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## **2012 LOAD IMPACT EVALUATION OF SDG&E SMALL COMMERCIAL PTR PROGRAM – SDG0267 FINAL REPORT**

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EnerNOC Utility Solutions Consulting  
500 Ygnacio Valley Road  
Suite 450  
Walnut Creek, CA 94596  
925.482.2000  
[www.enernoc.com](http://www.enernoc.com)

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This report was prepared by  
EnerNOC Utility Solutions Consulting  
500 Ygnacio Valley Blvd., Suite 450  
Walnut Creek, CA 94596  
Project Director: C. Williamson  
Project Manager: K. Marrin

# EXECUTIVE SUMMARY

## Introduction

SDG&E's Peak Time Rebate (PTR) program, also known as Reduce Your Use, is a default program for all residential and small commercial customers in SDG&E's territory. The PTR program provides small commercial customers with the opportunity to earn a bill credit for lowering their consumption during PTR events. For those that receive notification, the program also provides customers with day-ahead notification of an event.

The PTR rate is a two-level incentive program, providing a basic incentive level (\$0.75/kWh) to customers that reduce energy use through manual means and an additional incentive (\$1.25/kWh) to customers that reduce energy use through automated enabling technologies. In 2012 the only customers who were eligible for the enabling technology credit were those enrolled in the Summer Saver program. The incentive is paid to customers through a bill credit that is calculated based on each customer's event day reduction in electric usage below their established customer-specific reference level (CRL).

Throughout the evaluation we separate the small commercial participants into three subgroups defined below:

- Non-Notified Customers – these customers did not receive any official notification of PTR event days from SDG&E. It is possible however, that these customers may have heard about PTR events from other indirect sources, such as news, word of mouth, or the internet.
- My Account Customers – My Account is SDG&E's web interface which allows customers to pay and manage bills online. These customers receive a default notification email through My Account.
- Opt-in Alert Customers – these customers requested to be notified of PTR events through email, or text.

There are also two groups of customers that were specifically excluded from this evaluation; 284 net metering customers, and 4,005 Summer Saver participants. The Summer Saver participants will be evaluated separately in the Summer Saver evaluation. Table E-1 shows the number of customers and the average on-peak usage of the customers in each of the three groups after excluding the Summer Saver and net metering customers. The large majority of customers, 67%, did not receive any notification of PTR events. Nearly a third, about 32%, of the customers received an automated notification of PTR events via email through My Account. Only 341 participants signed up for email or text notification of events.

**Table E-1** *Customer Characteristics by Group*

Customer Type	Number of Customers	Average on-peak kW
No Notification	72,452	3.94
My Account	35,125	4.82
Opt-in Alerts	341	3.56
All Small Commercial	107,918	4.02

During the summer of 2012 SDG&E called seven PTR events, two of the events were called on Saturdays. Each of the events had several comparable non-event days throughout the summer

except one, Saturday September 15, 2012. The September 15 event was extremely hot compared to other events and compared to other days during the summer. One day, Friday September 14, was similar in temperature; however the difference between weekday and weekend load shapes for commercial customers makes this a less than ideal day for comparison to the Saturday event. Table 1-4 shows the average on-peak temperatures for the Inland and Coastal regions on each event day, averaged across event days, and for the entire summer.

**Table E-2 Average On-peak Event Day Temperatures**

Day Type	Inland	Coastal
20-Jul-12	83.4	78.2
9-Aug-12	86.1	79.5
10-Aug-12	86.9	80.9
11-Aug-12	86.3	82.4
14-Aug-12	87.1	80.3
21-Aug-12	80.3	76.1
15-Sep-12	97.0	96.1
Average PTR Day	86.7	81.8
Average All Summer	79.9	75.5

## Sample Design and Methodology

Because there are 107,918 small commercial PTR participants being considered in this evaluation and performing analysis on a population of that size is prohibitive, we used a large sample of participants for the analysis. SDG&E created a new Dynamic Load Profiling (DLP) sample for the small commercial class in summer of 2011. The sample consists of approximately 8,500 customers and was designed using typical stratified random sampling techniques to represent the small commercial population. We modified the DLP sample slightly in order to use it for this evaluation. First, all customers who requested notification of PTR events and were not already in the DLP sample were added to the analysis sample for evaluation as a census or certainty stratum for the Opt-in Alert customers. Second, we adjusted the sample weights to reflect the mix and usage of customers being evaluated as participants in the small commercial PTR program in 2012. In order to make these adjustments we post-stratified the sample by reassigning both sample and population customers to the appropriate stratum based on their 2012 summer average daily usage and climate zone.

Because of the very small expected savings and the lack of a formal control group, isolating and estimating *ex-post* impacts for the small commercial PTR program was difficult, and in most cases our estimates were insignificant and assumed to be zero. However, during this evaluation we used several different methods to attempt to isolate impacts in specific subgroups and to confirm and validate the statistically insignificant results.

A fixed-effects regression based approach was initially used to estimate the hourly impacts for each of the three subgroups on each event day, however most of those estimates were insignificant. In addition, it may be that the few significant estimates we were able to obtain, were merely a result of random variation, rather than a result of actions being taken by customers, a common phenomenon when making many estimates. Therefore, we also included both a load shape analysis, which is similar to a baseline analysis, and a matched control group analysis for the Opt-in Alert customers. We included the matched control group analysis for the Opt-in Alert customers because both the regression results and the load shape analysis indicated that those customers might be taking some actions.

## Program Impacts

After completing three separate analyses of ex-post impacts for the small commercial PTR program, the evaluation resulted in an official estimate of zero impact on an average PTR event day for all three groups. Within the Opt-in Alerts subgroup both the regression analysis and matched control group analysis suggested to presence of small impacts, however the impact across days could not be estimated due to a lack of statistical significance. On individual event days within the Opt-in Alerts group, there are three very small but statistically significant impacts; these impacts are at most 50 kW for the entire group, or about 0.14 kW per customer. Table E-3 shows the impact estimates based on the hourly regression models for each program subgroup, on each event day. The zeros with asterisks in the Opt-in Alert group represent positive impact estimates that were not significant at the 90% level.

**Table E-3** *Summary of Program Impacts Across Groups*

Event Day	Average Impact (MW) Non-Notified	Average Impact (MW) My Account	Average Impact (MW) Opt-In Alerts
20-Jul-12	0	0	0*
9-Aug-12	0	0	0.04
10-Aug-12	0	0	0.05
11-Aug-12	0	0	0
14-Aug-12	0	0	0.05
21-Aug-12	0	0	0*
15-Sep-12	0	0	0
Average PTR Day	0	0	0*

## Key Findings

The following were identified as key findings during the SmartHours 2012 impact evaluation:

- Based on the results of the regression analysis and the load shape analysis, we can conclude that the Non-Notified participants are not responding to PTR events.
- Again, based on the results of the regression analysis and the load shape analysis, we can conclude that the My Account participants are not responding to PTR events, and may actually be using more on PTR days.
- The analysis for the Opt-in Alert customers was somewhat inconclusive. Based on the regression analysis, some of the PTR events show small reductions in usage, around 3%. However, the matched control group analysis did not show any statistically significant reductions in usage during PTR event days. While our official estimate of savings for the group is zero, the mixed results indicate that one could logically conclude that some participants are likely to be taking action on some days; however the overall effect of such actions is small falling between 1% and 3%.
- Many industry studies have found small commercial customers to be much less price responsive than residential customers on dynamic pricing rates, and they are typically the least targeted for DR programs. Given this information, it is not surprising that we were unable to detect any impacts in this group of customers.

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## PEAK TIME REBATE PROGRAM SUMMARY

SDG&E's Peak Time Rebate (PTR) program, also known as Reduce Your Use, is a default program for all residential and small commercial customers in SDG&E's territory. This report presents the evaluation of the small commercial PTR participants. The PTR program is a default, rebate-only, dynamic pricing rate on which participants are paid a rebate for each kWh of energy that they reduce below their customer specific reference level on PTR event days.

While all of SDG&E's 112,199 small commercial customers are considered participants in the PTR program, not all of the customers received notification of PTR Events. Two groups of customers received event notifications, those that are My Account users, and those that specifically requested to be notified of events, known as Opt-in Alert participants. Approximately 37,077 (33%) of SDG&E's small commercial customers received notifications through their My Account email account and 341 requested notification either through email or text message.

This report includes the *ex-post* impact estimates for the small commercial PTR participants. We also include a summary of the total amount of rebates paid through the rate.

### Peak Time Rebate Program Description

The SDG&E small commercial PTR program was authorized by the CPUC in resolution E-4502 issued May 29<sup>th</sup> 2012 due to the fact that both Unit 2 and Unit 3 of SONGS were not operating last summer. Approximately 112,199 small commercial premises were automatically enrolled in the PTR program in July of 2012. In addition, a subset of approximately 341 customers requested to be notified by e-mail or text alert when PTR events occur. The program was scheduled to end on December 31<sup>st</sup> 2012 and SDG&E is not currently seeking to continue the program past that date.

The PTR program provides small commercial customers the opportunity to earn a bill credit for lowering their consumption during events. For those that receive notification, the program provides customers with day-ahead notification of an event. In emergency situations, an event can be called on a day-of basis, but day-of events are not the primary design or intended use of the program. There is no maximum number of PTR events that can be called, but the incentive payments were designed assuming that an average of nine events would be called each year.

The PTR rate is a two-level incentive program, providing a basic incentive level (\$0.75/kWh) to customers that reduce energy use through manual means and an additional incentive (\$1.25/kWh) to customers that reduce energy use through automated enabling technologies. In 2012 the only customers who were eligible for the enabling technology credit were those enrolled in the Summer Saver program.<sup>1</sup> The incentive is paid to customers through a bill credit that is calculated based on each customer's event day reduction in electric usage below their established customer-specific reference level (CRL).<sup>2</sup>

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<sup>1</sup> Load impacts for the summer saver program and the incremental impacts of summer saver over PTR were estimated in the Summer Saver evaluation. Therefore all Summer Saver customers were excluded from this analysis.

<sup>2</sup> The CRL for a weekday event is defined as the total consumption for the event period averaged over the three highest days from within the immediately preceding five similar non-holiday weekdays prior to the event. The highest days are defined to be the days with the highest total consumption between 11 AM and 6 PM. The similar days will exclude weekends, holidays, other event days, and will exclude other demand response program event days for customers participating in multiple demand response programs. The CRL

After being defaulted onto the rate, customers were provided with a PTR education kit including information on the program, how they can earn a rebate on event days and the benefit of enrolling for event notifications. The intent of the information is to assist customers in achieving the bill credit. The education kit encouraged customers to sign up for day-ahead electronic notifications of event days through e-mail and/or text. The kit also includes information on how to access information about their consumption history, CRL, event performance, and rebate calculation through web presentment, e-mail, and on their energy bill.

## Participant Characteristics

Throughout the evaluation we will be looking at the small commercial participants in three subgroups defined below:<sup>3</sup>

- Non-Notified Customers – These customers did not receive any official notification of PTR event days from SDG&E. It is possible however, that these customers may have heard about PTR events from other indirect sources, such as news, word of mouth, or the internet.
- My Account Customers – My Account is SDG&E's web interface which allows customers to pay and manage bills online. These customers receive a default notification email through My Account.
- Opt-in Alert Customers – These customers requested to be notified of PTR events through email, or text.

There are also two groups of customers that were specifically excluded from this evaluation; 284 net metering customers, and 4,005 Summer Saver participants that will be evaluated separately in the Summer Saver evaluation.

Table 1-1 shows the number of customers and the average on-peak usage of the customers in each of the three groups after excluding the Summer Saver and net metering customers.

**Table 1-1 Customer Characteristics by Group**

Customer Type	Number of Customers	Average on-peak kW
No Notification	72,452	3.94
My Account	35,125	4.82
Opt-in Alerts	341	3.56
All Small Commercial	107,918	4.02

The large majority of customers, 67%, did not receive any notification of PTR events. Nearly a third, about 32%, of the customers received an automated notification of PTR events via email through My Account. In addition, My Account customers use more energy on average than the remainder of the population with an average on-peak KW of 4.82 vs. 4.02 for the entire class. Only 341 customers requested to be notified of PTR days, which represents about 0.3% of the small commercial customers. Those customers that signed up for the Opt-in Alerts are also, on average, smaller than the general population with an average on-peak kW of 3.56. Table 1-2 shows the number of customers that signed up for Opt-in Alerts throughout the summer of 2012 by month.

for a weekend or holiday event is defined as the total consumption during the PTR even period for the highest day from within the immediately preceding three (3) weekend days.

<sup>3</sup> Because there is some overlap between each of the groups we defined them as follows to prevent multiple combinations of different groups. Non-notified customers did not receive notification either through My Account or via an Opt-in Alert. My Account customers are all My Account customers that did not request Opt-in Alerts, and Opt-in Alert customers include all those that requested notification regardless.

**Table 1-2 Opt-In Alert Enrollments by Month**

Month	Number of Participants
Jun-12	76
Jul-12	220
Aug-12	45

## Weather and Events

SDG&E divides its service territory into 4 weather zones, Coastal, Mountain, Inland, and Desert. Table 1-3 shows the number of small commercial customers by group in each of the 4 weather zones. SDG&E's population is heavily concentrated in the coastal zone with about 60% of businesses being located within that zone. Most of the remainder of the population is located in the Inland zone, only 1.6% of the population is located in the Mountain zone, and less than 1% in the Desert zone. The My Account customers are similarly distributed across the zones. Those who requested notifications are split mostly between the two densest zones, with 70% located along the coast and 30% located inland.

**Table 1-3 Percent of Customers by Type and Weather Zone**

Climate Zone	Non-Notified	My Account	Opt-in Alerts	Population
Zone 1 - Coastal	59.3%	62.3%	69.8%	60.3%
Zone 2 - Mountain	1.6%	1.5%	0.6%	1.6%
Zone 3 - Inland	38.8%	35.9%	29.6%	37.8%
Zone 4 - Desert	0.3%	0.2%	0.0%	0.3%

In practice, because the population is largely split between the Coastal and Inland zones, with very few businesses in the mountain and desert areas, any results reported by weather zone will fall into one of two regions, Coastal or Inland where Inland includes zones 2, 3, and 4 and Coastal includes zone 1.

During the summer of 2012 SDG&E called seven PTR events, two of the events were called on Saturdays. Each of the events had several comparable non-event days throughout the summer except one, Saturday September 15, 2012. The September 15 event was extremely hot compared to other events and compared to other days during the summer. One day, Friday September 14, was similar in temperature; however the difference between weekday and weekend load shapes for commercial customers makes this a less than ideal day for comparison to the Saturday event. Table 1-4 shows the average on-peak temperatures for the Inland and Coastal regions on each event day, averaged across event days, and for the entire summer.

**Table 1-4 Average On-peak Event Day Temperatures**

Day Type	Inland	Coastal
20-Jul-12	83.4	78.2
9-Aug-12	86.1	79.5
10-Aug-12	86.9	80.9
11-Aug-12	86.3	82.4
14-Aug-12	87.1	80.3
21-Aug-12	80.3	76.1
15-Sep-12	97.0	96.1
Average PTR Day	86.7	81.8
Average All Summer	79.9	75.5

In general temperatures inland are warmer than at the coast, with coastal temperatures remaining in the high 70's to very low 80's throughout the summer and on all PTR days except for the September 15 event. Inland temperatures were in the mid 80's for most of the PTR events, again except for the event on September 15.

## METHODOLOGY

The program evaluation activities were designed to estimate the actual or *ex-post* impacts for the small commercial PTR program. A secondary task was to provide summary settlement statistics for the rebates paid through the program based on the customer-specific reference load (CRL).

### Evaluation Goals

The primary goal of the load impact evaluation is to estimate the *ex-post* load impacts of the small commercial PTR program. This evaluation includes the following components:

- Average program level hourly load reduction on each PTR event day, and across all PTR event days
- Average per-participant hourly load reduction on each PTR event day, and across all PTR event days
- Hourly load reduction on PTR event days by various sub-groups including, customers that did not receive any notification of events, customers that receive default notification through My Account, and Opt-in Alert customers that specifically requested event notification.

We also include the following summary settlement statistics regarding PTR rebates, and a comparison of these statistics to the evaluation impacts:

- The number of customers who used less than their CRL for each event
- The total load reduction by event according to the CRL, including all customers
- The total load reduction by event according to the CRL, including only customers using less than their CRL.
- Total bill credits paid by event.
- Dollars per MW paid out according to the total load reduction estimated by the CRL
- Dollars per MW paid out according to the total load reduction estimated by the measurement and evaluation.

### Evaluation Challenges

Below we identify two key challenges associated with the evaluation of the small commercial PTR program:

- **Lack of control group.** SDG&E's PTR program was deployed as a default rate for all small commercial customers. In addition, since PTR is considered a "no lose" rate, participants are unable to opt-off of the rate. Because the entire population is technically participating in the program, creating a matched control group is challenging. However, after determining through regression and load shape analysis that those customers who are not being notified of events did not respond to PTR events, events, a matched

control group of those who were not notified of PTR events was used to further analyze load impact results among those that did receive notification.

- **Small expected energy reduction across all customers.** Based on the evidence presented in recent default PTR pilots both at ComEd and SDG&E, we would expect average energy savings for all participants to be very small, somewhere less than 5 percent. While on average the per customer savings is expected to be small, on an individual level we expect a wide variation in the level of savings, with a smaller subset of participants actively responding to events, and the large majority of participants responding very little, if at all. In this case, because of the default nature of the rate, and the fact that most customers have not proactively signed up for notification, the ratio of savers to non-savers is likely to be very small.

The analysis approach outlined below was designed specifically to meet each of the key evaluation goals while also addressing each of the challenges.

## Analysis Approach

The following sections describe in detail the analysis approach and methodology we used to estimate the *ex-post* impacts for the PTR participants. We first describe the sample that was used for the analysis. Next we describe the methods we used to validate the sample data. Finally we describe the approach we used to estimate and validate the *ex-post* impacts for PTR participants.

### Sample Design

Because there are 107,918 small commercial PTR participants being considered in this evaluation and performing analysis on a population of that size is prohibitive, we used a large sample of participants for the analysis. SDG&E created a new Dynamic Load Profiling (DLP) sample for the small commercial class in summer of 2011. The sample consists of approximately 8,500 customers and was designed using typical stratified random sampling techniques to represent the small commercial population. We decided to use the DLP sample for our analysis of the small commercial PTR program for several reasons:

- The DLP sample customers were distributed relatively proportionally across the subgroups of interest.
- Because the DLP sample customers were part of a load research sample they had more thoroughly validated and complete interval data, especially during the pre-treatment period.
- Using the DLP sample eliminated the need to select a new random stratified sample and submit an interval data request for that sample within the limited time available for this analysis.

However, because the DLP sample is a stratified random sample rather than a simple random sample it was important to treat the weights properly throughout the analysis. The small commercial DLP sample is stratified by average daily summer usage and climate zone. The original sample design is shown below in Table 2-1.

**Table 2-1 Original 2011 DLP Sample Design**

Stratum	2011 Sample	2011 Population
Coastal ≤ 30 kWh/day	2,447	44,209
Coastal 30 < kWh/day ≤ 114	1,614	22,217
Coastal > 114 kWh/day	548	7,360
Mountain/Inland ≤ 24 kWh/day	1,416	22,117
Mountain/Inland 24 < kWh/day ≤ 102	1,481	15,991
Mountain/Inland > 102	466	4,492
Desert ≤ 20 kWh/day	61	1,632
Desert 20 < kWh/day ≤ 95	88	733
Desert > 95 kWh/day	113	242
<b>Totals</b>	<b>8,234</b>	<b>118,993</b>

We needed to modify the existing DLP sample slightly in order to be able to use it for this evaluation. First, all customers who requested notification of PTR events and were not already in the DLP sample were added to the analysis sample for evaluation. The customers who requested notification that were also in the DLP sample were then removed from the DLP strata that they were originally assigned to, and combined with those customers added to the sample into a census or certainty stratum for the Opt-in Alert customers. Second, we adjusted the sample weights to reflect the mix and usage of customers being evaluated as participants in the small commercial PTR program in 2012. In order to make these adjustments we post-stratified the sample by reassigning both sample and population customers to the appropriate stratum based on their 2012 summer average daily usage and climate zone. We also excluded Summer Saver and Net Metering participants from both the population and the sample.

We then recalculated the case weights for the post-stratified design. We used the same average summer daily usage breakpoints that were calculated for the 2011 stratification.<sup>4</sup> The updated stratification for the DLP sample is below is Table 2-2.

<sup>4</sup> While using the same stratum breakpoints that were created for the 2011 distribution of summer average daily usage is not completely optimal, it should be fairly close, and is still a valid sample. The sample size in this case is sufficiently large that using suboptimal breakpoints is not likely to result in large changes in precision.

**Table 2-2 Post-stratification of the 2011 DLP Sample**

Stratum	2012 Sample	2012 Population	Change in Sample	Change in Population
Coastal ≤ 30 kWh/day	2,440	36,060	-0.3%	-22.6%
Coastal 30 < kWh/day ≤ 114	1,588	21,194	-1.6%	-4.8%
Coastal > 114 kWh/day	581	7,633	5.7%	3.6%
Mountain/Inland ≤ 24 kWh/day	1,406	21,788	-0.7%	-1.5%
Mountain/Inland 24 < kWh/day ≤ 102	1,464	14,459	-1.2%	-10.6%
Mountain/Inland > 102	492	4,537	5.3%	1.0%
Desert ≤ 20 kWh/day	70	1,183	12.9%	-38.0%
Desert 20 < kWh/day ≤ 95	91	619	3.3%	-18.4%
Desert > 95 kWh/day	102	194	-10.8%	-24.7%
Opt-In Alerts	341	341	-	-
<b>Totals</b>	<b>8,575</b>	<b>108,008</b>	<b>4.0%</b>	<b>10.2%</b>

Most of the movement, both in the sample and in the population occurred between strata within one weather zone classification. Because the summer of 2012 was a bit hotter on average than the summer of 2011, more customers fell above the upper average daily usage breakpoints. The overall population is smaller here, than in the original sample design which is a result of removing the 4,005 Summer Saver participants, and the Net metering customers. Finally, the sample grew by 341 customers when we added the census stratum of Opt-in Alert participants.

### Data Validation

We used a variety of methods to validate the interval data supplied by SDG&E which are consistent with methods of data validation we use in similar evaluation work. We obtained access to interval data (up to 24 months, depending on the installation date of the meter) for each sample participant a total of 8,575 customers<sup>5</sup>. We also obtained the VEE codes that indicate if a particular interval was estimated. Consistent with SDG&E's internal procedures, we first eliminated any estimated data. Because the sample is being used to create the Daily Load Profiles, the data undergoes additional VEE procedures at SDG&E, therefore we expected the data to be high quality and require very little editing or exclusions. This was confirmed when the data was screened for excessive zeros and erroneous values in order to identify participants with problematic data that needed to be excluded from the analysis. We did not eliminate any participants based on these secondary screens.

### 2012 Ex-Post PTR Impacts

Due to the challenges identified above, isolating and estimating *ex-post* impacts for the small commercial PTR program was difficult, and in most cases our estimates were insignificant and assumed to be zero. However, during this evaluation we used several different methods to attempt to isolate impacts in specific subgroups and to confirm and validate the statistically insignificant results.

<sup>5</sup> This total already excludes the Summer Saver, TOU, and Net Metering customers from the sample



A regression based approach was initially used to estimate the hourly impacts for each of the three subgroups on each event day, however nearly all of those estimates were insignificant. In addition, it is likely that the very few significant estimates we were able to obtain, were merely a result of random variation, rather than a result of actions being taken by customers, a very common phenomenon when making many estimates. Therefore, we also included both a load shape analysis, which is similar to a baseline analysis, and a matched control group analysis for the Opt-in Alert customers. We included the matched control group analysis for the Opt-in customers only because both the regression results and the load shape analysis indicated that those customers might be taking some actions.

### ***The Regression Approach***

We used hourly regression models for each subgroup of interest (Non-Notified, My Account, and Opt-in Alerts) to estimate the effect of a PTR event on customers' loads. Because the PTR events are called only on isolated days over the course of the program year, and on all other days the participants and non-participants face the same rate, the data conforms nicely to what researchers often call a repeated measures design. This simply means that all participants are subjected to the treatment at the same time, repeatedly over the course of the study. In this case the control can be defined as an absence of the treatment, which includes all non-PTR days. In addition we can use pre-treatment data, prior to participation in the PTR program to isolate any differences that result from the program on non-PTR days and to better isolate the effects of weather and other seasonal variables on usage.

First, we defined the treatment and pre-treatment periods. We defined the treatment period as beginning July 1, 2012 when customers were first defaulted onto the rate, and ending on October 31, 2012. The pre-treatment period will be defined as the 12 months prior to the treatment period, beginning July 1, 2011. We include pre-treatment data so that we can better estimate the effect of the program under a variety of weather conditions and day types.

After establishing a pre and post-treatment period, we evaluated various modeling frameworks for estimating the effect of a PTR event on the participants. In general, the data we used to analyze the participants included both a customer-specific component and a time component. This type of data is generally referred to as panel data and can be modeled in several different ways; however, it is important to recognize that panel data has some inherent issues. When estimating panel data, the variance of the error term is not constant due to correlation within and across individuals. Thus, the Ordinary Least Squares (OLS) is still consistent, but not optimal. For the estimation method we considered employing three different panel estimators: first-differencing (FD), fixed effects (FE), and random effects (RE). A crucial condition of FE and FD is that the independent variables in the model must have variation across each customer. When a full set of customer-specific dummy variables are included, as in our case, the estimation of time-constant variables such as location cannot be included in the model.

The FE estimator assumes that the error term is uncorrelated with the independent variables across all time periods for the time-variant portion of the error term ( $u_{i,t}$ ) but allows the time constant portion of the error term ( $a_i$ ) to be correlated with the explanatory variables in any time period since it will be purged from the equation during estimation. For a large number of observations, and a small number of time periods the choice to use FD or FE lies in the relative efficiency of the estimators determined by the serial correlation in ( $u_{i,t}$ ). When no serial correlation is present, FE is more efficient than FD. Random effects has the additional assumption that  $a_i$  is uncorrelated with the explanatory variables across all time periods (a very unlikely case).

Ultimately we decided to use the fixed-effect model with robust errors, which is a common approach for a repeated measures with pre-treatment and post-treatment design using panel

data in the industry.<sup>6</sup> A somewhat simplified version of the hourly model specification used to estimate the effects of PTR events for each subgroup is presented in Equation 1 below.

$$kwh(j)_{it} = \alpha_i + \gamma Seas_t + \beta_1 CDH(j)_{it} + \beta_2 CDHop_{it} + \beta_3 year12_{it} + \beta_4 PTR_{it} + \beta_5 (PTR_{it} * CDHop_{it}) + \varepsilon_{it} \quad (1)$$

Where:

$kwh(j)_{it}$  = the consumption in hour  $j$  of customer  $i$  on day  $t$ .

$\alpha_i$  = a fixed effect for each customer  $i$

$\gamma Seas_t$  = a vector of seasonal indicator variables i.e. month, year, and day of week

$\beta_1 CDH(j)_{it}$  = a variable capturing the effect of temperatures above 70 degrees in hour  $j$

$\beta_2 CDHop_{it}$  = a variable capturing the effect of temperatures above 70 degrees in the on-peak period

$\beta_3 year12_{it}$  = a dummy variable that indicates the treatment period

$\beta_4 PTR_{it}$  = a dummy variable indicating that day  $t$  was a PTR event day

$\beta_5 (PTR_{it} * CDHop_{it})$  = an interaction capturing weather related differences in response to a PTR event

$\varepsilon_{it}$  is the error for participant  $i$  in hour(j) on day  $t$

We estimated the model above for each subgroup individually rather than estimating one population level model to limit the complexity of the model by eliminating the interaction terms necessary to distinguish the impacts between each group. In addition we also estimated both a weekday and weekend version of this model in order to estimate the impact of weekend PTR events.

The model specified above allows us to estimate the average impact for each PTR event based on the average temperature during the on-peak period. The impact at a given temperature can be estimated for participants using Equation 2 below.

$$Impact(j), PTR\ event = \beta_4 PTR_{it} + \beta_5 (PTR_{it} * CDDop_{it}) \quad (2)$$

Where:

$\beta_4$  = the effect of a PTR event on usage in hour  $j$

$\beta_5$  = the incremental effect of a PTR event on usage for each CDH during the on-peak period in hour  $j$

There are two ways to estimate the impacts of PTR using the model. We can estimate the impact using the parameter estimates as described above, or we can use the model to estimate a baseline, defined as what the customer would have used in the absence of the PTR event, and compare that with what the customer actually used. We believe that the impact estimates using the model will be more consistent. While comparing actual usage to a baseline is appealing in concept, it adds all the error from the model on a particular day into the impact. While this should not systematically bias the estimates, since the errors should be unbiased, it adds variability to the impact estimate. Using the model parameters excludes that error from the impact estimate, so should provide more stable impact estimates.

<sup>6</sup> Freeman Sullivan & Co., 2011 Statewide Non-Residential Critical peak Pricing Evaluation, June 1, 2012  
The Brattle Group, BG&E's Smart Energy Pricing Pilot Summer 2008 Impact Evaluation, April 28 2009

In this case, we experimented with many different model specifications; however we were unable to estimate consistently statistically significant impacts for any of the subgroups using the model.<sup>7</sup> Therefore it was important to validate the accuracy of the model to ensure that modeling error was not preventing us from capturing the impacts of a PTR event.

We validated the results of the regression models in two different ways. The first and simplest form of validation was to look at the model precision on the hottest non-event days of the year. Table 2-3 shows the model precision on all the 2012 non-event days that had an average temperature over 80 degrees.

**Table 2-3 Model Precision on Hot Non-Event Days**

Date	Average Temperature	Actual Precision	Actual kW	Predicted kW
7-Aug-12	81.87	2.40%	3.41	3.32
8-Aug-12	82.26	2.36%	3.46	3.38
13-Aug-12	84.36	3.64%	3.56	3.43
15-Aug-12	80.01	0.50%	3.31	3.29
16-Aug-12	82.56	4.04%	3.43	3.30
17-Aug-12	86.46	4.03%	3.51	3.37
27-Aug-12	80.91	-0.63%	3.21	3.23
28-Aug-12	81.06	-2.17%	3.23	3.30
29-Aug-12	82.94	0.72%	3.42	3.40
30-Aug-12	81.83	2.94%	3.39	3.30
31-Aug-12	81.93	2.90%	3.29	3.20
4-Sep-12	83.50	1.13%	3.45	3.41
5-Sep-12	83.10	0.05%	3.43	3.43
6-Sep-12	81.39	3.28%	3.39	3.28
7-Sep-12	80.10	4.48%	3.27	3.12
10-Sep-12	81.86	2.59%	3.39	3.30
14-Sep-12	94.74	1.81%	3.63	3.56
20-Sep-12	80.42	3.83%	3.33	3.21
21-Sep-12	80.45	3.25%	3.23	3.12
24-Sep-12	80.12	1.03%	3.29	3.26
<b>Average</b>	<b>82.59</b>	<b>2.11%</b>	<b>3.38</b>	<b>3.31</b>

When we look at the average precision across all of the hot non-event days the predicted load is within 2.11% of the actual load. The model is generally underestimating the actual load on hot days, which is what we would expect considering that in general, models are most accurate at the mean and least accurate at the extremes. This tendency to underestimate the load would make it difficult for the model to detect very small changes in usage in response to PTR events. So while this level of precision should allow us to pick up changes in usage resulting from a PTR event that are in the 5% range, very small changes in usage are likely to be lost in the model variation and will be very hard to detect.

We also used what is known as a false experiment to determine if the model was picking up variation from other sources, such as weather, and assigning that variation to our event

<sup>7</sup> See Chapter 3, Regression Results section, for a table that shows the number of statistically significant event related variables for each population subgroup.

indicators. In this case, the event indicators themselves were rarely significant so we wanted to be sure that the false indicator variables we created were also insignificant. To do this we selected some similar non-event days and assigned them an event indicator, even though no event was actually called. Then we re-ran the model with these false events. We were able to confirm using this technique that both the false even indicators and the real event indicators were insignificant. The tells us that the model is doing a pretty good job of capturing changes in usage based on seasonal variation, and on weather, and that if participants were acting differently on PTR event days, and if those actions resulted in large enough changes in usage, we should be able to pick up those changes in the model.

### ***Load Shape Analysis***

Because the estimates from the regression analysis were, for the most part, insignificant and not statistically different from zero, our next step was to compare load shapes for the different subgroups of customers on similar days. The goal of the load shape analysis was to provide confirmation that the regression results were consistent with the data, and that our model was not flawed. This is possible because the load shape analysis is not dependent on any assumed relationship between energy and other variables, and so is not sensitive to errors in the specification of those relationships in the model. To create the load shapes we first compared the on-peak temperatures of PTR event days and non-PTR event days. Next we selected five weekdays with a similar average on-peak temperature to the five weekday PTR event days while ensuring that the days were as close as possible in time to the PTR event days. We also tried to approximate consecutive events by selecting similar temperature days that were also sequential if possible. For the two weekend events we used the average of the two hottest Saturdays, although there are no comparable days for the unusually hot September 15 Saturday event.

Table 2-4 shows the PTR events and the matched days including the average on-peak temperature for each day. The idea is not to match each day individually, but to create a good match across all days in order to compare average shapes on PTR event days and non-PTR days. These averages can then be used to determine if the load shapes indicate that any of the groups are changing their behavior in response to a PTR event. The temperature on the weekdays is very close, with only a 2 degree difference between PTR and non-PTR days. SDG&E actually called PTR events on slightly cooler days, rather than on the hottest days of the summer. On the weekends the match is less close with a 4 degree difference between average PTR and non-PTR days, due to the very extreme temperature on September 15, 2012.

**Table 2-4** *Average On-Peak Temperature on Comparison and PTR Event Days*

Comparison Days		PTR Event Days	
Date	CDH On-Peak	Date	CDH On-Peak
23-Jul-12	83.3	20-Jul-12	80.6
24-Jul-12	83.9	9-Aug-12	82.5
8-Aug-12	85.0	10-Aug-12	83.6
15-Aug-12	83.3	14-Aug-12	83.4
20-Aug-12	83.0	21-Aug-12	78.0
Average Weekday CDH	83.7	Average Weekday CDH	81.6
21-Jul-12	87.8	11-Aug-12	84.2
18-Aug-12	86.0	15-Sep-12	96.5
Average Weekend CDH	86.9	Average Weekend CDH	90.3

### ***Matched Control Group Analysis***

Nearly all the regression-based model estimates for the Opt-in Alert customers indicated a reduction in usage during PTR events, however most were not statistically significant. Therefore we decided to use a third analysis technique for the Opt-in Alert customers to attempt to detect

impacts on PTR event days. In addition to the load shape analysis we also performed a matched control group analysis for the Opt-in Alert customers.

Based the results of both the regression analysis and the load shape analysis we were confident that the Non-notified customers were not responding to PTR events; therefore we selected our control group customers from the Non-notified group. We used a propensity score model to match our 341 Opt-in Alert customers with their closest non-notified match. The propensity score model is a probit model that is used to predict the probability that a participant would sign up for Opt-in Alerts. This probability is estimated for all the participants included in the model, both Non-notified and Opt-in Alert customers. We can then match each Opt-in Alert customer to the most similar Non-notified customer where the similarity between customers is determined by the similarity in the propensity score or probability of participation. In our case, because we want to compare daily usage on event days, the parameters of the model include average daily summer usage on non-event days. By using these specific parameters we make the probability of participation, or the propensity score, dependent on average daily usage and therefore are able to closely match each Opt-in Alert participant with a Non-notified participant based on their daily usage.

After matching each Opt-in Alert customer to their closest Non-notified match using the propensity score generated by the model, we used a difference-in-difference (DID) analysis to calculate the impact on each PTR event day. A DID approach, in contrast to a simple difference, allows us to correct for pre-existing differences between the treatment group (Opt-in Alerts customers) and the control group. The impact is estimated in two steps. First we calculate the difference between the treatment group and the control group both on event days (the "treatment period") and on non-event days (the "pre-treatment period"). The pre-treatment difference captures the pre-existing differences between the two groups that is unrelated to the events. Then we take the second difference, which is the treatment period difference less the pre-treatment difference. This second difference gives an impact estimate that is corrected for any pre-existing differences between the two groups.

## IMPACT RESULTS

This chapter presents the results of our analysis. The first section presents the impacts estimated from the hourly regression models. The second section presents the results of the load shape analysis, and the third section presents the matched control group results

### Regression Results

As mentioned above, the regression approach yielded very few statistically significant estimates for the two event-related variables that we included in the models, see Equation 1 in chapter 2 above. In order to estimate the *ex-post* on-peak impacts of PTR events we estimated 7 hourly models, for two day-types (weekend and weekday) across three subgroups resulting in a total of 42 models and 84 parameters. Table 3-1 below presents the event-related parameter estimates for the 42 models and two event-related parameters that we estimated;  $\beta_4 PTR_{it}$  and  $\beta_5 (PTR_{it} * CDHop_{it})$ . The two coefficient estimates are color coded by level of significance, with grey being insignificant, blue being significant at the 10% level, green being significant at the 5% level, and orange being significant at the 1% level. We present the estimates in this format in order to provide both context and perspective for the impact estimates generated based on these parameters later in this section.

Overall only 16 of the 84 estimates are statistically significant at any level, 12 are significant at the 5% level, and only 2 are significant at the 1% level. Standard modeling procedures generally exclude any variables from the model that are not significant at the 5% level or better, and the higher the significance the more certain one can be that the parameter estimate is, in fact, different from zero. Looking at the table below, we can conclude that for the most part, except in a few cases, the parameters that are being used to estimate PTR event impacts are not statistically significantly different from zero, and that therefore based on the model, the best estimate of the impact on a PTR event day is in fact zero.

It is interesting to note that the My Account subgroup actually has the most significant estimates, however when using those estimates to calculate the impact on PTR days, the impact is more often negative than positive, indicating an increase in usage on event days rather than a decrease. In the non-notified group none of the estimates are significant indicating that the non-notified customers are not taking any action on a PTR event day. Finally, the parameters for the Opt-in Alerts are for the most part insignificant, but impacts calculated from those parameters are consistently positive. This led us to suspect that Opt-in Alerts customers might be taking some action on PTR event days.

**Table 3-1** *Significance of Event-Related Parameter Estimates*

Subgroup	Hour	Weekday $\beta_4$	Weekday $\beta_5$	Weekend $\beta_4$	Weekend $\beta_5$
Opt-In Alerts	12	0.209	-0.029	0.254	-0.019
	13	0.147	-0.022	0.148	-0.008
	14	0.205	-0.026	0.191	-0.011
	15	0.032	-0.019	0.019	-0.005
	16	-0.112	-0.001	-0.054	0.006
	17	0.019	-0.014	-0.016	0.006
	18	0.154	-0.025	0.118	-0.012
	Non-Notified	12	0.020	0.009	0.091
13		-0.025	0.011	0.042	0.001
14		-0.032	0.013	0.054	0.000
15		0.003	0.007	0.047	0.000
16		0.012	0.002	0.023	0.000
17		-0.031	0.002	-0.019	0.003
18		0.029	-0.001	0.069	-0.005
My Account		12	-0.043	0.010	0.164
	13	-0.085	0.015	0.131	-0.008
	14	-0.060	0.012	0.148	-0.008
	15	-0.100	0.020	0.114	-0.001
	16	-0.171	0.024	0.035	0.002
	17	-0.269	0.022	-0.110	0.010
	18	-0.202	0.017	-0.060	0.004

While the parameter estimates of these models would not normally be used to calculate impacts due to their insignificance, in order to comply with CPUC reporting requirements we have included impact tables for each PTR event by subgroup in the remainder of the section. We have also included the 90% confidence intervals for each impact. If the confidence interval includes zero, then the impact is assumed to be zero.

Table 3-2 presents the average impact for each event day for the Opt-in Alert customers. Three of the four impacts are statistically significant indicating a slight decrease in load of between 3% and 4% on August 9, August 10, and August 14. In addition, all but two of the impact estimates are positive with confidence intervals that are closer to zero on the negative side than the positive side. These results, while not completely consistent, do indicate that Opt-in Alert customers may be responding to the PTR events.

**Table 3-2 Opt-in Alert Customers: Load Impact Estimates**

Event Date	Accounts	% Load Reduction	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	Average Temp. During Event	90% CI	10% CI
20-Jul	274	2.7%	1.0	0.027	79.8	-0.006	0.059
9-Aug	315	3.1%	1.4	0.040	81.3	0.001	0.080
10-Aug	330	3.8%	1.4	0.050	82.5	0.005	0.095
11-Aug	332	-0.4%	0.9	-0.004	83.5	-0.044	0.037
14-Aug	337	3.4%	1.5	0.050	82.3	0.005	0.094
21-Aug	339	1.4%	1.3	0.018	77.5	-0.024	0.059
15-Sep	339	2.5%	1.0	0.024	96.4	-0.058	0.106
<b>Average</b>	<b>324</b>	<b>2.5%</b>	<b>1.2</b>	<b>0.029</b>	<b>83.3</b>	<b>-0.019</b>	<b>0.077</b>

Table 3-3 presents the average impacts on each PTR event day for those customers who were not officially notified of an event. None of the impacts in Table 3-3 are statistically different from zero. Therefore these results indicate that Non-notified customers are not responding to PTR events.

**Table 3-3 Non-Notified Customers: Load Impact Estimates**

Event Date	Accounts	% Load Reduction	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	Average Temp. During Event	90% CI	10% CI
20-Jul	71,642	-1.3%	293.2	-4.0	81.1	-8.5	0.5
9-Aug	71,712	-1.4%	324.7	-4.7	83.1	-9.6	0.2
10-Aug	71,682	-1.6%	316.4	-5.2	84.2	-10.6	0.2
11-Aug	71,406	-1.1%	239.4	-2.6	84.5	-7.1	1.8
14-Aug	71,690	-1.5%	328.9	-5.1	83.9	-10.4	0.2
21-Aug	71,741	-1.0%	307.3	-3.0	78.3	-7.8	1.7
15-Sep	71,302	-0.9%	242.9	-2.2	96.5	-11.1	6.8
<b>Average</b>	<b>71,596</b>	<b>-1.3%</b>	<b>293.2</b>	<b>-3.8</b>	<b>84.5</b>	<b>-9.5</b>	<b>1.8</b>

Table 3-4 presents the average impacts on each PTR event day for those customers who received automated notifications as a result of being enrolled in My Account. There are three event days with statistically significant impacts; however, these impacts indicate an increase rather than a decrease in load on PTR event days.



**Table 3-4 My Account Customers: Load Impact Estimates**

Event Date	Accounts	% Load Reduction	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	Average Temp. During Event	90% CI	10% CI
20-Jul	34,891	-0.7%	176.1	-1.2	81.0	-3.1	0.6
9-Aug	34,948	-1.1%	190.0	-2.1	83.0	-4.3	0.0
10-Aug	34,940	-1.5%	190.1	-2.9	84.2	-5.3	-0.4
11-Aug	34,807	-0.9%	145.5	-1.3	84.6	-3.2	0.5
14-Aug	34,919	-1.4%	197.6	-2.7	83.9	-5.1	-0.3
21-Aug	34,957	0.1%	183.0	0.2	78.3	-1.8	2.1
15-Sep	34,747	-0.4%	150.3	-0.6	96.7	-5.8	4.6
<b>Average</b>	<b>34,887</b>	<b>-0.9%</b>	<b>176.1</b>	<b>-1.5</b>	<b>84.5</b>	<b>-4.3</b>	<b>1.2</b>

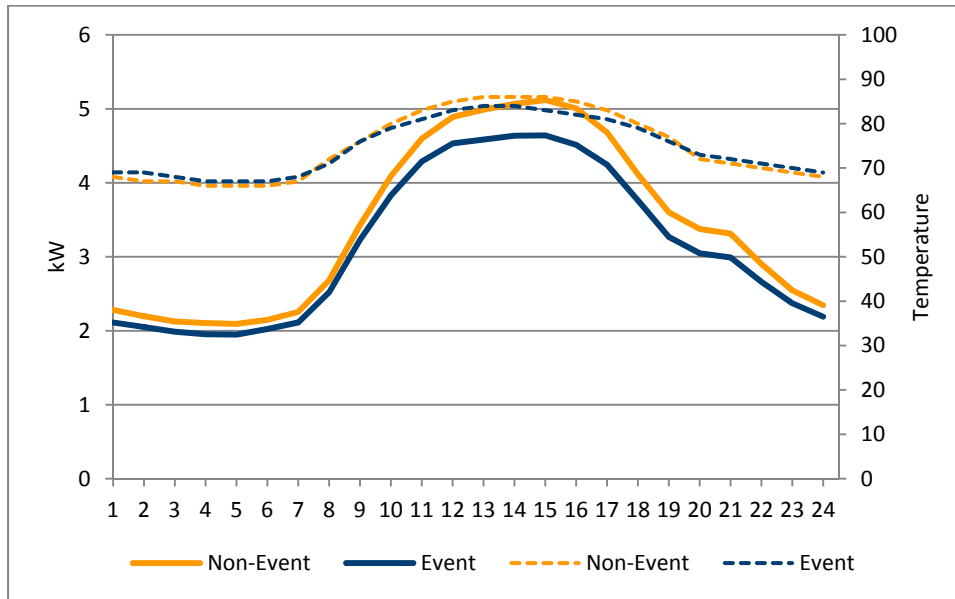
When considering all of the impacts, and the insignificance of the parameter estimates, there is very little evidence to support any actions being taken by small commercial customers in response to PTR events, except perhaps in the Opt-in Alert subgroup. Because the regression analysis was somewhat inconclusive, especially for the My Account and the Opt-in Alerts participants, we used two alternative methods to analyze participant usage on PTR event days. The results of the additional analyses are presented in the following two sections.

### Load Shape Analysis

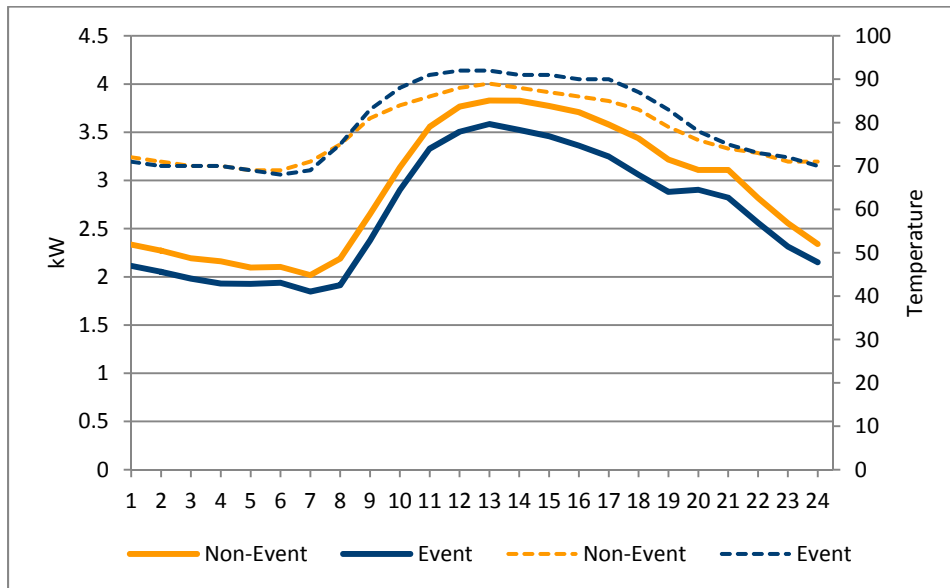
The load shape analysis allows us to look at the data in a different way in order to visually confirm and verify the regression results. We can do this by comparing event days and similar non-event days within each subgroup. We can then examine the load shapes looking for differences in load that look like event day load reduction. While this is not a statistically rigorous technique, it can provide very useful information about what participants are doing on event days, and may identify problems in the regression analysis.

The following figures (Figure 3-1 through Figure 3-6) show average event and non-event load shapes (the solid lines) along with average hourly temperatures (the dashed lines) for Non-notified, My Account, and Opt-in Alerts customers. Across subgroups, because weekday events tended to be a bit cooler than surrounding days, the non-event weekday usage is actually higher than the weekday event usage. Interestingly even though the two weekend events included the hottest day of the year, the weekend event usage tends to be lower than the non-event usage. However, irrespective of the weather related differences, in each of the figures below for the Non-notified and the My Account participants, the event and non-event day shapes are very similar and do not display any of the characteristics we would expect to see if the participants were responding to an event. Again, the Opt-in Alert participants do have some differences in their load shapes that could indicate a small response on some event days.

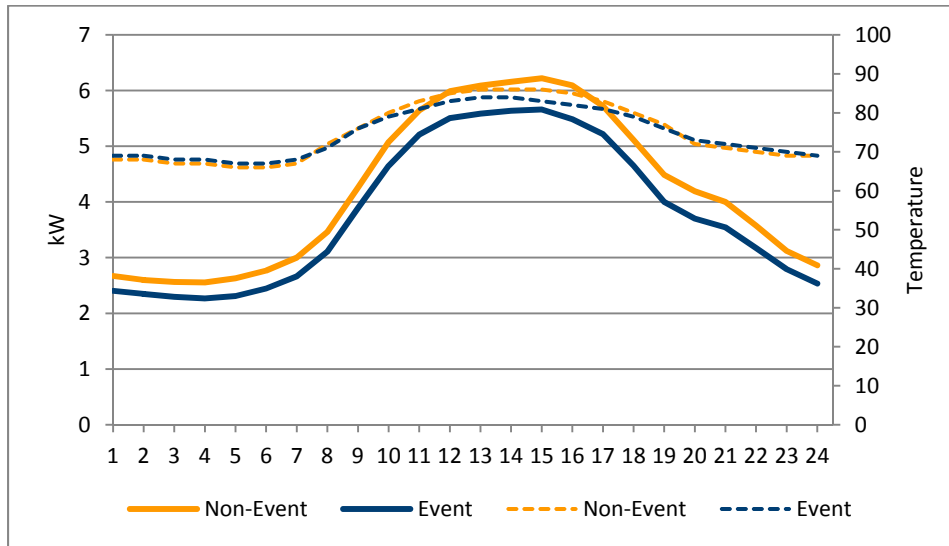
**Figure 3-1 Non-Notified: Weekday Load Shapes and Temperature**



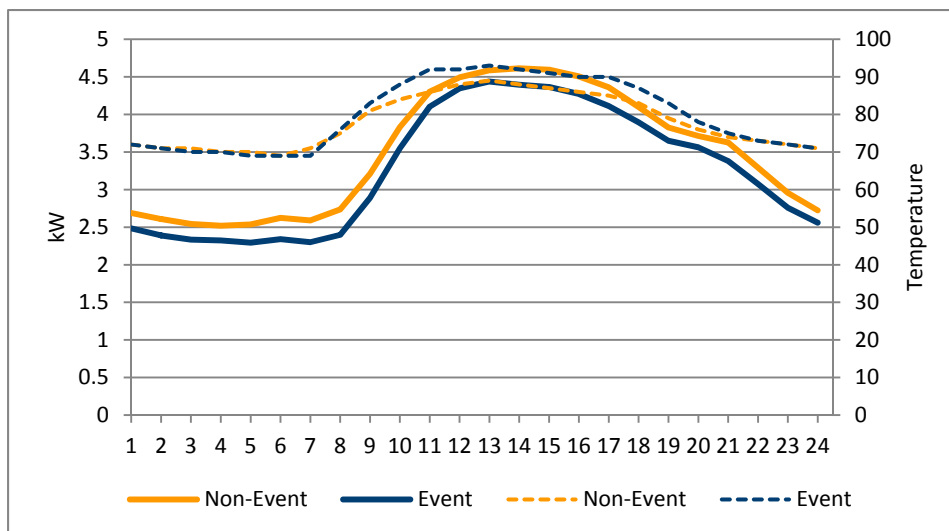
**Figure 3-2 Non-Notified: Weekend Load Shapes and Temperature**



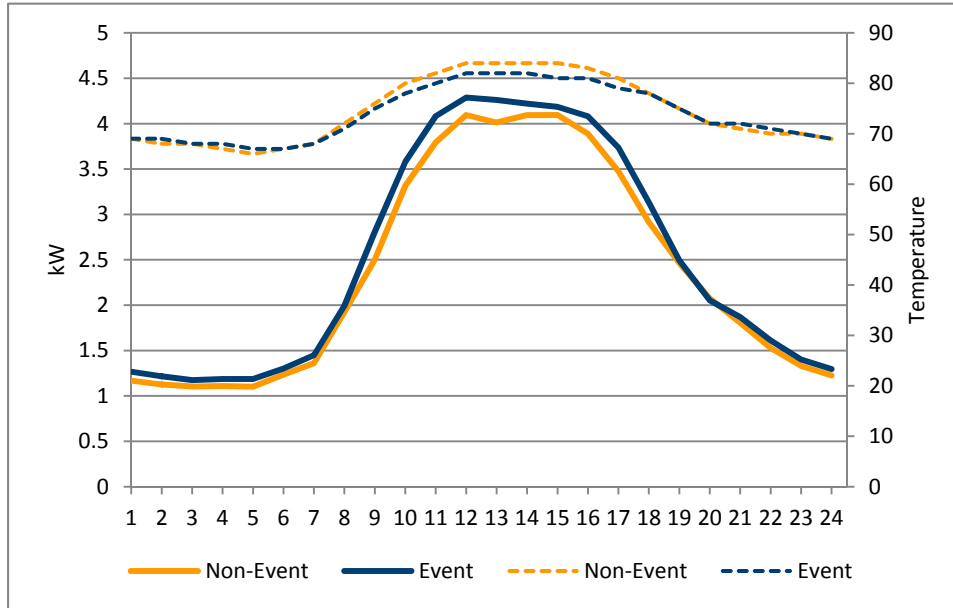
**Figure 3-3 My Account: Weekday Load Shapes and Temperature**



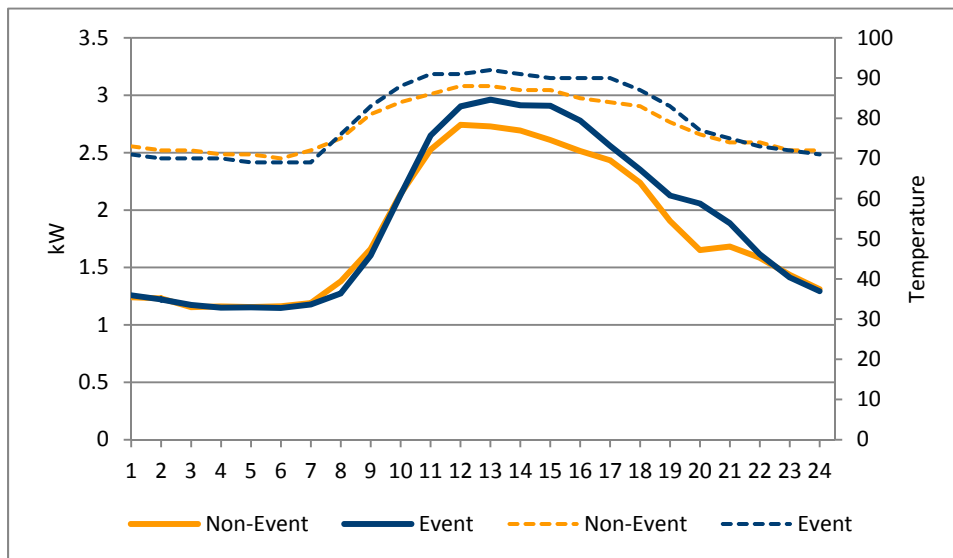
**Figure 3-4 My Account: Weekend Load Shapes and Temperature**



**Figure 3-5 Opt-In Alerts: Weekday Load Shapes and Temperature**



**Figure 3-6 Opt-In Alerts: Weekend Load Shapes and Temperature**



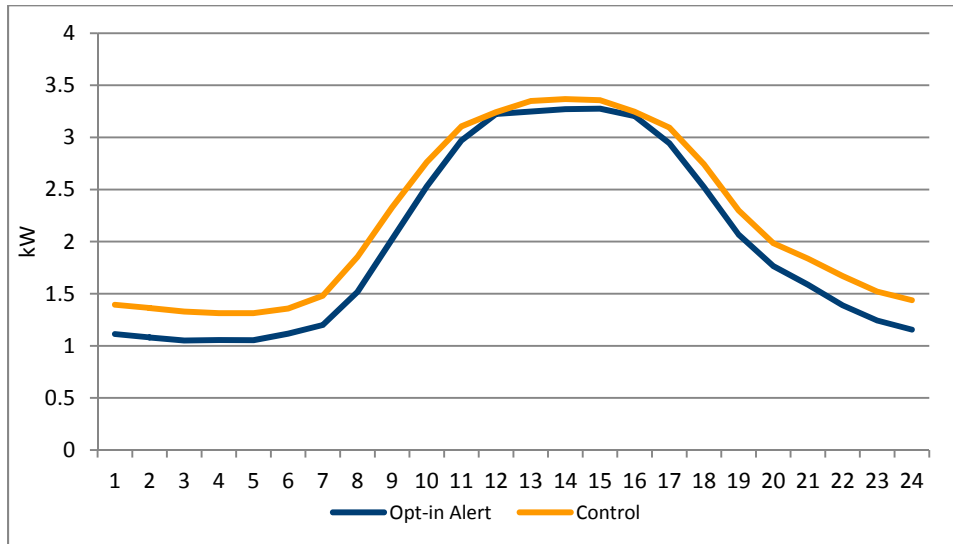
Overall, the load shape analysis confirms the regression results. Among the Non-notified and My Account customers, there is no evidence to support a response to PTR events, but among the Opt-in Alert customers the results are again somewhat inconclusive. In both the weekday and weekend shapes there are some differences during the on-peak period that may be the result of customers responding to PTR events, however because the group of customers is smaller (only 341) it is also more sensitive to variation in load among individual participants.

In order to more closely examine the Opt-in Alert participants, and in an effort to definitively identify savings if they existed, we also created a matched control group for the Opt-in Alerts group and performed a difference in difference (DID) analysis.

## Matched Control Group Analysis

This section presents the results of the matched control group analysis for the 341 Opt-in Alert customers. Figure 3-7 shows a comparison of the Opt-in Alert participants with the matched control group on an average non-event day in 2012.

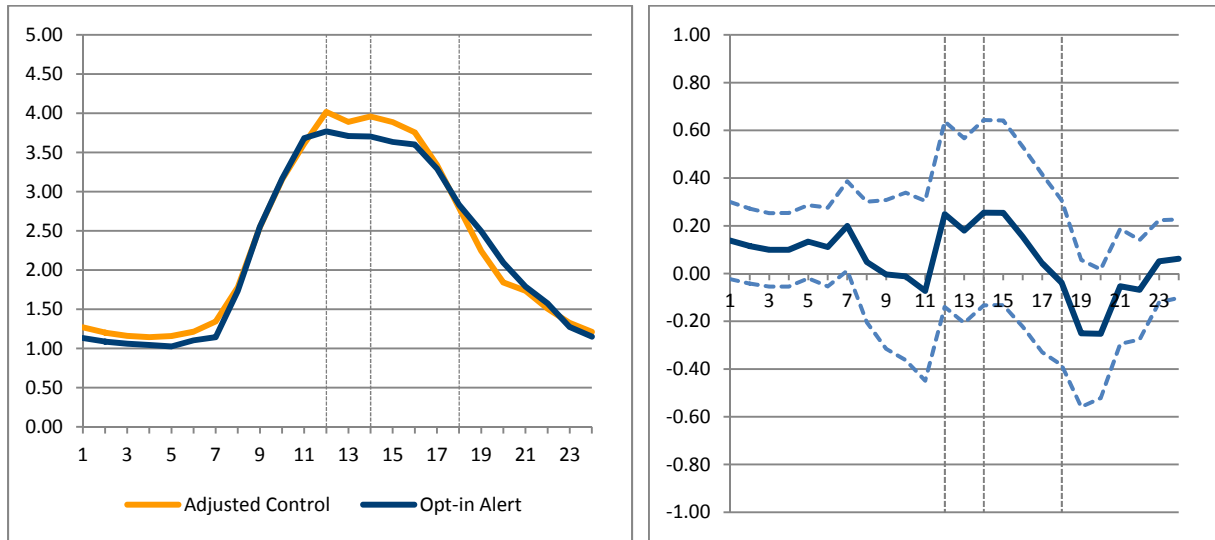
**Figure 3-7** *Opt-in Alert vs. Unadjusted Matched Control: 2012 Non-Event Days*



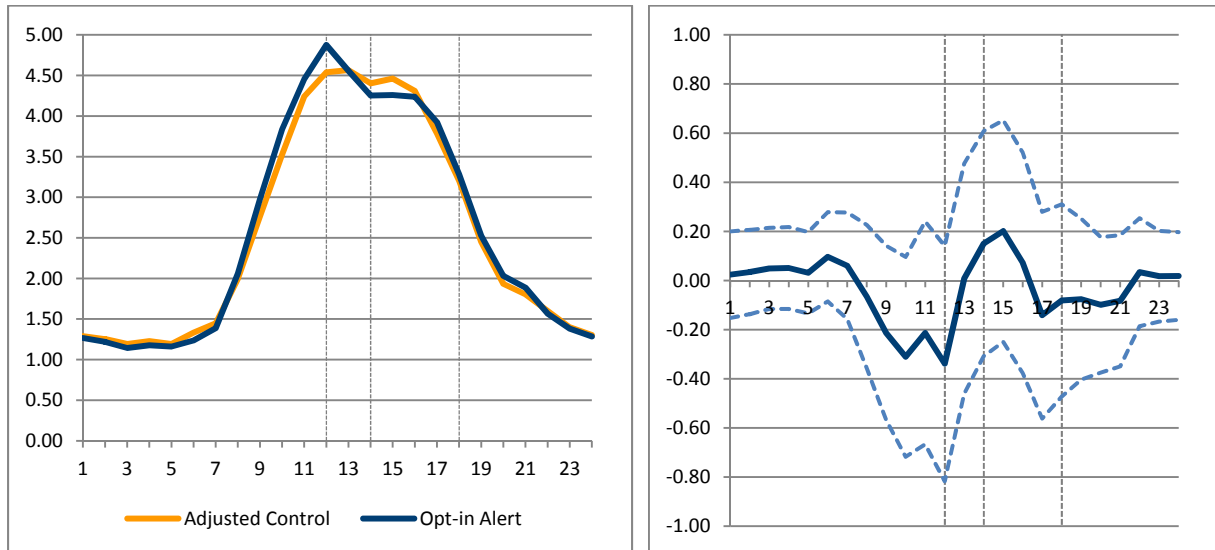
After creating the matched control group, we compared the two groups on each event day to determine if there were any statistically significant reductions in load among the Opt-in Alert customers. When we look at the quality of the match in Figure 3-7 above the two groups are the most similar during the on-peak period, but have some more significant differences during the off-peak period. The advantage of using a DID approach to compare the two groups is that we are able to adjust the control group load by subtracting out pre-existing differences in the two groups to provide a better estimate of what participants would have done on each event day.

Figure 3-8 through Figure 3-14 presents both a comparison of the Opt-in Alert participants with the matched control group, and the savings shape on each PTR event day. On the left side of each figure is the average load for each group on each event day, with vertical lines indicating the 11-6 p.m. event window and the 1-6 p.m. event window. On the right side, we show the savings shape, or the difference between the two groups, including the 90% confidence intervals.

**Figure 3-8** Average Per-Customer Load and Impact – July 20, 2012

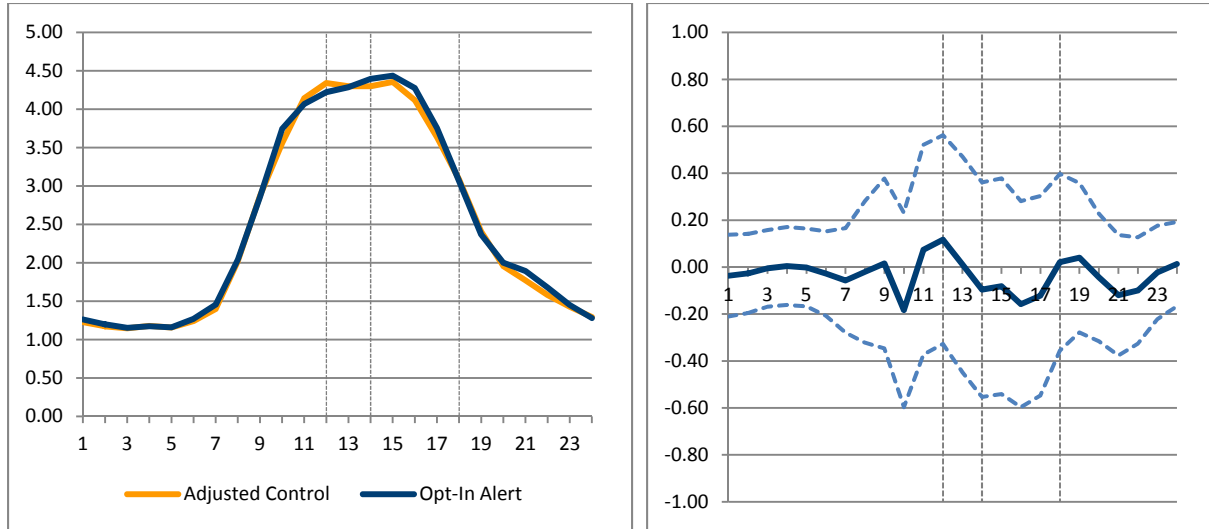


**Figure 3-9** Average Per-Customer Load and Impact – August 9, 2012



Figures 3-8 and 3-9 show the load shapes and savings shapes for the July, 20 and August 9 event days. The July 20 event was the first event of the summer and a test event. While it does appear that there may be some on-peak reduction in the Opt-in Alert group, when we look at the confidence intervals, that reduction is not statistically different from zero. Again, we see what might be a reduction in the later part of the event on August 9, but that difference is not significant. The large spike on August 9 was caused by one large customer shifting load earlier in the day. It is an important reminder that with a small group of customers, the actions of one or two large customers can move the average significantly.

**Figure 3-10 Average Per-Customer Load and Impact – August 10, 2012**



**Figure 3-11 Average Per-Customer Load and Impact – August 11, 2012**

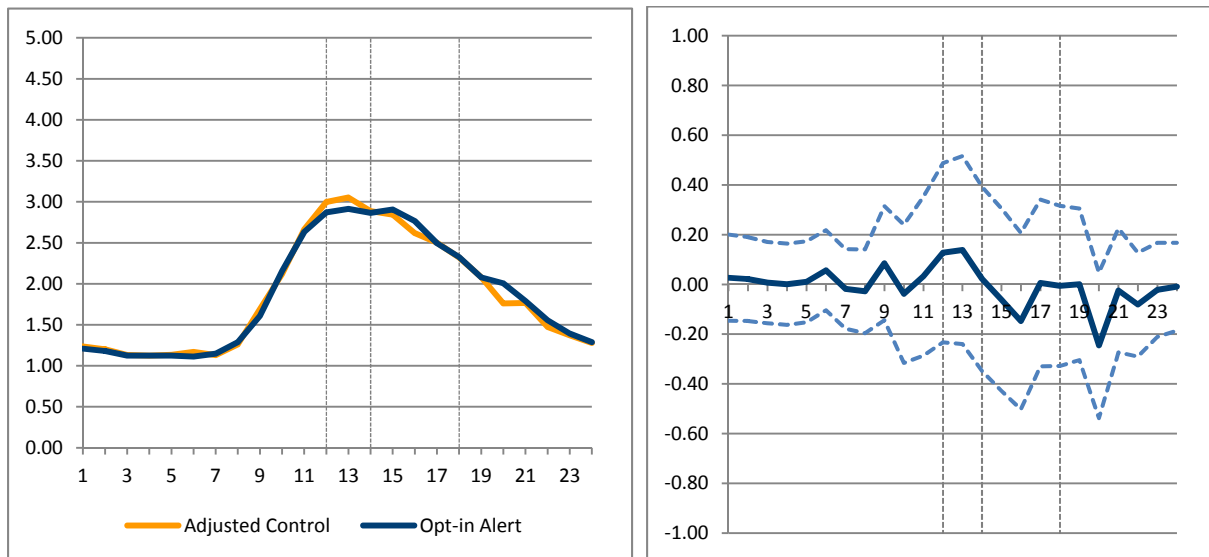
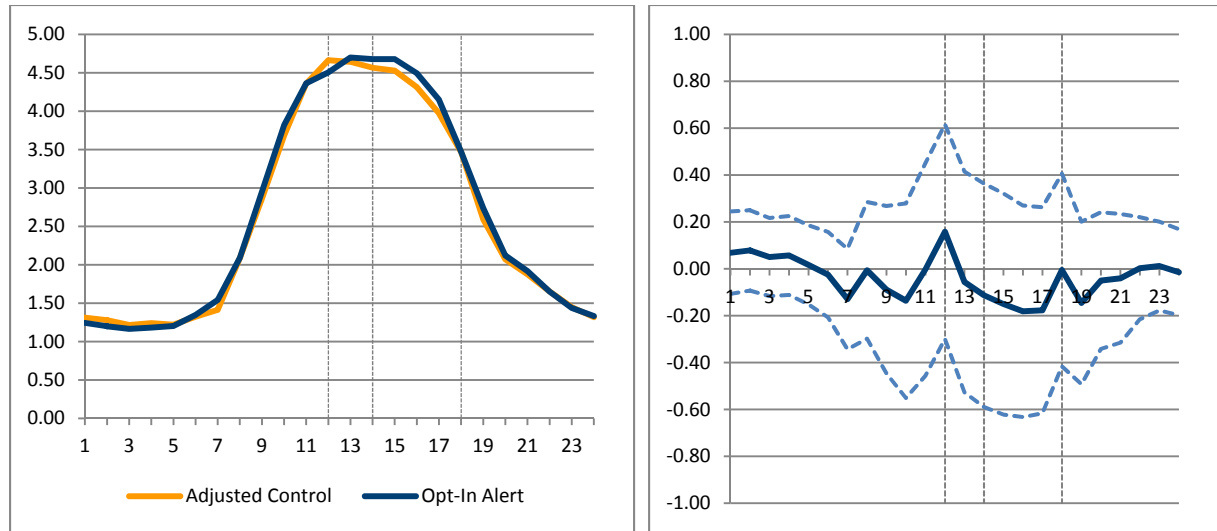


Figure 3-10 and Figure 3-11 show the load shapes and savings shapes for the August 10 and August 11 event days. On both of these days the Opt-in Alert customer load and the control group load are very close to each other with no notable deviations in usage during the on-peak period. The marked difference between the two shapes is a result of August 10 being a weekday and August 11 being a Saturday.

**Figure 3-12 Average Per-Customer Load and Impact – August 14, 2012**



**Figure 3-13 Average Per-Customer Load and Impact – August 21, 2012**

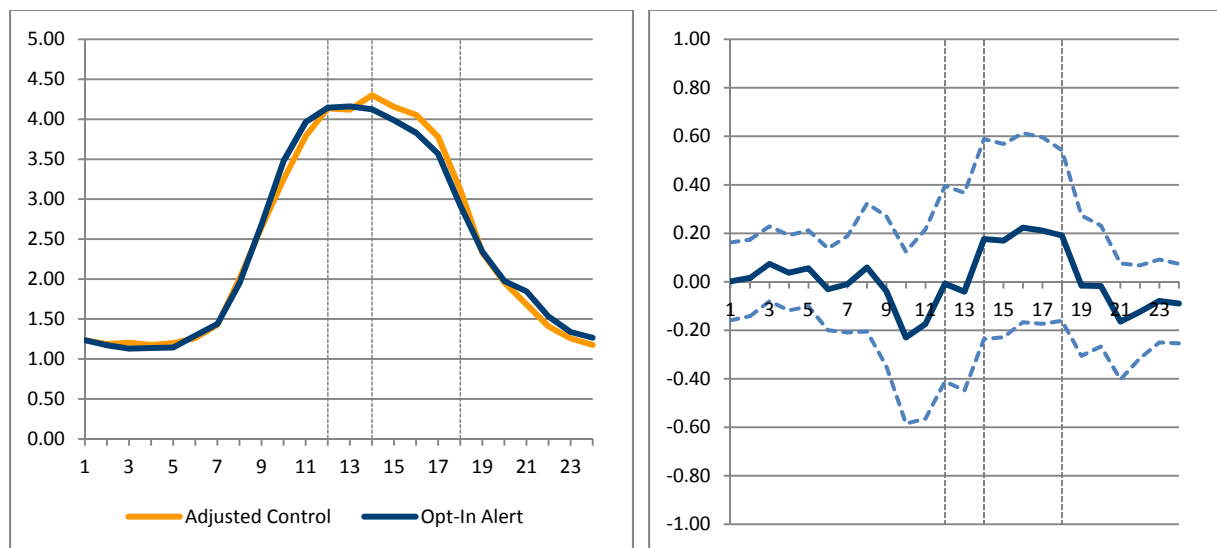
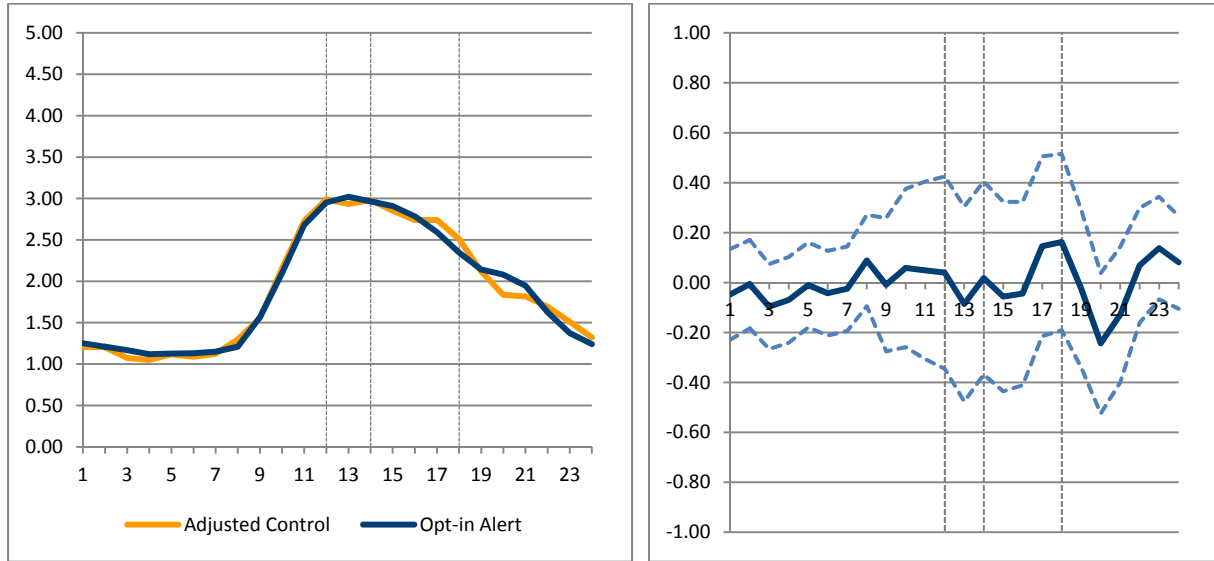


Figure 3-12, Figure 3-13, and Figure 3-14 (below) show the average daily load shapes and savings shapes for the events on August 14, August 21, and September 15. In all three figures the Opt-in Alert customer load and the control group load are very close to each other with no notable deviations in usage during the on-peak period. The average on-peak load on August 21 was about 0.5 kW lower than the load on August 9, 10, and 14 events because it was quite a bit cooler on that day, an average of 78°F vs. temperatures ranging from 81°F to 83°F during the other events. The September 15 event occurred on an isolated and extremely hot Saturday (95°F) with no truly comparable days, however the adjusted control load still follows the Opt-in Alert load very closely with little deviation.



**Figure 3-14 Average Per-Customer Load and Impact – September 15, 2012**



## CUSTOMER SPECIFIC REFERENCE LEVEL STATISTICS

This chapter presents several statistics related to the Customer Specific Reference Level (CRL). In contrast to the impact section of the report, the statistics presented below include the Summer Saver participants in both the savings and rebate calculations. It does not include an assessment of the validity or accuracy of the CRL, or an assessment of alternative CRL methods.

### CRL Based Load Reduction and Bill Credits

We calculated the following statistics based on the CRL:

- The number of customers who used less than their CRL for each event
- The total load reduction according the CRL including all customers by event
- The total load reduction by event according to the CRL including only customers using less than their CRL
- Total bill credits paid by event
- Dollars per MW paid out according to the total load reduction estimated by the CRL
- Dollars per MW paid out according to three separate load reduction scenarios.

Table 4-1 presents the number of customers who used less than their CRL, and the total number of customers who used more than their CRL, for each event.

**Table 4-1** *Number of Customers Using More or Less than their CRL by Event*

Event Date	Less than CRL	More than CRL	Total Participants
07/20/12	35,488	75,236	110,724
08/09/12	37,024	73,915	110,939
08/10/12	38,555	72,360	110,915
08/11/12	28,108	82,413	110,521
08/14/12	37,517	73,402	110,919
08/21/12	58,509	52,517	111,026
09/15/12	31,158	79,196	110,354

The total percentage of customers using less than their CRL remains relatively constant across events ranging between 25% and 35% on all event days except for August 21, 2012. On that day the percentage of customers using less than their CRL was significantly higher, near 60%.

Table 4-2 presents both the total energy reduction in MWh and the average demand reduction in MW across the event period, for all customers regardless of whether they used less than their CRL. Table 4-3 presents the same statistics for only those customers that used less than their CRL.

**Table 4-2 Load Reduction by Event: All Customers**

Event Date	MWh Reduction (Total Energy Reduced)	MW Impact (Average Demand Reduction)
07/20/12	38.5	5.5
08/09/12	50.1	7.2
08/10/12	99.4	14.2
08/11/12	-157.4	-22.5
08/14/12	52.0	7.4
08/21/12	371.5	53.1
09/15/12	-82.4	-11.8

For all customers, the event with the largest impact was the event on August 21, 2012 and the event with the lowest impacts were the two Saturday events, which both showed net increases in load based on the CRL. The August 21 event was called on a cool day that followed several consecutive warmer days; this likely caused the baseline to be too high for most participants resulting in additional PTR credits being paid on that day for many customers. Conversely on both of the Saturday events on August 11 and September 15 fewer people used less than their CRL likely because the preceding Saturdays were cooler than the event Saturdays resulting in a baseline that may have been too low for many customers, which would make it more difficult to achieve a rebate.

**Table 4-3 Load Reduction by Event: Customers using less than their CRL**

Event Date	MWh Reduction (Total Energy Reduced)	MW Impact (Average Demand Reduction)
07/20/12	216.0	30.9
08/09/12	190.0	27.1
08/10/12	261.4	37.3
08/11/12	181.2	25.9
08/14/12	206.7	29.5
08/21/12	430.6	61.5
09/15/12	223.8	32.0

In contrast, if we look at the load reduction based on the CRL for only those customers that used less than their CRL on each event day, the two weekend events had similar average load reductions to the other weekday events throughout the summer. However, like the results presented in Table 4-2, the August 21 event has the largest load reduction.

Table 4-4 presents the total bill credits paid to small commercial customers on each of the event days. In total SDG&E paid out \$1.28 million dollars in PTR rebates to small commercial customers over the seven events.

**Table 4-4 Total Rebates Paid**

Event Date	Total Bill Credits
07/20/12	\$167,113
08/09/12	\$147,047
08/10/12	\$202,516
08/11/12	\$141,884
08/14/12	\$159,596
08/21/12	\$334,933
09/15/12	\$175,197
Total	\$1,328,285

Table 4-5 presents the total dollars paid per MW of load reduction based on several scenarios. The first two columns show the \$/MW paid based on the CRL for all customers, and for only those that used less than their CRL. Because we were not able to identify consistent statistically significant impacts for any of the groups, we were not able to provide an estimate for the dollars paid per MW of load reduction based on the evaluation. However, we do provide the total dollars paid per MW after assuming three different levels of load reduction. We assumed an average load reduction of 1%, 3%, and 5% for every participant during each event, and then recalculated the total dollars paid per MW. The first two columns show the \$/kW paid where the load reduction (kW) is calculated by summing the CRL results for all customers, and by summing the results for all customers who used less than their CRL.

**Table 4-5 Dollars Paid per kW of Load Reduction**

Event Date	\$/kW All Customers CRL	\$/kW Customers < CRL	\$/kW 1% Load Reduction	\$/kW 3% Load Reduction	\$/kW 5% Load Reduction
7/20/2012	\$30.38	\$5.40	\$42.43	\$15.56	\$12.84
8/9/2012	\$20.56	\$5.40	\$35.48	\$13.49	\$11.47
8/10/2012	\$14,260	\$5.41	\$46.20	\$17.00	\$14.00
8/11/2012	-	\$5.46	\$45.46	\$15.97	\$12.73
8/14/2012	\$21.41	\$5.39	\$36.93	\$13.98	\$11.82
8/21/2012	\$6.31	\$5.44	\$75.58	\$27.71	\$22.60
9/15/2012	-	\$5.46	\$52.80	\$18.62	\$14.84
Average	\$10.25	\$5.40	\$42.43	\$15.56	\$12.84

In Table 4-5 above, we see that if on average the small commercial class were able to reduce load by 1% during PTR events SDG&E would pay approximately \$42/kW across all events. Similarly, assuming an average load reduction of 5% SDG&E would pay about \$13/kW across all events.

## KEY FINDINGS AND RECOMMENDATIONS

This chapter presents key findings of the small commercial PTR program, and some more general recommendations for small commercial dynamic pricing programs based on this evaluation.

### Key Findings

The following were identified as key findings during the Small Commercial PTR 2012 Impact Evaluation:

- Based on the results of the regression analysis and the load shape analysis, we can conclude that the Non-Notified participants are not responding to PTR events.
- Again, based on the results of the regression analysis and the load shape analysis, we can conclude that the My Account participants are not responding to PTR events.
- The analysis for the Opt-in Alert customers was somewhat inconclusive. Based on the regression analysis, some of the PTR events show small reductions in usage, around 3%. However, the matched control group analysis did not show any statistically significant reductions in usage during PTR event days. While our official estimate of savings for the group is zero, the mixed results indicate that one could logically conclude that some participants are likely to be taking action on some days; however the overall effect of such actions is small falling between 1% and 3%.
- Many industry studies have found small commercial customers to be much less price responsive than residential customers on dynamic pricing rates, and they are typically the least targeted for DR programs. Given this information, it is not surprising that we were unable to detect any impacts in this group of customers.

### Recommendations

While the small commercial PTR program is not currently planned to continue into 2013, there are still some relevant recommendations that can be made for small commercial dynamic pricing in general based on this evaluation and our experience evaluating other small commercial dynamic pricing programs.

- In any type of event driven program notification and communication of events is a key factor. If participants are not notified of an event at all, or if they are not notified using a method that is either not timely or not convenient, those participants are very unlikely to respond. Using multiple channels for notification, or even visual indicators through enabling technology, is more likely to elicit a response.
- PTR events were often called on cooler days, when fewer loads were likely to be available. Calling events on the warmest days in the season or month will often translate into higher reference load, and therefore higher load reduction. If the program is being

used as a resource, developing a protocol that targets forecasted monthly or annual system peaks will also generally result in events being called on the hottest days.

- Stronger price signals may help to engage small commercial customers. In this program the residential and commercial incentives were the same, however it may be more effective, given the low level of engagement seen here, to offer higher incentives or conversely stronger signals (i.e. higher on to off peak price ratios).
- Enabling technology has also been shown to improve response among small commercial customers. Programmable Communicating Thermostats (PCTs) can be a good option because either the customer or the utility can control the device depending on how the program is designed. Some programs are geared to customer satisfaction and allow for customer controlled response, even providing override capability during events. Others might control the devices during the event and limit overrides to ensure more reliable response. Still another option is to allow customers to choose which is more convenient for them, perhaps with an additional incentive for allowing utility control.

## **REGRESSION OUTPUT AND PARAMETER ESTIMATES**

Please attached spreadsheet

## About EnerNOC

EnerNOC's Utility Solutions Consulting team is part of EnerNOC's Utility Solutions, which provides a comprehensive suite of demand-side management (DSM) services to utilities and grid operators worldwide. Hundreds of utilities have leveraged our technology, our people, and our proven processes to make their energy efficiency (EE) and demand response (DR) initiatives a success. Utilities trust EnerNOC to work with them at every stage of the DSM program lifecycle – assessing market potential, designing effective programs, implementing those programs, and measuring program results.

EnerNOC's Utility Solutions deliver value to our utility clients through two separate practice areas – Implementation and Consulting.

- Our Implementation team leverages EnerNOC's deep "behind-the-meter expertise" and world-class technology platform to help utilities create and manage DR and EE programs that deliver reliable and cost-effective energy savings. We focus exclusively on the commercial and industrial (C&I) customer segments, with a track record of successful partnerships that spans more than a decade. Through a focus on high quality, measurable savings, EnerNOC has successfully delivered hundreds of thousands of MWh of energy efficiency for our utility clients, and we have thousands of MW of demand response capacity under management.
- The Consulting team provides expertise and analysis to support a broad range of utility DSM activities, including: potential assessments; end-use forecasts; integrated resource planning; EE, DR, and smart grid pilot and program design and administration; load research; technology assessments and demonstrations; evaluation, measurement and verification; and regulatory support.

The team has decades of combined experience in the utility DSM industry. The staff is comprised of professional electrical, mechanical, chemical, civil, industrial, and environmental engineers as well as economists, business planners, project managers, market researchers, load research professionals, and statisticians. Utilities view EnerNOC's experts as trusted advisors, and we work together collaboratively to make any DSM initiative a success.