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## 2011 California Statewide Non-residential Critical Peak Pricing Evaluation

### Ex Post Report

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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).<sup>1</sup> This report does not contain ex ante load impact estimates for the CPP program. Ex ante impact estimates will be developed following the Commission's final decision regarding the 2012-2014 DR Program applications.

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.<sup>2</sup> 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.<sup>3</sup> In addition, SDG&E had defaulted roughly 600 medium C&I customers<sup>4</sup> 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.

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<sup>1</sup> 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.

<sup>2</sup> 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.

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

<sup>4</sup> 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 SDG&E 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 reduction<sup>5</sup> 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 reduction on August 27, the weekend, and 18.6 MW (5.2%) of load reduction on September 7, the weekday.

<sup>5</sup> The “average event load reduction” is the arithmetic average of all of the individual load reductions for the year.

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)
<b>PG&amp;E</b>	2010	9	1,650	592.0	23.0	3.9%	90.2
	2011	9	1,750	473.4	27.8	5.9%	88.1
<b>SCE</b>	2010	12	4,100	1077.2	30.7	2.9%	84.7
	2011	12	3,000	615.4	35.0	5.7%	84.7
<b>SDG&amp;E</b>	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

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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 Report Organization

The remainder of this document is separated into six 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 load impacts. PG&E's ex post results are presented in Section 4, SCE's in Section 5 and SDG&E's in Section 6. 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.

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## 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.



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- 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&E<sup>6</sup>**

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.<sup>7</sup> 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 periods. Above the set level, a customer will pay the normal CPP price during an event. Customers

<sup>6</sup> 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.

<sup>7</sup> 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.

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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.

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### 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.<sup>8</sup> 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

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<sup>8</sup> 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.<sup>9</sup> 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:

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

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

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,

$$kW_{dt} = a + \sum_{i=2009}^{2011} b_i * year_{dti} + \sum_{j=2}^5 c_j * daytype_{dtj} + d * season_{dt} + e * cooling_{dt} + f * heating_{dt} + g * otherdrdt + h * actcppdt + l=13 i * eventdaydt + edt, t=\{1, 2, 3 \dots 24\} \quad (1)$$

$$kW_{dt} = a + \sum_{i=2009}^{2011} b_i * year_{dti} + \sum_{j=2}^5 c_j * daytype_{dtj} + \sum_{k=2}^{12} d_k * month_{dtk} + e * cooling_{dt} + f * heating_{dt} + g * otherdrdt + h * actcppdt + l=13 i * eventdaydt + edt, t=\{1, 2, 3 \dots 24\} \quad (2)$$

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

<sup>9</sup> 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 <sub>1 ...n</sub>	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 “eventdaynum<sub>1</sub>,” through “eventdaynum<sub>3</sub>,” 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

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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.<sup>10</sup> 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.<sup>11</sup>

## 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;

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<sup>10</sup> 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.

<sup>11</sup> 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.

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- 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.<sup>12</sup>

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.

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<sup>12</sup> 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,<sup>13</sup> 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%
4PM 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,

<sup>13</sup> 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 <sup>[1]</sup>	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 <sup>14</sup>	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

<sup>14</sup> 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.

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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 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.<sup>15</sup>

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<sup>15</sup> 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.

## 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

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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.

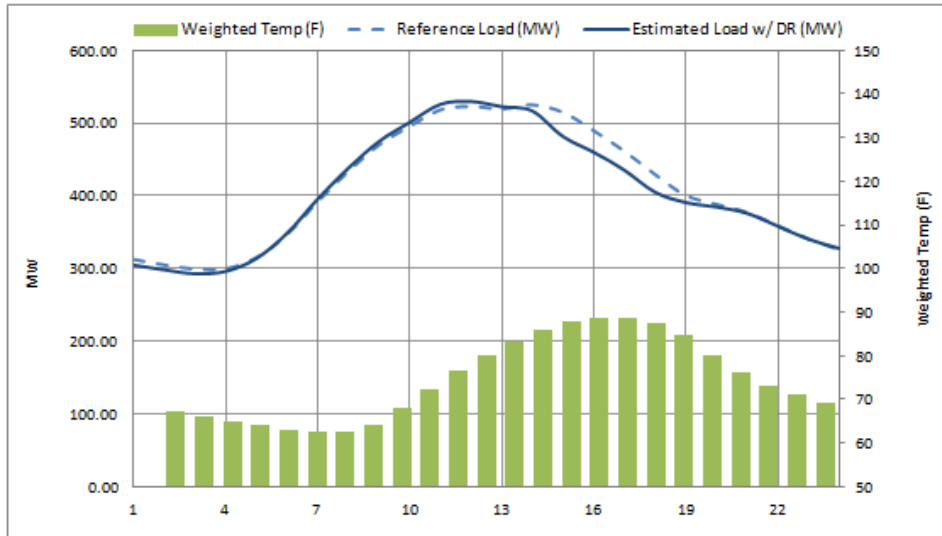
**Figure 4-1: Estimated Hourly Impacts for the Average Event Day  
2011 PG&E CPP Events**

**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
	<b>Reference Energy Use (MWh)</b>	<b>Estimated Energy Use w/ DR (MWh)</b>	<b>Total Load Impact (MWh)</b>	<b>% Daily Load Change</b>	<b>Cooling Degree Hours (Base 65)</b>
<b>Daily</b>	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.

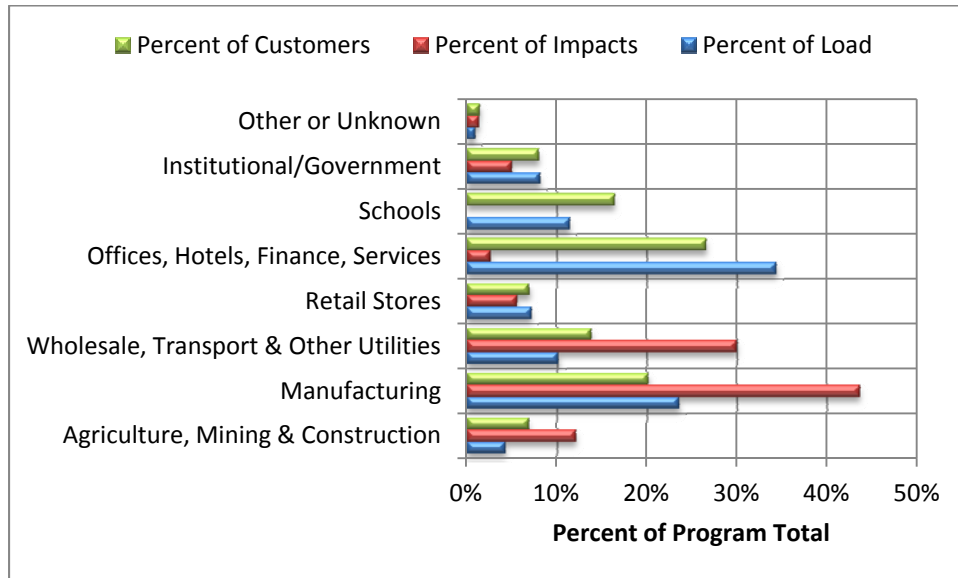
Load impacts for Schools were negligible, even though schools comprised roughly 16% of the number of participating accounts. The variation in school occupancy and resulting loads across the summer period make it very difficult to estimate load impacts for this segment. It may be that some schools provided 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

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## 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 10<sup>th</sup> through 90<sup>th</sup> 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 10<sup>th</sup> to 90<sup>th</sup> percentiles. At 34.2%, the average realization rate calculated at the 50<sup>th</sup> 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

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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.<sup>16</sup> 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

<sup>16</sup> See Appendix F for an illustration of the relationship between temperature and load impacts.



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## 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.

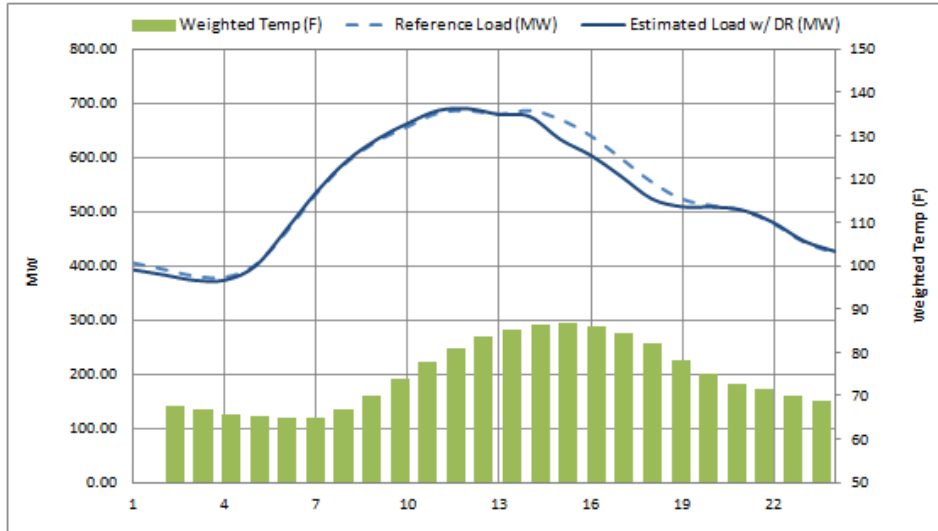
**Figure 5-1: Estimated Hourly Impacts for the Average Event Day  
2011 SCE CPP Events**

**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
	<b>Reference Energy Use (MWh)</b>	<b>Estimated Energy Use w/ DR (MWh)</b>	<b>Total Load Impact (MWh)</b>	<b>% Daily Load Change</b>	<b>Cooling Degree Hours (Base 65)</b>
<b>Daily</b>	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.

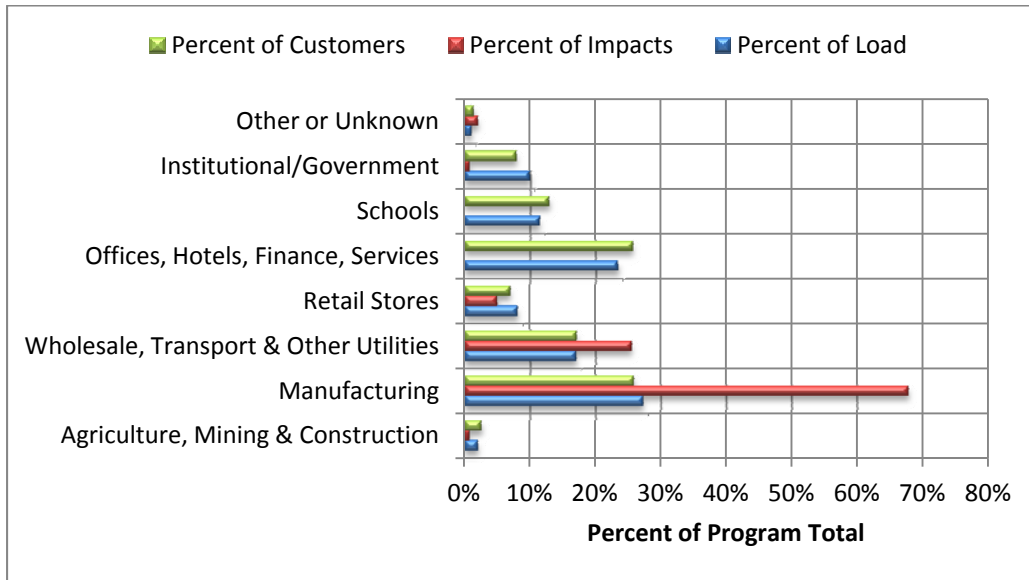
As with PG&E's CPP tariff, Schools accounted for a relatively large percent of program participants, 13%, but did not produce statistically significant load reductions. Several other business segments also accounted for a large share of enrollment but a small share of the load impacts. The Offices, Hotels, 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
Previously on Voluntary CPP	325	261	200	61	23%	20	85
Not Dually Enrolled	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.

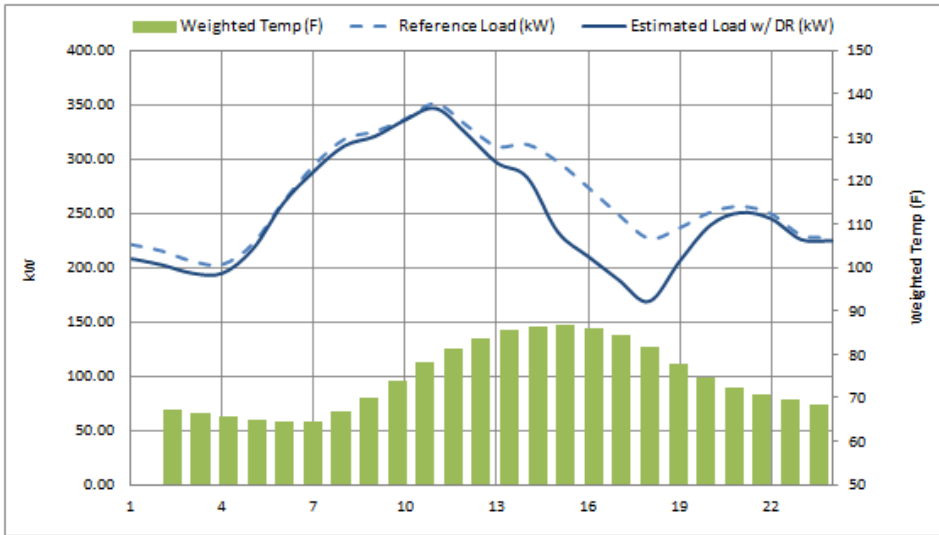
**Figure 5-3: 2011 Hourly Ex Post Load Impacts for Average Customer Previously Enrolled in Voluntary CPP on the Average Event Day**

**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	226.6	224.9	1.9	0.8%	68.4
	<b>Reference Energy Use (kWh)</b>	<b>Estimated Energy Use w/ DR (kWh)</b>	<b>Total Load Impact (kWh)</b>	<b>% Daily Load Change</b>	<b>Cooling Degree Hours (Base 65)</b>
<b>Daily</b>	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 10<sup>th</sup> to 90<sup>th</sup> 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.<sup>17</sup> 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

<sup>17</sup> 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 customer. 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.

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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

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

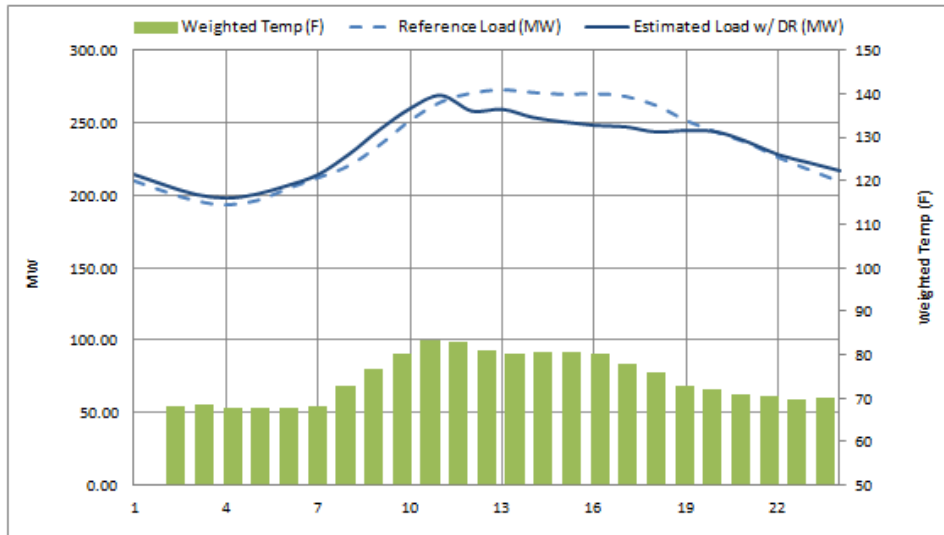
**Figure 6-1: Estimated Hourly Impacts  
SDG&E's August 27, 2011 Event**

**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
	<b>Reference Energy Use (MWh)</b>	<b>Estimated Energy Use w/ DR (MWh)</b>	<b>Total Load Impact (MWh)</b>	<b>% Daily Load Change</b>	<b>Cooling Degree Hours (Base 65)</b>
<b>Daily</b>	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.

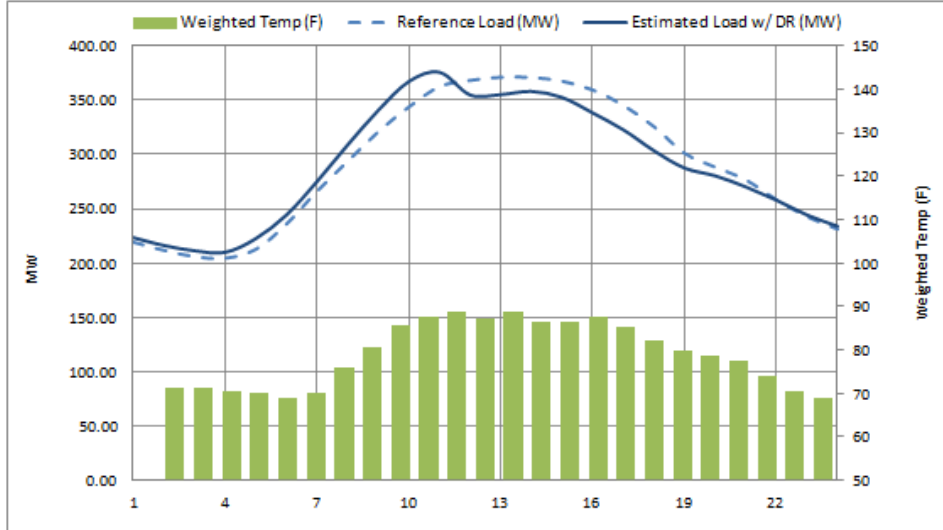
**Figure 6-2: Estimated Hourly Impacts  
SDG&E's September 7, 2011 Event**

**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
	<b>Reference Energy Use (MWh)</b>	<b>Estimated Energy Use w/ DR (MWh)</b>	<b>Total Load Impact (MWh)</b>	<b>% Daily Load Change</b>	<b>Cooling Degree Hours (Base 65)</b>
<b>Daily</b>	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.

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## 6.2 Load Impacts by Industry

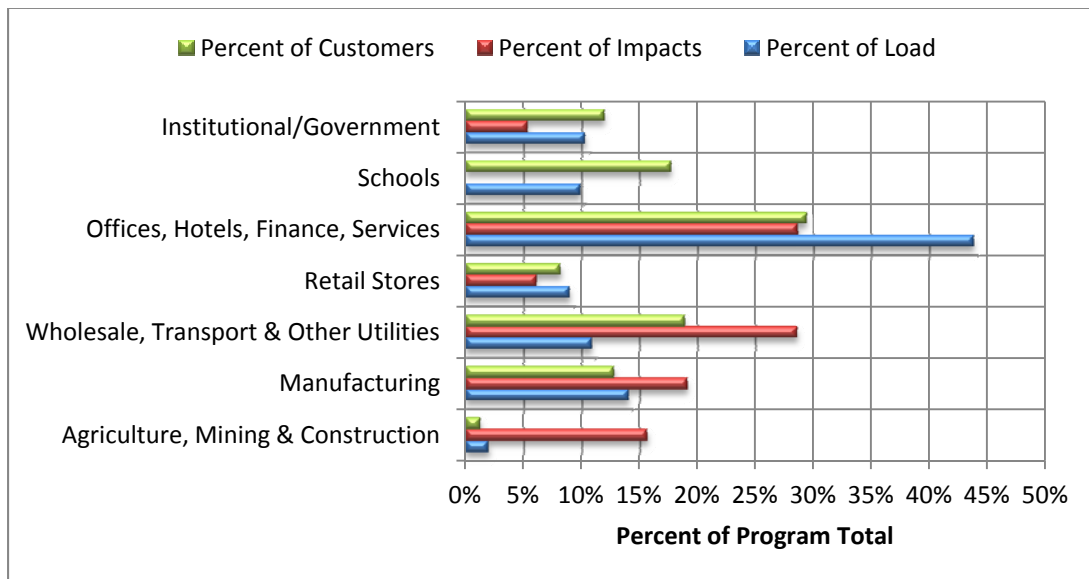
Table 6-2 shows the estimated ex post load impacts by industry. The distribution of impacts across industry segments is not as highly concentrated as is for PG&E and SCE. There are four industry segments that provided large aggregate load impacts. The 16 customers in the Agricultural, Mining & Construction 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

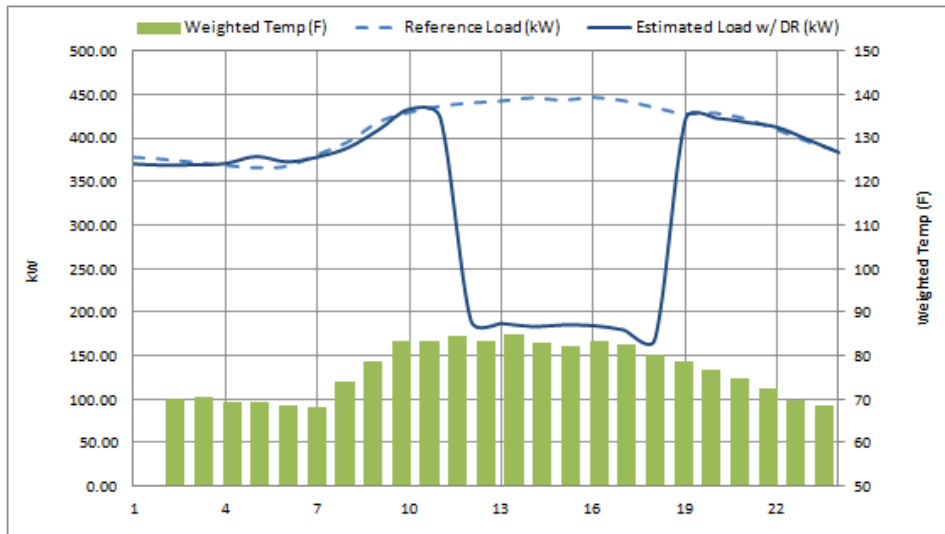
**Figure 6-4:  
2011 Hourly Ex Post Aggregate Load Impacts for BIP Customers Dually-enrolled in CPP  
September 7, 2011 Weekday Event**

**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
	<b>Reference Energy Use (kWh)</b>	<b>Estimated Energy Use w/ DR (kWh)</b>	<b>Total Load Impact (kWh)</b>	<b>% Daily Load Change</b>	<b>Cooling Degree Hours (Base 65)</b>
<b>Daily</b>	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

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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.

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## 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.<sup>18</sup> 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.

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<sup>18</sup> 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.

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### A.3. Control Group Analysis

To crosscheck results, FSC selected a matched control group of customers to use in a corroborating analysis.<sup>19</sup> 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).<sup>20</sup> 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,

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<sup>19</sup> 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.

<sup>20</sup> 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.<sup>21</sup> 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:

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

<sup>21</sup> 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**

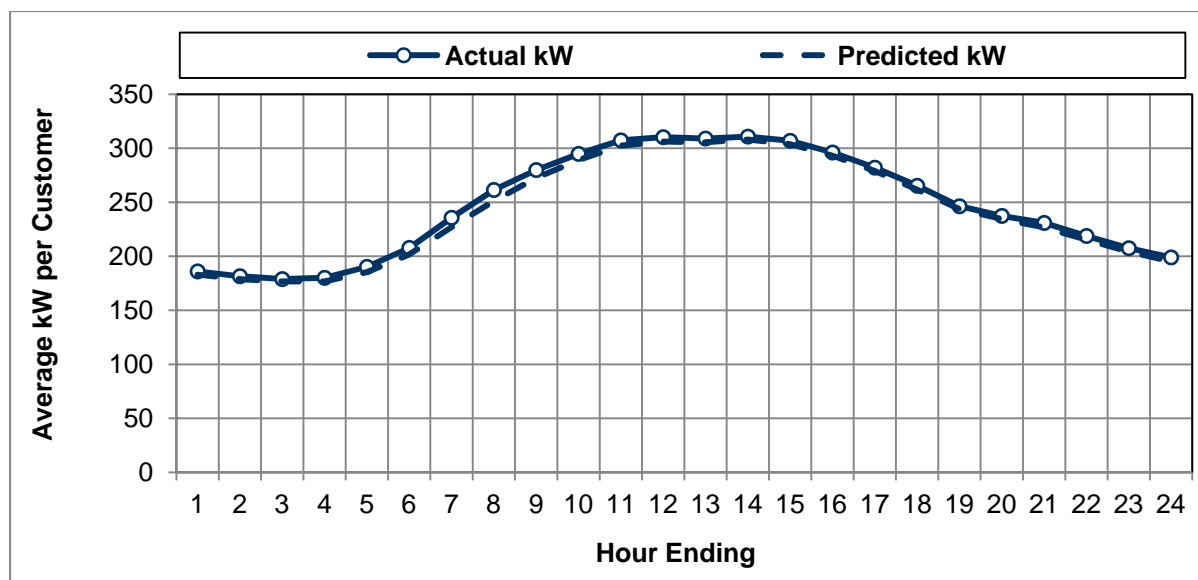


Table B-1 shows the average bias in the reference load predictions during event-like hours by industry. Depending on the specific group assessed, there is bias between -2.1% and 0.9%. Table B-1 also shows the percent of PG&E's CPP population within each industry segment. Customers in the Institutional/Government 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.<sup>22</sup> 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.

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<sup>22</sup> 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**

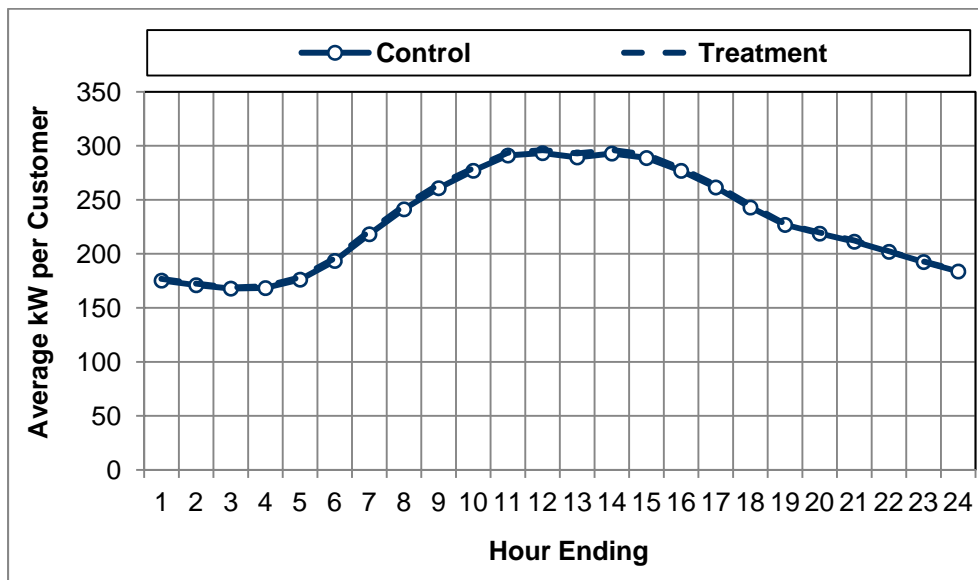
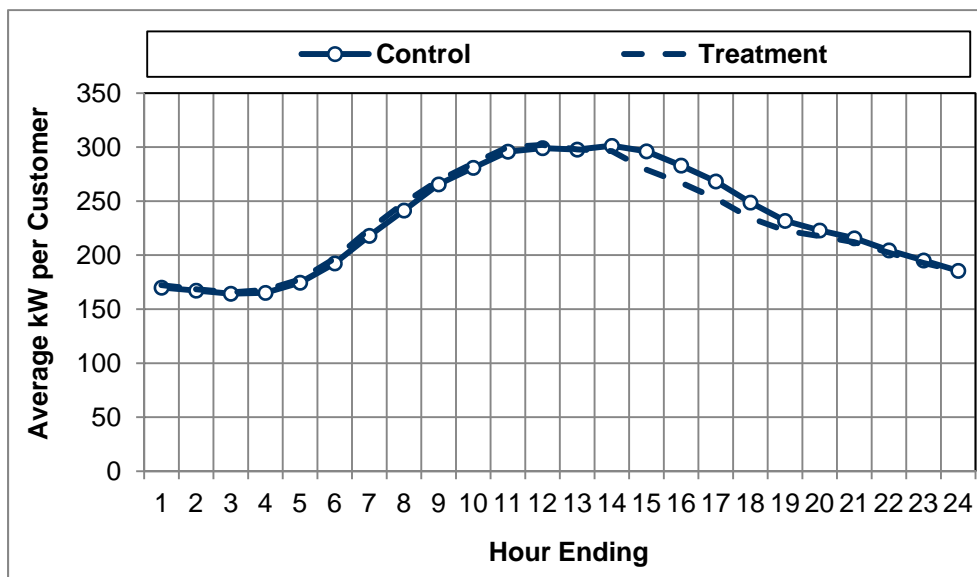


Figure B-3 shows the event day impact across PG&E's CPP population for the average 2011 CPP event. During the event hours of 2 PM to 6 PM, the control group analysis shows an average event impact of 15.8 kW (5.8%) for the average 2011 PG&E CPP event. The impacts from the control group analysis are very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

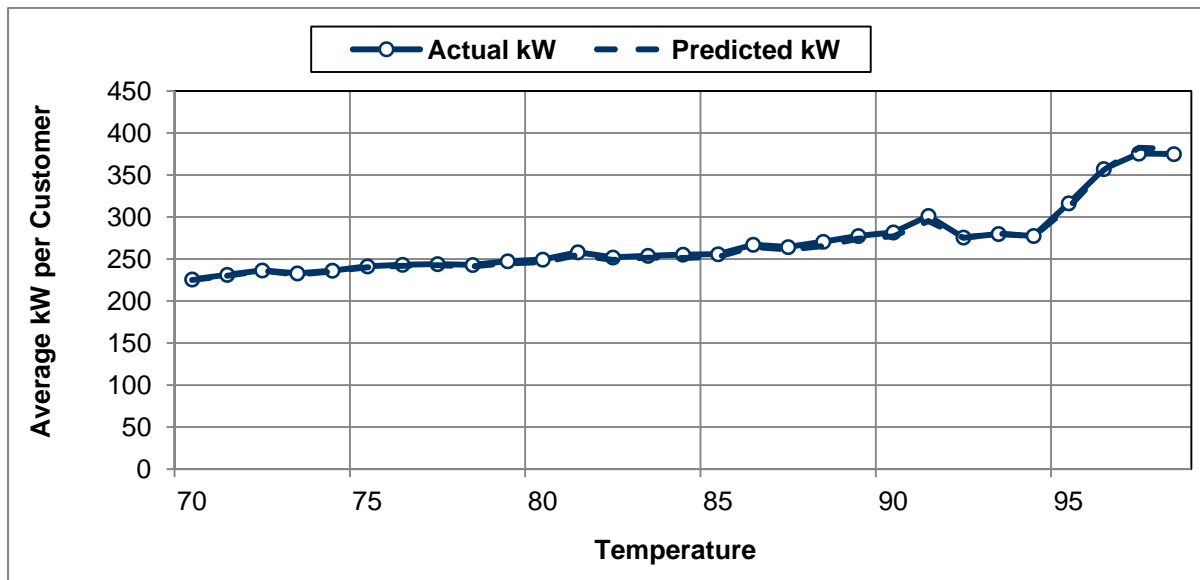
**Table B-4: R-squared Values for the Average Customer by Segment**

Customer Segment	R-squared
All Customers	0.96
<b>Industry</b>	
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
<b>Local Capacity Area</b>	
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**

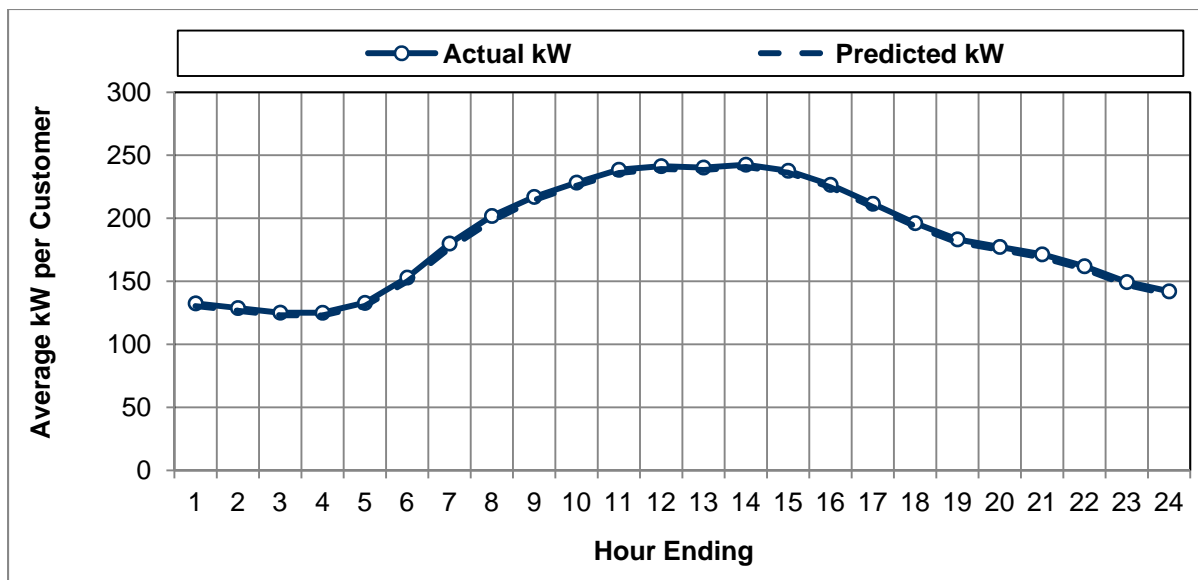


Table C-1 shows the average bias in the reference load predictions during event-like hours by industry. Depending on the specific group assessed, there is between -3.8% and 0.7% bias. Table C-1 also shows the percent of SCE's CPP population within each industry segment. Customers in the Other or Unknown 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.<sup>23</sup> 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.

<sup>23</sup> 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**

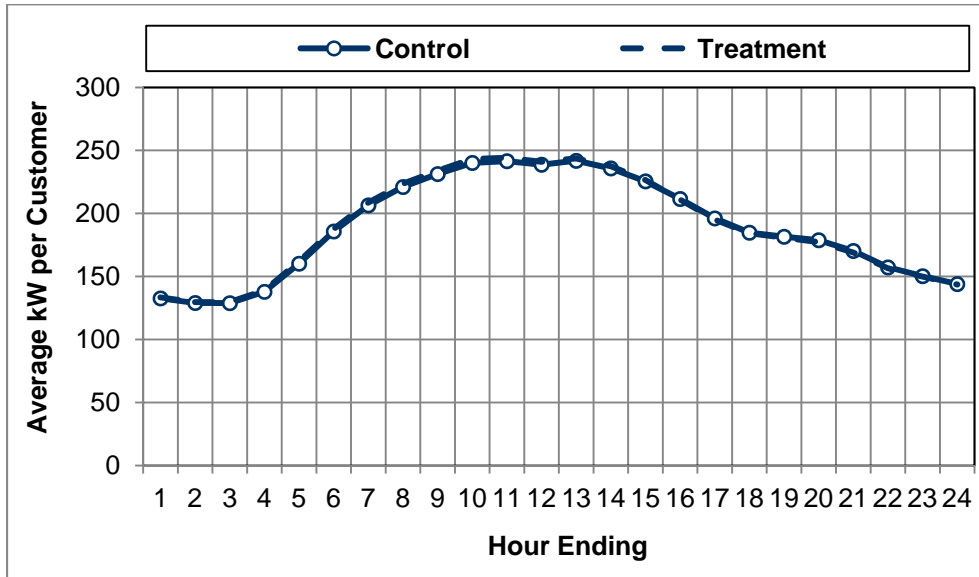
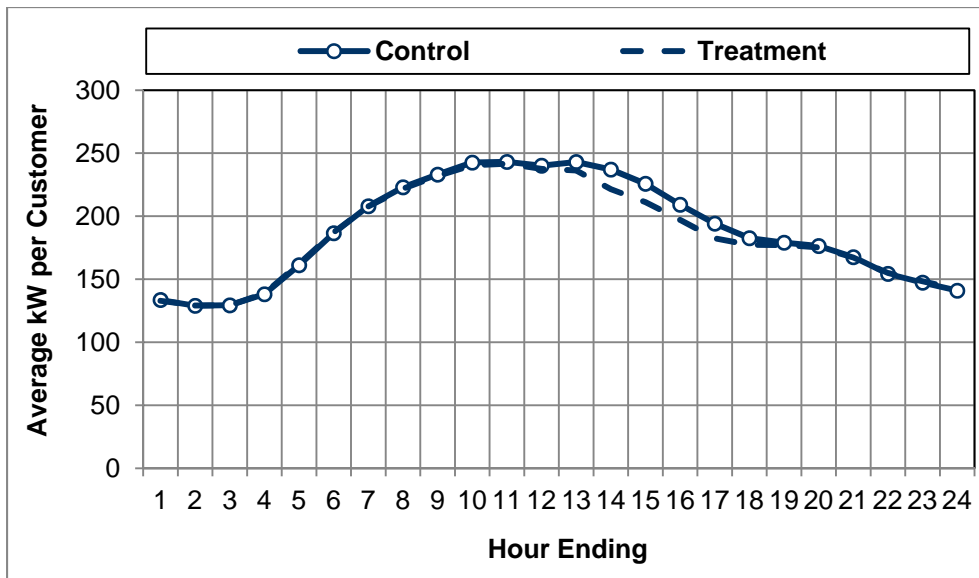


Figure C-3 shows the event day impact across SCE’s CPP population for the average 2011 CPP event. During the event hours of 2 PM to 6 PM, the control group analysis shows an average event impact of 10.9 kW (5.4%) for the average 2011 SCE CPP event. The impacts from the control group analysis are very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

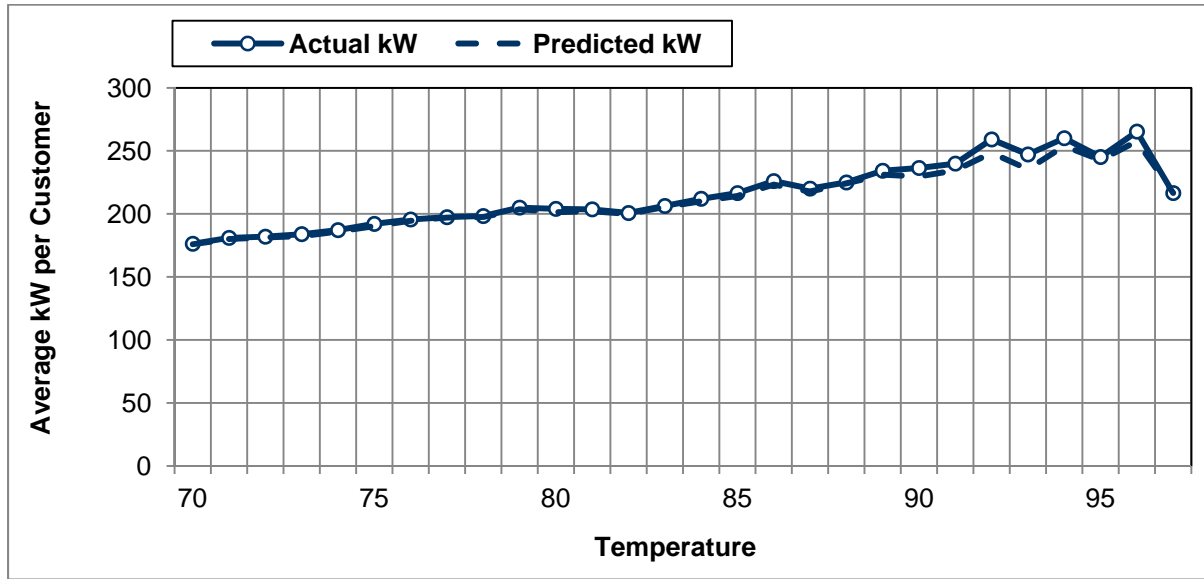
use. The explained variation varied from 48% to 98% across industries and local capacity areas. Apart from Wholesale, Transport & Other Utilities, only one of the industry or local capacity area has an R-squared value below 0.90 – Agriculture Mining and Construction (0.85).

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

<b>Customer Segment</b>	<b>R-squared</b>
All Customers	0.95
<b>Industry</b>	
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
<b>Local Capacity Area</b>	
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**

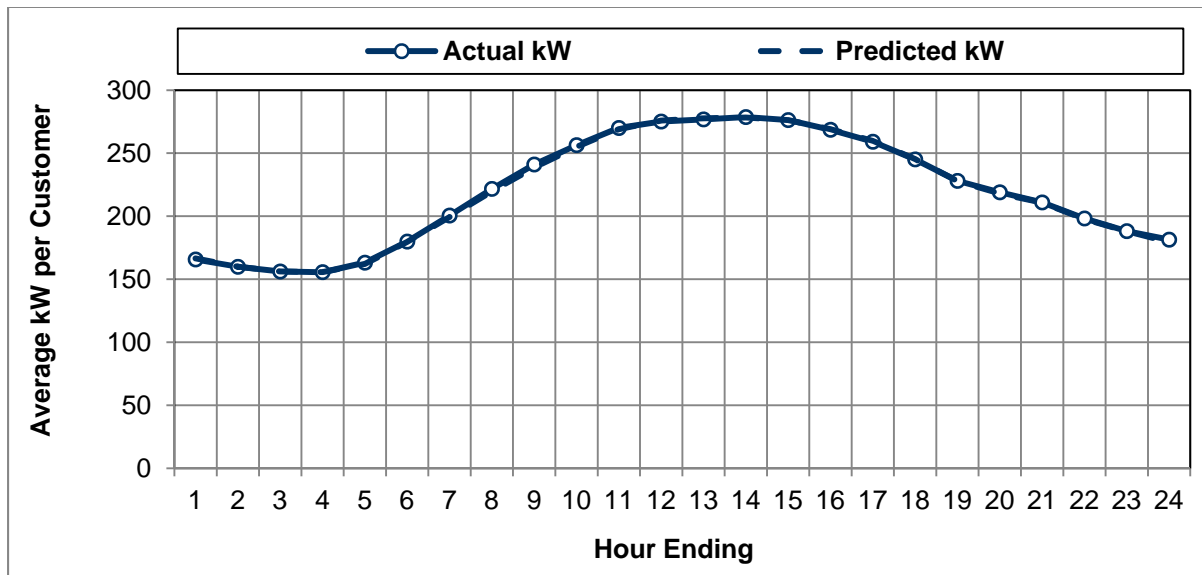


Table D-1 shows the average bias in the reference load predictions during event-like hours by industry. Depending on the specific segment assessed, there is between -1.5% and 2.0% bias. Table D-1 also shows the percent of SDG&E's CPP population within each industry segment. Customers in the Agricultural, 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

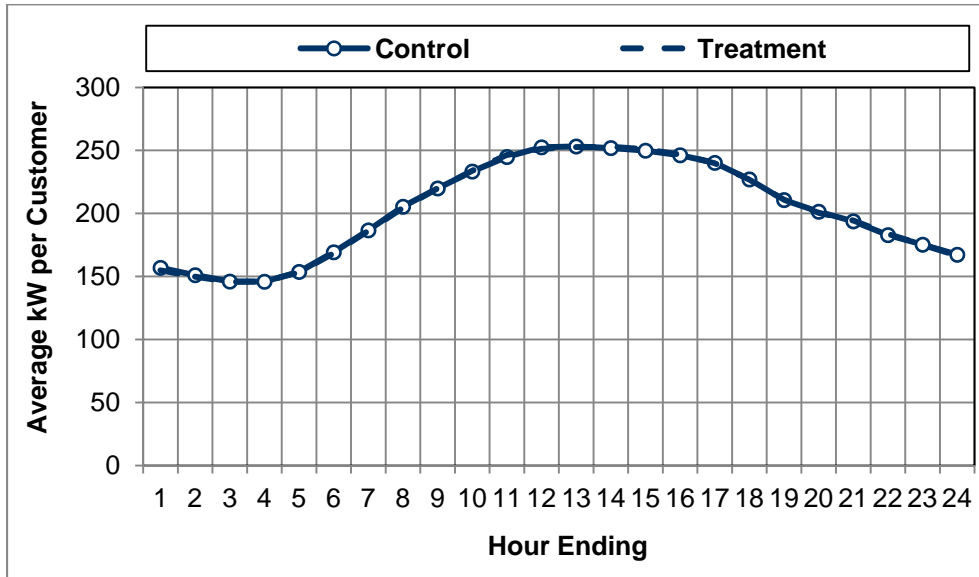
At SDG&E the control group results differ most from the individual customer regression results for the September 7 event. The PG&E analysis also showed the greatest difference between control group and individual customer regression results on this day. While an interesting coincidence, it is hard to 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

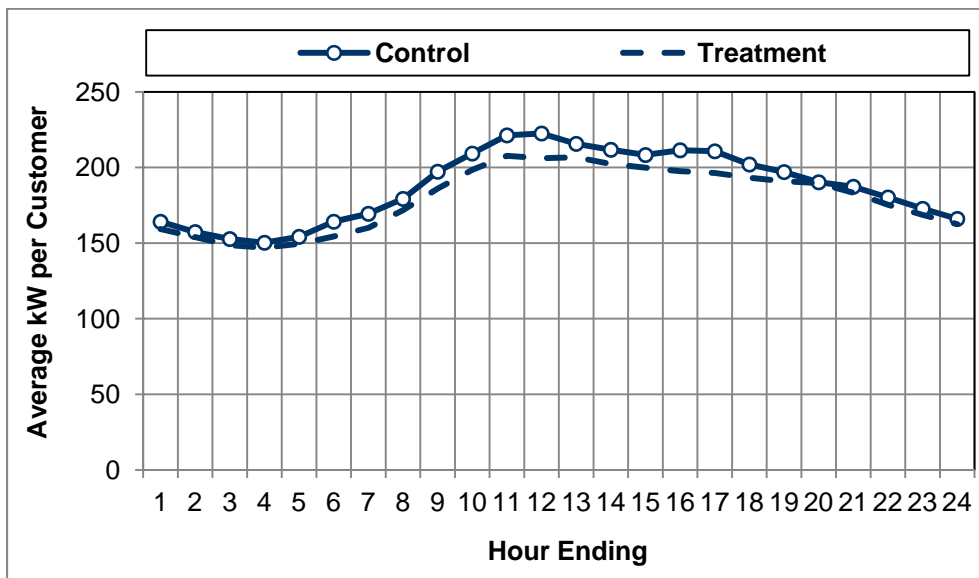
Figure D-2 shows the average control and treatment customer usage patterns on days similar to event days. The control group usage patterns were adjusted to account for systemic differences between opt-out TOU and CPP customers. Control and treatment loads under a variety of weather patterns were compared. 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**

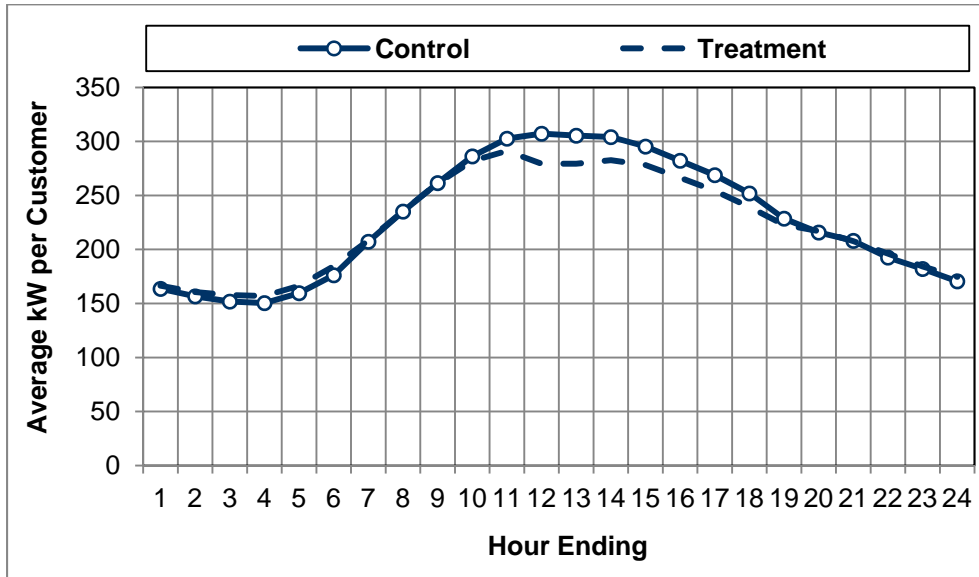


Figures D-3 through D-4 show the event day impacts across SDG&E’s CPP population for each 2011 CPP event. During the event hours of 11 AM to 6 PM, the control group analysis shows an average event impact of 11.5 kW (5.4%) for the August 27 event and 19.4 kW (6.7%) for the September 7 event. The impacts 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

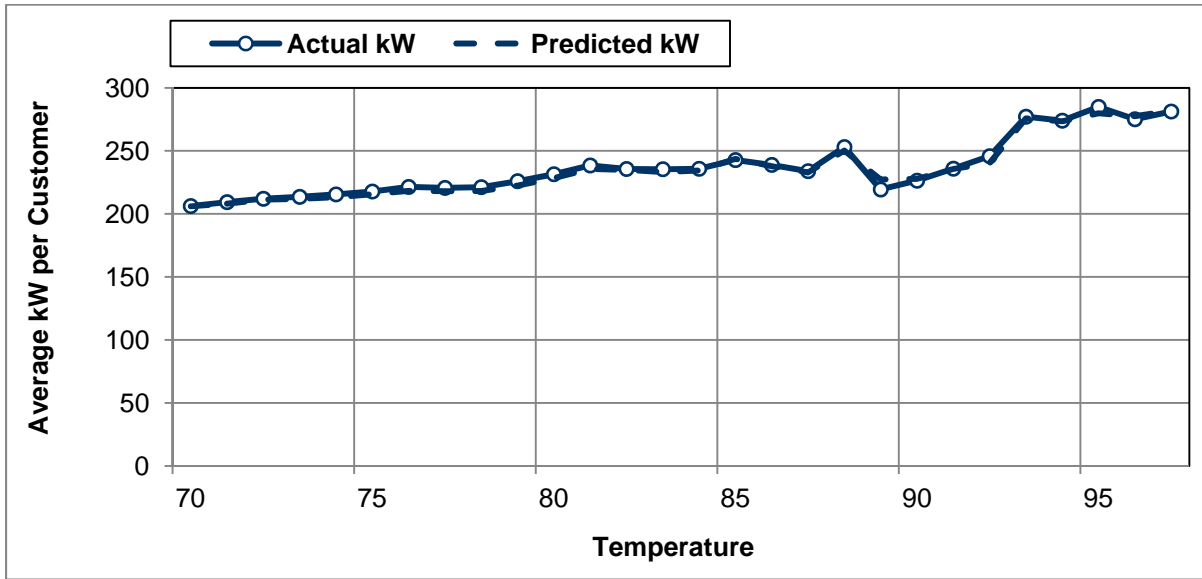
Table D-4 summarizes the amount of variation explained by the regression model for the average customer in specific segments. Depending on the specific group assessed, between 74% and 96% of the variation is explained. Customers in the Agriculture, Mining & Construction industry and the Wholesale, Transport & 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
<b>Industry</b>	
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

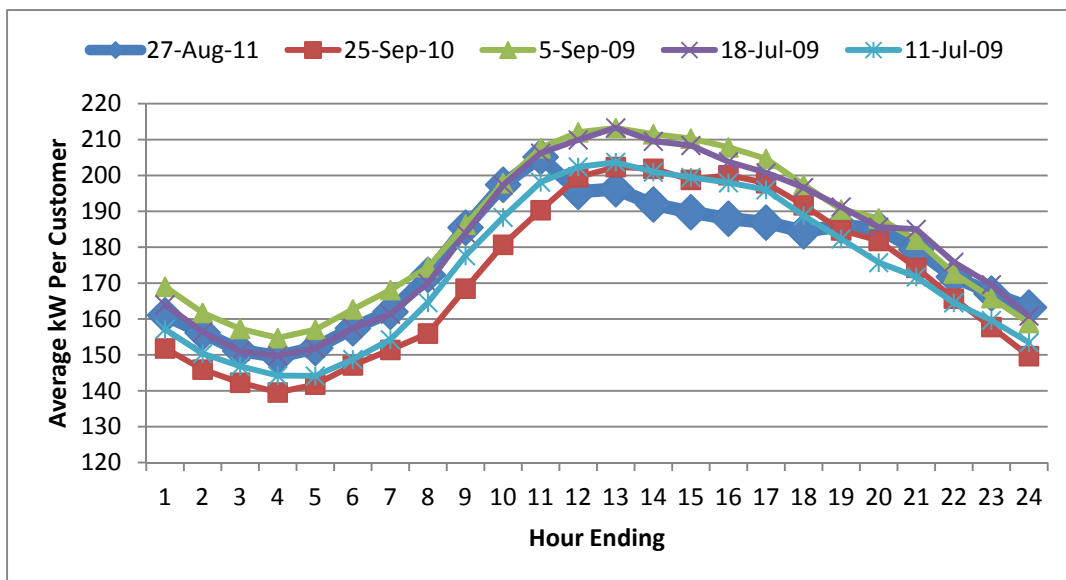


## Appendix E. Limitations of Individual Customer Regressions

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.

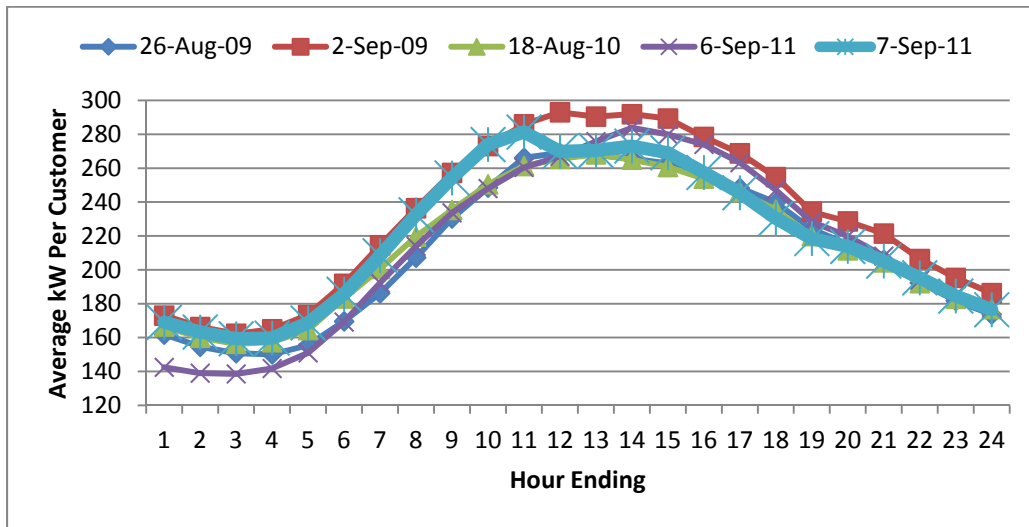
**Figure E-1: Average SDG&E CPP Customer Usage August 27, 2011 Event and Similar Weather Days**



**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**

