**REPORT**


# 2014 Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-Based Pricing Programs

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# 1 Executive Summary

This report presents ex post and ex ante load impact estimates for PG&E's residential time-based pricing tariffs for the 2014 program year. PG&E has three time-based tariffs in effect, although only two are open to new enrollment:

- SmartRate™ [1] is an overlay on other available tariffs, including CARE[2] versions of these tariffs. The program has a high price during the peak period on event days, referred to as SmartDays, and slightly lower prices at all other times during the summer. For the vast majority of SmartRate customers whose underlying tariff is E-1, prices vary by time of day only on SmartDays. The roughly 5,000 SmartRate customers who have E-6 or E-7 as their underlying tariff, prices will vary by time of day on all days but will be much higher during the peak period on SmartDays;
- Rate E-7 is a two-period, static time-of-use (TOU) rate with a peak period from 12 to 6 PM. This rate is closed to new enrollment; and
- Rate E-6 is a three-period TOU rate with a peak period from 1 to 7 PM in the summer and from 5 to 8 PM in the winter (when partial peak prices are in effect).

## 1.1 SmartRate Ex Post Evaluation Summary

*PG&E's SmartRate program had almost 130,000 participants in October 2014. The average peak period load reduction delivered by the program over the 12 SmartDays called in 2014 was 39 MW.*

SmartRate is PG&E's residential critical peak pricing program. Approximately 120,000 customers were enrolled in October 2013 and nearly 130,000 were enrolled in October 2014. The dually enrolled population, which consists of customers enrolled on both SmartRate and SmartAC—PG&E's central air conditioning (CAC) load control program—grew by about 7% between 2013 and 2014. Dually-enrolled participation equaled 40,468 in October 2014, or roughly 31% of the total SmartRate population.

Twelve SmartDays were called in 2014. Table 1-1 shows load impact estimates for the 2014 events for SmartRate-only customers and Table 1-2 shows estimates for dually enrolled customers. Table 1-2 also has a final column showing the total aggregate impacts over both customer segments. The average load impact across the 12 SmartDays in 2014 equaled 0.21 kW for SmartRate-only participants and 0.51 kW for dually enrolled participants. Aggregate load reduction for the average event was 18.3 MW and 20.4 MW for SmartRate-only customers and dually enrolled customers, respectively, which produced a total average aggregate impact of 39 MW. Average impacts in 2014 were about 20% less than the 2013 average in spite of comparable weather conditions on SmartDays across the two years. A detailed analysis of the potential cause of this drop in average impacts suggests at least two possibilities. One is a lack of persistence in price response for customers that were in the program across both years.

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[1] Any use of the term SmartMeter, SmartRate or SmartAC in this document is intended to refer to the trademarked term, whether or not ™ is included. SmartMeter™ is a trademark of SmartSynch, Inc. and is used by permission.

[2] CARE stands for California Alternate Rates for Energy and is a program through which low-income consumers receive lower rates than non-CARE customers.

Another possibility is that participants have changed their behavior to reduce loads during peak periods on all weekdays, not just on SmartDays. The impact evaluation methodology used to estimate load impacts measures the incremental load reduction on SmartDays relative to other weekdays with comparable weather conditions. If customers modify their usage during peak periods on non-event days, estimated SmartDay impacts will fall. Importantly, if this is the cause of the lower average impacts, it does not mean that total load reductions resulting from SmartRate have fallen, just the incremental reductions relative to non-event days. Put another way, the total reduction, which consists of the permanent load reduction plus the incremental load reduction relative to non-event days, may be the same or higher than it was in prior years before participants adopted more permanent behavioral changes.

**Table 1-1: Ex Post Load Impact Estimates for SmartRate-only Participants (Average Impacts from 2 to 7 PM)**

| Date | Enrolled Participants | Avg. Reference Load (kW) | Avg. Load Reduction (kW) | Percent Load Reduction (%) | Aggregate Load Reduction (MW) | Daily Maximum Temp (°F) |
|---|---|---|---|---|---|---|
| 14-May-14 | 84,532 | 1.19 | 0.15 | 13% | 13.0 | 93 |
| 9-Jun-14 | 88,694 | 1.77 | 0.27 | 15% | 24.2 | 91 |
| 30-Jun-14 | 89,748 | 1.71 | 0.27 | 16% | 24.3 | 90 |
| 1-Jul-14 | 89,653 | 1.50 | 0.19 | 13% | 17.2 | 83 |
| 7-Jul-14 | 89,487 | 1.33 | 0.16 | 12% | 14.0 | 83 |
| 14-Jul-14 | 89,478 | 1.60 | 0.22 | 14% | 19.8 | 87 |
| 25-Jul-14 | 89,583 | 1.63 | 0.24 | 15% | 21.9 | 94 |
| 28-Jul-14 | 89,552 | 1.47 | 0.19 | 13% | 17.1 | 85 |
| 29-Jul-14 | 89,517 | 1.58 | 0.21 | 13% | 18.8 | 88 |
| 31-Jul-14 | 89,504 | 1.67 | 0.21 | 13% | 19.1 | 88 |
| 11-Sep-14 | 89,488 | 1.35 | 0.17 | 13% | 15.3 | 89 |
| 12-Sep-14 | 89,493 | 1.42 | 0.17 | 12% | 15.2 | 89 |
| **Average Event Day** | **89,061** | **1.52** | **0.21** | **14%** | **18.3** | **88** |

**Table 1-2: SmartRate Ex Post Load Impact Estimates for Dually Enrolled Participants and Aggregate Impacts for All Participants (Average Impacts from 2 to 7 PM)**

| Date | Dually Enrolled Participants | | | | | | All SmartRate Participants | |
|---|---|---|---|---|---|---|---|---|
| | Enrolled Participants | Avg. Reference Load (kW) | Avg. Load Reduction (kW) | Percent Load Reduction (%) | Aggregate Load Reduction (MW) | Daily Maximum Temp (°F) | Enrolled Participants | Aggregate Load Reduction (MW) |
| 14-May-14 | 37,713 | 1.46 | 0.37 | 25% | 14.0 | 94 | 122,245 | 26.9 |
| 9-Jun-14 | 40,107 | 2.44 | 0.70 | 29% | 28.2 | 99 | 128,801 | 52.5 |
| 30-Jun-14 | 40,536 | 2.35 | 0.71 | 30% | 28.8 | 98 | 130,284 | 53.2 |
| 1-Jul-14 | 40,528 | 1.88 | 0.43 | 23% | 17.6 | 89 | 130,181 | 34.8 |
| 7-Jul-14 | 40,523 | 1.58 | 0.33 | 21% | 13.3 | 89 | 130,010 | 27.3 |
| 14-Jul-14 | 40,541 | 2.17 | 0.58 | 27% | 23.5 | 95 | 130,019 | 43.4 |
| 25-Jul-14 | 40,573 | 2.18 | 0.58 | 27% | 23.5 | 99 | 130,156 | 45.4 |
| 28-Jul-14 | 40,570 | 1.87 | 0.41 | 22% | 16.6 | 91 | 130,122 | 33.7 |
| 29-Jul-14 | 40,572 | 2.09 | 0.51 | 24% | 20.6 | 95 | 130,089 | 39.3 |
| 31-Jul-14 | 40,560 | 2.24 | 0.55 | 25% | 22.4 | 96 | 130,064 | 41.5 |
| 11-Sep-14 | 40,570 | 1.72 | 0.43 | 25% | 17.6 | 95 | 130,058 | 32.8 |
| 12-Sep-14 | 40,551 | 1.85 | 0.46 | 25% | 18.7 | 96 | 130,044 | 33.9 |
| **Average Event Day** | **40,279** | **1.99** | **0.51** | **25%** | **20.4** | **94** | **129,339** | **38.7** |

In addition to providing estimates of ex post load impacts for the participant population, this report presents results from the analysis of a wide variety of issues that can improve program performance and inform future pricing strategy. These include, but are not limited to, the following:

- The average load reduction for SmartRate-only CARE customers in 2014 was less than half as large as for non-CARE customers. This large difference is not evident between dually enrolled CARE and non-CARE customers.
- Event notification is highly correlated with load reductions, even among customers notified more than once.
- Air conditioning ownership is a strong driver of demand response.
- Customers enrolled in both SmartRate and SmartAC provided significantly greater demand response than those who are on SmartRate alone. Average impacts for dually enrolled customers were more than twice as large as for SmartRate only customers and the aggregate impact for dually enrolled customers was larger than for SmartRate only customers in spite of the fact that there were twice as many SmartRate only customers in the program.
- The vast majority of customers who sign up for SmartRate stay on the program. Attrition due to de-enrollment is quite low (less than 2.5%).
- Across the summer months of 2014, 95% of non-CARE and 92% of CARE SmartRate customers saved money compared with their otherwise applicable tariff (OAT). The average bill savings were around 5%.

## 1.2 SmartRate Ex Ante Evaluation Summary

Ex ante load impact estimates for SmartRate-only and dually enrolled customers for 2014 are shown in Table 1-3. Impacts in this table are based on ex ante weather conditions that are tied to PG&E's peak operational conditions, not the statewide CAISO operational conditions. Estimates based on weather coinciding with CAISO peak conditions are generally lower than the PG&E-based estimates and can be found in the body of the report.

***The SmartRate program is forecasted to provide almost 39 MW of load reduction on a typical event day under normal weather conditions and 47 MW on a typical event day under 1-in-10 year weather conditions. On the July monthly peak day, the demand response potential for the SmartRate program is estimated to equal 40 MW and 51 MW under normal and extreme weather***

The first and second (numerical) columns in Table 1-3 show the estimated average ex ante load reduction over the event period from 1 to 6 PM for SmartRate-only customers and dually enrolled customers, respectively. The third column shows the aggregate mean hourly impact for the SmartRate-only population while the fourth column shows the same measure for dually enrolled customers. The first set of rows corresponds to 1-in-2 year weather conditions while the second set covers 1-in-10 year weather conditions. The enrollment forecast underlying the ex ante estimates was provided by PG&E. Program enrollment is predicted to stay nearly flat over the forecast horizon and the mix between SmartRate-only and dually enrolled participants is expected to be constant. Both populations within the program are forecasted to provide their largest impacts on the July monthly peak day under both 1-in-2 and 1-in-10 year weather conditions. Under 1-in-2 year conditions, the aggregate impact in July is forecasted to equal 40 MW, with 55% of the total provided by dually enrolled customers. Under 1-in-10 year conditions, the predicted peak impact is 51 MW.

## 1.3 TOU Ex Post Evaluation Summary

PG&E has two time-of-use (TOU) tariffs—E-6 and E-7—with 44,000 and 64,000 residential customers, respectively. On both tariffs, prices during peak periods are substantially higher than during off-peak periods, particularly during summer months (May–October), encouraging customers to shift electricity use away from peak hours. The time-varying rates are in effect every weekday. The E-7 rate was closed to new enrollment in 2006 when it was replaced by E-6, but there are still more E-7 customers than E-6 customers on the tariff. Over 80% of the 44,000 E-6 customers and 20% of the E-7 customers are net metered. This evaluation excludes net-metered customers because they likely have solar panels and are already accounted for in the evaluation of solar programs. In total, the evaluation results presented here represent approximately 59,000 non net-metered E-6 and E-7 accounts.

This is the second year that the number of non-net metered customers was large enough to allow for estimation of impacts for E-6 separate from E-7. The methodology used to estimate impacts for E-6 allows for at least some correction for selection bias that can easily lead to over estimation of load impacts. The data available for E-7 does not allow for use of the same approach and very likely overstates what the true impacts are for this tariff. However, we have attempted to reduce the bias that is likely present based on reasonable assumptions and an estimate of the magnitude of bias that was identified (and controlled for) using the E-6 methodology.

**Table 1-3: 2014 SmartRate Ex Ante Load Impact Estimates by Weather Year and Day Type (Event Period 1 to 6 PM)**

| Weather Year | Day Type | Mean Hourly Per Customer Impact (SmartRate Only) (kW) | Mean Hourly Per Customer Impact (Dually Enrolled) (kW) | Aggregate Mean Hourly Impact (SmartRate Only) (MW) | Aggregate Mean Hourly Impact (Dually Enrolled) (MW) | Aggregate Mean Hourly Impact (Full Program) (MW) |
|---|---|---|---|---|---|---|
| 1-in-2 | Typical Event Day | 0.19 | 0.49 | 17.7 | 21.1 | 38.8 |
| | May Monthly Peak | 0.13 | 0.27 | 11.4 | 11.5 | 22.9 |
| | June Monthly Peak | 0.2 | 0.51 | 17.8 | 21.8 | 39.6 |
| | July Monthly Peak | 0.2 | 0.51 | 17.9 | 22 | 39.9 |
| | August Monthly Peak | 0.2 | 0.49 | 18.1 | 21.5 | 39.6 |
| | September Monthly Peak | 0.19 | 0.44 | 17.2 | 19.6 | 36.8 |
| | October Monthly Peak | 0.11 | 0.16 | 10.2 | 7.3 | 17.5 |
| 1-in-10 | Typical Event Day | 0.24 | 0.58 | 21.7 | 25.3 | 46.9 |
| | May Monthly Peak | 0.23 | 0.53 | 20.7 | 22.5 | 43.2 |
| | June Monthly Peak | 0.25 | 0.59 | 22.8 | 25.1 | 47.8 |
| | July Monthly Peak | 0.25 | 0.66 | 22.8 | 28.5 | 51.3 |
| | August Monthly Peak | 0.23 | 0.6 | 21.6 | 26.5 | 48.0 |
| | September Monthly Peak | 0.21 | 0.48 | 19.7 | 21.5 | 41.2 |
| | October Monthly Peak | 0.18 | 0.36 | 16.7 | 16.2 | 32.9 |

Tables 1-4 and 1-5 show the average load reduction on monthly system peak days for E-6 and E-7 customers during the time period covered by this analysis, from November 1, 2013 through October 31, 2014. TOU load reductions were greater over the summer (May–Oct) than the winter (Nov–Apr) for E-6 customers, when the difference between peak and off-peak prices is the largest and the peak period goes from 1 to 7 PM. During the summer, the average load reduction for E-6 customers was 0.22 kW, or 20%, and the aggregate load reduction was 1.9 MW. This is substantially less than the aggregate impacts for the SmartRate tariff and also less than for the E-7 tariff, as seen in Table 1-5. The average summer impact for E-7 is estimated to equal 0.15 kW and the aggregate impact is roughly 7.4 MW. Winter impacts are 50% to 70% less than the summer average.

**Table 1-4: E-6 Monthly System Peak Day Load Reductions (1 to 7 PM Summer, 5 to 8 PM Winter, November 2013 to October 2014)**

| Month | Average Reference Load (kW) | Average Load Impact (kW) | Aggregate Load Impact (MW) | Percent Reduction (%) | Average Peak Period Temperature (°F) |
|---|---|---|---|---|---|
| January | 1.25 | 0.12 | 1.05 | 10% | 57 |
| February | 1.25 | 0.07 | 0.6 | 6% | 50 |
| March | 1.1 | 0.05 | 0.43 | 4% | 49 |
| April | 1.1 | 0.21 | 1.86 | 19% | 85 |
| May | 0.97 | 0.22 | 1.88 | 22% | 90 |
| June | 1.25 | 0.3 | 2.61 | 24% | 84 |
| July | 1.15 | 0.2 | 1.71 | 17% | 81 |
| August | 1.22 | 0.2 | 1.69 | 16% | 82 |
| September | 1.02 | 0.21 | 1.85 | 21% | 83 |
| October | 0.93 | 0.17 | 1.43 | 18% | 83 |
| November | 1.23 | 0.08 | 0.68 | 6% | 58 |
| December | 1.64 | 0.10 | 0.86 | 6% | 42 |
| **Average** | **1.18** | **0.16** | **1.39** | **14%** | **70** |
| **Summer** | **1.09** | **0.22** | **1.86** | **20%** | **84** |
| **Winter** | **1.26** | **0.11** | **0.91** | **8%** | **57** |

**Table 1-5: E-7 Monthly System Peak Day Load Reductions (12 to 6 PM, November 2013 to October 2014)**

| Month | Average Reference Load (kW) | Average Load Impact (kW) | Aggregate Load Impact (MW) | Percent Reduction (%) | Average Temperature (°F) |
|---|---|---|---|---|---|
| January | 1.04 | 0.06 | 2.96 | 6% | 65 |
| February | 1.09 | 0.03 | 1.48 | 3% | 53 |
| March | 1.18 | 0.03 | 1.52 | 3% | 52 |
| April | 1.09 | 0.11 | 5.38 | 10% | 87 |
| May | 1.36 | 0.13 | 6.59 | 10% | 91 |
| June | 2.01 | 0.17 | 8.78 | 9% | 90 |
| July | 1.79 | 0.13 | 6.8 | 8% | 86 |
| August | 1.94 | 0.13 | 6.4 | 7% | 89 |
| September | 1.54 | 0.16 | 7.95 | 10% | 88 |
| October | 1.29 | 0.15 | 7.71 | 12% | 86 |
| November | 1.13 | 0.03 | 1.77 | 3% | 59 |
| December | 1.42 | 0.05 | 2.78 | 4% | 47 |
| **Average** | **1.41** | **0.1** | **5.01** | **7%** | **75** |
| **Summer** | **1.66** | **0.15** | **7.37** | **9%** | **88** |
| **Winter** | **1.16** | **0.05** | **2.65** | **5%** | **61** |

## 1.4 TOU Ex Ante Evaluation Summary

As with the ex post evaluation, the ex ante evaluation only includes non-net metered E-6 and E-7 customers. Because E-7 is a closed rate, no new customers will join during the forecast period, and the only factor affecting the population is attrition. The E-6 tariff allows new enrollment and is predicted to double over the forecast horizon.

Table 1-6 summarizes the ex ante load impact estimates for the two TOU rates for the 1-in-2 and 1-in-10 July monthly peak day based on PG&E peak operating conditions. Combined enrollment for the two rates increases by slightly more than 5% over the forecast horizon but the share of total enrollment for E-6 and E-7 customers changes significantly, with the share for E-6 going from less than 20% currently to more than 50% in 2025. Aggregate peak-period load reduction is estimated to equal 10.2 MW for the two rates combined in 2015 and to increase to 12.5 MW by 2025, an increase of more than 22%. Load reductions increase more than enrollment because average impacts for the E-6 tariff are larger than for the E-7 tariff on the July monthly peak day.

**Table 1-6: Summary of Aggregate Ex Ante Load Impacts for Non-net-metered Residential TOU by Year (Average 1 to 6 PM Peak Period Reduction on the July System Peak Day)**

| Weather Conditions | Year | Accounts | Reference Load (MW) | Load with DR (MW) | Load Impact (MW) | % Load Reduction (%) | Avg. Temp (°F) |
|---|---|---|---|---|---|---|---|
| 1-in-2 | 2015 | 58,029 | 92.8 | 82.6 | 10.2 | 11% | 90.5 |
| | 2016 | 57,769 | 91.1 | 80.7 | 10.3 | 11% | |
| | 2017 | 57,659 | 89.6 | 79.1 | 10.5 | 12% | |
| | 2018 | 57,690 | 88.4 | 77.7 | 10.7 | 12% | |
| | 2019 | 57,856 | 87.4 | 76.5 | 10.9 | 12% | |
| | 2020 | 58,149 | 86.7 | 75.5 | 11.1 | 13% | |
| | 2021 | 58,563 | 86.1 | 74.7 | 11.4 | 13% | |
| | 2022 | 59,092 | 85.7 | 74.1 | 11.6 | 14% | |
| | 2023 | 59,730 | 85.6 | 73.6 | 11.9 | 14% | |
| | 2024 | 60,470 | 85.6 | 73.4 | 12.2 | 14% | |
| | 2025 | 61,309 | 85.7 | 73.2 | 12.5 | 15% | |
| 1-in-10 | 2015 | 58,029 | 101.7 | 90.0 | 11.7 | 11% | 94.6 |
| | 2016 | 57,769 | 99.7 | 87.9 | 11.8 | 12% | |
| | 2017 | 57,659 | 98.1 | 86.1 | 12.0 | 12% | |
| | 2018 | 57,690 | 96.7 | 84.5 | 12.2 | 13% | |
| | 2019 | 57,856 | 95.5 | 83.1 | 12.4 | 13% | |
| | 2020 | 58,149 | 94.6 | 81.9 | 12.7 | 13% | |
| | 2021 | 58,563 | 93.9 | 81.0 | 13.0 | 14% | |
| | 2022 | 59,092 | 93.5 | 80.2 | 13.3 | 14% | |
| | 2023 | 59,730 | 93.2 | 79.7 | 13.6 | 15% | |
| | 2024 | 60,470 | 93.2 | 79.3 | 13.9 | 15% | |
| | 2025 | 61,309 | 93.3 | 79.0 | 14.3 | 15% | |

# 2 Overview of Time-varying Tariffs

PG&E has offered time-varying tariffs on a voluntary basis since the mid-1980s. The E-7 tariff was first offered in 1986. E-7 was targeted at large users with air conditioning (and therefore was not revenue neutral for the average PG&E customer) and succeeded in signing up a relatively large fraction of the target audience. Enrollment peaked at 130,000 customers in 1995. New enrollment essentially stopped in 1996 when the California Public Utilities Commission (CPUC) changed the payment policy for the time-of-use meters that were needed in order to be on the E-7 tariff. Prior to 1996, the incremental meter charges were collected in the form of a modest monthly meter charge. In 1996, the Commission changed the policy to require an upfront installation charge of roughly $200 to obtain a TOU meter. New enrollment essentially stopped after that point and program enrollment began a slow, steady decline due primarily to customer churn.

***PG&E has offered voluntary time varying rates to residential customers for almost three decades. In 2014,roughly 240,000 residential customers were on one of the three time varying rates available to PG&E's customers – SmartRate, E-6 TOU or E-7 TOU.***

The E-7 tariff was closed to new enrollment in 2006,[3] when it was replaced with the new E-6 tariff. E-6 was designed to be a revenue neutral tariff. As discussed below, enrollment in E-6 has been modest and is comprised largely of customers with rooftop solar installations.

PG&E's SmartRate tariff was initially offered to customers with SmartMeters starting in May 2008. Roughly 10,000 customers enrolled in the Kern County region in summer 2008, which was the only area that had a sufficiently large number of SmartMeters at the time. SmartRate was marketed much more broadly in 2009 since SmartMeter deployment was more widespread. Enrollment peaked at around 25,000 customers in 2009, after which PG&E ceased marketing the rate in response to the CPUC proposed decision leading to D.10-02-032 indicating that SmartRate would be closed in early 2011 and replaced with an alternative Peak Day Pricing (PDP) rate. Enrollment in SmartRate declined moderately in 2010 and 2011, due largely to customer churn. In November 2011, the Commission agreed to allow SmartRate to continue as an option and to eliminate the plan transition SmartRate customers to PDP on a default basis was obtained in Phase 2 of its 2014 General Rate Case. Starting in early 2012, SmartRate was marketed heavily, and enrollment more than tripled between the beginning and end of 2012, reaching 78,000 customers by October 2012. Enrollment continued to grow over the last two years and stood at roughly 129,000 customers by the end of 2014.

## 2.1 SmartRate Overview

SmartRate is a critical peak pricing (CPP) tariff that is an overlay on a customer's otherwise applicable tariff (OAT). The vast majority of SmartRate participants have PG&E's E-1 tariff as their underlying rate but over the last two years, the number of customer that have the E-6 or E-

[3] E-7 was re-opened briefly on January 1, 2007 for customers with rooftop solar installations, and again between January 1, 2008 through June 30, 2009 to solar customers with interconnections in progress who had filed interconnection agreements prior to December 31, 2007 (see Advice 3285-E, dated June 26, 2008).

7 tariff as their underlying rates has grown substantially. In 2012, only a handful of SmartRate customers were not on E-1. In 2013, the number of E-6/SmartRate customers had grown to about 2,000 and in 2014 dual enrollment had reached almost 4,600. In addition, there were roughly 350 SmartRate/E-7 customers.

SmartRate pricing consists of an incremental charge that applies during the peak period on SmartDays and a per kilowatt-hour credit that applies to all other hours from June through September. For residential customers, the additional peak-period charge on SmartDays is 60¢/kWh. The SmartRate credit has two components, both of which apply only during the months of June through September. The first SmartRate credit, 3¢/kWh, applies to all usage other than peak-period usage on SmartDays. An additional credit of 1¢/kWh applies to Tier 3 and higher usage for residential customers regardless of time period.

Under SmartRate, there can be up to 15 SmartDays (also referred to as event days) during the summer season, which runs from May 1 through October 31. SmartDays are called based on a trigger temperature that is equal to 98°F at the beginning of the summer and is adjusted up or down throughout the summer. When the average temperature[4] is expected to be above the trigger temperature based on a day-ahead forecast, customers are notified that the next day will be a SmartDay. Every two weeks, the trigger may be adjusted upward if there were more events than expected in the previous two weeks or downward if there were fewer. The goal is for there to be an average of 12 event days each summer, with no fewer than 9 and no more than 15 during any particular summer.

Unless a customer's underlying rate is also a time-of-use (TOU) rate, which is rare, prices vary by time of day on SmartDays only. The peak period on SmartDays is from 2 PM to 7 PM and customers are notified by 3 PM on the business day prior to the SmartDay. Customers have several options for receiving event notification (e.g., email, phone, etc.), including not being notified at all. Roughly 7% of SmartRate-only customers and 6% of dually enrolled customers either chose not to be notified or provided notification information that was initially incorrect or has become outdated.

Customers who enroll on SmartRate receive bill protection for the first full season. Bill protection is designed to address the risk aversion that research has shown to be a significant barrier to enrolling customers onto dynamic rates. Bill protection offers a risk-free trial and ensures that, during the first full season on SmartRate, customer's bills will not increase under the new rate option relative to what they would have been over the same period under the prior tariff.

PG&E's standard residential tariff, E-1, is a five-tier, increasing block rate, with the price per kWh increasing nearly threefold between Tier 1 and Tiers 4 & 5 (which have the same marginal price, which means it is effectively a four-tier rate). The usage levels where prices change are multiples of a baseline usage amount that varies by climate zone. Table 2-1 shows the prices at the end of 2014 for each tier for the E-1 tariff for both CARE and non-CARE customers who do not have all-electric homes. As shown in the table, the CARE discount is quite significant, especially for low income households that have usage in Tier 3 and above.

[4] The average is calculated from forecasts for Sacramento, Concord, San Jose, Red Bluff and Fresno.

**Table 2-1: E-1 CARE and Non-CARE Prices for PG&E[5]**

| Usage Tier | % of Baseline Usage | E-1 Price for Tier (¢/kWh) | CARE Price for Tier (¢/kWh) |
|---|---|---|---|
| 1 | 100% | 15.2 | 9.8 |
| 2 | 130% | 17.6 | 11.2 |
| 3 | 200% | 26.4 | 15.6 |
| 4 | 300% | 32.4 | 15.6 |
| 5 | >300% | 32.4 | 15.6 |

With the tiered pricing used in PG&E's service territory, the price ratio between peak-period prices on SmartDays and the average price on normal days on the SmartRate tariff (which is roughly 3¢/kWh lower than the averages in Table 2-1 because of the SmartRate credit during those hours), varies significantly with usage and also varies between CARE and non-CARE customers. For example, for a Tier 1 customer on the E-1 tariff, the peak-period price on SmartDays is roughly 6 times higher than on non-SmartDays. On the other hand, for a Tier 4 or 5 customer, the peak period price would equal roughly 93¢/kWh and the price ratio would be roughly 3 to 1. For CARE customers in Tier 1, the SmartDay peak-period price is approximately 68¢/kWh and the price ratio between SmartDay peak-period prices and non-SmartDay prices is roughly 10 to 1.

Customers who enroll in SmartRate may also enroll in PGE&'s SmartAC program. Smart AC is a program in which customers receive a payment from PG&E in return for having their air conditioner controlled at times of high system load. PG&E accomplishes this control through the use of switches that are installed directly on a customer's air conditioner or through the use of programmable communicating thermostats that can receive a radio signal. Customers who enroll in both programs are given the option of having their air conditioner controlled during the peak period on SmartDays. Choosing this option provides these customers with an automatic boost to their savings due to reduced air conditioning usage on SmartDays.[6]

Table 2-2 shows the proportion of customers in the PG&E residential population, the SmartRate-only population, and the dually enrolled population by LCA and CARE status. CARE customers represent roughly 25% of PG&E's customer population, and about 22% of the SmartRate population. They represent about 23% of the SmartRate-only population but only 21% of the dually enrolled population. Participants are distributed across LCAs roughly in proportion to the PG&E population in each LCA. For example, roughly 45% of program participation and 46% of the PG&E population are from the Greater Bay Area LCA. Table 2-3 shows the number of enrolled customers in each LCA at the end of 2013 and 2014. Participation grew by roughly 8% over this period.

[5] Both current and historical rates can be found here: http://www.pge.com/nots/rates/tariffs/electric.shtml#RESELEC.

[6] For more information about the SmartAC program see "2014 Load Impact Evaluation for Pacific Gas and Electric Company's Smart AC Program" which is available on the CALMAC website.

**Table 2-2: Customers in the PG&E Population and SmartRate Program by Local Capacity Area and CARE Status as of October 31, 2014**

| Local Capacity Area | SmartRate Participants (End of 2014) | | | | | | | | PG&E Residential Population | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SmartRate-Only | | | | Dually Enrolled | | | | | | | |
| | Non-CARE | % | CARE | % | Non-CARE | % | CARE | % | Non-CARE | % | CARE | % |
| Greater Bay Area | 38,338 | 56% | 5,275 | 25% | 13,679 | 42% | 1,392 | 17% | 1,739,874 | 50% | 370,336 | 32% |
| Greater Fresno Area | 3,272 | 5% | 2,891 | 14% | 2,454 | 8% | 1,587 | 19% | 190,246 | 5% | 152,134 | 13% |
| Humboldt | 819 | 1% | 427 | 2% | 161 | 1% | 54 | 1% | 86,948 | 2% | 36,384 | 3% |
| Kern | 3,109 | 5% | 3,634 | 18% | 1031 | 3% | 1003 | 12% | 114,185 | 3% | 92,309 | 8% |
| North Coast and North | 3,137 | 5% | 629 | 3% | 1,974 | 6% | 234 | 3% | 331,807 | 10% | 71,140 | 6% |
| Other | 12,325 | 18% | 4,310 | 21% | 5,936 | 18% | 1,990 | 24% | 683,110 | 20% | 276,807 | 24% |
| Sierra | 4,370 | 6% | 1,185 | 6% | 4,101 | 13% | 696 | 8% | 189,220 | 5% | 55,723 | 5% |
| Stockton | 3,234 | 5% | 2,381 | 11% | 2,888 | 9% | 1,288 | 16% | 154,132 | 4% | 85,551 | 8% |
| **Total** | **68,604** | **100%** | **20,732** | **100%** | **32,224** | **100%** | **8,244** | **100%** | **3,489,522** | **100%** | **1,140,384** | **100%** |

**Table 2-3: Comparison of 2013 and 2014 Participants by Local Capacity Area at the End of Each Summer (October 2013 and October 2014)**

| LCA | SmartRate-only | | | | Dually Enrolled | | | | All Customers | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2013 | % | 2014 | % | 2013 | % | 2014 | % | 2013 | % | 2014 | % |
| Greater Bay Area | 38,674 | 47% | 43,613 | 49% | 14,546 | 38% | 15,071 | 37% | 53,220 | 44% | 58,684 | 45% |
| Greater Fresno Area | 5,990 | 7% | 6,163 | 7% | 3,666 | 10% | 4,041 | 10% | 9,656 | 8% | 10,204 | 8% |
| Humboldt | 941 | 1% | 1,246 | 1% | 193 | 1% | 215 | 1% | 1,134 | 1% | 1,461 | 1% |
| Kern | 7,274 | 9% | 6,743 | 8% | 1,760 | 5% | 2,034 | 5% | 9,034 | 7% | 8,777 | 7% |
| Northern Coast | 3,246 | 4% | 3,766 | 4% | 2,103 | 6% | 2,208 | 5% | 5,349 | 4% | 5,974 | 5% |
| Other | 15,616 | 19% | 16,635 | 19% | 7,340 | 19% | 7,926 | 20% | 22,956 | 19% | 24,561 | 19% |
| Sierra | 5,500 | 7% | 5,555 | 6% | 4,468 | 12% | 4,797 | 12% | 9,968 | 8% | 10,352 | 8% |
| Stockton | 5,581 | 7% | 5,615 | 6% | 3,727 | 10% | 4,176 | 10% | 9,308 | 8% | 9,791 | 8% |
| **Total** | **82,822** | **100%** | **89,336** | **100%** | **37,803** | **100%** | **40,468** | **100%** | **120,625** | **100%** | **129,804** | **100%** |

## 2.2 TOU Overview

The E-7 tariff is a two-period rate, with a peak period from 12 to 6 PM on weekdays and off-peak prices in effect at all other times. The peak period is the same the entire year, although rates change seasonally. Summer rates are in effect from May 1 through October 31. The E-7 tariff has been closed to new customers since 2006 and the number of customers on the rate has been steadily decreasing as existing customers close their accounts or change rates.

The E-7 tariff was replaced by the E-6 tariff, which is a three-period TOU rate with rate periods that vary by season. During summer weekdays, the peak period is from 1 PM to 7 PM, and the partial peak period is from 10 AM to 1 PM and 7 PM to 9 PM; there is another partial peak from 5 PM to 8 PM on Saturdays and Sundays. All other hours are priced at the off-peak rate. In the winter, peak period prices do not apply, and partial peak prices occur from 5 PM to 8 PM on weekdays only. All other hours are at off-peak prices.

There are two versions of both E-7 and E-6: one for CARE customers and one for non-CARE customers. In addition, as with all California utilities, residential customers are charged more for electricity use above a certain baseline level each month to encourage conservation. Different prices apply as customers exceed the baseline level by 100%, 130%, 200% and 300%. Each of these percentage breaks is known as a tier. The baseline level varies by climate region and takes into account whether customers live in homes that receive both electric and gas service or receive all electric service.

Figure 2-1 illustrates the variation in prices across hours of the day for both rates. For simplicity, the figure only plots the hourly prices for summer weekdays, assuming Tier 2 usage levels (usage between 100% and 130% of the baseline level). During peak hours, the E-7 price signal is stronger than the E-6 signal. However, E-6 also includes a semi-peak period and encourages customers to shift loads for more hours. For both E-6 and E-7, CARE customers experience lower prices across all rate periods. Table 2-4 provides additional detail and shows the electricity price by rate period, tier and CARE status for E-6 and E-7 customers.

**Figure 2-1: Illustrative E-6 and E-7 Summer Weekday Hourly Prices**

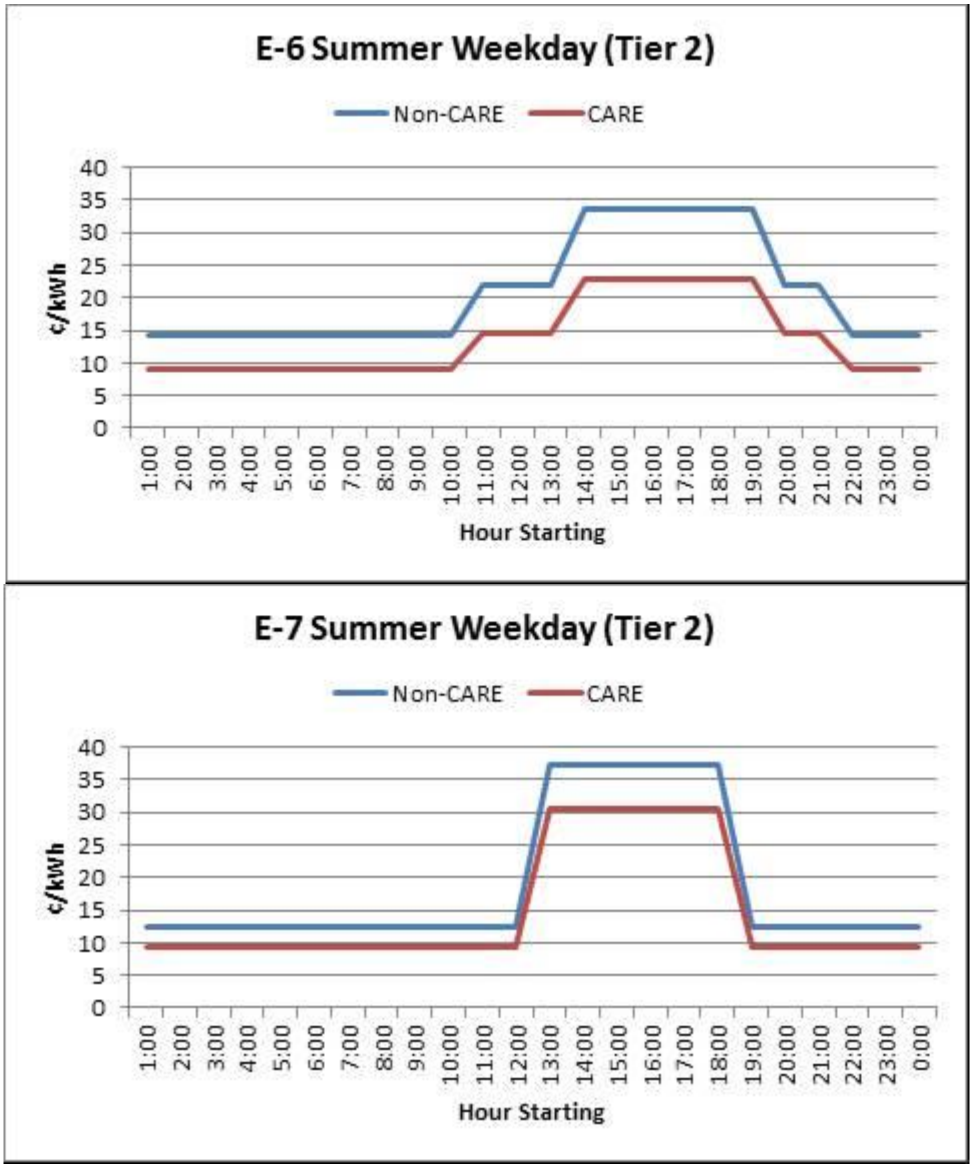

**Table 2-4: E-6 and E-7 Prices (October 1 through December 31, 2014)[7]**

| Rate | Rate Description | Season | TOU Period | Energy Charge (¢/kWh) Tier 1 (baseline) | Tier 2 (101- 130% of baseline) | Tier 3 (131-200% of baseline) | Tier 4 (201-300% of baseline) | Tier 5 (300% of baseline+) | Average Total Rate (¢/kWh) |
|---|---|---|---|---|---|---|---|---|---|
| E7 | Residential time-of-use | Summer | Peak | 34.9 | 37.3 | 46.1 | 52.1 | 52.1 | 18.0 |
| | | | Off-Peak | 10.1 | 12.5 | 21.3 | 27.3 | 27.3 | |
| | | Winter | Peak | 13.4 | 15.8 | 24.6 | 30.6 | 30.6 | |
| | | | Off-Peak | 10.4 | 12.8 | 21.6 | 27.6 | 27.6 | |
| EL-7 | Residential time-of-use, CARE | Summer | Peak | 28.9 | 30.6 | 43.4 | 43.4 | 43.4 | 10.9 |
| | | | Off-Peak | 7.6 | 9.3 | 12.4 | 12.4 | 12.4 | |
| | | Winter | Peak | 10.4 | 12.2 | 16.6 | 16.6 | 16.6 | |
| | | | Off-Peak | 7.9 | 9.6 | 12.8 | 12.8 | 12.8 | |
| E6 | Residential time-of-use | Summer | Peak | 31.2 | 33.6 | 42.3 | 48.3 | 48.3 | 19.4 |
| | | | Part-Peak | 19.7 | 22.0 | 30.8 | 36.8 | 36.8 | |
| | | | Off-Peak | 12.0 | 14.4 | 23.1 | 29.1 | 29.1 | |
| | | Winter | Part-Peak | 14.2 | 16.5 | 25.2 | 31.2 | 31.2 | |
| | | | Off-Peak | 12.5 | 14.8 | 23.5 | 29.5 | 29.5 | |
| EL-6 | Residential time-of-use, CARE | Summer | Peak | 21.5 | 23.0 | 32.7 | 32.7 | 32.7 | 10.6 |
| | | | Part-Peak | 13.1 | 14.6 | 20.4 | 20.4 | 20.4 | |
| | | | Off-Peak | 7.4 | 8.9 | 12.2 | 12.2 | 12.2 | |
| | | Winter | Part-Peak | 9.0 | 10.5 | 14.4 | 14.4 | 14.4 | |
| | | | Off-Peak | 7.7 | 9.2 | 12.6 | 12.6 | 12.6 | |

[7] The rates shown here were those in effect as of December 2014. Rates changed four times during the study period. Current and historical rates can be found online at http://www.pge.com/nots/rates/tariffs/electric.shtml#RESELEC_TOU.

In total, there were approximately 108,000 customers being served under the four versions of the TOU tariffs at the end of summer 2014, with about 44,000 on E-6 and approximately 64,000 on E-7. However, almost half of these customers had net meters and most net-metered customers own rooftop solar systems and, therefore, are excluded from this analysis. Table 2-5 shows the distribution of E-6 and E-7, non-net-metered customers across LCAs and by CARE and non-CARE status. As seen, there were 8,644 non-net-metered customers enrolled on the E-6 tariff and 50,621 non-net-metered E-7 customers. More than half of E-6 customers are located in the Greater Bay Area LCA whereas the Bay Area only accounts for roughly one third of E-7 customers.

**Table 2-5: E-6 and E-7 Enrollment Excluding Net Metered Customers**

| Local Capacity Area | Non-Net Metered TOU Participants (End of 2014) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | E-6 | | | | E-7 | | | | Total |
| | Non-CARE | % | CARE | % | Non-CARE | % | CARE | % | All |
| Greater Bay Area | 4,896 | 62% | 234 | 33% | 16,815 | 37% | 1,195 | 24% | 23,140 |
| Greater Fresno Area | 195 | 2% | 35 | 5% | 2,669 | 6% | 444 | 9% | 3,343 |
| Humboldt | 252 | 3% | 58 | 8% | 2,773 | 6% | 625 | 12% | 3,708 |
| Kern | 72 | 1% | 17 | 2% | 962 | 2% | 168 | 3% | 1,219 |
| North Coast and North | 752 | 9% | 133 | 19% | 5,994 | 13% | 419 | 8% | 7,298 |
| Other | 1,195 | 15% | 157 | 22% | 10,455 | 23% | 1,362 | 27% | 13,169 |
| Sierra | 376 | 5% | 53 | 7% | 3,900 | 9% | 521 | 10% | 4,850 |
| Stockton | 188 | 2% | 31 | 4% | 2,009 | 4% | 310 | 6% | 2,538 |
| **Total** | **7,926** | **100%** | **718** | **100%** | **45,577** | **100%** | **5,044** | **100%** | 59,265 |

Table 2-6 compares E-6 and E-7 non-net metered customers to customers on the standard (non-time varying) E-1 rate. E-6 and E-7 customers differ in several ways from the E-1 population. For example, customers on E-6 and E-7 are significantly less likely to be on the low income rate, CARE, than E-1 customers. While approximately 25% of PG&E's E-1 customers are CARE customers, only about 8% to 10% of E-6 and E-7 customers are on the CARE tariff. E-7 customers are also much more likely to be all electric households than E-1 customers. E-7 customers also have much higher saturations of electric space heat and central air conditioning compared with E-6 customers. This explains why E-7 customers have significantly higher annual electricity consumption compared with both E-1 and E-6 customers. The average annual electric consumption of E-7 customers is nearly 10,000 kWh, which is almost 60% higher than the 6,279 kWh average annual consumption of E-1 customers and roughly one-third larger than 7,405 kWh annual consumption of E-6 customers.

**Table 2-6: Customer Characteristics by Tariff**
**(E-6 and E-7 Excluding Net Metered Customers)**

| Characteristic | Rate | | |
|---|---|---|---|
| | E-1 | E-6 | E-7 |
| Accounts | 4,443,334 | 8,644 | 50,621 |
| Average Annual kWh | 6,279 | 7,405 | 9,866 |
| Average Summer kWh | 2,759 | 3,606 | 4,961 |
| Estimated % with AC[8] | 49% | 39% | 51% |
| % CARE | 25% | 8% | 10% |
| % All Electric | 15% | 18% | 33% |

## 2.3 Report Organization

The remainder of this report is organized as follows. Section 3 provides an overview of the ex post methodology used to evaluate SmartRate and Section 4 provides ex post results for SmartRate. Section 5 discusses the ex ante methods and results for SmartRate. Section 6 discusses the ex post load impact estimation methods for the E-6 and E-7 rates and Section 7 contains the ex post load impact estimates for these tariffs. Section 8 contains ex ante methods and results for E-6 and E-7.

[8] The A/C saturation estimates here are based on a model developed for PG&E by Nexant that predicts the likelihood of A/C ownership as a function of usage characteristics, location and other factors. The model was developed using RASS survey data but the estimates in the table are based on the model, not on a survey.

# 3 SmartRate Ex Post Methods and Validation

The fundamental problem for estimating load impacts is developing an estimate of the reference load. The reference load is an estimate of what load would have been in the absence of the price incentives that are in effect for participants. For this evaluation, the focus is on what load would have been on SmartDays in particular. It may be true that customer load is different on non-SmartDays due to the SmartRate bill credit or due to habit formation in energy conservation (these effects work in opposite directions); however, measuring such an effect is very difficult using the quasi-experimental methods applied here rather than through a controlled experiment.[9]

The evaluation methods used in the 2014 SmartRate evaluation are similar to those used for the 2012 and 2013 evaluations. The approach relies on selection of a control group using statistical matching, as explained in Section 3.1 below. In 2012, the SmartRate population changed significantly over the course of the summer, which required creating multiple control groups across SmartRate events. This year and in 2013, one matched control group was selected for the entire SmartRate population.

The matched control group method used for this analysis is superior to a within-subjects analysis because there is a large population of non-SmartRate customers to use as a pool for matching and because it eliminates the problem of model misspecification.[10] Any reference load model based on loads observed at non-event times requires the modeler to make assumptions about the relationships between load, time and temperature. If this assumed function does not reflect the true relationships between load, time and temperature, then the model can produce incorrect results. In contrast, the matched control group automatically deals with this problem by assuming that the customers who behave similarly to SmartRate customers during non-event periods would also behave similarly during event periods. This eliminates the need to specify load as a function of weather.

As discussed below, a within-subjects analysis is used for certain parts of this evaluation; however, in those cases the emphasis is on relative load impacts across different types of customers. It is a weaker assumption to believe that the biases this method produces are relatively stable across customer segments than to believe that we can completely eliminate them. Therefore, we use the matched control group method wherever possible, particularly for the primary impact estimates to be reported. We use the within-subjects analysis only to perform high responder analysis of customers where developing control groups within each segment would be infeasible.

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[9] The design necessary to measure such an effect would involve either a randomized control trial or a randomized encouragement design. These designs are more practical within the confines of a pricing pilot than with an actual program like SmartRate. For examples of how these methods have been used within a pricing pilot, see the interim report on Sacramento Municipal Utility District's Smart Pricing Options pilot: https://www.smartgrid.gov/sites/default/files/MASTER_SMUD%20CBS%20Interim%20Evaluation_Final_SUBMITTED%20TO%20TAG%2020131023.pdf .

[10] For a comparison of results using various research methods, including RCT/RED designs, statistical matching and within-subjects regression analysis, see the aforementioned SMUD pilot interim report.

## 3.1 Matched Control Group Methodology

The primary source of reference loads, and hence impact estimates, is a series of matched control groups. These control groups are assembled from among the non-SmartRate population. The methods used to assemble the groups are designed to ensure that the control group load on event days is an accurate estimate of what load would have been among SmartRate customers on event days.

The fundamental idea behind the matching process is to find customers who were not subject to SmartRate events that have similar characteristics to those who were subject to SmartRate events. Two different control groups were assembled: one for the SmartRate-only population and one for the group of SmartRate customers also enrolled in SmartAC.

The control groups were selected using a propensity score match to find customers who had load shapes most similar to SmartRate customers. In this procedure, a probit model is used to estimate a score for each customer based on a set of observable variables that are assumed to affect the decision to join SmartRate. A probit model is a regression model designed to estimate probabilities—in this case, the probability that a customer would choose SmartRate. The score can be interpreted two different ways. First, the propensity score can be thought of as a summary variable that includes all the relevant information in the observable variables about whether a customer would choose to be on SmartRate. Each customer in the SmartRate population is matched with a customer in the non-SmartRate population that has the closest propensity score. The second way to think of the propensity score is as the probability that a customer will join SmartRate based on the included independent variables. Thinking of it this way, each customer in the control group is matched to a SmartRate customer with a similar probability of joining SmartRate given the observed variables.

The match was performed within each LCA, usage quartile, and CARE status and was based on a set of variables that characterize load shape and the magnitude of electricity use on hot, non-event days. The set of usage variables in the propensity score model were the average hourly usage for each of the hours from 8 am to 10 pm, all calculated over the 9 hottest, non-event, non-holiday weekdays.[11] These days were chosen because they were the only days with temperatures that best reflected those on event days. Matches were tested based on other sets of hours and the final model was chosen because it resulted in the closet match between SmartRate and control customer average usage during event hours on hot, non-event days (discussed below). A match was found for each SmartRate customer, but the same control customer could be matched to multiple SmartRate customers, meaning that a control customer would be represented more than once in the control group.

Table 3-1 compares the final matched control group to the SmartRate sample based on LCA, CARE status and average monthly usage in June and July 2014. The last two columns of Table 3-1 show t-statistics and p-values for tests of the hypothesis that the mean values do not differ between the groups. The two groups match closely across LCAs. The only variable for which there is a statistically significant difference between the participant population and the matched

[11] The days were May 5, June 10, July 8, July 15, July 24, August 6, August 27, September 2, and September 15.

control group is peak period usage on hot non-event days. Although statistically significant, this difference is roughly 1% and, therefore, immaterial.

**Table 3-1: Distributions of LCA, Usage and CARE Status for SmartRate Customers and the Matched Control Group[12]**

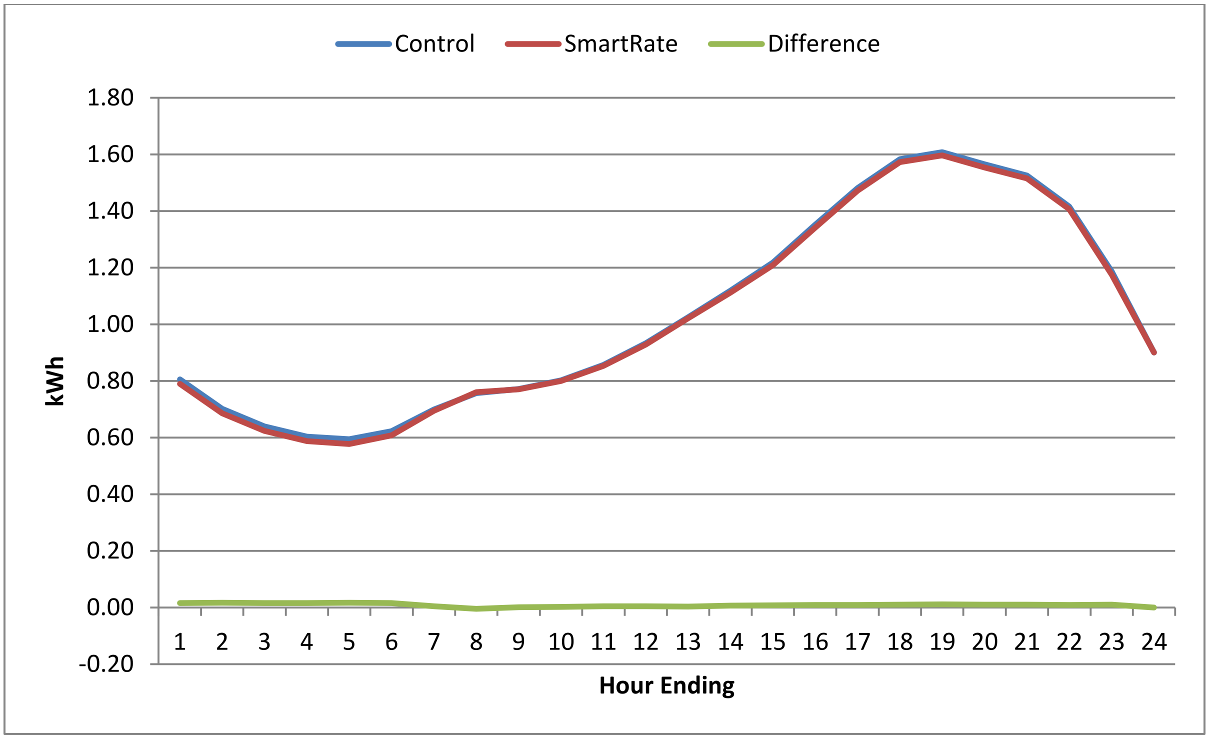
| Characteristic | SmartRate Population | Matched Control Group | t statistic | P value |
|---|---|---|---|---|
| Greater Bay Area | 45% | 45% | 0 | 1.00 |
| Greater Fresno | 8% | 8% | 0 | 1.00 |
| Humboldt | 1% | 1% | 0 | 1.00 |
| Kern | 7% | 7% | 0 | 1.00 |
| Northern Coast | 5% | 5% | 0 | 1.00 |
| Other | 19% | 19% | 0 | 1.00 |
| Sierra | 8% | 8% | 0 | 1.00 |
| Stockton | 8% | 8% | 0 | 1.00 |
| Event Hour Usage on Hot Non-Event Days | 1.48 | 1.50 | 4.12 | 0.00 |
| Non-CARE | 78% | 78% | 0 | 1.00 |
| CARE | 22% | 22% | 0 | 1.00 |

A potential source of bias in this methodology is that SmartRate customers may behave differently on non-event days than they would if they were not on SmartRate, either because they face slightly different rates than non-SmartRate customers due to SmartRate credits or due to energy saving habit formation. This means that there is a potential bias introduced by matching SmartRate customers to customers who have similar loads on hot, non-event days because those loads may not be an accurate representation of what SmartRate customers would have used if they were not on the program. This is impossible to identify or to correct for in the absence of having pretreatment data. If there is a bias, it is a downward bias. As discussed in Section 4, habit formation that manifests itself in lower peak period usage on non-event days is one possible explanation for the lower average impacts that are estimated this year compared with last year.

Figure 3-1 shows average hourly usage for SmartRate and matched control customers on hot, non-event days. Over the event period (2 to 7 PM), usage is very similar between the two groups, with a difference of about 1%, on average.

[12]These statistics are for the matched control group for the first set of event days for SmartRate-only customers. Analogous tables for later summer control groups and for dually enrolled control groups are in Appendix A.

**Figure 3-1: Average Usage on Hot, Non-event Days for SmartRate Customers and Control Group**




Once the control groups were matched and validated, load impacts were estimated using a difference-in-differences methodology. This methodology calculates the estimated impacts as the difference in average loads between SmartRate and control customers on event days minus the difference between the two groups on hot, non-event days. This calculation controls for residual differences in load between the groups that are not eliminated through the matching process, thus reducing bias.

The difference-in-differences model includes customer and day fixed effects to get the most statistically precise estimate possible given the data structure. The model was run separately for each hour, customer segment (e.g., CARE, non-CARE), local capacity area and for SmartRate only and dually enrolled customers.

**Equation 3-1: Model Specification for Difference-in-Differences**

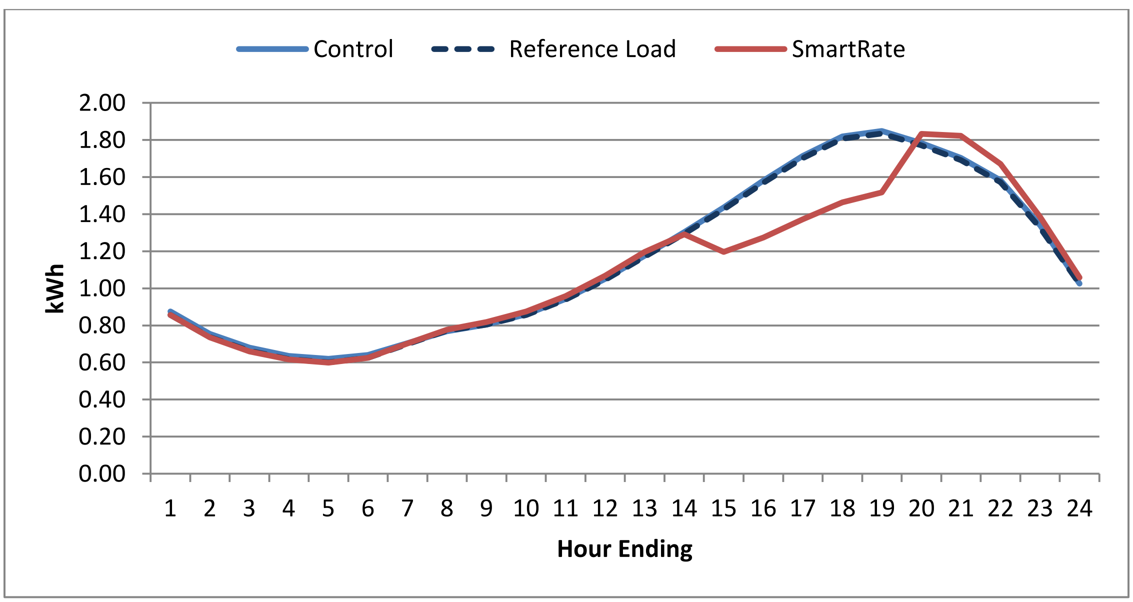
$$kW_{it} = a + b * SmartRate_i * Event_t + \sum_{cust=2nd\ cust}^{last\ cust} c_{cust} * C_i + \sum_{day=2nd\ day}^{last\ day} d_{day} * D_t + \varepsilon_{it}$$

**Table 3-2: Variables Used in Difference-in-Differences Regression Model**

| Variable | Description |
|---|---|
| a | an estimated constant |
| b | the estimated impact |
| c and d | customer and day fixed effects |
| SmartRate | a dummy variable indicating whether or not a customer is on SmartRate (=1) or not (=0) |
| Event | a dummy variable indicating whether a day is a SmartDay (=1) or not (=0) |
| C | a dummy variable indicating whether an observation belongs to that cust (=1) or not (=0) |
| D | a dummy variable indicating whether that observation belongs to that day (=1) or not (=0) |
| cust | indexes all customers, both control and treatment customers. |
| day | indexes each of the days, both proxy days and event days. |
| $\varepsilon$ | the error term |

Figure 3-2 illustrates the differences between the actual load for the control group and the reference load predicted by the regression model. The solid blue line shows the control group usage and the solid red line shows SmartRate usage. As the figure shows, the reference load is very similar to the control load, which should be expected since matching was done based on hot, non-event day load.

**Figure 3-2: Example of Control Group Usage Adjustment; Average Event Day, SmartRate-only**



After the adjustment, impact estimates are calculated by subtracting average hourly usage on each event day for SmartRate customers from average hourly reference usage on each event day. Sample sizes were sufficiently large that average usage in the treatment and control groups matched closely even when the population was broken down into smaller categories.

## 3.2 Individual Customer Regression Methodology

Having used the matched control group to estimate overall event impacts, the individual regressions were used to create impact estimates on a per-customer basis, which allows for relatively simple analyses of different segments of customers without repeatedly matching new control groups for each segment. The regression model used this year is the same as the one used for 2013. The regression is specified as follows:

**Equation 3-2: Model Specification for Individual Customer Regressions**

$$kW_t = a + b \cdot mean17_t + c \cdot eventday_t + \varepsilon_t$$

**Table 3-3: Variables Used for Individual Customer Regressions**

| Variable | Description |
|---|---|
| a | a is an estimated constant |
| b and c | b and c are estimated parameters |
| mean17 | The mean temperature from midnight until 5 PM |
| eventday | Dummy variables for the event period of each event day |
| $\varepsilon$ | The error term |

Table 3-4 shows predicted and actual usage during event hours on the 9 out-of-sample days used in this analysis. Because the individual regressions are only being used to predict impacts (as opposed to full event day load shapes), these are the only hours important to the analysis. On average, predicted values are no different than actual usage on the out-of-sample days. This difference on individual days is small and helps to validate the results of the regression model for the entire population.

**Table 3-4: Predicted Versus Actual Usage During Event Hours on Hot Non-event Days, SmartRate-only Customers**

| Date | Observed Load (kW) | Predicted Load (kW) | Error (kW) | Percent Error (%) |
|---|---|---|---|---|
| 13-May-14 | 1.02 | 1.17 | 0.15 | 15% |
| 10-Jun-14 | 1.22 | 1.34 | 0.13 | 10% |
| 8-Jul-14 | 1.47 | 1.45 | -0.02 | -1% |
| 15-Jul-14 | 1.49 | 1.46 | -0.04 | -3% |
| 24-Jul-14 | 1.47 | 1.45 | -0.02 | -1% |
| 6-Aug-14 | 1.36 | 1.26 | -0.10 | -7% |
| 27-Aug-14 | 1.34 | 1.30 | -0.04 | -3% |
| 25-Jul-13 | 1.29 | 1.28 | -0.02 | -1% |
| 2-Sep-14 | 1.37 | 1.34 | -0.03 | -2% |
| 15-Sep-14 | 1.33 | 1.34 | 0.00 | 0% |
| **All Days** | **1.34** | **1.34** | **0.00** | **0%** |

Event day impacts estimated using individual regressions for both the SmartRate and dually enrolled populations are significantly lower than impacts estimated using the matched control group. For example, for the SmartRate only population, the average load impact across all event days using individual customer regressions is 0.12 kW whereas the estimate using the matched control group is 0.21 KW (as seen in the next report section).

# 4 SmartRate 2014 Ex Post Load Impacts

This section summarizes the ex post load impact estimates for SmartRate for the 2014 program year. In keeping with the requirements for ex post load impact evaluations, results are presented for each hour of each event day for the average customer and for all customers enrolled at the time of each event. In addition to meeting the basic load impact protocol requirements, detailed analysis has been conducted to understand how load impacts vary across a number of factors, including:

> ***PG&E's SmartRate program had roughly 129,000 customers enrolled at the end of 2014. The average peak period load reduction delivered by the program over the 12 SmartDays called in 2014 was almost 39 MW.***

- SmartRate only and dually enrolled customers;
- Local capacity area;
- CARE status;
- Number of successful notifications; and
- Central AC saturation and temperature.

The characteristics of customers who provide greater-than-average load impacts are also discussed. The analysis presented here also addresses several important policy and planning questions, including:

- The magnitude of program attrition;
- Whether bill protection affects customer load impacts.

Different methods and models are used to analyze different issues. The primary impact evaluation and all of the estimates for various customer segments rely on the matched control group methodology summarized in Section 3.1. Only the high responder analysis uses individual customer regressions.

## 4.1 Average Event Impacts

Figure 4-1 shows the hourly load impacts for the average SmartRate-only customer across the 12 event days in 2014 and Figure 4-2 shows the hourly loads for dually-enrolled customers. In 2013, only 8 events were called, but in 2014 PG&E reached its target of calling 12 events.

The number of enrolled, SmartRate only customers shown in Figure 4-1, roughly 89,000, is the average number of enrolled customers across the 12 event days in 2014. The average impact for all events across the 5-hour, SmartRate event window was 0.21 kW, or 14%. The percentage load reduction was relatively constant across the hours from 3 to 6 PM but lower in the first hour from 2 to 3 PM and last hour from 6 to 7pm. Average hourly load impacts vary from a low of 0.16 kW in the first hour to a high of 0.23 kW in the hour between 5 to 6 PM. The reference load increases from a low of 1.31 kW from 2 to 3 PM, when the average temperature is 88°F, to a high of 1.67 kW between 6 and 7 PM. The load is higher between 6 and 7 PM even though the temperature is lower than in mid-afternoon because household loads typically increase when people return home from work. For the average customer, there is an increase in electricity consumption relative to the reference load in the evening hours following the end of the event. This snapback impact probably occurs because many customers voluntarily reduce their AC use during events and the AC unit must run more to cool the house after the event period ends than it would have in the absence of an event.

Figure 4-2 shows the hourly load impacts for the average dually enrolled customer across the 12 event days in 2014. The average impact for all events across the 5-hour event window was 0.51 kW, or 25% of the reference load. The absolute reduction is more than twice as large as for SmartRate-only customers. The reference load for dually enrolled customers is about 32% higher than for SmartRate- only customers. Both of these findings reflect the fact that all dually enrolled customers have central air conditioning whereas only a portion of SmartRate only customers have central air conditioning. Furthermore, dually enrolled customers have their air conditioners automatically controlled by PG&E, whereas SmartRate only customers with central air conditioning must manually control their air conditioner.

## Figure 4-1: Load Impact per Hour for the Average 2014 Event Day (Average SmartRate-only Participant)

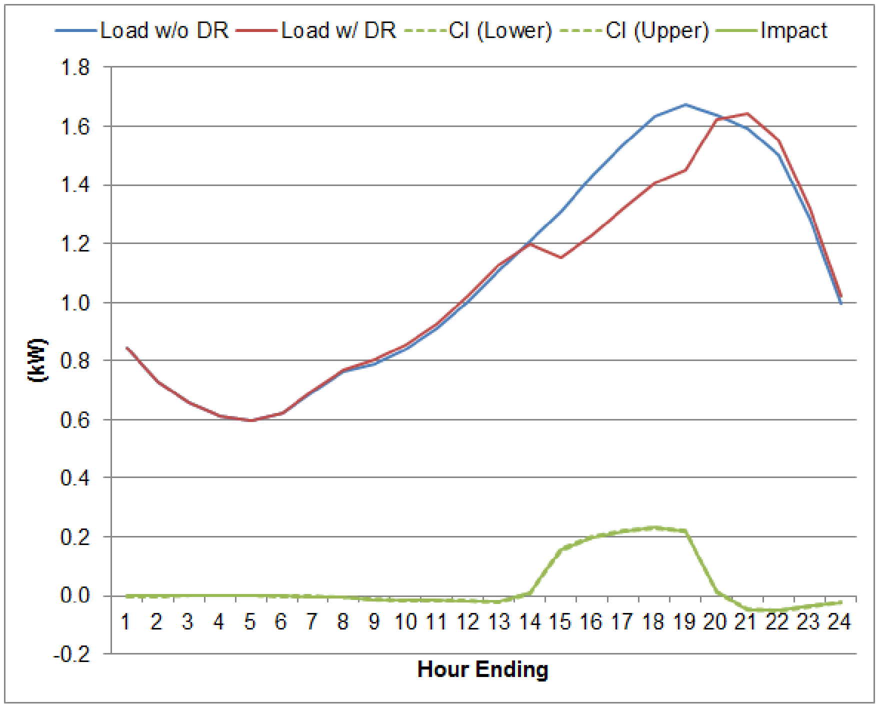
**TABLE 1: Menu options**

| | |
|---|---|
| Customer Segment | All |
| Date | Average Event Day |
| Result Type | Average Customer |
| Group | SmartRate Only |
| Enrolled Customers | 89,061 |

**TABLE 2: Event Day Information**

| | |
|---|---|
| Event Start | 2 PM |
| Event End | 7 PM |
| Average Temp. for Event Window | 87 |
| Mean17 | 75 |
| Load Reduction for Event Window | 0.21 |
| % Load Reduction for Event Window | 14% |

| Hour Ending | Load w/o DR (kW) | Load w/ DR (kW) | Impact (kW) | Impact (%) | Avg. Temp (°F) | Uncertainty Adjusted Impact – Percentiles 10th | 30th | 50th | 70th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.84 | 0.85 | 0.00 | 0% | 69 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 0.73 | 0.73 | 0.00 | 0% | 68 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | 0.66 | 0.66 | 0.00 | 0% | 67 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 4 | 0.61 | 0.61 | 0.00 | 0% | 66 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 5 | 0.60 | 0.60 | 0.00 | 0% | 65 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 6 | 0.62 | 0.62 | 0.00 | 0% | 64 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 7 | 0.69 | 0.70 | 0.00 | 0% | 64 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 8 | 0.76 | 0.77 | -0.01 | -1% | 67 | 0.00 | 0.00 | -0.01 | -0.01 | -0.01 |
| 9 | 0.79 | 0.80 | -0.01 | -2% | 70 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 |
| 10 | 0.84 | 0.85 | -0.02 | -2% | 74 | -0.01 | -0.01 | -0.02 | -0.02 | -0.02 |
| 11 | 0.91 | 0.93 | -0.02 | -2% | 78 | -0.01 | -0.02 | -0.02 | -0.02 | -0.02 |
| 12 | 1.00 | 1.02 | -0.02 | -2% | 82 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| 13 | 1.11 | 1.13 | -0.02 | -2% | 84 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| 14 | 1.21 | 1.20 | 0.01 | 1% | 86 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| 15 | 1.31 | 1.15 | 0.16 | 12% | 88 | 0.16 | 0.16 | 0.16 | 0.16 | 0.15 |
| 16 | 1.43 | 1.23 | 0.20 | 14% | 88 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |
| 17 | 1.54 | 1.32 | 0.22 | 14% | 88 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 |
| 18 | 1.63 | 1.40 | 0.23 | 14% | 87 | 0.24 | 0.23 | 0.23 | 0.23 | 0.23 |
| 19 | 1.67 | 1.45 | 0.22 | 13% | 85 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 |
| 20 | 1.64 | 1.62 | 0.01 | 1% | 81 | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 |
| 21 | 1.59 | 1.64 | -0.05 | -3% | 77 | -0.04 | -0.05 | -0.05 | -0.05 | -0.05 |
| 22 | 1.50 | 1.55 | -0.05 | -3% | 74 | -0.05 | -0.05 | -0.05 | -0.05 | -0.05 |
| 23 | 1.28 | 1.32 | -0.04 | -3% | 72 | -0.03 | -0.04 | -0.04 | -0.04 | -0.04 |
| 24 | 1.00 | 1.02 | -0.02 | -2% | 71 | -0.02 | -0.02 | -0.02 | -0.02 | -0.03 |
| Avg Hour in Event Window | 1.52 | 1.31 | 0.21 | 14% | 87 | 0.20 | 0.20 | 0.20 | 0.20 | 0.21 |



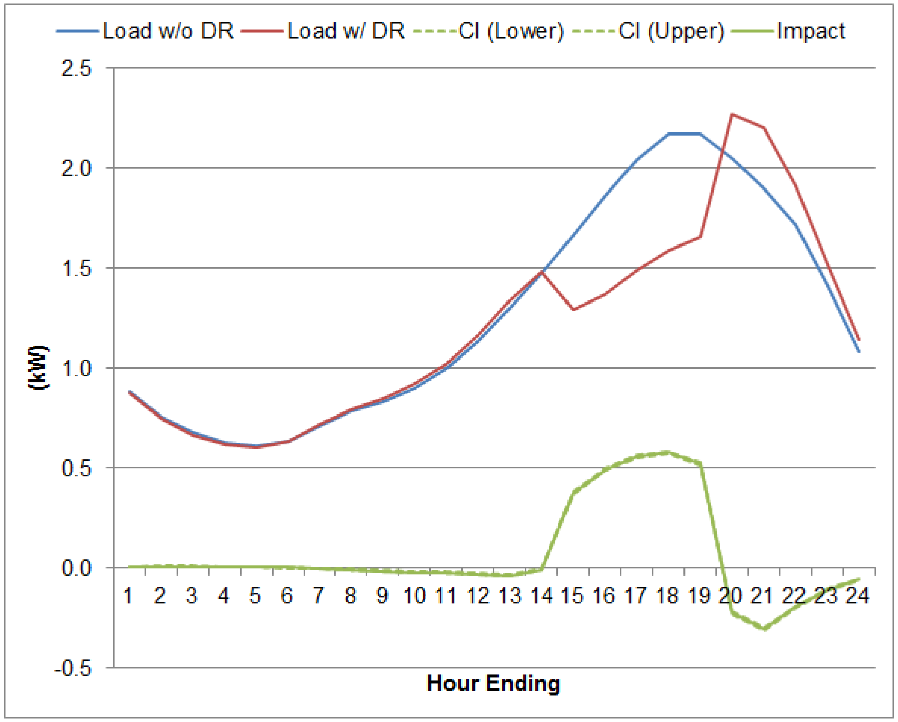
## Figure 4-2: Load Impact per Hour for Average 2014 Event Days (Average Dually Enrolled Participant)

**TABLE 1: Menu options**

| | |
|---|---|
| Customer Segment | All |
| Date | Average Event Day |
| Result Type | Average Customer |
| Group | Dually Enrolled |
| Enrolled Customers | 40,279 |

**TABLE 2: Event Day Information**

| | |
|---|---|
| Event Start | 2 PM |
| Event End | 7 PM |
| Average Temp. for Event Window | 93 |
| Mean17 | 78 |
| Load Reduction for Event Window | 0.51 |
| % Load Reduction for Event Window | 25% |

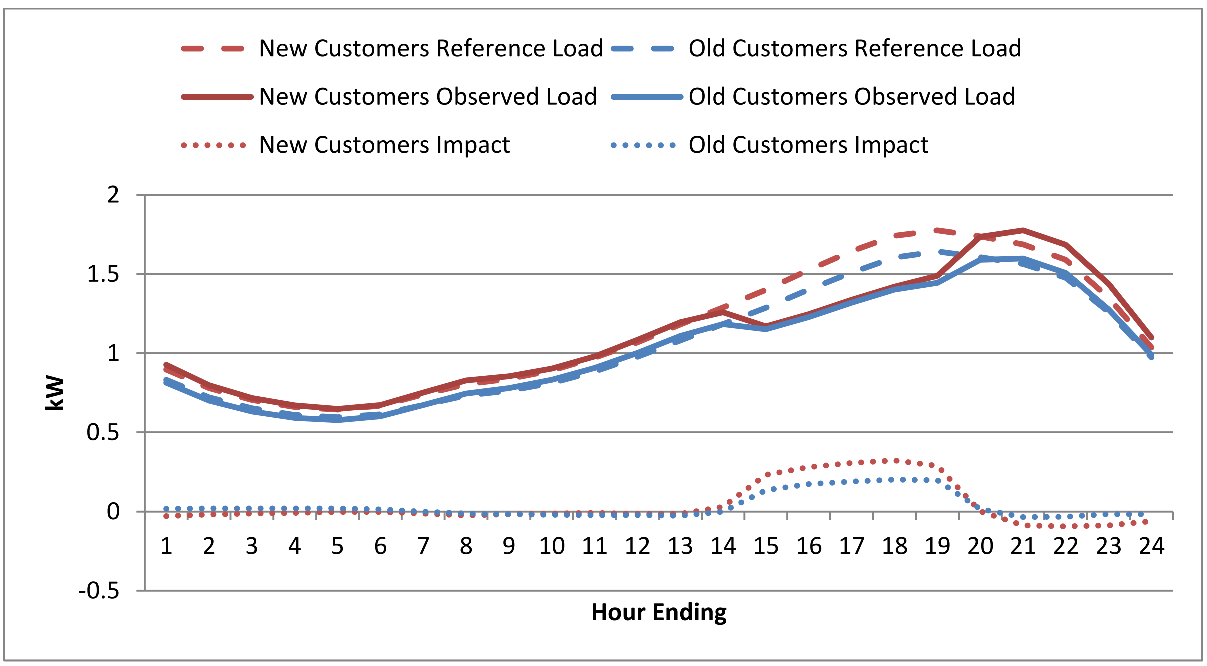



| Hour Ending | Load w/o DR (kW) | Load w/ DR (kW) | Impact (kW) | Impact (%) | Avg. Temp (°F) | Uncertainty Adjusted Impact – Percentiles 10th | 30th | 50th | 70th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.89 | 0.88 | 0.01 | 1% | 73 | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 |
| 2 | 0.76 | 0.75 | 0.01 | 1% | 71 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| 3 | 0.68 | 0.67 | 0.01 | 1% | 70 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| 4 | 0.63 | 0.62 | 0.01 | 1% | 69 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| 5 | 0.61 | 0.61 | 0.01 | 1% | 67 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 |
| 6 | 0.63 | 0.63 | 0.00 | 0% | 67 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 7 | 0.71 | 0.72 | 0.00 | -1% | 66 | 0.00 | 0.00 | 0.00 | 0.00 | -0.01 |
| 8 | 0.79 | 0.80 | -0.01 | -1% | 69 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 |
| 9 | 0.84 | 0.85 | -0.01 | -2% | 73 | -0.01 | -0.01 | -0.01 | -0.02 | -0.02 |
| 10 | 0.90 | 0.92 | -0.02 | -2% | 78 | -0.02 | -0.02 | -0.02 | -0.02 | -0.03 |
| 11 | 1.00 | 1.02 | -0.02 | -2% | 82 | -0.02 | -0.02 | -0.02 | -0.03 | -0.03 |
| 12 | 1.14 | 1.17 | -0.03 | -3% | 86 | -0.03 | -0.03 | -0.03 | -0.03 | -0.04 |
| 13 | 1.30 | 1.34 | -0.04 | -3% | 89 | -0.03 | -0.04 | -0.04 | -0.04 | -0.04 |
| 14 | 1.48 | 1.49 | -0.01 | -1% | 92 | 0.00 | -0.01 | -0.01 | -0.01 | -0.01 |
| 15 | 1.67 | 1.29 | 0.38 | 23% | 93 | 0.38 | 0.38 | 0.38 | 0.38 | 0.37 |
| 16 | 1.87 | 1.37 | 0.49 | 26% | 94 | 0.50 | 0.50 | 0.49 | 0.49 | 0.49 |
| 17 | 2.05 | 1.49 | 0.56 | 27% | 94 | 0.56 | 0.56 | 0.56 | 0.55 | 0.55 |
| 18 | 2.17 | 1.59 | 0.58 | 27% | 93 | 0.59 | 0.58 | 0.58 | 0.58 | 0.57 |
| 19 | 2.18 | 1.66 | 0.52 | 24% | 91 | 0.53 | 0.52 | 0.52 | 0.52 | 0.52 |
| 20 | 2.05 | 2.28 | -0.22 | -11% | 87 | -0.21 | -0.22 | -0.22 | -0.22 | -0.23 |
| 21 | 1.90 | 2.20 | -0.31 | -16% | 83 | -0.30 | -0.30 | -0.31 | -0.31 | -0.31 |
| 22 | 1.72 | 1.92 | -0.20 | -11% | 79 | -0.19 | -0.19 | -0.20 | -0.20 | -0.20 |
| 23 | 1.42 | 1.52 | -0.10 | -7% | 77 | -0.10 | -0.10 | -0.10 | -0.11 | -0.11 |
| 24 | 1.08 | 1.14 | -0.06 | -5% | 75 | -0.05 | -0.06 | -0.06 | -0.06 | -0.06 |
| Avg Hour in Event Window | 1.99 | 1.48 | 0.51 | 25% | 93 | 0.50 | 0.50 | 0.50 | 0.50 | 0.51 |

The average load reductions for both SmartRate only and dually-enrolled customers for the typical event day in 2014 are roughly 20% less than the average reduction in 2013. Average event day temperatures across the two years are quite similar and, thus, do not explain this difference. Although a different model specification was used for the 2014 analysis compared with 2013, a test was done to determine whether this might explain the difference and it does not. The load impacts were nearly identical when the 2013 model was used to estimate load impacts for the 2014 population.

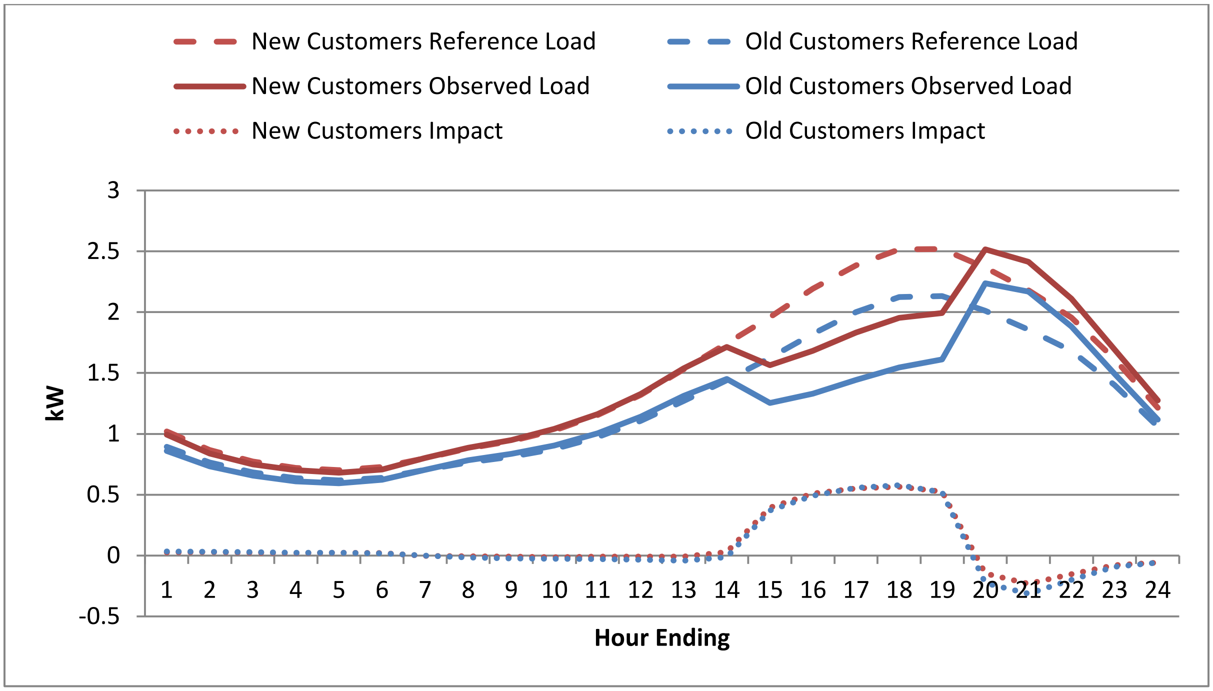
Another possible explanation is customer churn. Although total enrollment grew by only about 10,000 customers from October 2013 to October 2014, there were roughly 27,000 new customers in the program in 2014, with almost two-thirds of new enrollment going to replace customers that left the program due to customer churn or because they dropped off the tariff.[13] If new customers had significantly lower loads and load impacts than customers that had been in the program in 2013, that would at least partially explain the lower average impacts in 2014. Once again, this is not the case. Customers enrolled after October 2013 actually had higher loads and load impacts than customers that were enrolled in 2013. Figures 4-3 and 4-4 show the reference loads and load impacts for customers enrolled prior to (old) and following (new) October 2013. The reference loads are greater for the newer customers than for older participants for both SmartRate Only and dually enrolled customers. As seen in Figure 4-3, both new and old SmartRate only participants reduced their demand to approximately the same level but with the higher reference load for new customers, the estimated impact for new customers is greater. Both groups of dually-enrolled customers provide similar impacts, but the reference load and observed load are higher for the newer population.

**Figure 4-3: 2014 Reference Loads and Observed Loads for New and Old SmartRate Only Customers**




13 Drop outs have been quite low, only a few percent each year, so the vast majority of turnover is due to customer churn.

**Figure 4-4: 2014 Reference Loads and Observed Loads for New and Old Dually-enrolled Customers**




Two other possible explanations for the lower load impacts are that customers who have been in the program for multiple years are responding less to the time-based price signal than in prior years (e.g., lack of persistence) or, quite the opposite, these customers are reducing loads on non-event days in addition to event days (e.g., a spillover effect). If customers reduce loads on most or all days, rather than just on event days, the estimated impact on event days will be lower because it reflects the incremental impact compared with loads on non-event days. To investigate these possibilities, reference loads and load impacts were estimated for both 2013 and 2014 for the subset of SmartRate only and dually-enrolled customers that were enrolled in the program in both years. Figure 4-5 shows the results for SmartRate only customers and Figure 4-6 shows the results for dually-enrolled participants.[14]

As seen in the figures, for both segments, both the reference loads and load impacts were lower in 2014 compared with 2013. For SmartRate only customers, the difference in the load impacts across the two years is 38% while for dually-enrolled customers the difference is about 24%.[15] The difference in reference loads across the two years is about 10% in both cases. Thus, the lower reference loads explain about 25% to 40% of the difference in the estimated load impacts. Given that the temperature differences between the two years were quite small, one possible explanation for these lower reference loads would be the spillover effect described above. If, indeed, this is the cause, the estimated impacts on SmartDays reflect the incremental impact

[14] Figure 4-3 is based on data for approximately 60,000 SmartRate only customers and Figure 4-4 is based on data for approximately 35,000 dually-enrolled participants.

[15] These differences are larger than the roughly 20% difference between the 2013 and 2014 estimates for the entire enrolled population because customers who enrolled after October 31, 2013 had larger loads and load impacts, as previously mentioned.

relative to non-event days and understate the full impact of the program because this lowering of the reference load should be counted as a benefit.  Put another way, the event day impact reflects the total load reduction of the program on SmartDays relative to customers who are not on the program **minus** the reduction in load during peak periods that customers generate through more permanent changes in behavior such as increasing the temperature setting during the peak period on all days.

The remaining difference in load impacts for this subset of the population that was enrolled in both years would appear to be due to a lack of persistence in price response. The fact that the difference is larger for SmartRate only customers than for dually-enrolled customers is also consistent with this hypothesis, since impacts for dually-enrolled customers are due in part by behavior and in part by the operation of load control devices on event days.

**Figure 4-5: 2013 and 2014 Reference Loads and Observed Loads for SmartRate Only Customers Who Participated in the Program in Both Years**

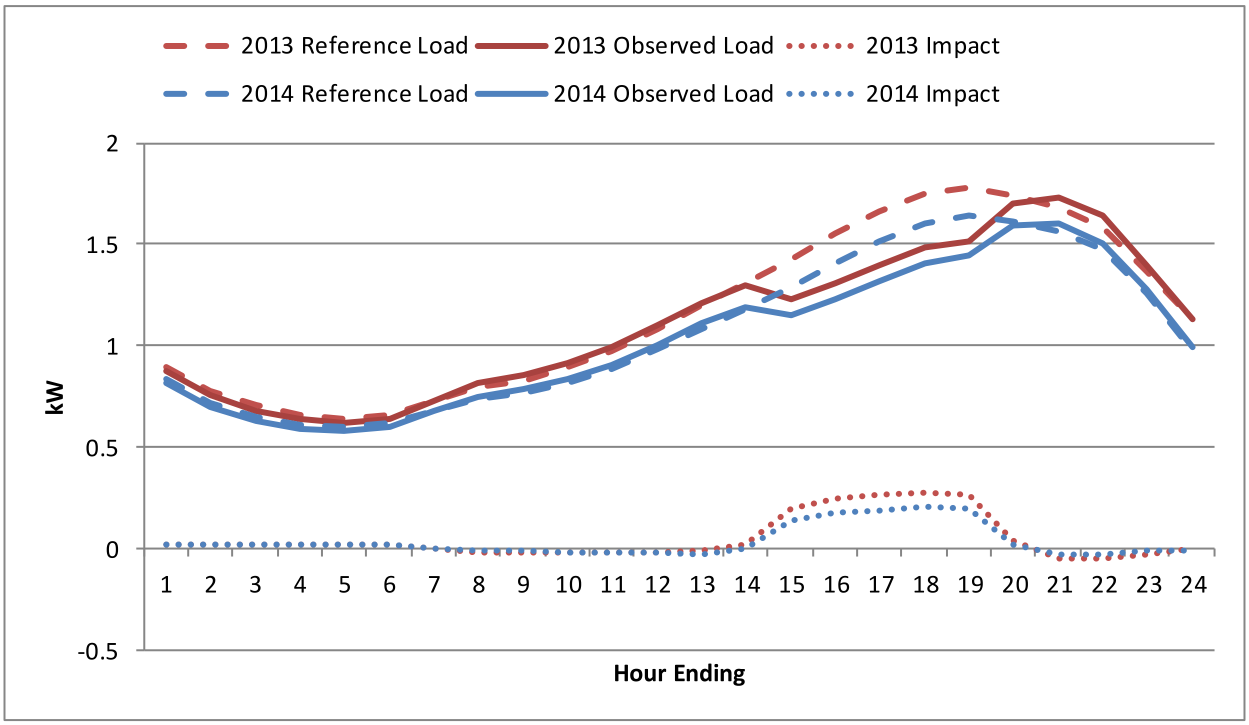


**Figure 4-6: 2013 and 2014 Reference Loads and Observed Loads for Dually-Enrolled Customers Who Participated in the Program in Both Years**

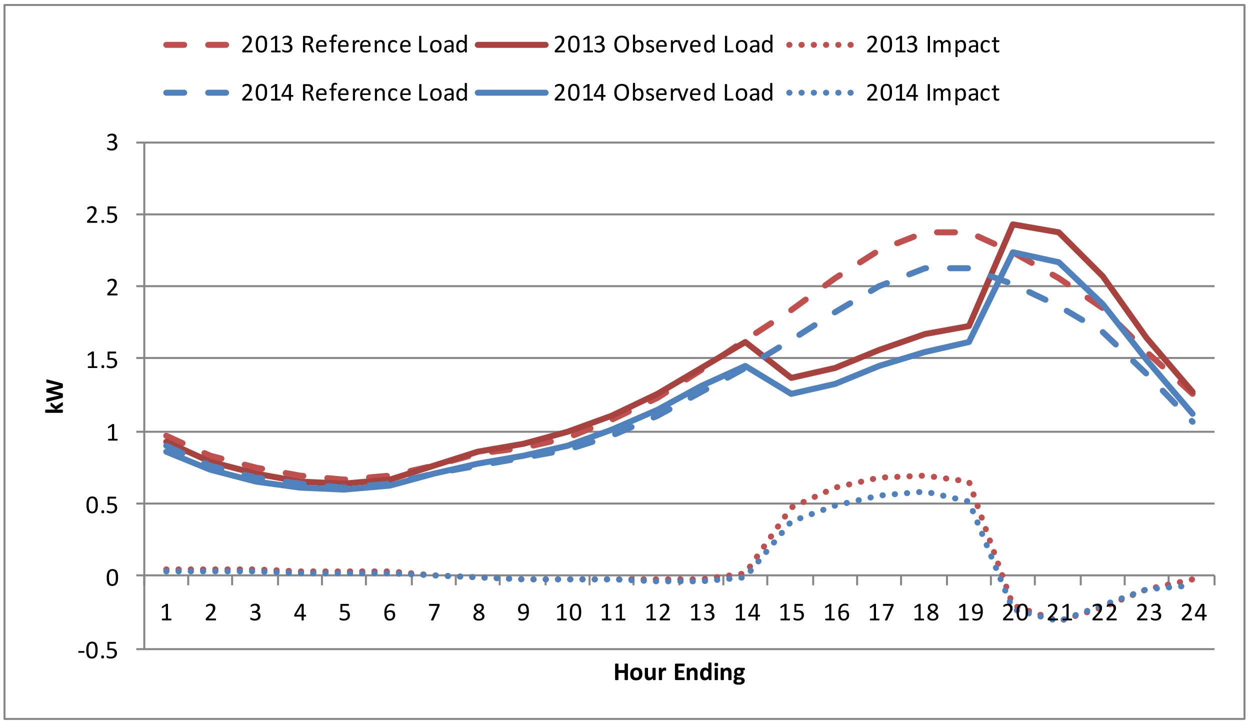



Table 4-1 summarizes the average load reduction across the five-hour event window provided by residential SmartRate-only customers on each event day during the summer of 2014. As shown, the average percent reduction ranged from a low of 12% on September 12 and July 7, to a high of 16% on June 30. An average reduction of 14% was obtained across the 12 event days. The average load reduction per participant ranged from a low of 0.15 kW to a high of 0.27 kW. Aggregate average reductions in demand on Smart Days ranged from 13 MW to more than 24 MW. Aggregate load reductions for the summer averaged 18.3 MW per event.

**Table 4-1: SmartRate-only Ex Post Load Impact Estimates[16]**

| Date | Enrolled Participants | Avg. Reference Load (kW) | Avg. Load Reduction (kW) | Percent Load Reduction (%) | Aggregate Load Reduction (MW) | Daily Maximum Temp (°F) |
|---|---|---|---|---|---|---|
| 14-May-14 | 84,532 | 1.19 | 0.15 | 13% | 13.0 | 93 |
| 9-Jun-14 | 88,694 | 1.77 | 0.27 | 15% | 24.2 | 91 |
| 30-Jun-14 | 89,748 | 1.71 | 0.27 | 16% | 24.3 | 90 |
| 1-Jul-14 | 89,653 | 1.50 | 0.19 | 13% | 17.2 | 83 |
| 7-Jul-14 | 89,487 | 1.33 | 0.16 | 12% | 14.0 | 83 |
| 14-Jul-14 | 89,478 | 1.60 | 0.22 | 14% | 19.8 | 87 |
| 25-Jul-14 | 89,583 | 1.63 | 0.24 | 15% | 21.9 | 94 |
| 28-Jul-14 | 89,552 | 1.47 | 0.19 | 13% | 17.1 | 85 |
| 29-Jul-14 | 89,517 | 1.58 | 0.21 | 13% | 18.8 | 88 |
| 31-Jul-14 | 89,504 | 1.67 | 0.21 | 13% | 19.1 | 88 |
| 11-Sep-14 | 89,488 | 1.35 | 0.17 | 13% | 15.3 | 89 |
| 12-Sep-14 | 89,493 | 1.42 | 0.17 | 12% | 15.2 | 89 |
| **Average Event Day** | **89,061** | **1.52** | **0.21** | **14%** | **18.3** | **88** |

Table 4-2 summarizes the average load reduction across the five-hour event window provided by residential dually-enrolled SmartRate customers on each event day during the summer of 2014. For this group, the average percent reduction ranged from a low of 21% on July 7 to a high of 30% on June 30. An average reduction of 25% was obtained across the 12 event days. The average load reduction per participant varied by more than a factor of two, ranging from a low of 0.33 kW to a high of 0.71 kW. Aggregate average reductions in demand on Smart Days varied from 14 MW to nearly 29 MW. Aggregate load reductions for the summer averaged 20l4 MW per event. The aggregate load reduction for dually enrolled customers is greater than for SmartRate only customers in spite of the fact that SmartRate only customers outnumber dually enrolled customers by roughly 2 to 1.

SmartRate only and dually enrolled customers together delivered 38.7 MW of load reduction on the average event day in 2014. The largest load reduction occurred on June 30, when the two groups reduced load by 53.2 MW. The lowest load reduction occurred on the first event of the season, when the program delivered 26.9 MW of demand response, almost exactly half of the load reduction provided on June 30.

[16] The estimating sample underlying the average and aggregate impact estimates represents customers for which Nexant received interval data. Nexant did not receive interval data for a small group of customers. The group size varied from roughly 5,600 SmartRate only and dually enrolled customers (combined) on the first event date to roughly 1,700 customers on the last event date. The aggregate impact estimates and enrollment values in these and other tables represent the full enrollment in the program, not just customers for whom interval data was provided.

**Table 4-2: Dually-Enrolled Ex Post Load Impact Estimates**

| Date | Enrolled Participants | Avg. Reference Load (kW) | Avg. Load Reduction (kW) | Percent Load Reduction (%) | Aggregate Load Reduction (MW) | Daily Maximum Temp (°F) |
|---|---|---|---|---|---|---|
| 14-May-14 | 37,713 | 1.46 | 0.37 | 25% | 14.0 | 94 |
| 9-Jun-14 | 40,107 | 2.44 | 0.70 | 29% | 28.2 | 99 |
| 30-Jun-14 | 40,536 | 2.35 | 0.71 | 30% | 28.8 | 98 |
| 1-Jul-14 | 40,528 | 1.88 | 0.43 | 23% | 17.6 | 89 |
| 7-Jul-14 | 40,523 | 1.58 | 0.33 | 21% | 13.3 | 89 |
| 14-Jul-14 | 40,541 | 2.17 | 0.58 | 27% | 23.5 | 95 |
| 25-Jul-14 | 40,573 | 2.18 | 0.58 | 27% | 23.5 | 99 |
| 28-Jul-14 | 40,570 | 1.87 | 0.41 | 22% | 16.6 | 91 |
| 29-Jul-14 | 40,572 | 2.09 | 0.51 | 24% | 20.6 | 95 |
| 31-Jul-14 | 40,560 | 2.24 | 0.55 | 25% | 22.4 | 96 |
| 11-Sep-14 | 40,570 | 1.72 | 0.43 | 25% | 17.6 | 95 |
| 12-Sep-14 | 40,551 | 1.85 | 0.46 | 25% | 18.7 | 96 |
| **Average Event Day** | **40,279** | **1.99** | **0.51** | **25%** | **20.4** | **94** |

## 4.2 Load Impacts for Specific Customer Segments

This subsection examines how load impacts vary across a number of customer segments, including:

- Local capacity area;
- CARE status;
- Number of successful notifications; and
- Central AC saturation and temperature.

The subsection also discusses the results of an analysis that identifies and characterizes high responders. The segment-specific results are based on the same treatment-control group methodology that was used to produce the SmartRate only and dually enrolled impacts summarized above. The high responder analysis was based on individual customer regressions, as discussed in Section 3.

### 4.2.1 Load Impacts by Local Capacity Area

PG&E's service territory is climatically diverse and the variation in temperature and AC use is significant, especially on summer days when the coastal fog is thick but the inland valleys are very hot. PG&E is comprised of eight resource planning zones known as local capacity areas (LCAs).[17] These areas are defined by the California Independent System Operator (CAISO)

[17] There are very few SmartRate customers in the Humboldt LCA.

based on transmission lines and the location of generation. LCAs differ significantly in terms of climate and population characteristics. Kern and Fresno are the hottest LCAs which, all other things equal, would produce larger load impacts compared with milder climate regions. However, as was seen in Table 2-2, the percent of enrolled customers on the CARE tariff is much greater in some of these hotter LCAs than in the cooler Bay Area, for example. CARE customers reduce electricity use during events significantly less than customers who are not enrolled in the CARE program. As such, the average load reduction across LCAs is influenced by at least two countervailing factors.

Tables 4-3 and 4-4 show the average hourly load reduction for the eight LCAs in PG&E's service territory for SmartRate-only and dually enrolled customers, respectively. These estimates are based on the same methodology involving statistically matched control groups as was used to develop the program level load impacts. Sierra and Greater Fresno provide the highest average load impacts for SmartRate only customers while Kern and Sierra have the highest average impacts for dually-enrolled customers. Because of the high enrollment in the Bay Area, the greatest aggregate impacts are produced by Bay Area customers for both groups.

**Table 4-3: SmartRate Only Average Hourly Load Reduction for Event Period (2 to 7 PM) by Local Capacity Area**

| Local Capacity Area | # of SmartRate Customers | Avg. Reference Load (kW) | Avg. Load Reduction (kW) | % Load Reduction | Aggregate Load Reduction (MW) | Average Temp. During Event (°F) |
|---|---|---|---|---|---|---|
| Greater Bay Area | 43,357 | 1.01 | 0.14 | 14% | 6.1 | 81 |
| Greater Fresno Area | 6,064 | 2.49 | 0.32 | 13% | 2.0 | 101 |
| Humboldt | 1,191 | 1.42 | 0.16 | 11% | 0.2 | 85 |
| Kern | 6,783 | 2.59 | 0.27 | 10% | 1.8 | 101 |
| North Coast and North Bay | 3,746 | 1.08 | 0.12 | 11% | 0.4 | 86 |
| Other | 16,644 | 1.63 | 0.22 | 14% | 3.7 | 87 |
| Sierra | 5,624 | 2.34 | 0.47 | 20% | 2.6 | 96 |
| Stockton | 5,653 | 2.29 | 0.27 | 12% | 1.5 | 97 |
| **All** | **89,061** | **1.52** | **0.21** | **14%** | **18.3** | **87** |

**Table 4-4: Dually Enrolled Average Hourly Load Reduction for Event Period (2 to 7 PM) by Local Capacity Area**

| Local Capacity Area | # of SmartRate Customers | Avg. Reference Load (kW) | Avg. Load Reduction (kW) | % Load Reduction | Aggregate Load Reduction (MW) | Average Temp. During Event (°F) |
|---|---|---|---|---|---|---|
| Greater Bay Area | 15,010 | 1.55 | 0.40 | 26% | 5.9 | 87 |
| Greater Fresno Area | 4,020 | 2.56 | 0.61 | 24% | 2.5 | 101 |
| Humboldt | 214 | 2.22 | 0.49 | 22% | 0.1 | 97 |
| Kern | 2,030 | 2.85 | 0.70 | 24% | 1.4 | 101 |
| North Coast and North Bay | 2,201 | 1.27 | 0.28 | 22% | 0.6 | 87 |
| Other | 7,878 | 2.11 | 0.53 | 25% | 4.2 | 97 |
| Sierra | 4,778 | 2.39 | 0.70 | 29% | 3.4 | 96 |
| Stockton | 4,149 | 2.26 | 0.55 | 24% | 2.3 | 97 |
| **All** | **40,279** | **1.99** | **0.51** | **25%** | **20.4** | **93** |

### 4.2.2 Load Impacts for Low Income Tariff Customers (CARE)

Low income consumers in California are eligible for lower rates through the California Alternate Rates for Energy program, known as CARE. Qualification for CARE is based on self-reported, household income and varies with the number of persons per household. About 22% of SmartRate customers are CARE customers, while CARE customers constitute about 35% of PG&E's customer population.

***Load reductions from SmartRate only CARE customers are significantly less than for SmartRate only non-CARE customers. However, reductions from dually enrolled CARE customers are comparable to those of non-CARE customers.***

Table 4-5 shows the average load reduction and percent load reduction for CARE and non-CARE SmartRate customers. The average load reduction for SmartRate-only CARE customers is roughly 58% less than the reduction for non-CARE customers. This is particularly interesting because non-CARE customers tend to be located in cooler areas than CARE customers. Across the 12 event days in 2014, SmartRate-only CARE customers reduced their peak period load on average by 0.10 kW, or 6%. Non-CARE customers, on the other hand, reduced load on average by 0.24 kW, or 17%.

**Table 4-5: Load Reductions for CARE and Non-CARE Participants**

| CARE Status | | # of Accounts | Average Reference Load (kW) | Average Estimated Load with DR (kW) | Average Load Reduction (kW) | % Load Reduction | Average Maximum Event Temperature (°F) |
|---|---|---|---|---|---|---|---|
| SMR-Only | Non-CARE | 68,491 | 1.43 | 1.19 | 0.24 | 17% | 86 |
| | CARE | 20,570 | 1.81 | 1.71 | 0.10 | 6% | 94 |
| Dually enrolled | Non-CARE | 32,115 | 1.91 | 1.39 | 0.52 | 27% | 94 |
| | CARE | 8,164 | 2.30 | 1.83 | 0.47 | 20% | 97 |

Table 4-5 also shows the average load reduction and percent load reduction for CARE and non-CARE dually enrolled customers. For this group, the average load reduction for CARE customers is still less than the reduction for non-CARE customers, but the difference is only about 10%, not 60%. Across the 12 event days in 2014, dually enrolled CARE customers reduced their peak period load on average by 0.47 kW, or 20%. Non-CARE customers, on the other hand, reduced load on average by 0.52 kW, or 27%. The incremental impact of load control is much greater for CARE customers than for non-CARE customers. This is consistent with a hypothesis that it is more difficult to notify CARE customers about event days due to more limited channels of communication (e.g., less access to the internet, fewer phone options, etc.). If effective notification is less for CARE customers compared with non-CARE customers, load control, which eliminates the need for notification to reduce air conditioning load, will be more impactful for CARE customers than for non-CARE customers.

### 4.2.3 Load Impacts and Event Notification

At the time they sign up for SmartRate, customers are asked to indicate whether or not they want to be notified about events and, if so, to provide up to four different notification options (e.g., one or more email addresses, one or more telephone numbers). Table 4-6 shows the percent of SmartRate-only customers who were successfully notified through one or more options for each event. The column labeled "none" in the table includes both customers who did not provide notification information as well as those who provided information that subsequently became invalid. As Table 4-6 shows, for the average event, 7% of customers were not successfully notified. 34% percent of customers were successfully notified once per event, 36% were notified twice per event and 23% were notified either three or four times for the average event.

***Successful event notification is essential to producing load reductions with event based programs like SmartRate. The magnitude of load reductions is highly correlated with the number of notification options provided by and used to reach a customer.***

**Table 4-6: Percent of SmartRate-only Customers Notified for Each Event**

| Date | Number of successful notifications | | | | |
|---|---|---|---|---|---|
| | None | 1 | 2 | 3 | 4 |
| 14-May-14 | 7% | 33% | 37% | 16% | 7% |
| 9-Jun-14 | 6% | 33% | 37% | 16% | 8% |
| 30-Jun-14 | 7% | 34% | 36% | 16% | 7% |
| 1-Jul-14 | 9% | 33% | 36% | 15% | 7% |
| 7-Jul-14 | 7% | 34% | 36% | 16% | 7% |
| 14-Jul-14 | 7% | 34% | 36% | 16% | 7% |
| 25-Jul-14 | 7% | 34% | 37% | 16% | 7% |
| 28-Jul-14 | 9% | 33% | 35% | 15% | 7% |
| 29-Jul-14 | 7% | 34% | 36% | 16% | 7% |
| 31-Jul-14 | 7% | 34% | 36% | 15% | 7% |
| 11-Sep-14 | 6% | 34% | 36% | 16% | 7% |
| 12-Sep-14 | 7% | 35% | 36% | 15% | 7% |
| **Average** | **7%** | **34%** | **36%** | **16%** | **7%** |

Table 4-7 shows the percentage of dually-enrolled customers who were successfully notified through one or more options for each event. For this group, for the average event, 6% of customers were not successfully notified. 35% percent of customers were successfully notified once per event, 39% were notified twice per event and 21% were notified either three or four times for the average event.

**Table 4-7: Percent of Dually Enrolled Customers Notified for Each Event**

| Date | Number of Successful Notifications | | | | |
|---|---|---|---|---|---|
| | None | 1 | 2 | 3 | 4 |
| 14-May-14 | 5% | 34% | 40% | 15% | 6% |
| 9-Jun-14 | 5% | 33% | 40% | 16% | 6% |
| 30-Jun-14 | 6% | 35% | 39% | 15% | 6% |
| 1-Jul-14 | 9% | 33% | 36% | 15% | 7% |
| 7-Jul-14 | 5% | 35% | 39% | 15% | 6% |
| 14-Jul-14 | 6% | 35% | 39% | 15% | 6% |
| 25-Jul-14 | 6% | 35% | 39% | 15% | 6% |
| 28-Jul-14 | 8% | 35% | 38% | 14% | 5% |
| 29-Jul-14 | 6% | 35% | 39% | 15% | 5% |
| 31-Jul-14 | 6% | 35% | 38% | 15% | 5% |
| 11-Sep-14 | 5% | 35% | 39% | 15% | 5% |
| 12-Sep-14 | 6% | 35% | 39% | 15% | 5% |
| **Average** | **6%** | **35%** | **39%** | **15%** | **6%** |

Table 4-8 shows the load impacts for successfully notified customers and compares them with the average load impacts for customers that never received a successful notification for any event (presumably because they never provided notification contact information or the information they did provide was inaccurate). One would expect load impacts for this group to be 0. These load impacts were calculated using matched control groups. As shown in the table, for SmartRate only customers, as expected, those who did not sign up for notification show no statistically significant demand reduction for the average event. Dually enrolled customers who did not sign up for notification actually produce quite large load reductions, but their average reduction is roughly a third less than the average for those who are notified. This, too, is expected, since dually enrolled customers who don't sign up for notification have their air conditioners cycled on event days but do not make other changes in their usage on event days because they are unaware of when events occur. While it is tempting to conclude that the difference in impacts for dually enrolled customers who are and are not notified represents the incremental impact of changes in behavior unrelated to air conditioning use, there may be selection effects at work that make this conclusion invalid. That is, those who choose not to be notified may have different usage patterns than those who do and those differences could explain some or all of the observed difference in impacts.

**Table 4-8: Comparison of Load Impacts Between Customers Who Do and Don't Receive Notifications**

| Customer Segment | Notification Status | # of Customers | Average Impact (kW) |
|---|---|---|---|
| SmartRate Only | Notified | 86,424 | 0.20 |
| | Never Notified | 2,416 | 0.01[18] |
| Dually Enrolled | Notified | 40,959 | 0.33 |
| | Never Notified | 771 | 0.51 |

Table 4-9 shows the average impact and percent load reduction by number of successful notifications averaged over all events. It is important to note that the numbers contained in the "Count" column represent the number of customers that received the number of notifications in each row on any given event day. For example, the row labeled "zero" does not represent the number of customers that were never notified on any day, it represents the number that had at least one day in which they were not successfully notified. Similarly, the row labeled "one" represents the number of customers that received only a single successful notification on at least one even day. With this in mind, one can see that successful notification is important for generating load impacts and load impacts increase significantly as the number of notifications increase, even for customers who are successfully notified more than once. Both the average and percentage load reduction nearly triple between SmartRate-only customers who are successfully notified through one option and those that receive four successful notifications. The percent and average load reduction for SmartRate-only customers who receive only a single notification, respectively, are 7% and 0.12 kW. The same values for customers who receive four successful notifications are 22% and 0.35 kW.

[18] Not statistically significant.

**Table 4-9: Average SmartRate Load Impacts and Percent Load Reductions by Number of Successful Notifications per Event**

| # of Successful Contacts | | Count | Average Load Impact (kW) | % Impact |
|---|---|---|---|---|
| SmartRate-only | Zero | 22,521 | 0.12 | 7% |
| | One | 60,651 | 0.19 | 12% |
| | Two | 61,396 | 0.23 | 15% |
| | Three | 32,565 | 0.29 | 18% |
| | Four | 14,822 | 0.35 | 22% |
| Dually enrolled | Zero | 10,447 | 0.38 | 19% |
| | One | 30,487 | 0.48 | 24% |
| | Two | 30,729 | 0.54 | 27% |
| | Three | 15,405 | 0.60 | 29% |
| | Four | 6,304 | 0.64 | 31% |

Dually enrolled customers who receive no notification still provide quite large load impacts due to the automatic control of their AC. However, they also provide increasing impacts as the number of notifications increase, which indicates that dually enrolled customers probably take significant steps to save energy aside from the AC load control. The percent and average reduction for dually enrolled customers receiving one notification equals 24% and 0.48 kW, and dually enrolled customers successfully notified four times reduced load on average by 31% and 0.64 kW.

It is difficult to determine from the existing data whether the significant increase in load reduction with the number of successful notifications is due to self-selection, greater event awareness or both. While it seems reasonable to assume that customers who are notified through multiple channels are more likely to be made aware of an upcoming event than are customers who are only notified through a single channel, it may also be true that those who provide multiple notification options are more interested in avoiding the high-priced periods on Smart Days.

### 4.2.4 Load Impacts and Central AC Ownership

***The likelihood of owning central air conditioning is positively correlated with load impacts for non-Care, SmartRate only customers. Dually enrolled customers, all of whom have central air conditioning, provide the largest average reduction among the SmartRate participant population.***

Load impact estimates for SmartRate participants are highly positively correlated with central AC ownership and temperature. PG&E does not have direct knowledge of AC ownership among the SmartRate population except for customers that are also enrolled in PG&E's SmartAC program. However, it has estimates of the likelihood of AC ownership for nearly every residential customer in its territory. In 2010, FSC (now Nexant) used the 2009 Residential Appliance Saturation Survey (RASS),[19] which includes information on air conditioning ownership, to develop econometric models of the likelihood of AC ownership that could be applied to PG&E's 4.5 million residential customers. This model was an update of a model developed in the 2009 evaluation of PG&E's SmartRate, TOU and SmartAC programs.[20] The model estimated AC ownership as a function of monthly usage data, weather sensitivity, location and enrollment on the low income CARE tariff and various other factors.[21]

Table 4-10 summarizes the AC saturation and percent of customers dually enrolled on SmartAC (meaning they definitely have CAC) for each LCA and CARE status. As expected, the saturation of AC ownership among SmartRate participants is lower in the more temperate zones such as the Bay Area and higher in hotter, inland zones such as Greater Fresno and Kern County. The estimated saturation of AC ownership among CARE customers (76%) is higher than among non-CARE customers (65%) due to their geographic location. Most CARE customers are located in the hottest areas—Kern and Fresno—and, as a result, are likely to own central AC units. Except for the Humboldt and Other LCAs, within each LCA, low income CARE customers have lower AC saturation levels than non-CARE customers, although AC ownership is generally comparable.

[19] See "2009 California Residential Appliance Saturation Survey," prepared for the California Energy Commission by KEMA, Inc.

[20] For model documentation see "2009 Load Impact Evaluation for Pacific Gas and Electric Company's Residential SmartRate™—Peak Day Pricing and TOU Tariffs and SmartAC Program, Volume 2: Ex Ante Load Impacts," prepared for PG&E by FSC.

[21] In a recent test of the model based on newly available survey data, the model's results were found to be highly accurate, even in distinguishing the likelihood of AC ownership among a group of customers who all had high likelihoods.

**Table 4-10: Central Air Conditioning Saturation for SmartRate Customers by Geographic Area and Low Income Tariff Enrollment**

| CARE Status | Local Capacity Area | Estimated Central AC Saturation | % Dually Enrolled on SmartAC |
|---|---|---|---|
| Non-CARE | Greater Bay Area | 51% | 27% |
| | Greater Fresno Area | 94% | 45% |
| | Humboldt | 51% | 18% |
| | Kern | 93% | 27% |
| | North Coast and North Bay | 63% | 40% |
| | Other | 67% | 34% |
| | Sierra | 93% | 50% |
| | Stockton | 92% | 49% |
| | **Total** | **65%** | **33%** |
| CARE | Greater Bay Area | 48% | 22% |
| | Greater Fresno Area | 91% | 38% |
| | Humboldt | 54% | 12% |
| | Kern | 90% | 23% |
| | North Coast and North Bay | 52% | 27% |
| | Other | 80% | 33% |
| | Sierra | 88% | 39% |
| | Stockton | 86% | 36% |
| | **Total** | **76%** | **30%** |

Table 4-11 shows the relationship between the likelihood of air conditioning ownership, CARE status, dual-enrollment and demand response. Several trends are noteworthy. First, for non-CARE customers, the absolute load reductions increase substantially with the likelihood of owning central AC although the percent reductions are relatively constant. Absolute impacts are three times higher for high likelihood households than for low likelihood households and impacts for dually-enrolled customers are about one third larger than for households with a 75% or higher likelihood of owning a central air conditioner. For CARE customers, there is a very modest increase in average load impact across the categories of AC likelihood, and percent reductions actually decrease significantly as the likelihood of air conditioning ownership increases. However, there is a very significant increase in average load reductions, to 0.48 kW, among dually enrolled customers. This highlights, once again, the value of load control to enable demand response for CARE customers.

**Table 4-11: SmartRate Load Impacts by Central Air Conditioning Ownership Likelihood and CARE Status**

| CARE Status | CAC Likelihood Bin | Impact (kW) | % Impact |
|---|---|---|---|
| Non-CARE | 0-25% | 0.13 | 17% |
| | 25-50% | 0.15 | 15% |
| | 50-75% | 0.24 | 16% |
| | 75-100% | 0.39 | 17% |
| | Dually Enrolled | 0.52 | 27% |
| CARE | 0-25% | 0.09 | 11% |
| | 25-50% | 0.08 | 8% |
| | 50-75% | 0.09 | 5% |
| | 75-100% | 0.13 | 5% |
| | Dually Enrolled | 0.48 | 21% |
| All | 0-25% | 0.13 | 17% |
| | 25-50% | 0.14 | 14% |
| | 50-75% | 0.19 | 13% |
| | 75-100% | 0.31 | 13% |
| | Dually Enrolled | 0.51 | 26% |

### 4.2.5 Characteristics of High Responders

Determining the characteristics of customers that provide above average load reductions is important for improving the cost effectiveness of demand response programs through better targeting. This subsection identifies SmartRate customers who appear to be high responders (i.e., customers who provide large impacts) and examines their characteristics.

*High responders are more likely to:*

- ***Be dually enrolled on SmartRate and SmartAC***
- ***Be from hot climate regions***
- ***Have high average electricity use***
- ***Be non-CARE customers***
- ***Have central air conditioning***
- ***Have recently enrolled in the program***

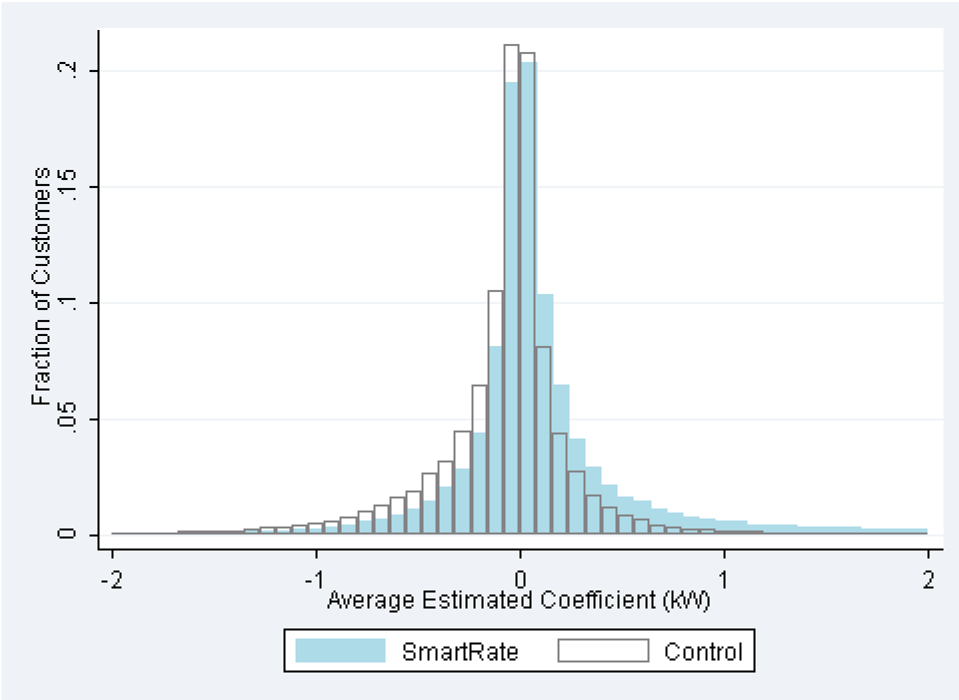
This analysis necessarily involves using impact estimates based on individual customer regressions. However, when examined at the individual customer level, these impact estimates include error or noise. This is an unavoidable aspect of regression methodology. If this was not the case, then it would not be necessary to use such large sets of customers for analysis. The fundamental assumption underlying all the analyses in this report is that these errors tend to cancel each other out when averaged over thousands of customers. There is a substantial body of evidence built up in both the program evaluation and statistics literatures over many years that this assumption holds up well. If this were not true, estimated program results would deviate unpredictably from year-to-year and there would be no value to these evaluations. Instead, results tend to vary mildly and usually due to identifiable causes. However, this is true on an aggregate basis. Without further investigation, it is not clear how large the errors are on an individual customer basis.

In order to assess how much noise there is around estimated customer-level impacts from individual customer regressions, these regressions were also run on the matched control group. These customers have very similar usage profiles to the SmartRate customer population but did not experience any events so their estimated impacts should be 0. Regression results for this group are a measure of the noise in the individual customer regression process for the SmartRate group.

Figure 4-7 shows two histograms. For the SmartRate-only group, it shows the distribution of average event impact estimates across customers. For the matched control group, it shows the distribution of average estimated coefficients for indicator variables that only equal one on SmartDays and over the SmartRate event hours. These are the same variables used to estimate the coefficients that yield estimated event impacts for SmartRate customers. However, for the matched control group, nothing happened at these times, which means that for every customer, the true effect is zero. Therefore, whenever the individual customer regression model produces a non-zero estimate for the matched control group, it is actually just a measure of the noise in the process. The histogram for the matched control group is a histogram of the noise in regression estimates for this group. Since customers in this group are similar to SmartRate customers across all observable characteristics, it is assumed that the level of noise in this group is similar to the level of noise in the SmartRate group.

The blue columns in Figure 4-7 show the distribution of estimated impacts for the SmartRate population. The median impact estimate for SmartRate customers is about 0.03 kW and the mean (or average) impact for SmartRate customers is 0.13 kW. The transparent columns outlined in black show the distribution of impacts for control customers. The mean impact estimates for these customers is -0.08. As discussed in Appendix A, the mean of these impacts is less important than their distribution and relationship.

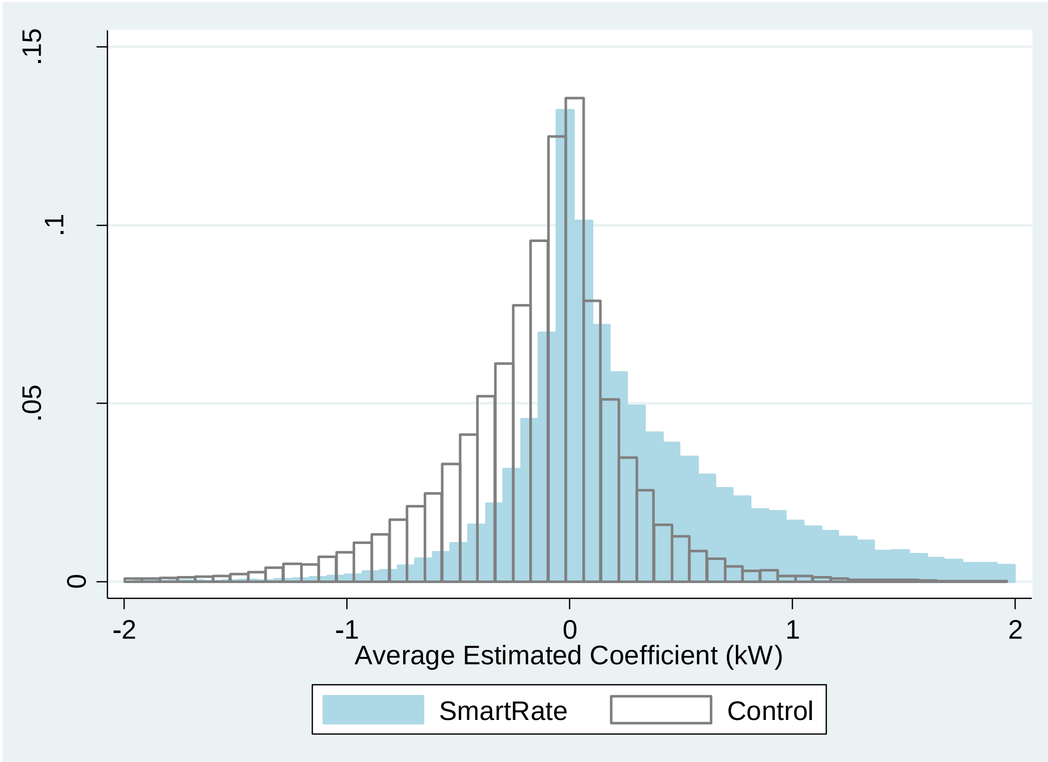
**Figure 4-7: Distribution of Average Event Impacts for SmartRate-only Customers**




Even though control customers have not reacted to events, a substantial fraction of them have estimated impacts that are far from zero. This noise arises because customer usage does not follow a precise function of temperature. Customers have daily routines that vary for many reasons other than temperature. The regression coefficient estimate of the SmartRate impact is an average of the usage observed on SmartDays subtracted from an average of the usage observed on non-event days with similar conditions. The regression specification determines the exact form that each average takes, but it remains a weighted average of these sets of data. If a customer happens to have low use on hot, non-event days, perhaps because he or she was on vacation for several of them, then the regression will produce a small, or even negative, estimated effect of SmartRate for that customer, even if the customer responded to the event. Conversely, if the customer had high usage on hot, non-event days, but was on vacation for several SmartDays, then the regression will produce a large estimated effect, even though the customer may have done nothing to respond to SmartRate. Without an unfeasibly detailed knowledge of customer behavior, this situation is unavoidable.

Figure 4-8 shows the same two histograms for dually enrolled customers, and the same basic points apply. In this case, the distribution of estimates for dually enrolled customers is more different from the distribution for matched control customers than in the SmartRate-only case, and the difference suggests stronger event response among dually enrolled customers. This makes sense given that we have already established that dually enrolled customers provide much larger average impacts. There is still a large amount of noise in the estimates, however, and the point that we cannot take individual estimates at face value remains true.

**Figure 4-8: Distribution of Average Event Impacts for Dually Enrolled Customers**




Within each figure, comparing the two distributions to one another provides insight into which SmartRate customers' impact estimates appear to provide strong evidence of response to SmartDays and which ones are more likely to be dominated by noise. The distribution of control group impact estimates serves as an estimate of the distribution of noise in the SmartRate group estimates. Assuming that the distribution of true impacts and the distribution of noise are independent (which is a strong assumption, but necessary to make useful inferences about high responders), probability assessments can be made about the true impact for SmartRate customers, given their estimated impact. For example, among SmartRate-only customers with estimated impact values above 0.50 kW, there is a 95% chance or greater that each customer's true impact is larger than 0.13 kW, which is the overall mean. That is, customers with impact estimates greater than or equal to 0.50 kW have at least a 95% probability of having impacts greater than the control group mean. Using the same logic, for dually enrolled SmartRate customers with estimated impact values above 0.78 kW, there is a 95% chance or greater that each customer's true impact is larger than 0.35 kW, which is the overall mean.

There are about 9,640 SmartRate only and 7,010 dually enrolled customers for which this is true.[22] This group is labeled high responders. Combined, high responders account for roughly 14% of the SmartRate population. They account for roughly 10% of the SmartRate-only population and 19.5% of the dually enrolled population. In order to understand some of the drivers of load impacts, the rest of this section will explore the demographics of this group of high responders. Tables 4-12 through 4-22 show the distribution of high responding customers

22 For details of this calculation see Appendix C.

across a variety of categories compared to the whole SmartRate population. The final column of each table shows the percentage point difference between high responders and the full SmartRate population for that category. Tables 4-12 and 4-13 show the distribution of high responders for SmartRate-only and dually enrolled customers across PG&E's territory compared to the SmartRate population. High responders in both groups are more likely to be located in hotter LCAs such as Fresno, Kern, Other and Sierra. Although almost half of SmartRate-only customers live in the Greater Bay Area, only 22% of SmartRate-only high responders are located in that LCA. For dually-enrolled customers, 35% are in the Bay Area but only 15% of high responders are in the Bay Area.

**Table 4-12: Distribution of SmartRate-only High Responders by LCA**

| LCA | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| Greater Bay Area | 21.8% | 48.7% | -26.9 |
| Greater Fresno Area | 16.9% | 6.9% | 10.0 |
| Humboldt | 1.3% | 1.3% | 0.0 |
| Kern | 12.9% | 7.6% | 5.3 |
| North Coast and North Bay | 2.1% | 4.3% | -2.2 |
| Other | 21.5% | 18.7% | 2.8 |
| Sierra | 14.5% | 6.3% | 8.1 |
| Stockton | 9.1% | 6.3% | 2.8 |
| Total | 100.0% | 100.0% | - |

**Table 4-13: Distribution of Dually Enrolled High Responders by LCA**

| LCA | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| Greater Bay Area | 14.6% | 35.3% | -20.7 |
| Greater Fresno Area | 20.1% | 10.6% | 9.5 |
| Humboldt | 0.5% | 0.5% | 0.0 |
| Kern | 11.1% | 5.5% | 5.7 |
| North Coast and North Bay | 1.2% | 4.5% | -3.3 |
| Other | 21.4% | 20.1% | 1.3 |
| Sierra | 19.1% | 12.6% | 6.4 |
| Stockton | 11.9% | 10.8% | 1.1 |
| Total | 100.0% | 100.0% | - |

Additionally, high responders are more likely to be non-CARE customers, as shown in Tables 4-14 and 4-15. 76% of SmartRate-only customers are not on the CARE rate but 82% of high responders are non-CARE customers. For dually-enrolled customers, 79% are non-CARE but only 74% of high responders are non-CARE. The difference is very similar.

**Table 4-14: Distribution of SmartRate-only High Responders by CARE Status**

| CARE Status | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| Non-CARE | 82.1% | 76.8% | 5.3 |
| CARE | 17.9% | 23.2% | -5.3 |
| Total | 100.0% | 100.0% | - |

**Table 4-15: Distribution of Dually Enrolled High Responders by CARE Status**

| CARE Status | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| Non-CARE | 74.4% | 78.9% | -4.5 |
| CARE | 25.6% | 21.1% | 4.5 |
| Total | 100.0% | 100.0% | - |

Bill protection does not appear to play a role in the size of impacts, as shown in Table 4-16 and 4-17. This is especially true for SmartRate only customers. Indeed, there is a higher percent of bill protected customers in the high responder group than in the general SmartRate population. It should be noted, however, that this finding may be the result of the recent targeting of high use, high responder customers rather than anything to do with bill protection itself.

**Table 4-16: Distribution of SmartRate-only High Responders by Bill Protection Status**

| Bill Protected | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| No | 67.8% | 77.5% | -9.7 |
| Yes | 32.2% | 22.5% | 9.7 |
| Total | 100.0% | 100.0% | - |

**Table 4-17: Distribution of Dually Enrolled High Responders by Bill Protection Status**

| Bill Protected | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| No | 87.1% | 88.1% | -1.0 |
| Yes | 12.9% | 11.9% | 1.0 |
| Total | 100.0% | 100.0% | - |

Monthly usage, however, is highly correlated with higher-than-average impacts, as shown in Tables 4-18 and 4-19. The higher the decile of average monthly usage a customer is in, the more likely he or she is to be a high responder, for both SmartRate-only and dually enrolled customers. This is not a surprising result. Only 13% of SmartRate-only high responders are found in the bottom five deciles of usage. On the other hand, roughly 28% of SmartRate-only high responders come from the 10$^{th}$ decile alone. The situation is similar for dually enrolled customers. Only 10% of dually enrolled high responders fall into the bottom five deciles of usage, while 28% of this group is in the 10$^{th}$ decile.

**Table 4-18: Distribution of SmartRate-only High Responders by Monthly Usage Decile**

| Monthly Usage Decile | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| 1 | 0.6% | 10.0% | -9.5 |
| 2 | 1.1% | 10.0% | -8.9 |
| 3 | 2.3% | 10.0% | -7.7 |
| 4 | 3.5% | 10.0% | -6.5 |
| 5 | 5.8% | 10.0% | -4.2 |
| 6 | 8.8% | 10.0% | -1.2 |
| 7 | 11.3% | 10.0% | 1.3 |
| 8 | 17.8% | 10.0% | 7.8 |
| 9 | 21.2% | 10.0% | 11.2 |
| 10 | 27.7% | 10.0% | 17.7 |
| Total | 100.0% | 100.0% | – |

**Table 4-19: Distribution of Dually Enrolled High Responders by Monthly Usage Decile**

| Monthly Usage Decile | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| 1 | 0.2% | 10.0% | -9.8 |
| 2 | 0.5% | 10.0% | -9.5 |
| 3 | 1.4% | 10.0% | -8.6 |
| 4 | 2.6% | 10.0% | -7.4 |
| 5 | 5.2% | 10.0% | -4.8 |
| 6 | 8.8% | 10.0% | -1.2 |
| 7 | 12.5% | 10.0% | 2.5 |
| 8 | 17.3% | 10.0% | 7.3 |
| 9 | 23.2% | 10.0% | 13.2 |
| 10 | 28.1% | 10.0% | 18.1 |
| Total | 100.0% | 100.0% | – |

Finally, Table 4-20 shows high responders by their likelihood of having central AC. There are very few high responders with CAC likelihood under 75%. In contrast, 25% of the general SmartRate population falls into those categories. This finding suggests that PG&E should continue to target SmartRate marketing to customers with high central AC likelihood and, particularly, customers on SmartAC.

**Table 4-20: Distribution of High Responders by CAC Likelihood[23]**

| CAC Likelihood | High Responders | SmartRate Population | Percentage Point Difference |
|---|---|---|---|
| 0%-25% | 4.06% | 24.76% | -20.7 |
| 25%-50% | 2.96% | 8.70% | -5.7 |
| 50%-75% | 4.87% | 6.77% | -1.9 |
| 75%-100% | 45.30% | 28.31% | 17.0 |
| Dually enrolled | 42.82% | 31.46% | 11.4 |
| Total | 100.00% | 100.00% | - |

[23] The percentage of dually enrolled customers is for customers who experienced all of the 2012 events and does not match the fraction in the descriptive population tables for the beginning of summer.

In exploring the characteristics of high responding customers, there are a few important takeaways. Customers with the following attributes are much more likely to be high responders:

- Non-CARE customers;
- Customers in hotter LCAs, such as Kern and Sierra;
- Customers with higher-than-average usage;
- Be dually enrolled in SmartRate and SmartAC; and
- Customers with central AC likelihoods of 75% or more.

It should be noted, of course, that most of these variables are correlated. For example, higher usage is correlated with high air conditioning likelihood which is correlated with LCA.

## 4.3 SmartRate Bill Impacts

Individual customer bills were estimated for SmartRate customers under SmartRate and the otherwise applicable tariff (OAT) using monthly usage data in order to quantify how much each customer saves or loses by being on SmartRate. For approximately 96% of SmartRate customers, the OAT is E-1.[24] Roughly 5,000 SmartRate customers are on either E-6 or E-7. Because SmartRate is an overlay onto each customer's already existing rate, savings and losses were estimated using Smart Meter data to calculate SmartRate credits and losses for each month and over the whole summer.

Table 4-21 shows the distribution of customer savings on SmartRate compared to what they would have spent on the OAT.[25] Four points are noteworthy:

- Between May and September, SmartRate customers saved an average of $9 (6%) compared to bills under the OAT;
- Savings were highest in August because customers experienced no events;
- Average monthly savings are lower than in 2013 ($9 compared to $15 in 2013), which is at least partially due to there being 12 events in 2014 as opposed to 8 in 2013; and
- Savings are negative in May because the SmartRate credits are not available in May, but events are still called. Savings were also negative in July because half of all events for the summer (6) were called in July.

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24 A very small number of SmartRate customers (25) are on TOU rates. An additional 300 customers are on E-8. These customers are excluded from the billing analysis because monthly usage data cannot be used to estimate their OAT bills.

25 The bill analysis results reported here are based on analysis of interval data for customers who were enrolled for the entire 2014 summer and were on E-1 and SmartRate. The impacts were estimated by calculating the bills under the same, post treatment usage profile for the 2014 summer period using the SmartRate tariff layered over E-1 and the E-1 tariff without the SmartRate overlay. These estimates for the average customer differ somewhat from the estimates of the number of customers receiving bill protection rebates because the bill protection rebates were calculated by PG&E and, in some cases, reflect usage spanning more than just the 2014 summer because a customer who enrolled in, say, July 2013 would have bill protection until the end of summer 2014.

**Table 4-21: SmartRate Customer Savings by Month**

| Month | Average SMR Bill | Savings | % Savings | % Winners |
|---|---|---|---|---|
| May–October | $660 | $42 | 6% | 94% |
| May | $114 | ($3) | -3% | 0% |
| June | $124 | $12 | 9% | 95% |
| July | $176 | ($4) | -2% | 45% |
| August | $129 | $24 | 16% | 100% |
| September | $117 | $13 | 10% | 98% |
| October | $106 | $0 | 0% | 0% |

Table 4-22 shows bill savings estimates by local capacity area (LCA). Average savings are highest for customers in the Kern LCA. They saved an average of $66 from May through October 2014.

**Table 4-22: SmartRate Customer Percent Winners and Savings by LCA**

| LCA | # of Customers | Total Summer SMR Bill | Savings | % Savings | % Winners |
|---|---|---|---|---|---|
| Greater Bay Area | 47,340 | $502 | $36 | 7% | 96% |
| Greater Fresno Area | 8,265 | $986 | $65 | 6% | 96% |
| Humboldt | 1,023 | $682 | $45 | 6% | 93% |
| Kern | 7,697 | $1,042 | $66 | 6% | 97% |
| Northern Coast | 4,731 | $518 | $37 | 7% | 96% |
| Other | 19,604 | $684 | $43 | 6% | 91% |
| Sierra | 8,168 | $794 | $49 | 6% | 91% |
| Stockton | 8,372 | $755 | $37 | 5% | 84% |

Table 4-23 shows average customer savings by CARE status. The size of the bill impacts for CARE and non-CARE customers is similar in absolute terms. CARE customers save about $40 while non-CARE customers save about $44. On a percentage basis, this comes out to 6% bill savings for non-CARE customers and a 5% savings for CARE customers.

**Table 4-23: SmartRate Customer Percent Winners and Savings by CARE Status**

| CARE Status | # of Customers | Total Summer SMR Bill | Savings | % Savings | % Winners |
|---|---|---|---|---|---|
| Non-CARE | 80,299 | $636 | $44 | 6% | 95% |
| CARE | 24,901 | $733 | $40 | 5% | 92% |

## 4.4 2014 Bill Protection and Reimbursements

In order to encourage enrollment, prospective SmartRate participants are offered bill protection to try the new rate with no risk. Bill protection is offered from the time a customer enrolls on SmartRate through the end of the first full summer they are on the rate (May 1 through October 31). With bill protection, customers will not pay more under SmartRate than they would have paid on the OAT for the first full summer and any partial summer that preceded it. If a bill protection eligible customer experiences higher bills under SmartRate than under the OAT, PG&E will pay the difference after the end of the event season. Customers still experience and must pay their monthly bills from May to October under the SmartRate tariff. During the summer of 2014, 41% of SmartRate customers were covered under bill protection. This is less than in 2013 when 61% of customers had bill protection.[26]

**Table 4-24: SmartRate Customers with Bill Protection**

| Bill Protected | # of customers | % of customers |
|---|---|---|
| No | 81,466 | 59% |
| Yes | 57,408 | 41% |
| Total | 138,874[27] | 100% |

Of the approximately 57,000 customers covered under bill protection in 2014, only 3,044 (5%) received refunds after the summer of 2014.

**Table 4-25: SmartRate Customers with Refunds (Bill Protected Customers Only)**

| Refund | # of Customers | % of Customers |
|---|---|---|
| No refund | 54,364 | 95% |
| Refund | 3,044 | 5% |
| Total | 57,408 | 100% |

[26] All of the data in this section come directly from a file provided by PG&E of bill credits paid to customers who joined recently.

[27] This number reflects the number of customers on SmartRate at any time over the entire summer.

## 4.5 SmartRate Retention Patterns

Retention rates are important components of program performance. They affect the overall load reduction level, costs and the cost-effectiveness of DR programs. There are two main types of attrition. The first is normal turnover due to accounts opening and closing as customers relocate. This is mainly a function of customer characteristics and is only incidentally related to participation in SmartRate. For example, a program with a high share of renters typically has higher participant turnover simply because renters relocate more frequently than homeowners.

***Very few SmartRate customers drop out of the program. Only about 1.5% of enrolled customers left the program between late 2012 and October 2013.***

The second type of attrition is active customer de-enrollment. These are instances when a participant actively requests to leave the program. There are several important questions associated with customer attrition, including:

- Do customers de-enroll at higher rates when SmartRate events are concentrated in particular months?
- Do CARE customers de-enroll at higher or lower rates?
- Do actual bill increases and decreases relative to the OAT have any relationship to attrition rates?
- Do attrition rates vary across geographic regions?

The majority of customers who leave SmartRate do so because their service accounts close. The main reason for this is that the customer changes addresses. These customers were not necessarily unhappy with the program, so this type of attrition should generally not be counted against the program. We have excluded this type of attrition from the analysis. We have also excluded customers who were de-enrolled from the program because they are customers of Marin Clean Energy, the Community Choice Aggregator in Marin County.

### 4.5.1 SmartRate Attrition Due to De-enrollment

Customers who actively de-enroll from the program may do so because of dissatisfaction with the program. Over the period from November 2013 to September 2014, 3,648 customers de-enrolled from SmartRate. Table 4-26 shows the number of customers who de-enrolled during each month. The majority of dropouts occurred in the spring when the program administrators notified participants that the program would be starting up again soon.

**Table 4-26: Customer De-enrollments by Month**

| Month | # of Drop Outs | % of Customers that Dropped Out |
|---|---|---|
| Nov. 2013 | 45 | 0.04% |
| Dec. 2013 | 89 | 0.08% |
| Jan. 2014 | 98 | 0.08% |
| Feb. 2014 | 96 | 0.08% |
| Mar. 2014 | 794 | 0.67% |
| Apr. 2014 | 293 | 0.25% |
| May. 2014 | 696 | 0.55% |
| Jun. 2014 | 408 | 0.31% |
| Jul. 2014 | 632 | 0.49% |
| Aug. 2014 | 325 | 0.25% |
| Sep. 2014 | 172 | 0.13% |
| Total | 3,648 | 2.54% |

Dropouts can also be analyzed by looking at customer demographics. Table 4-27 shows the number and percentage of customers who dropped out from November 2013 through September 2014 by LCA. The lowest dropout rate was in Kern county and the highest was in the Northern Coast LCA. The Sierra LCA also has an above average dropout rate. It should be noted, however, that the sample size underlying this analysis—3,646 de-enrolled customers—is small enough that no strong conclusions should be drawn from small differences in dropout rates across LCAs.

**Table 4-27: Customer De-enrollments by LCA**

| LCA | # of De-enrolled Customers | % of Customers De-enrolled |
|---|---|---|
| Greater Bay Area | 1,596 | 2.4% |
| Greater Fresno | 270 | 2.3% |
| Humboldt | 40 | 2.5% |
| Kern | 176 | 1.7% |
| Northern Coast | 233 | 5.3% |
| Other | 712 | 2.6% |
| Sierra | 392 | 3.3% |
| Stockton | 227 | 2.1% |
| **All** | **3,646** | **2.5%** |

Customer de-enrollments can also be broken down by CARE status. Table 4-28 shows that non-CARE customers de-enroll at a rate almost twice as high as CARE customer. Of course, it should be kept in mind that the dropout rate for both groups is quite low

**Table 4-28: Customer De-enrollments by CARE Status**

| CARE Status | # of De-enrolled Customers | % of Customers De-enrolled |
|---|---|---|
| Non-CARE | 3,195 | 2.8% |
| CARE | 451 | 1.5% |
| All | 3,646 | 2.5% |

There is also the question of how bill impacts affect customer dropout rates. However, in a summer with almost no losers, this effect may be trivial. Table 4-29 shows the average OAT and SmartRate monthly bills for active SmartRate customers and those who de-enrolled in a later month. Both groups generally showed savings over the summer months. Customers who were still active on SmartRate showed slightly higher savings than customers who de-enrolled.

**Table 4-29: Bill Impacts by Customer De-enrollment Status**

| Month | % Savings from OAT (Later De-Enrolled) | % Savings from OAT (Still Enrolled) |
|---|---|---|
| May | -3% | -3% |
| June | 9% | 8% |
| July | -2% | -3% |
| August | 16% | 15% |
| September | 10% | 9% |

# 5 SmartRate Ex Ante Methodology and Results

This section summarizes the modeling approach and results associated with ex ante impact estimation for the SmartRate program. Ex ante impacts are intended to represent what the SmartRate program can deliver under a standardized set of weather and event conditions given changes in enrollment over the forecast horizon. The weather used for ex ante load impact estimation is meant to reflect conditions on high demand days when there is a high likelihood that SmartRate events will be called under normal (1-in-2 years) and extreme (1-in-10 years) weather. The event window used for ex ante estimation is the Resource Adequacy (RA) window from 1 to 6 PM, which is different from the SmartRate event window that runs from 2 to 7 PM.

The methodology used to estimate ex ante impacts is summarized in Section 5.1. Section 5.2 summarizes the ex ante weather conditions that underlie the impact estimates, which are new this year and are estimated under two sets of assumptions, one based on PG&E-specific operating conditions and the other based on CAISO operating conditions. Estimated impacts are presented in Section 5.3 and a comparison of ex post and ex ante estimates is presented in Section 5.4.

## 5.1 Ex Ante Estimation Methodology

At a high level, ex ante impact estimates for SmartRate were developed using the following multi-step process (each step was performed separately for SmartRate-only and dually enrolled customers):

- First, ex post estimates were developed for SmartRate customers for 2013 and 2014 using the matched control group methodology described in Section 3.
- Second, regression models were estimated that relate ex post load impacts in each hour from 2 to 7 PM to average temperatures from midnight to 5 PM (referred to as mean17) on the event day. Separate models were estimated for SmartRate only and dually-enrolled customers. The same model specification was used to estimate reference loads, which are not used to estimate impacts but are needed to meet the requirements of the CPUC Load Impact Protocols and to produce the ex ante load impact tables that are filed electronically with this report.
- Third, ex ante weather conditions were used as input to the regression models to predict impacts for each hour for monthly system peak days from May through October and for the typical event day.
- Finally, ex ante impact estimates were adjusted to apply to the RA window from 1 to 6 PM rather than the current SmartRate event window from 2 to 7 PM. The hour from 1 to 2 PM was assumed to have no impact.

Events from both 2013 and 2014 were used for model estimation because the population has not changed dramatically within the two main customer segments across the two years. Prior to 2013, there was very significant growth and change in the enrolled population so a different approach to modeling was used for the 2012 program year evaluation. Given that there were 20 event days in 2013 and 2014 combined, a more robust model was able to be specified this year. Another difference in this year's approach is that separate models were estimated for each hour. In prior years, a single model was estimated for the average load across the

SmartRate peak period from 2 to 7 PM and then hourly values were estimated using ratios of impacts in each hour relative to the average impact across the event window. The hourly model used this year is simpler and more transparent. A comparison of results using the prior approach and this year's approach showed that impacts were nearly identical.

The final model specification used for both the SmartRate only and dually enrolled populations is shown below. The dependent variable equals the ex post impact for each event hour and the independent variables are the average temperature from midnight to 5 PM on the event day and dummy variables for each LCA (leaving out the Greater Bay Area). These dummy variables were used to account for between-LCA variation in typical event day impacts. This varies from last year's specification only in that it specifies a dummy for each LCA rather than dummies for each of the two LCAs that differed most from the norm. The final specification was:

$$Impact_d = a + b \cdot mean17_d + \sum_{l=Greater\ Fresno\ Area}^{Stockton} c_l \cdot LCA_{d,l} + \varepsilon_d$$

**Table 5-1: Description of SmartRate Ex Ante Load Regression Variables**

| Variable | Description |
|---|---|
| *Impact (kW)* | Per customer ex post load impact for each event day |
| *a* | Estimated constant |
| *b* | Marginal linear relationship between mean17 and per customer ex post load impact |
| *c* | Mean difference in per customer impact from the Greater Bay Area holding mean17 constant |
| *mean17* | Average temperature from midnight to 5 PM |
| *LCA* | Dummy variable for each LCA (Greater Bay Area not included) |
| *ε* | The error term, assumed to be a mean zero and uncorrelated with any of the independent variables |
| *d* | Indexes event days within a given LCA |
| *l* | Indexes LCA |

It is quite likely that event impacts depend on variables other than an average of recent temperatures, but with a limited number of ex post events and with virtually no other time-varying characteristics to use for modeling, it is not possible to identify these effects sufficiently accurately to be incorporated into the model.

Figures 5-1 and 5-2 show the results of the regressions for SmartRate only and dually enrolled customers at hour ending 4 PM for the Greater Bay Area LCA. The red circles show 2014 ex post values for the representative population and the blue circles show the same for 2013. The trend lines show the average impacts that were used as a basis for ex ante forecasts.

**Figure 5-1: Ex Post and Ex Ante Impacts versus *Mean17* for SmartRate Only Customers for the Greater Bay Area LCA**

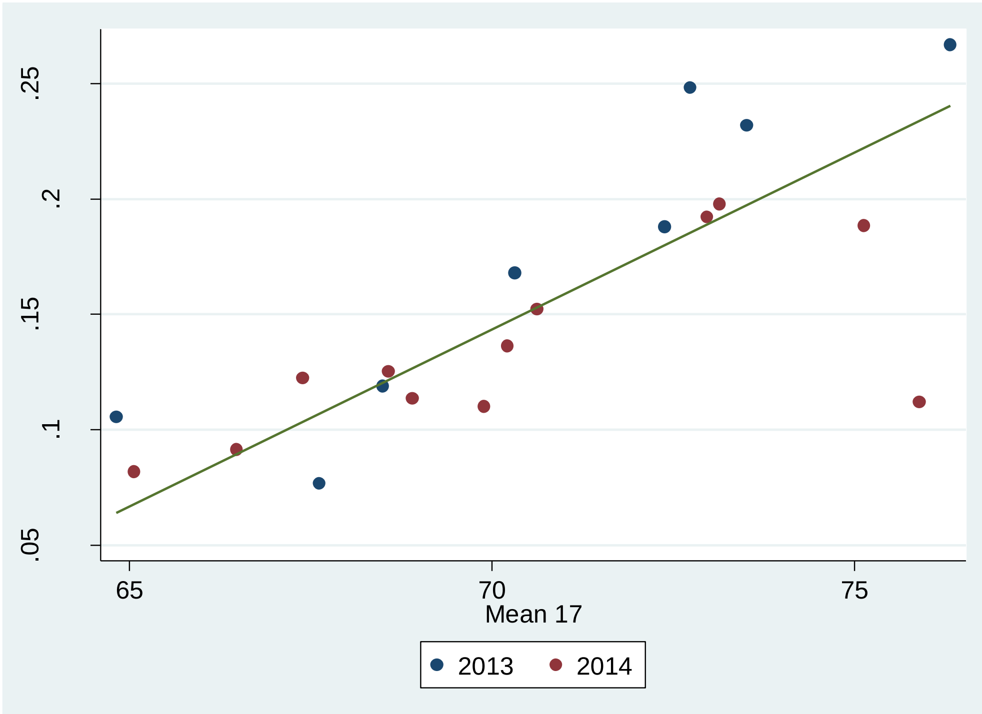
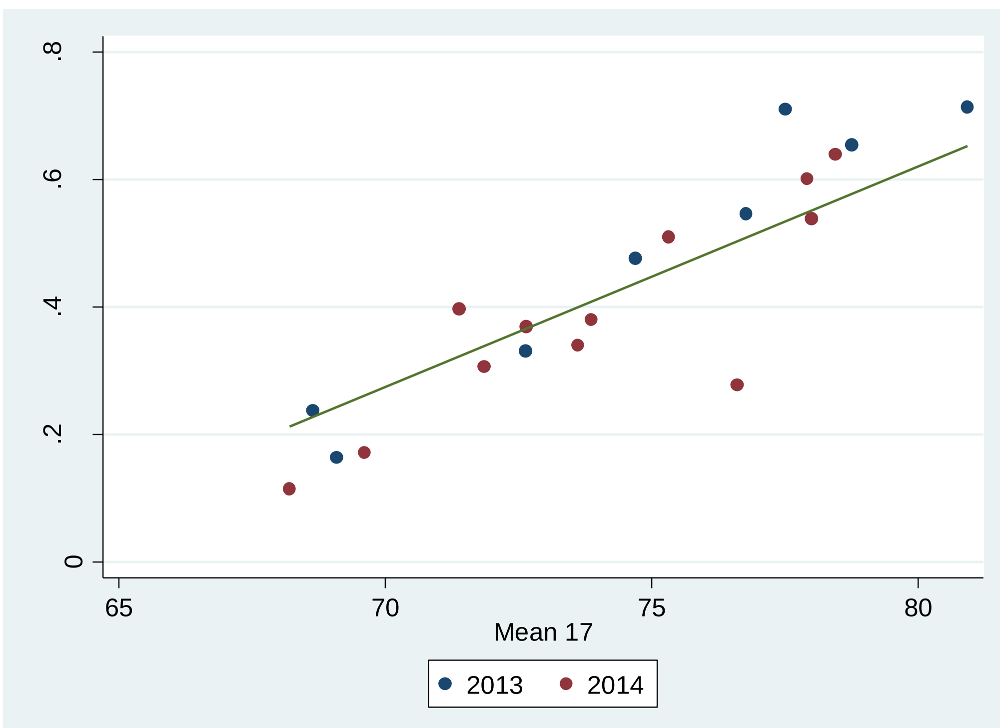



**Figure 5-2: Ex Post and Ex Ante Impacts versus *Mean17* for Dually Enrolled Customers for the Greater Bay Area LCA**



As mentioned above, although impacts were estimated for each event hour from 2 to 7 PM, the RA window is from 1 to 6 PM. In a 2011 RA decision (D.11-06-022), PG&E was ordered to change the SmartRate event hours for its 2012 RDW to match the RA event window. That application was only recently approved by the CPUC. However, in November 2014, PG&E filed its 2015 RDW application and proposed an alternative event window. In order to avoid customer confusion if the new rate window is approved, PG&E requested and received approval to keep the 2 to 7 PM event window for SmartRate until the 2015 RDW decision is issued. Given the uncertainty about future outcomes, PG&E has decided to base the RA window, ex ante forecasts this year on the current SmartRate event window. Since SmartRate cannot be called in the hour from 1 to 2 PM, what this means is that the average impacts across the event window will be significantly lower than in prior years because the impact in the first hour is 0. This change in assumptions reduces the average impact across the five hours from 1 to 6 PM by about 20% compared with ex ante impacts in prior years.

## 5.2 Estimating Ex Ante Weather Conditions

As already mentioned, the CPUC Load Impact Protocols[28] require that ex ante load impacts be estimated assuming weather conditions associated with both normal and extreme utility operating conditions. Normal conditions are defined as those that would be expected to occur once every two years (1-in-2 conditions) and extreme conditions are those that would be expected to occur once every ten years (1-in-10 conditions). Since 2008, the IOUs have based the ex ante weather conditions on system operating conditions specific to each individual utility. However, ex ante weather conditions could alternatively reflect 1-in-2 and 1-in-10 year operating conditions for the California Independent System Operator (CAISO) rather than the operating conditions for each IOU. While the protocols are silent on this issue, a letter from the CPUC Energy Division to the IOUs dated October 21, 2014 directed the utilities to provide impact estimates under two sets of operating conditions starting with the April 1, 2015 filings: one reflecting operating conditions for each IOU and one reflecting operating conditions for the CAISO system.

In order to meet this new requirement, California's IOUs contracted with Nexant to develop ex ante weather conditions based on the peaking conditions for each utility and for the CAISO system. The previous ex ante weather conditions for each utility were developed in 2009 and were updated this year along with the development of the new CAISO based conditions. Both sets of estimates used a common methodology, which is documented in a report delivered to the IOUs.[29]

The extent to which utility-specific ex ante weather conditions differ from CAISO ex ante weather conditions largely depends on the correlation between individual utility and CAISO peak loads. Based on CAISO and PG&E system peak loads for the top 25 CAISO system load days each year from 2006 to 2013, the correlation coefficient for PG&E is 0.68, indicating that there are many days on which the CAISO system loads are high while PG&E loads are more modest. This correlation for PG&E tends to be weakest when CAISO loads have been below 45,000

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28 See CPUC Rulemaking (R.) 07-01-041 Decision (D.) 08-04-050, "Adopting Protocols for Estimating Demand Response Load Impacts" and Attachment A, "Protocols."

29 See *Statewide Demand Response Ex Ante Weather Conditions*. Nexant, Inc. January 30, 2015.

MW. CAISO loads often reach 43,000 MW when Southern California loads are extreme but Northern California loads are moderate (or vice-versa). However, whenever CAISO loads have exceeded 45,000 MW, loads typically have been high across all three IOU's.

Table 5-2 shows the SmartRate, enrollment-weighted value for mean17 for the typical event day and the monthly system peak day under the four sets of weather for which load impacts are estimated. As seen, the differences in weather conditions based on PG&E peak conditions and CAISO peak conditions, and normal and extreme weather, vary significantly. There are also large differences across months. As seen in Section 5.3, even small differences in the value of *mean*17 can have large impacts on aggregate load impacts. For certain months, impacts vary by as much as 30% between PG&E and CAISO weather conditions.

**Table 5-2: SmartRate Enrollment Weighted Ex Ante Weather Values (mean17)**

| Day Type | PG&E Based Weather | | CAISO Based Weather | |
|---|---|---|---|---|
| | 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| Typical Event Day | 78.4 | 81.9 | 75.7 | 79.0 |
| May Peak Day | 71.9 | 80.8 | 70.8 | 75.0 |
| June Peak Day | 78.8 | 82.7 | 78.3 | 78.1[30] |
| July Peak Day | 78.8 | 83.6 | 77.2 | 81.9 |
| August Peak Day | 78.6 | 82.1 | 74.1 | 80.0 |
| September Peak Day | 77.4 | 79.4 | 73.3 | 76.1 |
| October Peak Day | 69.5 | 75.9 | 69.5 | 73.3 |

## 5.3 SmartRate Ex Ante Load Impact Results

Section 5.1 summarized the methodology used to develop ex ante impact estimates for the average customer that reflect ex ante weather conditions and event timing. Aggregate ex ante estimates combine these average estimates with projections of program enrollment provided by PG&E. Enrollment projections by local capacity area as of August of each year from 2015 through 2025 are shown in Table 5-3. The 2015 forecast is about 5% greater than 2014 enrollment and 2016 is about 3% greater than 2015. New enrollment is expected to just offset customer churn and drop outs from 2016 on so program enrollment is forecasted to remain constant over that period.

[30] As discussed above, CAISO demand can be high on days when PG&E's demand is more moderate due to the influence of coastal cooling in the PG&E territory when temperatures in the inland valleys and Southern California can be quite high. This is especially true in June, when San Francisco's "June gloom" can be prevalent on many days. The fact that PG&E's mean17 values under CAISO 1-in-10 year and 1-in-2 year weather conditions are roughly equal in June is a reflection of this type of cross-sectional variation in weather on the June peak days for the two years chosen to represent the normal and extreme weather conditions.

**Table 5-3: Projected Enrollment for August of Each Year (in Thousands)**

| LCA | SmartRate-only | | Dually Enrolled | |
|---|---|---|---|---|
| | 2015 | 2016–2025 | 2015 | 2016–2025 |
| Greater Bay Area | 45.1 | 46.0 | 16.4 | 17.2 |
| Greater Fresno | 6.3 | 6.4 | 4.4 | 4.6 |
| Humboldt | 1.3 | 1.3 | 0.2 | 0.2 |
| Kern | 6.9 | 7.0 | 2.3 | 2.4 |
| Northern Coast | 3.9 | 4.0 | 2.4 | 2.5 |
| Other | 17.1 | 17.5 | 8.6 | 9.0 |
| Sierra | 5.7 | 5.8 | 5.2 | 5.5 |
| Stockton | 5.8 | 5.9 | 4.5 | 4.8 |
| **Total** | **92.1** | **93.8** | **44.0** | **46.2** |

***The SmartRate program is forecasted to provide almost 39 MW of load reduction on a typical event day under normal weather conditions and 47 MW on a typical event day under 1-in-10 year weather conditions. On the July monthly peak day, the demand response potential for the SmartRate program is estimated to equal 40 MW and 51 MW under normal and extreme weather conditions.***

Ex ante load impact estimates for 2015 are shown in Tables 5-4 and 5-5. Table 5-4 shows the estimates for PG&E specific weather scenarios and Table 5-5 shows the estimates for CAISO peak-based weather scenarios. The first and second columns in each table show the average hourly per customer ex ante load impact estimate over the event period from 1 to 6 PM for SmartRate only customers and dually enrolled customers, respectively. The third column shows the aggregate mean hourly impact for the SmartRate only population while the fourth column shows the same measure for dually enrolled customers. The first set of rows corresponds to 1-in-2 year weather conditions while the second set covers 1-in-10 year weather conditions.

Looking at the SmartRate only population, and the PG&E-specific, 1-in-2 year weather, the highest estimated impacts are on the June, July, and August peak days, with aggregate impacts around 18 MW. Impacts in May and October are significantly less (closer to 10 MW). The largest demand reduction, 18.1 MW, is predicted to occur on the August monthly peak day. Under 1-in-10 year weather conditions, the greatest load reduction, 22.8 MW, occurred on both the June and July monthly peak days. Comparing estimates for SmartRate only customers using weather conditions based on the CAISO peak rather than PG&E's peak reduces the estimated impacts for both 1-in-2 and 1-in-10 year weather (see Table 5-5). For CAISO peaking conditions, the 1-in-2 year maximum load reduction is 17.7 MW and occurs in June rather than

August. This is only about 2% lower than the estimate based on PG&E peaking conditions in August. The maximum load reduction based on CAISO 1-in-10 weather, 21.1 MW, is about 7% less than under the PG&E weather conditions.

Although dually-enrolled customers account for less than a third of total SmartRate customers, their aggregate impacts are actually greater than the much larger group of SmartRate only customers. Average impacts for dually-enrolled customers on the typical event day are roughly 2.5 times larger than for SmartRate only customers. Using PG&E-based weather conditions, the 1-in-2 year maximum ex ante impacts for dually-enrolled customers occur on the August peak day and equal 22.0 MW. Under 1-in-10 year conditions, the maximum reduction is predicted to occur on the July peak day and to equal 28.5 MW. As with SmartRate only customers, the difference in impacts on the maximum load reduction days between PG&E and CAISO weather is only about 7%. However, the difference in select months can be much larger. For example, under 1-in-2 year conditions, the CAISO based impact is a third less than the PG&E based estimate in August and September. The May estimate under 1-in-10 year conditions is also roughly a third less for the CAISO based values compared with the PG&E based values.

**Table 5-4: 2015 SmartRate Ex Ante Load Impact Estimates by Weather Year and Day Type (Event Period 1 to 6 PM, PG&E-Specific Peaking Conditions)**

| Weather Year | Day Type | Mean Hourly Per Customer Impact (SmartRate- only) (kW) | Mean Hourly Per Customer Impact (Dually Enrolled) (kW) | Aggregate Mean Hourly Impact (SmartRate- only) (MW) | Aggregate Mean Hourly Impact (Dually Enrolled) (MW) | Aggregate Mean Hourly Impact (Full Program) (MW) |
|---|---|---|---|---|---|---|
| 1-in-2 | Typical Event Day | 0.19 | 0.49 | 17.7 | 21.1 | 38.8 |
| | May Monthly Peak | 0.13 | 0.27 | 11.4 | 11.5 | 22.9 |
| | June Monthly Peak | 0.20 | 0.51 | 17.8 | 21.8 | 39.6 |
| | July Monthly Peak | 0.20 | 0.51 | 17.9 | 22.0 | 39.9 |
| | August Monthly Peak | 0.20 | 0.49 | 18.1 | 21.5 | 39.6 |
| | September Monthly Peak | 0.19 | 0.44 | 17.2 | 19.6 | 36.8 |
| | October Monthly Peak | 0.11 | 0.16 | 10.2 | 7.3 | 17.5 |
| 1-in-10 | Typical Event Day | 0.24 | 0.58 | 21.7 | 25.3 | 46.9 |
| | May Monthly Peak | 0.23 | 0.53 | 20.7 | 22.5 | 43.2 |
| | June Monthly Peak | 0.25 | 0.59 | 22.8 | 25.1 | 47.8 |
| | July Monthly Peak | 0.25 | 0.66 | 22.8 | 28.5 | 51.3 |
| | August Monthly Peak | 0.23 | 0.60 | 21.6 | 26.5 | 48.0 |
| | September Monthly Peak | 0.21 | 0.48 | 19.7 | 21.5 | 41.2 |
| | October Monthly Peak | 0.18 | 0.36 | 16.7 | 16.2 | 32.9 |

**Table 5-5: 2015 SmartRate Ex Ante Load Impact Estimates by Weather Year and Day Type (Event Period 1 to 6 PM, CAISO Peaking Conditions)**

| Weather Year | Day Type | Mean Hourly Per Customer Impact (SmartRate- only) (kW) | Mean Hourly Per Customer Impact (Dually Enrolled) (kW) | Aggregate Mean Hourly Impact (SmartRate- only) (MW) | Aggregate Mean Hourly Impact (Dually Enrolled) (MW) | Aggregate Mean Hourly Impact (Full Program) (MW) |
|---|---|---|---|---|---|---|
| 1-in-2 | Typical Event Day | 0.17 | 0.39 | 15.4 | 16.9 | 32.3 |
| | May Monthly Peak | 0.11 | 0.24 | 10.1 | 10.4 | 20.4 |
| | June Monthly Peak | 0.19 | 0.48 | 17.7 | 20.5 | 38.2 |
| | July Monthly Peak | 0.18 | 0.45 | 16.4 | 19.7 | 36.1 |
| | August Monthly Peak | 0.15 | 0.33 | 14.0 | 14.4 | 28.5 |
| | September Monthly Peak | 0.15 | 0.30 | 13.5 | 13.1 | 26.6 |
| | October Monthly Peak | 0.11 | 0.16 | 10.1 | 7.2 | 17.3 |
| 1-in-10 | Typical Event Day | 0.20 | 0.50 | 18.5 | 21.7 | 40.2 |
| | May Monthly Peak | 0.16 | 0.36 | 14.5 | 15.4 | 29.9 |
| | June Monthly Peak | 0.19 | 0.46 | 17.7 | 19.7 | 37.4 |
| | July Monthly Peak | 0.23 | 0.60 | 21.1 | 26.0 | 47.2 |
| | August Monthly Peak | 0.21 | 0.54 | 19.3 | 23.8 | 43.2 |
| | September Monthly Peak | 0.17 | 0.40 | 16.0 | 17.6 | 33.6 |
| | October Monthly Peak | 0.15 | 0.30 | 13.6 | 13.5 | 27.1 |

Combining the SmartRate only and dually-enrolled customers produces maximum load reductions of 39.9 MW on the July peak day under PG&E 1-in-2 year weather conditions and 51.3 MW on the July peak day under 1-in-10 year weather conditions. The maximum load reduction estimates based on CAISO weather conditions are 38.2 MW (which occurs in June) and 47.2 MW (which occurs in July), respectively. These differences highlight the significant variation in load impacts with variation in weather for these highly weather sensitive programs such as SmartRate and SmartAC.

The values in Tables 5-4 and 5-5 are program specific. They are a forecast of what would happen if SmartRate was called but SmartAC was not. If a SmartAC event happens concurrently with a SmartRate event, the SmartRate program is allocated only the demand reductions that are over and above what is produced by the load control device for dually-enrolled customers. For the typical event day, roughly 70% of the program specific load reduction for dually-enrolled customers is estimated to come from the load control device and about 30% from behavioral changes by dually-enrolled households.

Even though enrollment increased by roughly 14% between 2013 and 2014, aggregate ex ante load impact estimates changed by only about 3%, from 37.6 MW to 38.8 MW based on PG&E 1-in-2 year weather conditions. For 1-in-10 year weather conditions, aggregate load impacts did not change. The primary reason why impacts changed very little in spite of enrollment growth is due to the change in assumptions about how the hour from 1 to 2 PM is treated over the forecast horizon. As discussed in Section 5.1, last year's estimates assumed that PG&E would change the SmartRate window from the current 2 to 7 PM period to the RA window from 1 to 6 PM. In this year's forecast, it is assumed that the current window is retained, which means that the hour from 1 to 2 PM shows no reduction at all because SmartRate can't be called during that hour. This change in assumptions reduces the average load impact across the RA window by about 20%. This change accounts for nearly all of the difference in the average and aggregate impact estimates between last year and this year.

## 5.4 Relationship Between Ex Post and Ex Ante Estimates

The ex post estimates presented in Section 4 and the ex ante estimates presented above differ for a number of reasons, including differences in weather, the event window, enrollment and estimation methodology. This section discusses the impact of each of these factors on the difference between ex post and ex ante impact estimates.

Table 5-6 summarizes the key factors that might lead to differences between ex post and ex ante estimates for the SmartRate program and the expected influence that these factors might have on the relationship between ex post and ex ante impacts. Given that the SmartRate load impacts are quite sensitive to variation in weather, even small changes in *mean*17 between ex post actual and ex ante weather conditions can produce relatively large differences in load impacts. For the typical event day, ex ante impacts will be somewhat higher based on PG&E ex ante weather and about the same as ex post values based on CAISO weather conditions. The largest difference in impacts between ex post and ex ante conditions stems from the shift from the SmartRate event window to the RA event window. This change reduces the average impacts by roughly 20%. Changes in enrollment between the values used for ex post estimation and the 2015 enrollment values are expected to increase impact estimates by about

7%. Finally, the fact that the ex ante model is based on ex post impacts from both 2013 and 2014 combined with the drop in average impacts between 2013 and 2014 will result in the ex ante model over predicting impacts based on ex post weather.

**Table 5-6: Summary of Factors Underlying Differences Between Ex Post and Ex Ante Impacts for the SmartRate Program for the Ex Ante Typical Event Day**

| Factor | Ex Post | Ex Ante | Expected Impact |
|---|---|---|---|
| Weather | SmartRate-only customers:<br>71< event day mean17 < 77<br>Average event day mean17 = 75<br><br>Dually enrolled customers:<br>75 <event day mean17 <83<br>Average event day mean17 = 78 | SmartRate only mean17 for 1-in-2 typical event day = 76.6 and 74.3 for PG&E and CAISO weather, respectively<br>Dually enrolled mean17 for 1-in-2 typical event day = 80.6 and 77.5 for PG&E and CAISO weather, respectively | SmartRate only ex ante estimates are highly sensitive to variation in mean17 – impacts will be higher based on PG&E weather and about the same based on CAISO weather |
| | | SmartRate only mean17 for 1-in-10 typical event day = 80.5 and 77.4 for PG&E and CAISO weather, respectively<br>Dually enrolled mean17 for 1-in-10 typical event day = 83.7 and 81.1 for PG&E and CAISO weather, respectively | Same as for SmartRate only |
| Event window | All events called from 2 to 7 PM | Common ex ante event window is 5 hours, from 1 to 6 PM, and 1 to 2 PM impact is assumed to be zero because it is outside the SmartRate window | Average ex ante impacts will be significantly lower (about 20%) |
| Enrollment | Enrollment grew modestly for SmartRate over the 2014 summer and was largely flat for dually enrolled customers | 2015 enrollment is forecast to be about 7% higher for both SmartRate only and dually-enrolled customers | Ex ante estimates will be about 7% higher than ex post |
| Methodology | 2014 impacts based on matched control groups and slight adjustment based on differences in pre-event hours. | Regression of ex post impacts against mean17 for each hour using two years' worth of ex post impacts | Average impacts in 2014 were roughly 20% less than in 2013. Basing the ex ante model on data pooled across the two years will produce higher impact estimates based on ex post weather than actually occurred |

Table 5-7 shows how aggregate load impacts change for the SmartRate only population as a result of differences in the factors underlying ex post and ex ante estimates. The third column reproduces the ex post values from Table 4-1. The next column grosses these estimates up by the difference in ex post and ex ante enrollment in August 2015. This produces only a modest increase in impacts of about 3%. The next column shows what the ex-ante model would produce using the same 2015 August enrollment figures and the ex post weather conditions for each event day. The ex ante model over predicts load reductions on average by about 7% compared with the 2014 ex post impacts. As discussed above, this is the result of estimating the model using both 2013 and 2014 ex post values and the fact that 2014 average impacts are about 20% less than 2013 impacts, for reasons discussed in Section 4.1. The next column shows the impact of the shift in the event window from the ex post period from 2 to 7 PM to the ex ante window from 1 to 6 PM. This produces a decrease in load impacts by 22% because SmartRate can't be called during the first hour of the RA window. The final four columns show how aggregate load reductions vary with the different ex ante weather scenarios. The CAISO 1-in-2 conditions are most similar to the 2014 PG&E ex post weather conditions on average across all event days and all regions, although for any given ex post day, the weather conditions can differ significantly. Using the PG&E 1-in-2 year conditions increases the average impacts by about 12% compared with ex post weather. The 1-in-10 year weather conditions based on both PG&E and CAISO operating conditions increase load reductions substantially compared with the ex post weather conditions for 2014.

Table 5-8 shows the relationship between ex post and ex ante estimates for dually enrolled customers. These differences follow the same pattern as for the SmartRate-only segment, although the over prediction by the model using ex post weather is not as great for dually enrolled customers as for SmartRate only customers. As discussed in Section 4.1, this is because the difference in ex post impacts between 2013 and 2014 is not as large for dually-enrolled customers as it is for SmartRate only customers.

**Table 5-7: Differences in Ex Post and Ex Ante Impacts Due to Key Factors for SmartRate Only Customers**

| Date | Mean17 (°F) | Ex Post Impact (MW) | Ex Post Impact with Ex Ante Enrollment (MW) | Ex Ante Model Ex Post Weather and Event Window (MW) | Ex Ante Model Ex Post Weather RA Event Window (MW) | CAISO 1-in-2 (MW) | PG&E 1-in-2 (MW) | CAISO 1-in-10 (MW) | PG&E 1-in-10 (MW) |
|---|---|---|---|---|---|---|---|---|---|
| 5/14/2014 | 76 | 13.0 | 14.0 | 21.7 | 17.1 | | | | |
| 6/9/2014 | 77 | 24.2 | 25.0 | 23.4 | 18.5 | | | | |
| 6/30/2014 | 77 | 24.3 | 24.8 | 22.7 | 17.9 | | | | |
| 7/1/2014 | 73 | 17.2 | 17.5 | 17.4 | 13.6 | | | | |
| 7/7/2014 | 71 | 14.0 | 14.3 | 15.6 | 12.2 | | | | |
| 7/14/2014 | 76 | 19.8 | 20.3 | 22.1 | 17.4 | | | | |
| 7/25/2014 | 77 | 21.9 | 22.4 | 23.1 | 18.2 | 15.4 | 17.7 | 18.5 | 21.7 |
| 7/28/2014 | 74 | 17.1 | 17.5 | 19.2 | 15.1 | | | | |
| 7/29/2014 | 75 | 18.8 | 19.2 | 20.4 | 16.1 | | | | |
| 7/31/2014 | 74 | 19.1 | 19.6 | 19.4 | 15.2 | | | | |
| 9/11/2014 | 73 | 15.3 | 15.6 | 17.9 | 14.1 | | | | |
| 9/12/2014 | 73 | 15.2 | 15.5 | 18.0 | 14.1 | | | | |
| Average | 75 | 18.3 | 18.8 | 20.1 | 15.8 | | | | |

**Table 5-8: Differences in Ex Post and Ex Ante Impacts Due to Key Factors for Dually Enrolled Customers**

| Date | Mean17 (°F) | Ex Post Impact (MW) | Ex Post Impact with Ex Ante Enrollment (MW) | Ex Ante Model Ex Post Weather and Event Window (MW) | Ex Ante Model Ex Post Weather RA Event Window (MW) | CAISO 1-in-2 (MW) | PG&E 1-in-2 (MW) | CAISO 1-in-10 (MW) | PG&E 1-in-10 (MW) |
|---|---|---|---|---|---|---|---|---|---|
| 5/14/2014 | 77 | 14.0 | 16.1 | 19.8 | 15.6 | 16.9 | 21.1 | 21.7 | 25.3 |
| 6/9/2014 | 83 | 28.2 | 30.5 | 29.8 | 23.7 | | | | |
| 6/30/2014 | 81 | 28.8 | 30.9 | 27.7 | 22.0 | | | | |
| 7/1/2014 | 77 | 17.6 | 18.9 | 19.7 | 15.6 | | | | |
| 7/7/2014 | 75 | 13.3 | 14.2 | 17.2 | 13.6 | | | | |
| 7/14/2014 | 81 | 23.5 | 25.2 | 27.7 | 22.0 | | | | |
| 7/25/2014 | 80 | 23.5 | 25.1 | 25.6 | 20.3 | | | | |
| 7/28/2014 | 77 | 16.6 | 17.7 | 21.3 | 16.8 | | | | |
| 7/29/2014 | 79 | 20.6 | 22.0 | 23.3 | 18.5 | | | | |
| 7/31/2014 | 79 | 22.4 | 23.9 | 23.3 | 18.5 | | | | |
| 9/11/2014 | 76 | 17.6 | 18.8 | 19.6 | 15.5 | | | | |
| 9/12/2014 | 77 | 18.7 | 20.1 | 20.3 | 16.0 | | | | |
| Average | 78 | 20.4 | 22.0 | 22.9 | 18.2 | | | | |

# 6 TOU Ex Post Evaluation Methodology

This section describes the control group selection and analysis methods used to estimate E-6 and E-7 load impacts. As noted earlier, the analysis excludes net-metered customers because they likely have solar panels and are already accounted for in the evaluation of solar programs.

The approach used to estimate impacts for E-6 and E-7 customers is conceptually similar to the approach used for the SmartRate evaluation in that both evaluations rely on statistical matching on observable variables to develop a control group that can be used as the reference load for customers on each rate. However, with SmartRate, matching was done based on loads on hot, non-event days during the summer period since the price impacts are assumed to not be in effect on those non-event days. For TOU rates such as E-6 and E-7, price effects influence usage by rate period on all days so it is not possible to match on hourly usage during the period after when customers enroll on a TOU rate. Ideally, matching would be done using hourly loads prior to customers going on the rate. This approach was used for E-6 customers since this tariff is relatively new and a sufficiently large group of E-6 customers enrolled after their interval meters had been in place for at least a year. Unfortunately, the E-7 tariff has been closed to new enrollment since 2006, when E-6 went into effect, and there is no hourly data available for these customers prior to when they went on the rate. As such, the statistical matching for E-7 customers was based on monthly usage data from the post enrollment period. This is far from ideal and may introduce a significant selection bias as discussed further below.

Selection bias is a concern with evaluation of any voluntary rate program. Customers that use a smaller share of their overall consumption during the peak period compared with the average customer are likely to see their bills go down under any TOU rate that is revenue neutral for the average customer. These structural winners will have load shapes that show lower usage during the peak period compared with the average customer. As long as pretreatment data exists, a suitable control group can be chosen by basing the statistical matching on pretreatment data, which would control for this type of load-shape selection bias. Other types of unobservable selection effects may exist that can only be controlled for using true experimental designs such as randomized controlled trials, but controlling for load shape effects based on observable, pretreatment date significantly reduces bias from this known selection issue. Unfortunately this approach is not possible for the E-7 tariff since pretreatment data does not exist as discussed above. Load impact estimates based on matching using post enrollment, monthly usage data, will be biased upward.

Although it is not possible to test for selection effects for the E-7 population because of the lack of pretreatment data, it is possible to do so for E-6. To test for selection effects for E-6 customers, the impacts were estimated two ways. One way used the preferred approach that selects a control group based on pretreatment, hourly data. This allows for matching on load shape so that control group customers that are structural winners but that did not enroll are matched with the structural winners that did enroll (and, likewise, non-winners are matched with non-winners). This reduces significantly or may completely eliminate any selection bias based on observable data. A second analysis was also done using the only approach available for the E-7 tariff, namely, statistical matching based on monthly usage data, which is inferior to the approach that was used for E-6. This approach masks any underlying load shape differences between customers on the tariff and those in the control group. Put another way, with monthly matching, if a customer enrolled because they already had a preferable load shape and, therefore, would see their bills fall even if they did nothing in response to the rate, but had the same monthly usage as a customer that had much more load during the peak period, that customer would be chosen for inclusion in the control group. The resulting impact estimate, calculated as the difference in peak period usage, would be biased upward. By comparing the impact estimates for E-6 customers using the two different methods, we can observe how much selection bias there is for E-6 customers with the inferior matching methodology.

Table 6-1 shows the ratio of load impacts estimated using the preferred approach based on pre-enrollment, hourly data and the alternative approach using post enrollment, monthly usage data. This is a summary measure of the amount of bias introduced by using the inferior methodology. As seen, the bias ratio varies significantly across months, ranging from 0.33 to 0.67. A ratio of 0.40 means that the peak impact based on statistical matching using pretreatment data is 60% less than the impact estimate based on matching on post enrollment, monthly usage. It means that, for this month, the inferior method leads to an estimate that is 60% too high compared to the preferred method. There is a fair amount of variation in these ratios across months but in both summer and winter, the ratios suggest that the E-7 impacts could be high by 50% on average and by as much as 70% in some months if the selection bias is similar for E-6 and E-7 customers. It is impossible to know if the amount of selection bias is similar across the two rate options. The two rates are structurally different and, as was seen in Section 2.2, E-6 and E-7 customers differ along several dimensions, including annual usage and electric space heat and air conditioning saturation. Nevertheless, TOU rates in general incent similar types of behavior in terms of selection issues and in the absence of a better alternative we believe it is best to assume that the magnitude of selection bias is similar for the two rates in both summer and winter. As such, the initial E-7 impact estimates are adjusted downward by multiplying them by the ratios shown in Table 6-1.

**Table 6-1: Ratio of Load Impact Estimates Using Two Methodologies**

| Month | Average Weekday | Monthly Peak Day |
|---|---|---|
| January | 0.54 | 0.62 |
| February | 0.33 | 0.34 |
| March | 0.35 | 0.30 |
| April | 0.39 | 0.63 |
| May | 0.39 | 0.45 |
| June | 0.41 | 0.46 |
| July | 0.41 | 0.40 |
| August | 0.45 | 0.40 |
| September | 0.48 | 0.51 |
| October | 0.67 | 0.58 |
| November | 0.46 | 0.44 |
| December | 0.55 | 0.56 |

The remainder of this section provides more details about the matching process that was used for the two tariffs and describes the regression models that were used to estimate ex post impacts once the control groups were selected.

## 6.1 Control Group Selection

As described above, control group customers for the E-6 tariff were chosen using pre-enrollment interval data. A sample of approximately 4,500 E-6 customers with one year of pre-enrollment interval data was matched to a group of E-1 customers. The average weekday profile was determined for each E-6 customer for a 12-month pretreatment period and the absolute difference between the E-6 load profiles and those of the control pool was calculated. For each E-6 customer, the E-1 customer with the smallest absolute difference was chosen as a control. This matching process was performed separately for summer and winter so that each E-6 customer could be matched to two different control customers. This is because two customers could have similar load shapes and overall usage in the summer but very different load shapes and usage in the winter if, for example, one had electric space heating and the other did not.

Figure 6-1 presents an average weekday load shape for E-6 and control group customers for July during the pre-enrollment period. This particular graph is for participants in the Greater Bay Area, where more than half of E-6 customers reside. Figure 6-2 shows average loads for the two groups in January during the pre-enrollment period. These graphs show that the matching process does a good job of selecting control group customers that have loads very similar to E-6 customers prior to enrollment.

**Figure 6-1: July Weekday Load Profile for Average E-6 and Control Customers (Greater Bay Area)**

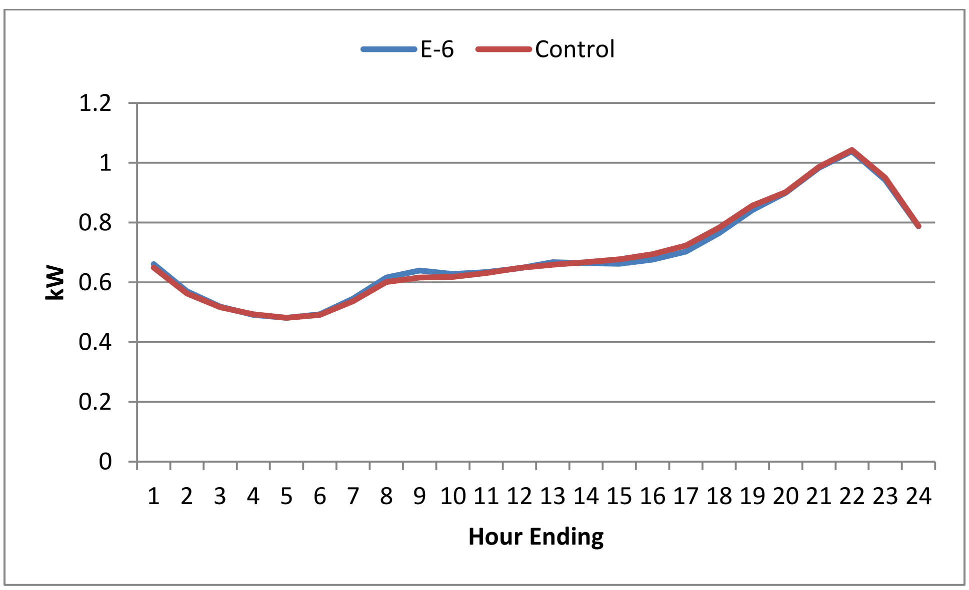



Table 6-2 compares E-6 and control group customers based on a number of other characteristics, once again illustrating that the control group is a good match for E-6 customers. Treatment and control customers have similar average weekday usage in both the summer and winter. Additionally, treatment and control customers are similarly distributed across climate zones. The percent of customers on CARE is 7% to 8% in all groups.

**Table 6-2: Comparison of E-6 Sample with Statistically Matched Control Group**

| Characteristic | E6 Population | E-1 Winter Control Group | E-1 Summer Control Group |
|---|---|---|---|
| Number of Customers | 4,539 | 3,949 | 3,884 |
| Winter Weekday Usage | 22.0 | 21.4 | n/a |
| Summer Weekday Usage | 19.8 | n/a | 19.1 |
| CARE | 8% | 7% | 8% |
| Percent all electric customers | 15% | 13% | 12% |
| Climate Zone R (e.g., Fresno) | 5% | 6% | 6% |
| Climate Zone S (e.g., Stockton/Sacramento) | 11% | 15% | 12% |
| Climate Zone T (Coastal) | 30% | 29% | 33% |
| Climate Zone X (e.g., San Jose/Concord) | 54% | 50% | 48% |

Control group selection for E-7 customers was done within each LCA using propensity score matching and post-enrollment, monthly usage data. In this case, the dimensions chosen for matching were:

- Winter or summer usage;
- CARE status.

The control group was chosen from the E-1 population. Table 6-3 compares the representative sample of E-7 TOU customers with smart meter data to the matched control groups. The participant and control groups are comparable across the observable metrics except for the percent of customers with electric space heating for the summer control group. This difference is expected given that matching for the summer-based control groups was not done based on winter usage when space heating occurs. In fact, this difference emphasizes the importance of drawing a separate control group for the summer and winter seasons, since matching well in one season does not guarantee a good match in the other and using a single match across the year will compromise the accuracy of the match in each season.

**Table 6-3: Comparison of E-7 Sample with Statistically Matched Control Group**

| Characteristic | E7 Population | E-1 Winter Control Group | E-1 Summer Control Group |
|---|---|---|---|
| Number of Customers | 47,653 | 41,884 | 43,067 |
| Winter Weekday Usage | 27.5 | 27.3 | n/a |
| Summer Weekday Usage | 27.3 | n/a | 27.1 |
| CARE | 10% | 9% | 9% |
| Percent all electric customers | 31% | 31% | 16% |
| Climate Zone R (e.g., Fresno) | 16% | 17% | 17% |
| Climate Zone S (e.g., Stockton/Sacramento) | 27% | 25% | 25% |
| Climate Zone T (Coastal) | 17% | 16% | 16% |
| Climate Zone X (e.g., San Jose/Concord) | 39% | 41% | 41% |

## 6.2 Analysis Method

Once the control groups were chosen for each tariff, a simple comparison of means, implemented with regression, was used to estimate demand reductions. For monthly system peak days, the model calculates the difference in loads between customers on E-6 and E-7 versus the control group for each month and hour. These results are identical to implementing a comparison of means using a t-test, a standard statistical technique used when control groups are available.[31] Standard errors are estimated allowing for correlation of the error term within customers.[32]

Separate regressions were calculated for:

- Each hour of the day (24);
- Two day types – monthly system peaks and average weekdays;
- Each month in the evaluation period (12); and
- Seven local capacity areas.

[31] Using regression allows this process to be quickly and easily automated.

[32] The propensity score model is treated as producing the correct control group without error. There is assumed to be no additional uncertainty due to the matching process itself.

The regression models can be expressed as:

| Day Type | | Regression Model |
|---|---|---|
| 1 | Monthly peak model | $kW_{i,h,m,l} = \alpha_{h,m,l} + \beta_{h,m,l} \cdot TOU_i$ |
| 2 | Average weekday model | $kW_{i,h,m,l,d} = \alpha_{h,m,l} + \beta_{h,m,l} \cdot TOU_i$ |

In the regressions, *i, h, m* and *l* are indicators for each customer, hour, month and local capacity area, respectively. The only difference between the monthly peak and average weekday model is that the latter includes multiple days, as noted by the indicator, *d*.

After initially estimating the impacts for the E-7 tariff using the models summarized above, the summer impacts were adjusted by multiplying them by the bias ratio in each month shown in Table 6-1, for reasons discussed in Section 6.1.

# 7 TOU 2014 Ex Post Load Impacts

This section summarizes the ex post load impact estimates for TOU customers. Separate estimates are produced for E-6 and E-7 customers for the monthly system peak day and the average weekday for each month from November 2013 through October 2014. The analysis excludes net-metered customers that have solar panels and are accounted for through the evaluation of solar programs.

## 7.1 2014 System Peak Day Load Impacts

Figure 7-1 shows estimates of hourly load impacts for the average E-6 customer on the annual system peak day, which occurred on July 30, 2014 and Figure 7-2 shows estimates for the average weekday in July. On the system peak day, the average reduction during the peak period from 1 to 7 PM was 0.20 kW, which equaled 17% of whole house load during that period. Load impacts in the first peak period hour equaled 0.16 kW and in the last hour equaled 0.19 kW. The greatest reduction, 0.23 kW, occurred between 5 and 6 PM. During the partial peak hours from 10 AM to 1 PM and 7 to 9 PM, load reductions were much smaller, ranging from a low of 0.06 kW between 8 and 9 PM to a high of 0.13 between noon and 1 PM. Load increased during off-peak hours, showing some load shifting. On the average weekday in July, reference loads and load impacts were a bit lower than on the system peak day. The average peak period reduction was 0.17 kW. Most of this difference was due to differences in the reference load, which was almost 17% lower than on the July peak day.

Figures 7-3 and 7-4 show load shapes for the July peak day and average July weekday for the E-7 tariff. Recall that the E-7 tariff is a two-period rate, with a peak period from noon to 6 PM. The average peak day impact is 0.13 kW or 7.5% of the reference load, which is much lower than for E-6 customers. On the average July weekday, the average load reduction across the six-hour peak period is 0.12 kW, which is 7.7% of the reference load and about one-third less than for the E-6 tariff.

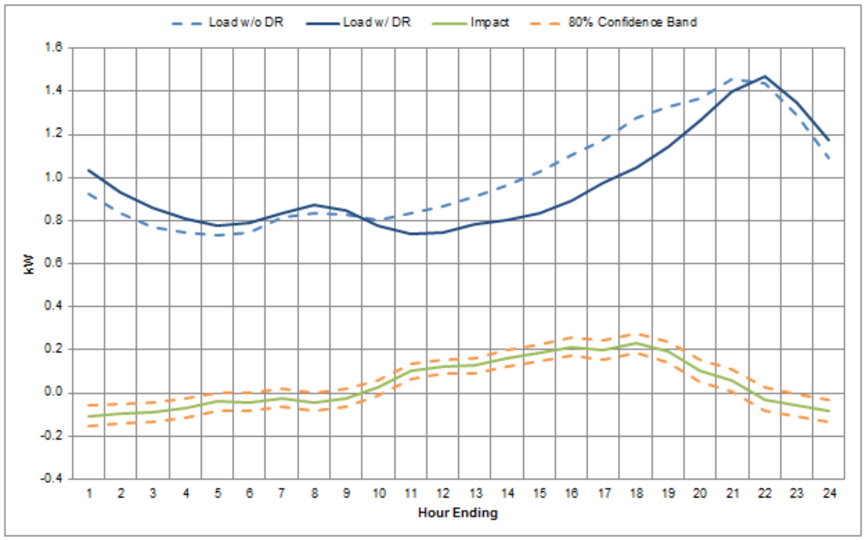
**Figure 7-1: Average Hourly Load Impact Estimates for E-6 Customers for Annual Peak Day (July 30, 2014)**

**Menu Options**

| | |
|---|---|
| Result Type | Individual Customer |
| Customer Type | E6 |
| LCA | All |
| Day Type | Monthly Peak |
| Month | July |

**Day Information**

| | |
|---|---|
| Peak Period Start | 1 PM |
| Peak Period End | 7 PM |
| Average Temp. for Peak Hours | 81 |
| Reference Load for Peak Hours | 1.15 |
| Load Reduction for Peak Hours | 0.20 |
| % Load Reduction for Peak Hour: | 17% |
| Population Size | 8,644 |




| Hour | Load w/o DR (kW) | Load w/ DR (kW) | Impact (kW) | % Load Impact (%) | Temp. (°F) | Uncertainty Adjusted Impact - Percentiles 10th | 30th | 50th | 70th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|
| 12 AM - 1 AM | 0.93 | 1.04 | -0.11 | -11.6% | 66.2 | -0.15 | -0.13 | -0.11 | -0.09 | -0.06 |
| 1 AM - 2 AM | 0.83 | 0.93 | -0.10 | -11.5% | 65.2 | -0.14 | -0.11 | -0.10 | -0.08 | -0.05 |
| 2 AM - 3 AM | 0.77 | 0.86 | -0.09 | -11.3% | 64.5 | -0.13 | -0.11 | -0.09 | -0.07 | -0.04 |
| 3 AM - 4 AM | 0.74 | 0.81 | -0.07 | -9.0% | 64.1 | -0.11 | -0.09 | -0.07 | -0.05 | -0.02 |
| 4 AM - 5 AM | 0.73 | 0.78 | -0.04 | -5.6% | 63.3 | -0.08 | -0.06 | -0.04 | -0.02 | 0.00 |
| 5 AM - 6 AM | 0.75 | 0.79 | -0.04 | -5.6% | 62.8 | -0.08 | -0.06 | -0.04 | -0.02 | 0.00 |
| 6 AM - 7 AM | 0.81 | 0.84 | -0.02 | -2.8% | 62.6 | -0.07 | -0.04 | -0.02 | 0.00 | 0.02 |
| 7 AM - 8 AM | 0.83 | 0.88 | -0.04 | -5.0% | 63.6 | -0.08 | -0.06 | -0.04 | -0.02 | 0.00 |
| 8 AM - 9 AM | 0.83 | 0.85 | -0.02 | -2.8% | 65.5 | -0.06 | -0.04 | -0.02 | -0.01 | 0.02 |
| 9 AM - 10 AM | 0.80 | 0.78 | 0.03 | 3.1% | 68.5 | -0.01 | 0.01 | 0.03 | 0.04 | 0.06 |
| 10 AM - 11 AM | 0.84 | 0.74 | 0.10 | 12.1% | 71.7 | 0.07 | 0.09 | 0.10 | 0.12 | 0.14 |
| 11 AM - 12 PM | 0.87 | 0.74 | 0.12 | 14.3% | 74.8 | 0.09 | 0.11 | 0.12 | 0.14 | 0.16 |
| 12 PM - 1 PM | 0.91 | 0.78 | 0.13 | 14.1% | 78.1 | 0.09 | 0.11 | 0.13 | 0.14 | 0.16 |
| 1 PM - 2 PM | 0.96 | 0.80 | 0.16 | 16.9% | 80.3 | 0.13 | 0.15 | 0.16 | 0.18 | 0.20 |
| 2 PM - 3 PM | 1.02 | 0.84 | 0.19 | 18.4% | 81.8 | 0.15 | 0.17 | 0.19 | 0.20 | 0.23 |
| 3 PM - 4 PM | 1.10 | 0.89 | 0.22 | 19.5% | 82.9 | 0.17 | 0.20 | 0.22 | 0.23 | 0.26 |
| 4 PM - 5 PM | 1.18 | 0.97 | 0.20 | 17.2% | 82.4 | 0.16 | 0.18 | 0.20 | 0.22 | 0.25 |
| 5 PM - 6 PM | 1.28 | 1.05 | 0.23 | 18.1% | 81.3 | 0.18 | 0.21 | 0.23 | 0.25 | 0.28 |
| 6 PM - 7 PM | 1.33 | 1.14 | 0.19 | 14.3% | 78.9 | 0.14 | 0.17 | 0.19 | 0.21 | 0.24 |
| 7 PM - 8 PM | 1.37 | 1.26 | 0.11 | 7.7% | 75.6 | 0.05 | 0.08 | 0.11 | 0.13 | 0.16 |
| 8 PM - 9 PM | 1.46 | 1.40 | 0.06 | 4.0% | 71.3 | 0.00 | 0.04 | 0.06 | 0.08 | 0.11 |
| 9 PM - 10 PM | 1.44 | 1.47 | -0.03 | -2.0% | 68.9 | -0.08 | -0.05 | -0.03 | -0.01 | 0.02 |
| 10 PM - 11 PM | 1.29 | 1.35 | -0.06 | -4.4% | 67.0 | -0.11 | -0.08 | -0.06 | -0.03 | 0.00 |
| 11 PM - 12 AM | 1.09 | 1.17 | -0.08 | -7.8% | 65.5 | -0.14 | -0.11 | -0.08 | -0.06 | -0.03 |
| **Entire Peak** | **1.15** | **0.95** | **0.20** | **17.3%** | **81.3** | **0.99** | **0.18** | **0.20** | **0.22** | **0.24** |
| **Entire Day** | **24.18** | **23.15** | **1.03** | **4.3%** | **71.1** | **0.99** | **1.01** | **1.03** | **1.05** | **1.08** |

**The impact percentiles indicate that it is uncertain whether the impact is positive or negative in this hour*

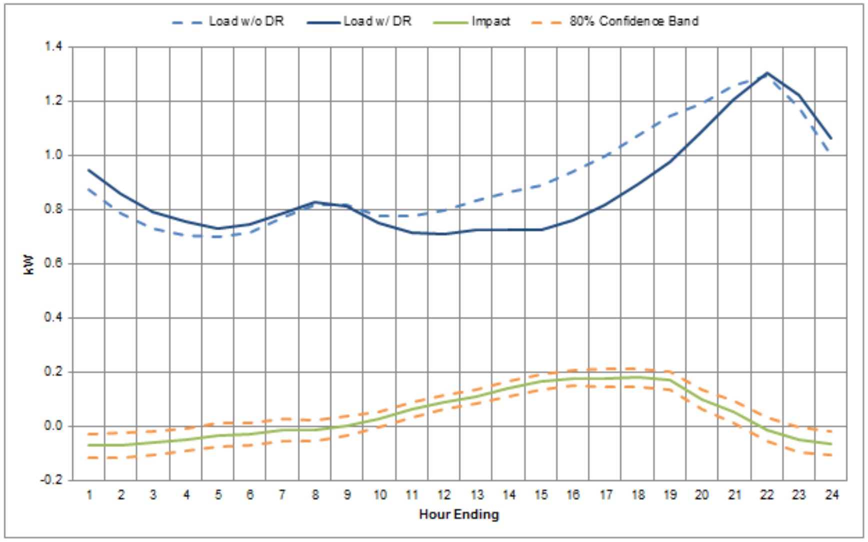
## Figure 7-2: Average Hourly Load Impact Estimates for E-6 Customers for Average July 2014 Weekday

**Menu Options**

| | |
|---|---|
| Result Type | Individual Customer |
| Customer Type | E6 |
| LCA | All |
| Day Type | Average Weekday |
| Month | July |

**Day Information**

| | |
|---|---|
| Peak Period Start | 1 PM |
| Peak Period End | 7 PM |
| Average Temp. for Peak Hours | 78 |
| Reference Load for Peak Hours | 0.99 |
| Load Reduction for Peak Hours | 0.17 |
| % Load Reduction for Peak Hours | 17% |
| Population Size | 8,644 |




| Hour | Load w/o DR (kW) | Load w/ DR (kW) | Impact (kW) | % Load Impact (%) | Temp. (°F) | Uncertainty Adjusted Impact - Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 10th | 30th | 50th | 70th | 90th |
| 12 AM - 1 AM | 0.87 | 0.94 | -0.07 | -8.3% | 64.3 | -0.12 | -0.09 | -0.07 | -0.05 | -0.03 |
| 1 AM - 2 AM | 0.79 | 0.86 | -0.07 | -8.8% | 63.6 | -0.11 | -0.09 | -0.07 | -0.05 | -0.03 |
| 2 AM - 3 AM | 0.73 | 0.79 | -0.06 | -8.3% | 63.0 | -0.10 | -0.08 | -0.06 | -0.04 | -0.02 |
| 3 AM - 4 AM | 0.71 | 0.76 | -0.05 | -6.9% | 62.4 | -0.09 | -0.07 | -0.05 | -0.03 | -0.01 |
| 4 AM - 5 AM | 0.70 | 0.73 | -0.03 | -4.5% | 62.0 | -0.07 | -0.05 | -0.03 | -0.01 | 0.01 |
| 5 AM - 6 AM | 0.72 | 0.74 | -0.03 | -4.0% | 61.7 | -0.07 | -0.05 | -0.03 | -0.01 | 0.01 |
| 6 AM - 7 AM | 0.77 | 0.79 | -0.01 | -1.8% | 61.7 | -0.06 | -0.03 | -0.01 | 0.00 | 0.03 |
| 7 AM - 8 AM | 0.82 | 0.83 | -0.01 | -1.7% | 63.3 | -0.05 | -0.03 | -0.01 | 0.00 | 0.03 |
| 8 AM - 9 AM | 0.82 | 0.82 | 0.00 | 0.1% | 65.6 | -0.04 | -0.01 | 0.00 | 0.02 | 0.04 |
| 9 AM - 10 AM | 0.78 | 0.75 | 0.03 | 3.3% | 68.5 | 0.00 | 0.01 | 0.03 | 0.04 | 0.05 |
| 10 AM - 11 AM | 0.78 | 0.72 | 0.06 | 7.9% | 71.4 | 0.04 | 0.05 | 0.06 | 0.07 | 0.09 |
| 11 AM - 12 PM | 0.80 | 0.71 | 0.09 | 11.1% | 74.3 | 0.06 | 0.08 | 0.09 | 0.10 | 0.11 |
| 12 PM - 1 PM | 0.84 | 0.73 | 0.11 | 13.0% | 76.7 | 0.08 | 0.10 | 0.11 | 0.12 | 0.14 |
| 1 PM - 2 PM | 0.86 | 0.73 | 0.14 | 16.0% | 78.3 | 0.11 | 0.13 | 0.14 | 0.15 | 0.17 |
| 2 PM - 3 PM | 0.89 | 0.73 | 0.16 | 18.4% | 79.1 | 0.14 | 0.15 | 0.16 | 0.18 | 0.19 |
| 3 PM - 4 PM | 0.94 | 0.76 | 0.18 | 19.0% | 79.3 | 0.15 | 0.17 | 0.18 | 0.19 | 0.21 |
| 4 PM - 5 PM | 1.00 | 0.82 | 0.18 | 18.0% | 78.8 | 0.15 | 0.17 | 0.18 | 0.19 | 0.21 |
| 5 PM - 6 PM | 1.08 | 0.90 | 0.18 | 16.7% | 77.7 | 0.15 | 0.17 | 0.18 | 0.19 | 0.21 |
| 6 PM - 7 PM | 1.15 | 0.98 | 0.17 | 14.8% | 75.6 | 0.13 | 0.16 | 0.17 | 0.18 | 0.20 |
| 7 PM - 8 PM | 1.19 | 1.09 | 0.10 | 8.4% | 72.9 | 0.06 | 0.09 | 0.10 | 0.12 | 0.14 |
| 8 PM - 9 PM | 1.26 | 1.21 | 0.05 | 4.3% | 69.7 | 0.02 | 0.04 | 0.05 | 0.07 | 0.09 |
| 9 PM - 10 PM | 1.30 | 1.31 | -0.01 | -0.8% | 67.4 | -0.06 | -0.03 | -0.01 | 0.01 | 0.03 |
| 10 PM - 11 PM | 1.18 | 1.22 | -0.05 | -4.0% | 66.0 | -0.09 | -0.07 | -0.05 | -0.03 | 0.00 |
| 11 PM - 12 AM | 1.00 | 1.07 | -0.06 | -6.3% | 65.0 | -0.11 | -0.08 | -0.06 | -0.05 | -0.02 |
| **Entire Peak** | **0.99** | **0.82** | **0.17** | **17.1%** | **78.1** | **0.96** | **0.16** | **0.17** | **0.18** | **0.20** |
| **Entire Day** | **21.97** | **20.98** | **0.99** | **4.5%** | **69.5** | **0.95** | **0.98** | **0.99** | **1.01** | **1.03** |

**The impact percentiles indicate that it is uncertain whether the impact is positive or negative in this hour*

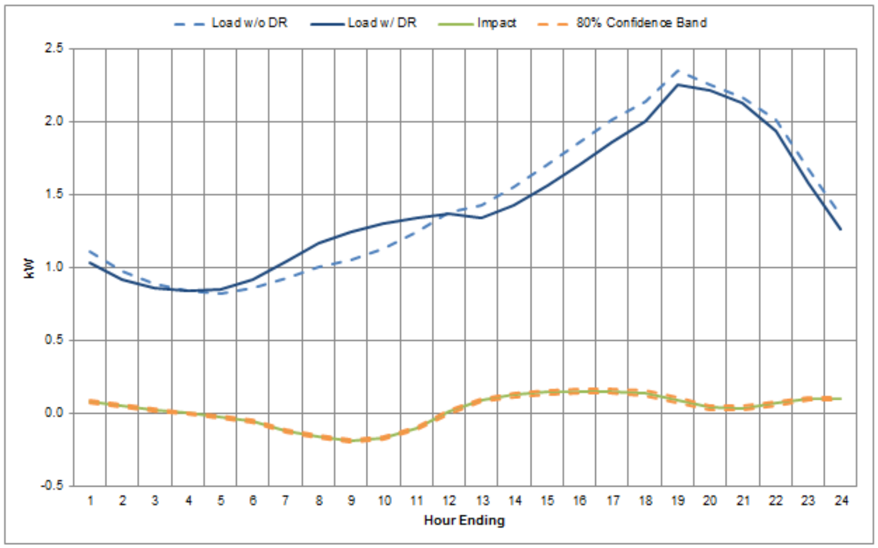
## Figure 7-3: Average Hourly Load Impact Estimates for E-7 Customers for Annual Peak Day (July 30, 2014)

**Menu Options**

| | |
|---|---|
| Result Type | Individual Customer |
| Customer Type | E7 |
| LCA | All |
| Day Type | Monthly Peak |
| Month | July |

**Day Information**

| | |
|---|---|
| Peak Period Start | 12 PM |
| Peak Period End | 6 PM |
| Average Temp. for Peak Hours | 86 |
| Reference Load for Peak Hours | 1.79 |
| Load Reduction for Peak Hours | 0.13 |
| % Load Reduction for Peak Hour: | 8% |
| Population Size | 50,621 |




| Hour | Load w/o DR (kW) | Load w/ DR (kW) | Impact (kW) | % Load Impact (%) | Temp. (°F) | Uncertainty Adjusted Impact - Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 10th | 30th | 50th | 70th | 90th |
| 12 AM - 1 AM | 1.11 | 1.03 | 0.08 | 7.4% | 70.1 | 0.07 | 0.08 | 0.08 | 0.09 | 0.09 |
| 1 AM - 2 AM | 0.97 | 0.92 | 0.05 | 5.2% | 68.6 | 0.04 | 0.05 | 0.05 | 0.05 | 0.06 |
| 2 AM - 3 AM | 0.89 | 0.87 | 0.02 | 2.4% | 67.8 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 |
| 3 AM - 4 AM | 0.84 | 0.84 | 0.00 | 0.1% | 67.2 | -0.01 | 0.00 | 0.00 | 0.00 | 0.01 |
| 4 AM - 5 AM | 0.82 | 0.85 | -0.02 | -2.8% | 66.1 | -0.03 | -0.03 | -0.02 | -0.02 | -0.02 |
| 5 AM - 6 AM | 0.86 | 0.92 | -0.06 | -6.5% | 65.4 | -0.06 | -0.06 | -0.06 | -0.05 | -0.05 |
| 6 AM - 7 AM | 0.93 | 1.05 | -0.12 | -12.7% | 65.1 | -0.13 | -0.12 | -0.12 | -0.11 | -0.11 |
| 7 AM - 8 AM | 1.00 | 1.17 | -0.16 | -16.1% | 66.6 | -0.17 | -0.17 | -0.16 | -0.16 | -0.15 |
| 8 AM - 9 AM | 1.06 | 1.24 | -0.19 | -17.6% | 69.2 | -0.20 | -0.19 | -0.19 | -0.18 | -0.18 |
| 9 AM - 10 AM | 1.14 | 1.31 | -0.17 | -15.0% | 72.7 | -0.18 | -0.17 | -0.17 | -0.17 | -0.16 |
| 10 AM - 11 AM | 1.25 | 1.35 | -0.10 | -8.0% | 76.4 | -0.11 | -0.10 | -0.10 | -0.10 | -0.09 |
| 11 AM - 12 PM | 1.39 | 1.37 | 0.01 | 0.8% | 79.7 | 0.00 | 0.01 | 0.01 | 0.02 | 0.02 |
| 12 PM - 1 PM | 1.43 | 1.34 | 0.09 | 6.3% | 82.9 | 0.08 | 0.08 | 0.09 | 0.09 | 0.10 |
| 1 PM - 2 PM | 1.56 | 1.43 | 0.13 | 8.1% | 85.1 | 0.11 | 0.12 | 0.13 | 0.13 | 0.14 |
| 2 PM - 3 PM | 1.71 | 1.56 | 0.14 | 8.5% | 86.7 | 0.13 | 0.14 | 0.14 | 0.15 | 0.16 |
| 3 PM - 4 PM | 1.86 | 1.71 | 0.15 | 8.2% | 88.3 | 0.14 | 0.15 | 0.15 | 0.16 | 0.17 |
| 4 PM - 5 PM | 2.01 | 1.86 | 0.15 | 7.6% | 88.3 | 0.14 | 0.15 | 0.15 | 0.16 | 0.17 |
| 5 PM - 6 PM | 2.14 | 2.00 | 0.14 | 6.5% | 87.3 | 0.12 | 0.13 | 0.14 | 0.15 | 0.16 |
| 6 PM - 7 PM | 2.35 | 2.26 | 0.09 | 4.0% | 85.1 | 0.08 | 0.09 | 0.09 | 0.10 | 0.11 |
| 7 PM - 8 PM | 2.26 | 2.22 | 0.04 | 1.7% | 81.8 | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 |
| 8 PM - 9 PM | 2.17 | 2.13 | 0.04 | 1.6% | 77.3 | 0.02 | 0.03 | 0.04 | 0.04 | 0.05 |
| 9 PM - 10 PM | 2.01 | 1.94 | 0.07 | 3.5% | 74.3 | 0.06 | 0.07 | 0.07 | 0.08 | 0.09 |
| 10 PM - 11 PM | 1.68 | 1.58 | 0.10 | 5.9% | 71.8 | 0.09 | 0.09 | 0.10 | 0.11 | 0.11 |
| 11 PM - 12 AM | 1.36 | 1.26 | 0.10 | 7.2% | 69.9 | 0.09 | 0.09 | 0.10 | 0.10 | 0.11 |
| **Entire Peak** | **1.79** | **1.65** | **0.13** | **7.5%** | **86.4** | **0.58** | **0.13** | **0.13** | **0.14** | **0.15** |
| **Entire Day** | **34.81** | **34.22** | **0.60** | **1.7%** | **75.6** | **0.58** | **0.59** | **0.60** | **0.60** | **0.61** |

**The impact percentiles indicate that it is uncertain whether the impact is positive or negative in this hour*

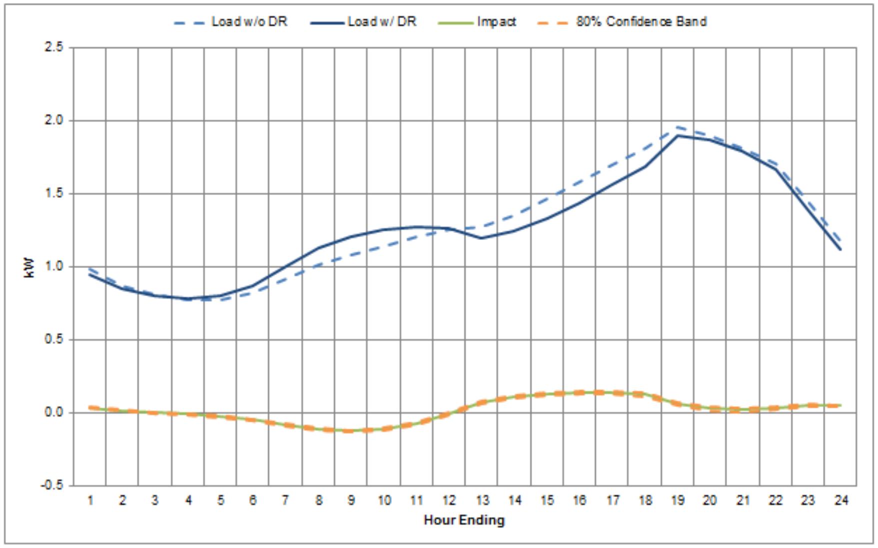
## Figure 7-4: Average Hourly Load Impact Estimates for E-7 Customers for Average July 2014 Weekday

**Menu Options**

| | |
|---|---|
| Result Type | Individual Customer |
| Customer Type | E7 |
| LCA | All |
| Day Type | Average Weekday |
| Month | July |

**Day Information**

| | |
|---|---|
| Peak Period Start | 12 PM |
| Peak Period End | 6 PM |
| Average Temp. for Peak Hours | 82 |
| Reference Load for Peak Hours | 1.53 |
| Load Reduction for Peak Hours | 0.12 |
| % Load Reduction for Peak Hour: | 8% |
| Population Size | 50,621 |




| Hour | Load w/o DR (kW) | Load w/ DR (kW) | Impact (kW) | % Load Impact (%) | Temp. (°F) | Uncertainty Adjusted Impact - Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 10th | 30th | 50th | 70th | 90th |
| 12 AM - 1 AM | 0.99 | 0.95 | 0.04 | 3.6% | 67.0 | 0.03 | 0.03 | 0.04 | 0.04 | 0.04 |
| 1 AM - 2 AM | 0.87 | 0.86 | 0.02 | 2.1% | 66.0 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 |
| 2 AM - 3 AM | 0.81 | 0.81 | 0.00 | 0.3% | 65.2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| 3 AM - 4 AM | 0.78 | 0.79 | -0.01 | -1.2% | 64.4 | -0.02 | -0.01 | -0.01 | -0.01 | 0.00 |
| 4 AM - 5 AM | 0.78 | 0.80 | -0.02 | -3.1% | 63.7 | -0.03 | -0.03 | -0.02 | -0.02 | -0.02 |
| 5 AM - 6 AM | 0.83 | 0.87 | -0.05 | -5.7% | 63.2 | -0.05 | -0.05 | -0.05 | -0.04 | -0.04 |
| 6 AM - 7 AM | 0.92 | 1.01 | -0.08 | -9.1% | 63.2 | -0.09 | -0.09 | -0.08 | -0.08 | -0.08 |
| 7 AM - 8 AM | 1.02 | 1.13 | -0.11 | -10.7% | 65.2 | -0.12 | -0.11 | -0.11 | -0.11 | -0.10 |
| 8 AM - 9 AM | 1.09 | 1.21 | -0.12 | -11.4% | 68.0 | -0.13 | -0.13 | -0.12 | -0.12 | -0.12 |
| 9 AM - 10 AM | 1.14 | 1.26 | -0.11 | -9.8% | 71.3 | -0.12 | -0.11 | -0.11 | -0.11 | -0.10 |
| 10 AM - 11 AM | 1.20 | 1.27 | -0.07 | -5.8% | 74.5 | -0.08 | -0.07 | -0.07 | -0.07 | -0.06 |
| 11 AM - 12 PM | 1.26 | 1.26 | 0.00 | -0.3% | 77.5 | -0.01 | -0.01 | 0.00 | 0.00 | 0.00 |
| 12 PM - 1 PM | 1.28 | 1.20 | 0.07 | 5.8% | 80.0 | 0.07 | 0.07 | 0.07 | 0.08 | 0.08 |
| 1 PM - 2 PM | 1.36 | 1.25 | 0.11 | 7.9% | 81.9 | 0.10 | 0.10 | 0.11 | 0.11 | 0.12 |
| 2 PM - 3 PM | 1.46 | 1.34 | 0.13 | 8.6% | 83.1 | 0.12 | 0.12 | 0.13 | 0.13 | 0.14 |
| 3 PM - 4 PM | 1.58 | 1.44 | 0.14 | 8.7% | 83.7 | 0.13 | 0.13 | 0.14 | 0.14 | 0.15 |
| 4 PM - 5 PM | 1.70 | 1.56 | 0.14 | 8.1% | 83.4 | 0.13 | 0.13 | 0.14 | 0.14 | 0.15 |
| 5 PM - 6 PM | 1.82 | 1.69 | 0.13 | 6.9% | 82.5 | 0.11 | 0.12 | 0.13 | 0.13 | 0.14 |
| 6 PM - 7 PM | 1.96 | 1.90 | 0.06 | 3.2% | 80.5 | 0.05 | 0.06 | 0.06 | 0.07 | 0.08 |
| 7 PM - 8 PM | 1.90 | 1.87 | 0.03 | 1.5% | 77.5 | 0.02 | 0.02 | 0.03 | 0.03 | 0.04 |
| 8 PM - 9 PM | 1.81 | 1.79 | 0.02 | 1.1% | 73.8 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 |
| 9 PM - 10 PM | 1.70 | 1.67 | 0.03 | 2.0% | 71.1 | 0.02 | 0.03 | 0.03 | 0.04 | 0.04 |
| 10 PM - 11 PM | 1.44 | 1.40 | 0.05 | 3.4% | 69.2 | 0.04 | 0.05 | 0.05 | 0.05 | 0.06 |
| 11 PM - 12 AM | 1.18 | 1.13 | 0.05 | 4.2% | 67.8 | 0.04 | 0.05 | 0.05 | 0.05 | 0.06 |
| **Entire Peak** | **1.53** | **1.41** | **0.12** | **7.7%** | **82.4** | **0.41** | **0.11** | **0.12** | **0.12** | **0.13** |
| **Entire Day** | **30.89** | **30.46** | **0.43** | **1.4%** | **72.7** | **0.42** | **0.42** | **0.43** | **0.43** | **0.43** |

**The impact percentiles indicate that it is uncertain whether the impact is positive or negative in this hour*

## 7.2 Monthly System Peak Day Load Impacts

Tables 7-1 and 7-2 show the average load reduction on monthly system peak days for E-6 and E-7 customers during the time period included in the analysis, from November 1, 2013 through October 31, 2014. For both rates, peak-period prices are higher in the summer rate period, which runs from May 1 through October 30. As shown in Table 7-1, load reductions for E-6 customers were greater during summer than winter, both in absolute and percentage terms. During the summer, the average load reduction was 0.22 kW, or 20%. E-7 customers provided average load reductions of 0.15 kW or 9% during the summer. All summer results are statistically significantly different from zero. Customers provided smaller demand reductions during winter months, when prices are lower, and only the impacts in January and April were statistically significant. On average, E-6 and E-7 customers had electricity use that was 8% and 5% lower than that of the control group during winter peak period hours, respectively.

**Table 7-1: E-6 Monthly System Peak Day Load Reductions (1 to 7 PM Summer, 5 to 8 PM Winter, November 2013–October 2014)**

| Month | Average Reference Load (kW) | Average Load Impact (kW) | Aggregate Load Impact (MW) | Percent Reduction (%) | Average Peak Period Temperature (°F) |
|---|---|---|---|---|---|
| January | 1.25 | 0.12 | 1.05 | 10% | 56.5 |
| February | 1.25 | 0.07 | 0.60 | 6% | 49.9 |
| March | 1.10 | 0.05 | 0.43 | 4% | 49.2 |
| April | 1.10 | 0.21 | 1.86 | 19% | 85.0 |
| May | 0.97 | 0.22 | 1.88 | 22% | 90.4 |
| June | 1.25 | 0.30 | 2.61 | 24% | 84.4 |
| July | 1.15 | 0.20 | 1.71 | 17% | 81.3 |
| August | 1.22 | 0.20 | 1.69 | 16% | 82.3 |
| September | 1.02 | 0.21 | 1.85 | 21% | 83.1 |
| October | 0.93 | 0.17 | 1.43 | 18% | 82.9 |
| November | 1.23 | 0.08 | 0.68 | 6% | 57.7 |
| December | 1.64 | 0.10 | 0.86 | 6% | 42.0 |
| **Average** | **1.18** | **0.16** | **1.39** | **14%** | **70.4** |
| **Summer** | **1.09** | **0.22** | **1.86** | **20%** | **84.0** |
| **Winter** | **1.26** | **0.11** | **0.91** | **8%** | **56.7** |

**Table 7-2: E-7 Monthly System Peak Day Load Reductions (12 PM to 6 PM, November 2013 to October 2014)**

| Month | Average Reference Load (kW) | Average Load Impact (kW) | Aggregate Load Impact (MW) | Percent Reduction (%) | Average Peak Period Temperature (°F) |
|---|---|---|---|---|---|
| January | 1.04 | 0.06 | 2.96 | 6% | 64.9 |
| February | 1.09 | 0.03 | 1.48 | 3% | 53.1 |
| March | 1.18 | 0.03 | 1.52 | 3% | 51.7 |
| April | 1.09 | 0.11 | 5.38 | 10% | 87.4 |
| May | 1.36 | 0.13 | 6.59 | 10% | 91.1 |
| June | 2.01 | 0.17 | 8.78 | 9% | 90.4 |
| July | 1.79 | 0.13 | 6.80 | 8% | 86.4 |
| August | 1.94 | 0.13 | 6.40 | 7% | 88.6 |
| September | 1.54 | 0.16 | 7.95 | 10% | 87.8 |
| October | 1.29 | 0.15 | 7.71 | 12% | 86.3 |
| November | 1.13 | 0.03 | 1.77 | 3% | 59.3 |
| December | 1.42 | 0.05 | 2.78 | 4% | 47.2 |
| **Average** | **1.41** | **0.10** | **5.01** | **7%** | **74.5** |
| **Summer** | **1.66** | **0.15** | **7.37** | **9%** | **88.4** |
| **Winter** | **1.16** | **0.05** | **2.65** | **5%** | **60.6** |

## 7.3 Average Weekday Load Impacts by Month

Table 7-3 and 7-4 show the change in peak-period energy use for the average weekday for each month for E-6 and E-7 customers, respectively. The average reduction across the year was 0.10 kW for E-6 customers and 0.07 for E-7 customers. Average weekday load impacts have a seasonal pattern similar to that of monthly peak day impacts, with summer reductions being significantly higher than winter reductions for both E-6 and E-7. The average weekday peak-period reduction in the summer months for E-6 customers is 0.13 kW or 15%, while the average in winter months is 0.07 kW or 6%. The largest average weekday load reduction for E-6 customers, 0.17 kW, occurred in July. The average load impacts for the E-7 tariff are about twice as large in the summer as in the winter. The largest impact for E-7, 0.12 kW, occurred in July.

**Table 7-3: E-6 Average Weekday Peak Period Load Reduction (1 to 7 PM Summer, 5 to 8 PM Winter, November 2013–October 2014)**

| Month | Average Reference Load (kW) | Average Load Impact (kW) | Aggregate Load Impact (MW) | Percent Reduction (%) | Average Peak Period Temperature (°F) |
|---|---|---|---|---|---|
| January | 1.24 | 0.08 | 0.72 | 7% | 56.0 |
| February | 1.14 | 0.05 | 0.43 | 4% | 56.4 |
| March | 0.94 | 0.06 | 0.48 | 6% | 62.6 |
| April | 0.89 | 0.06 | 0.55 | 7% | 65.6 |
| May | 0.77 | 0.09 | 0.78 | 12% | 74.4 |
| June | 0.86 | 0.13 | 1.10 | 15% | 75.4 |
| July | 0.99 | 0.17 | 1.46 | 17% | 78.1 |
| August | 0.91 | 0.14 | 1.22 | 16% | 77.0 |
| September | 0.86 | 0.13 | 1.09 | 15% | 77.2 |
| October | 0.77 | 0.10 | 0.86 | 13% | 73.7 |
| November | 1.18 | 0.07 | 0.58 | 6% | 58.2 |
| December | 1.44 | 0.10 | 0.87 | 7% | 49.9 |
| **Average** | **1.00** | **0.10** | **0.85** | **10%** | **67.0** |
| **Summer** | **0.86** | **0.13** | **1.08** | **15%** | **76.0** |
| **Winter** | **1.14** | **0.07** | **0.61** | **6%** | **58.1** |

**Table 7-4: E-7 Average Weekday Peak Period Load Reduction (12 PM to 6 PM, November 2013–October 2014**

| Month | Average Reference Load (kW) | Average Load Impact (kW) | Aggregate Load Impact (MW) | Percent Reduction (%) | Average Peak Period Temperature (°F) |
|---|---|---|---|---|---|
| January | 1.08 | 0.05 | 2.51 | 5% | 62.6 |
| February | 1.02 | 0.03 | 1.43 | 3% | 60.0 |
| March | 0.93 | 0.03 | 1.54 | 3% | 65.3 |
| April | 0.94 | 0.04 | 2.17 | 5% | 69.6 |
| May | 1.05 | 0.06 | 3.03 | 6% | 76.7 |
| June | 1.28 | 0.10 | 4.98 | 8% | 79.4 |
| July | 1.53 | 0.12 | 5.98 | 8% | 82.4 |
| August | 1.35 | 0.11 | 5.76 | 8% | 80.8 |
| September | 1.23 | 0.11 | 5.40 | 9% | 80.4 |
| October | 0.99 | 0.07 | 3.54 | 7% | 75.4 |
| November | 1.08 | 0.04 | 1.81 | 3% | 64.4 |
| December | 1.29 | 0.04 | 2.24 | 3% | 56.3 |
| **Average** | **1.15** | **0.07** | **3.37** | **6%** | **71.1** |
| **Summer** | **1.24** | **0.09** | **4.78** | **8%** | **79.2** |
| **Winter** | **1.06** | **0.04** | **1.95** | **4%** | **63.0** |

## 7.4 Load Impacts by Geographic Region

Results by LCA are less reliable than the overall results for all customers because sample sizes are smaller. This is particularly true for monthly peak results, which include fewer days for impact estimation than the average weekday results, and for E-6 in general, since enrollment is much less than for E-7.

Tables 7-5 and 7-6 show the average impacts on the annual system peak day, July 30, by LCA for each rate. E-6 customers with the greatest absolute load reductions, 1.27 kW, were located in the Kern area, but only 33 customers were included in this estimate so this value has a high degree of uncertainty. Sierra and Stockton saw the greatest absolute load reduction among E-7 customers.

**Table 7-5: E-6 Peak Period (1 to 7 PM) Load Reductions by Local Capacity Area Annual Peak Day (July 30, 2014)**

| LCA | Treatment Sample Size | Reference Load (kW) | Estimated Load with DR (kW) | Load Impact (kW) | Percent Reduction (%) | Average Peak Temp. (°F) |
|---|---|---|---|---|---|---|
| Greater Bay Area | 3,038 | 0.89 | 0.75 | 0.14 | 16% | 77.9 |
| Greater Fresno Area | 86 | 2.27 | 1.80 | 0.47 | 21% | 97.5 |
| Humboldt | 106 | 1.35 | 1.10 | 0.26 | 19% | 70.8 |
| Kern | 33 | 3.18 | 1.91 | 1.27 | 40% | 100.4 |
| North Coast and North Bay | 420 | 0.75 | 0.63 | 0.12 | 16% | 84.5 |
| Other | 597 | 1.42 | 1.14 | 0.28 | 20% | 82.7 |
| Sierra | 186 | 2.45 | 2.01 | 0.45 | 18% | 96.6 |
| Stockton | 73 | 2.27 | 2.14 | 0.12 | 5% | 97.6 |
| **All** | **4,539** | **1.15** | **0.95** | **0.20** | **17%** | **81.3** |

**Table 7-6: E-7 Peak Period (12 to 6 PM) Load Reductions by Local Capacity Area Annual Peak Day (July 30, 2014)**

| LCA | Treatment Sample Size | Reference Load (kW) | Estimated Load with DR (kW) | Load Impact (kW) | Percent Reduction (%) | Average Peak Temp. (°F) |
|---|---|---|---|---|---|---|
| Greater Bay Area | 17,946 | 1.51 | 1.42 | 0.09 | 6% | 80.9 |
| Greater Fresno Area | 3,123 | 2.55 | 2.35 | 0.19 | 8% | 96.1 |
| Humboldt | 2,631 | 1.27 | 1.17 | 0.11 | 9% | 78.3 |
| Kern | 1,161 | 3.02 | 2.81 | 0.21 | 7% | 100.0 |
| North Coast and North Bay | 5,324 | 1.24 | 1.18 | 0.07 | 5% | 84.5 |
| Other | 11,038 | 1.92 | 1.75 | 0.17 | 9% | 88.6 |
| Sierra | 4,277 | 2.47 | 2.23 | 0.24 | 10% | 96.5 |
| Stockton | 2,203 | 2.54 | 2.31 | 0.24 | 9% | 97.0 |
| **All** | **47,703** | **1.79** | **1.65** | **0.13** | **8%** | **86.4** |

Tables 7-7 and 7-8 show the impacts for each LCA and rate for the average weekday peak period during the summer and winter months. Once again, it is important to note the small sample sizes in some regions for the E-6 rate, especially in the Kern, Stockton and Fresno LCAs. Roughly two thirds of all E-6 customers in the sample are from the Bay Area while roughly one third of E-7 customers are in the Bay Area LCA. The Bay Area has one of the lowest average impacts in both summer and winter for both the E-6 and E-7 tariffs.

**Table 7-7: E-6 Load Reductions for Peak Period (1 to 7 PM Summer, 5 to 8 PM Winter) by Season and Local Capacity Area**

| Season | LCA | Reference Load (kW) | Estimated Load with DR (kW) | Load Impact (kW) | Percent Reduction (%) | Average Peak Temp. (°F) |
|---|---|---|---|---|---|---|
| Summer (May-Oct) | Greater Bay Area | 0.69 | 0.61 | 0.08 | 12% | 74.1 |
| | Greater Fresno Area | 1.70 | 1.39 | 0.31 | 18% | 91.0 |
| | Humboldt | 1.23 | 0.99 | 0.24 | 20% | 67.5 |
| | Kern | 2.08 | 1.46 | 0.61 | 30% | 90.9 |
| | North Coast and North Bay | 0.68 | 0.58 | 0.09 | 14% | 77.6 |
| | Other | 1.03 | 0.85 | 0.18 | 17% | 76.8 |
| | Sierra | 1.44 | 1.19 | 0.25 | 17% | 82.9 |
| | Stockton | 1.34 | 1.16 | 0.18 | 14% | 84.8 |
| | **All** | **0.86** | **0.73** | **0.13** | **15%** | **76.0** |
| Winter (Nov-Apr) | Greater Bay Area | 1.01 | 0.96 | 0.05 | 5% | 58.7 |
| | Greater Fresno Area | 1.38 | 1.31 | 0.06 | 4% | 62.9 |
| | Humboldt | 2.06 | 1.83 | 0.23 | 11% | 52.1 |
| | Kern | 1.17 | 0.92 | 0.25 | 22% | 63.1 |
| | North Coast and North Bay | 1.14 | 1.04 | 0.10 | 9% | 57.3 |
| | Other | 1.18 | 1.14 | 0.04 | 4% | 58.0 |
| | Sierra | 1.58 | 1.47 | 0.11 | 7% | 54.1 |
| | Stockton | 1.41 | 1.21 | 0.21 | 15% | 58.4 |
| | **All** | **1.14** | **1.07** | **0.07** | **6%** | **58.1** |

**Table 7-8: E-7 Load Reductions for Peak Period (12 to 6 PM) by Season and Local Capacity Area**

| Season | LCA | Reference Load (kW) | Estimated Load with DR (kW) | Load Impact (kW) | Percent Reduction (%) | Average Peak Temp. (°F) |
|---|---|---|---|---|---|---|
| Summer (May-Oct) | Greater Bay Area | 1.07 | 1.00 | 0.07 | 6% | 76.0 |
| | Greater Fresno Area | 1.91 | 1.74 | 0.17 | 9% | 90.2 |
| | Humboldt | 0.99 | 0.92 | 0.07 | 7% | 71.5 |
| | Kern | 1.98 | 1.83 | 0.14 | 7% | 90.1 |
| | North Coast and North Bay | 1.06 | 1.01 | 0.05 | 5% | 77.7 |
| | Other | 1.30 | 1.18 | 0.12 | 9% | 80.6 |
| | Sierra | 1.42 | 1.27 | 0.14 | 10% | 82.6 |
| | Stockton | 1.51 | 1.36 | 0.15 | 10% | 84.7 |
| | **All** | **1.24** | **1.14** | **0.09** | **8%** | **79.2** |
| Winter (Nov-Apr) | Greater Bay Area | 0.97 | 0.95 | 0.03 | 3% | 62.9 |
| | Greater Fresno Area | 1.03 | 0.98 | 0.05 | 5% | 66.7 |
| | Humboldt | 1.11 | 1.06 | 0.05 | 4% | 57.9 |
| | Kern | 0.93 | 0.89 | 0.04 | 4% | 67.0 |
| | North Coast and North Bay | 1.08 | 1.05 | 0.03 | 3% | 63.2 |
| | Other | 1.11 | 1.06 | 0.05 | 4% | 64.0 |
| | Sierra | 1.18 | 1.13 | 0.05 | 4% | 61.0 |
| | Stockton | 1.14 | 1.08 | 0.06 | 5% | 63.5 |
| | **All** | **1.06** | **1.02** | **0.04** | **4%** | **63.0** |

## 7.5 Bill Impacts for TOU

Table 7-9 shows the average monthly, seasonal and annual bills under rates E-1, E-6 and E-7 for the sample of currently enrolled E-6 and E-7 customers. In addition, the table shows the percent change in bills these customers experienced by being on E-6 or E-7; it also shows the percentage of customers that experienced lower bills. The average customer experienced bill decreases in all winter months and average bill increases in summer months. Bill decreases were greatest during the winter when, on average, customers saved 18%. Over the course of the entire year, the average customer in the sample saved about 5%, while 76% of customers experienced bill savings of some kind. Most customers experienced bill savings because they have responded to the price signals inherent in the E-6 and E-7 tariffs: they consume less electricity during expensive peak periods than they increase usage during cheaper off-peak periods.

Bills were calculated using hourly interval data for the sample of 50,000 currently enrolled E-6 and E-7 customers. This interval data was used to calculate both the E-1, E-6 and E-7 bills because the model used to determine the E-6 and E-7 impacts does not predict what customers' usage would have been if they had been E-1 customers. Thus, both bills in Table 7-9 are calculated using the E-6 and E-7 sample's actual load profiles.

The rate schedules used to calculate bills were those in effect in the summer of 2014. The 4,700 CARE customers in the sample are billed under the CARE rate. Thus, the bills shown in Table 7-9 average both CARE and non-CARE bills. In addition, customers are allotted a baseline allowance based on their end usage (basic service versus all-electric service) and climate zone, as is the case when PG&E calculates actual customer bills.

**Table 7-9: TOU Treatment Group Customer Bill Impacts by Month**

| Month | Average Bill | | Percent Change | 90% of Customers Experience Change Between… | | Percent of Customers Experiencing Lower Bills |
|---|---|---|---|---|---|---|
| | E-1 | E-6 and E-7 | | Lower Bound | Upper Bound | |
| Nov-14 | $111 | $90 | -19% | -34% | -3% | 98% |
| Dec-14 | $155 | $129 | -17% | -32% | -2% | 97% |
| Jan-15 | $129 | $105 | -18% | -34% | -3% | 97% |
| Feb-15 | $106 | $86 | -18% | -34% | -3% | 97% |
| Mar-15 | $97 | $78 | -19% | -34% | -4% | 98% |
| Apr-15 | $99 | $80 | -19% | -34% | -4% | 97% |
| May-15 | $108 | $113 | 5% | -20% | 30% | 34% |
| Jun-15 | $120 | $130 | 9% | -14% | 32% | 23% |
| Jul-15 | $156 | $169 | 9% | -17% | 34% | 25% |
| Aug-15 | $125 | $136 | 9% | -17% | 35% | 23% |
| Sep-15 | $119 | $127 | 7% | -17% | 31% | 30% |
| Oct-15 | $107 | $114 | 6% | -21% | 33% | 28% |
| **Summer** | **$711** | **$764** | **8%** | **-16%** | **32%** | **25%** |
| **Winter** | **$669** | **$545** | **-18%** | **-33%** | **-4%** | **97%** |
| **Annual** | **$1,298** | **$1,232** | **-5%** | **-23%** | **13%** | **76%** |

# 8 TOU Ex Ante Load Impacts

This section summarizes the ex ante evaluation methodology and results for the E-6 and E-7 tariffs. The estimates presented here exclude the approximately 65,000 net-metered customers that have solar panels because they are already accounted for through the evaluation of solar programs.

## 8.1 Methodology

The ex ante methodology used here is conceptually similar to the methodology used to estimate ex ante SmartRate impacts that was described in Section 5 but the details differ. For the E-6 tariff, the approach uses the ex post estimates described in Section 7 as the dependent variable in a regression model relating load impacts to weather conditions. The estimates were developed through the following four steps:

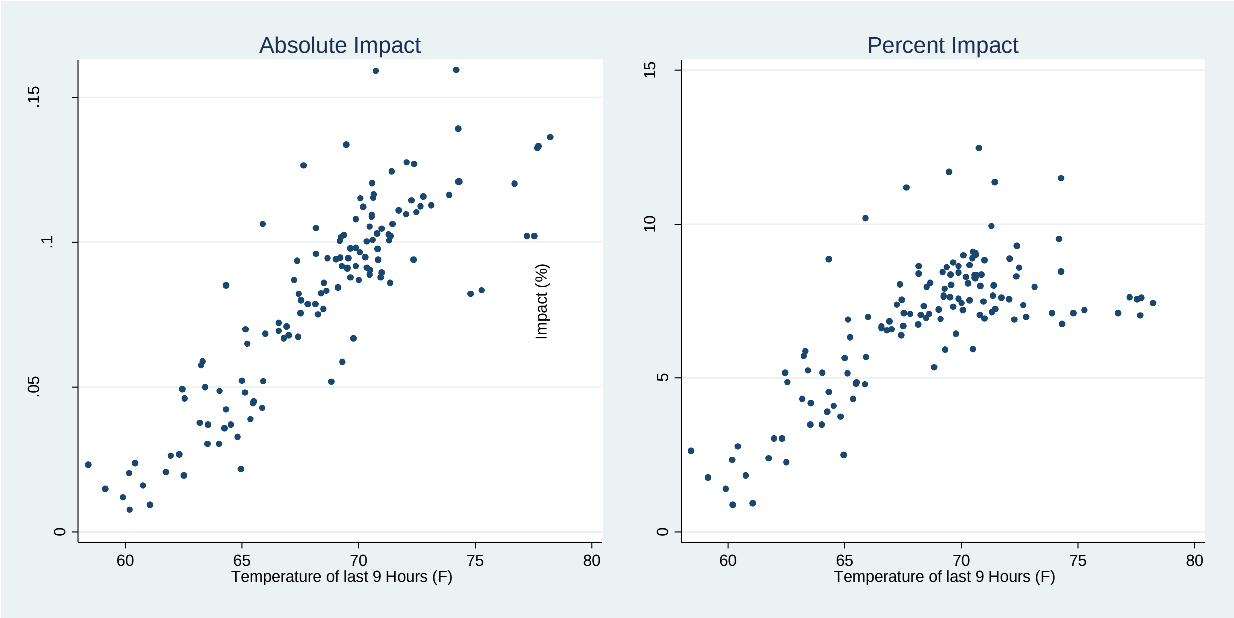
1. Assess how TOU impacts in each hour vary, by LCA, as a function of weather conditions using regression.
2. Assess how reference load in each hour varies, by LCA, as a function of weather conditions using regression.
3. Predict the reference loads and load impacts as a function of ex ante weather conditions for both PG&E and CAISO peak scenarios.
4. Combine the reference loads and load impacts to fulfill the requirements of the CPUC Load Impact Protocols showing load with and without DR in effect.

For the E-7 tariff, the above steps were followed but instead of using the impacts before making the adjustment for self-selection as described in Section 6, Table 6-1, the regression was estimated using the adjusted impacts. Only 2014 data was used to estimate the ex ante impacts this year because this is the only year that has sufficient data to estimate separate models for the E-6 and E-7 rates.

Figures 8-1 and 8-2 show scatter plots of absolute (kW) and relative (percentage) E-6 and E-7 TOU impacts during the peak period from 1 to 6 PM by temperature for summer weekdays. As seen, there is a very strong relationship between temperature and TOU demand reductions, although there is also a fair amount of variation across different days with similar weather conditions.

**Figure 8-1: Average Peak Period Impacts by Temperature (mean9) for the E-6 Tariff**


**Figure 8-2: Average Peak Period Impacts by Temperature (mean9) for the E-7 Tariff**




Separate regression models relating TOU load impacts and reference loads to weather were estimated for each hour, season (summer/winter), and local capacity area. Both the impact and reference load models used the same explanatory variable, which is the average temperature for the nine hours preceding each hour. Mathematically, the models used for ex ante estimation can be expressed by the following two equations (Table 8-1 defines the variables and terms in the regressions).

| | |
|---|---|
| **Variation in TOU Impacts** | $\Delta kW_{t,LCA,season} = a + b * \text{last\_nine\_temp}_{t,LCA,season} + \epsilon$ |
| **Variation in Reference loads** | $kW_{t,LCA,season} = a + b * \text{last\_nine\_temp}_{t,LCA,season} + \epsilon$ |

**Table 8-1: Impact Regression Parameters and Description**

| Variable | Description |
|---|---|
| $\Delta kW$ | The difference between the control group and TOU groups for each hour and date in 2014. The treatment and control groups are the same as those used for the ex post evaluation. |
| *kW* | Load in each hour |
| *a,b* | Estimated coefficients |
| $t, LCA, season$ | Indicators for the unit of analysis. The model is estimated for each LCA at each hour of the day for each season (winter or summer). |
| mean9 | Average temperature over the last nine hours for the specific hour (˚F). |
| $\epsilon$ | The error term. |

Separate regression models were estimated for each hour using hourly impacts (or loads for the reference load modeling) for each weekday. This dataset works very well for estimating impacts and reference loads for the average weekday. The same model is used to predict impacts for the average weekday and the monthly peak day. It will also predict well for the monthly peak day if the relationship between weather and impacts is linear. As it turns out, the model appears to under predict for monthly peak days, suggesting the relationship is not linear. For future evaluations, a non-linear specification might be considered or, alternatively, a separate model could be estimated using data from weekdays with temperatures exceeding a certain temperature threshold or using only the top five highest load days from each month for example.

In keeping with the requirements of the CPUC Load Impact Protocols, ex ante impact estimates were developed for the following customer segments and event conditions:

- 24 day types in each year (i.e., the monthly system peak day and average weekday for each month);
- 8 local capacity area (LCA) regions plus the service territory as a whole;
- 2 weather years (i.e., with 1-in-10 and 1-in-2 year conditions);
- 2 peak operational conditions (PG&E and CAISO);
- 11 forecast years (i.e., 2015 through 2025); and
- 2 customer groups (i.e., average and aggregate).

Hourly estimates for the almost 17,000 distinct combinations of the above factors are provided electronically with this report.

## 8.2 Enrollment Forecast

E-7 is a closed rate. Customers not currently served under the rate schedule are not allowed to obtain E-7 service. Because of this, the only factor impacting enrollment for the E-7 rate is attrition, as customers drop out or close their accounts over time. The assumed annual attrition rate is roughly 6% which leads to 45% drop in the E-7 population between 2015 and 2025. On the other hand, the E-6 population is forecasted to increase significantly over the forecast horizon, more than tripling from almost 10,000 customers in 2015 to 35,000 in 2025. This estimate is similar to last year's ex ante forecast, which predicted E-6 enrollment of almost 32,000 by 2024. These two trends combined produce a modest increase in enrollment for roughly 6% for the two rates combined. As another reminder, these forecasts represent non-net metered customers only. Enrollment by net-metered (e.g., solar) customers has been much greater in recent years than for non-net-metered customers and that is expected to continue.

**Table 8-2: Residential TOU Population Forecast, 2015 though 2025**

| Year | E6 Non Net-Metered | E7 Non Net-Metered | Total |
|---|---|---|---|
| 2015 | 10,143 | 47,887 | 58,029 |
| 2016 | 12,678 | 45,091 | 57,769 |
| 2017 | 15,200 | 42,459 | 57,659 |
| 2018 | 17,710 | 39,980 | 57,690 |
| 2019 | 20,209 | 37,646 | 57,856 |
| 2020 | 22,700 | 35,449 | 58,149 |
| 2021 | 25,184 | 33,379 | 58,563 |
| 2022 | 27,661 | 31,431 | 59,092 |
| 2023 | 30,134 | 29,596 | 59,730 |
| 2024 | 32,602 | 27,868 | 60,470 |
| 2025 | 35,068 | 26,241 | 61,309 |

## 8.3 TOU Ex Ante Load Impacts

This section summarizes the estimated load impacts for E-6 and E-7 based on ex ante weather conditions and the RA event window from 1 to 6 PM in the summer and from 4 to 9 PM in the winter. As explained in Section 5.2, ex ante load impacts are required for both normal (1-in-2 years) and extreme (1-in-10 years) weather conditions and, for the first time this year, for weather scenarios based on both PG&E-specific and CAISO-specific operating conditions. The CPUC Load Impact Protocols also require that impacts be developed for the monthly system peak day and the average weekday for non-event based programs such as TOU rates. As such, load impact estimates have been developed for 8 different sets of ex ante conditions for each TOU rate (e.g., monthly peak day and average weekday for normal and extreme weather conditions based on PG&E and CAISO operating conditions).

Both the E-6 and E-7 tariffs have peak periods in the summer that cover the entire RA window from 1 to 6 PM. In the winter, the RA window is from 4 to 9 PM. For the E-6 tariff, peak prices are not in effect in the winter and partial peak prices are only in effect from 5 to 8 PM. For the E-7 tariff, the summer peak period from noon to 6 PM is still in effect. Given these differences in rate periods and the RA window, ex ante impacts in the winter are quite modest for both rates because off-peak prices are actually in effect during much of the RA window. For the E-6 tariff, off-peak prices are in effect from 4 to 5 PM and from 8 to 9 PM and for the E-7 tariff, off-peak prices are in effect from 6 to 9 PM.

Tables 8-3 and 8-4 show the ex ante, aggregate load impact estimates for the E-6 tariff for monthly peak days and for the average weekday, respectively, for four sets of weather conditions and two forecast years, 2015 and 2025. The tables also show the percent reductions in each month, which do not change over the forecast horizon, and the average temperatures during the RA window in each month, which are also constant across years.

Looking first at the monthly peak day values, aggregate impacts are greatest in July under both normal and extreme weather scenarios based on PG&E operational conditions and also for the CAISO based 1-in-10 year weather conditions. The largest aggregate impact under CAISO 1-in-2 year weather conditions occurs in June. Temperatures during the RA window are lower under the CAISO scenarios than under the PG&E scenarios and lead to lower impacts, in the range of 5 to 15% lower in summer months. Although the load reductions are in the range of 20% of household load during the peak summer months, the 8,900 customers expected to be enrolled in 2015 collectively only produce peak period impacts between 2 and 3 MW in the summer. The aggregate impacts in each month more than triple over the forecast horizon due to the increase in enrolment. Load impacts are much lower in both percentage and absolute terms in the winter than in the summer due, at least in part, to the misalignment between rate periods and the RA window in the winter.

A careful review of the tables will find that there are instances where impacts appear to be identical for different weather scenarios that have slightly different temperatures and instances where the reported temperatures are the same but impacts are slightly different. This is because the ex ante estimates are based on a model that uses the average temperature in the 9 hours preceding each hour to capture the influence of heat buildup rather than the average temperature across the RA event window. Put another way, the temperatures in the table are a rough guide to variation across months and weather scenarios, but they are not the variables that are used in the model and there are days that have the same RA window temperatures but different temperatures in the hours leading up to the event window, which can lead to differences in impacts.

Table 8-4 summarizes impact estimates for the average weekday in each month. In the summer months, average weekday impacts are 25% to 40% lower than monthly peak day impacts. In the winter, average weekday impacts are actually a bit higher than monthly peak day estimates. The variation in impacts across months and weather scenarios is similar for average weekday estimates and monthly peak day estimates.

## Table 8-3: E-6 Monthly System Peak Day Aggregate Impact Estimates

| Weather Conditions | Forecast Year | Accounts | Variable | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PG&E 1-in-2 | 2015 | 8,869 | MW Impact | 0.42 | 0.46 | 0.52 | 0.76 | 1.68 | 2.26 | 2.38 | 2.36 | 2.31 | 1.62 | 0.66 | 0.59 |
| | 2025 | 33,835 | MW Impact | 1.59 | 1.74 | 1.91 | 2.74 | 6.00 | 7.94 | 8.23 | 8.05 | 7.75 | 5.37 | 2.15 | 1.90 |
| | 2015-2015 | | % Impact | 4% | 4% | 5% | 7% | 17% | 20% | 20% | 20% | 19% | 16% | 5% | 4% |
| | | | Avg. Peak Temp | 45 | 49 | 51 | 70 | 81 | 87 | 89 | 89 | 89 | 80 | 53 | 48 |
| PG&E 1-in-10 | 2015 | 8,869 | MW Impact | 0.39 | 0.43 | 0.55 | 0.89 | 2.39 | 2.65 | 2.71 | 2.64 | 2.42 | 2.26 | 0.74 | 0.50 |
| | 2025 | 33,835 | MW Impact | 1.49 | 1.63 | 2.01 | 3.24 | 8.53 | 9.30 | 9.37 | 8.98 | 8.14 | 7.49 | 2.41 | 1.62 |
| | 2015-2015 | | % Impact | 3% | 4% | 5% | 9% | 20% | 21% | 21% | 21% | 20% | 19% | 6% | 3% |
| | | | Avg. Peak Temp | 43 | 45 | 53 | 81 | 90 | 95 | 93 | 92 | 91 | 90 | 57 | 42 |
| CAISO 1-in-2 | 2015 | 8,869 | MW Impact | 0.42 | 0.46 | 0.52 | 0.77 | 1.59 | 2.26 | 2.21 | 2.01 | 1.97 | 1.68 | 0.78 | 0.61 |
| | 2025 | 33,835 | MW Impact | 1.60 | 1.73 | 1.91 | 2.78 | 5.67 | 7.94 | 7.65 | 6.83 | 6.60 | 5.57 | 2.54 | 1.96 |
| | 2015-2015 | | % Impact | 4% | 4% | 5% | 8% | 17% | 20% | 19% | 18% | 18% | 17% | 6% | 4% |
| | | | Avg. Peak Temp | 46 | 48 | 52 | 72 | 78 | 89 | 85 | 86 | 84 | 83 | 61 | 50 |
| CAISO 1-in-10 | 2015 | 8,869 | MW Impact | 0.41 | 0.50 | 0.66 | 0.87 | 1.97 | 2.27 | 2.60 | 2.48 | 2.23 | 2.02 | 0.79 | 0.54 |
| | 2025 | 33,835 | MW Impact | 1.55 | 1.87 | 2.42 | 3.17 | 7.03 | 7.97 | 8.99 | 8.46 | 7.50 | 6.70 | 2.59 | 1.75 |
| | 2015-2015 | | % Impact | 4% | 4% | 6% | 9% | 19% | 20% | 21% | 20% | 19% | 18% | 6% | 4% |
| | | | Avg. Peak Temp | 44 | 51 | 62 | 81 | 85 | 88 | 92 | 89 | 88 | 84 | 63 | 45 |

## Table 8-4: E-6 Average Weekday Aggregate Impact Estimates

| Weather Conditions | Forecast Year | Accounts | Variable | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PG&E 1-in-2 | 2015 | 8,869 | MW Impact | 0.48 | 0.51 | 0.57 | 0.61 | 0.96 | 1.41 | 1.76 | 1.73 | 1.41 | 0.96 | 0.69 | 0.61 |
| | 2025 | 33,835 | MW Impact | 1.82 | 1.93 | 2.09 | 2.21 | 3.44 | 4.94 | 6.08 | 5.88 | 4.75 | 3.16 | 2.26 | 1.98 |
| | 2015-2015 | | % Impact | 4% | 5% | 5% | 5% | 13% | 16% | 17% | 17% | 15% | 12% | 5% | 4% |
| | | | Avg. Peak Temp | 50 | 53 | 56 | 60 | 71 | 76 | 80 | 80 | 76 | 71 | 56 | 51 |
| PG&E 1-in-10 | 2015 | 8,869 | MW Impact | 0.47 | 0.50 | 0.50 | 0.66 | 1.44 | 1.68 | 1.99 | 1.95 | 1.73 | 1.18 | 0.72 | 0.57 |
| | 2025 | 33,835 | MW Impact | 1.80 | 1.89 | 1.86 | 2.40 | 5.12 | 5.89 | 6.89 | 6.64 | 5.81 | 3.90 | 2.35 | 1.83 |
| | 2015-2015 | | % Impact | 4% | 5% | 4% | 6% | 16% | 17% | 18% | 18% | 17% | 13% | 6% | 4% |
| | | | Avg. Peak Temp | 50 | 52 | 50 | 63 | 78 | 78 | 83 | 83 | 81 | 74 | 57 | 47 |
| CAISO 1-in-2 | 2015 | 8,869 | MW Impact | 0.47 | 0.53 | 0.55 | 0.63 | 1.07 | 1.34 | 1.88 | 1.79 | 1.51 | 0.96 | 0.70 | 0.63 |
| | 2025 | 33,835 | MW Impact | 1.79 | 1.99 | 2.01 | 2.30 | 3.82 | 4.69 | 6.51 | 6.08 | 5.07 | 3.16 | 2.28 | 2.04 |
| | 2015-2015 | | % Impact | 4% | 5% | 5% | 6% | 13% | 15% | 18% | 17% | 16% | 12% | 5% | 5% |
| | | | Avg. Peak Temp | 50 | 55 | 53 | 62 | 71 | 76 | 82 | 81 | 79 | 71 | 55 | 53 |
| CAISO 1-in-10 | 2015 | 8,869 | MW Impact | 0.47 | 0.57 | 0.50 | 0.66 | 1.03 | 1.55 | 1.80 | 1.76 | 1.78 | 1.12 | 0.69 | 0.60 |
| | 2025 | 33,835 | MW Impact | 1.80 | 2.13 | 1.86 | 2.40 | 3.67 | 5.46 | 6.21 | 5.99 | 5.97 | 3.70 | 2.26 | 1.94 |
| | 2015-2015 | | % Impact | 4% | 5% | 4% | 6% | 13% | 16% | 17% | 17% | 17% | 13% | 5% | 4% |
| | | | Avg. Peak Temp | 50 | 57 | 50 | 63 | 73 | 79 | 81 | 80 | 81 | 75 | 56 | 49 |

Tables 8-5 and 8-6 summarize the ex ante monthly peak day and average weekday load impact estimates for the E-7 tariff. There are roughly five times more customers enrolled in E-7 compared with E-6 in 2015 but enrollment drops significantly over the forecast horizon. By 2025, E-6 enrollment is 25% greater than E-7 enrollment and aggregate impacts for E-6 are roughly 90% greater than for E-7.

Aggregate monthly peak day impacts in 2015 for the E-7 tariff are the largest in July under 1-in-2 year weather conditions for the PG&E operational scenarios and largest in June under 1-in-10 year weather conditions. The maximum aggregate load reductions equal 7.8 MW under normal weather conditions and 9.0 MW under extreme weather conditions. The maximum load reductions under the CAISO weather scenarios are 7.7 MW for June 1-in-2 year weather and 8.6 MW for July 1-in-10 year weather conditions. These reductions equal roughly 10% of household load during the peak period. Average weekday load reductions during the summer months are in the 8 to 9% range but the reference loads are lower on the average weekday than on the monthly peak day. As such, aggregate impacts for the average weekday are 30% to 40% less than for the monthly peak day. As was true for the E-6 tariff, the winter load impacts are slightly higher for the average weekday than for the monthly peak day. Given that off-peak prices are in effect for much of the RA window in the winter for the E-7 tariff, aggregate load impacts for the nearly 50,000 customers on the rate in 2015 amount to less than 1 MW and, in fact, are quite similar in magnitude to impacts for the E-6 tariff in spite of the much smaller number of enrolled customers.

Figures 8-3 and 8-4 show estimates of hourly load impacts for the July monthly peak day for the average E-6 and E-7 customer, respectively, based on the PG&E 1-in-2 year weather conditions. For E-6, the average impacts per customer across the RA window from 1 to 6 PM equal 0.23 kW, or 20% of household load. The impacts vary from a low of 0.19 kW in the hour from 1 to 2 PM to a high of 0.27 kW in the hour from 5 to 6 PM. Percent reductions range from 18% to 21%, with the highest percent reduction occurring between 2 and 4 PM. The average impact for E-7 is 0.16 kW, or 10% of whole house load. As with E-6, the absolute and percent reductions are lowest in the first hour. However, unlike with E-6, the last hour from 5 to 6 PM sees a drop off in load reductions. Figures 8-5 and 8-6 represent the July monthly peak day based on the CAISO weather conditions and show a similar pattern as for the PG&E weather conditions, although the average impacts are a bit lower overall.

**Table 8-5: E-7 Monthly System Peak Day Aggregate Impact Estimates**

| Weather Conditions | Forecast Year | Accounts | Variable | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PG&E 1-in-2 | 2015 | 49,349 | MW Impact | 0.48 | 0.55 | 0.60 | 0.89 | 5.80 | 7.66 | 7.82 | 7.55 | 7.17 | 4.84 | 0.61 | 0.51 |
| | 2025 | 27,042 | MW Impact | 0.26 | 0.30 | 0.33 | 0.49 | 3.18 | 4.20 | 4.29 | 4.14 | 3.93 | 2.65 | 0.33 | 0.28 |
| | 2015-2015 | | % Impact | 1% | 1% | 1% | 1% | 9% | 10% | 10% | 10% | 9% | 8% | 1% | 1% |
| | | | Avg. Peak Temp | 45 | 49 | 51 | 71 | 83 | 90 | 92 | 91 | 91 | 81 | 53 | 48 |
| PG&E 1-in-10 | 2015 | 49,349 | MW Impact | 0.46 | 0.51 | 0.63 | 1.02 | 8.35 | 8.98 | 8.94 | 8.45 | 7.62 | 6.82 | 0.68 | 0.44 |
| | 2025 | 27,042 | MW Impact | 0.25 | 0.28 | 0.35 | 0.56 | 4.57 | 4.92 | 4.90 | 4.63 | 4.17 | 3.74 | 0.37 | 0.24 |
| | 2015-2015 | | % Impact | 1% | 1% | 1% | 2% | 10% | 10% | 10% | 10% | 10% | 9% | 1% | 1% |
| | | | Avg. Peak Temp | 42 | 45 | 53 | 82 | 92 | 97 | 96 | 94 | 93 | 91 | 57 | 42 |
| CAISO 1-in-2 | 2015 | 49,349 | MW Impact | 0.50 | 0.55 | 0.60 | 0.89 | 5.44 | 7.66 | 7.17 | 6.29 | 5.98 | 4.98 | 0.70 | 0.54 |
| | 2025 | 27,042 | MW Impact | 0.27 | 0.30 | 0.33 | 0.49 | 2.98 | 4.20 | 3.93 | 3.45 | 3.28 | 2.73 | 0.38 | 0.30 |
| | 2015-2015 | | % Impact | 1% | 1% | 1% | 1% | 8% | 10% | 9% | 9% | 9% | 8% | 1% | 1% |
| | | | Avg. Peak Temp | 46 | 47 | 52 | 73 | 80 | 91 | 87 | 88 | 86 | 84 | 61 | 49 |
| CAISO 1-in-10 | 2015 | 49,349 | MW Impact | 0.47 | 0.58 | 0.78 | 1.00 | 6.70 | 7.62 | 8.56 | 7.95 | 6.88 | 6.04 | 0.73 | 0.47 |
| | 2025 | 27,042 | MW Impact | 0.26 | 0.32 | 0.43 | 0.55 | 3.67 | 4.17 | 4.69 | 4.36 | 3.77 | 3.31 | 0.40 | 0.26 |
| | 2015-2015 | | % Impact | 1% | 1% | 1% | 2% | 9% | 10% | 10% | 10% | 9% | 9% | 1% | 1% |
| | | | Avg. Peak Temp | 43 | 50 | 63 | 82 | 87 | 90 | 94 | 91 | 90 | 85 | 62 | 45 |

### Table 8-6: E-7 Average Weekday Aggregate Impact Estimates

| Weather Conditions | Forecast Year | Accounts | Variable | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PG&E 1-in-2 | 2015 | 49,349 | MW Impact | 0.57 | 0.60 | 0.66 | 0.69 | 3.15 | 4.60 | 5.66 | 5.41 | 4.37 | 2.81 | 0.64 | 0.56 |
| | 2025 | 27,042 | MW Impact | 0.31 | 0.33 | 0.36 | 0.38 | 1.73 | 2.52 | 3.10 | 2.97 | 2.39 | 1.54 | 0.35 | 0.30 |
| | 2015-2015 | | % Impact | 1% | 1% | 1% | 1% | 6% | 8% | 9% | 8% | 8% | 6% | 1% | 1% |
| | | | Avg. Peak Temp | 50 | 53 | 56 | 60 | 71 | 78 | 81 | 81 | 77 | 72 | 56 | 51 |
| PG&E 1-in-10 | 2015 | 49,349 | MW Impact | 0.57 | 0.59 | 0.58 | 0.76 | 4.83 | 5.55 | 6.46 | 6.14 | 5.29 | 3.50 | 0.67 | 0.50 |
| | 2025 | 27,042 | MW Impact | 0.31 | 0.32 | 0.32 | 0.42 | 2.65 | 3.04 | 3.54 | 3.36 | 2.90 | 1.92 | 0.37 | 0.27 |
| | 2015-2015 | | % Impact | 1% | 1% | 1% | 1% | 8% | 9% | 9% | 9% | 8% | 7% | 1% | 1% |
| | | | Avg. Peak Temp | 49 | 51 | 50 | 64 | 79 | 80 | 85 | 85 | 82 | 75 | 57 | 46 |
| CAISO 1-in-2 | 2015 | 49,349 | MW Impact | 0.53 | 0.64 | 0.64 | 0.72 | 3.58 | 4.32 | 6.09 | 5.62 | 4.61 | 2.81 | 0.65 | 0.57 |
| | 2025 | 27,042 | MW Impact | 0.29 | 0.35 | 0.35 | 0.40 | 1.96 | 2.37 | 3.34 | 3.08 | 2.53 | 1.54 | 0.36 | 0.31 |
| | 2015-2015 | | % Impact | 1% | 1% | 1% | 1% | 7% | 8% | 9% | 9% | 8% | 6% | 1% | 1% |
| | | | Avg. Peak Temp | 49 | 55 | 53 | 62 | 72 | 77 | 83 | 83 | 80 | 72 | 55 | 53 |
| CAISO 1-in-10 | 2015 | 49,349 | MW Impact | 0.57 | 0.68 | 0.58 | 0.76 | 3.45 | 5.13 | 5.79 | 5.48 | 5.46 | 3.29 | 0.64 | 0.53 |
| | 2025 | 27,042 | MW Impact | 0.31 | 0.37 | 0.32 | 0.42 | 1.89 | 2.81 | 3.17 | 3.00 | 2.99 | 1.80 | 0.35 | 0.29 |
| | 2015-2015 | | % Impact | 1% | 1% | 1% | 1% | 7% | 8% | 9% | 9% | 9% | 7% | 1% | 1% |
| | | | Avg. Peak Temp | 49 | 57 | 50 | 64 | 74 | 80 | 83 | 82 | 83 | 76 | 56 | 49 |

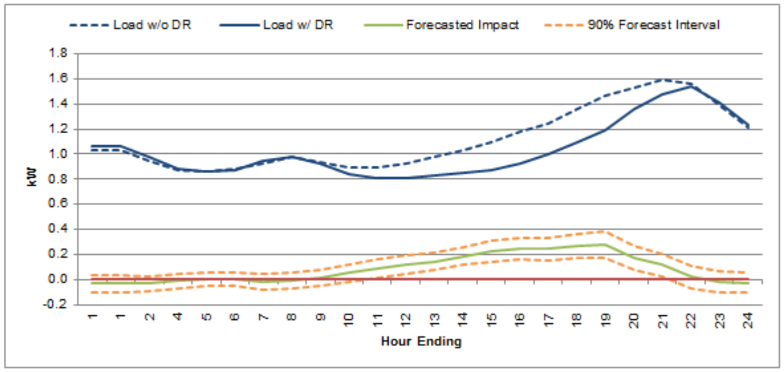
## Figure 8-3: Average E-6 Non-net Metered Customer Hourly Load Impact Estimates (July Monthly Peak Day, PG&E 1-in-2 Year Weather Conditions)

**Menu Options**

| | |
|---|---|
| Result Type | Average Customer |
| Day Type | Monthly System Peak Day |
| Weather Scenario | PG&E |
| Month | July |
| Weather Year | 1-in-2 |
| Capacity Area | All |
| Year | 2015 |
| Rate | E6 |

**Peak Information**

| | |
|---|---|
| Population (2015) | 10,143 |
| Peak Period Start | 1 PM |
| Peak Period Stop | 6 PM |
| Peak Period Reference Load (kW) | 1.18 |
| Peak Period Reduction (kW) | 0.23 |
| Peak Period Reduction (%) | 20% |




| Hour Ending | Load w/o DR | Load w/ DR | Impact | Impact | Temp. | Uncertainty Adjusted Impact Percentiles | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (kW) | (kW) | (kW) | (%) | (°F) | 10% | 30% | 50% | 70% | 90% | * |
| 1 | 1.03 | 1.07 | -0.03 | -3.0% | 66.9 | -0.10 | -0.06 | -0.03 | 0.00 | 0.04 | * |
| 2 | 1.03 | 1.07 | -0.03 | -3.0% | 66.9 | -0.10 | -0.06 | -0.03 | 0.00 | 0.04 | * |
| 3 | 0.95 | 0.98 | -0.03 | -3.3% | 65.8 | -0.09 | -0.06 | -0.03 | -0.01 | 0.03 | * |
| 4 | 0.87 | 0.88 | -0.01 | -1.3% | 63.7 | -0.07 | -0.03 | -0.01 | 0.01 | 0.04 | * |
| 5 | 0.87 | 0.86 | 0.01 | 0.7% | 62.9 | -0.05 | -0.02 | 0.01 | 0.03 | 0.06 | * |
| 6 | 0.88 | 0.88 | 0.00 | 0.4% | 62.4 | -0.05 | -0.02 | 0.00 | 0.03 | 0.06 | * |
| 7 | 0.93 | 0.94 | -0.01 | -1.5% | 62.7 | -0.08 | -0.04 | -0.01 | 0.01 | 0.05 | * |
| 8 | 0.97 | 0.98 | -0.01 | -0.8% | 66.3 | -0.07 | -0.03 | -0.01 | 0.02 | 0.06 | * |
| 9 | 0.94 | 0.93 | 0.01 | 1.4% | 70.8 | -0.05 | -0.01 | 0.01 | 0.04 | 0.08 | * |
| 10 | 0.90 | 0.84 | 0.05 | 6.0% | 75.4 | -0.01 | 0.03 | 0.05 | 0.08 | 0.12 | * |
| 11 | 0.89 | 0.80 | 0.09 | 10.0% | 79.6 | 0.02 | 0.06 | 0.09 | 0.12 | 0.16 | |
| 12 | 0.92 | 0.80 | 0.12 | 13.1% | 83.3 | 0.05 | 0.09 | 0.12 | 0.15 | 0.19 | |
| 13 | 0.98 | 0.83 | 0.15 | 15.0% | 86.3 | 0.08 | 0.12 | 0.15 | 0.18 | 0.22 | |
| 14 | 1.04 | 0.85 | 0.19 | 18% | 88.6 | 0.12 | 0.16 | 0.19 | 0.22 | 0.26 | |
| 15 | 1.10 | 0.87 | 0.23 | 21% | 89.7 | 0.14 | 0.19 | 0.23 | 0.26 | 0.31 | |
| 16 | 1.18 | 0.93 | 0.25 | 21% | 90.0 | 0.16 | 0.21 | 0.25 | 0.28 | 0.33 | |
| 17 | 1.25 | 1.00 | 0.25 | 20% | 89.5 | 0.16 | 0.21 | 0.25 | 0.28 | 0.34 | |
| 18 | 1.36 | 1.09 | 0.27 | 20% | 88.3 | 0.17 | 0.23 | 0.27 | 0.31 | 0.36 | |
| 19 | 1.47 | 1.19 | 0.28 | 19% | 85.7 | 0.18 | 0.24 | 0.28 | 0.32 | 0.38 | |
| 20 | 1.53 | 1.35 | 0.18 | 12% | 81.7 | 0.08 | 0.14 | 0.18 | 0.22 | 0.27 | * |
| 21 | 1.59 | 1.47 | 0.12 | 7% | 76.6 | 0.02 | 0.08 | 0.12 | 0.15 | 0.21 | * |
| 22 | 1.56 | 1.54 | 0.02 | 1.5% | 72.8 | -0.07 | -0.01 | 0.02 | 0.06 | 0.11 | * |
| 23 | 1.39 | 1.41 | -0.02 | -1.3% | 70.4 | -0.10 | -0.05 | -0.02 | 0.02 | 0.07 | * |
| 24 | 1.21 | 1.23 | -0.02 | -1.9% | 68.6 | -0.10 | -0.05 | -0.02 | 0.01 | 0.05 | |
| **Peak** | **1.18** | **0.95** | **0.23** | **19.9%** | **89.2** | **0.15** | **0.20** | **0.23** | **0.27** | **0.32** | |

** The impacts in this hour are not statistically significant at the 95% level.*

Note: Program Specific and Portfolio Adjusted impacts are the same for Residential TOU

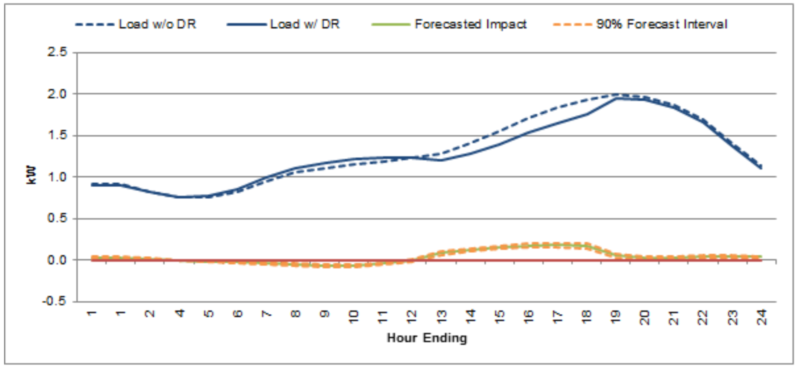
**Figure 8-4: Average E-7 Non-net Metered Customer Hourly Load Impact Estimates (July Monthly Peak Day, PG&E 1-in-2 Year Weather Conditions)**

**Menu Options**

| | |
|---|---|
| Result Type | Average Customer |
| Day Type | Monthly System Peak Day |
| Weather Scenario | PG&E |
| Month | July |
| Weather Year | 1-in-2 |
| Capacity Area | All |
| Year | 2015 |
| Rate | E7 |

**Peak Information**

| | |
|---|---|
| Population (2015) | 47,887 |
| Peak Period Start | 1 PM |
| Peak Period Stop | 6 PM |
| Peak Period Reference Load (kW) | 1.69 |
| Peak Period Reduction (kW) | 0.16 |
| Peak Period Reduction (%) | 10% |




| Hour Ending | Load w/o DR (kW) | Load w/ DR (kW) | Impact (kW) | Impact (%) | Temp. (°F) | Uncertainty Adjusted Impact Percentiles 10% | 30% | 50% | 70% | 90% |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.92 | 0.90 | 0.03 | 2.7% | 68.5 | 0.01 | 0.02 | 0.03 | 0.03 | 0.04 |
| 2 | 0.92 | 0.90 | 0.03 | 2.7% | 68.5 | 0.01 | 0.02 | 0.03 | 0.03 | 0.04 |
| 3 | 0.83 | 0.82 | 0.01 | 1.6% | 67.1 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 |
| 4 | 0.75 | 0.76 | 0.00 | -0.6% | 64.8 | -0.01 | -0.01 | 0.00 | 0.00 | 0.00 |
| 5 | 0.76 | 0.77 | -0.01 | -1.8% | 63.9 | -0.02 | -0.02 | -0.01 | -0.01 | -0.01 |
| 6 | 0.82 | 0.85 | -0.03 | -3.1% | 63.3 | -0.03 | -0.03 | -0.03 | -0.02 | -0.02 |
| 7 | 0.95 | 0.99 | -0.04 | -4.5% | 63.6 | -0.05 | -0.05 | -0.04 | -0.04 | -0.03 |
| 8 | 1.06 | 1.11 | -0.05 | -5.1% | 67.4 | -0.07 | -0.06 | -0.05 | -0.05 | -0.04 |
| 9 | 1.11 | 1.17 | -0.07 | -6.2% | 72.2 | -0.08 | -0.07 | -0.07 | -0.06 | -0.06 |
| 10 | 1.15 | 1.22 | -0.07 | -5.7% | 76.9 | -0.08 | -0.07 | -0.07 | -0.06 | -0.05 |
| 11 | 1.19 | 1.24 | -0.04 | -3.6% | 81.3 | -0.06 | -0.05 | -0.04 | -0.04 | -0.03 |
| 12 | 1.23 | 1.24 | 0.00 | -0.2% | 85.1 | -0.02 | -0.01 | 0.00 | 0.00 | 0.01 |
| 13 | 1.28 | 1.20 | 0.08 | 6.6% | 88.2 | 0.07 | 0.08 | 0.08 | 0.09 | 0.10 |
| 14 | 1.41 | 1.28 | 0.13 | 9% | 90.7 | 0.11 | 0.12 | 0.13 | 0.14 | 0.15 |
| 15 | 1.55 | 1.40 | 0.16 | 10% | 92.1 | 0.13 | 0.15 | 0.16 | 0.16 | 0.18 |
| 16 | 1.71 | 1.53 | 0.18 | 10% | 92.5 | 0.15 | 0.17 | 0.18 | 0.19 | 0.20 |
| 17 | 1.84 | 1.65 | 0.18 | 10% | 92.2 | 0.16 | 0.17 | 0.18 | 0.19 | 0.21 |
| 18 | 1.93 | 1.76 | 0.17 | 9% | 91.2 | 0.15 | 0.16 | 0.17 | 0.18 | 0.20 |
| 19 | 2.00 | 1.95 | 0.05 | 3% | 88.8 | 0.03 | 0.04 | 0.05 | 0.06 | 0.07 |
| 20 | 1.96 | 1.93 | 0.03 | 2% | 84.6 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 |
| 21 | 1.87 | 1.83 | 0.03 | 2% | 79.2 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 |
| 22 | 1.70 | 1.66 | 0.04 | 2.3% | 75.3 | 0.02 | 0.03 | 0.04 | 0.05 | 0.05 |
| 23 | 1.41 | 1.37 | 0.04 | 2.9% | 72.6 | 0.03 | 0.04 | 0.04 | 0.05 | 0.05 |
| 24 | 1.14 | 1.10 | 0.04 | 3.3% | 70.6 | 0.03 | 0.03 | 0.04 | 0.04 | 0.05 |
| **Peak** | **1.69** | **1.52** | **0.16** | **9.7%** | **91.8** | **0.14** | **0.15** | **0.16** | **0.17** | **0.19** |

** The impacts in this hour are not statistically significant at the 95% level*

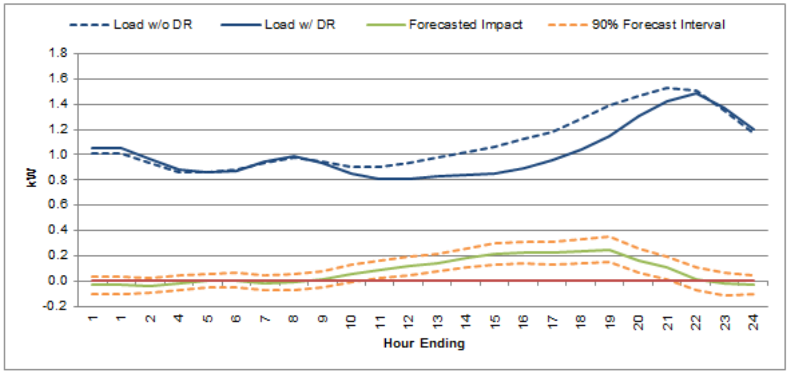
**Figure 8-5: Average E-6 Non-net Metered Customer Hourly Load Impact Estimates (July Monthly Peak Day, CAISO 1-in-2 Year Weather Conditions)**

**Menu Options**

| | |
|---|---|
| Result Type | Average Customer |
| Day Type | Monthly System Peak Day |
| Weather Scenario | CAISO |
| Month | July |
| Weather Year | 1-in-2 |
| Capacity Area | All |
| Year | 2015 |
| Rate | E6 |

**Peak Information**

| | |
|---|---|
| Population (2015) | 10,143 |
| Peak Period Start | 1 PM |
| Peak Period Stop | 6 PM |
| Peak Period Reference Load (kW) | 1.14 |
| Peak Period Reduction (kW) | 0.22 |
| Peak Period Reduction (%) | 19% |




| Hour Ending | Load w/o DR | Load w/ DR | Impact | Impact | Temp. | Uncertainty Adjusted Impact Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (kW) | (kW) | (kW) | (%) | (°F) | 10% | 30% | 50% | 70% | 90% |
| 1 | 1.01 | 1.05 | -0.03 | -3.2% | 67.2 | -0.10 | -0.06 | -0.03 | -0.01 | 0.03 |
| 2 | 1.01 | 1.05 | -0.03 | -3.2% | 67.2 | -0.10 | -0.06 | -0.03 | -0.01 | 0.03 |
| 3 | 0.93 | 0.96 | -0.03 | -3.5% | 66.2 | -0.09 | -0.06 | -0.03 | -0.01 | 0.03 |
| 4 | 0.87 | 0.88 | -0.01 | -1.4% | 64.7 | -0.07 | -0.03 | -0.01 | 0.01 | 0.04 |
| 5 | 0.87 | 0.86 | 0.01 | 0.7% | 64.2 | -0.05 | -0.02 | 0.01 | 0.03 | 0.06 |
| 6 | 0.88 | 0.88 | 0.00 | 0.6% | 63.8 | -0.05 | -0.02 | 0.00 | 0.03 | 0.06 |
| 7 | 0.93 | 0.95 | -0.01 | -1.3% | 63.9 | -0.07 | -0.04 | -0.01 | 0.01 | 0.05 |
| 8 | 0.98 | 0.98 | -0.01 | -0.6% | 66.1 | -0.07 | -0.03 | -0.01 | 0.02 | 0.06 |
| 9 | 0.95 | 0.93 | 0.01 | 1.5% | 69.5 | -0.05 | -0.01 | 0.01 | 0.04 | 0.08 |
| 10 | 0.91 | 0.85 | 0.06 | 6.4% | 72.9 | -0.01 | 0.03 | 0.06 | 0.09 | 0.13 |
| 11 | 0.90 | 0.81 | 0.09 | 10.3% | 76.5 | 0.02 | 0.06 | 0.09 | 0.12 | 0.16 |
| 12 | 0.93 | 0.81 | 0.12 | 13.2% | 79.6 | 0.05 | 0.09 | 0.12 | 0.15 | 0.20 |
| 13 | 0.97 | 0.83 | 0.15 | 14.9% | 82.3 | 0.07 | 0.12 | 0.15 | 0.17 | 0.22 |
| 14 | 1.02 | 0.84 | 0.18 | 18% | 84.3 | 0.11 | 0.15 | 0.18 | 0.21 | 0.25 |
| 15 | 1.06 | 0.85 | 0.21 | 20% | 85.3 | 0.13 | 0.18 | 0.21 | 0.25 | 0.30 |
| 16 | 1.13 | 0.90 | 0.23 | 20% | 85.5 | 0.14 | 0.19 | 0.23 | 0.26 | 0.31 |
| 17 | 1.18 | 0.96 | 0.22 | 19% | 85.2 | 0.13 | 0.19 | 0.22 | 0.26 | 0.31 |
| 18 | 1.28 | 1.05 | 0.24 | 19% | 84.1 | 0.14 | 0.20 | 0.24 | 0.28 | 0.34 |
| 19 | 1.39 | 1.14 | 0.25 | 18% | 82.3 | 0.15 | 0.21 | 0.25 | 0.29 | 0.36 |
| 20 | 1.47 | 1.31 | 0.16 | 11% | 78.9 | 0.06 | 0.12 | 0.16 | 0.20 | 0.26 |
| 21 | 1.53 | 1.42 | 0.11 | 7% | 74.9 | 0.01 | 0.07 | 0.11 | 0.14 | 0.20 |
| 22 | 1.51 | 1.49 | 0.02 | 1.2% | 72.1 | -0.07 | -0.02 | 0.02 | 0.06 | 0.11 |
| 23 | 1.35 | 1.37 | -0.02 | -1.6% | 70.2 | -0.11 | -0.06 | -0.02 | 0.01 | 0.07 |
| 24 | 1.17 | 1.20 | -0.03 | -2.2% | 68.8 | -0.10 | -0.06 | -0.03 | 0.01 | 0.05 |
| **Peak** | **1.14** | **0.92** | **0.22** | **19.2%** | **84.9** | **0.13** | **0.18** | **0.22** | **0.25** | **0.30** |

** The impacts in this hour are not statistically significant at the 95% level*

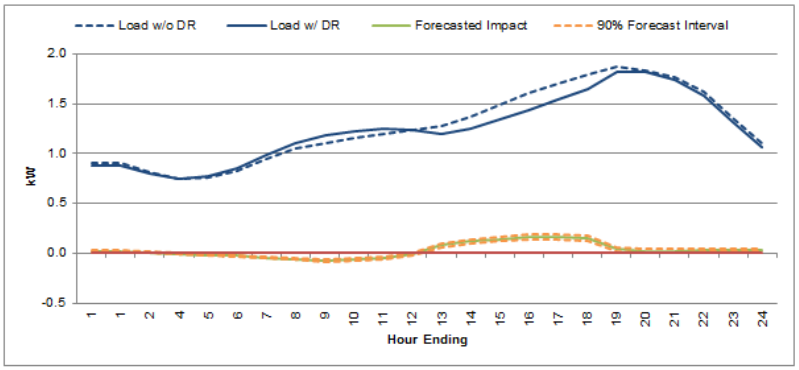
**Figure 8-6: Average E-7 Non-net Metered Customer Hourly Load Impact Estimates (July Monthly Peak Day, CAISO 1-in-2 Year Weather Conditions)**

**Menu Options**

| | |
|---|---|
| Result Type | Average Customer |
| Day Type | Monthly System Peak Day |
| Weather Scenario | CAISO |
| Month | July |
| Weather Year | 1-in-2 |
| Capacity Area | All |
| Year | 2015 |
| Rate | E7 |

**Peak Information**

| | |
|---|---|
| Population (2015) | 47,887 |
| Peak Period Start | 1 PM |
| Peak Period Stop | 6 PM |
| Peak Period Reference Load (kW) | 1.59 |
| Peak Period Reduction (kW) | 0.15 |
| Peak Period Reduction (%) | 9% |




| Hour Ending | Load w/o DR (kW) | Load w/ DR (kW) | Impact (kW) | Impact (%) | Temp. (°F) | Uncertainty Adjusted Impact Percentiles 10% | 30% | 50% | 70% | 90% |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.90 | 0.88 | 0.02 | 2.4% | 68.7 | 0.01 | 0.02 | 0.02 | 0.03 | 0.03 |
| 2 | 0.90 | 0.88 | 0.02 | 2.4% | 68.7 | 0.01 | 0.02 | 0.02 | 0.03 | 0.03 |
| 3 | 0.81 | 0.80 | 0.01 | 1.4% | 67.6 | 0.00 | 0.01 | 0.01 | 0.01 | 0.02 |
| 4 | 0.75 | 0.75 | -0.01 | -0.7% | 65.9 | -0.01 | -0.01 | -0.01 | 0.00 | 0.00 |
| 5 | 0.76 | 0.77 | -0.01 | -1.8% | 65.4 | -0.02 | -0.02 | -0.01 | -0.01 | -0.01 |
| 6 | 0.82 | 0.85 | -0.03 | -3.1% | 64.9 | -0.03 | -0.03 | -0.03 | -0.02 | -0.02 |
| 7 | 0.95 | 0.99 | -0.04 | -4.5% | 64.9 | -0.05 | -0.05 | -0.04 | -0.04 | -0.03 |
| 8 | 1.06 | 1.11 | -0.05 | -5.1% | 67.3 | -0.07 | -0.06 | -0.05 | -0.05 | -0.04 |
| 9 | 1.11 | 1.18 | -0.07 | -6.2% | 70.9 | -0.08 | -0.07 | -0.07 | -0.06 | -0.06 |
| 10 | 1.16 | 1.22 | -0.07 | -5.6% | 74.4 | -0.08 | -0.07 | -0.07 | -0.06 | -0.05 |
| 11 | 1.20 | 1.25 | -0.04 | -3.5% | 78.0 | -0.06 | -0.05 | -0.04 | -0.04 | -0.03 |
| 12 | 1.24 | 1.24 | 0.00 | -0.2% | 81.3 | -0.02 | -0.01 | 0.00 | 0.00 | 0.01 |
| 13 | 1.27 | 1.19 | 0.08 | 6.5% | 84.0 | 0.06 | 0.08 | 0.08 | 0.09 | 0.10 |
| 14 | 1.37 | 1.25 | 0.12 | 9% | 86.1 | 0.10 | 0.11 | 0.12 | 0.13 | 0.14 |
| 15 | 1.49 | 1.34 | 0.15 | 10% | 87.1 | 0.12 | 0.14 | 0.15 | 0.15 | 0.17 |
| 16 | 1.60 | 1.44 | 0.16 | 10% | 87.5 | 0.14 | 0.15 | 0.16 | 0.17 | 0.19 |
| 17 | 1.71 | 1.54 | 0.17 | 10% | 87.3 | 0.14 | 0.16 | 0.17 | 0.18 | 0.19 |
| 18 | 1.79 | 1.64 | 0.15 | 9% | 86.2 | 0.13 | 0.14 | 0.15 | 0.16 | 0.18 |
| 19 | 1.87 | 1.82 | 0.04 | 2% | 84.4 | 0.02 | 0.04 | 0.04 | 0.05 | 0.06 |
| 20 | 1.84 | 1.81 | 0.03 | 1% | 81.1 | 0.01 | 0.02 | 0.03 | 0.03 | 0.04 |
| 21 | 1.77 | 1.74 | 0.02 | 1% | 76.8 | 0.01 | 0.02 | 0.02 | 0.03 | 0.04 |
| 22 | 1.62 | 1.58 | 0.03 | 2.0% | 73.8 | 0.02 | 0.03 | 0.03 | 0.04 | 0.05 |
| 23 | 1.36 | 1.32 | 0.03 | 2.5% | 71.7 | 0.02 | 0.03 | 0.03 | 0.04 | 0.05 |
| 24 | 1.10 | 1.07 | 0.03 | 2.9% | 70.3 | 0.02 | 0.03 | 0.03 | 0.04 | 0.04 |
| **Peak** | **1.59** | **1.44** | **0.15** | **9.4%** | **86.9** | **0.13** | **0.14** | **0.15** | **0.16** | **0.17** |

** The impacts in this hour are not statistically significant at the 95% level*

## 8.4 Relationship Between Ex Post and Ex Ante Estimates

The ex post estimates presented in Section 7 and the ex ante estimates presented above differ for a number of reasons, including differences in weather, the event window, enrollment and estimation methodology. This section discusses the impact of each of these factors on the difference between ex post and ex ante load impacts.

Table 8-7 summarizes the key factors that might lead to differences in ex post and ex ante estimates for the TOU program. Differences in weather between ex post and ex ante conditions will lead to differences in load impacts. The magnitude and direction of the influence of weather varies with the weather scenario being used. Differences between the rate window and the RA window are expected to be minor in the summer because the rate windows overlap well with the RA window. This is not the case in the winter period when the RA window and the peak rate periods do not overlap well at all. Differential changes in enrollment for E-6, which is increasing, and E-7, which is declining, will have significant impacts on aggregate load reductions compared with ex post values and on the average impacts for the two rates combined as the enrollment mix between the two rates shifts dramatically over the forecast horizon. Finally, the ex ante model is expected to forecast accurately for the average weekday, at least on average for the summer and winter periods. It may do less well for the monthly peak day if the relationship between weather and load impacts is non-linear.

Table 8-8 shows how aggregate load impacts change as a result of differences in most of the factors underlying ex post and ex ante estimates for E-6 for each month of the year and on average over the summer, winter and the entire year. All of the values in the table are based on the RA window, not the peak period associated with each tariff. However, a comparison of the impacts in column C in Table 8-8 with the aggregate load impact column in Table 7-3 in Section 7 shows that this factor has only a minor impact during summer months but a significant impact in the winter. In the summer, the average ex post aggregate impact from Table 7-3 is 1.08 MW based on the E-6 peak period. This drops to 1.05 MW using the summer RA window, a difference of less than 3%. In the winter, the ex post impacts equal 0.61 MW on average based on the E-6 winter peak period from 5 to 8 PM and 0.49 MW based on the RA window from 4 to 9 PM, a difference of roughly 20%.

Columns C and D compare ex post estimates with predicted values using the ex ante model with ex post weather for the average weekday. As seen, the model predicts very accurately on average across the summer and winter periods. However, there can be significant differences for specific months. Model accuracy is not as great for monthly peak day impacts, which are not shown in the table. On average during the summer, the ex ante model under predicts monthly peak day impacts by about 20%. In July, the model under predicts by 37%. A recommendation for the 2015 evaluation is to estimate separate models for the average weekday and monthly peak day forecasts.

**Table 8-7: Summary of Factors Underlying Differences Between Ex Post and Ex Ante Impacts for the TOU Program**

| Factor | Ex Post | Ex Ante | Expected Impact |
|---|---|---|---|
| Weather | The average weekday peak period temperature across the 6 summer months = 76 for E-6 and 80 for E-7<br>Average weekday winter temperature = 58 for both E-6 and E-7 | Average weekday peak period temperature across the 6 summer months for<br>PG&E weather conditions:<br>76 for 1-in-2<br>80 for 1-in-10<br>For CAISO weather conditions:<br>77 for 1-in-2<br>78 for 1-in-10<br>Average winter weather ranges from 53 to 55 for both tariffs | Impacts could go up or down depending on which weather conditions are used and which tariff is being analyzed |
| Peak Period | 1 to 7 PM for E-6 12 to 6 PM for E-7 in summer<br>5 to 8 PM for E-6 and 12 to 6 PM for E-7 in winter | RA window is from 1 to 6 PM in the summer and 4 to 9 PM in the winter | The impact of changing to the RA window is minor in the summer for both rates<br>The impact is quite significant for both tariffs in the winter because of the misalignment of the RA window with the peak or shoulder period rates for each tariff |
| Enrollment | E-7 enrollment is more than 5 times larger than E-6 in 2014 | E-7 enrollment declines steadily over forecast horizon while E-6 enrollment is forecast to double – by 2025, E-7 enrollment is predicted to be about 40% larger than E-6 | Aggregate impacts for E-6 will rise steadily over the forecast horizon and E-7 impacts will fall steadily |
| Modeling | Ex post estimates based on statistically matched control group using pretreatment interval data for E-6<br>Initial ex post estimates for E-7 based on statistically matched control group using monthly usage data from post-enrollment period – these are adjusted downward for assumed selection bias using estimate of selection bias for E-6 population | Ex ante model regresses hourly ex post estimates against *mean*9 weather – separate models for each hour, season and LCA. Same model used for estimating impacts for average weekday and monthly peak day | Model should predict very well for average weekday impacts<br>May be less accurate for monthly peak day impacts if relationship between weather and impacts is non-linear |

Columns D and E in Table 8-8 show the influence of changes in enrollment. The growth in E-6 enrollment between 2014 and 2015 is expected to increase average aggregate impacts in the summer by about 20%.

The remainder of Table 8-8 shows the impact of differences between ex post and ex ante weather for the four sets of weather conditions. A comparison of columns G, I, K and M with column E shows how each set of weather conditions influences load reductions compared with ex post weather. The ex ante weather scenarios increase load reductions by 10% to 33% depending on the weather conditions used. It is important to note that the weather values shown in the table represent average values for the RA event window. The weather variable used in the ex ante model for each hourly regression is *mean*9, which captures the impact of the hours leading up to each hour. The same average temperature during the RA window can occur for days that have very different *mean*9 values for the hours leading up to each event hour. As such, temperatures in the table that have the same or very similar values can have different impacts because they don't capture the impact of weather outside the RA window.

Another thing to note about the weather values in Table 8-8 (and also in Table 8-9 for the E-7 tariff) is that, in some cases, there may be very little difference in values between 1-in-2 and 1-in-10 year weather conditions. In fact, in a couple of instances, the 1-in-10 year values are less than the 1-in-2 year values. This is because the weather years are selected based only on high demand days (peaking conditions). The values in these tables represent average weekday temperatures. It's very possible that, across all weekdays in a given month, the average temperatures in a 1-in-10 year will be less than in a 1-in-2 year even though the 1-in-10 year peak day values are much higher.

**Table 8-8: E-6 Differences in Ex Post and Ex Ante Aggregate Impacts Due to Key Factors for Average Monthly Weekday (All Impacts Are for the RA Event Window, Not E-6 Peak Period)[33]**

| Month | Ex Post Weather | | | | PGE Ex Ante Weather | | | | CAISO Ex Ante Weather | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2014 Ex Post Temp | Ex Post Impacts | Ex Post Weather, Predicted Using Model | Ex Post Weather, Predicted Using Model, Ex Ante Enrollment | 1-in-2 Temp | 1-in-2 Impact | 1-in-10 Temp | 1-in-10 Impact | 1-in-2 Temp | 1-in-2 Impact | 1-in-10 Temp | 1-in-10 Impact |
| A | B | C | D | E | F | G | H | I | J | K | L | M |
| January | 57 | 0.60 | 0.48 | 0.57 | 50 | 0.56 | 50 | 0.55 | 50 | 0.55 | 50 | 0.55 |
| February | 57 | 0.31 | 0.46 | 0.55 | 53 | 0.59 | 52 | 0.57 | 55 | 0.61 | 57 | 0.65 |
| March | 63 | 0.38 | 0.51 | 0.61 | 56 | 0.63 | 50 | 0.56 | 53 | 0.61 | 50 | 0.56 |
| April | 65 | 0.49 | 0.55 | 0.65 | 60 | 0.66 | 63 | 0.72 | 62 | 0.69 | 63 | 0.72 |
| May | 75 | 0.75 | 0.93 | 1.11 | 71 | 1.03 | 78 | 1.53 | 71 | 1.14 | 73 | 1.10 |
| June | 76 | 1.06 | 1.04 | 1.25 | 76 | 1.47 | 78 | 1.75 | 76 | 1.39 | 79 | 1.62 |
| July | 79 | 1.45 | 1.25 | 1.50 | 80 | 1.79 | 83 | 2.03 | 82 | 1.92 | 81 | 1.83 |
| August | 77 | 1.18 | 1.15 | 1.38 | 80 | 1.73 | 83 | 1.95 | 81 | 1.79 | 80 | 1.76 |
| September | 78 | 1.02 | 1.10 | 1.31 | 76 | 1.39 | 81 | 1.70 | 79 | 1.48 | 81 | 1.74 |
| October | 74 | 0.82 | 0.85 | 1.02 | 71 | 0.92 | 74 | 1.13 | 71 | 0.92 | 75 | 1.08 |
| November | 59 | 0.46 | 0.51 | 0.61 | 56 | 0.65 | 57 | 0.68 | 55 | 0.66 | 56 | 0.65 |
| December | 50 | 0.70 | 0.42 | 0.50 | 51 | 0.57 | 47 | 0.52 | 53 | 0.59 | 49 | 0.56 |
| Average | 67 | 0.77 | 0.77 | 0.92 | 65 | 1.00 | 66 | 1.14 | 66 | 1.03 | 66 | 1.07 |
| Summer | 76 | 1.05 | 1.05 | 1.26 | 76 | 1.39 | 80 | 1.68 | 77 | 1.44 | 78 | 1.52 |
| Winter | 58 | 0.49 | 0.49 | 0.58 | 54 | 0.61 | 53 | 0.60 | 55 | 0.62 | 54 | 0.62 |

33 Because these impacts represent the RA event window, impacts in the summer differ slightly from those reported in Section 7 and impacts in the winter differ significantly from those in Section 7 because the RA event window does not overlap well with the E-6 rate period in the winter.

Table 8-9 summarizes the impact of various factors underlying the differences between ex post and ex ante impact estimates for the E-7 tariff. A comparison of the impacts representing the RA window in Table 8-9 with the impacts in Table 7-4 in Section 7 shows the influence of a shift from the E-7 peak period to the RA window. The average summer impact in Table 8-9 is 5.29 MW and the comparable value in Table 7-4 is 4.78 MW, a difference of roughly 10%. In the winter, the RA window impacts from Table 8-9 equal 0.83 MW while the average winter impacts in Table 7-4 equal 1.95, a difference of almost 60%. This is because peak period prices under the E-7 tariff are only in effect for 2 of the 5 RA window hours in the winter season.

For the E-7 tariff, impacts based on the ex ante model and ex post weather (column D) are very similar to the actual ex post values (column C) within the summer and winter seasons. Indeed, the difference amounts to roughly 1% in both seasons. The relatively large (20%) downward bias in the ex ante model for predicting monthly system peak days that was seen for the E-6 tariff is much smaller for the E-7 tariff. The ex ante model using ex post weather estimates that aggregate demand reductions on monthly system peak days will average 7.45 MW. The actual ex post average for 2014 was 7.97 MW, a difference of about 8%. This smaller bias may be due to the fact that a much larger percent of E-7 customers are located in the hotter climate regions compared with E-6 customers. As such, the variation in temperatures across days during the summer will not be as large for E-7 participants compared with E-6 participants and the ex ante model for E-7 will predict more accurately on hot days than it does the E-6 model.

Declining enrollment between 2014 and 2015 is predicted to reduce aggregate weekday demand for the E-7 tariff by 7%. The influence of weather on ex ante impacts varies across scenarios. For the average weekday, impacts are lower under three of the four weather scenarios compared with ex post weather, including the 1-in-10 year CAISO weather scenario. Only the PG&E 1-in-10 year weather scenario produces aggregate impacts that are larger than the model predicts using ex post weather.

**Table 8-9: E-7 Differences in Ex Post and Ex Ante Aggregate Impacts Due to Key Factors for Average Monthly Weekday (All Impacts Are for RA Event Window, Not E-7 Peak Period)[34]**

| Month | Ex Post Weather | | | | PGE Ex Ante Weather | | | | CAISO Ex Ante Weather | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2014 Ex Post Temp | Ex Post Impacts | Ex Post Weather, Predicted Using Model | Ex Post Weather, Predicted Using Model, Ex Ante Enrollment | 1-in-2 Temp | 1-in-2 Impact | 1-in-10 Temp | 1-in-10 Impact | 1-in-2 Temp | 1-in-2 Impact | 1-in-10 Temp | 1-in-10 Impact |
| A | B | C | D | E | F | G | H | I | J | K | L | M |
| January | 56 | 0.74 | 0.70 | 0.66 | 50 | 0.55 | 49 | 0.55 | 49 | 0.52 | 49 | 0.55 |
| February | 56 | 0.70 | 0.69 | 0.65 | 53 | 0.58 | 51 | 0.58 | 55 | 0.62 | 57 | 0.66 |
| March | 63 | 0.91 | 0.77 | 0.72 | 56 | 0.65 | 50 | 0.57 | 53 | 0.62 | 50 | 0.57 |
| April | 67 | 1.08 | 0.83 | 0.78 | 60 | 0.67 | 64 | 0.75 | 62 | 0.71 | 64 | 0.75 |
| May | 77 | 3.43 | 4.53 | 4.26 | 71 | 3.10 | 79 | 4.76 | 72 | 3.53 | 74 | 3.40 |
| June | 80 | 5.44 | 5.44 | 5.12 | 78 | 4.55 | 80 | 5.50 | 77 | 4.27 | 80 | 5.08 |
| July | 83 | 6.42 | 6.52 | 6.14 | 81 | 5.64 | 85 | 6.43 | 83 | 6.06 | 83 | 5.76 |
| August | 81 | 6.33 | 5.90 | 5.55 | 81 | 5.41 | 85 | 6.14 | 83 | 5.62 | 82 | 5.48 |
| September | 81 | 6.03 | 5.47 | 5.15 | 77 | 4.39 | 82 | 5.32 | 80 | 4.63 | 83 | 5.49 |
| October | 76 | 4.09 | 3.95 | 3.72 | 72 | 2.83 | 75 | 3.53 | 72 | 2.83 | 76 | 3.32 |
| November | 58 | 0.36 | 0.75 | 0.70 | 56 | 0.65 | 57 | 0.68 | 55 | 0.66 | 56 | 0.65 |
| December | 49 | 1.19 | 0.62 | 0.58 | 51 | 0.57 | 46 | 0.51 | 53 | 0.59 | 49 | 0.54 |
| Average | 69 | 3.06 | 3.01 | 2.84 | 65 | 2.47 | 67 | 2.94 | 66 | 2.56 | 67 | 2.69 |
| Summer | 80 | 5.29 | 5.30 | 4.99 | 77 | 4.32 | 81 | 5.28 | 78 | 4.49 | 80 | 4.75 |
| Winter | 58 | 0.83 | 0.73 | 0.68 | 54 | 0.61 | 53 | 0.60 | 55 | 0.62 | 54 | 0.62 |

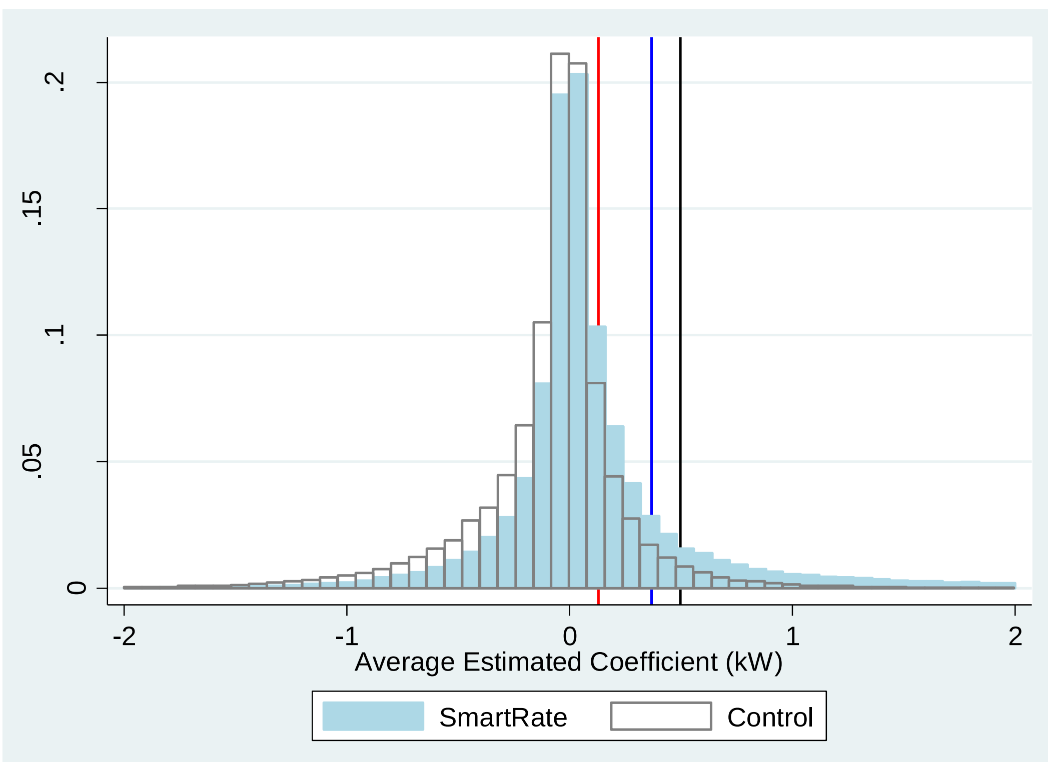
34 Because these impacts represent the RA event window, impacts in the summer differ slightly from those reported in Section 7 and impacts in the winter differ significantly from those in Section 7 because the RA event window does not overlap well with the E-7 rate period in the winter.

# Appendix A Details for Determining High Responders

All results in this section are outputs of our within-subjects analysis, not our matched control group analysis. To identify customers who are likely to provide true SmartRate-only impacts greater than the average impact of 0.13 kW, we note that only 5% of customers in the control group have a noise estimate greater than 0.37 kW. Given that the mean SmartRate-only impact is 0.13 kW (per the individual customer regressions), any customer with a load impact estimate greater than 0.50 kW has a 95% or greater of having a true impact greater than 0.13 kW.[35] This is a fairly weak statement, since only a relatively small fraction of customers have impact estimates above 0.50 kW. This is due to the inherently large amount of noise in the within-subjects calculation at the individual customer level, as demonstrated by the histogram of false impact estimates in the control group.

This calculation assumes the distribution of the noise is independent of the true impact distribution. Abandoning this assumption would weaken our ability to make inferences about high responders, not strengthen it. Figure A-1 shows the distribution of estimated coefficients for both the SmartRate-only population and its control group. The three reference lines show the relevant values mentioned above. The red line marks 0.13 kW, the blue line is at 0.37 kW and the black line is at 0.50 kW. All customers in the SmartRate-only group (the light blue distribution) to the right of the black reference line are considered high responders.

**Figure A-1: Distribution of Average Estimated Coefficients for SmartRate-only and Control Group Customers**




[35] This calculation is explained in detail in the next paragraph.

To calculate the value 0.50 kW as the relevant threshold, the following steps and equations are used. The first equation shown below is a statement of what the analysis is solving for. The analysis is solving for the impact threshold, $t$, for which there is a 95% probability that the true impact is above the average impact (0.13 kWh) given that the estimated impact equals threshold $t$ (Equation 1). It is a given that the estimated impact ($\hat{\imath}$) is equal to the true impact ($i$) plus noise, $\varepsilon$ (Equation 2). Rearranging Equation 2 results in Equation 3, which shows that the true impact is equal to the estimated impact minus the noise term. Substituting Equation 3 for $i$ in Equation 1 produces Equation 4. To get to Equation 5, threshold $t$ is substituted in for the estimated impact based on the given statement that the estimated impact is equal to threshold $t$. Next, Equation 5 is rearranged so that the noise term is the only variable on the left side of the inequality. The distribution of the noise term, $\varepsilon$, is known and is shown in the clear histogram. Based on this known distribution, there is a 95% probability that a customer will have a noise term that is less than 0.37 kWh (Equation 7). Equations 6 and 7 are both statements about the distribution of the noise term. Both are statements describing the 95$^{th}$ percentile of the noise distribution, therefore both expressions of the value of the 95$^{th}$ percentile can be set equal to each other to get Equation 8. Solving Equation 8 for $t$, leaves Equation 9 which shows that threshold $t$ equals 0.50 kWh.

$$P(i > 0.13 \mid \hat{\imath} = t) = 95\% \quad \text{(Equation 1)}$$

$$\hat{\imath} = i + \varepsilon \quad \text{(Equation 2)}$$

$$i = \hat{\imath} - \varepsilon \quad \text{(Equation 3)}$$

$$P(\hat{\imath} - \varepsilon > 0.13 \mid \hat{\imath} = t) = 95\% \quad \text{(Equation 4)}$$

$$P(t - \varepsilon > 0.13) = 95\% \quad \text{(Equation 5)}$$

$$P(\varepsilon < t - 0.13) = 95\% \quad \text{(Equation 6)}$$

$$P(\varepsilon < 0.37) = 95\% \quad \text{(Equation 7)}$$

$$0.37 = t - 0.13 \quad \text{(Equation 8)}$$

$$t = 0.50 \quad \text{(Equation 9)}$$

Similarly, to identify dually enrolled customers who are high responders, we note that only 5% of customers in the control group have a noise estimate greater than 0.44 kW. Given that the mean SmartRate impact is 0.35 kW for dually enrolled customers, any customer with a load impact estimate greater than 0.78 kW has a 95% or greater of having a true impact greater than 0.35 kW.[36] Figure **XX**-2 shows the distribution of estimated coefficients for both the dually enrolled population and control group. The red line marks 0.35 kW, the blue line is at 0.44 kW and the black line is at 0.78 kW. All customers in the dually enrolled SmartRate group (the light blue distribution) to the right of the black reference line are considered high responders.

[36] This calculation is explained in detail in the next paragraph.

**Figure A-2: Distribution of Average Estimated Coefficients for Dually Enrolled and Control Group Customers**