CHRISTENSEN ASSOCIATES ENERGY CONSULTING

2012 Load Impact Evaluation of San Diego Gas & Electric's Peak Time Rebate Program

CALMAC Study ID SDG0266.01

for

San Diego Gas & Electric

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EXECUTIVE SUMMARY

This report documents the *ex post* and *ex ante* load impact evaluations of San Diego Gas & Electric's (SDG&E) 2012 Peak Time Rebate (PTR) program. In 2012, all SDG&E residential customers were automatically enrolled in PTR. SDG&E arranged for day-ahead public announcements (*e.g.*, through radio and TV news, and weather features) of PTR events (which are also referred to as "Reduce Your Use" days), and all customers have the opportunity to earn bill credits for usage reductions during event hours. Customers are also encouraged to sign up to receive electronic notification, or alerts, of events through email or text messages (or both).

The impact evaluation also includes an analysis of a subset of customers located in the City of San Diego who enrolled in the San Diego Energy Challenge (SDEC). The SDEC is a separate effort within the PTR (Reduce Your Use) program that involves a competition among middle schools in the San Diego Unified School District, in which schools earn entries into a sweepstakes for every percentage point of their school population that signs up.

Project Objectives

The primary goals of the project are to estimate *ex post* and *ex ante* load impacts, or usage reductions, associated with the overall PTR program and with SDEC in particular.[1] In addition, the *ex post* evaluation is required to estimate event-day usage reductions for a range of subgroups of PTR participants, such as by climate zone, and by customers who requested electronic notification of events, and to evaluate the effect of SDEC participation on customers' overall average summer energy usage (*i.e.*, conservation). The *ex post* evaluation also includes an analysis of the performance of the program's *customer-specific reference level* (CRL), which is used in settlement to estimate customers' usage reductions during event hours for purposes of calculating bill credits.

Analysis Approach

The evaluation approach involved first designing and selecting samples of customers from two populations of SDG&E residential customers – the approximately 41,000 customers who opted to receive electronic notification, or alerts of PTR events, and the approximately one million non-Summer Saver customers, other than SDEC and alert customers, who did not receive electronic event notification. Customer-level regression equations were then estimated using hourly load data for all of approximately 4,600 SDEC participants, 650 customers with installed In-Home Display (IHD) or Programmable Communicating Thermostat (PCT) devices, and samples of 17,000 opt-in alert customers, and 35,000 customers in the remaining population. These regressions resulted in estimates of hourly load impacts for each analyzed customer, for each of the seven PTR events called in 2012. Results from the estimated equations were then tabulated and summarized for the various requested categories of customers.

[1] The analysis in this evaluation excludes customers who are enrolled in the Summer Saver air conditioner cycling program, as their PTR load impacts have been estimated in the context of the Summer Saver evaluation. For completeness, the PTR load impacts of the Summer Saver participants are reported in *ex post* and *ex ante* tables in this report.

Key Study Findings

Ex post load impacts

The primary overall finding from this study is that, on average, only customers who opted to receive electronic notifications, or alerts, of PTR events reduced their electricity usage during PTR event hours. They did so by relatively small but statistically significant amounts of 0.064 to 0.070 kWh per hour, or 5.0 to 8.5 percent of their reference load.[2] These opt-in alert customers include about 850 of the SDEC customers (the remaining SDEC customers received default email notifications through the program) and 41,000 customers from the general population.[3] Approximately 650 customers with IHD devices also reduced usage in comparable amounts. However, the average customer in the remaining population of more than 1 million customers did not reduce usage by any significant amount.

Table ES–1 summarizes PTR usage impact results for the average event for each of the major relevant SDG&E customer sub-groups, differentiated by climate zone. The first three rows in each panel show usage impacts for: 1) SDEC participants; 2) those customers opting to receive PTR alerts; and 3) those customers with IHD/PCT devices. Overall, those three groups reduced usage on average during PTR events by 2.2, 5.0, and 2.7 percent respectively, relative to their reference loads. The PTR usage impacts for the 2,917 Summer Saver participants who opted to receive PTR alerts are shown in the last line of the "All" results, since those results were not reported by climate zone.

The remaining population of non-opt-in alert customers is divided approximately evenly between those who registered for My Account and those that did not. Little difference was found between these groups, and the average estimated load impacts for both imply usage *increases* during PTR events. These estimates are not statistically significant, and likely reflect event-day responses to weather conditions or other factors that are not fully explained by the regression equations.

Table ES–1: Estimated PTR Usage Impacts by Major Customer Group

[2] Close examination of customer-level results indicates that approximately 25 to 35 percent of the opt-in alert customers, differentiated by climate zone and size, reduced usage by consistent and statistically significant amounts on the order of 5 to 6 times the magnitude of the average opt-in alert customer.
[3] Approximately 2,900 Summer Saver participants also opted to receive PTR alerts, and they reduced usage on average by 0.4 kW, or 23 percent, where these greater usage reductions are presumably due in part to their air conditioning usage capacity, which is larger than for non-SS customers.

Customer Group	Climate Zone	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
All SDEC	Coastal	3,106	0.70	0.017	2.2	0.05	2.4%	82.5
Opt-in Alert		23,689	1.06	0.062	25.2	1.47	5.8%	80.6
IHD/PCT		359	1.88	0.076	0.7	0.03	4.0%	81.6
MyAccount		318,849	0.93	-0.010	296.7	-3.34	-1.1%	80.9
Non-MyAccount		343,859	0.91	-0.019	311.8	-6.52	-2.1%	80.8
Total/Average		**689,861**	**0.92**	**-0.012**	**636.6**	**-8.31**	**-1.3%**	**80.9**
All SDEC	Inland	1,525	1.05	0.018	1.6	0.03	1.8%	85.5
Opt-in Alert		17,554	1.58	0.067	27.8	1.18	4.2%	86.8
IHD/PCT		295	2.55	0.039	0.8	0.01	1.5%	86.6
MyAccount		234,138	1.52	-0.046	354.9	-10.74	-3.0%	86.4
Non-MyAccount		257,300	1.33	-0.040	343.3	-10.29	-3.0%	86.3
Total/Average		**510,812**	**1.43**	**-0.039**	**728.3**	**-19.81**	**-2.7%**	**86.4**
All SDEC	All	4,631	0.81	0.018	3.8	0.08	2.2%	83.8
Opt-in Alert		41,243	1.29	0.064	53.0	2.65	5.0%	83.9
IHD/PCT		654	2.18	0.059	1.4	0.04	2.7%	84.3
MyAccount		552,987	1.18	-0.025	651.6	-14.08	-2.2%	83.9
Non-MyAccount		601,158	1.09	-0.028	655.2	-16.80	-2.6%	83.7
SS Opt-in Alert		*2,917*	*1.69*	*0.392*	*4.9*	*1.14*	*23.2%*	*84.7*
Total/Average		**1,203,590**	**1.14**	**-0.022**	**1,369.9**	**-26.98**	**-2.0%**	**83.8**

The above findings are generally comparable to those from last year's evaluation of the 2011 PTR pilot program. That study, which faced challenges due to the unusual nature of several of the events, found an average 0.06 kWh per hour usage reduction on the most typical of the five events, which translated into a 4.5 percent reduction.

Among the more detailed findings of the current study are the following:

- The SDEC customers who received only default notification reduced usage by an average of only a tenth of the amount of those who opted to receive alerts.
- Usage reductions of the average opt-in alert customer in the general population were quite consistent across the two climate zones, three customer size categories, and standard vs. low income tariff.
- Approximately half of the population of customers who did not opt-in to receive alerts did register for My Account, which allows online access to their energy usage data and bill payments. However, the average My Account customer did not reduce usage on PTR events by a statistically significant amount.
- The approximately 650 customers who received an IHD or PCT device reduced usage on average by about the same amount as the average opt-in alert customer, although that amount represented a smaller *percentage* reduction because the IHD customers generally had somewhat higher usage levels.
- Analysis of a sample of customers who were separately surveyed as part of a process evaluation found that among three groups of customers who received alerts – SDEC

default alerts, SDEC opt-in PTR alerts, and non-SDEC opt-in alerts – those who reported being *aware* of a specific recent PTR event had average event-hour usage reductions that were substantially greater than the usage reductions of those who said they were not aware of the event. However, for customers in the non-SDEC population (both My Account and non-My Account) who did not receive any form of alert, no significant usage reductions were found for either aware or non-aware customers.

SDEC conservation effects

A separate analysis was conducted to evaluate whether SDEC participants changed their *overall* summer energy consumption (as distinct from their usage during PTR events) in response to the program. This analysis consisted of a difference-in-differences approach that compared average summer usage between 2011 and 2012 for the SDEC participants and a matched control group selected from the available sample of the non-opt-in alert population. The analysis found an overall reduction in average summer (August and September) usage for SDEC participants of approximately 6 percent relative to the control group.

CRL settlement and baseline analysis

The CRL baseline analysis assessed the accuracy and bias of the CRL method for representing customers' baseline loads for each of the seven actual events, as well as for eight simulated event days that were similar to the actual event days. The study found generally poor CRL accuracy, with average absolute errors for weekday and weekend events in the range of 0.28 to 0.50 kW, or 30 to 50 percent relative to the true baseline load. In terms of bias, the *mean* errors on weekday events averaged 0.11 and 0.16 kW for the actual and simulated events, with relatively large standard deviations of 0.5 and 0.7 kW.

In addition, the CRLs generally had an *upward bias*. Looking at the distribution of errors for actual weekday events, the errors for the middle half of all customers fell in the range of -0.05 kW to 0.20 kW (*i.e.*, a downward bias of about 5 percent to an upward bias of about 20 percent). For a quarter of the remaining customers, the CRLs *understated* the true baseline by more than 0.05 kW, and they *overstated* the true baseline for another quarter of customers by more than 0.20 kW.

Since the CRL for a given event depends on customers' usage on prior days, the nature of baseline errors can vary substantially across events, depending in part on prior weather conditions. Two examples for PTR in 2012 illustrate the point. First, the weekday event called on August 21 occurred on a relatively mild day following a series of relatively hot days. The previous hot days produced *overstated* CRLs for nearly all customers. In contrast, two weekend events were called on days that were substantially hotter than previous weekend days, which resulted in CRLs that *understated* the true baselines of about half of all customers, in some cases by relatively large amounts (*e.g.*, 0.25 to 1 kWh per hour).

In addition, a review of CRL settlement data indicates, as shown in Table ES–2, that net load impacts measured by the CRLs were uniformly greater than the comparable *ex post* load impacts, ranging from 50 percent greater for the opt-in alert customers, to twice as great for the IHD customers, and four times as great for SDEC customers. Most importantly, as shown in the last row of the table, for the much larger number of customers in the remaining population, the CRL-based net impacts indicate net *usage reductions* of 9.9 MW, while the *ex post* impact estimates represent load *increases* of 14.4 MW (though they are not statistically significant). However, PTR bill credits are paid for *usage reductions* relative to CRLs, not net impacts, and these amounted to an average event-hour value of 244.8 MW for the non-alert population.

Table ES–2: Average Hourly PTR Usage Impacts (MW) by Customer Type

Group	Number of Reducers	Reducers as Percent of Total	Impact of *Reducers* per Hour (CRL)	Impact of *Increasers* per Hour (CRL)	Net Impact per Hour (CRL)	Impact per Hour (Ex-Post Analysis)
SDEC	3,065	66%	0.94	-0.60	0.34	0.08
Opt-in Alert	26,768	65%	13.0	-8.83	4.1	2.65
IHD/PCT	404	62%	0.30	-0.22	0.08	0.04
Population	691,682	60%	244.8	-234.9	9.9	-14.4

Conclusions and Recommendations

This study found small but statistically significant usage reductions on PTR event days in 2012 for the average of the 855 SDEC participants and 41,000 other SDG&E customers who opted to receive electronic event notification, or alerts.[4] Customers with IHD devices reduced usage by comparable amounts. In contrast, the more than 1 million customers who did not receive PTR alerts, including those who registered for My Account, showed virtually no usage reductions. Analysis of a separate sample of customers who were identified in a post-event survey as "aware" of the event found substantially greater usage reductions among aware customers than for those who were not aware, even among opt-in alert customers.

In addition to reporting on the nature of PTR usage impacts, this study found that the program's CRL baseline method for calculating usage changes and bill credits performed relatively poorly. In addition to raising fairness issues (*e.g.*, some customers being paid for "false" usage reductions and others not being paid due to under-stated usage reductions), these results suggest that customers could become wary about the value of making efforts to reduce usage. Discussion of ways to improve the CRL method seems warranted.

The above findings that significant PTR load impacts were largely limited to customers who opted to receive electronic alerts, and that the program's CRL method produced substantial errors in measuring customers' true baselines suggests two recommendations. One is that PTR bill credits be restricted to only those customers who opt to receive program alerts. The other is that efforts be made to improve the CRL baseline method, such as applying day-of adjustments.

[4] Approximately 2,900 Summer Saver participants also opted to receive alerts and reduced usage by even greater amounts, as reported in a separate evaluation of the Summer Saver program.

1. INTRODUCTION AND KEY ISSUES

This report documents the *ex post* and *ex ante* load impact evaluations of San Diego Gas & Electric's (SDG&E) 2012 Peak Time Rebate (PTR) program. In 2012, all SDG&E residential customers were automatically enrolled in PTR. SDG&E arranged for day-ahead public announcements (*e.g.*, through radio and TV news, and weather features) of PTR events (which are also referred to as "Reduce Your Use" days), and all customers have the opportunity to earn bill credits for usage reductions during event hours. Customers are also encouraged to sign up to receive electronic notification, or alerts, of events through email or text messages (or both).

The impact evaluation also includes an analysis of a subset of customers located in the City of San Diego who enrolled in the San Diego Energy Challenge (SDEC). The SDEC is a separate effort within the PTR (Reduce Your Use) program that involves a competition among middle schools in the San Diego Unified School District, in which schools earn entries into a sweepstakes for every percentage point of their school population that signs up. In addition, participation points can be earned through usage reductions on PTR event days of customers who affiliate with a school. The school with the highest participation points for each event wins a cash prize for school supplies, and individual prizes may be won by customers. All SDEC participants received email alerts of PTR events by default from SDG&E under the SDEC "brand", regardless of whether they had enrolled to receive separate electronic alerts from SDG&E.

1.1 Project Goals

The primary goals of the project are to estimate *ex post* and *ex ante* load impacts, or usage reductions, associated with the overall PTR program and with SDEC. In addition, the *ex post* evaluation is required to estimate event-day usage reductions for certain subgroups within PTR. The overall evaluation includes the following specific activities:

In the *ex post* evaluation, for each PTR (Reduce Your Use) event day, estimate:

1. Program-level hourly load reductions;
2. Average participants' hourly load reduction;
3. Hourly load reductions by various subgroups, including the following:
    a. by climate zone (Coastal and Inland),
    b. by choice of event notification (*e.g.*, requested alerts by email or text message),
    c. presence of in-home display (IHD) units,
    d. presence of PCTs curtailed by a third-party vendor,
    e. presence of solar systems,
    f. by size category (*e.g.*, low, medium, and high-usage),
    g. by *low-income* customers (*i.e.*, those on tariff DRLI),
    h. for customers who have enrolled in the online My Account website,
    i. for customers identified as "aware" of PTR events in post-event web surveys; and
    j. for customers located in Orange County, at the northern edge of SDG&E's service area;
    k. Hourly load reductions of SDEC participants; and

    l. Incremental load reductions due to the SDEC program.[5]
4. Estimate the conservation effects of the SDEC program (*i.e.*, the changes in summer energy usage for the SDEC participants between 2011 and 2012.
5. As part of the *ex post* evaluation, conduct an analysis of the performance of the program's *customer-specific reference level* (CRL), which is used to estimate usage reductions during event hours for purposes of calculating bill credits.
6. In the *ex ante* evaluation, estimate the following:
    a. Program-level hourly load reductions on monthly system peak days and a typical event day, for 1-in-2 and 1-in-10 weather years;
    b. Average participant's hourly load reductions for the same day types.

The baseline analysis of the CRL involves two main activities. One summarizes a variety of statistics on usage reductions and bill credits paid, as calculated by SDG&E using the CRLs, and as implied by the customer-level regressions estimated in this measurement and evaluation (M&E) project. The other activity consists of an evaluation of the accuracy and bias of the CRL method for measuring customer-level baselines on both event days and event-like non-event days. In the latter case, CRLs for "synthetic," or test events are compared to observed loads on those days. In the former case, CRLs for actual events are compared to baselines constructed from the customer-level regressions that are estimated in the *ex post* evaluation. As part of the baseline analysis, we also report the frequency of "over-payments" and "under-payments" that are implied by the CRL calculations, compared to both the regression-based baselines (for actual events) and the observed loads (for synthetic events).

1.2 Roadmap to Report

Section 2 describes features of the PTR program. Section 3 discusses technical issues and the methodology used in conducting the study. Section 4 presents *ex post* load impact results. Section 5 presents the CRL baseline analysis. Section 6 describes a separate analysis of the overall energy savings (conservation) effect of SDEC. Section 7 presents the *ex ante* forecast of PTR load impacts. Section 8 offers conclusions and recommendations.

[5] SDG&E is also interested in investigating changes in overall energy consumption of SDEC customers, as discussed below.

2. RESOURCES COVERED IN THE STUDY

This section begins by describing the features of the PTR program. It then lists the events that were called in 2012. Finally, it characterizes the nature of the participants in the various subgroups of interest.

2.1 Program Features

SDG&E's PTR (Reduce Your Use) program includes the following features:

- Two rebate levels are available—a basic level of $0.75/kWh and a premium level of $1.25/kWh for customers who use automated enabling technology installed through a SDG&E program. For 2012, only those customers who are enrolled in SDG&E's Summer Saver air conditioner direct load control program are eligible for the premium level.[6]
- Load reductions for rebate purposes are measured relative to a customer-specific reference level (CRL) based on an average of the highest 3 out of the most recent 5 similar non-event days.[7]
- There is no maximum number of events, though rebate levels were designed assuming nine events each year. Seven events were called in 2012 through mid-September. The event window is 11 a.m. to 6 p.m.
- Customers received an educational kit containing information on the PTR program, how they can earn bill credits by reducing usage on event days, and the benefit of enrolling to receive day-ahead event notification through email and/or text message. Customers also have access to online information through My Account on their consumption history, CRL, event performance, and online rebate calculation.

2.2 PTR Events in 2012

Table 2–1 summarizes the seven PTR events that were called in 2012. It shows the SDG&E maximum system demand, day of week, average temperature, day type, and type of event (*e.g.*, test). The two Saturday events are shaded. The California ISO called Flex Alert days on two of the PTR event days, August 10 and 14, and did not call any additional Flex Alert days.

Table 2–1: PTR Event Days

[6] Usage reductions for Summer Saver participants will be estimated in the evaluation of that program.

[7] The "highest" days are those with the highest total consumption between the event window hours of 11 a.m. to 6 p.m. For events called on weekend or holiday days, the CRL is total consumption during the above hours on the highest of the three preceding weekend days.

DATE	Maximum System Load (MW)	Day Of Week	Average Daily Temperature	Day-Type	Event Type
20-Jul-12	3,521	Friday	73	Weekday	Test
9-Aug-12	3,925	Thursday	75	Weekday	Event
10-Aug-12	4,137	Friday*	76	Weekday	Event
11-Aug-12	3,711	Saturday	77	Weekend	Event
14-Aug-12	4,137	Tuesday*	75	Weekday	Event
21-Aug-12	3,642	Tuesday	72	Weekday	Event
15-Sep-12	4,304	Saturday	85	Weekend	Event
* Also CAISO Flex Alert day					

2.3 Participant Characteristics

This section provides information on the customers in various subgroups and samples of PTR participants that were used in the evaluation. Due to the large overall number of participants, samples of some large categories of customers were designed and their load data were included in the evaluation. For smaller categories, the entire population in the category was included. Table 2–2 provides an overview of the eligible PTR population, its breakdown into various subgroups of interest into which the population was segmented, and the samples for some of those groups that were used in the evaluation. The methods used to design the samples are described in Section 3.

As indicated in the table, Summer Saver participants were excluded from this evaluation and were analyzed in the context of the evaluation of that program. All SDEC and IHD/PCT customers were included in the evaluation, with the exception of a few due to data issues. Relatively large samples of the Opt-in Alert customers and the remaining population (after excluding all of the other subgroups), were designed, selected, and analyzed. In some cases, such as the approximately 50 percent of the population that signed up for MyAccount, customers in that category were represented as drawn in the samples.

Table 2–2: PTR Subgroup Populations and Sample Sizes

PTR Subgroup	Population	Analysis Samples
Summer Saver (excluded)	23,998	-
SDEC (excluding SS)	4,633	4,631
Alert Opt-in	41,243	13,745
IHD/PCT	663	655
Remaining Population	1,154,144	29,692
Total (Excluding SS)	1,200,683	48,723

The following subsections illustrate the characteristics of the customers in the largest subgroups. Those who enrolled in the San Diego Energy Challenge are presented first, followed by descriptions of the sample of the "Opt-in Alert" customers who enrolled to receive day-ahead electronic notification, or alerts, of PTR events. Finally, we describe the population and sample of the remaining participants who did not enroll in SDEC or to receive Alerts.

2.3.1 Participant characteristics – SDEC

Table 2–3 summarizes the number and summer average hourly usage of the customers enrolled in SDEC in 2012.[8] Values are provided by climate zone, enrollment to receive electronic event notification (alerts), and rate (standard or low-income).[9] Two types of percentage values are shown in the table. The rows that indicate the two climate zones show overall values for participants in the two climate zones relative to the total. All other values show percentages relative to the total *within* each climate zone. As shown, two-thirds of SDEC participants reside in the Coastal climate zone, and as a result have somewhat lower average summer usage than the overall average. In both climate zones, nearly 20 percent of participants enrolled to receive email or text message alerts of PTR events, while the remainder received default SDEC alerts. Overall, about 34 percent of SDEC participants were served under the low-income (DRLI) tariff, and they were somewhat less likely to enroll to receive email or text alerts, especially in the Inland climate zone.

[8] The values in the table do not include SDEC participants who were also enrolled in the Summer Saver program, as usage reductions for these customers will be estimated and included in the Summer Saver evaluation.

[9] Customers enrolled in SDEC actually received separate default email alerts from SDG&E, which mention the opportunity to win points through the challenge for usage reductions during the event hours on the following day. Thus, in the SDEC portion of this overall PTR evaluation, we refer to customers who did not opt to receive email or text alerts of Reduce Your Use days as "SDEC Alert Only."

Table 2–3: SDEC PTR Participants

Climate Zone	Alert	Rate	Count	% of Total (Bold) or Climate zone	Average Hourly Summer Use (kWh)
Coastal			**3108**	**67%**	**0.52**
	Opt-in Alert		583	19%	0.55
		Standard	415	13%	0.54
		Low Income	168	5%	0.56
	SDEC Alert Only		2525	81%	0.51
		Standard	1760	57%	0.53
		Low Income	765	25%	0.48
Inland			**1525**	**33%**	**0.64**
	Opt-in Alert		273	18%	0.64
		Standard	179	12%	0.66
		Low Income	94	6%	0.60
	SDEC Alert Only		1252	82%	0.64
		Standard	708	46%	0.67
		Low Income	544	36%	0.60
Total			**4,633**		**0.56**

Table 2–4 indicates the percentage of customers who requested PTR alerts, and the breakdown by type of alert—email, text message, or both. The majority requested emails only.

Table 2–4: Type of Notifications Requested by SDEC PTR Participants

Alert Type	Coastal	Inland	Total
SDEC Alert Only	81%	82%	82%
Opt-in Alert	19%	18%	18%
Opt-in Alert by Type			
Email	60%	54%	58%
Text	17%	19%	17%
Both	23%	27%	24%

2.3.2 Customer characteristics – Opt-in Alert

Table 2–5 summarizes the characteristics of the sample that represents the population of Opt-in Alert customers. The sample was based on a stratified random design, as described in Section 3, in which relatively higher fractions of high-use and medium-use customers were selected, due to the greater variability in their usage patterns.

Table 2–5: Characteristics of the Opt-in Alert Sample

Climate Zone	Size	Total Count	Sample	Sample Fraction
Coastal	Low	7,832	1,113	14%
	Medium	12,600	3,693	29%
	High	3,257	3,056	94%
	All	23,689	7,862	33%
Inland	Low	3,609	488	14%
	Medium	10,234	2,822	28%
	High	3,711	2,573	69%
	All	17,554	5,883	34%
Overall Total		41,243	13,745	

Table 2–6 summarizes the types of alerts that were requested by the opt-in alert customers. Similar to the SDEC participants, a majority requested only email alerts

Table 2–6: Type of Notifications Requested by Opt-in Alert Customers

Alert Type	Coastal	Inland	Total
Email	61%	54%	58%
Text	14%	17%	15%
Both	25%	29%	26%

2.3.3 Customer characteristics – Sample of non-alert population

Table 2–7 summarizes characteristics of the sample representing the remaining population of PTR customers. As for the Alert sample, the "remaining population" sample was skewed toward high-use and medium-use customers.

Table 2–7: Sample Characteristics of the Remaining Population

Climate Zone	Size	Total Count	Sample	Sample Fraction
Coastal	Low	306,394	3,471	1.1%
	Medium	290,463	9,168	3.2%
	High	65,851	5,651	8.6%
	All	662,708	18,290	2.8%
Inland	Low	158,312	2,155	1.4%
	Medium	254,138	5,426	2.1%
	High	78,986	3,821	4.8%
	All	491,436	11,402	2.3%
Overall Total		1,154,144	29,692	

2.4 Observed Loads on Selected Event Days and Non-event Days

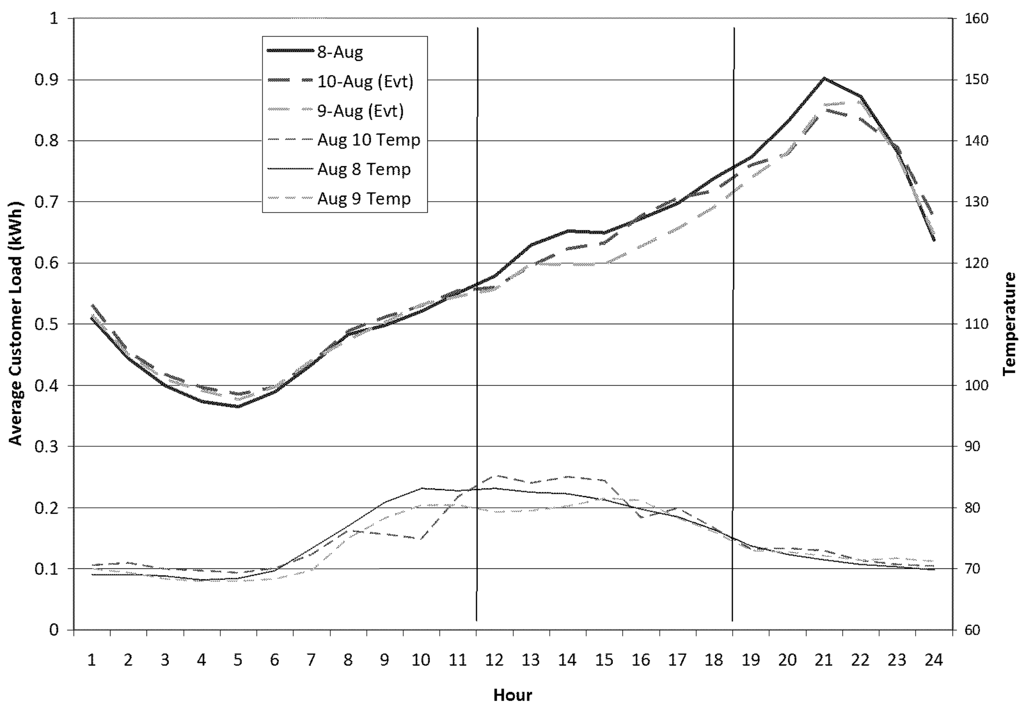
This sub-section lays the groundwork for determining likely magnitudes of estimated PTR usage reductions by providing the reader with examples of observed average-customer load profiles for selected customer groups on certain event and non-event days. We focus first on the SDEC customers. The differences in load profiles are indicative of the estimated PTR load impacts reported in Section 4. However, a lack of fully comparable non-event days limits the extent to which load impacts may be observed directly as differences between event and non-event day load profiles. The formal estimates of *ex post* load impacts designed to meet the Protocols are produced by the regression-based methodology described in Section 3, and are presented in Section 4.

2.4.1 SDEC

The following figures show hourly load and temperature profiles for the average "SDEC Alert Only" and "Opt-in Alert" customer in both climate zones, on selected event days and non-event days, to illustrate differences in event-hour usage patterns between customer groups and between event and non-event days.

Figure 2–1 shows the average loads for the Coastal *SDEC-Alert Only* customers for August 8 – 10, where the 9th and 10th were event days. It is difficult to assign specific load differences in this figure to reductions due to the event. For example, the lower load on August 9 is consistent with relatively lower temperatures on that day up to the middle of the event window, which could imply some combination of a weather effect and/or event usage reductions. Also, the fact that the loads on the 8th and 10th were similar even though temperatures were higher on the 10th could imply some event response. Small usage reductions for both event days were estimated by the regression analysis.

Figure 2–1: Observed Average Customer Loads for August 9 and 10 Event Days
Coastal; SDEC Alert Only



SB_GT&S_0888739

Figure 2–2 shows load profiles for the same days for the average *Opt-in Alert* customer in the Coastal group. In this case, the loads on both event days lie substantially below the load on August 8. This result is consistent with the relatively larger and significant usage reductions for this group that were estimated in the regressions.

Figure 2–2: Observed Average Customer Loads for August 9 and 10 Event Days
Coastal; Opt-in Alert

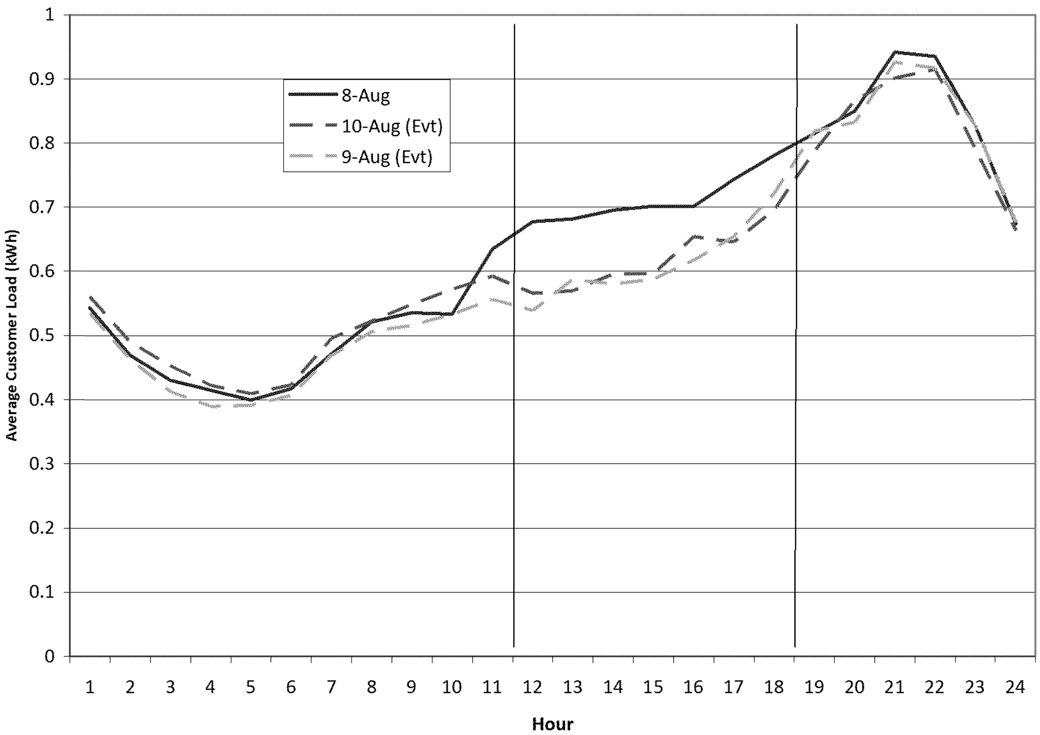


Figure 2–3 shows loads and temperature for the same days for the average customer in the Inland group that received *SDEC alerts only*. Similar to the case with the Coastal customers, the lower load on August 9 is consistent with relatively lower temperatures on that day. The somewhat lower load on the 10th compared to the 8th, even though temperatures were generally higher on the 10th during the event window could imply some event response, as estimated in the regression.

Figure 2–3: Observed Average Customer Loads for August 9 and 10 Event Days
Inland; SDEC Alert Only

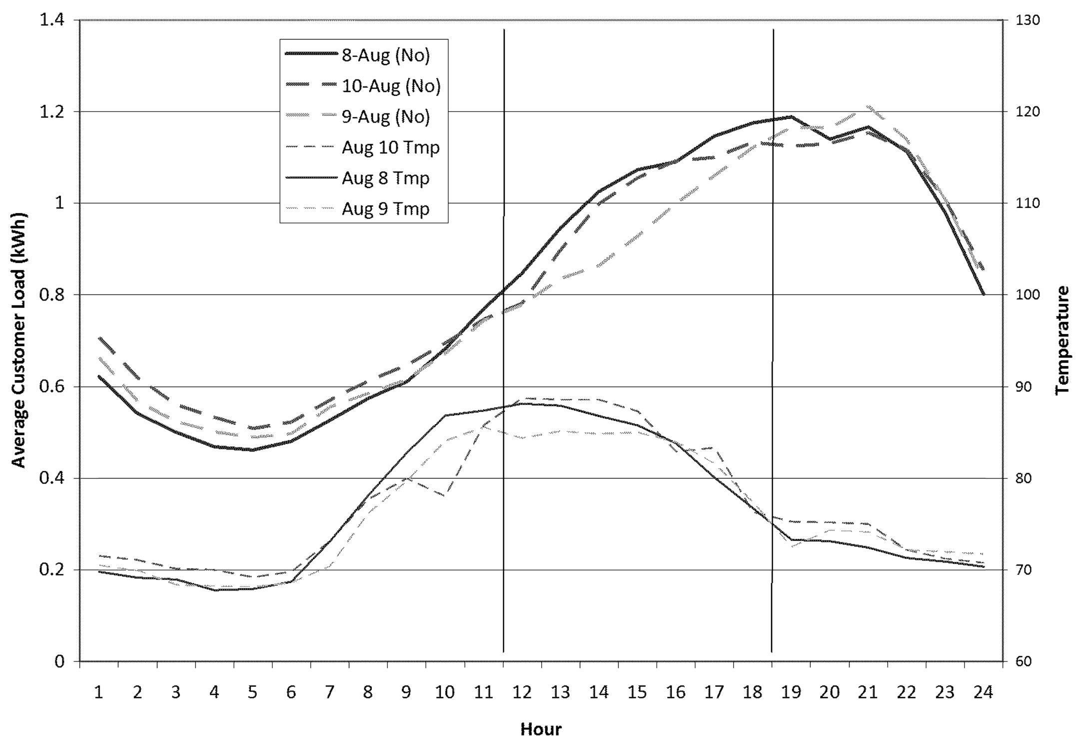
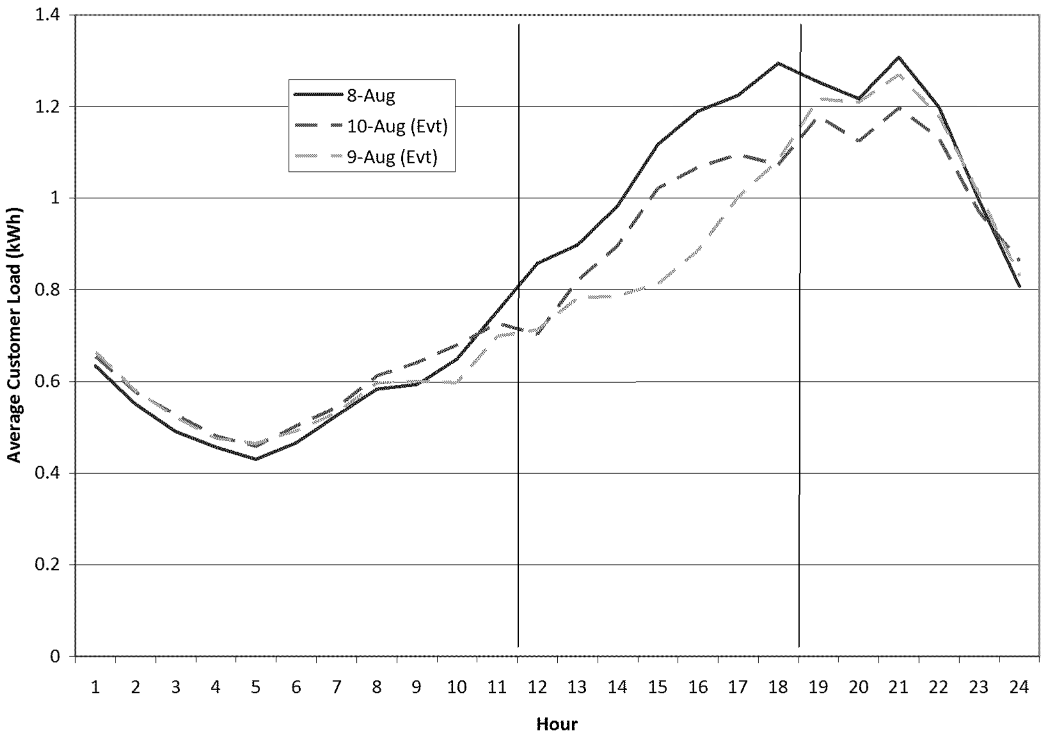


Figure 2–4 shows load profiles for the same days for the average *Opt-in Alert* customer in the Inland group. Similar to the comparable Coastal group, the loads on both event days lie substantially below the August 8 load. These results are consistent with the significant usage reductions estimated in the regressions.

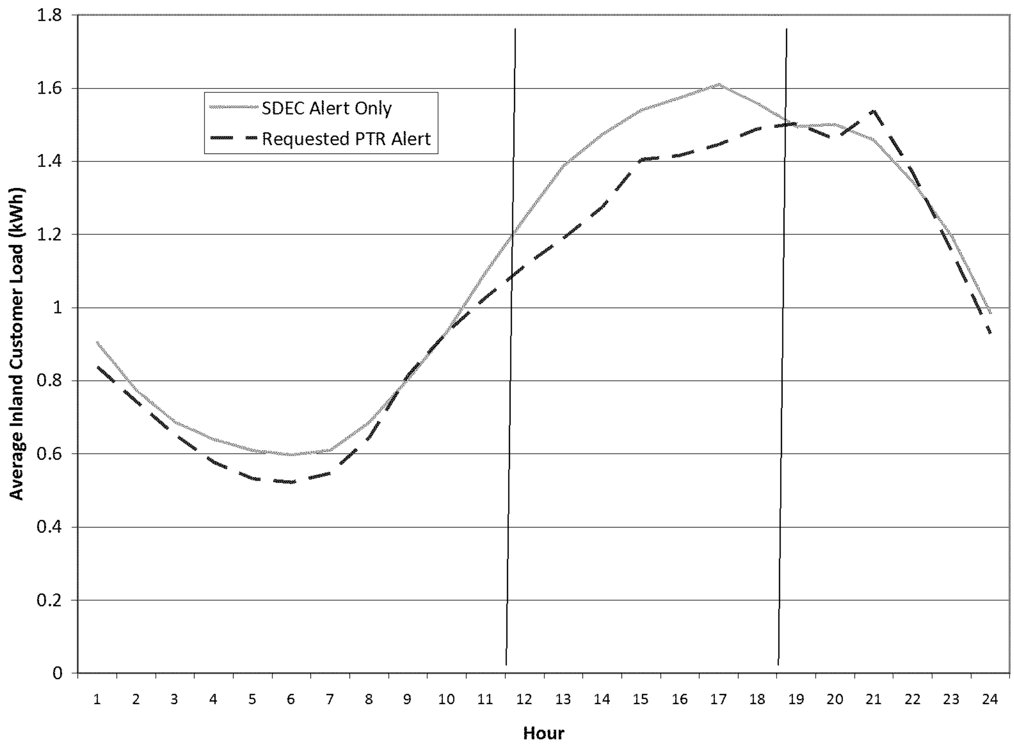
Figure 2–4: Observed Average Customer Loads for August 9 and 10 Event Days
Inland; Opt-in Alert



SB_GT&S_0888742

Figure 2–5 shows the average customer loads for the September 15 event for the Inland *SDEC alerts only* group and the *Opt-in Alert* group. This day had the highest temperature of any of the events, and is also unique in that it is a Saturday, and the high temperatures on that day and the previous day were isolated occurrences after a string of moderate days. The load for the Opt-in Alert group is substantially lower than the SDEC alert only group, which is consistent with the differences in estimated usage reductions.

Figure 2–5: Observed Average Customer Loads for September 15 Event;
Inland; SDEC Alert Only and Opt-in Alert



2.4.2 Opt-in Alert and population customers

While no formal control group was available to assist in estimating PTR load impacts, the findings of no significant usage reductions on the part of the non-alert population customers suggests comparing the average population customer load to the average Alert customer load to view potential load impacts. The following figures make that comparison for several events for the average customer in the Inland climate zone. Figure 2–6 makes the comparison for the July 20 event and the prior non-event day. The top and bottom solid lines within the event window show the Alert and Population loads respectively on July 19. The two dashed lines in the middle show the loads for the same customers on the July 20 event day, with the Alert load beginning above the Population and then dropping below during the event window, suggesting response to the PTR event.

Figure 2–6: Observed Average Customer Loads – July 20 Event
Inland; Opt-in Alert and Population

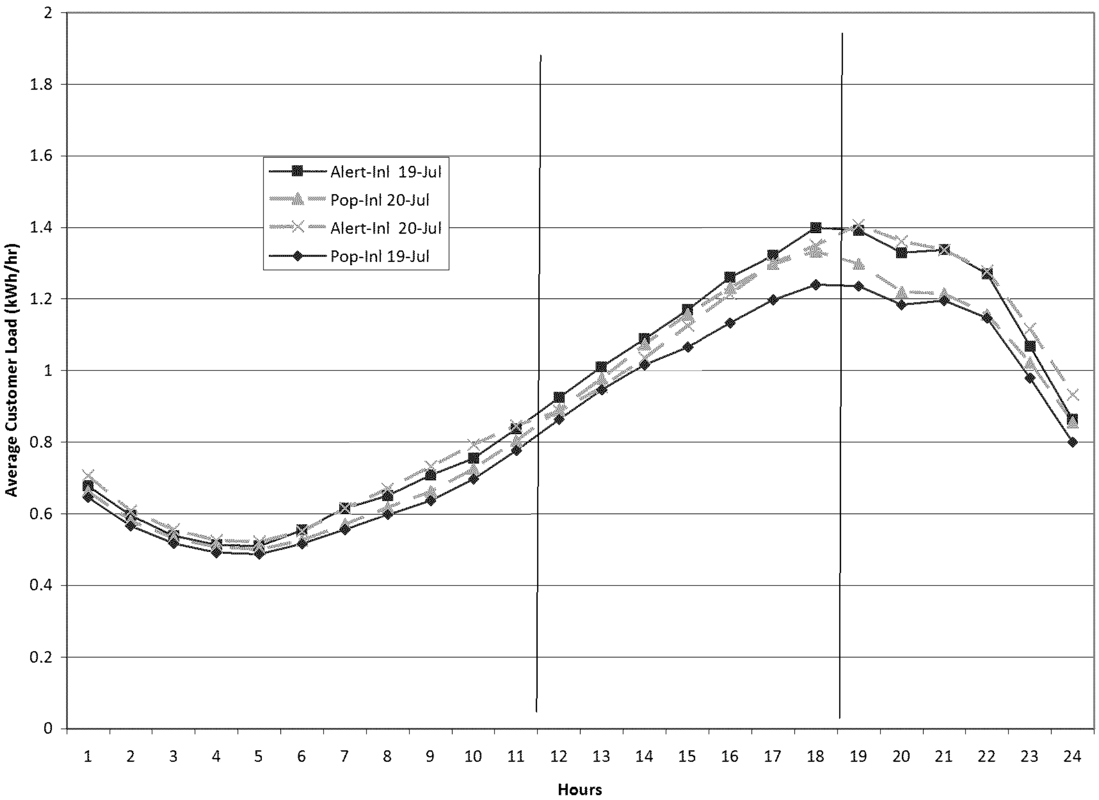


Figure 2–7 shows comparable pairs of load profiles for August 8 and the following two event days on August 9 and 10. As in the previous figure, the Alert load lies above the Population load on the non-event day, but the profiles are much closer on both event days, which is consistent with event-day usage reductions on the part of Alert customers relative to the Population.

Figure 2–7: Observed Average Customer Loads – August 9 & 10 Events
Inland; Opt-in Alert and Population

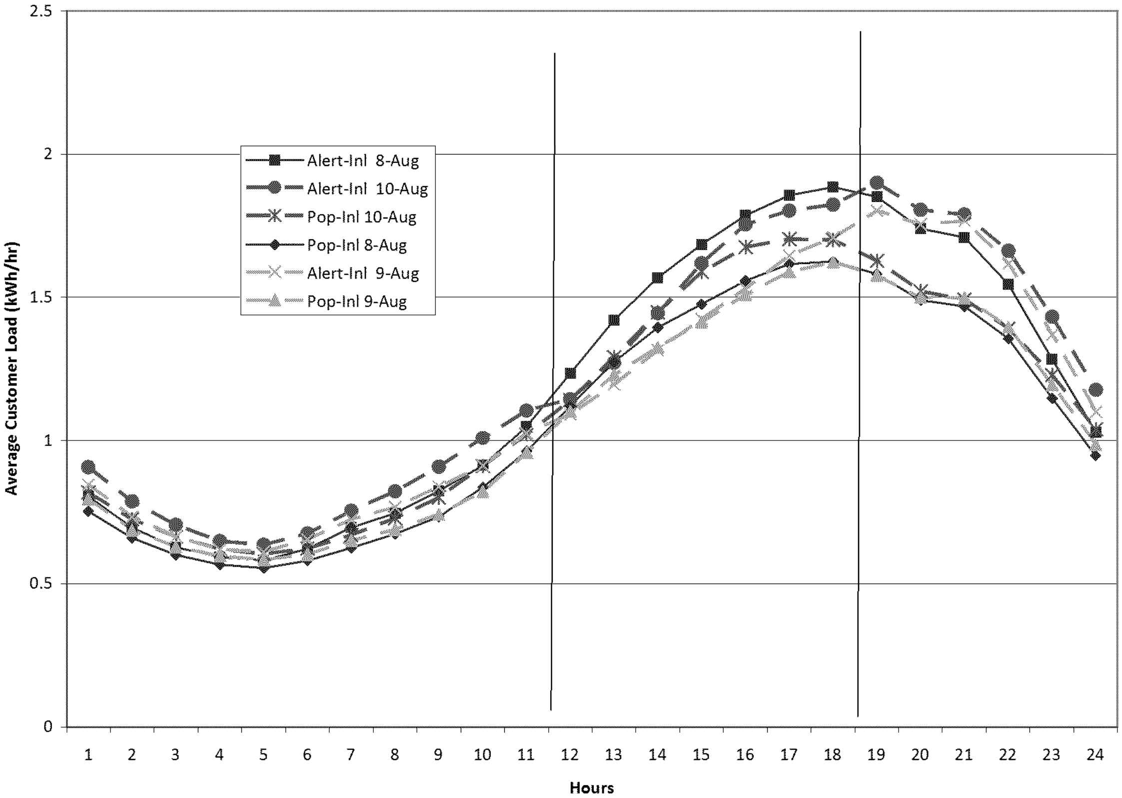
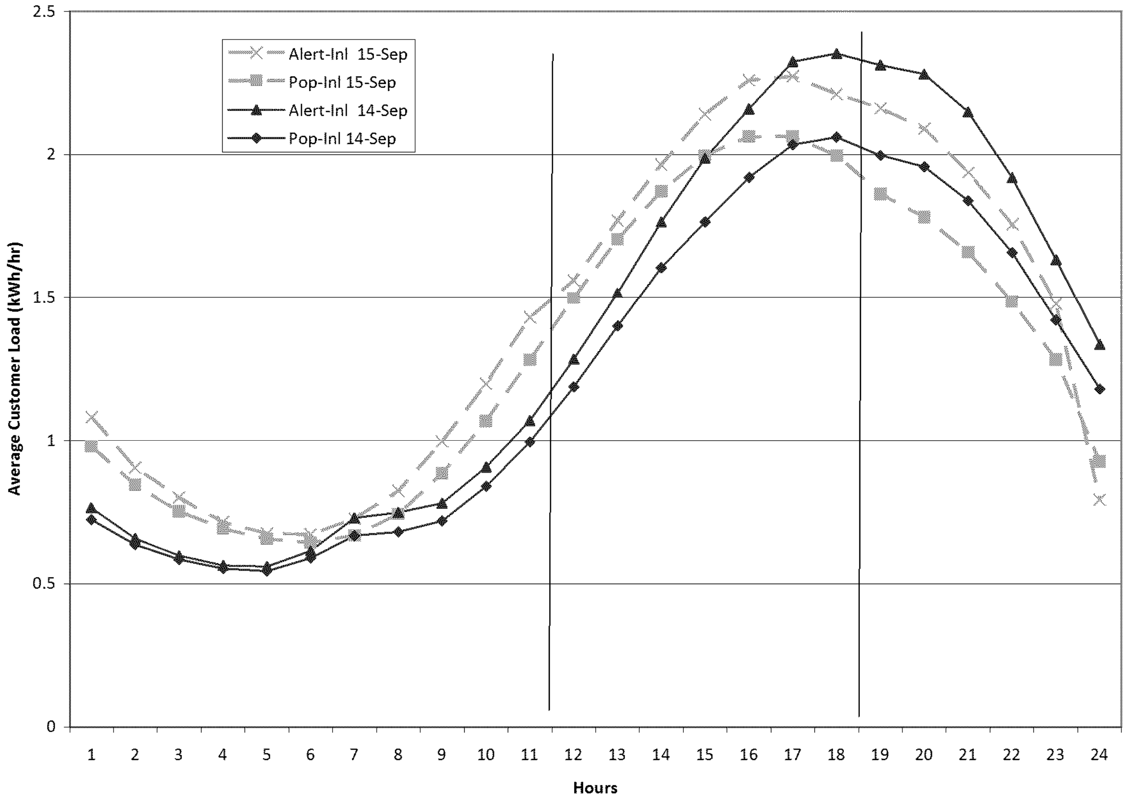

Average Customer Load (kWh/hr)
Hours
Alert-Inl 8-Aug
Alert-Inl 10-Aug
Pop-Inl 10-Aug
Pop-Inl 8-Aug
Alert-Inl 9-Aug
Pop-Inl 9-Aug
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

Figure 2–8 compares Alert and Population loads on the final event day, on Saturday September 15, and the prior non-event day. As in the previous figures, the Alert load on the non-event day is higher than that of the Population load. On the event day, the Alert load begins above the Population load, then appears to "kink" downward somewhat, unlike the other three loads, suggesting some event-day response.

Figure 2–8: Observed Average Customer Loads – September 15 Event
Inland; Alert and Population



3. ANALYSIS METHODS

This section discusses technical issues that need to be addressed in the *ex post* evaluation portion of this study, including sample design and methods for estimating *ex post* load impacts. Methods for developing the *ex ante* forecasts are described in Section 7. Sample design was based on customer and usage data provided by SDG&E, and was guided by targeted levels of precision in estimating load impacts. Our approach for conducting the *ex post* impact evaluation involves exploration and testing of regression-based methods for estimating load impacts for event-based demand response programs. These methods apply regression analysis to hourly load data for populations and samples of participating customers in various groups of interest. Customers' loads on non-event days are used as controls for their use on event days (*i.e., "participant-only"* approach). The analysis controls for factors other than PTR events that influence customers' load profiles, including hour of day, day of week, and weather conditions, and also includes hourly variables that indicate event days. The coefficients on the event variables allow direct estimation of hourly PTR load impacts for each event day.

3.1 Sample Design

The key factors that guided the sample design were the number of characteristics by which the sample should be stratified (*e.g.*, climate zone and customer size), as well as possible separate treatment of certain key population groups (*e.g.*, enrollment in SDEC and presence of IHD), and the required sample sizes. Discussions with SDG&E staff at the PI meeting and subsequently led to the following overall sample design framework:

- Summer Saver participants were excluded from the target population and their PTR load response will be estimated in a separate evaluation.
- The SDEC participants (approximately 4,600) were treated as a separate "certainty" sample due to their relatively small number and strong interest by SDG&E in load impact results for that group.
- The IHD participants (approximately 600) were also treated as a separate "certainty" sample.
- The Alert group (about 48,000) was removed from the remaining population and over-sampled to achieve a designed 95/5 degree of confidence and precision.
- Net-metering customers with solar installations were also held out of the target population and analyzed separately.
- The remaining eligible target population of approximately a million customers was sampled at a rate designed to obtain 90/10 precision at the climate zone level. The sample was stratified by climate zone (Coastal and Inland) and size (small, medium, and high-use customers, based on summer average daily usage). Information on usage variability by climate zone and size obtained from the 2011 PTR pilot, along with population counts from the target population were combined to allocate the sample to strata using Neyman allocation methods.
- A control group of SCE customers may be selected in a separate sample design undertaken in conjunction with an impact evaluation of SCE's PTR program.

- The remaining sub-groups of interest (CARE/low-income customers, My Account customers, and Orange County customers) were to be evaluated using the relevant customers of those types that were drawn into the analysis samples or subgroups.

Sample size requirements are generally related to two primary factors: 1) the variability in usage across customers, and 2) the expected size of the event-day usage reductions that need to be estimated. We worked closely with SDG&E staff on the sample design and selection of customers. As described above, CA Energy Consulting designed separate samples of Alert customers and customers in the remaining eligible population, and SDG&E selected customers at random according to the design parameters (*i.e.*, sample sizes and sample strata). The sample sizes and comparable target populations were summarized in Section 2.3.

3.2 Level of Analysis

The relatively large number of customer types for which PTR load impact results have been requested suggested that the most straightforward approach to the evaluation would be to use *customer-level* regression analysis, which allows results for customers to be aggregated into any relevant category.

In a preliminary analysis of SDEC customers, we conducted initial tests of the performance of various possible regression specifications using data for the average customer in four subgroups of participants, differentiated by *climate zone* (Coastal and Inland) and type of *event notification* ("Requested PTR Alert" and "SDEC Alert Only"). The regression testing focused on the selection of the most effective set of weather variables. We applied the selected models to data for the average customer in each group to produce preliminary estimates of PTR load impacts by group and event.

Similar testing was conducted for the Alert and "Remaining population" groups, as described in Appendix A. The selected regression models were applied to customer-level data for the customers in each of the certainty subgroups and the samples.

3.3 Estimating *Ex post* Load Impacts

The model presented below represents the "base" *ex post* load impact model that was used to estimate hourly impacts for each event day, for the individual customer accounts, while controlling for factors such as weather conditions and regular daily and monthly usage patterns (*i.e.*, accounting for differences in load levels across hours of the day, days of the week, and months of the year). The base model is:

$$
\begin{aligned}
Q_t &= \alpha + \sum_{Evt=1}^{E} \sum_{i=1}^{24} (\beta_i^{Evt} \times h_{i,t} \times DR_t) + \sum_{i=1}^{24} (\beta_i^{Wth} \times h_{i,t} \times Wth_t) + \sum_{i=1}^{24} \beta_i^{MornLoad} \times MornLoad_t \\
&+ \sum_{i=1}^{7} \sum_{j=1}^{24} (\beta_{i,j}^{DT,H} \times DT_{i,t} \times h_{j,t}) + \sum_{i=8}^{9} (\beta_i^{MONTH} \times MONTH_{i,t}) + \sum_{i=2}^{24} (\beta_i^{Sep} \times SEP_{i,t} \times h_{i,t}) + e_t
\end{aligned}
$$

The variables are explained in the table below.

Variable Name / Term	Variable / Term Description
Q_t	the customer's demand in hour *t*
α and the various βs	the estimated parameters
$h_{i,t}$	a dummy variable for hour *i*
DR_t	an indicator variable for program event days
Wth_t	weather conditions during hour *t* (*e.g.*, measured by CDD, CDH, or THI)
E	the number of event days that occurred during the program year
$MornLoad_t$	a variable equal to the average of the day's load in hours 1 through 10
$DT_{i,t}$	a dummy variable for day type *i*
$MONTH_{i,t}$	a series of dummy variables for each month
$SEP_{i,t}$	a dummy variable for the month of September
e_t	the error term.

The first term in the equation that contains the double summation signs is the component of the equation that allows estimation of *hourly load impacts* (the b^{Evt}_i coefficients). It does so via the hourly indicator variables $h_{i,t}$ interacted with the event variables (indicated by DR_t). The remaining terms in the equation are designed to control for weather and other periodic factors (*e.g.*, hours, days, and months) that determine customers' loads. The interaction of day-type indicators with the hourly indicators is designed to account for potentially different hourly load profiles on different days of the workweek and weekends.

We allow for a different hourly profile during the month of September to account for changes in usage patterns that may occur when summer ends and children return to school. The "morning load" variable is used in the same spirit as the optional day-of adjustment to the 10-in-10 baseline method currently used in some DR programs (*e.g.*, Demand Bidding Program). That is, it is intended to adjust the reference load (*i.e.*, the regression-based estimate of the loads that are expected to occur on a given day, including the load that would have occurred on event days if the events had not been called) for unobservable exogenous factors that cause loads to vary from day to day.[10] Finally, the models were estimated using Newey-West standard errors that account for autocorrelation of one hour.

We have tested a variety of specifications to determine the regression model that performs best according to several performance and validity tests. As noted above, these tests are conducted using average-customer data (*e.g.*, by climate zone) rather than at the individual customer level. The model variations and the performance statistics are reported in an appendix.

[10] The use of the morning load variable assumes that variations in the morning load are related to variations in reference loads later in the day; but that the changes in the morning load are not part of the customer's response to the event itself (*e.g.*, pre-cooling). If customers do shift usage to morning hours, the presence of the morning variable could produce an upward bias in the load impact estimate. (That is, the reference load will be shifted too high under the assumption that exogenous factors have increased the customer's reference load.) In our experience, there does not appear to be a significant amount of pre-cooling or other load shifting behavior, at least into hours 1 through 10 on event days, and the presence of the morning load variable has helped to estimate more reasonable load impacts in some difficult cases of highly variable loads. We will continue to examine event-day behavior for the 2012 program year to ensure that this remains the case, and remove the variable if we determine that it is not improving the load impact estimates.

4. STUDY FINDINGS – *EX POST* LOAD IMPACTS

This section reports the following types of findings from the *ex post* load impact analysis:

- Average hourly reference loads and load impacts for the average customer and in aggregate, for each event day and a typical, or average, event day for each of the primary customer groups of interest;
- Load impacts for the average event for sub-groups such as by customer size; standard and low-income rates; and by survey-based awareness measures;
- A summary of load impacts for the average event for the major groups of interest;
- Load impacts at the program level, based on analysis of aggregated load data, including confidence intervals around the estimated load impacts;
- Illustrative hourly load impacts for selected customer groups and event days; and
- Findings from the customer-level analysis on percentages of opt-in alert and non-alert customers who display statistically significant usage reductions.

Results are shown first for the SDEC customers. These are followed by similar results for the Opt-in Alert customers, including Summer Saver participants, and for the IHD customers.

4.1 SDEC Load Impacts

Estimated average hourly reference loads and usage reductions, or load impacts (LI), at an average customer and aggregate level, are shown in Table 4–1 for each event, for all SDEC participants, differentiated by climate zone (Coastal and Inland) and type of notification (SDEC alert only and Opt-in PTR alert). Also shown are the number of customer accounts in each group and the average event temperature. The estimated usage reductions are illustrated in Figure 4–1.

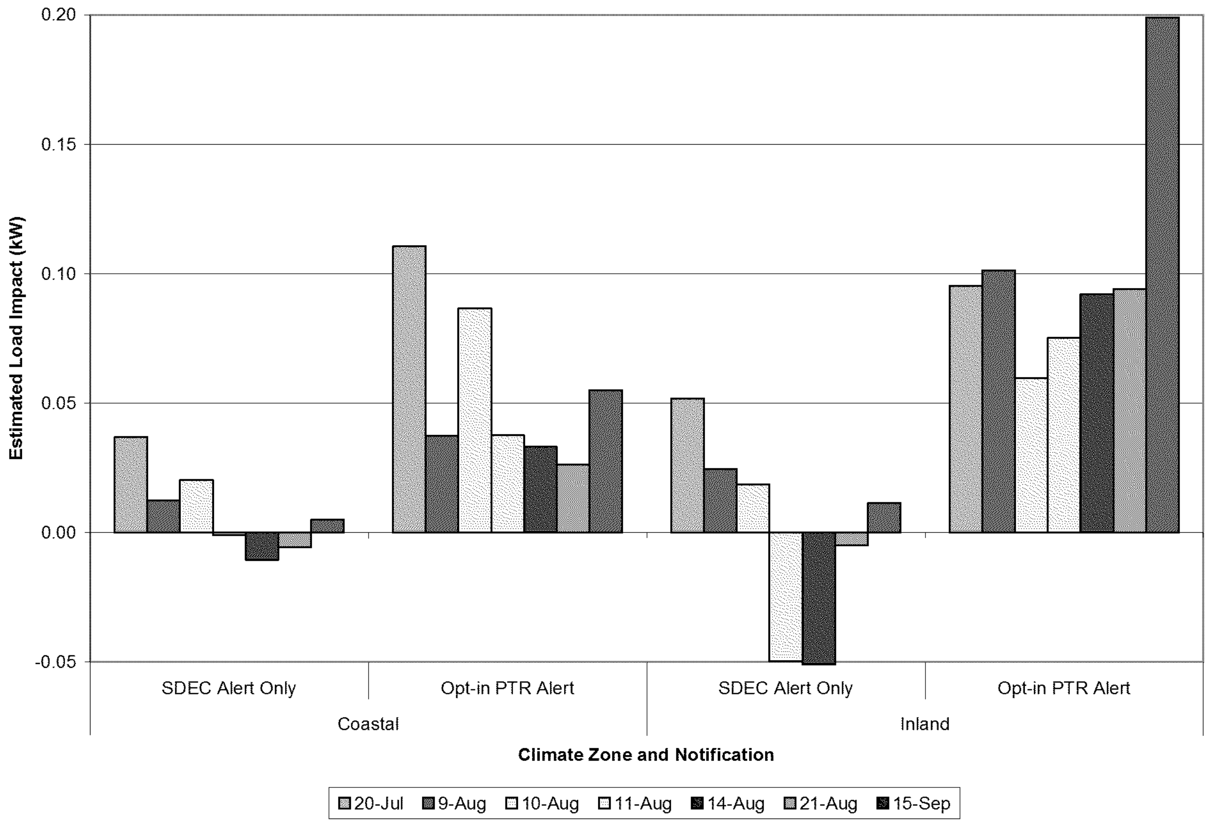
Estimated usage reductions for the two groups that requested PTR alerts are statistically significant and reasonably consistent across events, averaging 0.055 kWh per hour for customers in the Coastal zone and 0.10 kW for those in the Inland zone. Estimates for the groups receiving only default SDEC alerts are generally smaller and more variable, with statistically significant reductions in a few hours for the first two or three events, but also several cases of usage increases and non-significant reductions. The usage reductions for the Coastal and Inland Opt-in PTR alert groups average 7.7 percent and 9.7 percent respectively, with the Inland estimates less variable across events. As shown in the last row, the aggregate load impact provided by the 4,631 SDEC participants is 0.08 MW for the average event.[11]

[11] This count of SDEC participants differs slightly from the value shown in Section 2 due to data availability. The count also excludes approximately 200 Summer Saver participants who also participated in SDEC, but were analyzed in the Summer Saver evaluation.

Table 4–1: Estimated Per-Customer and Aggregate PTR Usage Reductions – SDEC Participants

				Average Customer		Aggregate			
Event Date	Climate Zone	Notice	Num. of Accounts	Reference Load (kW)	Load Impact (kW)	Reference Load (MW)	Load Impact (MW)	% Load Impact	Ave. Event Temp.
07/20/2012	Coastal	SDEC Alert Only	2,524	0.60	0.037	1.51	0.093	6.2%	79.0
08/09/2012			2,524	0.63	0.012	1.59	0.031	2.0%	79.8
08/10/2012			2,524	0.67	0.020	1.68	0.051	3.1%	82.5
08/11/2012			2,524	0.74	-0.001	1.86	-0.002	-0.1%	83.1
08/14/2012			2,524	0.67	-0.011	1.69	-0.027	-1.6%	81.7
08/21/2012			2,524	0.59	-0.006	1.49	-0.014	-0.9%	75.2
09/15/2012			2,524	0.95	0.005	2.39	0.013	0.5%	96.2
Tot./Ave.			**2,524**	**0.69**	**0.008**	**1.75**	**0.021**	**1.2%**	**82.5**
07/20/2012	Coastal	Opt-in PTR Alert	582	0.64	0.111	0.37	0.064	17.4%	79.0
08/09/2012			582	0.65	0.038	0.38	0.022	5.8%	79.8
08/10/2012			582	0.70	0.087	0.41	0.050	12.3%	82.7
08/11/2012			582	0.77	0.038	0.45	0.022	4.9%	83.1
08/14/2012			582	0.70	0.033	0.41	0.019	4.7%	81.9
08/21/2012			582	0.60	0.026	0.35	0.015	4.4%	75.2
09/15/2012			582	0.99	0.055	0.57	0.032	5.6%	96.2
Tot./Ave.			**582**	**0.72**	**0.055**	**0.42**	**0.032**	**7.7%**	**82.6**
07/20/2012	Coastal	All	3,106	0.61	0.051	1.88	0.158	8.4%	79.0
08/09/2012			3,106	0.63	0.017	1.97	0.053	2.7%	79.8
08/10/2012			3,106	0.67	0.033	2.09	0.102	4.9%	82.5
08/11/2012			3,106	0.74	0.006	2.31	0.020	0.9%	83.1
08/14/2012			3,106	0.68	-0.002	2.10	-0.007	-0.3%	81.8
08/21/2012			3,106	0.59	0.000	1.84	0.001	0.1%	75.2
09/15/2012			3,106	0.96	0.014	2.97	0.045	1.5%	96.2
Tot./Ave.	**Coastal**		**3,106**	**0.70**	**0.017**	**2.17**	**0.053**	**2.4%**	**82.5**
07/20/2012	Inland	SDEC Alert Only	1,252	0.86	0.052	1.08	0.065	6.0%	82.5
08/09/2012			1,252	0.97	0.025	1.21	0.031	2.5%	83.8
08/10/2012			1,252	1.03	0.019	1.29	0.023	1.8%	85.6
08/11/2012			1,252	1.08	-0.050	1.35	-0.062	-4.6%	85.2
08/14/2012			1,252	1.06	-0.051	1.33	-0.064	-4.8%	86.5
08/21/2012			1,252	0.83	-0.005	1.03	-0.006	-0.6%	78.4
09/15/2012			1,252	1.50	0.011	1.87	0.014	0.8%	96.9
Tot./Ave.			**1,252**	**1.05**	**0.000**	**1.31**	**0.000**	**0.0%**	**85.6**
07/20/2012	Inland	Opt-in PTR Alert	273	0.83	0.095	0.23	0.026	11.4%	82.1
08/09/2012			273	0.97	0.101	0.26	0.028	10.5%	83.5
08/10/2012			273	1.01	0.060	0.28	0.016	5.9%	85.5
08/11/2012			273	1.12	0.075	0.30	0.021	6.8%	85.1
08/14/2012			273	1.07	0.092	0.29	0.025	8.6%	86.0
08/21/2012			273	0.84	0.094	0.23	0.026	11.2%	78.0
09/15/2012			273	1.53	0.199	0.42	0.054	13.0%	96.9
Tot./Ave.			**273**	**1.05**	**0.102**	**0.29**	**0.028**	**9.7%**	**85.3**
07/20/2012	Inland	All	1,525	0.86	0.060	1.31	0.091	7.0%	82.4
08/09/2012			1,525	0.97	0.038	1.47	0.058	4.0%	83.8
08/10/2012			1,525	1.02	0.026	1.56	0.040	2.5%	85.6
08/11/2012			1,525	1.09	-0.027	1.65	-0.042	-2.5%	85.2
08/14/2012			1,525	1.06	-0.025	1.62	-0.039	-2.4%	86.4
08/21/2012			1,525	0.83	0.013	1.26	0.020	1.6%	78.3
09/15/2012			1,525	1.50	0.045	2.29	0.069	3.0%	96.9
Tot./Ave.	**Inland**		**1,525**	**1.05**	**0.018**	**1.60**	**0.028**	**1.8%**	**85.5**
07/20/2012	All	All	4,631	0.69	0.054	3.19	0.248	7.8%	80.4
08/09/2012			4,631	0.74	0.024	3.44	0.111	3.2%	81.5
08/10/2012			4,631	0.79	0.031	3.65	0.141	3.9%	83.8
08/11/2012			4,631	0.86	-0.005	3.97	-0.022	-0.5%	84.0
08/14/2012			4,631	0.80	-0.010	3.72	-0.046	-1.2%	83.8
08/21/2012			4,631	0.67	0.005	3.10	0.021	0.7%	76.4
09/15/2012			4,631	1.14	0.024	5.26	0.113	2.2%	96.5
Tot./Ave.	**All**	**All**	**4,631**	**0.81**	**0.018**	**3.76**	**0.081**	**2.2%**	**83.8**

Figure 4–1: Estimated PTR Usage Reductions for SDEC Participants
Average Hourly Load Impacts (kWh), by Customer Group & Event



4.2 Load Impacts for Non-SDEC Opt-in Alert Customers, including Summer Saver Participants

Estimated load impacts for the approximately 41,000 customers outside of SDEC who opted to receive electronic event notifications, or alerts, are shown in Table 4–2 for each PTR event.[12] The average customer in the Coastal and Inland climate zones reduced usage by 0.062 kW and 0.067 kW respectively during event hours. Results varied considerably across events, particularly for the Inland climate zone. The estimated load impacts represent 5.8 percent and 4.2 percent of the reference loads for the two groups. Aggregate hourly usage reductions across both climate zones totaled 2.65 MW.

Table 4–2: Estimated Per-Customer and Aggregate PTR Usage Reductions – *Non-SDEC Opt-in Alert*

[12] The results shown are based on analysis of the sample of opt-in Alert customers. These results are then scaled up to the full group based on appropriate sample scaling factors.

Event Date	Climate Zone	Notice	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
07/20/2012	Coastal	Opt-In Alert	23,689	0.90	0.112	21.2	2.64	12.5%	76.9
08/09/2012			23,689	0.95	0.027	22.5	0.65	2.9%	78.0
08/10/2012			23,689	1.01	0.064	23.9	1.52	6.4%	80.0
08/11/2012			23,689	1.13	0.037	26.7	0.87	3.3%	81.3
08/14/2012			23,689	1.02	0.002	24.1	0.05	0.2%	79.3
08/21/2012			23,689	0.89	0.059	21.1	1.40	6.6%	75.2
09/15/2012			23,689	1.56	0.133	37.1	3.14	8.5%	93.8
Tot./Ave.			**23,689**	**1.06**	**0.062**	**25.2**	**1.47**	**5.8%**	**80.6**
07/20/2012	Inland	Opt-In Alert	17,554	1.27	0.145	22.3	2.55	11.5%	83.5
08/09/2012			17,554	1.49	0.074	26.2	1.30	5.0%	86.2
08/10/2012			17,554	1.59	0.034	27.8	0.60	2.1%	87.1
08/11/2012			17,554	1.71	-0.021	30.1	-0.36	-1.2%	86.8
08/14/2012			17,554	1.59	-0.015	27.9	-0.27	-1.0%	87.8
08/21/2012			17,554	1.21	0.059	21.3	1.03	4.9%	79.8
09/15/2012			17,554	2.22	0.193	38.9	3.39	8.7%	96.3
Tot./Ave.			**17,554**	**1.58**	**0.067**	**27.8**	**1.18**	**4.2%**	**86.8**
07/20/2012	All	Opt-In Alert	41,243	1.05	0.126	43.5	5.19	11.9%	80.3
08/09/2012			41,243	1.18	0.047	48.7	1.95	4.0%	82.4
08/10/2012			41,243	1.25	0.051	51.8	2.12	4.1%	83.8
08/11/2012			41,243	1.38	0.012	56.7	0.51	0.9%	84.2
08/14/2012			41,243	1.26	-0.005	52.0	-0.22	-0.4%	83.8
08/21/2012			41,243	1.03	0.059	42.4	2.44	5.7%	77.5
09/15/2012			41,243	1.84	0.158	76.0	6.53	8.6%	95.1
Tot./Ave.			**41,243**	**1.29**	**0.064**	**53.0**	**2.65**	**5.0%**	**83.9**

Table 4–3 summarizes estimated PTR load impacts for all three groups of opt-in alert customers: 1) Summer Saver participants who also opted to receive PTR alerts, 2) those SDEC participants who opted to receive PTR alerts (as reported in Table 4–1), and 3) the opt-in alert customers whose results are reported in Table 4–2. The Summer Saver results were developed in that program's evaluation, and are reported here and in the associated Protocol tables for completeness.[13] The PTR usage reductions of Summer Saver participants who opted to receive PTR alerts are notably larger in both level and percentage terms than the opt-in alert customers in the other two groups.[14] They also have substantially larger reference loads. Aggregate PTR load impacts across the three groups of opt-in alert customers total 3.9 MW for the average event, or 6.6 percent of the total reference load.

[13] The Summer Saver evaluation is documented in "2012 *Ex post* and *Ex ante* Load Impact Evaluation of San Diego Gas & Electric Company's Summer Saver Program and Peak Time Rebate Program for Summer Saver Customers," April 1, 2013, by Freeman, Sullivan and Company.

[14] Like the current study, the evaluation of PTR load impacts for Summer Saver participants found no significant usage reductions for those who did not opt to receive PTR alerts.

Table 4–3: Per-Customer and Aggregate PTR Usage Reductions –
All Opt-in Alert, including Summer Saver and SDEC

Event Date	Climate Zone	Notice	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
07/20/2012	All	Summer Saver Opt In Alert	2,917	1.24	0.323	3.63	0.943	26.0%	81.3
08/09/2012			2,917	1.60	0.431	4.67	1.256	26.9%	83.1
08/10/2012			2,917	1.58	0.344	4.62	1.002	21.7%	84.1
08/11/2012			2,917	1.85	0.417	5.41	1.217	22.5%	84.4
08/14/2012			2,917	1.89	0.453	5.53	1.322	23.9%	83.8
08/21/2012			2,917	1.12	0.190	3.26	0.554	17.0%	78.1
09/15/2012			2,917	2.54	0.583	7.41	1.702	23.0%	97.8
Average			**2,917**	**1.69**	**0.392**	**4.932**	**1.142**	**23.2%**	**84.7**
07/20/2012	All	SDEC Opt-In Alert	855	0.70	0.106	0.60	0.090	7.8%	80.4
08/09/2012			855	0.75	0.058	0.64	0.050	3.2%	81.5
08/10/2012			855	0.80	0.078	0.69	0.067	3.9%	83.8
08/11/2012			855	0.88	0.050	0.75	0.042	-0.5%	84.0
08/14/2012			855	0.82	0.052	0.70	0.044	-1.2%	83.8
08/21/2012			855	0.68	0.048	0.58	0.041	0.7%	76.4
09/15/2012			855	1.16	0.101	0.99	0.086	2.2%	96.5
Average			**855**	**0.83**	**0.070**	**0.71**	**0.060**	**8.5%**	**83.8**
07/20/2012	All	Non-SS, Non-SDEC Opt-In Alert	41,243	1.05	0.126	43.5	5.19	11.9%	80.3
08/09/2012			41,243	1.18	0.047	48.7	1.95	4.0%	82.4
08/10/2012			41,243	1.25	0.051	51.8	2.12	4.1%	83.8
08/11/2012			41,243	1.38	0.012	56.7	0.51	0.9%	84.2
08/14/2012			41,243	1.26	-0.005	52.0	-0.22	-0.4%	83.8
08/21/2012			41,243	1.03	0.059	42.4	2.44	5.7%	77.5
09/15/2012			41,243	1.84	0.158	76.0	6.53	8.6%	95.1
Average			**41,243**	**1.29**	**0.064**	**53.0**	**2.65**	**5.0%**	**83.9**
07/20/2012	All	All Opt-In Alert	45,015	1.06	0.138	47.7	6.23	13.0%	80.3
08/09/2012			45,015	1.20	0.072	54.0	3.25	6.0%	82.4
08/10/2012			45,015	1.27	0.071	57.1	3.19	5.6%	83.8
08/11/2012			45,015	1.40	0.039	62.9	1.77	2.8%	84.2
08/14/2012			45,015	1.29	0.026	58.2	1.15	2.0%	83.8
08/21/2012			45,015	1.03	0.067	46.2	3.03	6.6%	77.5
09/15/2012			45,015	1.88	0.185	84.4	8.32	9.9%	95.3
Average			**45,015**	**1.30**	**0.085**	**58.6**	**3.85**	**6.6%**	**83.9**

4.3 Load Impacts of IHD Customers

Table 4–4 reports per-customer and aggregate load impacts for the customers with installed IHD devices. The average hourly per-customer load impacts are comparable in magnitude to those of the opt-in alert customers, at 0.6 kW. However, the reference loads are greater, resulting in smaller percentage load impacts.

Table 4–4: Per-Customer and Aggregate PTR Usage Reductions –
IHD Customers

Event Date	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
20-Jul-12	655	1.86	0.23	1.22	0.15	12%	72.7
9-Aug-12	654	2.04	0.05	1.34	0.03	2%	75.3
10-Aug-12	654	2.19	0.06	1.43	0.04	3%	76.2
11-Aug-12	654	2.30	-0.02	1.51	-0.02	-1%	76.5
14-Aug-12	654	2.17	-0.05	1.42	-0.03	-2%	75.9
21-Aug-12	653	1.80	0.05	1.17	0.03	3%	72.4
15-Sep-12	652	2.92	0.10	1.90	0.07	4%	83.8
Average	**654**	**2.18**	**0.06**	**1.43**	**0.04**	**3%**	**76.1**

4.4 Load Impacts by Customer Size, Standard/Low-income Rates, and Awareness

This section reports additional breakdowns of *ex post* load impacts by the following categories of customers:

- Customer size (low, medium, and high-usage categories);
- Income category, defined by the domestic tariffs (standard or low-income); and
- Customers who were categorized as "aware" of specific PTR events on the basis of their responses to a separate customer survey.

4.4.1 Results by customer size and income category

The breakdowns by customer size and income category are shown in Table 4–5 for the SDEC participants and opt-in Alert groups, the only ones to provide significant usage reductions. The pattern of usage reductions across customer size generally follows the size of reference load, with the exception of the high-usage SDEC group. The percentage load impacts for the opt-in Alert customers are close to 5 percent for each usage category. The average low-income customers in both groups have slightly lower reference loads and load impacts, resulting in somewhat smaller percentage load impacts than the standard tariff customers.

Table 4–5: Estimated PTR Usage Impacts by Usage Level and Low Income –
SDEC and Opt-in Alert

			Average Customer		Aggregate			
Notice	Customer Group	Number of Accounts	Reference Load (kW)	Load Impact (kW)	Reference Load (MW)	Load Impact (MW)	% Load Impact	Average Event Temp.
SDEC	Low	2,009	0.36	0.011	0.7	0.022	3.0%	82.9
	Medium	2,315	0.98	0.024	2.3	0.054	2.4%	83.8
	High	307	2.50	0.016	0.8	0.005	0.6%	84.4
	Total/Average	**4,631**	**0.81**	**0.018**	**3.8**	**0.081**	**2.2%**	**83.5**
Opt-in Alert	Low	11,441	0.41	0.018	4.7	0.210	4.5%	82.5
	Medium	22,834	1.21	0.059	27.7	1.352	4.9%	83.6
	High	6,968	2.97	0.155	20.7	1.083	5.2%	84.5
	Total/Average	**41,243**	**1.29**	**0.064**	**53.0**	**2.646**	**5.0%**	**83.4**
SDEC	Standard	3,061	0.84	0.020	2.6	0.061	2.4%	83.8
	Low Income	1,570	0.75	0.013	1.2	0.020	1.7%	83.7
	Total/Average	**4,631**	**0.81**	**0.018**	**3.8**	**0.081**	**2.2%**	**83.8**
Opt-in Alert	Standard	31,852	1.33	0.067	42.4	2.143	5.1%	83.6
	Low Income	9,391	1.13	0.054	10.6	0.503	4.7%	84.8
	Total/Average	**41,243**	**1.29**	**0.064**	**53.0**	**2.646**	**5.0%**	**83.9**

4.4.2 Results by customer awareness

To examine the effect of customer awareness on estimated PTR usage reductions, we conducted a separate analysis of load data for a sample of customers who responded to a post-event survey of SDG&E customers that was conducted as part of the PTR process evaluation. Approximately 2,000 non-Summer Saver customers were surveyed, the majority of which were conducted online. The customers were asked a series of questions regarding their general awareness of the PTR program and their ability to earn credits. One specific question asked about their specific awareness of the September 15 event, shortly after which the survey was undertaken. We used their response to that question as an indicator of awareness, and compared usage changes for "aware" and "non-aware" customer groups.

The surveyed customers were drawn from the following four customer groups for which we have reported estimated usage reductions:

- SDEC customers receiving only default SDEC alerts;
- SDEC customers who opted to receive PTR alerts;
- Non-SDEC customers who opted to receive PTR alerts (Opt-in alert);
- Non-SDEC customers who received no alerts (no-alert population).

We divided the surveyed customers into eight groups, consisting of "aware" and "non-aware" versions of each of the above four groups. We then averaged the hourly loads across all sample customers in each group, and applied our standard regression model to estimate hourly load impacts for each event. The resulting reference loads and load impacts are summarized in Table 4–6. With the exception of the "No Alert" group in the last row, the aware customers show greater usage reductions than non-aware customers, especially for the two Opt-in Alert groups

(SDEC and non-SDEC), for which the estimated load impacts are substantially larger. On the basis of this limited information, it appears that the combination of taking the initiative to request electronic notification of events and understanding the operation of the program sufficiently to be aware when events are called tends to produce the greatest usage reductions on event days.

Table 4–6: Effect of Awareness on Estimated PTR Usage Reductions – *(Customers Responding to Post-Event Survey)*

Group	Notice Type	Aware?	Number of Survey Responses	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	% Load Impact	Average Event Temp.
SDEC	Default Alert	No	165	0.79	0.028	3.5%	83.3
		Yes	286	0.78	0.030	3.9%	83.5
	Opt-in Alert	No	43	0.85	0.018	2.1%	83.6
		Yes	103	0.78	0.115	14.8%	83.0
PTR (Non-SDEC)	Opt-in Alert	No	205	1.36	0.061	4.5%	82.4
		Yes	395	1.30	0.099	7.6%	83.0
	No Alert	No	499	1.33	-0.018	-1.4%	83.1
		Yes	358	1.35	-0.009	-0.7%	83.0

4.5 Summary of PTR Load Impacts for the Average Event across Major Customer Groups

No significant usage reductions were found for the average customer in the population that did not participate in SDEC, receive an IHD or PCT device, or opt in to receive PTR alerts. Thus, a presentation of results by event for these customers is of little value. Instead, Table 4–7 summarizes results for the average event for all relevant SDG&E customer groups, differentiated by climate zone where available. The first three rows in each panel show results for SDEC participants, those customers opting to receive PTR alerts, and those with IHD/PCT devices. Overall, those groups reduced usage on average during PTR events by 2.2, 5.0, and 2.7 percent respectively. The PTR usage impacts for the Summer Saver participants who opted to receive PTR alerts are shown in the last line of the "All" results, since those results were not reported by climate zone.

The remaining population is shown divided approximately evenly among those who registered for MyAccount and those that did not. Little difference was found between those two groups, and the average estimated load impacts implied usage *increases* during PTR events, though those estimated increases were not statistically significant (see below). These estimates likely reflect event-day responses to weather or other unknown factors that are not fully explained by the regression equations.

Table 4–7: Estimated PTR Usage Impacts by Major Customer Group

Customer Group	Climate Zone	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
All SDEC	Coastal	3,106	0.70	0.017	2.2	0.05	2.4%	82.5
Opt-in Alert		23,689	1.06	0.062	25.2	1.47	5.8%	80.6
IHD/PCT		359	1.88	0.076	0.7	0.03	4.0%	81.6
MyAccount		318,849	0.93	-0.010	296.7	-3.34	-1.1%	80.9
Non-MyAccount		343,859	0.91	-0.019	311.8	-6.52	-2.1%	80.8
Total/Average		**689,861**	**0.92**	**-0.012**	**636.6**	**-8.31**	**-1.3%**	**80.9**
All SDEC	Inland	1,525	1.05	0.018	1.6	0.03	1.8%	85.5
Opt-in Alert		17,554	1.58	0.067	27.8	1.18	4.2%	86.8
IHD/PCT		295	2.55	0.039	0.8	0.01	1.5%	86.6
MyAccount		234,138	1.52	-0.046	354.9	-10.74	-3.0%	86.4
Non-MyAccount		257,300	1.33	-0.040	343.3	-10.29	-3.0%	86.3
Total/Average		**510,812**	**1.43**	**-0.039**	**728.3**	**-19.81**	**-2.7%**	**86.4**
All SDEC	All	4,631	0.81	0.018	3.8	0.08	2.2%	83.8
Opt-in Alert		41,243	1.29	0.064	53.0	2.65	5.0%	83.9
IHD/PCT		654	2.18	0.059	1.4	0.04	2.7%	84.3
MyAccount		552,987	1.18	-0.025	651.6	-14.08	-2.2%	83.9
Non-MyAccount		601,158	1.09	-0.028	655.2	-16.80	-2.6%	83.7
SS Opt-in Alert		*2,917*	*1.69*	*0.392*	*4.9*	*1.14*	*23.2%*	*84.7*
Total/Average		**1,203,590**	**1.14**	**-0.022**	**1,369.9**	**-26.98**	**-2.0%**	**83.8**

4.6 Program-Level Load Impacts and Confidence Intervals

It is of interest to examine confidence intervals around the estimated PTR load *reductions* for the Opt-in Alert customers and the load *increases* estimated for the remaining population. Table 4–8 shows customer counts, reference loads, estimated load impacts (for the average event-hour of the average event), and 90% confidence intervals for the above two groups of SDG&E PTR customers in 2012. The first row in the table shows results for the opt-in Alert group. The second row shows results for the general population, excluding opt-in Alert customers and SDEC participants. The Alert group shows an overall load reduction of 3.1 MW, or nearly 6 percent of their aggregate reference load. The estimated load impacts are statistically significant, and a 90 percent confidence interval ranges from 1.7 to 4.6 MW of load reduction.[15]

The estimated load impacts for the general non-alert population are negative, indicating higher usage on event days than predicted by the other variables in the regression models, including weather effects. However, the estimates are not statistically significant (that is, they cannot be

[15] To simplify the calculation of confidence intervals, the values in this table are developed from group-level models, rather than the customer-level regressions, where the groups are distinguished by climate zone and customer size. Load impact coefficients and standard errors from the six group-level models for the opt-in Alert and non-alert population were then combined using appropriate sample scaling factors to produce standard errors for the two overall groups.

distinguished statistically from zero), which produces a relatively wide 90 percent confidence interval, ranging from a usage *increase* of 4.0 percent to a usage reduction of 0.7 percent.

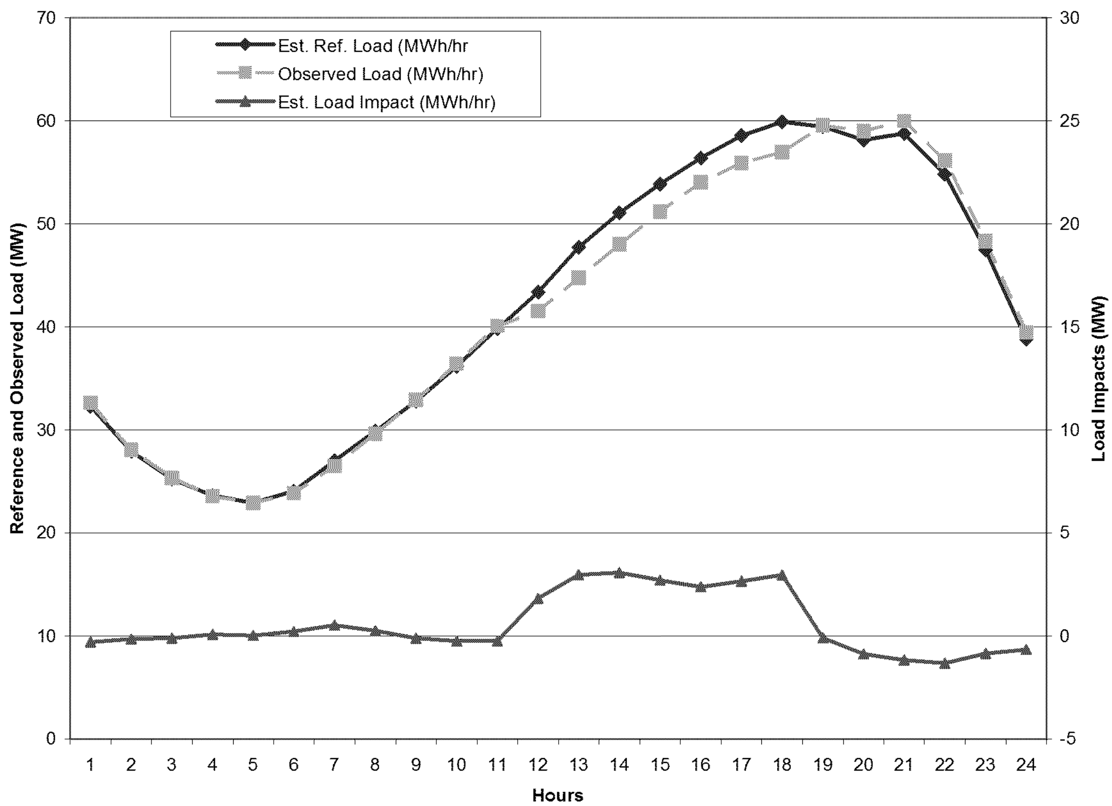
Table 4–8: Overall PTR Usage Reductions and Confidence Intervals –
Opt-in Alert and Non-Alert Population

Group	Count	Ave. LI (kW)	Stand. Error	Tot. Ref. Load (MW)	Tot. LI (MW)	Conf. Interval (90%) Lower	Conf. Interval (90%) Upper
Opt-in Alert	41,243	0.076	0.021	53	3.1	1.7	4.6
% of Ref. Load					5.8%	3.1%	8.5%
Population (Non-Alert)	1,154,144	-0.018	0.015	1,227	-20.3	-49.4	8.8
% of Ref. Load					-1.7%	-4.0%	0.7%

4.7 Hourly PTR Load Impacts

Figure 4–2 illustrates the hourly profile of the estimated reference load, observed load and estimated load impacts for the overall opt-in Alert group on the average PTR event day. Note the observable kink in the observed load in the first hour of the event (hour-ending 12 noon) and the relatively constant estimated usage reduction of about 3 MWh/hour over the event period.

Figure 4–2: Hourly Estimated Reference Load, Observed Load, and Estimated Load Impacts –
Opt-in Alert; Average Event



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4.8 Customer-Level Load Impacts

This section provides summary statistics from the customer-level regressions on the fractions of customers in various groups whose estimated load impacts were either negative and significant (*i.e.*, load reductions) or positive and significant (*i.e.*, load increases). The first two columns in Table 4–9 show percentages of customers whose estimated load impacts implied statistically significant load reductions on average across all events and event hours.[16] The six categories of Alert and non-Alert Population customers are defined by climate zone and usage levels. The percentages of significant "reducers" range from about 25 percent for low-usage customers in the Coastal climate zone to 38 percent for high-usage customers in the same zone. While the average population customer showed no significant reduction, as reported in Section 4.2, the table shows that 17 to 21 percent of those customers were found to have significantly reduced usage.

The last two columns show percentages of customers in the six groups whose estimated load impacts were positive and significant, indicating higher usage during PTR event periods. Since there is no logical reason for customers to increase usage *because of* the event, we can only surmise that the event variables in the regression are picking up the effect of some unknown omitted variable, such as an extreme weather effect that is not accounted for by the weather variables in the regression. Nevertheless, even in the overall responsive Alert group, 14 to 24 percent of customers were found to have positive and significant event coefficients. Those percentages are higher in the Population groups, ranging from 18 to 32 percent.

Table 4–9: Fractions of Significant Customer-Level Usage Reductions and Increases –
Opt-in Alert and Non-Alert Population

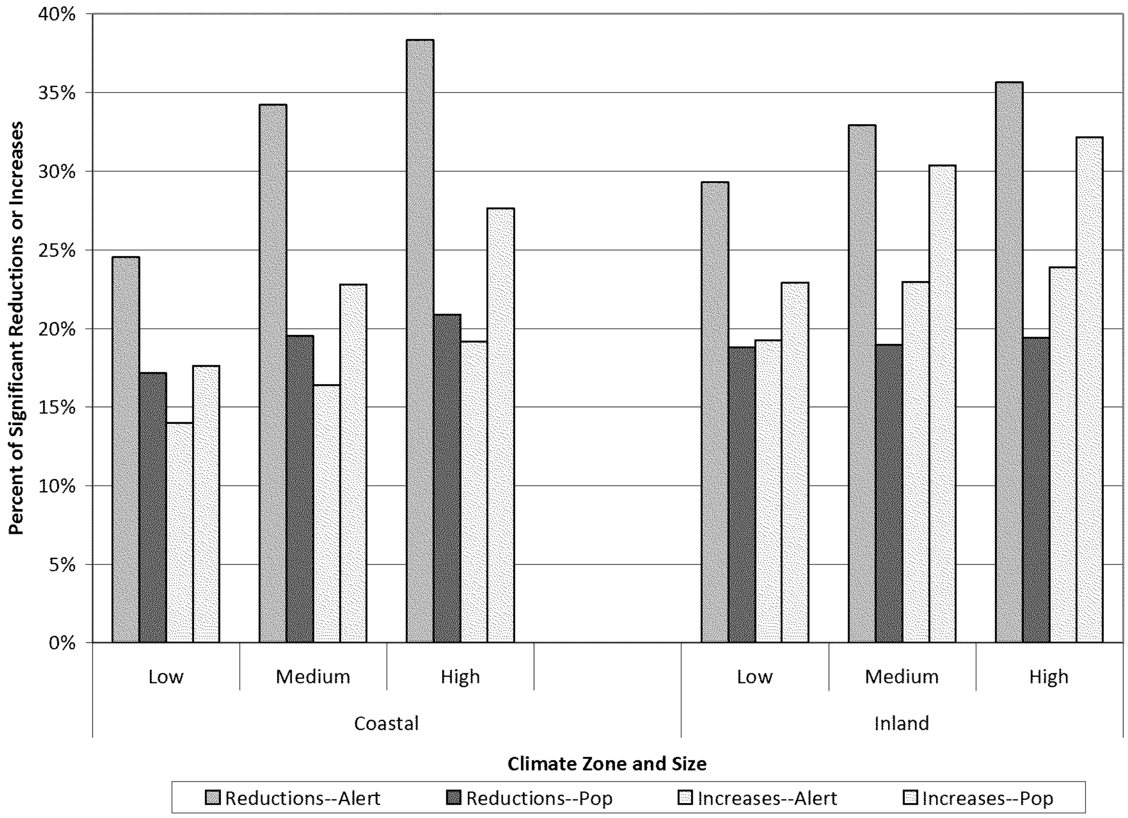
Climate Zone /	Percent Signif. Reductions		Percent Signif. Increases	
Usage Category	Opt-in Alert	Population	Opt-in Alert	Population
Coastal				
Low	24.5%	17.2%	14.0%	17.6%
Medium	34.2%	19.5%	16.4%	22.8%
High	38.4%	20.9%	19.1%	27.6%
Inland				
Low	29.3%	18.8%	19.3%	22.9%
Medium	32.9%	19.0%	23.0%	30.4%
High	35.6%	19.4%	23.9%	32.2%

Averaging the estimated load impacts across the opt-in alert responders produces average usage reductions for the average event of 0.31 and 0.45 kWh per hour for the Coastal and Inland climate zones respectively, or 0.37 kWh per hour for the whole group of opt-in alert responders. This contrasts with the estimated 0.06 kWh per hour usage reduction for the average opt-in alert customer (including responders and non-responders).

[16] This criterion is relatively strict and indicative of consistent usage reductions. That is, load impacts were estimated for each hour of each event, and the criterion used to calculate the percentage of, for example, significant "reducers" is that the average load impact across all hours and events was negative and significant.

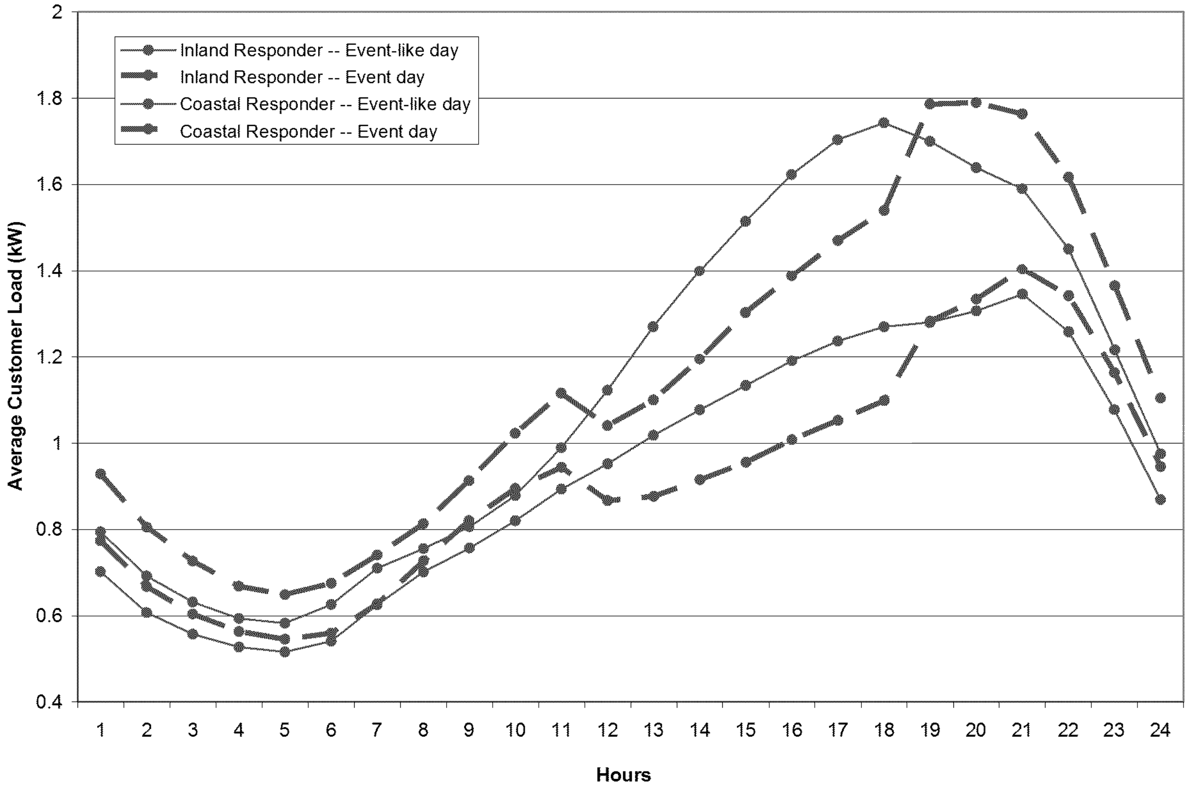
Figure 4–3 illustrates the findings shown in Table 4–9. The bars show generally larger percentages of significant "reducers" at higher levels of usage among the Alert groups and relatively constant percentages for the Population groups. On the flip side, percentages of "increasers" tend to increase with usage level for the Population groups and increase by lesser amounts for the Alert groups. All of the above trends are consistent with the overall finding of statistically significant usage reductions for the Alert customers, and not statistically significant usage increases for Population customers.

Figure 4–3: Fractions of Significant Customer-Level Usage Reductions and Increases – ***Opt-in Alert and Non-Alert Population***



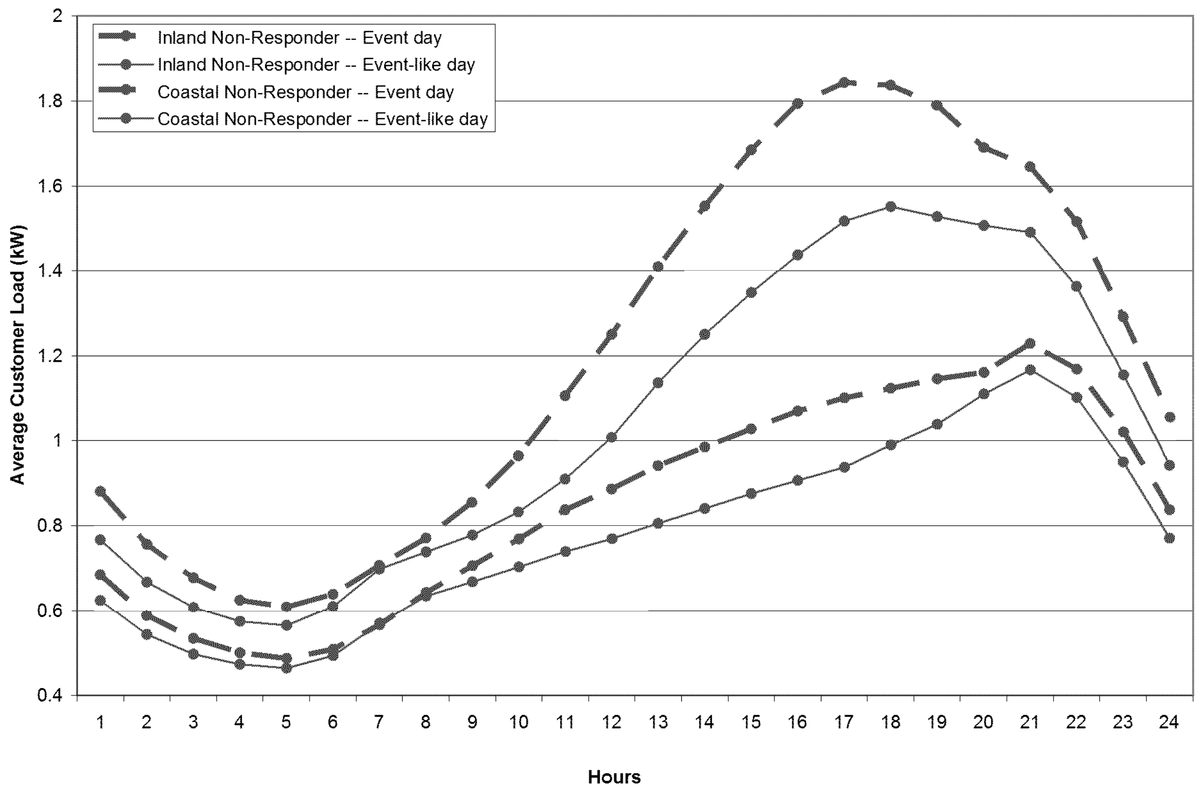
To illustrate the usage patterns of the customers who were found to be "responders," Figure 4–4 shows the average responder load profile (collapsed across usage category) for the average event day and the average event-type day, for the Coastal and Inland climate zones. The event-day load profiles, shown in heavy dashed lines, display clear evidence of "notched" usage reductions during the seven-hour event period. In contrast, the average loads on event-like non-event days show no such notched behavior.

Figure 4–4: Average Load Profiles for Responders on Events and Event-like Days – ***Opt-in Alert; Coastal and Inland***



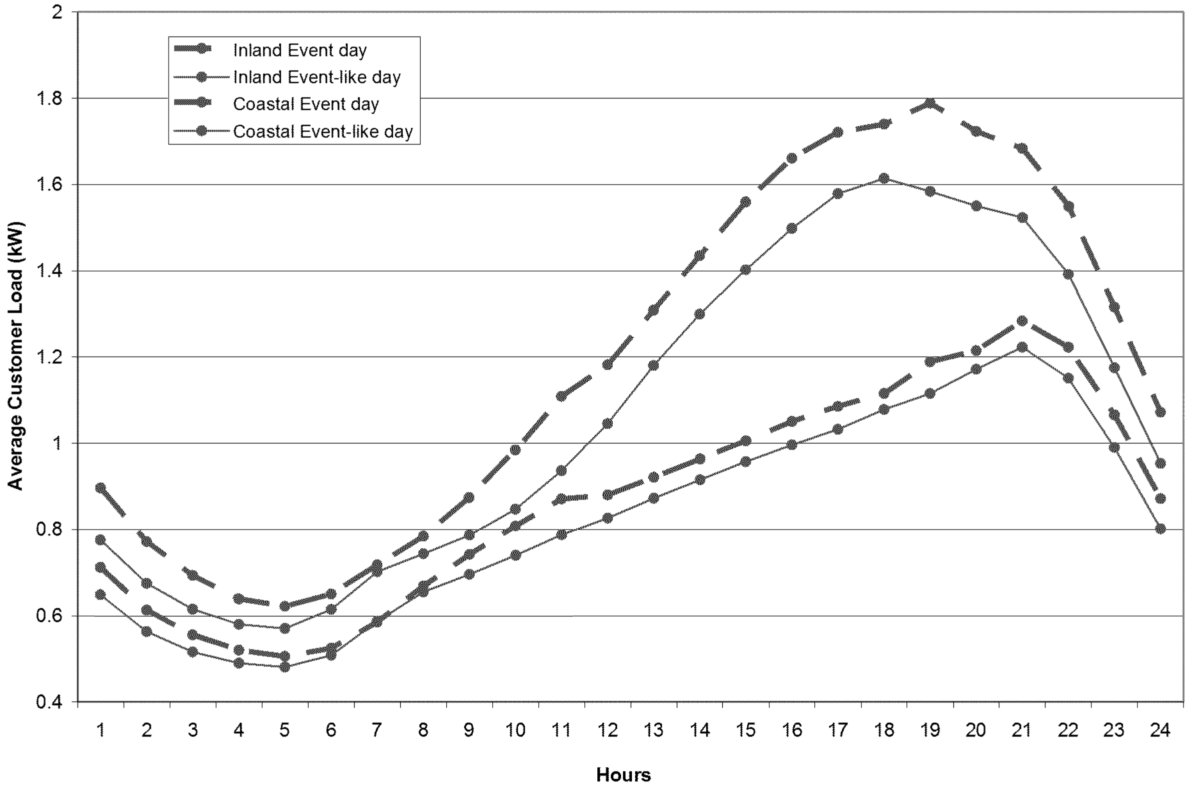
In contrast, Figure 4–5 shows load profiles averaged across the same days for all opt-in alert customers except the responders shown in the previous figure, including those found to have increased usage by significant amounts. In this case, the event-day loads are higher than the non-event day loads, substantially so for the Inland customers, and show no evidence of event-day usage reductions.

Figure 4–5: Average Load Profiles for Non-Responders on Events and Event-like Days – ***Opt-in Alert; Coastal and Inland***



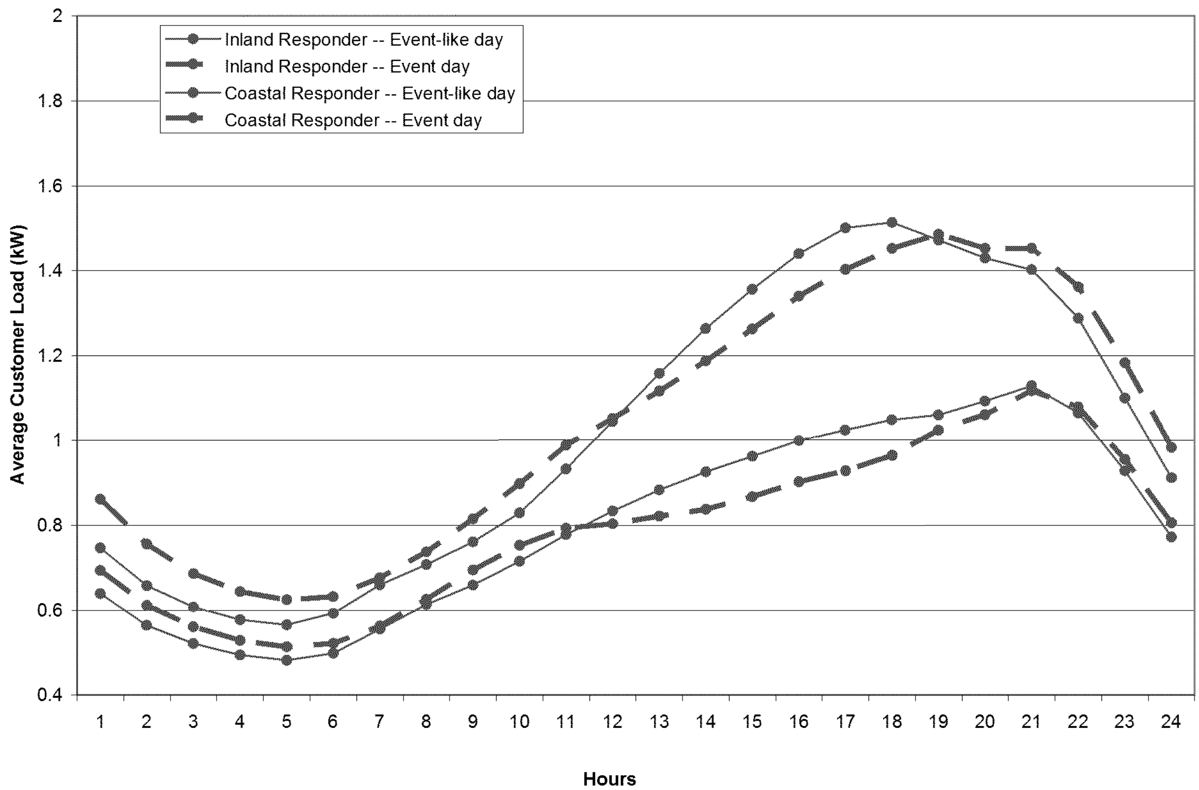
To complete the picture for opt-in alert customers, Figure 4–6 shows event-day and non-event day load profiles averaged across all of those customers, by climate zone. It is effectively this type of averaging that is done when reporting the average customer usage impacts in the *ex post* evaluation. Focusing on the heavy dashed event-day lines, it is possible to see slight event-period notches beginning in hour-ending 12 and ending in hour-ending 18. These slight notches, formed by combining the strongly significant usage reductions of the "responders" in Figure 4–4 with the non-responders in Figure 4–5, represent the small but statistically significant usage reductions (*e.g.*, 0.07 kWh per hour) reported for the average opt-in alert customer.

Figure 4–6: Average Load Profiles for All Opt-in Alert Customers on Events and Event-like Days – ***Coastal and Inland***



In contrast to the well-defined notches of event-period usage reductions for the opt-in alert "responders," Figure 4–7 shows only slightly-defined reductions for the average customer in the non-alert population with statistically significant usage reductions.

Figure 4–7: Average Load Profiles for Responders on Events and Event-like Days –
Non-Alert Population; Coastal and Inland



4.9 Summary of *Ex Post* Load Impacts

The primary overall finding from the *ex post* portion of the study is that only customers who opted to receive electronic notifications, or alerts, of PTR events reduced their electricity usage on average during PTR event hours. They did so by relatively small but statistically significant amounts of 0.064 to 0.07 kWh per hour, or 5 to 8.5 percent of their reference load.[17] These opt-in alert customers include 855 of the SDEC customers (the remaining SDEC customers received default email notifications through the program), and 41,000 customers from the general population.[18] Approximately 650 customers with IHD devices also reduce usage in comparable amounts. However, the average customer in the remaining population of more than 1 million customers did not reduce usage by any significant amount. In fact, most estimates indicated increases in usage (not statistically significant), likely due to unknown factors such as potentially greater weather-sensitive usage on event days than could be explained by the regression models.

[17] Close examination of customer-level results indicates that about 25 to 35 percent of the opt-in alert customers, differentiated by climate zone and size, reduced usage by consistent and statistically significant amounts on the order of 5 to 6 times the magnitude of the average opt-in alert customer.

[18] Approximately 2,900 Summer Saver participants also opted to receive PTR alerts, and they reduced usage on average by 0.4 kW, or 23 percent, where these greater usage reductions are presumably due in part to their air conditioning usage capacity, which is larger than for non-SS customers.

5. CRL SETTLEMENT AND BASELINE ANALYSIS

5.1 Introduction

One additional objective of the *ex post* evaluation is to report a number of statistics on the relationship between customers' CRLs (*i.e.*, the program baselines) and their observed usage levels during 2012 PTR event hours. Another is to assess the performance of the program CRL method in representing customers' loads on event days and event-like days. As mentioned in Section 1, customers' CRLs, which serve as the basis for settlement and bill credits, are based on an average of their highest 3 out of the most recent 5 similar non-event days.[19]

The first category of analysis involves summarizing PTR event-day usage changes as measured by the program CRL and comparing those values to load impacts estimated in the *ex post* evaluation and reported in Section 4. A second category of analysis involves a baseline analysis of the performance of the CRL in representing customers' baseline usage levels during event days or event-like days. As part of this analysis, we examine the frequency with which customers appear to have been *over-paid* or *under-paid* for usage reductions, where the findings are based on estimated usage reductions from the customer-level regressions in the *ex post* evaluation.[20]

The first category of CRL analysis involves producing the following statistics:

- The number (and percent) of customers who used less than their CRL for each event;
- The total load reduction measured according to the CRL, by event, including data for all customers; and
- The total load reduction by event according to the CRL, for only those customers who used less than their CRL (this amount represents the PTR load reduction for which SDG&E paid bill credits).

5.2 Methodology

The calculations of customers' usage relative to their CRLs were conducted in the following steps:

- Construct CRLs for each event and each customer included in the *ex post* load impact evaluation;
- Compare those values to the customers' *observed* usage during the event;

[19] The "highest" days are those with the highest total consumption between the event window hours of 11 a.m. to 6 p.m. For events called on weekend or holiday days, the CRL is total consumption during the above hours on the highest of the three preceding weekend days.

[20] Some have referred to the case of over-payments as "free ridership," presumably as an analog to the case of customers receiving energy efficiency payments for actions that they would have taken in any case. However, the analogy is not strictly appropriate for demand response programs, since customers have no incentive to reduce usage without the bill credit offer. In addition, others have pointed out the importance of the flip side of under-payments in cases where the CRL under-states what customers' loads would have been on an event day. It is generally accepted that the best estimate of that load is the reference load implied by the customer-level *ex post* regressions.

- Summarize differences in usage relative the CBLs, for those whose usage fell below their CRL, those whose usage was greater than the CRL, and for all customers; and
- Compare the overall CBL-based usage reductions to those estimated in the *ex post* evaluation.

The CRL baseline analysis was conducted for both *actual* event days in 2012, as well as a set of event-like non-event days, or *simulated* events, in July, August, and September. In the case of *actual events*, customers' CRLs were compared to the reference loads implied by the customer-level regression analyses conducted in the 2012 *ex post* evaluation (*i.e.*, estimated load impacts are added to the observed event-day loads to create a "but for the event" reference load). In the case of selected *simulated* events, the *observed loads* during the event window on the event-like days serve as true baselines, which are then compared to the calculated CRLs.

Two types of performance metrics were calculated for the CRL baseline: 1) measures of *accuracy* (*e.g.*, the average of absolute values of the errors), and 2) measures of *bias* (*i.e.*, the tendency of a baseline to under-state or over-state the true baseline). In both types of metrics, the calculations begin with the basic notion of a *baseline error*, which is the difference between the baseline for that period that is "predicted" by the program CRL method and the "actual," or "true," baseline during an event window. Under this convention, a positive error implies that the CRL prediction *exceeds* the true baseline (*i.e.*, it is biased upward). Given stakeholders' interest in the bill credit impacts suggested by baseline errors, most of the baseline performance results are reported in terms of levels of errors. However, since levels of errors can differ substantially across customers due to differences in load *levels*, it can also be useful to divide baseline errors by the level of the true baseline load to produce *percentage* errors. These are discussed below. It is also instructive to calculate and report baseline performance statistics for different types of events (*e.g.*, events on weekdays and weekends, or isolated hot days vs. consecutive events), and to report distributions of baseline errors as well as mean or median values.

5.2.1 Accuracy

A common accuracy metric is the average of the absolute values of the errors or percent errors over the relevant observations, such as customers and events, where smaller values represent greater accuracy. The key feature of these measures is that the absolute values treat positive and negative errors equally, rather than, for example, allowing them to cancel each other in the averaging process. The relevant formulas for Mean Absolute Error (MAE), or Mean Absolute Percentage Error (MAPE), are the following:

$MAE = (1/n) \sum |(L^P_i - L^A_i)|$, and
$MAPE = (1/n) \sum |(L^P_i - L^A_i)| / L^A_i$,
where the summation is over all observations, i = 1 to n of customers and event hours,
L^A_h is the "actual" observed or regression-based baseline load, and
L^P_h is the CRL *predicted* baseline load.

5.2.2 Bias

Bias metrics are designed to measure the extent to which errors tend to be positive or negative, or in the present application, for the CRL method to have a tendency to under-state or over-state true baseline values. Three basic metrics have been used in previous baseline studies to indicate the degree of bias—*mean* error, *median* error, and *percentiles* of the distribution of errors, where the errors may be stated in levels or percentages. The *mean* error is simply the average of errors across events and/or customers. The *median* error is the midpoint of the distribution of errors.

A principle advantage of the median, rather than the mean in the context of baseline errors, is that errors and percentage errors for some customers can be quite large, and can sometimes dominate the mean value, making it not representative of the full distribution. Presenting percentile statistics provides a more comprehensive picture of the full distribution of baseline errors than either the mean or median values alone. This study reports mean and median errors, along with standard deviations, and the following percentile values: 10%, 25%, 50% (the median value), 75%, and 90%.

5.3 CRL settlement and baseline analysis results

5.3.1 CRL-based statistics

Table 5–1 reports total changes in usage relative to the CRL, in PTR event-windows, on each event day, for three categories of customers—those who were observed to have reduced usage relative to their CRL ("reducers"), those who increased usage relative to their CRL ("increasers"), and net effect for all customers.[21] The first three columns show the event date, the number of customers who reduced usage, and their percentage of the total. The next three columns show the total usage changes of reducers, increasers, and all customers. The last two columns show the net impacts per hour for the seven-hour event window, and that net impact per hour per customer.

The percentage of reducers relative to the program CRL averages 60 percent, and ranges from somewhat more than half of all consumers on the two Saturday events (August 11 and September 15) to 80 percent on the August 21 event. Total energy *reductions* of the "reducers" during event hours averaged 1,711 MWh, ranging from approximately 1,100 to 3,500 MWh across events. Total *increases* in energy consumption relative to the CRL for the "increasers" averaged 1,613 MWh, and ranged from 362 to nearly 3,000 MWh. The overall net impact measured by the CRLs averaged a reduction of about 100 MWh, or 14.0 MW per event-hour, and ranged from an estimated net reduction of more than 3,000 MWh on the August 21 event to a net increase of nearly 1,500 MWh on August 11.

Table 5–1: PTR Usage Impacts by Reducers and Increasers

[21] By convention, reductions in usage are shown as positive values and increases in usage as negative values.

Event	Number of Reducers	Reducers as Percent of Total	Total Impact of Reducers (MWh)	Total Impact of Increasers (MWh)	Total Net Impact (MWh)	Net Impact per Hour (MW)
20-Jul-12	690,708	58%	1,070	-1,395	-325	-46.4
9-Aug-12	685,615	60%	1,292	-1,132	160	22.8
10-Aug-12	639,059	56%	1,246	-1,526	-280	-39.9
11-Aug-12	597,541	53%	1,510	-2,977	-1,467	-209.5
14-Aug-12	678,356	60%	1,495	-1,230	266	37.9
21-Aug-12	906,797	80%	3,481	-362	3,119	445.6
15-Sep-12	621,470	55%	1,879	-2,667	-789	-112.7
Average	**688,507**	**60%**	**1,711**	**-1,613**	**98**	**14.0**

Table 5–2 converts the changes in usage for the average event in Table 5–1 to average event hour values (*i.e.*, by dividing the average event values by 7), and shows how they are distributed across key customer groups, including the SDEC customers, customers who opted to receive electronic alerts, those with IHDs or PCTs, and the remaining population. The last column reproduces the average hourly *ex post* load impacts for the same groups, as reported in Section 4. The third column, showing the total CRL-based usage reductions of "reducers," represents the total amount of average hourly usage reductions (244.8 MW) for which SDG&E paid bill credits in 2012, for each event-hour on average. However, those usage reductions were offset by the usage increases shown in the fourth column, with net effects shown in the next column. Those values may be compared to the *ex post* load impacts in the last column.

The net impacts as measured by the CRLs are uniformly greater than the *ex post* load impacts in the first three rows, ranging from 50 percent greater for the opt-in alert customers, and twice as great for the IHD customers, to four times as great for SDEC customers. For the much larger number of customers in the remaining population, the CRL-based impacts indicate net average hourly *usage reductions* of 10 MW, while the *ex post* impact estimates represent load *increases* of 14 MW (though they are not statistically significant). At the same time, bill credits are paid for the 245 MW of average hourly usage reductions measured relative to the CRLs.

Table 5–2: Average Hourly PTR Usage Impacts (MW) by Customer Group and Method

Group	Number of Reducers	Reducers as Percent of Total	Impact of *Reducers* per Hour (CRL)	Impact of *Increasers* per Hour (CRL)	Net Impact per Hour (CRL)	Impact per Hour (Ex-Post Analysis)
SDEC	3,065	66%	0.94	-0.60	0.34	0.08
Opt-in Alert	26,768	65%	13.0	-8.83	4.1	2.65
IHD/PCT	404	62%	0.30	-0.22	0.08	0.04
Population	691,682	60%	244.8	-234.9	9.9	-14.4

5.3.2 CRL baseline analysis

The CRL baseline analysis was conducted at the individual customer level, and then aggregated to the group level (*e.g.*, each of the six alert and population sample sub-groups), and finally to the overall level, using appropriate sample weights. Tables 5–3 and 5–4 summarize the performance of the CRL method at the highest level: that is, averaging across all customers and all events, and showing results by event-type and day-type. Table 5–3 shows CRL performance in terms of errors in levels of average kWh per hour, while Table 5–4 shows statistics on percent errors. The first two columns of Table 5–3 indicate the event type (Actual or Simulated) and day type (weekday or weekend). The next two columns report the overall average event-hour CRL and true baseline values for the average customer and event. The following three columns show mean errors and standard deviations, and mean absolute errors, all in units of kWh per event-hour. The final set of columns reports percentile values of the errors, where the median value is the 50th percentile.

Table 5–3: Overall CRL Baseline Performance, by Event Type and Day Type
Errors in kWh/hour

Event Type	Day Type	Average kWh/event-hour: CRL	True BL	Mean Error	Std Dev	Mean Abs. Error	Percentiles of CRL Errors (kWh/hour): p10	p25	Median	p75	p90
Actual	WD	1.13	1.02	0.11	0.52	0.28	-0.26	-0.05	0.04	0.20	0.56
	WE	1.23	1.38	-0.14	0.83	0.47	-1.03	-0.27	0.00	0.18	0.48
Simulated	WD	1.11	0.95	0.16	0.69	0.38	-0.30	-0.03	0.06	0.27	0.77
	WE	1.46	1.18	0.28	0.87	0.52	-0.32	-0.02	0.13	0.47	1.13

Focusing first on overall accuracy, the mean absolute error (MAE) for weekday events was 0.28 kW for actual events and 0.4 kW for simulated events, or approximately 30 to 40 percent relative to the average true baseline load of approximately 1 kW. The MAEs on weekend events were somewhat larger, at approximately 0.5 kW, or approximately 40 to 45 percent of the true baseline load. Turning to measures of bias, and allowing positive and negative errors to cancel, the mean errors on weekday events are 0.11 and 0.16 kW for actual and simulated events, with relatively large standard deviations of 0.5 and 0.7 kW respectively. The *median* errors are much smaller than the mean errors, implying that positive errors are more frequent and larger than negative errors. This implies that the CRLs generally had an upward bias in 2012, which is confirmed by comparing the upper to lower percentile values, where the positive values at each percentile (*e.g.*, p75) are larger than the negative values at the corresponding lower percentile (*e.g.*, p25).

Table 5–4 presents statistics in the same format for CRL *percent errors*.[22] The patterns of the percent errors are similar to those of the errors in levels, although the average percent errors and their standard deviations are quite large. This is a common result when reporting percent baseline errors across a large number of customers.

[22] Note that the discussion of the CRL errors in Table 5–3 characterized them in both levels and as percentages of the true baseline load (*e.g.*, the mean absolute error for actual weekday events was 0.28, or 30 percent of the true baseline). However, the mean of the absolute *percent* errors, as shown in Table 5–4, is 41 percent.

Table 5–4: Overall CRL Baseline Performance, by Event Type and Day Type
Percent Errors

		Average kWh/hour		CRL Percent Errors			Percentiles of CRL Percent Errors				
Event Type	Day Type	CRL	True BL	Mean Pct. Error	Std Dev	Mean Abs. Pct. Error	p10	p25	Median	p75	p90
Actual	WD	1.13	1.02	19%	883%	41%	-28.6%	-8.2%	8.1%	30.5%	66.9%
	WE	1.23	1.38	-20%	6093%	105%	-47.4%	-24.3%	0.2%	30.6%	77.0%
Simulated	WD	1.11	0.95	50%	316%	63%	-26.4%	-5.8%	14.3%	53.5%	133.4%
	WE	1.46	1.18	76%	349%	90%	-25.8%	-3.3%	20.2%	71.5%	189.4%

Figure 5–1 illustrates the MAE, mean errors, and standard deviations shown in Table 5–3, while Figure 5–2 illustrates the percentiles of CRL errors. The relatively wide range of errors may be seen in both the standard deviations around the mean, and in the percentiles of errors.

Figure 5–1: Overall CRL Baseline Performance, by Event Type and Day Type

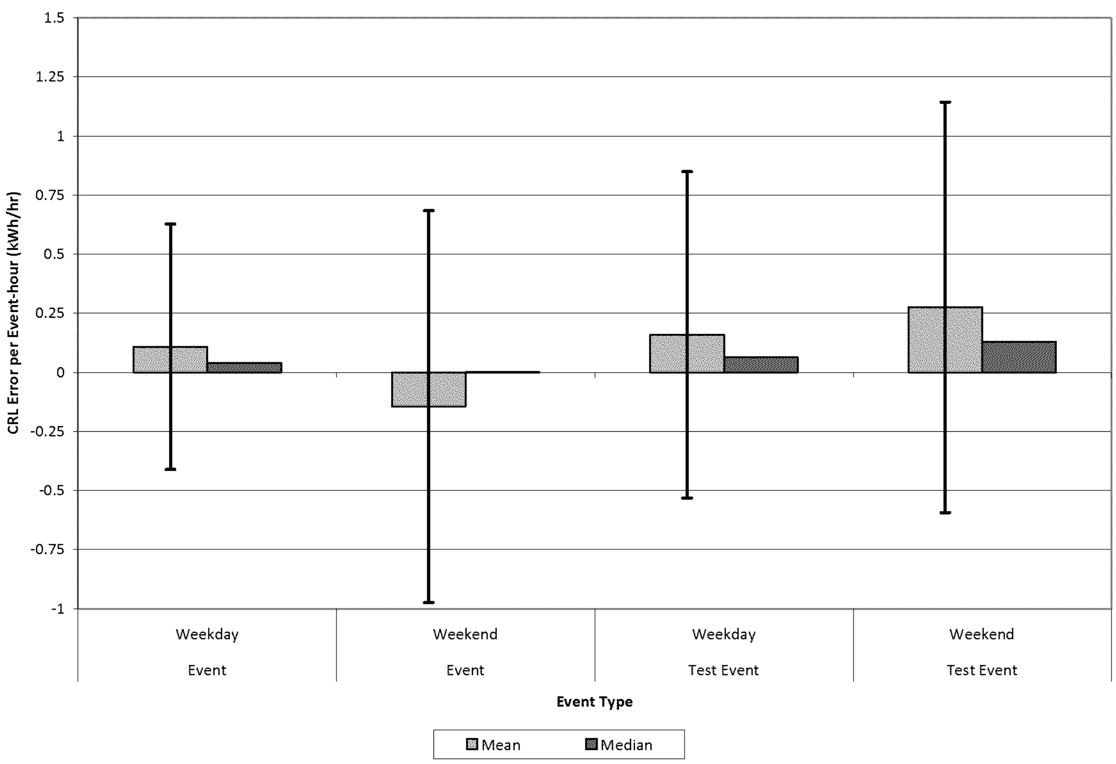
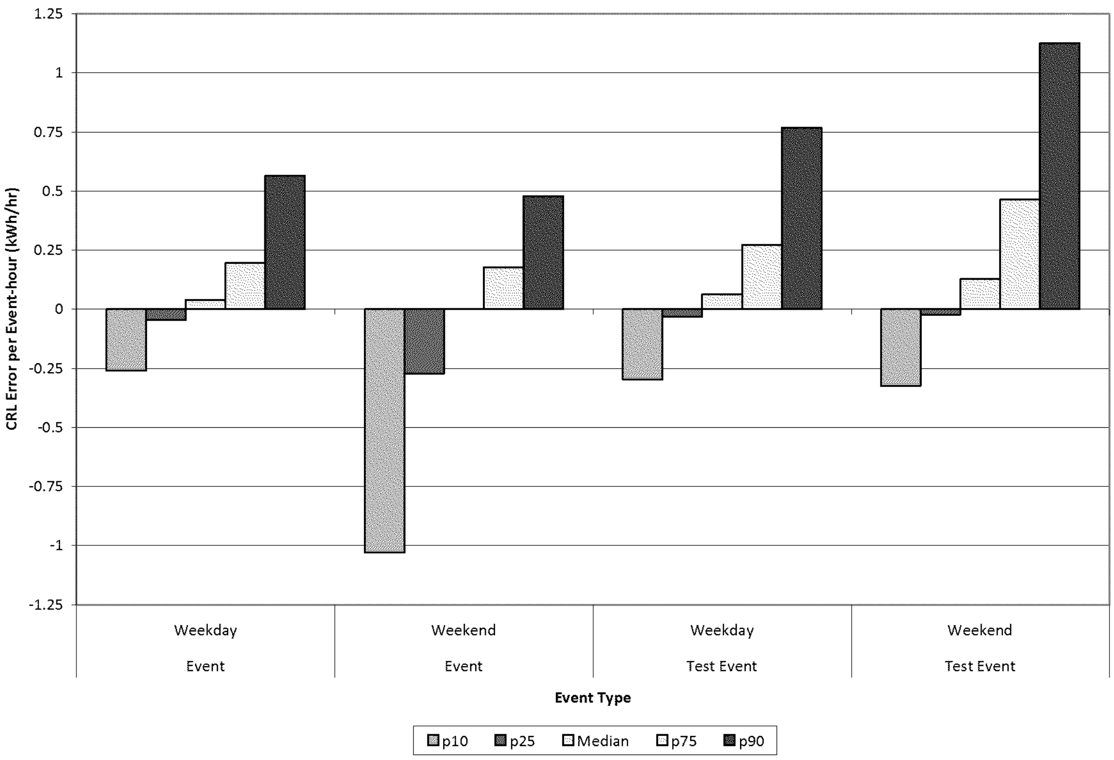


Figure 5–2: Percentiles of CRL Baseline Errors, by Event Type and Day Type



Given the large variability of CRL errors, it is of interest to examine potential underlying factors, such as differences across events. As shown in Table 5–5 and the following figures, the CRL errors vary considerably across events. The table shows the dates of the actual and simulated events (shaded rows indicate weekend days, all Saturdays), the average CRLs and true baselines, average errors and associated standard deviations, median error, and mean absolute error. The last two columns show average temperatures for the event window and for the average of same period on the days included in the CRLs.

SB_GT&S_0888773

Table 5–5: Overall CRL Baseline Performance, by Event (kW)

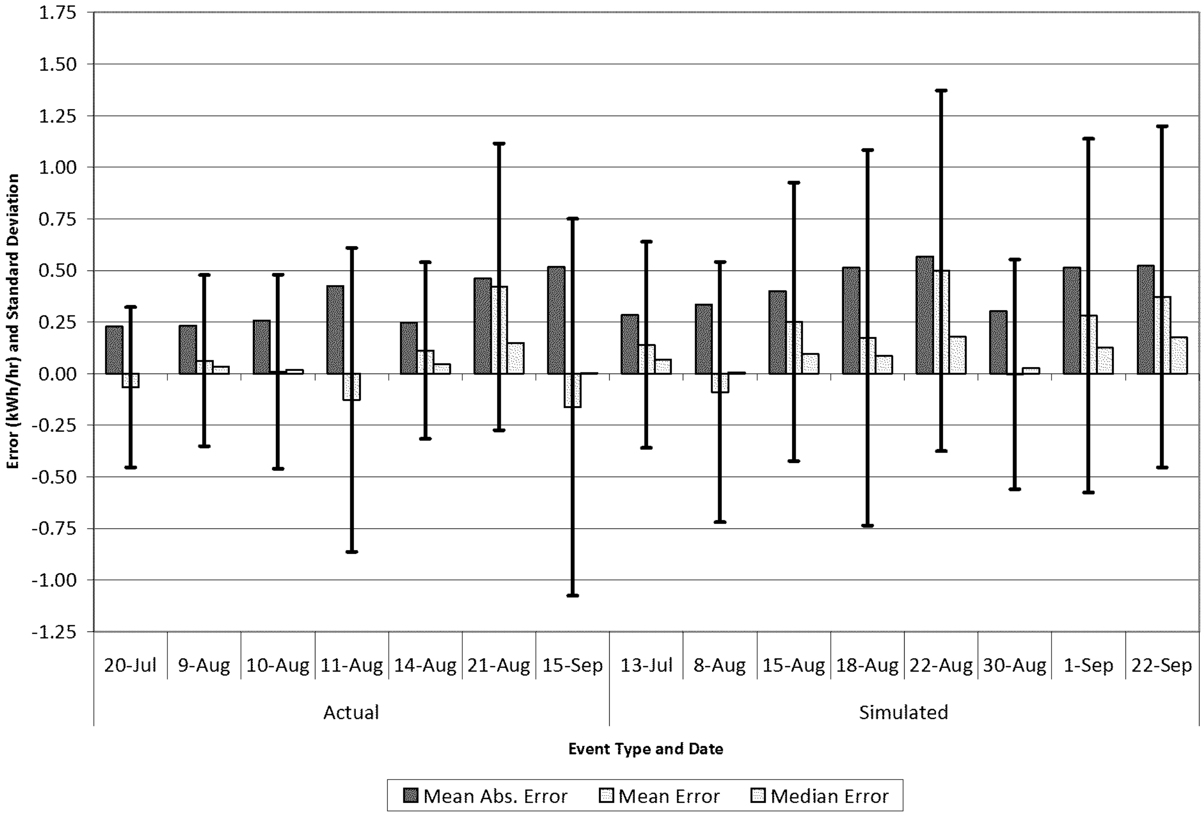
Event Type	Event Date	Ave. CRL	Ave. True BL	Mean Error	Std. Dev.	Median Error	Mean Abs. Error	Ave. Temp	Ave. CRL Temp
Actual	20-Jul	0.87	0.94	-0.07	0.39	0.000	0.23	79.4	75.7
	9-Aug	1.11	1.05	0.06	0.41	0.033	0.23	80.8	78.7
	10-Aug	1.11	1.10	0.01	0.47	0.018	0.26	82.5	78.7
	11-Aug	1.06	1.18	**-0.13**	**0.74**	0.000	**0.42**	**83.1**	**74.0**
	14-Aug	1.23	1.12	0.11	0.43	0.047	0.25	82.4	80.7
	21-Aug	1.35	0.93	**0.42**	**0.69**	0.149	**0.46**	**76.8**	**82.8**
	15-Sep	1.41	1.57	**-0.16**	**0.91**	0.003	**0.52**	**95.0**	**79.3**
Simulated	13-Jul	0.91	0.77	0.14	0.50	0.066	0.28	77.7	75.5
	8-Aug	1.02	1.11	-0.09	0.63	0.006	0.34	81.6	77.3
	15-Aug	1.23	0.98	0.25	0.67	0.095	0.40	80.0	80.7
	18-Aug	1.48	1.31	0.17	0.91	0.085	0.51	84.7	81.0
	22-Aug	1.35	0.85	0.50	0.87	0.178	0.57	**75.3**	**82.8**
	30-Aug	1.05	1.06	0.00	0.56	0.026	0.30	81.5	79.0
	1-Sep	1.41	1.13	0.28	0.86	0.125	0.51	82.9	79.6
	22-Sep	1.48	1.11	0.37	0.83	0.175	0.52	82.6	79.5

Two notable results are the following. First, for the events on July 20, August 11, and September 15 (where the latter two event days are Saturdays), the median errors are nearly zero and the mean errors are negative. That is, the CRL tended to *understate* the true baseline for those events. The last two columns indicate that average temperatures on those event days were substantially higher than average temperatures on the days included in the associated CRLs, particularly for the two Saturday events.

Second, the mean and median errors for the sixth event, on August 21, are both much larger than for the other weekday events. This result is consistent with the unusually high percentage of estimated "reducers" shown for that event in Table 5–1, suggesting that the customer CRLs tended to *overstate* the true baselines on that event. Note that the mean and median errors for the following day, which was selected as a simulated event, are comparably large and positive. The values in the last two columns indicate that August 21 and 22 had relatively mild temperatures compared to the days included in the CRLs. Such conditions likely explain why the CRLs exceeded the true baseline loads for those days. Thus, the accuracy of the CRLs in representing customers' baseline loads appears to depend critically on the similarity of the weather conditions on the event days and the days included in the CRL calculations.

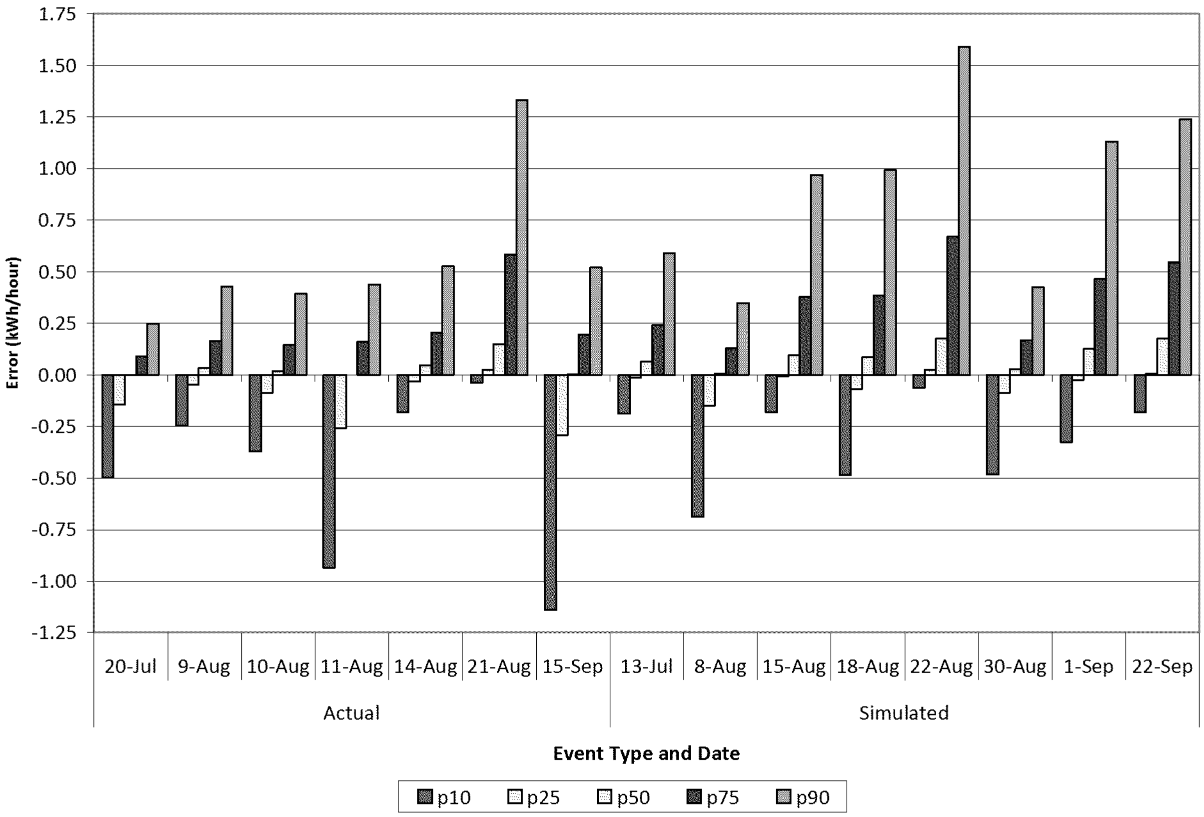
Figure 5–3 illustrates the median and mean error, and standard deviation of the CRL baseline errors for each actual and simulated event, which are shown in Table 5–4. The downward bias of the CRLs on the July 20, August 11, and September 15 actual events, as well as the August 8 simulated event may be seen, along with relatively large standard deviations. Similarly, the large upward biases of the CRLs on August 21 and 22 are apparent, along with wide standard deviations.

Figure 5–3: Overall CRL Baseline Performance by Event



The percentiles of CRL errors shown in Figure 5–4 for each event illustrate that most customers were likely overpaid in bill credits for the event on August 21, and would have been similarly overpaid on the following day if an event had been called (*i.e.*, nearly all of the errors are positive on both days). In contrast, with nearly zero medians and relatively large negative errors, about half of the customers were likely underpaid on the two Saturday events (August 11 and September 15).

Figure 5–4: Percentiles of CRL Baseline Errors, by Event



5.4 Summary of CRL Settlement and Baseline Analysis

At an overall level, combining results across all customers and events, we found that the CRL baseline method produced relatively high average errors (measured by the mean absolute error) in 2012, in the range of *30 to 50 percent* of the true baseline load (which averages about 1.1 kW on weekday events and 1.2 to 1.5 on weekend events). In addition, the CRLs generally had an *upward bias*. For actual weekday events, the errors for the middle half of all customers fell in the range of -0.05 kW to 0.20 kW (*i.e.*, a downward bias of about 5 percent to an upward bias of about 20 percent). For a quarter of the remaining customers, the CRLs *understated* the true baseline by more than 0.05 kW, and they *overstated* the true baseline for another quarter of customers by more than 0.20 kW.

Since the CRL for a given event depends on customers' usage on prior days, the nature of baseline errors can vary substantially across events, depending in part on weather conditions. Two examples for PTR in 2012 illustrate the point. First, the weekday event called on August 21 occurred on a relatively mild day following a series of relatively hot days. The customers' loads on the previous hot days produced *overstated*, or upward biased, CRLs for nearly all customers. In contrast, two weekend events were called on substantially hotter days than previous weekend days, which resulted in CRLs that *understated* the true baselines of about half of all customers, in some cases by relatively large amounts (*e.g.*, 0.25 to 1 kWh per hour).

In addition, a review of CRL settlement data indicated that net load impacts as measured by the CRLs were uniformly greater than the comparable *ex post* load impacts, ranging from 50 percent greater for the opt-in alert customers, to twice as great for the IHD customers, and four times as great for SDEC customers. Most importantly, for the much larger number of customers in the remaining population, the CRL-based net impacts indicate *usage reductions* of 10 MW, while the *ex post* impact estimates represent load *increases* of 14 MW (though they are not statistically significant). However, PTR bill credits are paid for *usage reductions* relative to CRLs, not net impacts, and these amounted to an average event-hour value of 245 MW for the non-alert population.

6. SDEC CONSERVATION EFFECTS

In addition to analyzing the effects of SDEC participation on usage reductions during PTR event hours, SDG&E is also interested in examining effects on overall electricity consumption. In particular, SDG&E wishes to measure energy usage changes of SDEC participants between the summer months of 2011 and 2012. An important barrier to estimating the conservation effects of SDEC participation over this time frame is the major difference in summer weather conditions between the two years; that is, the summer of 2011 was considerably milder than the summer of 2012, leading to nominally higher electricity use in 2012.

6.1 Analysis Approach

To aid in disentangling potential conservation effects of SDEC from differences in weather conditions, our analysis included selection of a control group of comparable non-SDEC customers, which allows a comparison of differences in energy consumption between the summers of 2011 and 2012 for SDEC participants to similar differences for the control group customers.

To identify customers for the control group that matched the SDEC participants, we constructed usage metrics for each SDEC participant and potential control group customer, and then compared them to determine the best matches. Specifically, for each SDEC participant, 25 average usage measures, for the 24 hours and the average across hours for August and September of 2011, were compared to the same usage measures for all customers from the population sample within the same zip code. The measures were compared using standard, or z-scores, which normalize differences in measures by standard deviations of the measure in the population. Z-scores were calculated for each matching candidate, and the population customer with the lowest z-score was selected as the match and included in the control group.

Formally, for each SDEC participant, z-scores were calculated for each hourly load measure, and then averaged across hours and added to the score for average usage, as follows:

$$z_i^1 = \frac{|\, measure1_i - measure1_{SDECj} \,|}{\sigma_{measure1}}$$

$$Z_{Ai} = \frac{\sum_{h=1}^{24} z_i^h}{24}$$

$$Z_{Bi} = z_i^{avgkWh} \text{, and}$$

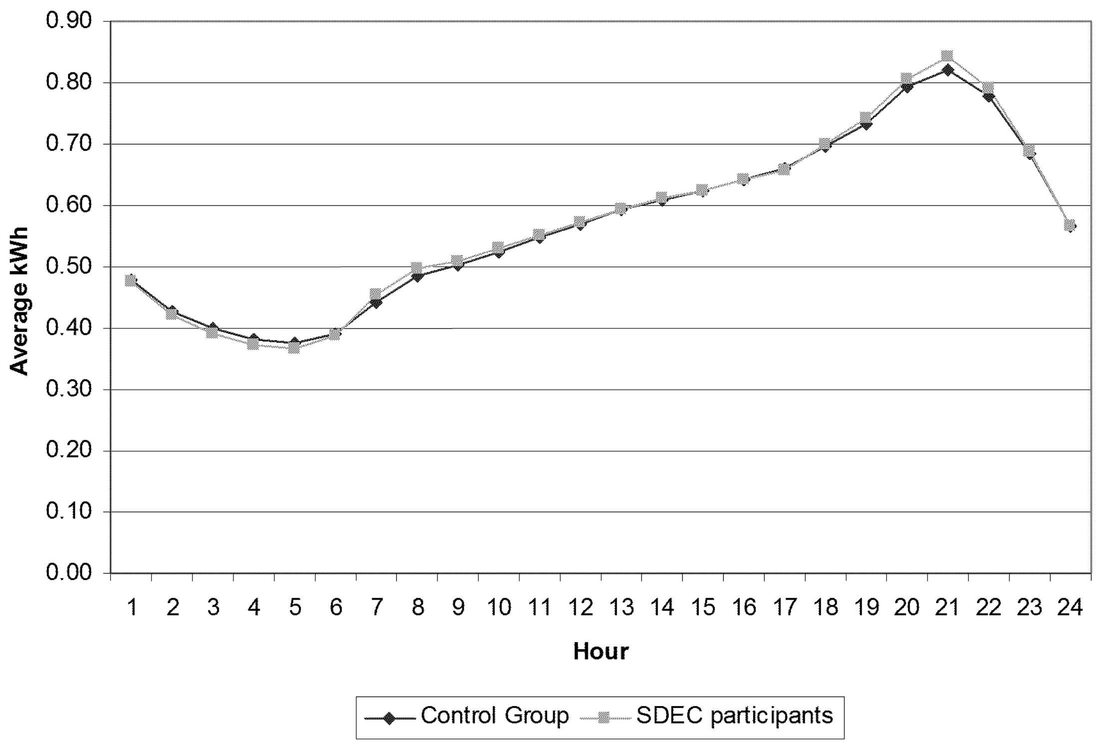
$$Z_i = Z_{Ai} + Z_{Bi}$$

$SDEC_j$ represents the SDEC customer for which a match is required, the subscript *i* represents each potential match from the sample population in the relevant ZIP code, and σ represents the standard deviation of the usage measure across all potential matches. That is, the z-scores for the 24 hourly kWh measures are averaged to produce Z_{Ai}, which is added to the z-score for the 25th measure, Z_{Bi}, average kWh across August and September. The service account with the lowest overall z-score, Z_i, was included in the control group. Population service accounts may be matched to multiple SDEC participants and are weighted according to the number of SDEC participant matches.

6.2 Comparison of Treatment and Control Usage Profiles in 2011 and 2012

To illustrate the comparability of usage patterns of the SDEC participants and the matched control group, Figure 6–1 illustrates average hourly electricity usage for the two groups in 2011, before customers were invited to participate in SDEC.[23] As shown, profiles for the two groups are almost identical with the exception of hours in the morning and evening where SDEC energy consumption is slightly higher than that of the control group.[24]

Figure 6–1: Average Daily Load Profiles of SDEC and Control Group Customers – *August–September 2011*



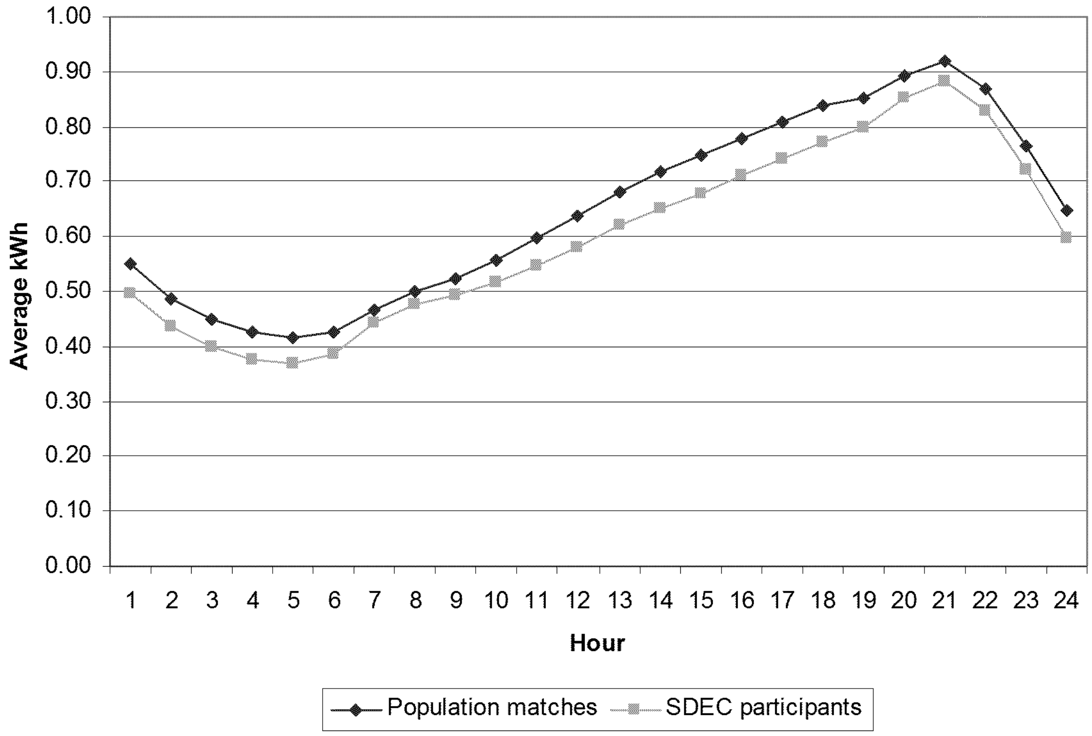
To provide an initial comparison of post-SDEC usage patterns, Figure 6–2 shows average hourly usage in August and September 2012 for the same customers represented in Figure 6–1. The shape of the 2012 load profile for SDEC participants is similar to that for the control group but is

[23] As noted above, matched population service accounts are weighted based on the number of SDEC participants to which the account is matched.

[24] Averaging over 24 hours, the mean percent error (MPE) between treatment and control group load profiles is -0.2% and the mean absolute percent error (MAPE) is 1.2%. When analyzed by zip code, of which there are 29, there is somewhat more variation between treatment and control load profiles. However, the fit is still quite good. All zip codes but one have MPEs between -1.3% and 0.8% and MAPEs less than 3.8%. The outlying zip code, which only has 21 of 4,227 SDEC customers included in this analysis, has an MPE of -6.5% and a MAPE of 9.9%.

lower in all hours. A fundamental question is the extent to which this difference represents an SDEC conservation effect or the result of some other factors that were omitted in the matching process (*e.g.* differences in weather sensitivity). For example, as noted above, weather in summer 2011 was milder than that in 2012, which could mean that the 2011 electricity usage data used to determine treatment and control matches was based largely on usage other than air conditioning energy consumption. If there is an underlying difference in the presence and usage of air conditioning between population and SDEC service accounts, then we would expect 2012 usage profiles to differ between the groups as a result of higher temperatures, with or without conservation effects.

Figure 6–2: Average Daily Load Profiles of SDEC and Control Group Customers – *August–September 2012*



6.3 SDEC Conservation Impacts

6.3.1 Basic statistical analysis

The availability of usage data for periods before and after SDEC participation, and for both the SDEC treatment customers and a matched control group, allows the calculation of a basic estimate of SDEC conservation effects by using a straightforward *difference-in-differences* approach. The results from this basis statistical approach are shown in Table 6–1. The first row shows average hourly kWh usage for August through September 2011 for SDEC participants and the control group. The second row shows comparable values for 2012, and the third row calculates the year-to-year differences. As shown in the third row, average hourly electricity usage for SDEC participants increased by 0.096 kWh between 2011 and 2012. In contrast, the control group saw an average increase of 0.154 kWh. The difference between these two values (difference-in-differences) is shown in the bottom row and represents one measure of the SDEC conservation effect: 0.058 kWh, or 8% of the 2012 control group average hourly load. While these values represent one estimate of the SDEC conservation effect, they do not account for possible differences between the treatment and control customers and the conditions that they faced in the two years. The potential effect of these factors is explored in regression modeling approaches in the next sub-section.

Table 6–1: Observed Differences in SDEC and Control Group Usage –
Average Hourly Consumption (August and September, 2011 and 2012)

Year	SDEC Participants	Control Group
2011	0.575	0.573
2012	0.670	0.727
Difference	0.096	0.154
Difference-in-differences	**0.058**	**8.0%**

6.3.2 Fixed-effects models of conservation

We can formalize and expand the basic difference-in-differences approach applied above by specifying a fixed-effects regression model, and applying it to average kWh data for all of the SDEC and control group customers. The first and most basic fixed-effects model is specified as follows:

$$Q_{ti} = \beta_1 \times yr2012 + \beta_2 \times (yr2012 \times SDEC_i) + v_i + \varepsilon_t$$

where:

i represents a treatment or control customer;
t represents year;
Q_{it} represents average hourly kWh usage during August and September for customer i in year t;
yr2012 is an indicator variable that equals one in 2012 and zero otherwise;
$yr2012xSDEC_i$ equals one for SDEC participants during 2012 and zero otherwise;
v_i is the fixed effect for customer i;[25] and
ε_t is the error term.

The model includes two observations per customer, one representing average hourly kWh during August through September 2011, and another for the same period in 2012. The model also includes independent variables for customer-specific fixed effects, which account for differences in average usage levels between customers, and an indicator for *yr2012*. Finally, an interaction term between *yr2012* and $SDEC_i$ participation is also included and provides the

[25] Although these models are estimated by a fixed effects estimator, the procedure is equivalent to ordinary least squares when a dummy variable, or indicator variable, is included for each customer.

estimated coefficient of interest. That is, the coefficient on that variable represents the difference between the average SDEC participant and the average control group customer in their change in average usage between 2011 and 2012.

Table 6–2 presents the estimated coefficients from the fixed-effects model described above. The right column contains estimated coefficients for a variant of the model where the dependent variable is calculated over non-event days only (*i.e.* excludes data for the six days in 2012 on which PTR events were called). Excluding the 2012 event days in calculating average hourly energy use potentially allows investigation of the confounding effects of the PTR program on energy usage reductions. In both models, the estimated constant term represents average hourly kWh electricity usage in 2011 for treatment and control customers. The second coefficient indicates that average hourly electricity usage for both customer types increased by 0.154 kWh (or 0.146 kWh) in 2012. However, the third coefficient indicates that participation in the SDEC program *reduces* the 2012 increase by 0.058 kWh (or 0.056 kWh in the second model) to only 0.096 kWh (0.096 = 0.154 – 0.058) in the first model. *That coefficient on the interaction term represents the estimated conservation effect and corresponds to, and is in fact the same as the basic difference-in-differences statistical calculation of 0.058 kWh in Table 6–1.*

Table 6–2: Basic Fixed Effects Model Estimate of SDEC Conservation Effect

Variable	**Dependent variable:**	
	Average Hourly Aug. & Sept. kWh	**Average Hourly *Non-Event* kWh**
Constant	0.574++	0.574++
	(0.002)	(0.002)
yr2012	0.154++	0.146++
	(0.004)	(0.004)
yr2012*SDEC	**-0.058++**	**-0.056++**
	(0.006)	(0.006)
Observations	16,906	16,906
R-squared	0.176	0.166
Number of service accounts	7,137	7,137
Standard errors in parentheses. ++ p<0.01, + p<0.05		

As illustrated in Figure 6–2 above, the usage reductions of the average SDEC participant and control group customer appear to take place in all hours of the day.[26] This feature raises questions about what behaviors the treatment customers may have undertaken in order to reduce usage in all hours.[27] In an attempt to verify the conservation findings and to further disentangle weather effects, an additional fixed-effects model was estimated using *daily*, rather than yearly, average usage data, along with a weather variable. The *daily* fixed-effects model is specified as follows:

[26] Conservation effects during all hours were also verified by estimating 24 hourly fixed-effects models, yielding hourly estimates of conservation. While there was variation from hour to hour in the size of the effects, all 24 hours showed load reductions ranging from -0.04 kWh to -0.083 kWh.

[27] Behaviors such as reducing thermostat set points could result in such shifts in usage patterns to the extent that air conditioning is needed during overnight hours.

$$Q_{ti} = \beta_1 \times yr2012 + \beta_2 \times (yr2012 \times SDEC_i) + \beta_3 \times CDD65 + \sum_{d=1}^{6} \beta_d^{Dtype} \times DType_t + \nu_i + \varepsilon_t$$

Where the additional variables are:

CDD65 equals the difference between the day's average temperature and 65 if the average temperature is above 65 and equals zero otherwise; and

$DType_d$ is an indicator variable for each day of the week.

This equation models customers' average hourly kWh electricity usage per day as a function of weather (represented by cooling degree days), day of the week, year, and year interacted with SDEC treatment. Two variations of the model are estimated, where one includes additional interactions between weather and SDEC and year indicator variables. Results for the daily fixed effect-models are reported in Table 6–3.

Table 6–3: Daily Fixed Effects Models of SDEC Conservation Effect

Variable	Dependent variable:		
	Average kWh	Average kWh	Average kWh
Constant	0.531++	0.531++	0.547++
	(0.001)	(0.001)	(0.001)
yr2012	0.062++	0.060++	-0.008++
	(0.001)	(0.001)	(0.002)
yr2012*SDEC	**-0.059++**	**-0.055++**	**-0.044++**
	(0.001)	**(0.001)**	**(0.002)**
Monday	-0.018++	-0.018++	-0.017++
	(0.001)	(0.001)	(0.001)
Tuesday	-0.043++	-0.043++	-0.038++
	(0.001)	(0.001)	(0.001)
Wednesday	-0.045++	-0.045++	-0.040++
	(0.001)	(0.001)	(0.001)
Thursday	-0.064++	-0.064++	-0.059++
	(0.001)	(0.001)	(0.001)
Friday	-0.048++	-0.048++	-0.049++
	(0.001)	(0.001)	(0.001)
Saturday	-0.018++	-0.018++	-0.020++
	(0.001)	(0.001)	(0.001)
CDD65	0.016++	0.017++	0.013++
	(0.000)	(0.000)	(0.000)
CDD65*SDEC		-0.001++	0.000
		(0.000)	(0.000)
CDD65*yr2012			0.009++
			(0.000)
CDD65*SDEC*yr2012			-0.001++
			(0.000)
Observations	1,026,768	1,026,768	1,026,768
R-squared	0.105	0.105	0.108
Number of service accounts	7,138	7,138	7,138
Standard errors in parentheses. ++ p<0.01, + p<0.05			

Again, the estimated coefficients on the interaction term *yr2012*SDEC* represent the conservation effect of interest. In the first model, the conservation effect is estimated to be 0.059 kWh (see bold values in the table), which is very similar to the results presented in Tables 6–1 and 6–2. The remaining two models include interaction terms that allow weather sensitivity to vary across treatment status and across years. This added flexibility results in somewhat smaller conservation estimates of 0.055 and 0.044 kWh. Given the strongly significant coefficients on the interactive variables, we conclude that the most comprehensive model, shown in the third column does the best job of controlling for as many factors as possible in estimating SDEC conservation effects.

6.4 Conclusions Regarding SDEC Conservation Effects

Table 6–4 summarizes the estimates of average hourly SDEC conservation effects from the alternative analysis methods described above, where the signs of the coefficients have been changed so that positive values represent usage reductions. As noted above, we conclude that the estimate of 0.044 kWh per hour from the most comprehensive daily fixed-effects model represents the best estimate of average hourly summer usage reductions of SDEC participants relative to the control group customers. This effect represents a 6.1 percent usage reduction, measured relative to the average hourly control group customer usage in 2012. Converting the average hourly value to a daily value translates into 1.1 kWh per day, or 64.4 kWh for the 61 days in August and September, for the average SDEC participant. Multiplying the average value by the 4,633 SDEC participants produces an estimate of total energy savings in August and September of approximately 300 MWh.

Table 6–4: Summary of Estimates of SDEC Conservation Effects

Analysis Method	SDEC Conservation Effect (Average kW)	Percent Impact
Observed differences (Summer 2011-2012)	0.058	8.0%
Summer fixed-effects model		
All days	0.058	8.0%
Non-event days	0.056	7.7%
Daily fixed-effects model		
Same weather response	0.059	8.1%
Separate SDEC weather response	0.055	7.6%
Separate SDEC and 2012 weather response	**0.044**	**6.1%**

7. *EX ANTE* EVALUATION

This section describes the *ex ante* load impact requirements, methods used, assumptions made, and the resulting load impact forecasts.

7.1 *Ex ante* Load Impact Requirements

The DR Load Impact Evaluation Protocols require that hourly load impact forecasts for event-based DR resources must be reported at the program level and by Local Capacity Area (LCA)[28] for the following scenarios:

- For a typical event day in each year; and
- For the monthly system peak load day in each month for which the resource is available;

under both:

- 1-in-2 weather-year conditions, and
- 1-in-10 weather-year conditions.

at both:

- the program level (*i.e.*, in which only the program in question is called), and
- the portfolio level (*i.e.*, in which all demand response programs are called).

The program-level load impacts include load impacts from customers dually enrolled in PTR and Summer Saver. The portfolio-level load impacts exclude customers enrolled in the Summer Saver program.

7.2 Description of Methods

This section describes the methods used to develop reference loads for the relevant customer base and event day-types, and to develop percentage load impacts for a typical event day.

7.2.1 Development of Reference Loads and Load Impacts

Reference loads and load impacts for all of the required factors were developed in the following series of steps:

1. Define data sources
2. Estimate *ex ante* regressions and simulate reference loads by customer group and scenario
3. Calculate percentage load impacts by customer group
4. Apply percentage load impacts to the reference loads
5. Scale the reference loads using enrollment forecasts

Each of these steps is described below.

[28] SDG&E's entire service area is considered to be one LCA.

Define data sources
In the *ex ante* forecast, we consider only opt-in alert customers. The majority of these customers are represented by the sample of approximately 17,000 customers. Some additional opt-in alert customers are contained in the sub-set of SDEC customers. These are merged in with the larger sample of customers to represent all opt-in alert PTR customers.

The percentage load impacts that are applied to the reference loads to create hourly load impacts are based upon the *ex post* load impacts from the 2012 *ex post* evaluation. Because the *ex ante* forecast includes non-summer months (*i.e.*, because PTR events may be called in any month of the year) but we do not observe any events during those months, we use information from the Statewide Pricing Pilot (SPP) to adjust the summer load impacts to the conditions in the non-summer months.[29]

Simulate reference loads
In order to develop reference loads, we first re-estimated regression equations for the average customer in each cell defined by climate zone, size, and whether the customer was in SDEC. Separate equations were estimated for the summer months of May through October, and for the remaining non-summer months. These equations were then used to simulate reference loads by customer type under the various scenarios required by the Protocols (*e.g.*, the typical event day in a 1-in-2 weather year).

For the summer months, the re-estimated regression equations were similar in design to the *ex post* load impact equations described in Section 3.3, differing in two ways. First, the *ex ante* models excluded the morning-usage variables. While these variables are useful for improving accuracy in estimating *ex post* load impacts for particular events, they complicate the use of the equations in *ex ante* simulation. That is, they would require a separate simulation of the level of the morning load. The second difference between the *ex post* and *ex ante* models is that the *ex ante* models use CDH65 as the weather variables in place of the weather variables used in the *ex post* regressions. The primary reason for this is that *ex ante* weather days were selected based on current-day temperatures, not factoring in lagged values. Therefore, we determined that this method is the most consistent way of reflecting the 1-in-2 and 1-in-10 weather conditions in the reference loads.

Because PTR events may be called in any month of the year, we estimated separate regression models to allow us to simulate non-summer reference loads. The non-summer model is shown below. This model is estimated separately from the summer *ex ante* model. It only differs from the summer model in three ways: it includes HDH_t variables, where the summer model does not; the month dummies relate to a different set of months; and the event variables are

[29] The California SPP included a voluntary CPP rate for residential and small commercial customers, as well as a TOU rate, an information-only component, and a residential enabling technology component. Customers' price response was modeled by a demand model for which an elasticity of substitution and overall elasticity were estimated. In this study, we used the relevant model for voluntary CPP.

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removed (because no event days occurred during the regression timeframe). Table 6–1 describes the terms included in the equation.

$$Q_t = a + \sum_{i=1}^{24}(b_i^{CDH} \times h_{i,t} \times CDH_t) + \sum_{i=1}^{24}(b_i^{HDH} \times h_{i,t} \times HDH_t) + \sum_{i=2}^{24}(b_i^{MON} \times h_{i,t} \times MON_t)$$
$$+ \sum_{i=2}^{24}(b_i^{FRI} \times h_{i,t} \times FRI_t) + \sum_{i=2}^{24}(b_i^{h} \times h_{i,t}) + \sum_{i=2}^{5}(b_i^{DTYPE} \times DTYPE_{i,t})$$
$$+ \sum_{i=2-5,10-12}(b_i^{MONTH} \times MONTH_{i,t}) + e_t$$

Table 6–1: Descriptions of Terms included in the *Ex ante* Regression Equation

Variable Name	Variable Description
Q_t	the demand in hour *t* for the modeled customer group
The various *b*'s	the estimated parameters
$h_{i,t}$	a dummy variable for hour *i*
CDH_t	cooling degree hours
HDH_t	heating degree hours[30]
MON_t	a dummy variable for Monday
FRI_t	a dummy variable for Friday
$DTYPE_{i,t}$	a series of dummy variables for each day of the week
$MONTH_{i,t}$	a series of dummy variables for each month
e_t	the error term.

Once these models were estimated, we simulated 24-hour load profiles for each required scenario. The typical event day was assumed to occur in August. Much of the differences across scenarios can be attributed to varying weather conditions. The definitions of the 1-in-2 and 1-in-10 weather years were provided by SDG&E.

Calculate forecast percentage load impacts

The *ex ante* percentage load impacts are based on the estimated ex load impacts from the 2012 program year. That is, we calculate the average hourly percentage load impacts across the event days. To account for the effect of changing weather conditions and seasons on customer price responsiveness, we varied the hourly percentage load impacts from the *ex post* typical event day using the estimated elasticity of substitution equations from the SPP. In those equations, the elasticity of substitution varies with the weather conditions (the difference between peak and off-peak cooling degree hours), the central air conditioning saturation rate, and season (summer, winter, and "inner" winter).

[30] Heating degree hours (HDH) was defined as MAX[0, 60 – TMP], where TMP is the hourly temperature expressed in degrees Fahrenheit. Customer-group-specific HDH values are calculated using data from the most appropriate weather station. In the non-summer model, CDH variables are also calculated with a threshold of 60 degrees Fahrenheit.

Using these SPP equations, we simulated the elasticity of substitution for the *ex post* typical event day using the conditions averaged across the PY2012 event days. We then performed the same calculation for each of the Protocol scenarios. The hourly percentage load impacts for each Protocol scenario were then calculated as the *ex post* typical event day percentage load impacts multiplied by the ratio of the SPP elasticity of substitution for the Protocol day divided by the value for the PY2012 typical event day.

The uncertainty-adjusted scenarios of load impacts were developed using the variability of the percentage load impacts across the event days. Specifically, we calculated the standard deviation of the percentage load impacts for each hour of the typical event day. These values were adjusted using the SPP-based elasticity ratios described above.

Finally, the percentage load impacts are shifted to account for the event windows required by the Protocols, which are 1:00 to 6:00 p.m. from April through October and 4:00 to 9:00 p.m. in all other months. The event window is reduced from the historical window of seven hours to the forecast window of five hours as follows: the 2nd and 3rd hours of the historical window are averaged together to form the 2nd hour of the forecast window; and the 4th and 5th hours of the historical window are averaged together to form the 3rd hour of the forecast window. To account for the timing of the window, the load impacts are shifted back two hours (for April through October) to four hours (for all other months), with zero load impact values inserted at the beginning of the day.

Apply percentage load impacts to reference loads for each event scenario. In this step, the percentage load impacts were applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts.

Apply forecast enrollments to produce program-level load impacts. The enrollment forecast provided by SDG&E was used to scale up the per-customer reference loads and load impacts for each customer group. We then added results across customer groups as necessary for reporting purposes.

7.3 Enrollment Forecasts

Table 7–1 shows the PTR enrollment forecast provided by SDG&E, which includes only customers who are assumed to opt into event notification. SDG&E expects a significant increase in these customer between 2013 and 2014 (increasing by 16 percent), with the growth rate converging to 1.1 percent in subsequent years. SDEC customers are assumed to continue in the program in their current numbers, with only those opting to receive PTR alerts included in these enrollments. Increases in enrollment for the remaining customers are spread proportionately across the climate zone and size groups.

Table 7–1: PTR Enrollment Forecast

Yea r	August Opt-in Alert Enrollment
201	63,221

3	
2014	73,221
2015	73,807
2016	74,675
2017	75,522
2018	76,355
2019	77,183
2020	78,003
2021	78,826
2022	79,658
2023	80,499

7.4 Reference Loads and Load Impacts

We provide the following illustrative information regarding the load impact forecasts, including the hourly profile of reference loads and load impacts for typical event days; and the pattern of estimate load impacts across months. Figure 7–1 shows estimated reference load, event-day load, and load impacts (right axis) for the *portfolio-level* results (*i.e.*, excluding Summer Saver customers, since both SS and PTR programs are assumed to be called) for opt-in alert PTR customers on the August peak day in 2015 in the 1-in-2 weather scenario. Figure 7–2 shows program-level results (*i.e.*, including the PTR load impacts of customers who are dually enrolled in the Summer Saver program), for the same scenario.[31]

Figure 7–1: PTR Opt-in Alert Reference Load and Load Impacts –
(August Peak Day; 2015; 1-in-2 Weather Scenario; Portfolio-level)

[31] Note that the *ex ante* protocols specify a five-hour event window, so PTR load impacts are shown only for those hours. This contrasts with the seven event hours shown in *ex post* results.

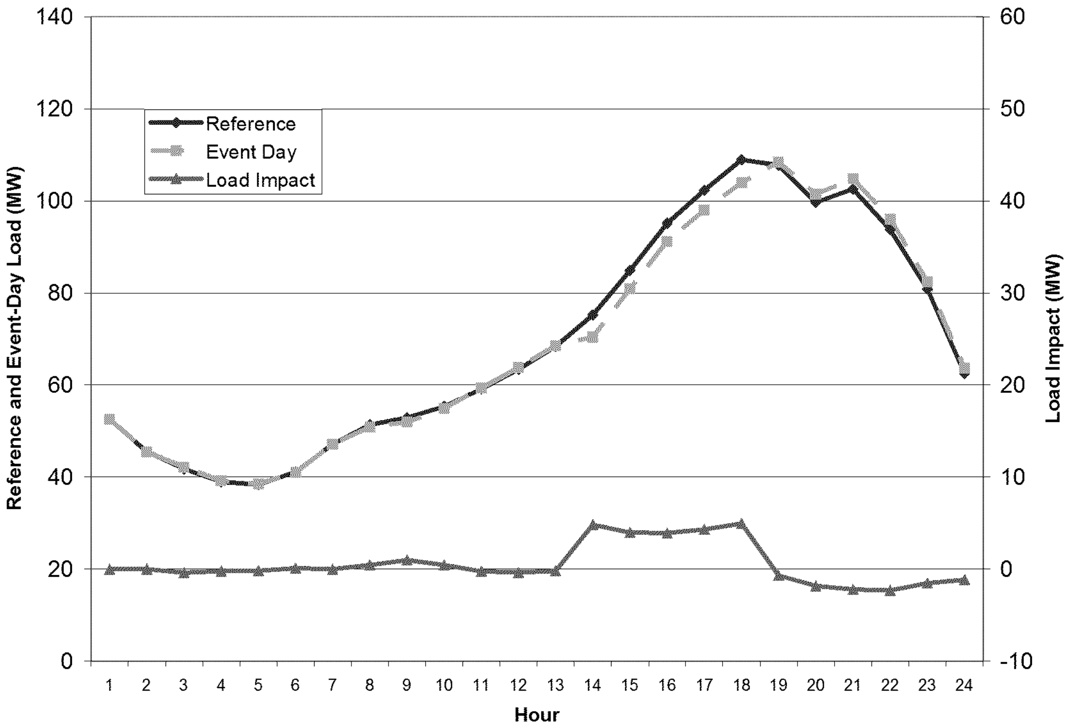


Figure 7–2: PTR Opt-in Alert Reference Load and Load Impacts –
(August Peak Day; 2015; 1-in-2 Weather Scenario; Program-level)

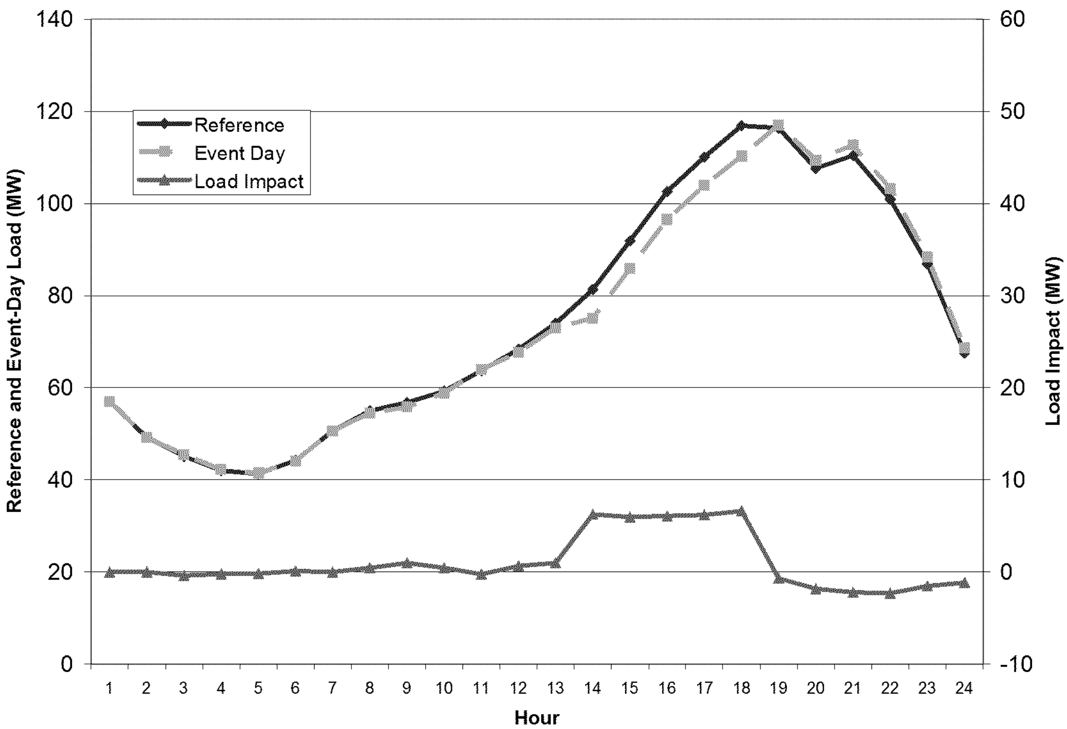


Figure 7–3 illustrates the average event-hour *ex ante* load impacts for August of each forecast month. Results are differentiated by program versus portfolio level and weather year (1-in2 versus 1-in-10), in units of MW. Load impacts increase sharply between the last historical year of 2012, and 2013 and 2014, in parallel with the enrollment forecast. The program-level load impacts shown in the top two lines differ between weather scenarios by more than the portfolio-level results shown in the lower two lines. This outcome is due to the larger size and greater weather sensitivity of the Summer Saver customers, who are included only in the program-level load impacts.

Figure 7–3: PTR Average Event-Hour Load Impacts for August of Each Forecast Year, by Program/Portfolio Level and Weather Scenario *(Opt-in Alert Customers)*

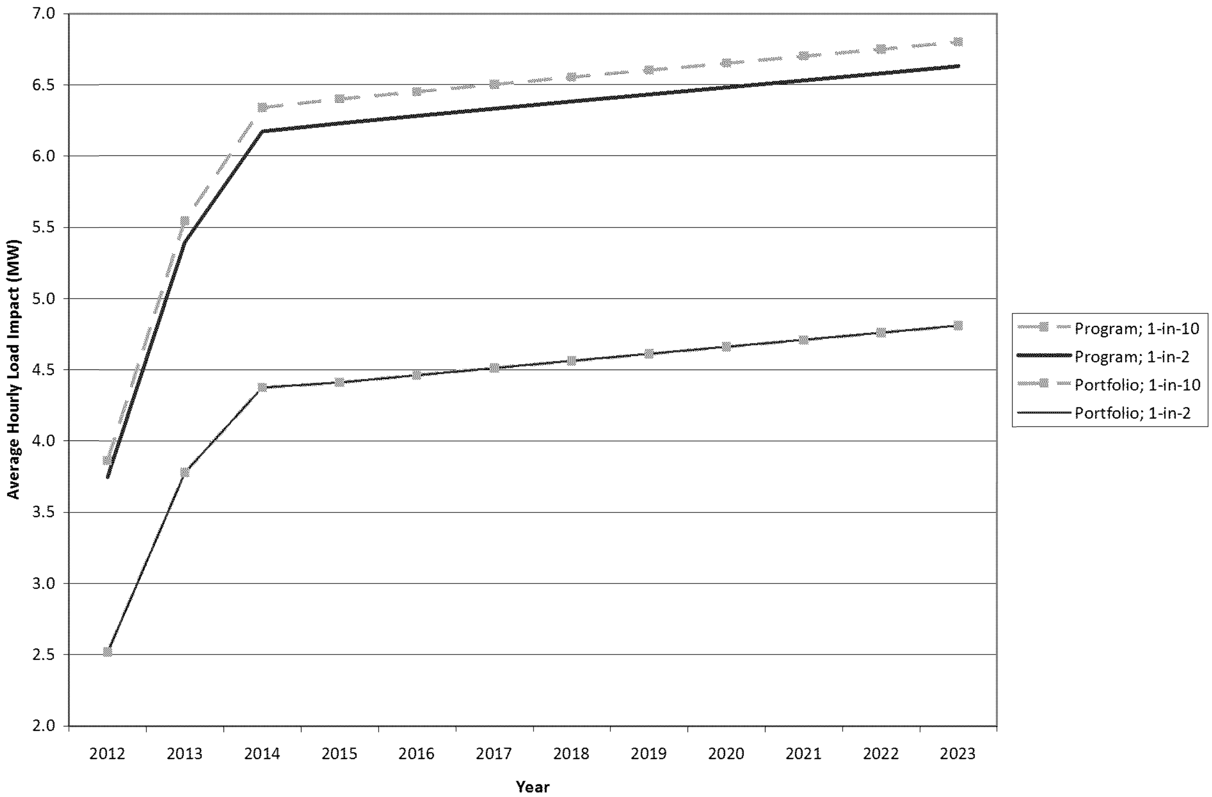
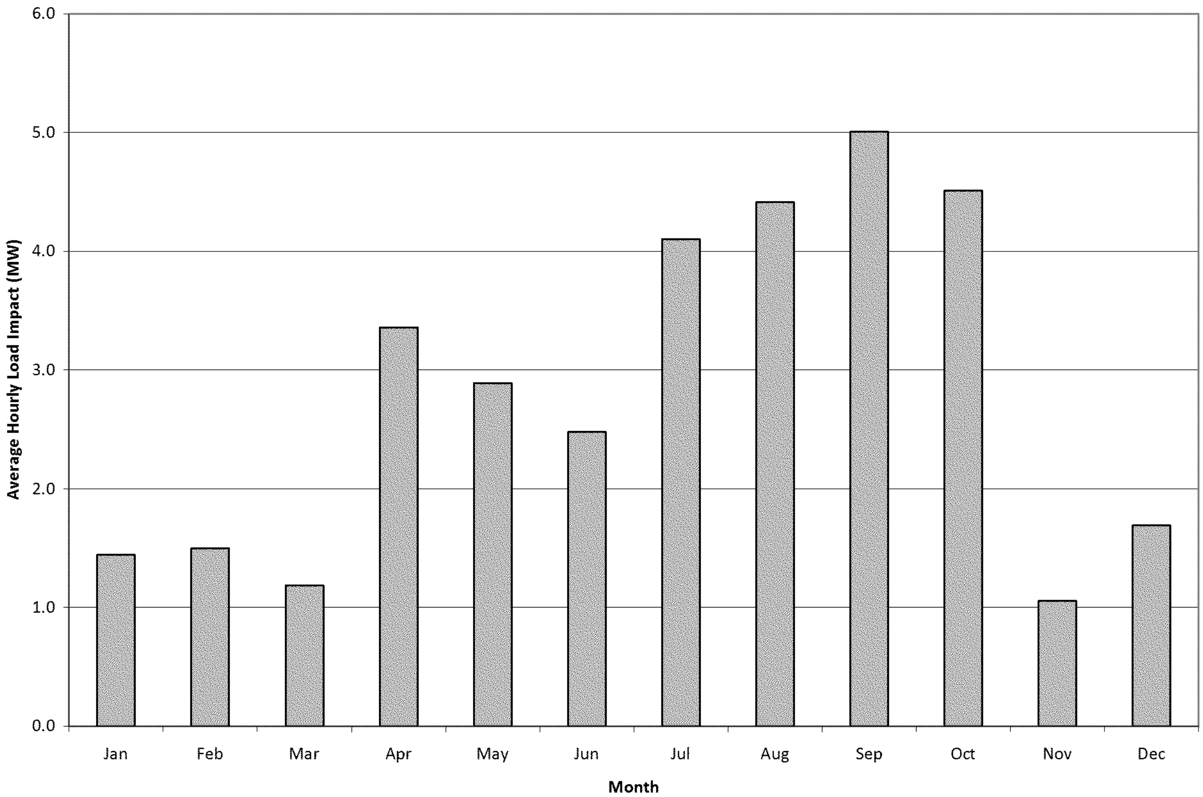


Figure 7–4 illustrates the pattern of average portfolio-level event-hour load impacts across months in 2015 in a 1-in-2 weather year. Estimated load impacts are greatest during summer months, reaching their highest level in September.

[32] *Ex ante* event hours are 1 p.m. – 6 p.m. in summer and 4 p.m. – 9 p.m. in non-summer months.

Figure 7–4: Opt-in Alert PTR Portfolio-Level Average Event-Hour Load Impacts: by Monthly Peak Day *(2015; 1-in-2 Weather Scenario)*[32]



All of the tables required by the DR Protocols are provided in an Appendix.

[32] *Ex ante* event hours are 1 p.m. – 6 p.m. in summer and 4 p.m. – 9 p.m. in non-summer months.

8. CONCLUSIONS AND RECOMMENDATIONS

This study found small but statistically significant usage reductions on PTR event days in 2012 for the average of the 855 SDEC participants and 41,000 other SDG&E customers who opted to receive electronic event notification, or alerts.[33] Customers with IHD devices reduced usage by comparable amounts. In contrast, the more than 1 million customers who did not receive PTR alerts, including those who registered for My Account, showed virtually no usage reductions. Analysis of a separate sample of customers who were identified in a post-event survey as "aware" of the event found substantially greater usage reductions among aware customers than for those who were not aware, even among opt-in alert customers.

In addition to reporting on the nature of PTR usage impacts, this study found that the program's CRL baseline method for calculating usage changes and bill credits performed relatively poorly. In addition to raising fairness issues (*e.g.*, some customers being paid for "false" usage reductions and others not being paid due to under-stated usage reductions), these results suggest that customers could become wary about the value of making efforts to reduce usage. Discussion of ways to improve the CRL method seems warranted.

The above findings that significant PTR load impacts were largely limited to customers who opted to receive electronic alerts, and that the program's CRL method produced substantial errors in measuring customers' true baselines suggests two recommendations. One is that PTR bill credits be restricted to only those customers who opt to receive program alerts. The other is that efforts be made to improve the CRL baseline method, such as applying day-of adjustments.

[33] Approximately 2,900 Summer Saver participants also opted to receive alerts and reduced usage by even greater amounts, as reported in a separate evaluation of the Summer Saver program.

APPENDIX A. MODEL SELECTION AND VALIDITY ASSESSMENT

A.1 Model Specification Tests

A range of model specifications were tested before arriving at the model used in the *ex post* load impact analysis. The basic structure of the model is shown in Section 3.3. The tests are conducted using average-customer data by customer group, where customer groups are defined by region (coastal or inland), size, and whether they opted to receive an event alert.[34]

The model variations are based on differing methods of characterizing weather conditions. We tested 18 different combinations of weather variables. The weather variables include: heat index (HI)[35]; the 3-hour moving average if HI; temperature-humidity index (THI)[36]; the 3-hour moving average of THI; the 24-hour moving average of THI; cooling degree hours (CDH)[37], including both a 60 and 65 degree Fahrenheit threshold; the 3-hour moving average of CDH; the 24-hour moving average of CDH; and the one-day lag of cooling degree days (CDD)[38], including both a 60 and 65 degree Fahrenheit threshold. A list of the 18 combinations of these variables that we tested is provided in Table A–1.

Table A–1: Weather Variables Included in the Tested Specifications

Model Number	Included Weather Variables
1	HI
2	HI, HI_MA3
3	HI, HI_MA3, LagCDD65
4	CDH60, LagCDD60
5	CDH65, LagCDD65
6	CDH65, CDD65, LagCDD65
7	HI, CDD60, LagCDD60
8	THI, CDD60, LagCDD60
9	THI, CDD65, LagCDD65
10	CDH60, CDH60_MA3, LagCDD60
11	CDH65, CDH65_MA3,

[34] A separate set of validation models was estimated for the SDEC customers, using average customer load profiles for four customer groups defined by climate zone and whether the customer opted into event notification (versus being defaulted onto it).

[35] $HI = c_1 + c_2T + c_3R + c_4TR + c_5T^2 + c_6R^2 + c_7T^2R + c_8TR^2 + c_9T^2R^2 + c_{10}T^3 + c_{11}R^3 + c_{12}T^3R + c_{13}TR^3 + c_{14}T^3R^2 + c_{15}T^2R^3 + c_{16}T^3R^3$, where T = ambient dry-bulb temperature in degrees Fahrenheit and R = relative humidity (where 10 percent is expressed as "10"). The values for the various *c*'s may be found here: http://en.wikipedia.org/wiki/Heat_index.

[36] THI = T – 0.55 x (1 – *HUM*) x (T – 58) if T>=58 or THI = T if T<58, where T = ambient dry-bulb temperature in degrees Fahrenheit and *HUM* = relative humidity (where 10 percent is expressed as "0.10").

[37] Cooling degree hours (CDH) was defined as MAX[0, Temperature – Threshold], where Temperature is the hourly temperature in degrees Fahrenheit and Threshold is either 60 or 65 degrees Fahrenheit. Customer-specific CDH values are calculated using data from the most appropriate weather station.

[38] Cooling degree days (CDD) are defined as MAX[0, (Max Temp + Min Temp) / 2 – Threshold], where Max Temp is the daily maximum temperature in degrees Fahrenheit and Min Temp is the daily minimum temperature. Customer-specific CDD values are calculated using data from the most appropriate weather station.

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	LagCDD65
12	THI, THI_MA3, LagCDD65
13	CDH60_MA3, CDH60_MA24
14	CDH65_MA3, CDH65_MA24
15	THI_MA3, THI_MA24
16	CDH60_MA3, LagCDD60
17	CDH65_MA3, LagCDD65
18	THI_MA3, LagCDD65

The model variations are evaluated according to two primary validation tests:

1. Ability to predict usage on event-like *non-event days*. Specifically, we identified a set of days that were similar to event days, but were not called as event days (*i.e.*, "test days"). The use of non-event test days allows us to test model performance against known "reference loads," or customer usage in the absence of an event. We estimate the model excluding one of the test days and use the estimates to make out-of-sample predictions of customer loads on that day. The process is repeated for all of the test days. The model fit (*i.e.*, the difference between the actual and predicted loads on the test days, during afternoon hours in which events are typically called) is evaluated using mean absolute percentage error (MAPE) as a measure of accuracy, and mean percentage error (MPE) as a measure of bias.
2. Performance on *synthetic* event days (*e.g.*, event-like non-event days that are treated as event days in estimation), to test for "event" coefficients that demonstrate statistically significant bias, as opposed to expected non-significance, since customers have no reason to modify usage on days that are not actual events. This is an extension of the previous test. The same test days are used, with a set of hourly "synthetic" event variables included in addition to the rest of the specification to test whether non-zero load impacts are estimated for these days. A successful test involves synthetic event load impact coefficients that are not statistically significantly different from zero.

A.1.1 Selection of Event-Like Non-Event Days

In order to select event-like non-event days, we created an average weather profile using the load-weighted average across customers, each of which is associated with a weather station. We "scored" each day (separately for weekends and weekdays) by comparing the values of HI, CDH65, and the one-day lag of CDH65 to the values for each event day. For example, we calculated the following statistic for each day relative to the first day: abs($HI_t - HI_{Evt}$) / StdDev(HI). A similar score was calculated for the other two weather measures, and the sum of the three was used to rank the days. We selected the three lowest-scoring days (low scores indicate greater similarity to the event day) for each event day. Days were excluded from the list as necessary (*e.g.*, to exclude other event days).

Table A–2: List of Event-Like Non-Event Days by Event Day Type

Weekday	Weekend
7/13/201 2	8/18/201 2
8/6/2012	9/1/2012

8/7/2012	9/22/2012
8/8/2012	
8/15/2012	
8/22/2012	
8/30/2012	
9/10/2012	
9/13/2012	
9/19/2012	
9/20/2012	

A.1.2 Results from Tests of Alternative Weather Specifications

As described above, we tested 18 different sets of weather variables for each of 12 customer sub-groups. The tests are conducted by estimating one model for every customer group (12), specification (18), and event-like day (14). Each model excludes one event-like day from the estimation model and uses the estimated parameters to predict the usage for that day. The MPE and MAPE are calculated across the event windows of the withheld days.

Table A–3 shows the adjusted R-squared, mean percentage error (MPE), and mean absolute percentage error (MAPE) for the selected ("winning") specification for each utility and program, which was specification 14 from Table A-1 (which uses the 3-hour and 24-hour moving averages of CDH65). The values in parentheses are the standard deviations of the statistic across the 18 specifications. The adjusted R-squared values are uniformly high (in excess of 0.96) and vary little across the specifications tested. The bias (measured using MPE) tends to be positive, indicating a tendency for the model to overstate true baselines. However, the bias results are mixed for the most responsive groups found in the bottom two rows of the table (with opt-in notice, in the inland zone, for the medium and large sizes). The biases generally tend to be small. However, the -1.6 percent bias for the high-use, opt-in notice, coastal customers is an exception, and is reasonably large given the relatively small magnitude of the estimated load impacts.

Model error, as measured by MAPE, ranges from 2.0 percent to 7.0 percent across the customer groups. The error rate does not display much variation across the alternative specifications (as indicated by the small standard errors).

Table A–3: Specification Test Results for the "Winning" Model

Opted into Alert?	Region	Size Group	MPE	MAPE	Adjusted R^2
No	Coastal	Low Use	0.3%	2.0%	0.988

			(0.2%)	(0.2%)	(0.002)
		Medium Use	0.1% (0.4%)	2.6% (0.4%)	0.989 (0.004)
		High Use	-1.1% (0.5%)	3.0% (0.3%)	0.988 (0.004)
	Inland	Low Use	0.7% (0.5%)	3.6% (0.6%)	0.981 (0.005)
		Medium Use	0.8% (0.7%)	4.9% (0.9%)	0.983 (0.005)
		High Use	0.1% (0.6%)	3.9% (0.9%)	0.986 (0.005)
Yes	Coastal	Low Use	1.1% (0.2%)	3.8% (0.2%)	0.981 (0.003)
		Medium Use	0.2% (0.4%)	4.0% (0.3%)	0.984 (0.005)
		High Use	-1.6% (0.6%)	4.8% (0.2%)	0.982 (0.006)
	Inland	Low Use	0.4% (0.5%)	7.0% (0.3%)	0.963 (0.005)
		Medium Use	0.8% (0.7%)	5.7% (0.9%)	0.979 (0.006)
		High Use	-0.5% (0.7%)	4.9% (1.0%)	0.983 (0.005)

For each specification, we estimated a single model that included all of the days (*i.e.*, not withholding any event-like days), but using a single set of actual event variables (*i.e.*, a 24-hour profile of the average event-day load impacts). The results of these tests demonstrate the implication on estimated load impacts associated with each tested specification.

Figures A–1 through A–8 show the estimated hourly load impacts for the average event for each of the 18 level models by notice/climate zone/size. (For brevity, we omit the figures for the low-use groups since they account for a very small share of total load impacts.) The first four figures show the results for the “population” customers (*i.e.*, those that did not opt into notification alerts). For each group, the estimated load impacts are uniformly wrong signed during event hours. The specification we selected, which is shown by the bold line, tends to minimize the extent of this effect. The model results show that different weather specifications can have strong effects on estimated load impacts, but cannot completely remove wrong-signed load impacts from the estimates (presumably because there are no load impacts to be found for these groups).

Figure A–1: Average Event-Hour Load Impacts by Specification: *Population, Coastal, Medium Use*

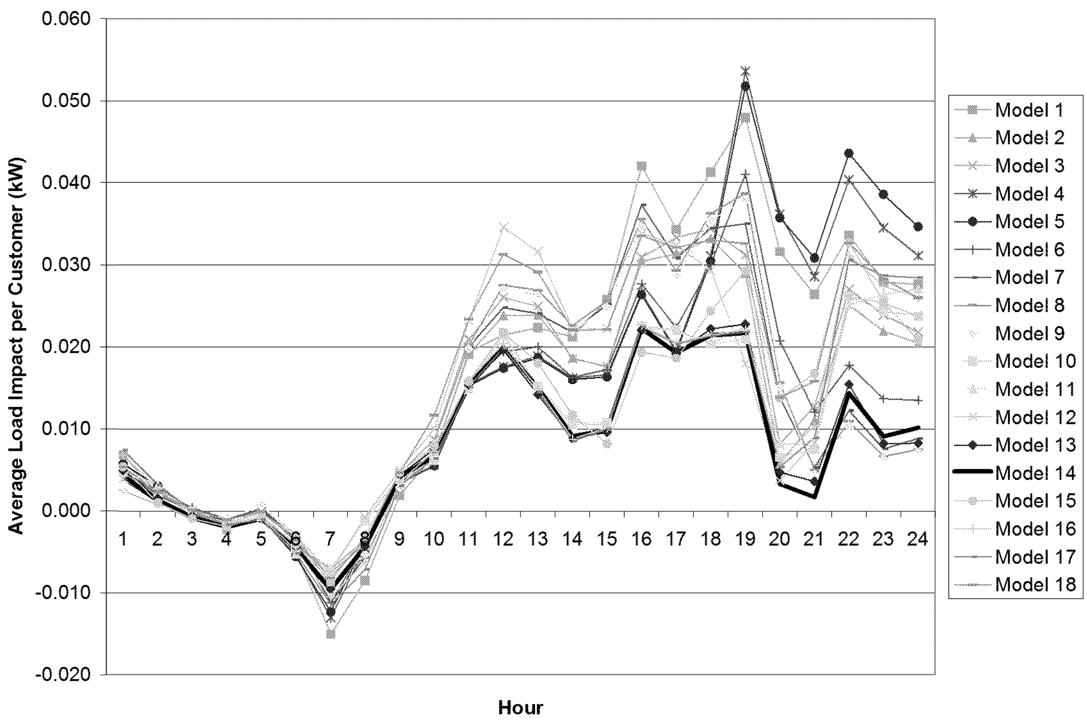
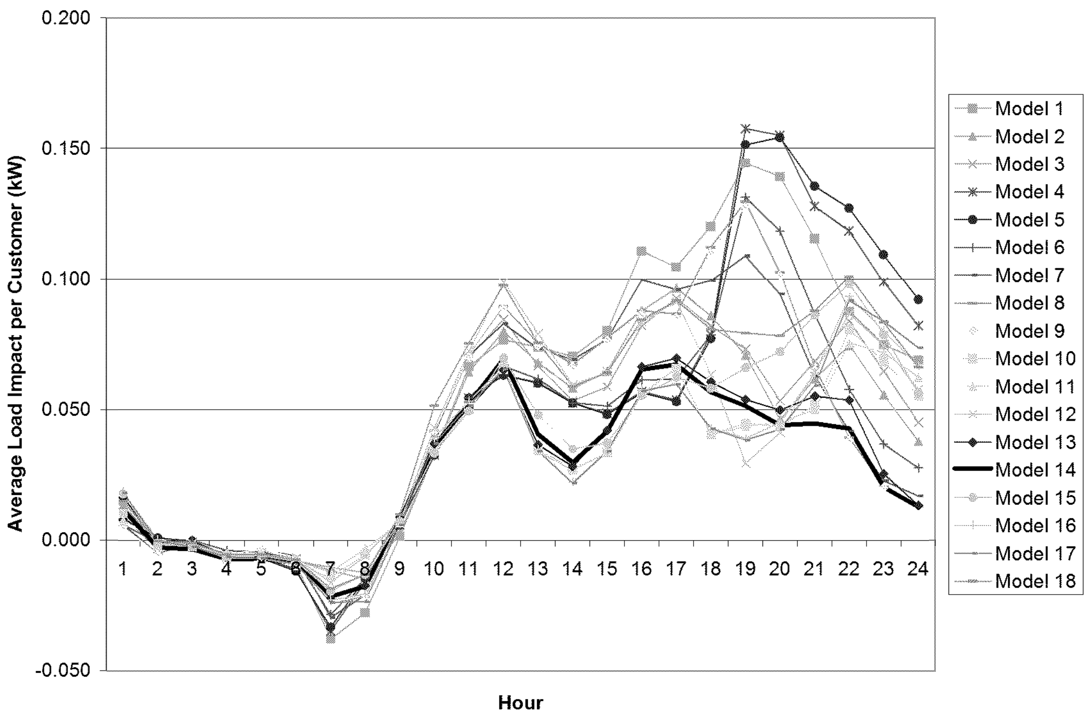


Figure A–2: Average Event-Hour Load Impacts by Specification, *Population, Coastal, High Use*



SB_GT&S_0888798

Figure A–3: Average Event-Hour Load Impacts by Specification, *Population, Inland, Med. Use*

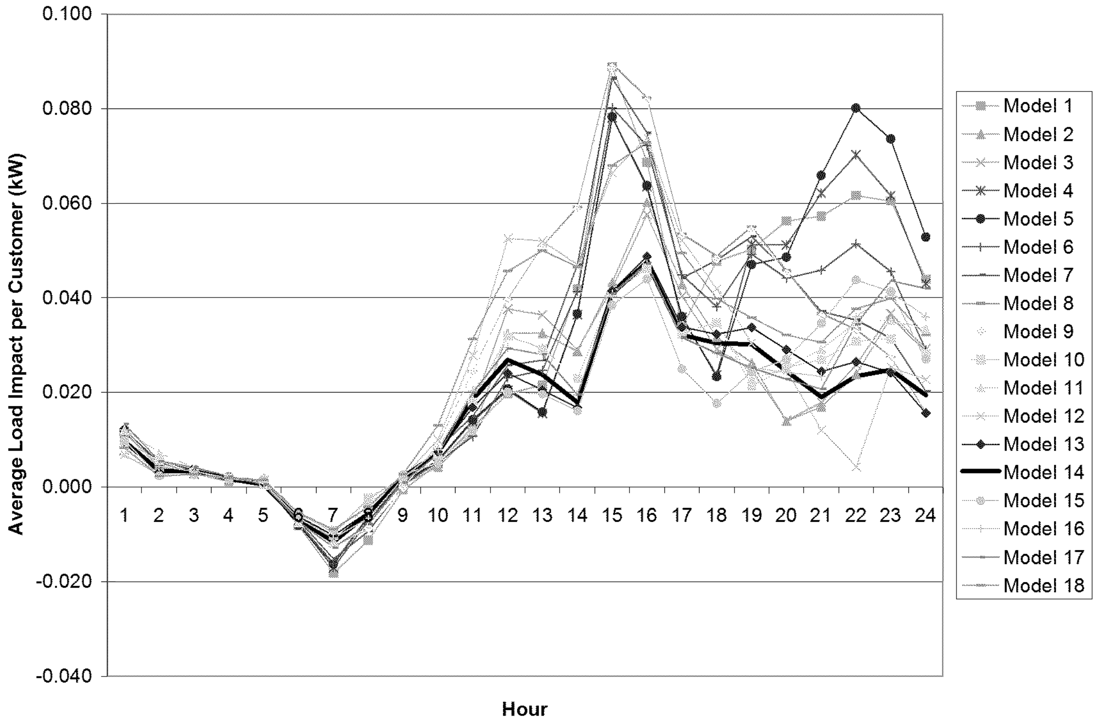
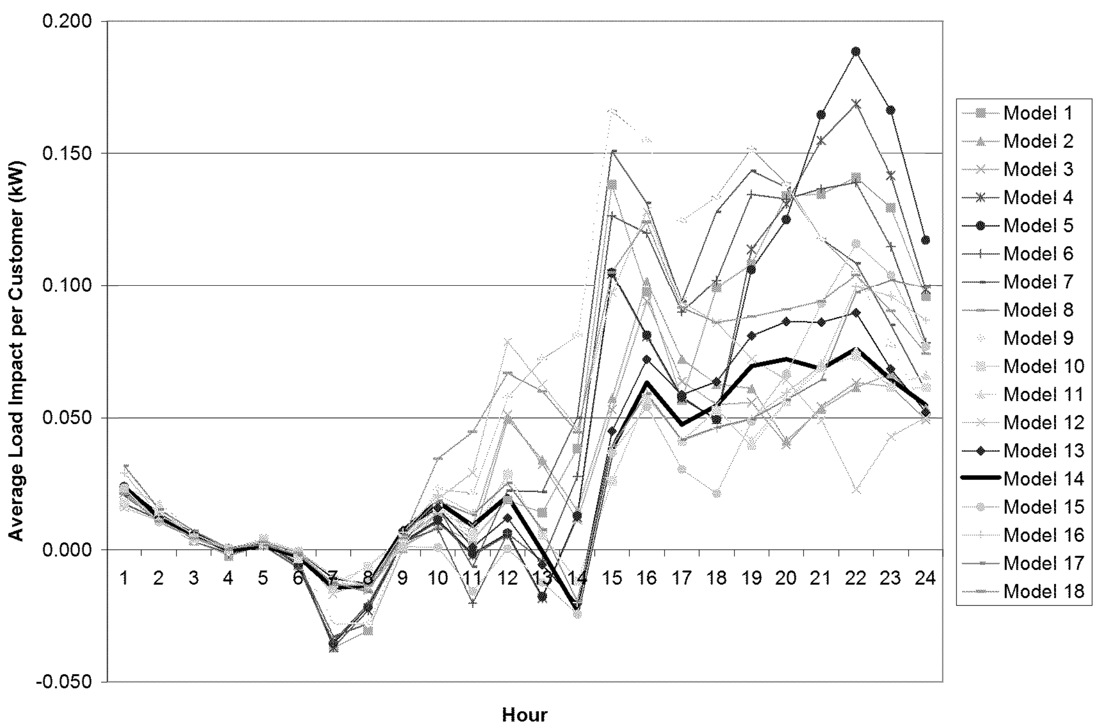
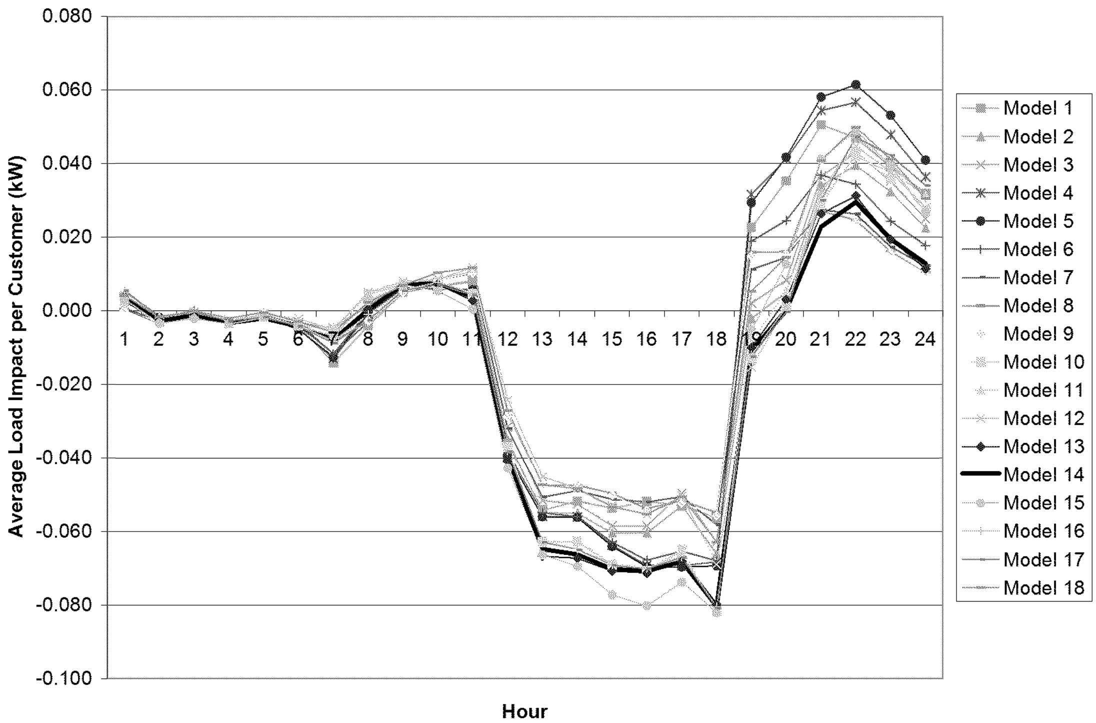


Figure A–4: Average Event-Hour Load Impacts by Specification, *Population, Inland, High Use*



Figures A-5 through A-8 show the range of estimated load impacts for customers who opted into the alert notifications. The range of estimated load impacts across models tends to be smaller for these customers than it is for the population customers. This is likely due to the fact that the customers exhibited more demand response, such that the event days have a response "signal" to identify. In the absence of that, the event variables will attempt to account for any unexplained variations, which could be positively or negatively signed.

Figure A–5: Average Event-Hour Load Impacts by Specification, *Opt-in Alert, Coastal, Med. Use*



SB_GT&S_0888800

Figure A–6: Average Event-Hour Load Impacts by Specification, *Opt-in Alert, Coastal, High Use*

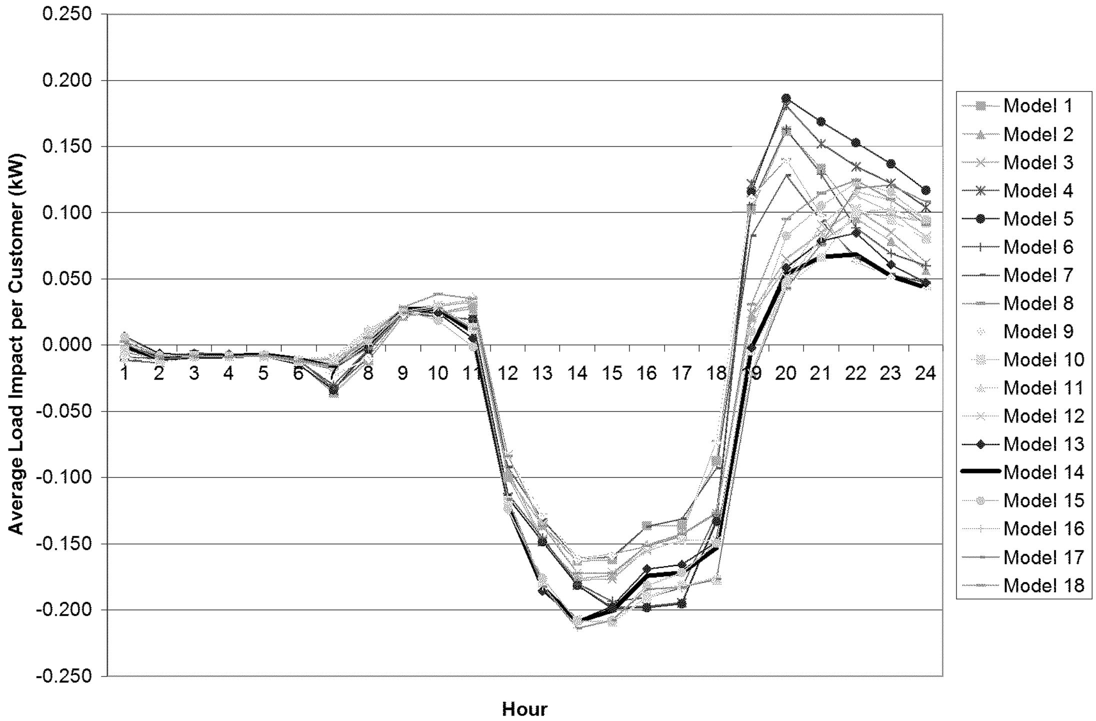


Figure A–7: Average Event-Hour Load Impacts by Specification, *Opt-in Alert, Inland, Med. Use*

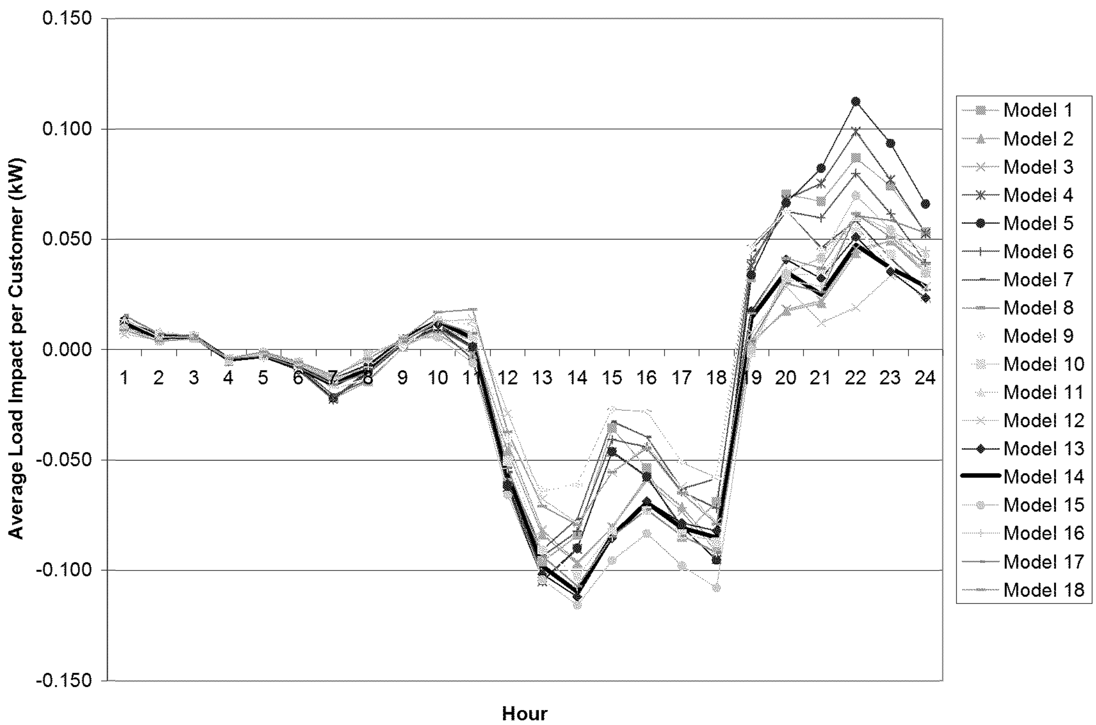
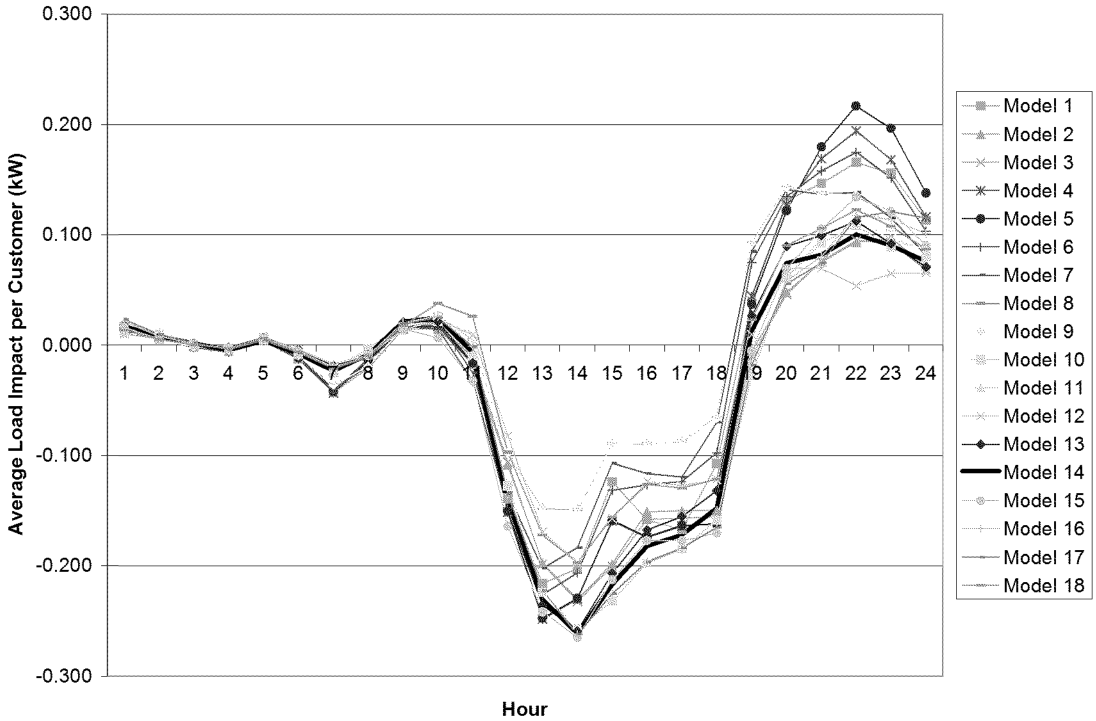


Figure A–8: Average Event-Hour Load Impacts by Specification, *Opt-in Alert, Inland, High Use*



A.1.3 Synthetic Event Day Tests

For the specification selected from the testing described in Section A.1.2, we conducted an additional test. The selected specification was estimated on the aggregate customer data, including a set of 24 hourly "synthetic" event-day variables. These variables equaled one on the days listed in Table A–1, with a separate estimate for each hour of the day.

If the model produces synthetic event-day coefficients that are not statistically significantly different from zero, the test provides some added confidence that our actual event-day coefficients are not biased. That is, the absence of statistically significant results for the synthetic event days indicates that the remainder of the model is capable of explaining the loads on those days.

Tables A–4 and A-5 present the results of this test for each customer group, showing only the coefficients during a typical event window of hours-ending 12 through 18. Bold type indicates that the estimated coefficient is statistically significantly different from zero with 90 percent confidence. The majority of the estimated coefficients pass the test (they are not statistically significantly different from zero). The notable exceptions are found in the two coastal high use customer groups, which have six statistically significant coefficients between them. The positive sign of these coefficients indicates the potential that the load impacts are underestimated for these groups.[39] However, Figures A-2 and A-6 show that the estimated load impacts for actual

[39] It is also possible that the event-like non-event days are sufficiently different from the actual event days that the results of Table A-4 represent differences in the model's ability to explain usage on the different types of event

event days are not increased by selecting a different specification. Therefore, while it is possible that the results in the tables indicate that we have conservative load impact estimates, we did not discover a model that improves the situation.

Table A–4: Synthetic Event-Day Tests by Customer Group, *Population Customers*

Hour	Coastal			Inland		
	Low Use	Medium Use	High Use	Low Use	Medium Use	High Use
12	0.000	-0.001	0.023	-0.001	-0.004	-0.005
13	0.002	0.002	0.031	0.000	-0.004	0.009
14	0.001	0.007	**0.050**	-0.002	-0.003	0.008
15	0.001	0.005	**0.056**	-0.001	0.000	0.016
16	0.000	0.001	0.040	-0.005	-0.010	-0.006
17	-0.004	-0.003	0.029	0.001	-0.007	0.008
18	-0.003	0.000	0.032	0.002	-0.010	0.009

Table A–5: Synthetic Event-Day Tests by Customer Group, *Alert Customers*

Hour	Coastal			Inland		
	Low Use	Medium Use	High Use	Low Use	Medium Use	High Use
12	0.001	0.001	0.034	-0.001	-0.001	0.024
13	-0.001	0.000	0.038	0.006	0.002	0.035
14	-0.001	0.005	**0.059**	0.015	0.001	0.031
15	0.002	0.003	**0.074**	0.006	0.003	0.046
16	-0.008	0.000	**0.064**	0.000	-0.012	0.025
17	**-0.009**	-0.004	**0.058**	-0.002	-0.001	0.037
18	-0.004	0.003	0.046	0.000	0.001	0.039

ADDITIONAL APPENDICES

The following Appendices accompany this report. Both are Excel files that produce the tables required by the Protocols.

Study Appendix B	SDG&E PTR *Ex-Post* Load Impact Tables
Study Appendix C	SDG&E PTR *Ex-Ante* Load Impact Tables

days, rather than indicating that the model systematically underestimates load impacts for two of the twelve customer groups.