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Behavioral Demand Response Study - Load Impact Evaluation Report

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Prepared for Pacific Gas & Electric Company

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Executive Summary

Pacific Gas & Electric Company (PG&E) conducted the Behavioral Demand Response (BDR) study to assess the impact of BDR on residential peak electricity usage on designated "Summer Saving Days." The BDR study was part of PG&E's Demand Response Transmission and Distribution pilot and was implemented by Opower, which also implements the PG&E Home Energy Reports (HER) program.¹ The study targeted residential customers served by 31 substations within PG&E's system that have been identified as high priority areas for reducing peak loads. BDR does not offer any financial incentives for customers to reduce their usage, nor does it require the installation of technology at a customer's premise. Instead, it provides customers with pre/post-event communications and social comparisons specifically aimed at reducing usage on event days. The fundamental concepts of BDR are very similar to those in the well-established HER program, with the key difference being that BDR is designed to target only a few hours on days when electricity demand is high.

The BDR study was first implemented during the summer of 2015 as a randomized control trial (RCT) within the structure of the HER program to allow for a comparison of the impacts for customers who do and do not already receive HERs. The experimental design then and moving forward is shown in Table 1.

| Cohort | Assignment | HER Recipients | HER Control Customers | Total |
|--------|---------------|-------------------|--------------------------|---------|
| | BDR Treatment | 30,200 | 9,800 | 40,000 |
| 2015 | BDR Control | 26,400 | 8,500 | 34,900 |
| | Total | 56,600 | 18,300 | 74,900 |
| | BDR Treatment | 11,474 | 3,526 | 15,000 |
| 2016 | BDR Control | 9,497 | 3,003 | 12,500 |
| | Total | 20,971 | 6,529 | 27,500 |
| | BDR Treatment | 41,674 | 13,326 | 55,000 |
| Total | BDR Control | 35,897 | 11,503 | 47,400 |
| | Total | 77,571 | 24,829 | 102,400 |

Table 1: BDR Experimental Design

The design, first implemented in 2015, can be interpreted as facilitating two separate BDR experiments – one within a sample of HER recipients and the second within a sample of HER control customers.² Designing the study in this way allows for BDR impacts to be estimated separately within each HER group and then compared in order to assess whether BDR impacts are different for HER recipients and HER control customers. In the 2016 evaluation, 15,000 new BDR treatment customers were added to the program with 12,500 additional control customers.



¹ The HER program is a behavioral intervention that delivers personalized usage information to customers by mail or email. As in BDR, a key feature of the information feedback is a comparison of each customer's usage to that of their neighbors.

 $^{^{2}}$ HER control customers are a large group of residential customers (approximately 600,000) that have been specifically set aside as a comparison group for measuring the impacts of the HER program.

The 2016 cohort³ was not sampled separately from within HER recipients and HER control customers, but rather from the entire HER-eligible population. While Nexant does estimate BDR impacts separately within each HER group in this evaluation, the focus is on overall impacts, and comparisons between the 2015 and 2016 cohorts.

In an RCT design with large sample sizes, load impacts can be accurately estimated by calculating the difference in average peak period (in this case, 5 to 8pm) usage between customers in the treatment and control groups on each Summer Saving Day. These differences were calculated using a regression model and the results for each event day are shown in Table 2 below. Based on the three event days, on average, BDR produces a 2.1% reduction in peak usage.

| Event | Accounts | Reference Load (kW) | Observed Load (kW) | Impact (kW) | 95% CI (kW) | Aggregate Impact (MW) | Percent Impact (%) |
|------------|----------|------------------------|-----------------------|----------------|----------------|-----------------------------|--------------------------|
| 8/16/2016 | 49,420 | 2.36 | 2.29 | 0.06 | (0.04; 0.09) | 3.20 | 2.75% |
| 8/17/2016 | 49,409 | 2.51 | 2.47 | 0.04 | (0.01; 0.06) | 1.91 | 1.54% |
| 9/27/2016 | 48,945 | 2.21 | 2.16 | 0.05 | (0.03; 0.07) | 2.28 | 2.11% |
| Avg. Event | 49,258 | 2.36 | 2.31 | 0.05 | (0.03; 0.07) | 2.46 | 2.12% |

Table 2: Average Peak Period Load Impacts on Event Days

Nexant estimated load impacts for various subgroups. For the average event day, the 2015 cohort delivered higher impacts in both absolute and percentage terms. The 2015 cohort's percent impact was 2.31% on the average event day, while the 2016 cohort's percent impact was 1.72%. However, the difference between the cohorts was not significant at the 5% level.⁴ As was observed in the 2015 evaluation, impacts for HER recipients are consistently lower than those for HER control customers (1.65% vs 2.87% on the average event day). This result indicates that there may be diminishing returns for the behavioral intervention because HER recipients are either desensitized to contact or have already implemented some energy savings measures in response to receiving HER communications.

In addition to encouraging customers to reduce usage on Summer Saving Days, there is also evidence that the impacts of BDR spill over into non-event days. Figure 1 shows the estimated difference in peak period usage for BDR treatment and control customers for every day of the summer. Impacts on days following event days are statistically significant at the 5% level. Furthermore, in the pre-treatment period, BDR treatment customers consistently have slightly lower peak usage than customers in the BDR control group. When the period is examined for each cohort separately, the difference is observed for the 2015 cohort, but not for the 2016 cohort, which suggests that the 2015 cohort was subject to random sampling variation that resulted in the slight difference in usage in pre-treatment period. Nexant estimated separate

³ "Cohort" is an evaluation term that is used in this report to describe a group of customers.

⁴ 5% level refers to a p-value of 0.05 or below, which corresponds with a result that is statistically significant.

impacts for the 2015 and 2016 cohort, and the 2015 cohort was found to deliver larger load impacts. Much of this difference is likely explained by the pre-treatment difference in load between control and BDR treatment customers among the 2015 cohort.



Figure 1: Average Impact on Each Day

An unaddressed question from the 2015 evaluation was whether BDR impacts would persist during 2016 for customers who enrolled in 2015. Impacts in 2015 were lower at the end of the summer, which raised the issue. By restricting an analysis to persistent customers enrolled throughout both 2015 and 2016, and estimating impacts over both years, Nexant was able to establish that 2016 impacts were similar to those observed in 2015. As shown in Figure 2, BDR impacts remain around the 2015 average (2%) or higher for customers enrolled in consecutive years. However, it is important to note that temperatures were quite a bit lower for the 2016 events as compared to the 2015 events. For the average 2016 event, persistent customers experienced event period temperatures of 88.7 °F on average, which is 5.5 degrees cooler than that of the average 2015 event (94.2 °F).



Figure 2: Persistent Customer Percent Load Impacts on 2015 and 2016 Event Days

Given that the effect of BDR on energy consumption is not confined to the hours of the peak period for event days and is somewhat persistent from day to day throughout the summer season, BDR has the potential to yield energy savings as well, similar to the HER program. However, it is important to note that because of the persistence of BDR impacts, exposing HER control customers to BDR runs the risk of changing their baseline energy use and complicating the estimation of HER impacts. The net benefits of BDR for HER control customers are uncertain and should be carefully considered by portfolio managers when assessing which populations to include for participation in BDR.

Finally, a key unanswered question related to this study is how it applies to the rest of PG&E's service territory. This study was confined to 31 substations where PG&E is attempting to limit load growth. It is unknown whether load reductions in other locations would be comparable to what was observed in this study.

The remainder of this report documents the above findings in detail. Section 1 describes the BDR study and goals of the experiment. Section 2 describes the research methodology including the experimental design, sampling procedures, and analytical framework. Section 3 describes the results of the study and Section 4 provides conclusions and recommendations.

1 Introduction

PG&E continued the BDR study in the summer of 2016 to investigate the load impacts that could be produced by engaging customers using communications and social comparisons prior to designated "Summer Saving Days." This is the second year of the study⁵; it was first implemented during the summer of 2015. Therefore, the 2016 study also assesses the persistence of impacts when the same customers are included in the study group for a second year. The study targeted residential customers served by 31 substations within PG&E's system that have been identified as high priority areas for reducing peak loads. The remainder of this section introduces BDR and discusses the specific goals of the study.

1.1 Behavioral Demand Response

Opower's BDR product builds on the fundamental concepts of Home Energy Reports (HER) to encourage residential customers to reduce peak usage. BDR relies on pre/post-event communications and social comparisons to provide customers with information and motivation to reduce their electricity usage on days of high peak usage that are referred to as "Summer Saving Days." Importantly, BDR does not offer any financial incentives for customers to reduce their usage, nor does it require the installation of technology at a customer's premise. As with the HER program, BDR is most cost-effective when run on an opt-out basis due to its relatively modest per-customer impacts and low marginal cost of sending out additional email and Interactive Voice Response (IVR) communications.⁶

Whereas the HER program is designed to stimulate energy conservation every day, BDR is designed to target only a few hours during days when electricity demand is high. For the 2016 study, three Summer Saving Days were called to test the performance of BDR on three weekdays in August through September 2016 between the hours of 5 and 8pm. The three event days were on August 16, August 17, and September 27.

Around the first of July, BDR was introduced to study participants in a welcome letter that described the concept of Summer Saving Days and explained how customers could participate (Figure 1-1). The welcome letter was sent by the Postal Service to the address on file for each participant.

⁶ BDR uses much of the same infrastructure as HER so that most of the cost associated with customer communication has already been incurred.



⁵ The 2015 results are summarized in a prior version of this report dated January 11, 2016.

Figure 1-1: Pre-season Welcome Letter



Calling an event required coordination between the PG&E and Opower program teams in order to deliver personalized customer communications via email or an automated phone call (using IVR for landlines only). Approximately 65% of study participants received event communications through IVR only, due to PG&E not having an email address for those customers. Around 17% received communications though email only, and the remaining 18% of participants received both an email and phone call to a landline. During the summer, PG&E monitored weather and system conditions and identified Summer Saving Days on a day-ahead basis. Upon deciding that an event would occur on the following day, PG&E informed Opower, which would initiate pre-event communications with customers. The pre-event communication consisted of an email and/or automated phone call to announce the event, provide a peak event normative comparison of each customer's peak usage to that of their neighbors for the most recent event, and suggest actionable tips for reducing peak usage during the event (Figure 1-2).

Figure 1-2: Sample Pre-event Email Communication



After the event, Opower imported AMI interval data from the relevant PG&E SmartMeters for all participating customers on the day of the event and developed personalized neighbor comparisons for each participant. These comparisons, plus additional energy saving tips, were distributed to customers 24 to 48 hours after the event via another email or automated phone call (Figure 1-3).





This cycle – pre-event communication, event, post-event communication – is repeated before, during, and after each event and takes approximately 60 hours from start to finish. As a consequence, PG&E recognized that consecutive event days could become confusing to participants since the post-event communication for the first event would not have been received prior to the second event. PG&E did not test consecutive events in 2015, but did in 2016 on August 16 and 17. As shown in Section 3.1, the aggregate impact of BDR was 40% lower on the second day (1.9 MW) as compared to the first day (3.2 MW).



1.2 Study Context and Goals

PG&E is experimenting with several forms of demand response in capacity constrained areas of their distribution system to help defer costly capital investments that would otherwise be needed to keep up with growing peak demand. The primary goal of the BDR study evaluation is to obtain robust estimates of the load reductions that are caused by the program. Understanding the load reduction potential (and cost) of different DR resources will help PG&E determine which programs/technologies are most promising to pursue as components of their DR portfolio.

Secondary goals of this particular study were to understand how BDR interacts with the existing HER program that Opower runs in PG&E's service territory, and to evaluate whether the load impacts of the 2015 cohort were subject to attrition in 2016. The HER program has been shown to reduce usage during all hours of the day and therefore would be expected to reduce usage during a Summer Saving Day. To investigate the incremental impacts of BDR, both HER treatment and HER control customers were included in the study. In other utility jurisdictions,⁷ Opower has found that a BDR program is complementary to HER and can provide additional load reductions. To investigate any intertemporal effects on the impacts of the 2015 cohort, Nexant estimated load impacts for 2015 and 2016 events for customers enrolled in every event across both years.

Nexant's specific tasks in the study were to work with Opower to develop an experimental design that would measure the effects of BDR and conduct an independent evaluation of the load impacts. The study design is discussed in Section 2, while the remainder of the report describes the load impacts that were observed for customers in the experimental treatment cells.

⁷ For more information, see: https://opower.com/news-and-press/opower-scales-behavioral-demand-response-to-1-5-million-homes



2 Methodology

The load impact evaluation for the BDR study is based on a randomized control trial (RCT) design involving approximately 100,000 HER-eligible customers spread across 31 capacity constrained substations in PG&E's service territory. This section outlines the details of the RCT design and the methods used to estimate the load impacts of the program.

2.1 Sample Design

Customers were selected for the treatment and control groups in the BDR study based on the following criteria:

- Located in one of the 31 substations of interest,⁸ but not on any feeders listed on the SmartAC T&D exclusion list;⁹
- Eligible for HER program, but not part of the Gamma wave;¹⁰
- Have either an email address or a non-cellular phone number in PG&E/Opower's database management system;
- Not a participant in other PG&E DR programs (SmartAC, SmartRate); and
- Must not be on PG&E's "do not contact" list.

Once pools of HER recipients and HER control customers who met these eligibility criteria were identified, Nexant randomly assigned customers into groups shown in Table 2-1. In 2015, there were 40,000 BDR treatment customers and 34,900 BDR control customers. These comprised 56,600 HER recipients and 18,300 HER control customers. In 2016, there were 15,000 BDR treatment customers and 12,500 BDR control customers. The ratio of treatment to control customers is similar across years, allowing each year's assignments to be pooled for the 2016 evaluation. In total, there were 55,000 BDR treatment customers and 47,400 BDR control customers.

¹⁰ The Gamma wave was one of several different cohorts of HER participants for PG&E. Launched in 2012, the Gamma wave was one of the first HER deployments at PG&E and included approximately 75,000 treatment and 75,000 control customers throughout the service territory.



⁸ In alphabetical order, the 31 substations are: Ashlan Ave., Barton, Bogue, Bonnie Nook, Bullard, Clarksville, Clayton, Contra Costa, Cordelia, Davis, Edenvale, Elk Creek, Figarden, Hicks, Lakewood, Lammers, Manteca, Martell, Menlo, Panama, Peabody, Pleasant Grove, Red Bluff, San Ramon, Shady Glen, Shingle Springs, Stockdale, Tassajara, Tracy, Vacaville and Woodward.

⁹ PG&E conducted various marketing, incentive and participation option tests for its SmartAC direct load control program based on certain feeders/substations in its territory. Customers from these locations were excluded from the BDR study to avoid interfering with other SmartAC-related activities.

| Cohort | Assignment | HER Recipients | HER Control Customers | Total |
|--------|---------------|-------------------|--------------------------|---------|
| | BDR Treatment | 30,200 | 9,800 | 40,000 |
| 2015 | BDR Control | 26,400 | 8,500 | 34,900 |
| | Total | 56,600 | 18,300 | 74,900 |
| | BDR Treatment | 11,474 | 3,526 | 15,000 |
| 2016 | BDR Control | 9,497 | 3,003 | 12,500 |
| | Total | 20,971 | 6,529 | 27,500 |
| | BDR Treatment | 41,674 | 13,326 | 55,000 |
| Total | BDR Control | 35,897 | 11,503 | 47,400 |
| | Total | 77,571 | 24,829 | 102,400 |

Table 2-1: BDR Experimental Design

The experimental design in Table 2-1 is a randomized control trial that can be used to detect the impact of the BDR treatment, including when the treatment is applied to customers who have and have not been previously exposed to HER. After randomly assigning customers, Nexant delivered the final sample to Opower in order to prepare their communications system for BDR events.

Customers were able to opt out from BDR event communications at any point. Once a customer elected to opt out, they were excluded from the program and all event notifications.¹¹ To analyze opt-out behavior, Opower provided a list of customers who opted out throughout 2015 and 2016, and the date they did so. Overall, there was total of 4,133 opt-outs across both years, which is 7.5% of the 55,000 total customers selected for BDR treatment. Table 2-2 summarizes the 2015 and 2016 BDR opt-out rates for each event group. Given that the two September 2015 events and two August 2016 events were called within a day or two of each other, customer opt-outs could not be attributed to one event or the other, so those events are grouped together in the table and the opt-out rates are divided by two in order to adjust for the number of events called. In general, the opt-out rates are consistent throughout 2015 and 2016, ranging from 0.9% to 1.8% per event called. BDR opt-out rates tend to decrease throughout each summer, which is most likely due to the fact that disinterested customers had already opted out earlier in the summer.

¹¹ Nonetheless, customers who unsubscribed were still included in the analysis. Their exclusion would invalidate the experiment because Nexant cannot observe which customers in the control group would unsubscribe, and excluding only BDR treatment customers who unsubscribed would yield biased estimates of load impacts.



| Year | Event Group | Enrolled and Active BDR Participants | Total Opt-outs | Opt-out Rate per Event |
|---------|--------------|--|-------------------|---------------------------|
| 2015 | Jul. 29 | 38,500 | 650 | 1.7% |
| | Aug. 27 | 37,467 | 550 | 1.5% |
| | Sept. 9 & 11 | 36,685 | 849 | 1.2% |
| 2016 | Aug. 16 & 17 | 47,371 | 1,659 | 1.8% |
| | Sept. 27 | 45,237 | 425 | 0.9% |
| Overall | | 55,000 | 4,133 | 7.5% |

2.2 Load Impact Estimation

In an RCT design, load impacts are measured as the difference in average usage of BDR treatment and control customers on Summer Saving Days. To implement this approach, a linear regression model was specified to include dummy variables indicating the experimental group to which the customer was assigned and the date. The linear model was estimated using ordinary least squares (OLS) regression so that the average of the treatment group was subtracted from the average load of the control group on each event day. The key assumption of the model is that the usage of the control group accurately predicts what usage would have been for treatment customers if they had not experienced the treatment. With large samples, this assumption is satisfied by virtue of the random assignment of the BDR treatment. To reduce the standard error of the impact estimates, date fixed effects were also included controlling for changing weather and other factors that change with time. Clustered standard errors at the customer level were used to account for likely serial correlation that exists between hourly observations for the same customer.

Separate specifications were used to estimate average hourly impacts during the event for the average event and for each individual event. These specifications are shown as Equations 1 and 2. In all equations, the dependent variable was the average load (kW) during each hour and the regression errors were specified to be robust to serial correlation.

Average

Event $kW_{i,t} = a + b \cdot Treatment_i + u_t + \varepsilon_{i,t}$ for $i \in \{1, ..., n_i\}$ and $t \in \{1, ..., n_t\}$ (1) Equation:

Individual
Event
Equation:

$$kW_{i,t} = a + \sum_{t=1}^{max} b_t \cdot (Treatment_i \cdot Date_t) + u_t + \varepsilon_{i,t} \text{ for } i \in \{1, ..., n_i\} \text{ and } t \qquad (2)$$

$$\in \{1, ..., n_t\}$$

In order to obtain hourly load impact estimates for each event, the individual event equation was estimated separately for each hour. In addition, the model was estimated separately for subgroups of interest, in order to identify the effect of BDR in each group.

Table 2-3 provides the definition of variables and parameters that appear in Equations 1 and 2.

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| Variable | Definition |
|-----------|---|
| i, t | Indicate observations for each individual i , date t and event number n , where the number of events varies by utility and is denoted max |
| а | The model constant |
| b | The difference between BDR and control group customer during event days – this is the coefficient of interest |
| и | Time effects for each date that control for unobserved factors that are common to all treatment and control customers but unique to the time period |
| ε | The error for each individual customer and time period |
| Treatment | A binary indicator or whether or not the customer is part of the treatment (BDR) or control group |
| Date | A binary indicator of date |

Table 2-3: Definitions of Model Variables and Parameters

The regression analysis employed a simple model that relies on no explanatory variables other than the treatment and time effects. This model does not rely on modeling the relationship between customers' electricity usage and other factors such as weather; it is informed by control group customers that experience the event day weather, but do not experience the BDR treatment.

3 Load Impact Results

This section summarizes the load impact estimates on Summer Saving Days. Three events were called in the summer of 2016 on August 16, August 17, and September 27. Each event ran from 5 to 8pm (hours ending 18, 19 and 20). The average number of customers participating in the three events was 49,258. A small amount of variation in the number of customers participating in each event exists due to account turnover and attrition as some customers opted out of the study over the summer. The highest enrollment (49,420 customers) occurred during the August 16 event, while the lowest enrollment (48,945 customers) occurred during the September 27 event. Note that the number of customers participating in the 2016 events is lower than the 55,000 customers that make up enrollment from the 2015 and 2016 cohorts based on the study design. This discrepancy is principally due to account turnover and attrition among the 2015 cohort, which occurred at the usual rate of customer "churn" for the PG&E residential population. The attrition among the 2015 cohort occurred at equal rates among control and treatment group customers, hence load impact estimates remain internally valid.

3.1 Event Day Impacts

Figure 3-1 shows the average customer's hourly load shapes and impacts on the average event day. The reference load, shown in blue, is the load that was observed in the absence of the BDR treatment, i.e., the control group. The observed load, shown in red, is the load observed in the treatment group on the average event day. The raw load shapes are associated with the left-most y axis and event hours are denoted by filled in circles. The impact (orange) is the difference between observed load and reference load, which is measured on the right y axis. The 95% confidence interval for the impact is shown in grey. The estimated load impacts are largest in the event hours 5 to 8pm (hours ending 18, 19 and 20). Impacts in pre-event hours are smaller than impacts occurring in the event hours, but are still statistically significant.





Figure 3-2 shows the average customer's hourly load shapes and impacts on each of the three individual event days as well as the average event day. Peak load is noticeably higher on the August 17 event, but otherwise the load shapes and pattern of impacts throughout the day remain fairly constant across event days. Individual event day results are less precisely estimated than the average event day impacts (thereby having wider confidence intervals) since the individual day estimates are based on a single day of data rather than all three event days.



Figure 3-2: Load Shapes for Individual Event Days

Table 3-1 shows load impact estimates for each event day and for the average event day in 2016. Percent impacts range from 1.54% to 2.75%; average impacts range from 0.04 kW to 0.06 kW; and aggregate impacts range from 1.91 MW to 3.20 MW. The highest impacts and the lowest impacts each occurred on the consecutive event days of August 16 and August 17. The lower impacts on August 17 may be due to customer fatigue, but customer confusion could have played a role because participants receive nearly the same message on consecutive days. Despite lower impacts occurring on August 17, all impacts are significant at the 5% level. On the average event day, the average participant reduced peak period load by 2.1%. In aggregate, BDR customers reduced load by an average of 2.5 MW across the three event days in 2016.

| Event | Accounts | Reference Load (kW) | Observed Load (kW) | Impact (kW) | 95% CI (kW) | Aggregate Impact (MW) | Percent Impact (%) |
|------------|----------|------------------------|-----------------------|----------------|----------------|-----------------------------|--------------------------|
| 8/16/2016 | 49,420 | 2.36 | 2.29 | 0.06 | (0.04; 0.09) | 3.20 | 2.75% |
| 8/17/2016 | 49,409 | 2.51 | 2.47 | 0.04 | (0.01; 0.06) | 1.91 | 1.54% |
| 9/27/2016 | 48,945 | 2.21 | 2.16 | 0.05 | (0.03; 0.07) | 2.28 | 2.11% |
| Avg. Event | 49,258 | 2.36 | 2.31 | 0.05 | (0.03; 0.07) | 2.46 | 2.12% |

| Table 3-1: Average | Load | Impacts | on | Event | Days |
|--------------------|------|---------|----|-------|------|
|--------------------|------|---------|----|-------|------|

Table 3-2 shows average hourly impacts during the peak period of each event. Impact estimates for all event hours and the average event hour are shown for each event day as well as the average event day. Hourly impacts vary modestly during the three hour event window. For all event days, impacts are highest in the second event hour (6-7pm), and lowest in the final hour (7-8pm). This decline coincides with the average customers' usage pattern that shows a relatively steep decline in load by 8pm as temperatures decrease in the evening, after load peaked at around 6 or 7pm.

| Event Date | Hour Ending | Impact (kW) | Standard Error (kW) |
|------------|-----------------|-------------|------------------------|
| | 18 | 0.066 | 0.012 |
| 9/16/2016 | 19 | 0.067 | 0.012 |
| 0/10/2010 | 20 | 0.061 | 0.011 |
| | Avg. Event Hour | 0.065 | 0.012 |
| | 18 | 0.041 | 0.013 |
| 9/17/2016 | 19 | 0.044 | 0.013 |
| 0/17/2010 | 20 | 0.031 | 0.012 |
| | Avg. Event Hour | 0.039 | 0.012 |
| | 18 | 0.048 | 0.012 |
| 0/07/0046 | 19 | 0.054 | 0.011 |
| 9/27/2016 | 20 | 0.038 | 0.010 |
| | Avg. Event Hour | 0.047 | 0.011 |
| | 18 | 0.052 | 0.011 |
| Ave Evert | 19 | 0.055 | 0.010 |
| Avg. Event | 20 | 0.043 | 0.009 |
| | Avg. Event Hour | 0.050 | 0.010 |

Table 3-2: Hourly Load Impact Estimates for Event Days

3.2 Load Impacts by HER Status

Table 3-3 compares load impacts for each event day and for the average event day for both HER recipients and HER control customers. Impacts for HER recipients are consistently lower than those for HER control customers (1.65% vs 2.87% on the average event day). This result indicates that there may be diminishing returns for the behavioral intervention because HER recipients are either desensitized to contact based on having already implemented some energy savings measures in response to receiving HER. The reference load of HER recipients is consistently 2% to 3% lower than that of HER control customers, further indicating that HER recipients may already have realized the energy savings that HER control customers achieved during the BDR event as a consequence of ongoing HER treatment. The lower percent reductions and lower reference load of HER recipients results in lower absolute impacts.

| Category | Event | Accounts | Reference Load (kW) | Observed Load (kW) | Impact (kW) | 95% CI (kW) | Aggregate Impact (MW) | Percent Impact (%) |
|-------------------|------------|----------|------------------------|-----------------------|----------------|----------------|-----------------------------|--------------------------|
| | 8/16/2016 | 19,694 | 2.40 | 2.31 | 0.09 | (0.05; 0.13) | 1.78 | 3.78% |
| HER | 8/17/2016 | 19,689 | 2.55 | 2.50 | 0.05 | (0.01; 0.08) | 0.89 | 1.78% |
| Control | 9/27/2016 | 19,501 | 2.24 | 2.17 | 0.07 | (0.04; 0.10) | 1.37 | 3.14% |
| | Avg. Event | 19,628 | 2.40 | 2.33 | 0.07 | (0.04; 0.10) | 1.35 | 2.87% |
| | 8/16/2016 | 29,726 | 2.33 | 2.28 | 0.05 | (0.02; 0.08) | 1.45 | 2.10% |
| HER Recipients | 8/17/2016 | 29,720 | 2.49 | 2.45 | 0.04 | (0.00; 0.07) | 1.04 | 1.41% |
| | 9/27/2016 | 29,444 | 2.19 | 2.16 | 0.03 | (0.00; 0.06) | 0.93 | 1.45% |
| | Avg. Event | 29,630 | 2.34 | 2.30 | 0.04 | (0.01; 0.06) | 1.14 | 1.65% |

Table 3-3: Load Impact Estimates by HER Status

3.3 Load Impacts by Cohort

Table 3-4 shows load impacts for each event day and for the average event day for both the 2015 cohort and the 2016 cohort. For the average event day, the 2015 cohort delivered higher impacts in both absolute and percentage terms. The 2015 cohort's percent impact was 2.31% on the average event day, while the 2016 cohort's percent impact was 1.72%.

| Enrollment Cohort | Event | Accounts | Reference Load (kW) | Observed Load (kW) | Impact (kW) | 95% CI (kW) | Aggregate Impact (MW) | Percent Impact (%) |
|----------------------|------------|----------|------------------------|-----------------------|----------------|----------------|-----------------------------|--------------------------|
| | 8/16/2016 | 34,894 | 2.33 | 2.26 | 0.07 | (0.05; 0.10) | 2.54 | 3.12% |
| 2015 | 8/17/2016 | 34,884 | 2.49 | 2.45 | 0.04 | (0.02; 0.07) | 1.54 | 1.77% |
| 2015 | 9/27/2016 | 34,524 | 2.23 | 2.18 | 0.05 | (0.02; 0.07) | 1.58 | 2.06% |
| | Avg. Event | 34,767 | 2.35 | 2.30 | 0.05 | (0.03; 0.08) | 1.89 | 2.31% |
| 2016 | 8/16/2016 | 14,526 | 2.41 | 2.36 | 0.05 | (0.01; 0.09) | 0.71 | 2.02% |
| | 8/17/2016 | 14,525 | 2.56 | 2.54 | 0.03 | (-0.02; 0.07) | 0.41 | 1.09% |
| | 9/27/2016 | 14,421 | 2.17 | 2.12 | 0.05 | (0.01; 0.09) | 0.67 | 2.15% |
| | Avg. Event | 14,490 | 2.38 | 2.34 | 0.04 | (0.01; 0.08) | 0.59 | 1.72% |

Table 3-4: Load Impacts Estimates by Cohort

There are several possible explanations for higher impacts among 2015 customers. Before considering these possible causes, it is important to first emphasize that the difference between the impacts of each cohort is not statistically significant, so there is insufficient evidence to conclude the difference did not occur by chance. The 2015 cohort was exposed to the treatment in the summer of 2015, so there may be learning effects, whereby customers become adept at responding to events through developing habits or routines that facilitate demand reductions. There may also be persistence of effects after events if routines or habits formed in response to events persist after the events. For example, an individual may increase their thermostat set point prior to the event, and retain the setting indefinitely having found the change easy to accommodate.

Another possibility is that the 2015 cohort has been subject to more attrition than the 2016 cohort. The 2015 cohort is now made up of customers who have remained active for over a year. If customers who become inactive are systematically different from those who remain, then the 2015 sample has been subject to more attrition. In this case, because both treatment and control customers are subject to attrition at equal rates, the estimates remain internally valid. However, estimates may be externally invalid if customers who become inactive tend to deliver different impacts from those who remain active.

A final possibility is that the 2015 cohort exhibited large impacts by chance due to sampling variation. Despite the large sample sizes involved in this study, the impacts are sufficiently small that small differences between treatment and control group load on event days, or characteristics correlated with load on event days, can result in relatively large percent differences in impacts. This idea is supported by the fact that the difference is statistically insignificant, as exhibited in the confidence intervals of the impacts: each cohort's average impacts is well within the confidence interval of the other.

3.4 Load Impacts by A/C Usage

Table 3-5 shows load impacts for the average event day for customers with varying estimated A/C usage patterns. High A/C usage customers delivered higher impacts in absolute terms, but



lower impacts in percentage terms. On the average event day, high A/C usage customers delivered load impacts of 0.5 kW, on average. Their percent impact was 1.51% on the average event day, while impacts for customers with lower A/C usage ranged from 1.74% to 2.75%. While these results are statistically insignificant, it is worthwhile to further study whether customers with high A/C usage consistently provide higher kW impacts.

| A/C Usage | Accounts | Reference Load (kW) | Observed Load (kW) | Impact (kW) | 95% CI (kW) | Aggregate Impact (MW) | Percent Impact (%) |
|-----------|----------|------------------------|--------------------------|----------------|----------------|-----------------------------|-----------------------|
| High A/C | 25,191 | 3.15 | 3.11 | 0.05 | (0.02; 0.07) | 1.20 | 1.51% |
| Med A/C | 13,467 | 1.92 | 1.89 | 0.03 | (0.01; 0.06) | 0.45 | 1.74% |
| Low A/C | 6,906 | 1.09 | 1.06 | 0.03 | (0.00; 0.06) | 0.21 | 2.75% |
| No A/C | 3,665 | 0.75 | 0.73 | 0.02 | (-0.02; 0.05) | 0.06 | 2.09% |

Table 3-5: Load Impacts Estimates by A/C Usage for the Average Event Day

3.5 Load Impacts by Delivery Channel

As noted in Section 1.1, event notifications were delivered via email or an automated phone call (using IVR for landlines only). Table 3-6 shows the average event day impact estimates by delivery channel. The 65% of study participants who received event communications only through IVR provided comparable percent impacts to those of customers receiving emails (with or without an accompanying IVR call). The absolute impacts for IVR-only customers are slightly lower, due to their lower reference loads. Nonetheless, these results show that BDR provides comparable results regardless of delivery channel.

| Delivery Channel | Accounts | Reference Load (kW) | Observed Load (kW) | Impact (kW) | 95% CI (kW) | Aggregate Impact (MW) | Percent Impact (%) |
|------------------------------|----------|------------------------|--------------------------|----------------|--------------|-----------------------------|-----------------------|
| IVR Only | 31,725 | 2.23 | 2.18 | 0.05 | (0.03; 0.07) | 1.59 | 2.25% |
| Email Only or Email + IVR | 17,404 | 2.60 | 2.54 | 0.06 | (0.02; 0.09) | 0.98 | 2.17% |

Table 3-6: Load Impacts Estimates by Delivery Channel for the Average Event Day

3.6 Load Impacts by Geography

Table 3-7 shows load impacts for the average event day segmented by geography as defined by division in the PG&E service territory. Divisions with impacts that are statistically significant at the 5% level are shaded, including Diablo, Sacramento, Sierra, and Stockton. Per participant impacts in those divisions tended to be larger than in the rest, ranging from 0.07 kW to 0.09 kW on the average event day. Among divisions with statistically significant impacts, percent impacts were fairly similar, ranging from 2.94% to 3.82%. The largest impacts in both absolute and percentage terms were observed in Stockton. The smallest impacts were in Kern, which actually showed higher usage among treatment customers, but the sample size was relatively low and



the overall result was statistically insignificant, so it cannot be concluded that BDR led to negative impacts.

| Division | Accounts | Reference Load (kW) | Observed Load (kW) | Impact (kW) | 95% Cl (kW) | Aggregate Impact (MW) | Percent Impact (%) |
|--------------|----------|------------------------|--------------------------|----------------|---------------|-----------------------------|-----------------------|
| De Anza | 1,046 | 1.88 | 1.81 | 0.07 | (-0.06; 0.19) | 0.07 | 3.48% |
| Diablo | 12,037 | 2.41 | 2.34 | 0.07 | (0.03; 0.12) | 0.88 | 3.03% |
| Fresno | 8,432 | 2.79 | 2.76 | 0.03 | (-0.02; 0.07) | 0.23 | 1.00% |
| Kern | 2,623 | 2.79 | 2.82 | -0.04 | (-0.11; 0.03) | -0.10 | -1.40% |
| Mission | 3,612 | 1.83 | 1.79 | 0.04 | (-0.02; 0.10) | 0.14 | 2.08% |
| North Valley | 320 | 2.26 | 2.21 | 0.05 | (-0.16; 0.26) | 0.02 | 2.16% |
| Peninsula | 1,188 | 1.30 | 1.28 | 0.03 | (-0.07; 0.12) | 0.03 | 1.96% |
| Sacramento | 5,470 | 2.23 | 2.16 | 0.07 | (0.01; 0.12) | 0.36 | 2.96% |
| San Jose | 7,525 | 1.70 | 1.68 | 0.02 | (-0.02; 0.07) | 0.18 | 1.40% |
| Sierra | 3,364 | 3.04 | 2.95 | 0.09 | (0.01; 0.17) | 0.30 | 2.94% |
| Stockton | 3,638 | 2.84 | 2.73 | 0.11 | (0.04; 0.18) | 0.40 | 3.82% |

Table 3-7: Load Impacts Estimates by PG&E Division for the Average Event Day

3.7 Comparison between 2015 and 2016 Load Impacts

A key research question addressed in this evaluation is whether the impacts of customers enrolled in consecutive years remain consistent. Comparing impacts from the 2016 evaluation to the 2015 evaluation is not sufficient to address this question because of changes in enrollment and customer churn. To better understand year-over-year impacts, persistent customers that were enrolled and have interval data for every event in 2015 and 2016 were analyzed separately.

Table 3-8 shows persistent customer load impact estimates for each event day in 2015 and 2016, and for the average event day. In total, there are 34,482 persistent customers that were enrolled and have interval data for every event in 2015 and 2016. For these customers, percent impacts range from 1.54% to 3.2%; average impacts range from 0.04 kW to 0.07 kW; and aggregate impacts range from 1.45 MW to 2.58 MW. On the average event day, the average participant reduced peak period load by 2.1%, which is almost identical to the percent impact for the average event day in 2016. Indeed, percent impacts from the 2015 events are very similar to those from the 2016 events. While these results suggest that impacts remain consistent for customers enrolled in the program in consecutive years, it is also important to note that customer-weighted average temperatures during the event period were quite a bit lower for the 2016 events as compared to the 2015 events, as shown in the table. For the average 2016 event, persistent customers experienced event period temperatures of 88.7 °F on average, which is 5.5 degrees cooler than that of the average 2015 event (94.2 °F).



| Event | Avg. Event Temp. (°F, 5-8pm) | Accounts | Reference Load (kW) | Observed Load (kW) | Impact (kW) | 95% CI (kW) | Aggregate Impact (MW) | Percent Impact (%) |
|------------|------------------------------------|----------|------------------------|--------------------------|----------------|----------------|-----------------------------|--------------------------|
| 7/29/2015 | 95.6 | 34,482 | 3.26 | 3.19 | 0.07 | (0.04; 0.11) | 2.51 | 2.23% |
| 8/27/2015 | 91.4 | 34,482 | 2.79 | 2.73 | 0.06 | (0.03; 0.09) | 2.11 | 2.19% |
| 9/9/2015 | 97.0 | 34,482 | 2.99 | 2.93 | 0.06 | (0.03; 0.09) | 1.99 | 1.93% |
| 9/11/2015 | 92.8 | 34,482 | 2.72 | 2.68 | 0.04 | (0.01; 0.07) | 1.45 | 1.54% |
| 8/16/2016 | 88.3 | 34,482 | 2.34 | 2.26 | 0.07 | (0.05; 0.10) | 2.58 | 3.20% |
| 8/17/2016 | 88.6 | 34,482 | 2.50 | 2.45 | 0.04 | (0.02; 0.07) | 1.55 | 1.80% |
| 9/27/2016 | 89.1 | 34,482 | 2.23 | 2.18 | 0.04 | (0.02; 0.07) | 1.55 | 2.02% |
| Avg. Event | 91.8 | 34,482 | 2.69 | 2.63 | 0.06 | (0.03; 0.08) | 1.96 | 2.11% |

| Table 3-8: Persistent Customer Average Load | Impacts on 2015 and 2016 Event Days |
|---|-------------------------------------|
|---|-------------------------------------|

3.8 Non-event Day Impacts

Analysis performed in the 2015 evaluation suggested there were some spillover effects of the BDR treatment into non-event days. Nexant repeated this analysis in the 2016 evaluation by estimating load impact estimates for all days during the summer. These estimates were computed using the same regression model and event window that were used to estimate event day load impacts.

Figure 3-3 shows average customer impacts for the average event window hour throughout the summer. Orange dots represent event days, and green dots represent non-event days. The 95% confidence interval is shaded in grey. Several interesting results can be seen in the graph. Impacts on non-event days immediately following event days tend to be larger than the average non-event day. This suggests some amount of spillover for load reduction actions implemented on (or immediately before) event days. This spillover persists throughout the summer, but is small in magnitude so that differences on most non-event days are not significant at the 95% level. This is an important result. If demand reductions from an event day persist into the following days, then calling consecutive event days may not be necessary, especially when the lower impacts on the second day are considered. Furthermore, the spillover effects are not limited to days immediately following event days. Some modest energy savings are apparent during event hours throughout late August and September.



Figure 3-3: Average Impact on Each Day

There are observable non-zero differences between BDR treatment and control group loads prior to any event days. While differences between the BDR treatment and control groups prior to the first event on August 16 are generally very small, the differences tend to be above zero, particularly in July onwards. These differences may be non-random differences associated with receipt of the welcome letter (on or about July 1st), or they may be random differences that result from sampling variation, whereby, for example, the control group load is by chance slightly more weather sensitive than the treatment group load. This effect was also observed in the 2015 evaluation, and while its cause was unknown, the most reasonable explanation was the effect of the welcome letter, but also may be due to sampling variation.

Figures 3-4 and 3-5 show average customer impacts for the average event window hour throughout the summer, separately for each cohort. Pre-treatment differences in Figure 3-4 are well-centered around zero. However, in Figure 3-5, pre-treatment differences are consistently above zero. While the differences tend to be larger after the welcome letters are sent, they are also observed before it was sent on July 1. This suggests that the pre-treatment differences are the result of random sampling variation among the 2015 cohort, and if an estimation model were to account for these pre-treatment differences, the resulting unbiased impacts may be much more similar to those of the 2016 cohort. As discussed in Section 4-2, future BDR implementations should consider alternative impact estimation strategies that incorporate pre-treatment data, given the relatively small effect size and sampling variation from one cohort to the next. However, testing of alternative estimation strategies was not part of the scope or research design for this evaluation.



Figure 3-4: Average Impact on Each Day for the 2016 Cohort

Figure 3-5: Average Impact on Each Day for the 2015 Cohort





4 Conclusions and Recommendations

This section summarizes key conclusions and recommendations from the 2016 PG&E BDR study.

4.1 Conclusions

This study has conclusively demonstrated that a BDR treatment can cause small but statistically significant reductions in residential peak period energy consumption for customers located in certain substations on the PG&E system. If aggregated over a large number of customers, these small changes (i.e., 0.04 to 0.06 kW) could result in sizeable reductions in peak period energy consumption during critical hours (i.e., 5 to 8pm in summer). However, it is important to note that BDR currently requires PG&E to initiate the DR event process more than 24 hours in advance of the events, so this type of program may not be applicable to all situations in which peak load reductions may be required. Nonetheless, while the event lead-time may be relatively long, this study has demonstrated that BDR can be launched relatively quickly in targeted areas if needed.

An unaddressed question from the 2015 evaluation was whether BDR impacts would persist in 2016 for customers who enrolled in 2015. Impacts in 2015 were lower at the end of the summer than at the start, which raised the issue. By restricting an analysis to persistent customers enrolled throughout both 2015 and 2016, and estimating impacts over both years, Nexant was able to establish that 2016 impacts were similar to those observed in 2015. BDR impacts appear to remain around 2% for customers enrolled in consecutive years. However, it is important to note that temperatures were quite a bit lower for the 2016 events as compared to the 2015 events.

Given that the effect of BDR on energy consumption is not confined to the hours of the peak period for event days and is somewhat persistent from day to day throughout the summer season, BDR has the potential to yield energy savings as well, similar to the HER program. However, it is important to note that because of the persistence of BDR impacts, exposing HER control customers to BDR runs the risk of changing their baseline energy use and complicating the estimation of HER impacts. The net benefits of BDR for HER control customers are uncertain and should be carefully considered by portfolio managers in assessing which populations to include for participation in BDR.

Finally, a key unanswered question about this study is how it applies to the rest of PG&E's service territory. This study was confined to 31 substations where PG&E is attempting to limit load growth. It is unknown whether load reductions in other locations would be comparable to what was observed in this study.

4.2 Recommendations

BDR appears to be an effective mechanism for reducing residential energy consumption during critical time periods and has the potential to be a complement to customers receiving HER and thereby increasing energy savings. However, exposing HER control customers to BDR also runs the risk of changing their baseline energy use and complicating the estimation of HER impacts. Due to the complexities that would be introduced as a result of exposing the current



HER control customers to BDR, it is recommended that BDR be withheld from the HER control customers at this time.

Given that this study was confined to 31 substations where PG&E is attempting to limit load growth, it is unknown whether load reductions in other locations would be comparable to what was observed in the study. As discussed in Section 3.6, there is some evidence to suggest that impacts vary by geography. Due to these uncertainties, an additional round of testing is recommended to include samples of customers outside the currently targeted substations and study the persistence of BDR impacts for HER recipients under repeated exposure.

Finally, this study yielded several insights to inform future implementations of BDR, including:

- Given that impacts on non-event days immediately following event days tend to be larger than the average non-event day, future BDR implementations may consider avoiding consecutive event days in order to reduce the number of customer communications within a short period of time (an alternative option would be to call multi-day events);
- Given the relatively small effect size and sampling variation from one cohort to the next, future BDR implementations should consider alternative impact estimation strategies that incorporate pre-treatment data, especially if further saturation is sought in local areas with limited numbers of customers to sample; and
- High A/C usage customers delivered higher impacts, so they should be targeted in future BDR implementations. However, customers with lower A/C usage tend to reduce a higher percentage of their base load.