84.9
	2022	6856	255	235	20	8.0%	84.9
1-in-2 August System Peak Day	2012	-	-	-	-	-	-
	2013	-	-	-	-	-	-
	2014	9513	336	313	23	6.9%	82.6
	2015	7096	252	238	14	5.7%	82.5
	2016	6317	224	211	13	5.7%	82.5
	2017	6403	227	214	13	5.7%	82.5
	2018	6493	230	217	13	5.7%	82.5
	2019	6581	233	220	13	5.7%	82.5
	2020	6674	237	223	14	5.7%	82.5
	2021	6765	240	226	14	5.7%	82.5
	2022	6856	243	229	14	5.7%	82.5

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 2014, the 80% confidence interval for 1-in-2 impacts range from 21 MW up to 25 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 14 default CPP events to date enable us to examine impacts across different conditions to some extent. However, there is still relatively limited data about impacts under the more extreme conditions. As the history of events grows, the impact estimates will grow more reliable.

**Table 9-7:
Aggregate Portfolio Annual Peak Day Load Impacts for Medium Customers with Uncertainty
(Hourly Average Reduction in MW Over 11 AM to 6 PM)**

Weather Year	Year	Avg. Load impact	Impact Uncertainty Percentiles				
		(MW 11 am-6 pm)	10th	30th	50th	70th	90th
1-in-10 August System Peak Day	2012	-	-	-	-	-	-
	2013	-	-	-	-	-	-
	2014	32	30	31	32	32	34
	2015	21	19	20	21	22	23
	2016	19	17	18	19	19	20
	2017	19	17	18	19	20	21
	2018	19	18	19	19	20	21
	2019	20	18	19	20	20	21
	2020	20	18	19	20	21	22
	2021	20	18	19	20	21	22
	2022	20	19	20	20	21	22
1-in-2 August System Peak Day	2012	-	-	-	-	-	-
	2013	-	-	-	-	-	-
	2014	23	21	22	23	24	25
	2015	14	12	14	14	15	16
	2016	13	11	12	13	14	15
	2017	13	11	12	13	14	15
	2018	13	11	12	13	14	15
	2019	13	11	13	13	14	15
	2020	14	12	13	14	14	15
	2021	14	12	13	14	15	16
	2022	14	12	13	14	15	16

10 Recommendations

Last year, FSC provided detailed recommendations on additional research to better understand the load responsiveness of customers who were defaulted onto CPP rates. Since then, the utilities have implemented several of the recommendations or are in the process of doing so. They have standardized the tracking of CPP event notification data and launched research to understand why some customers respond better to the CPP price signals than others. In addition, in comparison to their first year of default CPP implementation, the percent demand reductions improved for both SCE and PG&E, increasing from 2.9% to 5.7% and from 3.9% to 5.9%, respectively. Currently, customers enrolled in CPP deliver reduce their demand by 5% to 6% at each of the utilities during events.

In light of the above, the recommendations are concise:

- *Reduce the uncertainty associated with defaulting small and medium C&I customers onto CPP.* Substantial uncertainty remains for the future transition of small and/or medium C&I customers to dynamic pricing and affects both short term implementation plans and long term resource planning. A large source of uncertainty is whether small and/or medium (SMB) customers will in fact be defaulted onto CPP rates or be offered those rates on a voluntary basis. This uncertainty is tied to ongoing regulatory litigation. In addition, 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 a shift to default dynamic rates among these customers. There is no empirical data on the share of customers that will remain on CPP rates if defaulted, or the extent to which they will reduce demand under a default CPP rate. If CPP will be implemented on a default basis for these customer segments, we recommend a multi-stage deployment process, where utilities test the default CPP process with a smaller, random sub-set of customers prior to full implementation. This would allow utilities the opportunity to test the default process, learn, and make appropriate adjustments prior to full implementation. It also reduces the uncertainty associated with the implementation of default dynamic pricing.
- *Provide customers "best practice" information about the steps they can take to reduce load during CPP event days both at the time they defaulted and at the start of each summer.* Each utility takes steps to ensure their customers are ready for the summer period. The improvement in the PG&E and SCE CPP performance may be due, in part, to additional steps they undertook to ensure customers were prepared for CPP events. While it is difficult to isolate the effect of continuing education efforts from other factors, the anecdotal evidence indicates customers welcomed summer preparedness reminders. Utilities should track the steps taken to prepare customers for CPP events so that program activities that may help explain changes customer responsiveness can be readily identified. In addition, utilities should share with each other the steps they undertake to ready their customers for CPP events prior to the summer in order to identify best practices.
- *If the weather conditions allow for it, SDG&E should call more CPP events in 2012.* Currently, the SDG&E ex ante results are highly sensitive to weather. However, the weather trend is highly sensitive due to the limited number of events and can be influenced by the addition or exclusion of individual ex post event results. Calling additional events will help SDG&E better understand the relationship between weather conditions and the magnitude of demand reductions.

Appendix A. Validity Assessments

Assessing the accuracy of regression models is important because doing so helps ensure that the results are valid. A systematic assessment of accuracy is particularly important when the percent load reductions are small and difficult to distinguish from spurious variation in the data. With small percent load reductions, small biases in the reference load can lead to significant errors in the impact estimates. Three approaches for assessing accuracy are out-of-sample testing, the use of false experiments and cross-checking individual customer regression results with the results of a separate control group analysis.

In the first two cases, the “true” answers are known. Out-of-sample testing helps assess how accurately regressions predict electricity use patterns under event-like conditions.²¹ False experiments test if the treatment variables confound load impacts with other factors under event-like conditions. The check of results using an external control group is useful for determining if a consistent answer is obtained when an entirely different evaluation approach is applied. Together these validation procedures give a reasonable indication of the accuracy of the regression models used. The final regression specification is selected based on a holistic approach that includes considering the ex post impacts, ex ante impacts and the above-mentioned validity assessments.

A.1. Out-of-sample Testing

Out-of-sample testing refers to holding back data on event-like days from the model-fitting process in order to test model accuracy. The process involves running the regressions without allowing the model to use a five of the seven hottest non-event days. The regression model is used to predict electricity use on the event-like days that were withheld, and then the model’s predictions are compared directly to actual electricity use observed on those days. If the predictions are close to the true load, it indicates that the model can predict accurately for the event-days selected. It is important not to fit the model to the event-like days and less than perfect out-of-sample predictions shouldn’t be interpreted as problematic. Over-fitting the model to the event-like days selected and obtaining highly accurate predictions for the out-of-sample tests gives a false sense of a regression model’s predictive power and often the more “honest” model with slightly worse out-of-sample predictions is actually performs better under a greater variety of event-like conditions.

A.2. False Event Coefficient Tests

To conduct false experiments, false event day variables are included in the regression specification to determine if error is being confounded with event-like conditions. The coefficients on the false event-day variables should be insignificant and centered around zero. The coefficients on the false event day variables are often significant due to the volume of data used for analysis and incorrect standard error calculations. Looking at the percent by which the false event day coefficients impact kW can produce more useable insights than explicitly looking at the significance of the false event coefficients. The default assumption is that the false event coefficients should have 0% impact on the dependent variable because there is technically no event effect to be picked up by the false event variables.

²¹ Though the term “event-like days” is used throughout these appendices to refer to the set of days used for the out-of-sample tests, these days are more extreme in temperature than the actual event days observed in a milder year like 2011. Holding back 5 of the 7 hottest days creates a more stringent out-of-sample test than picking days that match the actual event days and more closely simulates the ex ante conditions over which the model will have to predict accurately.

A.3. Control Group Analysis

To crosscheck results, FSC selected a matched control group of customers to use in a corroborating analysis.²² Such a strategy is especially useful in the case where there are only a few very hot days during the entire summer or when a treatment such as the CPP rate discount is in effect for prolonged periods. Individual customer regression results for events on days with no historical precedent in terms of temperature are necessarily extrapolations. A matched control group provides an important check on these extrapolations. A well-matched control group is also less likely to confound CPP rate discounts with factors such as weather and seasonality that are correlated to the time periods when the discounts are in effect. Individual customer regressions are within-subject estimators that use customer's electricity use patterns during days when they are not exposed to event day prices or rate discounts to estimate the counterfactual. With control groups electricity use from the group that is not exposed to CPP is used to infer the counterfactual.

When a control group is used, the accuracy of results is tied to the quality of the control group. Using a control group does not guarantee more accurate results on its own. A good control group has customers that, on average, look like and behave identically to participants on all days except CPP event days. Because the customers who are used as controls are customers who opted out of default CPP programs, they likely exhibit behavioral differences as compared to CPP customers. A control group that does not control for self-selection and differs substantially from participants can produce biased results. Drawing quality control groups is also difficult with larger customers because of more inherent variation in their electricity use.

Opt-out TOU customers were matched to CPP customers using propensity score matching. Propensity score matching is based on regression analysis. A number of variables are used to quantify difference between the participants and control group candidates and to generate a single score – the likelihood that customers are part of the CPP group given their characteristics. Customers are selected into the control group based on how closely they match participants based on this score. The propensity score matching exercise was done with a replacement. In other words, different treatment group (CPP) customers could be matched to the same opt-out TOU customers. The variables used for the propensity score matching exercise included industry, weather station, variables meant to capture the relationship between weather and usage, as well as variables meant to capture usage patterns on proxy event days during months when both CPP and TOU customers faced similar rates (Nov-May).

The difference-in-differences approach is a standard statistical approach for reducing error from control groups. In the first step, we estimated the difference in hourly loads between the CPP and TOU groups on non-event days when both sets of customers faced identical rates (Nov-May).²³ This produced an estimate of the bias or error in the reference load produced by the control group. This was done for five different temperature bins, as defined by Cooling Degree Days. In the second step,

²² FSC has used this strategy in various forms in several recent evaluations, such as the 2010 PG&E SmartAC evaluation, the 2010 PG&E SmartRate evaluation, the 2010 Statewide CPP evaluation and the 2010 evaluation of PG&E's Customer Web Presentment and Energy Alerts Programs. FSC also used a randomly-drawn (rather than matched) control group in the 2010 SDG&E Summer Saver Program.

²³ As mentioned earlier, the prices that SDG&E CPP customers experience in winter are actually slightly lower than the prices they would experience on the opt-out TOU rate, but the difference in prices is nominal compared with the price differential in the summer season.

the difference observed between opt-out TOU and CPP load profiles on non-event days with similar temperatures was netted out of the opt-out TOU load profiles on the actual event days at the hourly level. That is, the bias observed between opt-out TOU and CPP load profiles on the proxy event days was netted out of the opt-out TOU load profiles on the actual event days at the hourly level, by temperature bin.²⁴ Because the impacts are calculated as the difference between the adjusted control and participant group loads, mathematically, it is equivalent to a standard difference-in-differences calculation.

The control group analysis works better when there are plenty of candidates in the control pool to match to treatment customers, otherwise the same customer may be selected as a match multiple times, if it is closest to match for multiple participants. With too few candidates, the matching may not reflect the full range of variation in the participant population. It is also important for the control group to be relatively similar to the treatment group so that the difference-in-differences approach does not have to be relied on too heavily. At SDG&E there were not many opt-out TOU customers to match to CPP customers, but the customers who were available were relatively similar to CPP customers. The challenges in the PG&E and SCE control group analysis were different. While there were many opt-out TOU customers to match to CPP customers at these utilities, the customers differed greatly in size and the analysis relied more heavily on the difference-in-differences component.

The control group is used mainly as a crosscheck of the individual regression results. Because of the above-mentioned issues, the control group results for individual event days should be used cautiously even though they do corroborate the individual customer regression results for the average event.

A.4. In-sample Precision and Goodness-of-fit Measures

The R-squared goodness-of-fit statistic is calculated as an indication of the in-sample predictive accuracy of the model across customer segments and in the aggregate. In addition to the R-squared metric, in-sample predictions are plotted across the spectrum of event-like temperatures to determine how well the model predicts for event-like conditions in-sample.

In order to estimate the average customer R-squared values for each industry, LCA or in the aggregate, the regression-predicted and actual electricity usage values were averaged across all customers by segment. This process enables the calculation of the R-squared value. The R-squared values for the average customer by segment were estimated using the following formula:

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

²⁴ To adjust the opt-out TOU group loads on the actual event days, the following formula was used:

$$kWh_TOU_adj = kWh_TOU - (cntrl_days_kWh_TOU - cntrl_days_kWh_CPP).$$

Table A-1: 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

Appendix B. PG&E Validity Assessment

This section discusses the validation analysis that was done for the PG&E evaluation.

B.1. Out-of-sample Tests

The out-of-sample test results for PG&E show the bias in the reference load predictions on days similar to event days. Figure B-1 compares the actual and predicted load for each hour for the five false event days over which the regression specifications were tested. On average there is -1.1% bias during event-like hours and never more than -1.3% bias during event-like hours. The model exhibits more error in the mid-morning hours. The bias calculated for the out-of-sample tests indicates that the regression produces predictions with about 1% downward bias on the event-like days selected for the out-of-sample tests. It would be reasonable to conclude that the reported ex post load impacts are biased in a similar direction and by a similar amount, though a visual check of the ex post results suggests that the model does better than this on the ex post days. As mentioned earlier, the regression specification is chosen based on the ex post results, the ex ante results and the validation assessments. While models were tested that showed less bias for the out-of-sample tests, these models did not perform as well across all of the criteria used for model selection.

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

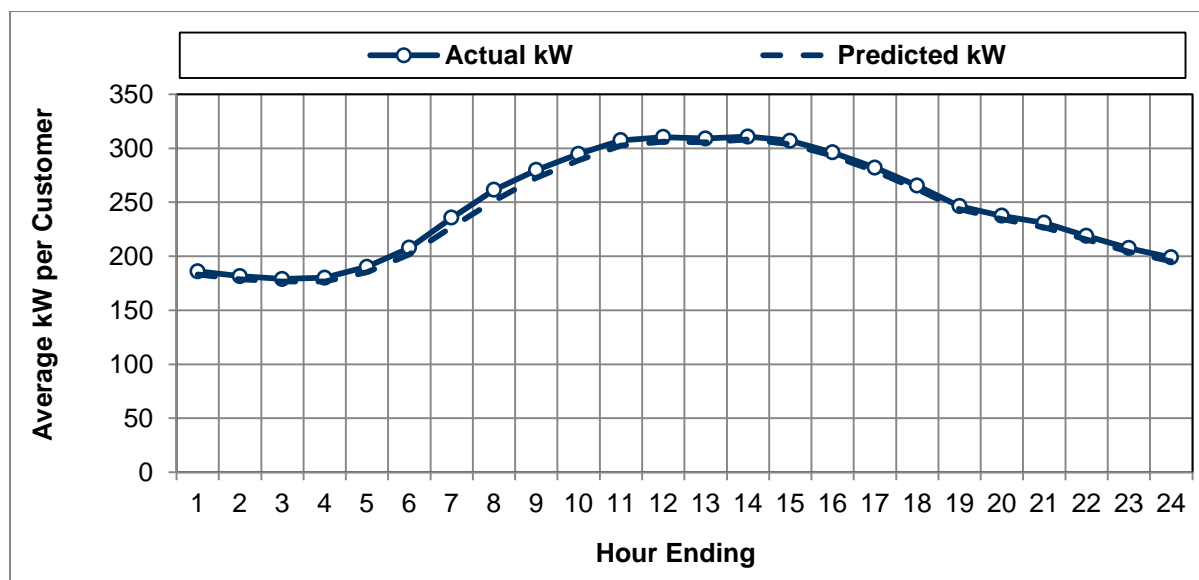


Table B-1 shows the average bias in the reference load predictions during event-like hours by industry. Depending on the specific group assessed, there is bias between -2.1% and 0.9%. Table B-1 also shows the percent of PG&E's CPP population within each industry segment. Customers in the Institutional/Government segment show the most bias during event-like hours, however, at -2.1%, the bias is still relatively low. Across the other industry segments, there is less than absolute bias of 2% during event-like hours.

**Table B-1: Actual v. Predicted Average Load by Industry for PG&E CPP Customers
False Event Hours**

Industry	% Population	Actual kW	Predicted kW	Bias	% Bias
Agriculture, Mining & Construction	7.2%	142.6	140.4	-2.2	-1.5%
Manufacturing	19.9%	295.9	294.4	-1.6	-0.5%
Wholesale, Transport & Other Utilities	13.5%	202.4	200.8	-1.6	-0.8%
Retail Stores	7.5%	314.5	317.2	2.7	0.9%
Offices, Hotels, Finance, Services	26.7%	405.7	398.0	-7.7	-1.9%
Schools	16.1%	169.4	169.4	0.0	0.0%
Institutional/Government	7.8%	334.2	327.1	-7.1	-2.1%
Other or Unknown	1.4%	179.7	180.8	1.1	0.6%

Table B-2 shows the average bias in the reference load predictions for PG&E's CPP customers during event-like hours by size category. Depending on the specific group assessed, there is between -3.2% and -0.7% bias. Table B-2 also shows the percent of PG&E's CPP population within each size category. Though there are far fewer customers in the Over 500 Average kW category, the reference loads of these customers are predicted accurately. The reference load predictions are most biased for the customers below 50 average kW.

**Table B-2: Actual v. Predicted Average Load by Size Category for PG&E CPP Customers
False Event Hours**

Size Bins	% Population	Actual kW	Predicted kW	Bias	% Bias
Under 50 Average kW	15.0%	32.0	31.0	-1.0	-3.2%
50 to 100 Average kW	22.3%	122.3	120.4	-1.9	-1.5%
100-200 Average kW	35.4%	221.6	219.5	-2.1	-0.9%
200-500 Average kW	21.0%	437.2	431.4	-5.9	-1.3%
Over 500 Average kW	6.3%	1285.5	1276.3	-9.3	-0.7%

B.2. False Event Coefficient Tests

Dividing the actual sum of kW for each hour by the sum of betas on the false event day variables gives the percent by which the estimated coefficients impact actual kW. The default assumption is that false event day variables should have 0% impact on the dependent variable, otherwise there is evidence that the betas are correlated with the error term. Table B-3 shows the results from the false event coefficient tests. The percent bias is well under 2% for all event-like hours.

Table B-3: Percent Bias from Aggregate False Event Coefficients

Hour	Sum of kWh	Sum of Betas	% Bias
12	3,038,507	31,926	1.1%
13	2,931,301	35,417	1.2%
14	2,792,229	36,164	1.3%
15	2,626,293	39,139	1.5%
Total	1,1400,000	142,646	1.3%

B.3. Control Group Analysis

Across all of the 2011 event days, impacts from the control group analysis match reasonably well with the impacts from the individual customer regressions at PG&E. However, the variation in control group impacts is much wider than the variation in impacts from the individual customer regressions. Impacts from the control group analysis range from 22.0 MW to 34.6 MW, while impacts from individual customer regressions range from 26.2 MW to 29.0 MW.

There are several potential explanations for the differences in impacts between the two methods. The binning approach used in the control group analysis can overstate or understate impacts if the control group is imperfect or the difference-in-differences approach is imperfect. Individual customer regressions also have drawbacks. In the individual customer regressions, treatment variables are defined to capture how event impacts vary with temperature. That is, regression-estimated impacts are only allowed to vary from event day to event day across the dimension of temperature.²⁵ Individual customer regressions will not pick up the idiosyncratic characteristics of individual event days that are not related to temperature. Both approaches have drawbacks, but the relative consistency of results between the two methods supports the results of both analyses.

²⁵ The alternative, specifying a variable for each event hour for each customer, leads the event variables to absorb all prediction errors since the regression lacks information to be able to distinguish what is different about that particular hour from error in the prediction of electricity use.

**Table B-4: Estimated Ex Post Load Impacts by Event Day and Analysis Method
2011 PG&E CPP Events**

Event Date	Number of Participants	% Load Impact - Regressions	Aggregate Load Impact - Regressions (MW)	% Load Impact - Control Group	Aggregate Load Impact - Control Group (MW)	Average Temperature During Event (°F)
6/21/2011	1,726	5.7%	26.7	5.9%	28.0	92.8
7/5/2011	1,729	6.0%	27.5	7.1%	32.6	90.2
7/29/2011	1,752	6.2%	26.2	5.1%	22.0	82.1
8/23/2011	1,753	5.9%	29.0	5.7%	28.3	90.0
8/29/2011	1,757	5.9%	27.2	6.6%	31.7	82.4
9/2/2011	1,753	6.2%	28.8	7.3%	34.6	86.5
9/6/2011	1,760	5.7%	27.7	5.0%	24.1	87.2
9/7/2011	1,755	5.8%	28.7	4.5%	22.1	91.0
9/20/2011	1,761	5.6%	28.3	4.9%	25.2	91.2
Average Event	1,750	5.9%	27.8	5.8%	27.6	88.1

Figure B-2 shows the average control and treatment customer usage patterns on days similar to event days. The control group usage patterns were adjusted to account for systemic differences between opt-out TOU and CPP customers. Control and treatment loads under a variety of weather patterns were compared. The final control group loads are net of consistent biases observed between opt-out TOU and CPP customers on days with similar weather profiles. On average, there is a -0.9% difference between the adjusted control and treatment group loads during event-like hours. The maximum bias observed at any point for this average event-like day is -1.3%.

**Figure B-2: Average PG&E CPP and Opt-out TOU Customer Usage
Control and Treatment Groups on Days Similar to Event Days**

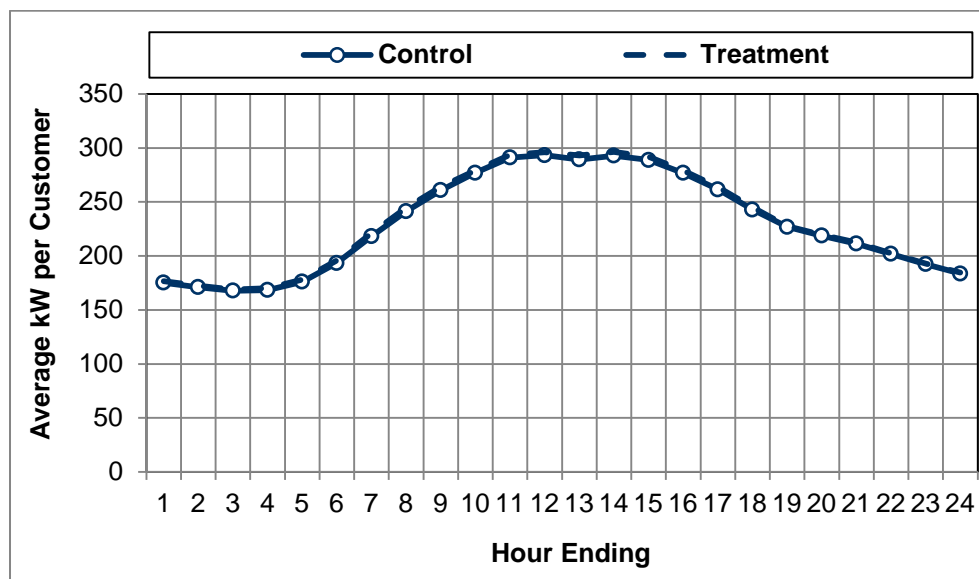
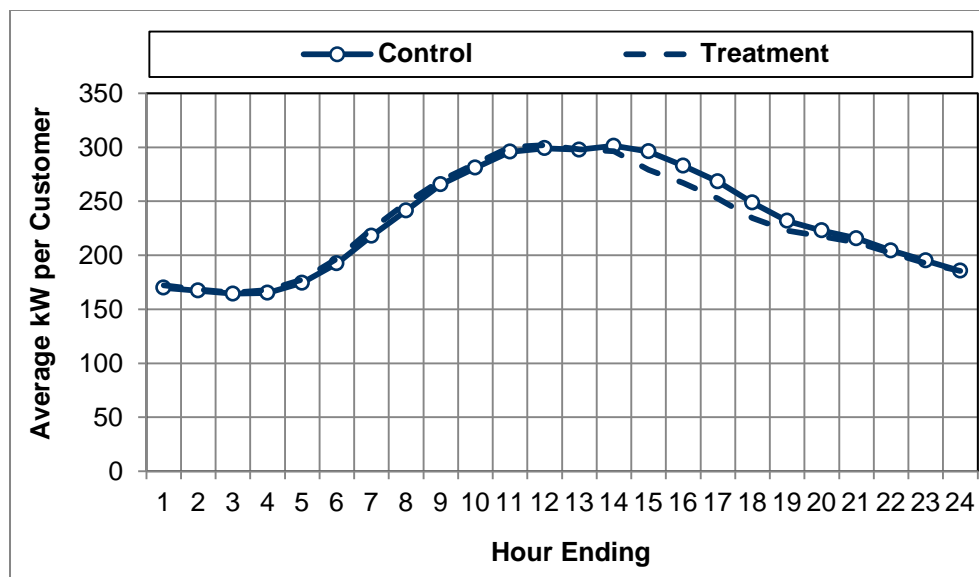


Figure B-3 shows the event day impact across PG&E's CPP population for the average 2011 CPP event. During the event hours of 2 PM to 6 PM, the control group analysis shows an average event impact of 15.8 kW (5.8%) for the average 2011 PG&E CPP event. The impacts from the control group analysis are very similar to those from the individual customer regressions for the average event.

**Figure B-3: Average PG&E CPP and Opt-out TOU Customer Usage
Average 2011 CPP Event**



B.4. In-sample Precision and Goodness-of-fit Measures

Table B-4 summarizes the amount of variation explained by the regression model for the average customer in specific segments. Depending on the specific group assessed, between 79% and 99% of the variation is explained. Customers in the Agriculture, Mining & Construction industry have the lowest R-squared value at 0.79. Barring Wholesale, Transport & Other Utilities, in the other industries and LCAs 90% or more of the variation in hourly energy use is explained.

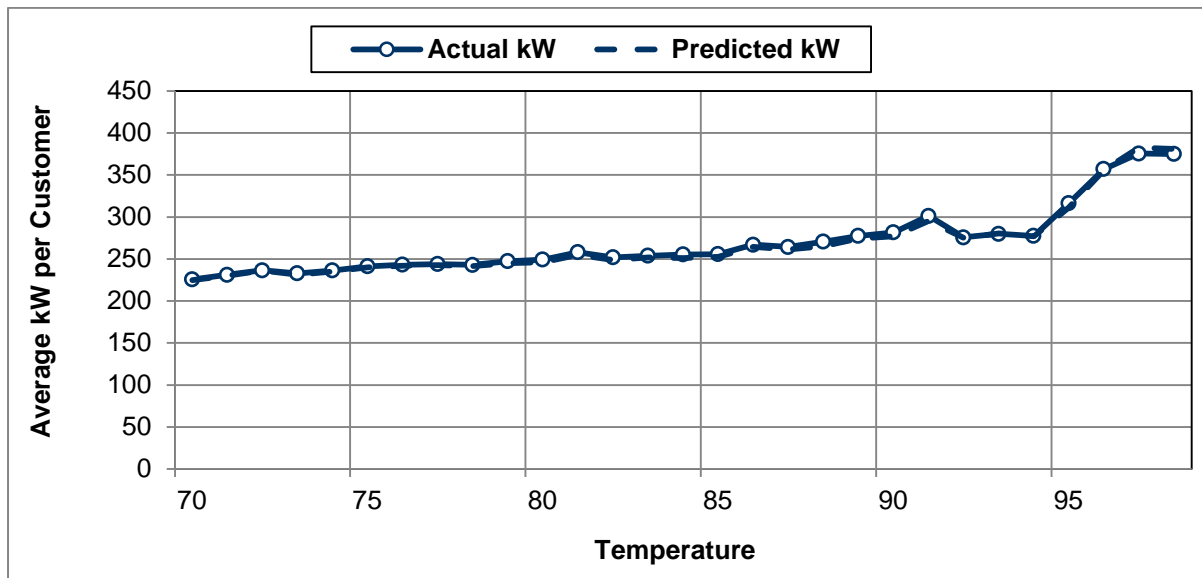
Table B-4: R-squared Values for the Average Customer by Segment

Customer Segment	R-squared
All Customers	0.96
Industry	
Agriculture, Mining & Construction	0.79
Manufacturing	0.93
Wholesale, Transport, other utilities	0.83
Retail stores	0.99
Offices, Hotels, Finance, Services	0.98
Schools	0.90
Institutional/Government	0.98
Other or undefined	0.93

Customer Segment	R-squared
Local Capacity Area	
Greater Bay Area	0.97
Greater Fresno	0.92
Kern	0.95
Northern Coast	0.94
Sierra	0.92
Stockton	0.93
Other	0.92

Figure B-4 shows how well the aggregate model predicts across various temperatures. The average error in the temperature range between 70 and 99°F is equal to -.65%. On average the model predicts just as well at higher temperatures. At 95°F and above the average error is 0.48%.

Figure B-4: Actual v. Predicted Aggregate Load by Temperature for PG&E CPP Customers



Appendix C. SCE Validity Assessment

This section discusses the validation analysis that was done for the SCE evaluation.

C.1. Out-of-sample Tests

The out-of-sample test results for SCE show the bias in the reference load predictions on days similar to event days. Figure C-1 compares the actual and predicted load for each hour for the five false event days over which the regression specifications were tested. On average, there is -1.0% bias during event-like hours and never more than -1.3% bias during event-like hours. The model exhibits more error in the mid-morning hours. The bias calculated for the out-of-sample tests indicates that the regression produces predictions with about 1% downward bias on the event-like days selected for the out-of-sample tests. It would be reasonable to conclude that the reported ex post load impacts are biased in a similar direction and by a similar amount, though a visual check of the ex post results suggests that the model does better than this on the ex post days. As mentioned above, the regression specification is chosen based on the ex post results, the ex ante results and the validation assessments. While models were tested that showed less bias for the out-of-sample tests, these models did not perform as well across all of the criteria used for model selection.

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

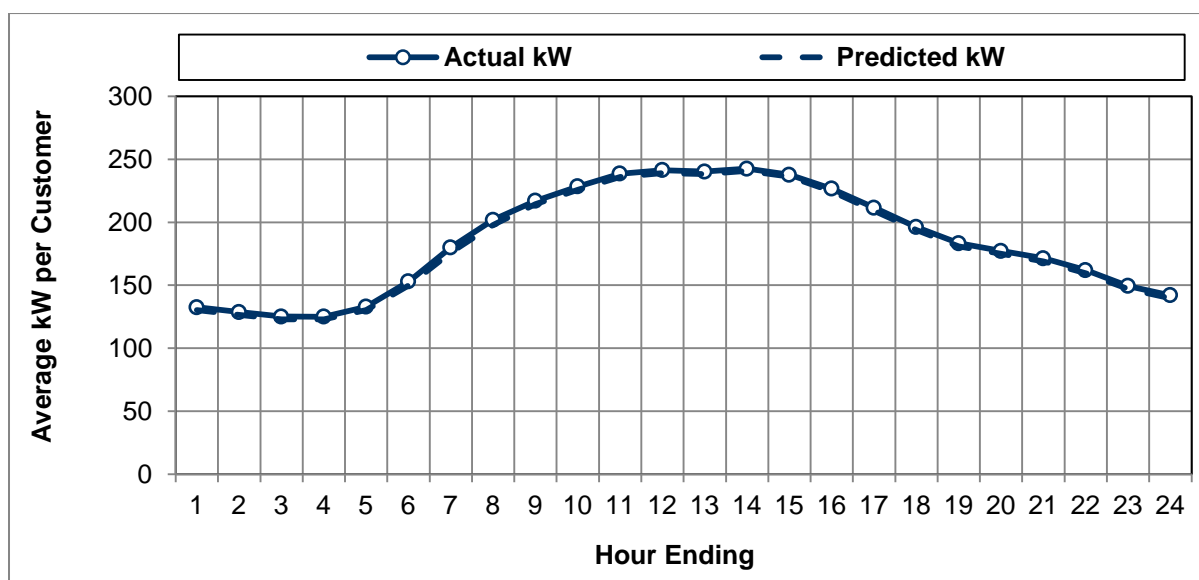


Table C-1 shows the average bias in the reference load predictions during event-like hours by industry. Depending on the specific group assessed, there is between -3.8% and 0.7% bias. Table C-1 also shows the percent of SCE's CPP population within each industry segment. Customers in the Other or Unknown segment show the most bias during event-like hours, however, they make up such a small part of the overall population that it is not a cause for concern. Across the other industry segments, there is absolute bias of 2% or less during event-like hours.

**Table C-1: Actual v. Predicted Average Load by Industry for SCE CPP Customers
False Event Hours**

Industry	% Population	Actual kW	Predicted kW	Bias	% Bias
Agriculture, Mining & Construction	2.4%	136.8	137.7	0.9	0.7%
Manufacturing	24.6%	227.1	225.9	-1.2	-0.5%
Wholesale, Transport & Other Utilities	16.5%	220.7	217.0	-3.7	-1.7%
Retail Stores	7.0%	248.1	247.2	-0.9	-0.4%
Offices, Hotels, Finance, Services	28.3%	187.2	184.7	-2.5	-1.3%
Schools	12.3%	232.7	232.7	0.0	0.0%
Institutional/Government	7.5%	285.5	279.7	-5.8	-2.0%
Other or Unknown	1.3%	167.8	161.4	-6.4	-3.8%

Table C-2 shows the average bias in the reference load predictions for SCE's CPP customers during event-like hours by size category. Depending on the specific group assessed, there is between -1.9% and -0.6% bias. Table C-2 also shows the percent of SCE's CPP population within each size category. Though there are far fewer customers in the Over 500 Average kW category, the reference loads of these customers are predicted accurately. The reference load predictions are most biased for the customers between 50 and 100 average kW.

**Table C-2: Actual v. Predicted Average Load by Size Category for SCE CPP Customers
False Event Hours**

Size Bins	% Population	Actual kW	Predicted kW	Bias	% Bias
Under 50 Average kW	22.4%	35.0	34.4	-0.6	-1.6%
50 to 100 Average kW	29.2%	140.5	137.8	-2.6	-1.9%
100-200 Average kW	29.9%	218.0	216.6	-1.4	-0.6%
200-500 Average kW	15.0%	414.3	411.6	-2.8	-0.7%
Over 500 Average kW	3.6%	1194.9	1181.8	-13.1	-1.1%

C.2. False Event Coefficient Tests

Dividing the actual sum of kW for each hour by the sum of betas on the false event day variables gives the percent by which the estimated coefficients impact actual kW. The default assumption is that false event day variables should have 0% impact on the dependent variable, otherwise there is evidence that the betas are correlated with the error term. Table C-3 shows the results from the false event coefficient tests. The percent bias is equal to or under 2% for all event-like hours.

Table C-3: Percent Bias from Aggregate False Event Coefficients

Hour	Sum of kWh	Sum of Betas	% Bias
15	4361017	73841	1.7%
16	4157217	78233	1.9%
17	3880637	77080	2.0%
18	3598896	62189	1.7%
Total	16000000	291343	1.8%

C.3. Control Group Analysis

Across all of the 2011 event days, impacts from the control group analysis match reasonably well with the impacts from the individual customer regressions at SCE. However, the variation in control group impacts is much wider than the variation in impacts from the individual customer regressions. Impacts from the control group analysis range from 23.5 MW to 46.2 MW, while impacts from individual customer regressions range from 32.7 MW to 36.7 MW.

There are several potential explanations for the differences in impacts between the two methods. The binning approach used in the control group analysis can overstate or understate impacts if the control group is imperfect or the difference-in-differences approach is imperfect. Individual customer regressions also have drawbacks. In the individual customer regressions, treatment variables are defined to capture how event impacts vary with temperature. That is, regression-estimated impacts are only allowed to vary from event day to event day across the dimension of temperature.²⁶ Individual customer regressions will not pick up the idiosyncratic characteristics of individual event days that are not related to temperature. Both approaches have drawbacks, but the relative consistency of results between the two methods supports the results of both analyses.

²⁶ The alternative, specifying a variable for each event hour for each customer, leads the event variables to absorb all prediction errors since the regression lacks information to be able to distinguish what is different about that particular hour from error in the prediction of electricity use.

**Table C-4: Estimated Ex Post Load Impacts by Event Day and Analysis Method
2011 SCE CPP Events**

Event Date	Number of Participants	% Load Impact - Regressions	Aggregate Load Impact - Regressions (MW)	% Load Impact - Control Group	Aggregate Load Impact - Control Group (MW)	Average Temperature During Event (°F)
6/21/2011	2,935	5.4%	33.9	4.1%	23.5	82.0
7/5/2011	2,953	5.6%	36.7	4.6%	27.5	85.8
7/19/2011	2,872	5.8%	35.6	5.5%	31.9	84.6
8/1/2011	2,992	5.9%	36.4	6.9%	42.5	86.7
8/3/2011	3,015	5.8%	36.1	4.6%	27.7	84.8
8/12/2011	3,094	5.7%	32.7	7.9%	46.2	78.1
8/16/2011	3,014	5.6%	33.6	6.4%	39.8	83.6
8/18/2011	3,014	5.6%	34.0	4.6%	28.5	83.6
8/23/2011	3,024	5.6%	34.6	4.2%	25.9	86.4
8/26/2011	3,038	6.0%	36.6	6.3%	40.6	90.3
9/6/2011	3,077	5.5%	36.6	4.6%	31.2	90.9
9/23/2011	3,047	5.7%	32.7	5.1%	30.1	79.9
Average Event	3,006	5.7%	35.0	5.4%	32.9	84.7

Figure C-2 shows the average control and treatment customer usage patterns on days similar to event days. The control group usage patterns were adjusted to account for systemic differences between opt-out TOU and CPP customers. Control and treatment loads under a variety of weather patterns were compared. The final control group loads are net of consistent biases observed between opt-out TOU and CPP customers on days with similar weather profiles. On average, there is a 0.1% difference between the adjusted control and treatment group loads during event-like hours. The maximum bias observed at any point for this average event-like day is -1.3%.

Figure C-2: Average SCE CPP and Opt-out TOU Customer Usage Control and Treatment Groups on Days Similar to Event Days

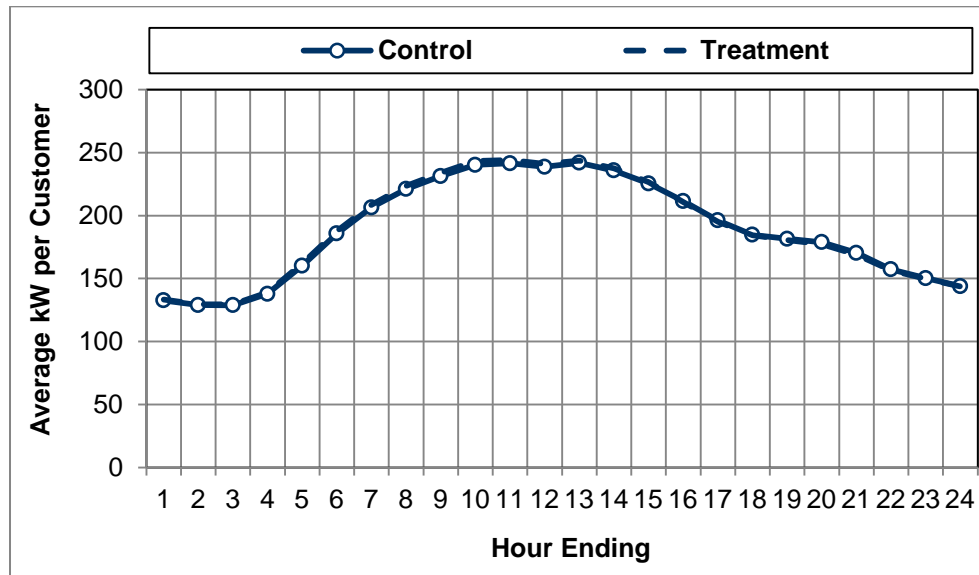
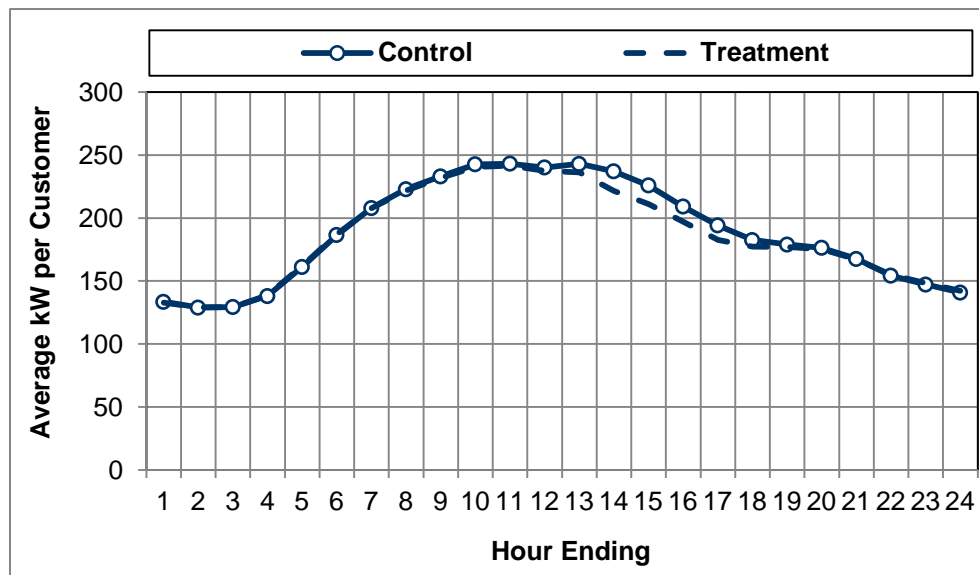


Figure C-3 shows the event day impact across SCE's CPP population for the average 2011 CPP event. During the event hours of 2 PM to 6 PM, the control group analysis shows an average event impact of 10.9 kW (5.4%) for the average 2011 SCE CPP event. The impacts from the control group analysis are very similar to those from the individual customer regressions for the average event.

Figure C-3: Average SCE CPP and Opt-out TOU Customer Usage Average 2011 CPP Event



C.4. In-sample Precision and Goodness-of-fit Measures

Table C-5 summarizes the amount of variation explained by the regression model for the average customer in specific segments. In the aggregate the model explained 95% of the variation in energy

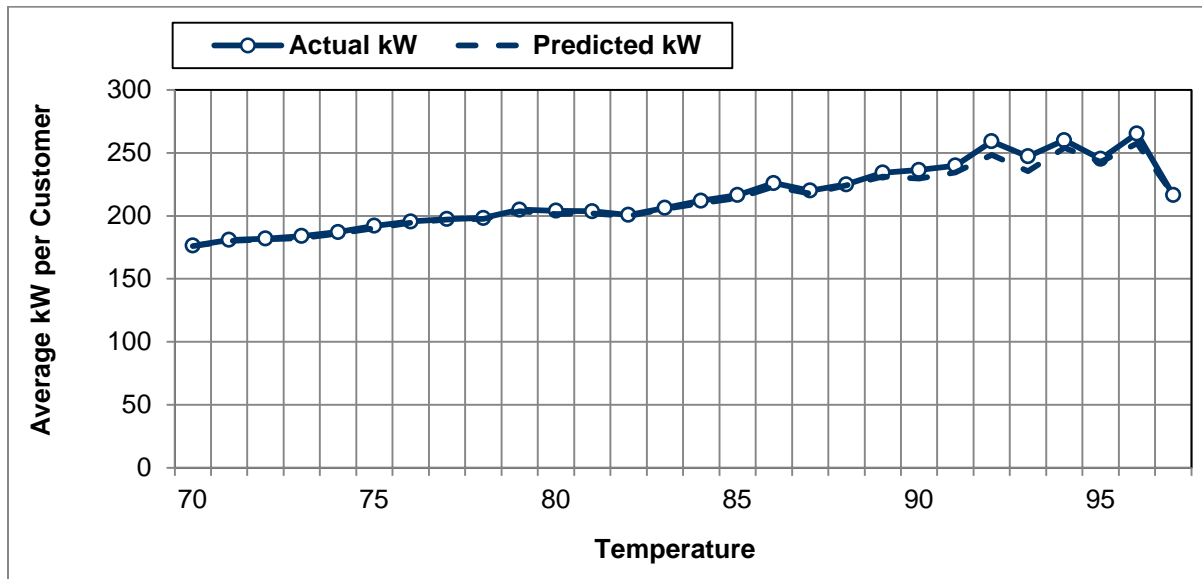
use. The explained variation varied from 48% to 98% across industries and local capacity areas. Apart from Wholesale, Transport & Other Utilities, only one of the industry or local capacity area has an R-squared value below 0.90 – Agriculture Mining and Construction (0.85).

Table C-5: R-squared Values for the Average Customer by Segment

Customer Segment	R-squared
All Customers	0.95
Industry	
Agriculture, Mining & Construction	0.85
Manufacturing	0.94
Wholesale, Transport, other utilities	0.48
Retail stores	0.98
Offices, Hotels, Finance, Services	0.98
Schools	0.91
Institutional/Government	0.98
Other or undefined	0.90
Local Capacity Area	
LA Basin	0.95
Outside LA Basin	0.93
Ventura	0.98

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 C-4, the model predicts well across various temperatures, with the average error for temperatures between 70 to 97°F equal to -1.3%. The model is most off between 90 and 94°F, where it under predicts by -3.3%.

Figure C-4: Actual v. Predicted Average Load by Temperature for SCE CPP Customers



Appendix D. SDG&E Validity Assessment

This section discusses the validation analysis that was done for the SDG&E evaluation.

D.1. Out-of-sample Tests

The out-of-sample test results for SDG&E show the bias in the reference load predictions on days similar to event days. Figure D-1 compares the actual and predicted load for each hour for the five false event days over which the regression specifications were tested. On average, there is 0.2% bias during event-like hours and never more than 0.3% bias during event-like hours. The model exhibits more error in the mid-morning hours. The bias calculated for the out-of-sample tests indicates that the regression produces predictions with about 0.2% upward bias on the event-like days selected for the out-of-sample tests. It would be reasonable to conclude that the reported ex post load impacts are biased in a similar direction and by a similar amount, though a visual check of the ex post results suggests that the model significantly under predicts. As mentioned above, the regression specification is chosen based on the ex post results, the ex ante results and the validation assessments. The very small degree of bias observed in the out-of-sample tests as compared to PG&E and SCE, which show very plausible ex post results, adds confidence that the pre-event “bias” observed in the ex post results is due to customers shifting load and not due to the regression specification.

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

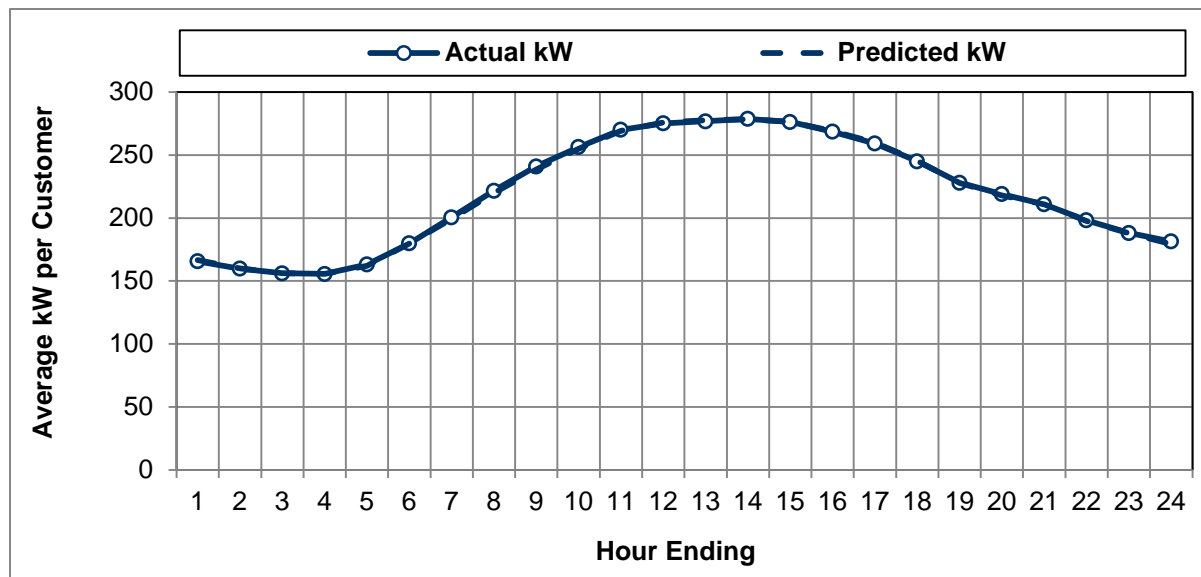


Table D-1 shows the average bias in the reference load predictions during event-like hours by industry. Depending on the specific segment assessed, there is between -1.5% and 2.0% bias. Table D-1 also shows the percent of SDG&E's CPP population within each industry segment. Customers in the Agricultural, Mining & Construction segment show the most bias during event-like hours. There are few customers in this segment so bias is expected to be higher. Across the other industry segments, there is absolute bias of 1.5% or less during event-like hours.

**Table D-1: Actual v. Predicted Average Load by Industry for SDG&E CPP Customers
False Event Hours**

Industry	% Population	Actual kW	Predicted kW	Bias	% Bias
Agriculture, Mining & Construction	1.2%	300.4	306.5	6.1	2.0%
Manufacturing	12.7%	305.2	300.5	-4.6	-1.5%
Wholesale, Transport & Other Utilities	18.9%	157.7	158.5	0.8	0.5%
Retail Stores	8.1%	310.2	312.4	2.3	0.7%
Offices, Hotels, Finance, Services	29.6%	399.2	400.4	1.2	0.3%
Schools	17.7%	142.0	142.0	0.0	0.0%
Institutional/Government	11.9%	232.7	234.6	1.9	0.8%

Table D-2 shows the average bias in the reference load predictions for SDG&E's CPP customers during event-like hours by size category. Depending on the specific group assessed, there is between -0.9% and 0.8% bias. Table D-2 also shows the percent of SDG&E's CPP population within each size category. Though there are far fewer customers in the Over 500 Average kW category, the reference loads of these customers are predicted accurately. The reference load predictions are most biased for the customers under 50 average kW, but at less than 1%, the bias for this segment is still minimal.

**Table D-2: Actual v. Predicted Average Load by Size Category for SDG&E CPP Customers
False Event Hours**

Size Bins	% Population	Actual kW	Predicted kW	Bias	% Bias
Under 50 Average kW	24.8%	41.4	41.0	-0.4	-0.9%
50 to 100 Average kW	20.3%	129.0	128.9	-0.2	-0.1%
100-200 Average kW	26.7%	218.9	218.6	-0.3	-0.1%
200-500 Average kW	21.3%	426.8	426.5	-0.3	-0.1%
Over 500 Average kW	6.9%	1213.3	1222.7	9.5	0.8%

D.2. False Event Coefficient Tests

Dividing the actual sum of kW for each hour by the sum of betas on the false event day variables gives us the percent by which the estimated coefficients impact actual kW. The default assumption is that false event day variables should have 0% impact on the dependent variable, otherwise there is evidence that the betas are correlated with the error term. Table D-3 shows the results from the false event coefficient tests. The percent bias is under 1% for all event-like hours.

Table D-3: Percent Bias from Aggregate False Event Coefficients

Hour	Sum of kWh	Sum of Betas	% Bias
12	1752581	8367.232	0.48%
13	1763283	6506.693	0.37%
14	1775194	15876.77	0.89%
15	1759962	13385.87	0.76%
16	1710845	8166.796	0.48%
17	1650428	3241.77	0.20%
18	1561135	4987.382	0.32%
Total	12000000	60532.51	0.50%

D.3. Control Group Analysis

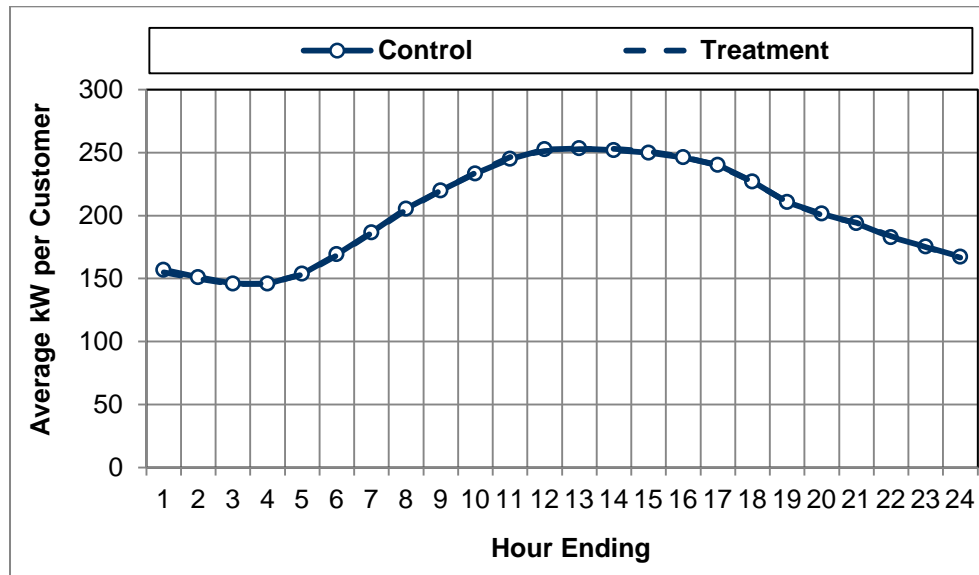
At SDG&E the control group results differ most from the individual customer regression results for the September 7 event. The PG&E analysis also showed the greatest difference between control group and individual customer regression results on this day. While an interesting coincidence, it is hard to draw conclusions concerning why the greatest difference between the two methods at each utility occurred on this day. Despite the limitations of both the control group analysis and the individual customer regression analysis at SDG&E due to lack of opt-out TOU customer data and few event days being called, the impacts line up reasonably well across the different methods, bolstering confidence in the results of both analyses.

**Table D-4: Estimated Ex Post Load Impacts by Event Day and Analysis Method
2011 SDG&E CPP Events**

Event Date	Number of Participants	% Load Impact - Regressions	Aggregate Load Impact - Regressions (MW)	% Load Impact - Control Group	Aggregate Load Impact - Control Group (MW)	Average Temperature During Event (°F)
8/27/2011	1,291	6.3%	16.9	5.4%	14.8	79.5
9/7/2011	1,293	5.2%	18.6	6.7%	25.0	86.3

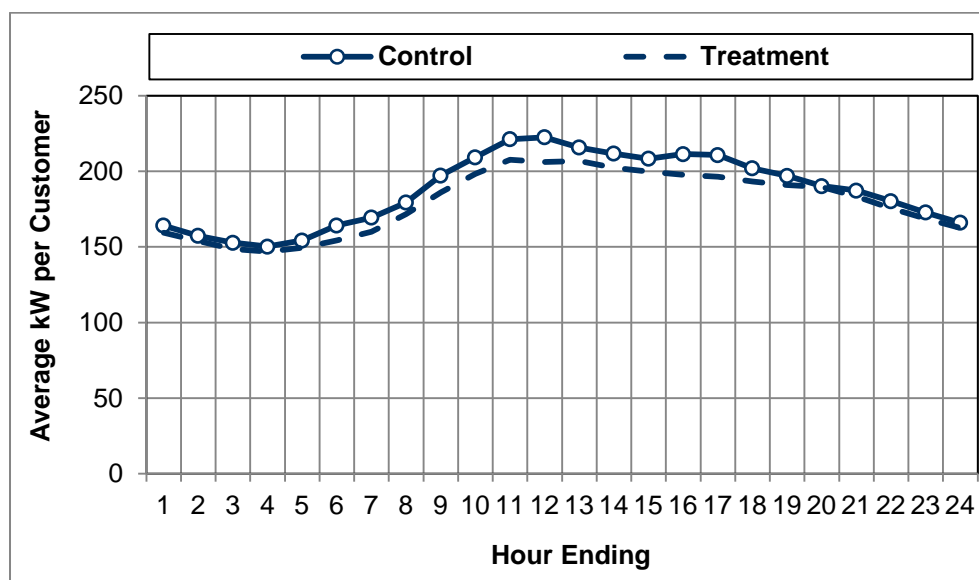
Figure D-2 shows the average control and treatment customer usage patterns on days similar to event days. The control group usage patterns were adjusted to account for systemic differences between opt-out TOU and CPP customers. Control and treatment loads under a variety of weather patterns were compared. The final control group loads are net of consistent biases observed between opt-out TOU and CPP customers on days with similar weather profiles. On average, there is a 0.0% difference between the adjusted control and treatment group loads during event-like hours. The maximum bias observed at any point for this average event-like day is 1.29%.

**Figure D-2: Average SDG&E CPP and Opt-out TOU Customer Usage
Control and Treatment Groups on Days Similar to Event Days**

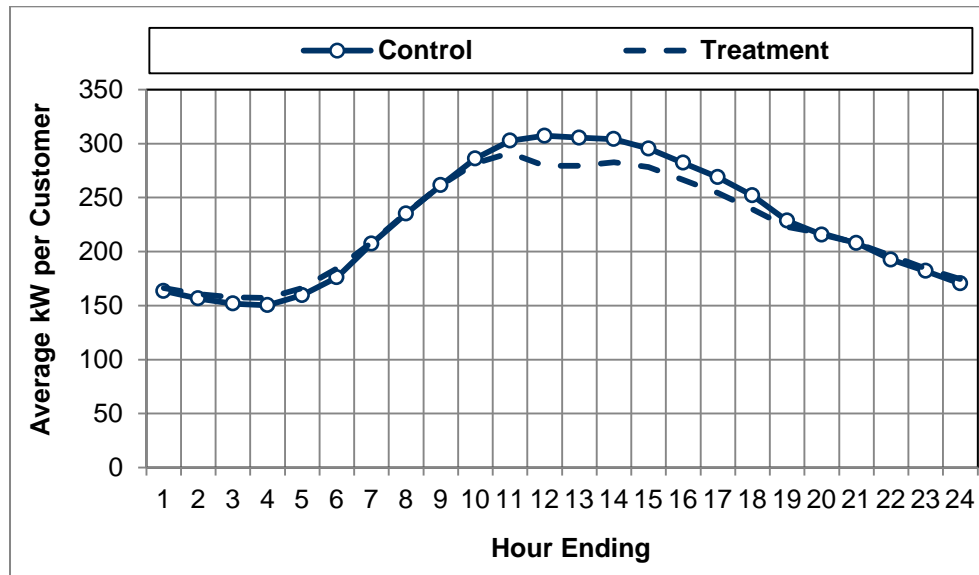


Figures D-3 through D-4 show the event day impacts across SDG&E's CPP population for each 2011 CPP event. During the event hours of 11 AM to 6 PM, the control group analysis shows an average event impact of 11.5 kW (5.4%) for the August 27 event and 19.4 kW (6.7%) for the September 7 event. The impacts from the control group analysis deviate from the individual customer regressions by about 1 percentage point for the first event and 1.5 percentage points for the second event. Given the uncertainty surrounding both methods for calculating event impacts, these differences should not be interpreted as problematic and confidence in the use of either method for reporting reliable impacts is increased.

**Figure D-3: Average SDG&E CPP and Opt-out TOU Customer Usage
August 27, 2011 Event**



**Figure D-4: Average SDG&E CPP and Opt-out TOU Customer Usage
September 7, 2011 Event**



D.4. Goodness-of-fit Measures

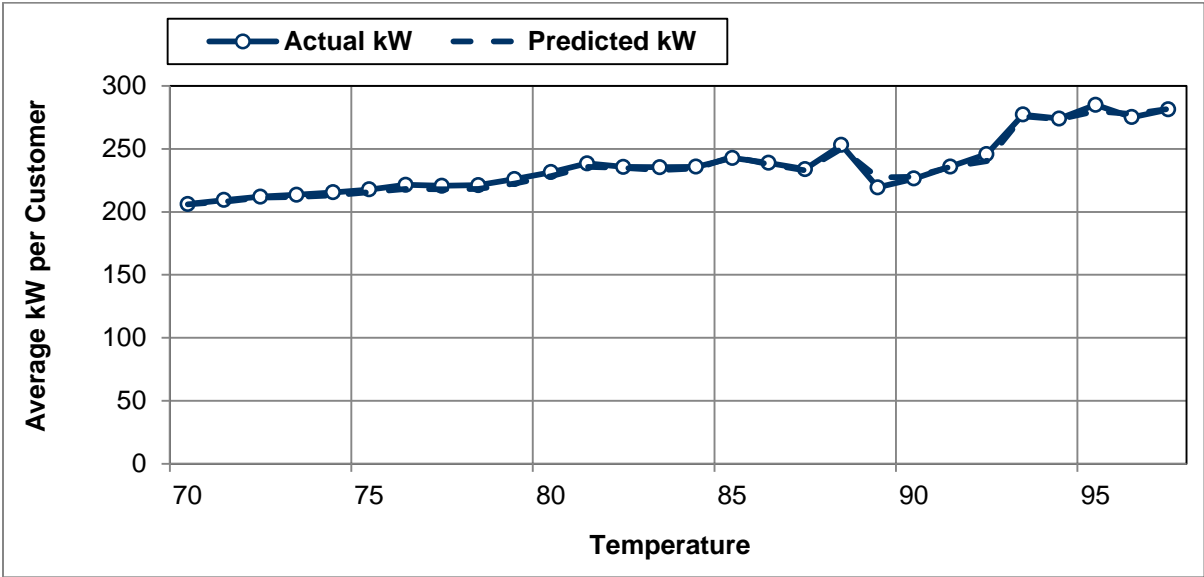
Table D-4 summarizes the amount of variation explained by the regression model for the average customer in specific segments. Depending on the specific group assessed, between 74% and 96% of the variation is explained. Customers in the Agriculture, Mining & Construction industry and the Wholesale, Transport & Other Utilities industry have the lowest R-squared values. In the other industries about 90% or more of the variation in hourly energy use is explained.

Table D-4: R-squared Values for the Average Customer by Segment

Customer Segment	R-squared
All Customers	0.93
Industry	
Agriculture, Mining & Construction	0.78
Manufacturing	0.91
Wholesale, Transport, other utilities	0.74
Retail stores	0.96
Offices, Hotels, Finance, Services	0.93
Schools	0.89
Institutional/Government	0.93
Other or Undefined	0.92

As seen in Figure D-5, the aggregate model also predicts well across various temperatures, with the average error from 70 to 97°F equal to -.5%. Between 90 and 94°F, where the SCE regressions had the most trouble, the average error is -0.5%.

Figure D-5: Actual v. Predicted Aggregate Load by Temperature for SDG&E CPP Customers

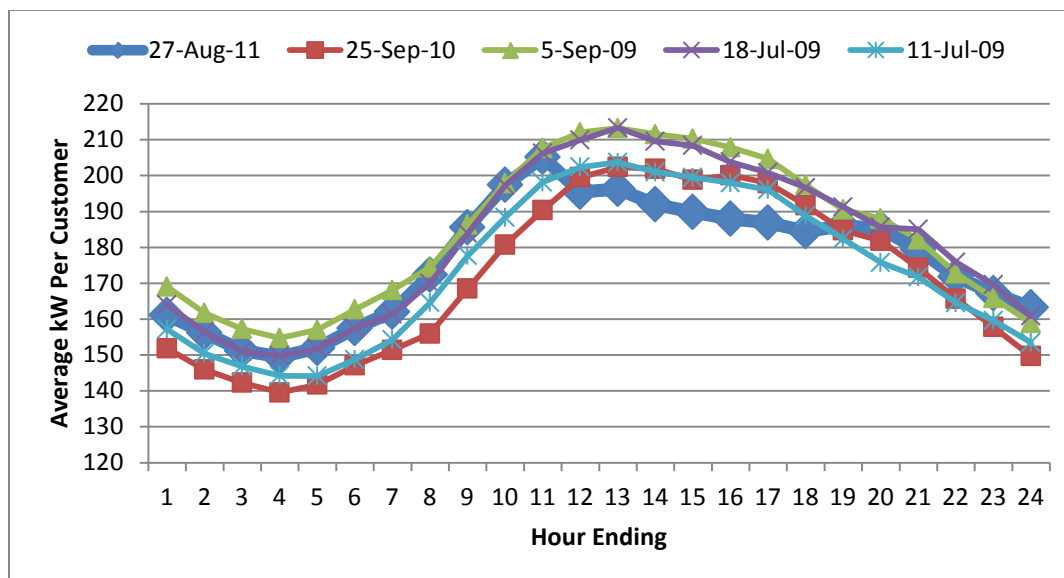


Appendix E. Limitations of Individual Customer Regressions

Individual customer regressions are less reliable when few events are called or when event day temperatures differ substantially from non-event days. This is because there is less information to inform the regression. When many events are called, the regression has plenty of event days from which to derive coefficients on the event day variables. In general, results for individual event days have wider uncertainty than results for the average of multiple events.

Figure E-1 shows average customer load across the SDG&E CPP population on August 27, the Saturday when SDG&E's first 2011 event was called. The figure also shows usage profiles on Saturdays with similar weather conditions. Table 3-1 shows the maximum daily temperature on the five days as well as CDD – CDD is calculated as the max of zero and mean temperature for the day less 65°F. Figure 3-2 shows the September 7, 2011 event next to four weekdays with similar weather profiles when no events were called. Table 3-2 shows the temperature characteristics of these days. The graphs and tables make clear that even on days with similar weather conditions, there can be variation in usage at the program level. Some of these differences can be captured with trend variables such as year, day type and month, but others are unobservable. The regression-derived counterfactual cannot adjust for the unobservable characteristics of unique event days and average event impacts have less certainty when too few events are called.

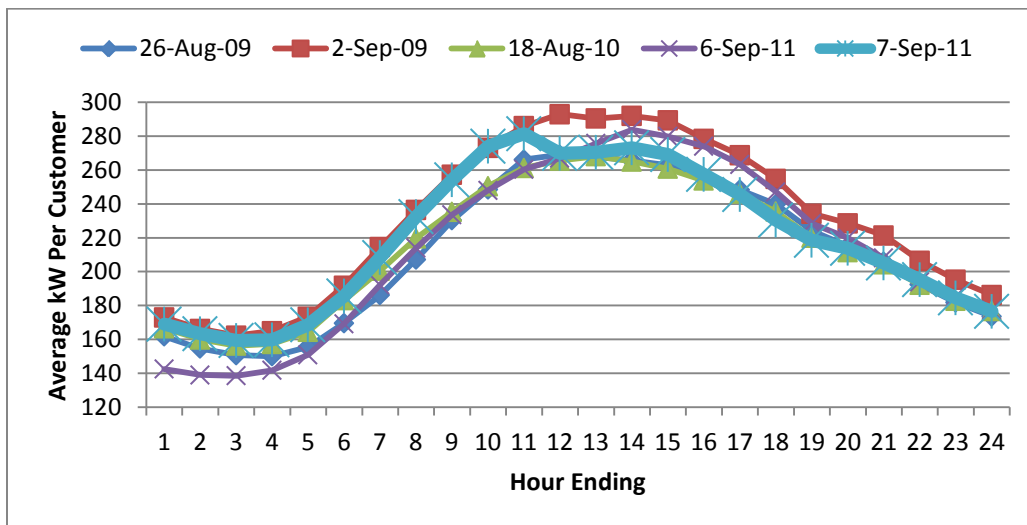
**Figure E-1: Average SDG&E CPP Customer Usage
August 27, 2011 Event and Similar Weather Days**



**Table E-1: Temperature Characteristics
August 27, 2011 Event and Similar Weather Days**

Date	CDD	Daily Max (°F)
11-Jul-09	6.87	81.01
18-Jul-09	7.47	83.87
5-Sep-09	8.45	82.86
25-Sep-10	8.51	84.70
27-Aug-11	9.38	83.48

**Figure E-2:
Average SDG&E CPP Customer Usage
September 7, 2011 Event and Similar Weather Days**



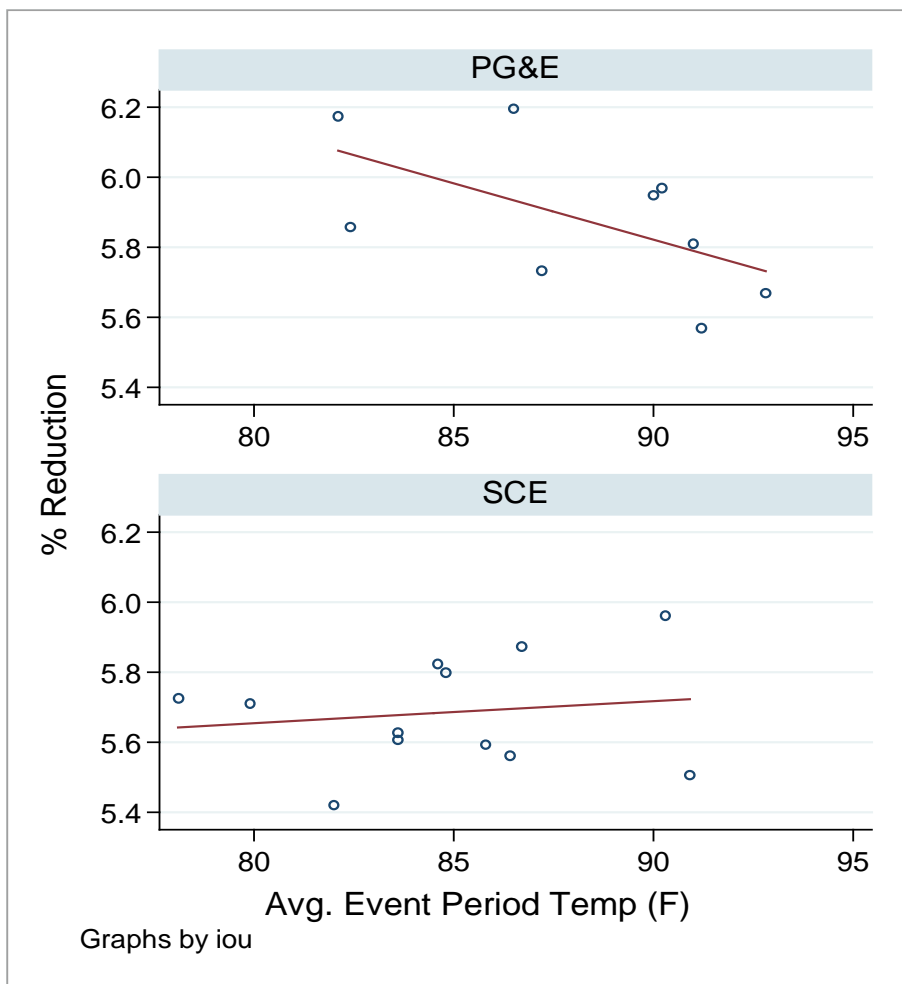
**Table E-2: Temperature Characteristics
September 7, 2011 Event and Similar Weather Days**

Date	CDD	Daily Max (°F)
26-Aug-09	12.06	87.67
2-Sep-09	12.33	87.95
18-Aug-10	11.48	87.43
6-Sep-11	13.33	93.09
7-Sep-11	13.86	88.80

Appendix F. Percent Impacts by Temperature

Figure F-1 is a scatter plot of percent impacts and associated temperatures for each 2011 CPP event at PG&E and SCE. SDG&E is omitted from this chart because there were only two events at SDG&E in 2011 and they occurred on very different types of days (a weekends and a weekday). The percent impacts at PG&E appear mildly negatively correlated with weather. Given that events occur on different day types and at different point in the summer, it is not likely that the approximately 6.2% impact on the coolest event day is different than the approximately 5.7% impact on the hottest event day due to differing customer response to temperature. Further, there is strong evidence that percent impacts vary at similar temperatures: two events occur at approximately 83°F and show impacts that differ by just under 0.4 percentage points; two events occur at approximately 87°F and show impacts that differ by about 0.5 percentage points; and four events occur at approximately 90 to 92°F and show impacts that differ by about 0.4 percentage points. The data for SCE exhibits a nearly flat trends line. The reader should be cautioned that with such a small number of data points the trends at both PG&E and SCE cannot be considered very informative and could change substantially given more data.

**Figure F-1: Percent Impacts and Temperature by Event 2011
CPP Events at PG&E and SCE**

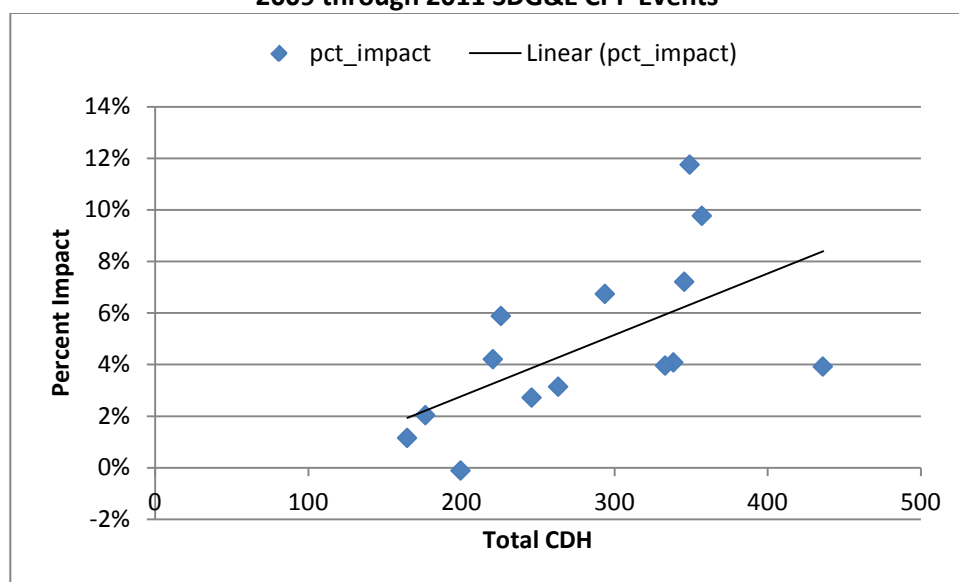


Appendix G. Estimating SDG&E Ex Ante Impacts with Limited Ex Post Temperature Variation

SDG&E has called 14 CPP events since 2009, 2 of which were on weekend days. As a result, it has fewer historical events during weekdays that either SCE or PG&E. With a limited number of events, it is difficult to identify factors that may explain variation in the demand reductions delivered. In addition, the estimates reflect both actual variation in the demand reductions and estimation error for individual events.

Figure G-1 shows the percent impacts from each of the 14 events called in SDG&E's territory between 2009 and 2011 along with the sum of cooling degree hours for each of those event days. Importantly, the percent impacts are not the percent impact reported in the 2009 through 2011 evaluations, but reflect the historical reductions of customers enrolled at the end of 2011 using the same model for each year, with separate variables for each event. The figure makes clear that there is a trend between temperature and percent impacts. However, the trend should be interpreted with caution. Given the number of events called, the trend is highly sensitive to outliers and individual day results.

Figure G-1:
Percent Impacts as a Function of Temperature
2009 through 2011 SDG&E CPP Events



In producing ex ante impact estimates for SDG&E, we did not extrapolate the trend outside of the range observed. The closest in-sample percent impacts (based on weather) were applied to out-of-sample ex ante conditions. This process produces a similar end result as capping weather variables. For most months and weather years, the weather variables are within the range of those observed ex post under all system conditions. However, the 1-in-2 conditions in May and June have weather variables that take on values considerably lower than those observed ex post and are, therefore, effectively capped to avoid extrapolating outside of the observed range of event day temperature conditions.

Appendix H. PG&E Large and Medium C&I Ex ante Load Impacts

Table H-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
	1 PM - 6 PM											
2012	-	-	-	-	27.5	30.2	30.3	29.8	28.5	26.8	-	-
2012	-	-	-	-	32.7	35.8	36.0	35.4	33.7	31.9	-	-
2013	-	-	-	-	38.1	41.9	42.2	41.4	39.3	37.1	-	-
2014	-	-	-	-	63.4	70.9	85.7	76.0	70.9	49.0	-	-
2015	-	-	-	-	79.7	94.4	118.6	101.5	94.2	60.1	-	-
2016	-	-	-	-	86.0	105.2	132.8	113.1	104.2	64.9	-	-
2017	-	-	-	-	84.6	102.8	129.6	110.5	102.0	63.8	-	-
2018	-	-	-	-	85.0	103.3	130.4	111.1	102.5	64.0	-	-
2019	-	-	-	-	85.4	103.8	131.1	111.7	103.0	64.2	-	-
2020	-	-	-	-	85.7	104.3	131.8	112.2	103.5	64.4	-	-
2021	-	-	-	-	86.1	104.8	132.5	112.8	104.0	64.6	-	-

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

Table H-2:
1-in-10 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
	1 PM - 6 PM											
2012	-	-	-	-	30.1	31.7	32.9	31.6	32.5	30.3	-	-
2013	-	-	-	-	35.7	37.6	38.9	37.3	38.5	36.0	-	-
2014	-	-	-	-	41.8	44.2	45.7	43.7	44.9	41.7	-	-
2015	-	-	-	-	78.5	89.0	97.8	95.8	81.1	67.5	-	-
2016	-	-	-	-	103.8	125.4	137.1	130.9	108.8	86.8	-	-
2017	-	-	-	-	115.8	142.7	155.6	147.1	122.2	95.4	-	-
2018	-	-	-	-	113.2	138.9	151.6	143.6	119.3	93.5	-	-
2019	-	-	-	-	113.8	139.7	152.5	144.5	119.9	93.9	-	-
2020	-	-	-	-	114.4	140.5	153.3	145.3	120.5	94.3	-	-
2021	-	-	-	-	115.0	141.2	154.2	146.1	121.1	94.7	-	-
2022	-	-	-	-	115.5	142.0	155.0	146.9	121.7	95.1	-	-

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	25.9	28.5	28.6	28.1	26.8	25.3	-	-
2013	-	-	-	-	31.1	34.1	34.2	33.7	32.1	30.5	-	-
2014	-	-	-	-	36.4	40.1	40.4	39.6	37.6	35.5	-	-
2015	-	-	-	-	61.7	69.1	83.9	74.2	69.1	47.4	-	-
2016	-	-	-	-	78.0	92.6	116.8	99.7	92.5	58.5	-	-
2017	-	-	-	-	84.2	103.4	130.9	111.3	102.5	63.4	-	-
2018	-	-	-	-	82.9	101.0	127.8	108.7	100.3	62.2	-	-
2019	-	-	-	-	83.3	101.5	128.5	109.3	100.8	62.4	-	-
2020	-	-	-	-	83.6	102.0	129.2	109.9	101.3	62.7	-	-
2021	-	-	-	-	84.0	102.5	129.9	110.4	101.8	62.9	-	-
2022	-	-	-	-	84.4	103.0	130.6	111.0	102.3	63.1	-	-

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	28.3	30.0	31.0	29.7	30.6	28.5	-	-
2013	-	-	-	-	34.0	35.8	36.9	35.4	36.6	34.2	-	-
2014	-	-	-	-	39.9	42.4	43.6	41.7	42.9	39.8	-	-
2015	-	-	-	-	76.7	87.1	95.7	93.8	79.1	65.7	-	-
2016	-	-	-	-	101.9	123.5	135.0	128.9	106.8	84.9	-	-
2017	-	-	-	-	114.0	140.8	153.5	145.1	120.3	93.5	-	-
2018	-	-	-	-	111.4	137.0	149.5	141.6	117.3	91.6	-	-
2019	-	-	-	-	112.0	137.8	150.4	142.5	117.9	92.0	-	-
2020	-	-	-	-	112.6	138.6	151.3	143.3	118.5	92.4	-	-
2021	-	-	-	-	113.1	139.4	152.1	144.1	119.1	92.9	-	-
2022	-	-	-	-	113.7	140.1	152.9	144.9	119.7	93.2	-	-

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

Appendix I. SCE Large and Medium C&I Ex ante Load Impacts

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	-	29.7	28.9	28.4	28.6	-	-	-
2013	-	-	-	-	-	30.3	29.5	29.0	29.2	-	-	-
2014	-	-	-	-	-	30.9	30.1	29.5	29.8	-	-	-
2015	-	-	-	-	-	31.2	30.4	29.7	30.0	-	-	-
2016	-	-	-	-	-	31.2	30.4	29.7	30.0	-	-	-
2017	-	-	-	-	-	31.2	30.4	29.7	30.0	-	-	-
2018	-	-	-	-	-	31.2	30.4	29.7	30.0	-	-	-
2019	-	-	-	-	-	31.2	30.4	29.7	30.0	-	-	-
2020	-	-	-	-	-	31.2	30.4	29.7	30.0	-	-	-
2021	-	-	-	-	-	31.2	30.4	29.7	30.0	-	-	-
2022	-	-	-	-	-	31.2	30.4	29.7	30.0	-	-	-

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	-	28.7	28.1	27.7	28.2	-	-	-
2013	-	-	-	-	-	29.3	28.7	28.2	28.8	-	-	-
2014	-	-	-	-	-	29.9	29.3	28.8	29.4	-	-	-
2015	-	-	-	-	-	30.2	29.5	29.0	29.5	-	-	-
2016	-	-	-	-	-	30.2	29.5	29.0	29.5	-	-	-
2017	-	-	-	-	-	30.2	29.5	29.0	29.5	-	-	-
2018	-	-	-	-	-	30.2	29.5	29.0	29.5	-	-	-
2019	-	-	-	-	-	30.2	29.5	29.0	29.5	-	-	-
2020	-	-	-	-	-	30.2	29.5	29.0	29.5	-	-	-
2021	-	-	-	-	-	30.2	29.5	29.0	29.5	-	-	-
2022	-	-	-	-	-	30.2	29.5	29.0	29.5	-	-	-

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	-	28.7	27.9	27.3	27.5	-	-	-
2013	-	-	-	-	-	29.3	28.5	27.9	28.1	-	-	-
2014	-	-	-	-	-	29.9	29.1	28.4	28.7	-	-	-
2015	-	-	-	-	-	30.2	29.3	28.6	28.8	-	-	-
2016	-	-	-	-	-	30.2	29.3	28.6	28.8	-	-	-
2017	-	-	-	-	-	30.2	29.3	28.6	28.8	-	-	-
2018	-	-	-	-	-	30.2	29.3	28.6	28.8	-	-	-
2019	-	-	-	-	-	30.2	29.3	28.6	28.8	-	-	-
2020	-	-	-	-	-	30.2	29.3	28.6	28.8	-	-	-
2021	-	-	-	-	-	30.2	29.3	28.6	28.8	-	-	-
2022	-	-	-	-	-	30.2	29.3	28.6	28.8	-	-	-

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	-	27.7	27.0	26.5	27.1	-	-	-
2013	-	-	-	-	-	28.3	27.6	27.1	27.7	-	-	-
2014	-	-	-	-	-	28.8	28.1	27.6	28.3	-	-	-
2015	-	-	-	-	-	29.1	28.4	27.8	28.4	-	-	-
2016	-	-	-	-	-	29.1	28.4	27.8	28.4	-	-	-
2017	-	-	-	-	-	29.1	28.4	27.8	28.4	-	-	-
2018	-	-	-	-	-	29.1	28.4	27.8	28.4	-	-	-
2019	-	-	-	-	-	29.1	28.4	27.8	28.4	-	-	-
2020	-	-	-	-	-	29.1	28.4	27.8	28.4	-	-	-
2021	-	-	-	-	-	29.1	28.4	27.8	28.4	-	-	-
2022	-	-	-	-	-	29.1	28.4	27.8	28.4	-	-	-

Appendix J. SDG&E Large and Medium C&I Ex ante Load Impacts

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	10	10	13	12	21	-	-	-
2013	-	-	-	-	11	11	14	12	22	-	-	-
2014	-	-	-	-	32	32	49	37	57	-	-	-
2015	-	-	-	-	25	25	39	29	46	-	-	-
2016	-	-	-	-	24	24	37	27	44	-	-	-
2017	-	-	-	-	24	24	37	28	45	-	-	-
2018	-	-	-	-	24	24	37	28	45	-	-	-
2019	-	-	-	-	25	25	38	28	46	-	-	-
2020	-	-	-	-	25	25	38	29	46	-	-	-
2021	-	-	-	-	25	25	39	29	47	-	-	-
2022	-	-	-	-	26	25	39	29	48	-	-	-

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	13	14	14	18	27	-	-	-
2013	-	-	-	-	14	14	14	19	28	-	-	-
2014	-	-	-	-	45	42	42	53	61	-	-	-
2015	-	-	-	-	35	33	34	42	51	-	-	-
2016	-	-	-	-	33	31	32	40	49	-	-	-
2017	-	-	-	-	34	32	32	41	49	-	-	-
2018	-	-	-	-	34	32	33	41	50	-	-	-
2019	-	-	-	-	35	33	33	42	50	-	-	-
2020	-	-	-	-	35	33	34	42	51	-	-	-
2021	-	-	-	-	35	33	34	43	52	-	-	-
2022	-	-	-	-	36	34	34	43	52	-	-	-

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

	Month and Resource Adequacy Window
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	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	10	10	13	11	21	-	-	-
2013	-	-	-	-	10	10	14	12	21	-	-	-
2014	-	-	-	-	32	31	49	37	57	-	-	-
2015	-	-	-	-	25	25	39	28	46	-	-	-
2016	-	-	-	-	23	23	36	27	44	-	-	-
2017	-	-	-	-	24	24	37	27	44	-	-	-
2018	-	-	-	-	24	24	37	27	45	-	-	-
2019	-	-	-	-	24	24	37	28	45	-	-	-
2020	-	-	-	-	25	24	38	28	46	-	-	-
2021	-	-	-	-	25	25	38	28	46	-	-	-
2022	-	-	-	-	25	25	39	29	47	-	-	-

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

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 PM - 6 PM											
2012	-	-	-	-	13	13	13	17	26	-	-	-
2013	-	-	-	-	13	14	14	18	28	-	-	-
2014	-	-	-	-	44	41	42	52	60	-	-	-
2015	-	-	-	-	35	33	33	42	50	-	-	-
2016	-	-	-	-	33	31	31	40	48	-	-	-
2017	-	-	-	-	33	31	32	40	48	-	-	-
2018	-	-	-	-	34	32	32	41	49	-	-	-
2019	-	-	-	-	34	32	33	41	50	-	-	-
2020	-	-	-	-	34	32	33	42	50	-	-	-
2021	-	-	-	-	35	33	33	42	51	-	-	-
2022	-	-	-	-	35	33	34	43	52	-	-	-

Appendix K. PG&E Program Specific Ex Ante Impacts for Annual Peak Days

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

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 1-6 pm)	(MW 1-6 pm)	(MW 1-6 pm)	(1-6 pm)	(°F)
1-in-10 August System Peak Day	2012	1,453	470	440	31	6.5%	94.9
	2013	1,727	560	524	37	6.5%	95.0
	2014	1,918	634	591	43	6.8%	94.7
	2015	1,929	637	593	43	6.8%	94.7
	2016	1,926	635	592	43	6.8%	94.7
	2017	1,924	634	591	43	6.8%	94.7
	2018	1,922	633	590	43	6.8%	94.7
	2019	1,920	632	589	43	6.8%	94.7
	2020	1,919	632	589	43	6.8%	94.7
	2021	1,918	631	588	43	6.8%	94.7
	2022	1,918	631	588	43	6.8%	94.8
1-in-2 August System Peak Day	2012	1,453	468	438	29	6.3%	94.1
	2013	1,727	557	522	35	6.3%	94.2
	2014	1,918	630	589	41	6.5%	93.6
	2015	1,929	633	592	41	6.5%	93.6
	2016	1,926	631	590	41	6.5%	93.6
	2017	1,924	630	589	41	6.5%	93.6
	2018	1,922	629	588	41	6.5%	93.6
	2019	1,920	628	587	41	6.5%	93.6
	2020	1,919	628	587	41	6.5%	93.6
	2021	1,918	627	586	41	6.5%	93.6
	2022	1,918	627	586	41	6.5%	93.6

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

Table K-2:
Program Annual Peak Day Load Impacts for Medium PG&E CPP Customers
(Hourly Average Reduction in MW Over Event Day Period - 1 PM to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 1-6 pm)	(MW 1-6 pm)	(MW 1-6 pm)	(1-6 pm)	(°F)
1-in-10 August System Peak Day	2012	198	7	7	1	10.6%	94.3
	2013	200	8	7	1	10.3%	94.5
	2014	200	8	7	1	10.6%	94.6
	2015	12295	465	413	53	11.3%	94.6
	2016	24941	982	894	88	8.9%	94.6
	2017	30630	1221	1117	104	8.5%	94.6
	2018	29339	1167	1067	101	8.6%	94.6
	2019	29589	1177	1076	101	8.6%	94.6
	2020	29836	1187	1085	102	8.6%	94.6
	2021	30078	1197	1094	103	8.6%	94.6
	2022	30309	1206	1102	104	8.6%	94.6
1-in-2 August System Peak Day	2012	198	7	6	1	7.4%	93.5
	2013	200	7	7	1	7.2%	93.6
	2014	200	7	7	1	7.4%	93.6
	2015	12295	442	407	35	7.9%	93.6
	2016	24941	937	876	61	6.5%	93.6
	2017	30630	1168	1096	72	6.2%	93.6
	2018	29339	1116	1046	70	6.2%	93.6
	2019	29589	1125	1055	70	6.2%	93.6
	2020	29836	1135	1064	71	6.2%	93.6
	2021	30078	1144	1072	71	6.2%	93.6
	2022	30309	1152	1081	72	6.2%	93.6

*The forecasts for 2012 and 2013 reflect the historic 2 PM to 6 PM event window

Appendix L. SCE Program Specific Ex Ante Impacts for Annual Peak Days

Table L-1:
Program Annual Peak Day Load Impacts for Large SCE CPP Customers
(Hourly Average Reduction in MW Over Event Day Period - 1 PM to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 1-6 pm)	(MW 1-6 pm)	(MW 1-6 pm)	(1-6 pm)	(°F)
1-in-10 August System Peak Day	2012	3,294	216	207	8	3.9%	96.0
	2013	3,361	216	207	8	3.9%	96.0
	2014	3,429	216	207	8	3.9%	96.0
	2015	3,452	216	207	8	3.9%	96.0
	2016	3,452	216	207	8	3.9%	96.0
	2017	3,452	216	207	8	3.9%	96.0
	2018	3,452	216	207	8	3.9%	96.0
	2019	3,452	216	207	8	3.9%	96.0
	2020	3,452	216	207	8	3.9%	96.0
	2021	3,452	216	207	8	3.9%	96.0
	2022	3,452	216	207	8	3.9%	96.0
1-in-2 August System Peak Day	2012	3,294	211	202	9	4.1%	93.5
	2013	3,361	211	202	9	4.1%	93.5
	2014	3,429	211	202	9	4.1%	93.5
	2015	3,452	211	202	9	4.1%	93.5
	2016	3,452	211	202	9	4.1%	93.5
	2017	3,452	211	202	9	4.1%	93.5
	2018	3,452	211	202	9	4.1%	93.5
	2019	3,452	211	202	9	4.1%	93.5
	2020	3,452	211	202	9	4.1%	93.5
	2021	3,452	211	202	9	4.1%	93.5
	2022	3,452	211	202	9	4.1%	93.5

Appendix M. SDG&E Program Specific Ex Ante Impacts for Annual Peak Days

Table M-1:
Program Annual Peak Day Load Impacts for Large SDG&E CPP Customers
(Hourly Average Reduction in MW Over Historic Event Day Period – 11 AM to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 11 am-6 pm)	(MW 11 am-6 pm)	(MW 11 am-6 pm)	(11 am-6 pm)	(°F)
1-in-10 August System Peak Day	2012	1,165	397	379	18	4.5%	84.3
	2013	1,181	405	386	19	4.6%	84.3
	2014	1,197	413	393	20	4.7%	84.2
	2015	1,213	419	399	20	4.8%	84.2
	2016	1,230	425	404	20	4.8%	84.2
	2017	1,247	430	410	21	4.8%	84.2
	2018	1,264	436	415	21	4.8%	84.2
	2019	1,282	442	421	21	4.7%	84.2
	2020	1,300	448	427	21	4.7%	84.2
	2021	1,318	454	432	21	4.7%	84.2
	2022	1,336	460	438	22	4.7%	84.2
1-in-2 August System Peak Day	2012	1,165	384	372	12	3.1%	81.8
	2013	1,181	391	379	13	3.2%	81.8
	2014	1,197	399	386	13	3.3%	81.8
	2015	1,213	405	391	14	3.3%	81.8
	2016	1,230	410	397	14	3.3%	81.8
	2017	1,247	416	402	14	3.3%	81.8
	2018	1,264	421	407	14	3.3%	81.8
	2019	1,282	427	413	14	3.3%	81.8
	2020	1,300	433	419	14	3.3%	81.8
	2021	1,318	439	424	14	3.3%	81.8
	2022	1,336	444	430	15	3.3%	81.8

**Table M-2:
Program Annual Peak Day Load Impacts for Medium SDG&E CPP Customers
(Hourly Average Reduction in MW Over Historic Event Day Period – 11 AM to 6 PM)**

Weather Year	Year	Enrolled Accts (Forecast)	Avg. Reference Load	Avg. Estimated Load w DR	Avg. Load impact	% Load Reduction	Weighted Temp
			(MW 11 am-6 pm)	(MW 11 am-6 pm)	(MW 11 am-6 pm)	(11 am-6 pm)	(°F)
1-in-10 August System Peak Day	2012	-	-	-	-	-	-
	2013	-	-	-	-	-	-
	2014	9513	353	322	32	8.9%	94.6
	2015	7096	265	244	21	8.0%	94.6
	2016	6317	235	217	19	8.0%	94.6
	2017	6403	239	219	19	8.0%	94.6
	2018	6493	242	223	19	8.0%	94.6
	2019	6581	245	226	20	8.0%	94.6
	2020	6674	249	229	20	8.0%	94.6
	2021	6765	252	232	20	8.0%	94.6
	2022	6856	255	235	20	8.0%	94.6
1-in-2 August System Peak Day	2012	-	-	-	-	-	-
	2013	-	-	-	-	-	-
	2014	9513	336	313	23	6.9%	93.6
	2015	7096	252	238	14	5.7%	93.6
	2016	6317	224	211	13	5.7%	93.6
	2017	6403	227	214	13	5.7%	93.6
	2018	6493	230	217	13	5.7%	93.6
	2019	6581	233	220	13	5.7%	93.6
	2020	6674	237	223	14	5.7%	93.6
	2021	6765	240	226	14	5.7%	93.6
	2022	6856	243	229	14	5.7%	93.6