The Reliability of Behavioral Demand Response

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ABSTRACT

Behavioral Demand Response (BDR) is a relatively new and rapidly growing way of implementing demand response (DR) programs. Given BDR relies on participants to actively opt-in to DR events by voluntarily curtailing usage, there has been some skepticism over its reliability as a resource. To date, five utilities have deployed BDR programs reaching over 200,000 households. Preliminary findings show average demand savings of 3% per event, and these savings are acheived year-over-year, suggesting BDR savings are reliable.

This study provides evidence of the reliability of BDR demand savings, as well as implications for program design and implementation pertaining to the interaction with Home Energy Report (HER) programs. First, this study presents findings from the evaluation of a BDR pilot program implemented by DTE Energy beginning in 2015. Using regression analysis of AMI data, this study measures savings in 2015 and 2016, identifying whether demand savings are acheived year-over-year. Second, this study examines whether BDR savings are different when the household is also a HER recipient. With high penetrations of HER programs in many jurisdictions, it is important to determine whether and how these two programs interact to influence the reliability of the BDR resource. DTE Energy designed the 2016 BDR pilot to target housholds in the HER program, allowing this specific question to be answered.

Our findings are consistent with other studies and show that demand savings of approximately 3% per event can be achieved in each of the first two years, and layering BDR on top of HER does not create an interactive savings effect.

Introduction

Demand Response (DR) is an approach to demand-side management where utilities generally offer customers incentives to curtail usage during periods of peak usage or high cost. Behavioral Demand Response (BDR) is a relatively new and rapidly growing type of DR program in which customers voluntarily reduce demand in response to a notification as opposed to a price signal or other financial incentive, or the direct control of end uses. Given BDR relies on participants to voluntarily curtail usage, there has been some concern over its reliability as a resource (see for example Buckley, 2016). To date, five utilities have deployed BDR programs, reaching over 200,000 households, and researchers are just beginning to analyze their effect on load reduction.

Given the high penetration of Home Energy Report (HER) programs in many jurisdictions, it is important to determine whether and how the HER and BDR programs interact and influences BDRsavings. HER programs provide customers with information on energy consumption through a variety of communciation methods to change consumers' energy use behavior. On the one hand, customers that receive HERs may have adopted habitual changes in behavior that are not isolated to peak periods, yielding relatively low peak demand savings during BDR events. On the other hand, customers that receive HERs may have higher awareness of the actions they can take, yielding relatively high peak demand savings during BDR events. Thayer et al. (2016) provide some evidence that households treated with both HER and BDR messaging deliver *less* demand savings relative to households receiving only BDR messaging (1.8% versus 2.4%), though the differences were not statistically significant.

In 2015, DTE Energy, in conjunction with Oracle, launched a BDR pilot program to answer the following research questions:

(1) What are BDR-only demand savings?

(2) Do BDR demand savings rates change year-over-year?

(3) What are BDR plus HER demand savings?

DTE Energy's BDR program used an experimental design in which households were randomly assigned to either a treatment or control group. The treatment group received a message by email or voice, depending on the customer's preference, by 6 PM on the day before an event. The message informed the customer an event would be called betweeen 3 PM and 7 PM the next day, and provided tips on how to conserve energy. Approximately one to three days following the event, the customer received an event summary by email detailing performance during the event, with a similar home comparison.

The 2015 wave of the pilot was designed to measure BDR savings and, as a result, was designed to target customers not in the HER program. The 2016 wave of the pilot differed from the 2015 wave in that it was designed specifically to test whether BDR savings are different when the participant is also a recipient of the utility's HER program (answering question (3) above). In the 2016 wave, DTE Energy randomly assigned households to a BDR treatment and control group within existing HER treatment and control groups.

Table 1 presents the number of households within each cell of the program's design. As noted above, the 2015 wave did not explicitly target HER households but randomly assigned households to BDR treatment and control groups. However, a relatively small number of households did overlap with the HER program. The 2016 wave explicitly targeted HER households, randomly assigning BDR treatment and control groups across HER treatment and control groups. Our review of the data identified a handful of households that were not in the HER program.

Table 1. Experimental design of DTE Energy's BDR pilot program

	HER treatment group	HER control group	Neither	Total
2015 BDR treatment group	2,283	1,394	36,307	39,984
2015 BDR control group	1,139	635	18,187	19,961
2016 BDR treatment group	53,932	17,986	14	71,932
2016 BDR control group	63,620	20,929	29	84,578

Note: While the program targeted customers (1) for whom AMI data were available, and (2) were not on the interruptible air conditioning rate code, there were a small number of customers which were not screened out. The counts presented in this table, and the analysis that follows, exclude these customers. *Source:* Navigant.

Table 2 presents the dates of the 2015 and 2016 BDR events. In 2015, DTE Energy called a total of six BDR events, in 2016 the utility called ten events. All events lasted from 3 PM to 7 PM.

Table 2. 2015 and 2016
DTE Energy BDR
Event Dates

Event	2015	2016
1	7/17/2015	7/6/2016
2	7/28/2015	7/22/2016
3	7/29/2015	7/27/2016
4	8/14/2015	8/4/2016
5	8/18/2015	8/5/2016
6	9/2/2015	8/10/2016
7		8/11/2016
8		8/19/2016
9		8/30/2016
10		9/7/2016

Source: DTE Energy.

Table 3 presents the average and maximum daily heat index on 2015 and 2016 BDR event days. On average, 2016 event days were hotter compared to 2015.

Table 3. Weather summary on event days

Event	Average Daily Heat Index (°F)	Average Maximum Daily Heat Index (°F)
2015	79	109
2016	84	124

Source: Navigant Analysis of NOAA Data.

Methodology

To conduct the analysis, we employed regression analysis using AMI data from 2014 through 2016. Due to the experimental design, the regression model used only event-day data with lagged hourly demand for the pre-program period acting as a control for any small systematic differences between treatment and control groups.[1] This model measures the difference in average demand between the BDR treatment and control groups. Formally, the model is:

$$kW_{it} = \sum_{t=1}^{24} \beta_{1t} hour_t + \sum_{d=1}^{7} \beta_{2d} day_d + \beta_3 \cdot PreUse_{it} + \beta_4 PreSeason_{it} + \sum_{t=1}^{4} \beta_{5t} Treatment_i \cdot EventHour_t + \sum_{t=1}^{2} \beta_{6t} Treatment_i \cdot Snapback_t + \sum_{t=1}^{2} \beta_{7t} Treatment_i \cdot PreEvent_t + \varepsilon_{it}$$

Where,

kW_{it} is demand for customer *i* during hour *t*

$hour_t$ is a dummy variable for hour of the day

day_d is a dummy variable for day of the week

$PreUse_{it}$ is demand during hour *t* during the same month *m* in the pre-program period. For example, for customer *i* during hour 16:00 on each day in July 2016, $PreUse$ is average demand during hour 16:00 during July 2015 if customer *i* is in the 2016 BDR Cohort and during July 2014 if customer *i* is in the 2015 BDR Cohort

$PreSeason_{it}$ is demand during hour *t* of the most recent month without any events. For example, for customer *i* during hour 16:00 on each day in July and August 2016, $PreSeason$ is demand during hour 16:00 during June 2016

$Treatment_i$ is a dummy variable indicating if customer *i* is in the treatment or control group

$EventHour_t$ is a dummy variable indicating if hour *t* is during a peak event

$Snapback_t$ is a dummy variable indicating if hour *t* is during the two hours after a peak event

$PreEvent_t$ is a dummy variable indicating if hour *t* is during the two hours before a peak event

[1] As a first step in the analysis, we verified randomization across the BDR pilot treatment and control groups to ensure the experimental design could be leveraged for the analysis.

Results

BDR-Only Demand Savings

To answer questions (1) and (2) above (what are BDR-only demand savings, and do BDR demand savings rates change year-over-year), we first present the savings estimates for the 2015 BDR cohort (in 2015 and 2016),[2] and the 2016 BDR cohort that did not overlap with the HER treatment group (in 2016).[3] These results only include customers who do not receive HERs, the interaction between BDR and HER (question 3) is presented further down in the results. As shown in Figure 1, across all three cohorts impacts range from 2.3% to 4.4%, all of which are statistically significant at the 99% confidence level.

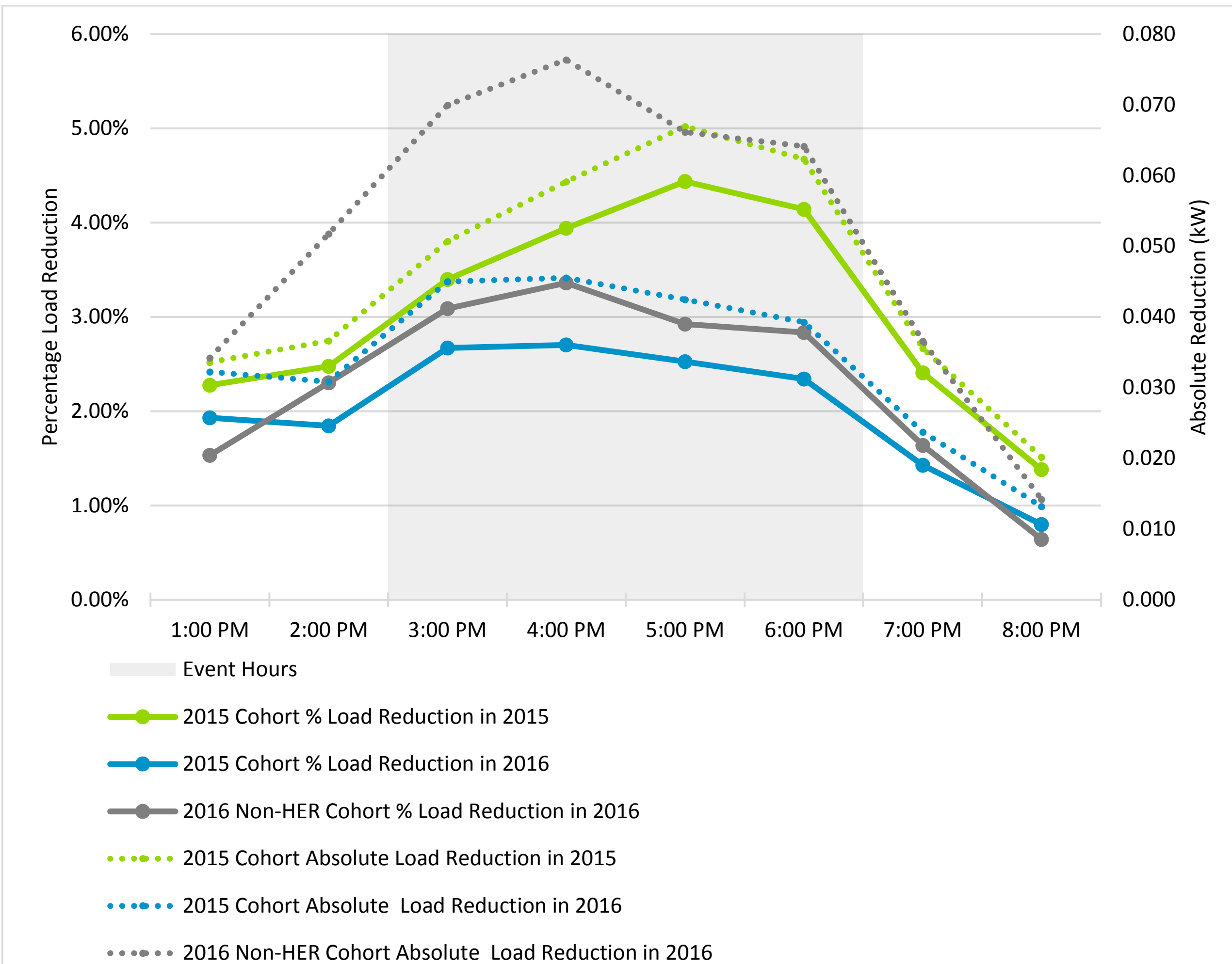

Figure 1. 2015 and 2016 savings estimates (no HER overlap) *Source:* Navigant.

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[2] The 2015 cohort was designed to target customers who were not also participating in the HER program. However, approximately 3,500 customers were HER recipients (Table 1). These customers were excluded from the analysis to identify a BDR-only savings estimate.

[3] The 2016 cohort was designed to target customers who were also participating in the HER program. As this portion of the analysis is focused on identifying a BDR-only savings estimate, the 2016 cohort primarily comprised of HER controls (Table 1).

Table 4 presents average hourly event impacts for the 2015 cohort in 2015 and 2016, and the 2016 non-HER cohort in 2016.

Table 4. Average hourly event impacts (2015 cohort in 2015 and 2016, 2016 non-HER cohort in 2016)

Event Hour	2015 Cohort in 2015	2015 Cohort in 2016	2016 Non-HER Cohort in 2016
3 PM	3.4%	2.7%	3.1%
4 PM	3.9%	2.7%	3.4%
5 PM	4.4%	2.5%	2.9%
6 PM	4.1%	2.3%	2.8%
Event Average	4.0%	2.6%	3.1%

Source: Navigant.

The impact profiles for the BDR pilot program are notably different from those associated with air conditioning-based DR programs, whether switch or thermostat. First, BDR achieved statistically significant savings in the hours leading up to the event, and in the hours following the event. The characteristic increase in demand during pre-cooling or post-recovery periods was not observed. Second, the largest demand impact was not necessarily observed during the first hour of the event, and impacts did not consistently degrade over the duration of the event. Both findings suggest customers are likely relying on a variety of end-uses (not just air conditioning) to manage demand, and that their behavioral changes spill over into non-event hours.

The 2015 cohort participated in the BDR pilot program for two consecutive years providing some evidence as to whether BDR impacts degraded year-over-year. Savings decreased between 2015 and 2016 from 4.0% (0.06 kW) to 2.6% (0.04 kW), with the difference being statistically significant at the 90% level. There are several factors which could have contributed to this result: (1) event days in 2016 were hotter than in 2015, with an average maximum head index of 124°F compared to 109°F in 2015; (2) more events were called in 2016 (10 events compared to six in 2015); and (3) it was the second year of the BDR program which could have affected customer response. To test whether customer fatigue from the additional events in 2016 caused savings to be lower, we estimated savings for just the first six events of 2016. This did not significantly change the savings estimates indicating customer fatigue was not a contributing factor.

In absolute terms, the 2016 (non-HER) cohort had the highest levels of demand savings. This may be explained by the pilot program targeting customers in the HER program (the HER controls are in this cohort) which had higher baseline usage relative to the 2015 cohort. A comparison between the 2015 and 2016 BDR cohorts in 2016 (0.04 kW vs 0.07 kW) suggests customers with higher baseline usage achieved higher demand savings.

BDR plus HER Demand Savings

Next, to answer question (3) above (what are BDR plus HER demand savings), we present savings estimates for the 2016 BDR cohort that were also in an HER treatment group. As shown in Figure 3, savings for the BDR plus HER group were slightly smaller than for BDR-only (2.9% versus 3.1%), though these differences were not statistically significant. This finding is consistent with the results from Thayer et al. (2016), though the difference in the point estimate was much smaller. This result should provide some assurance that the HER program does not appear to influence BDR savings. However, given the systematic difference in point estimates found in this study and Thayer et al. (2016), additional research may be warranted.

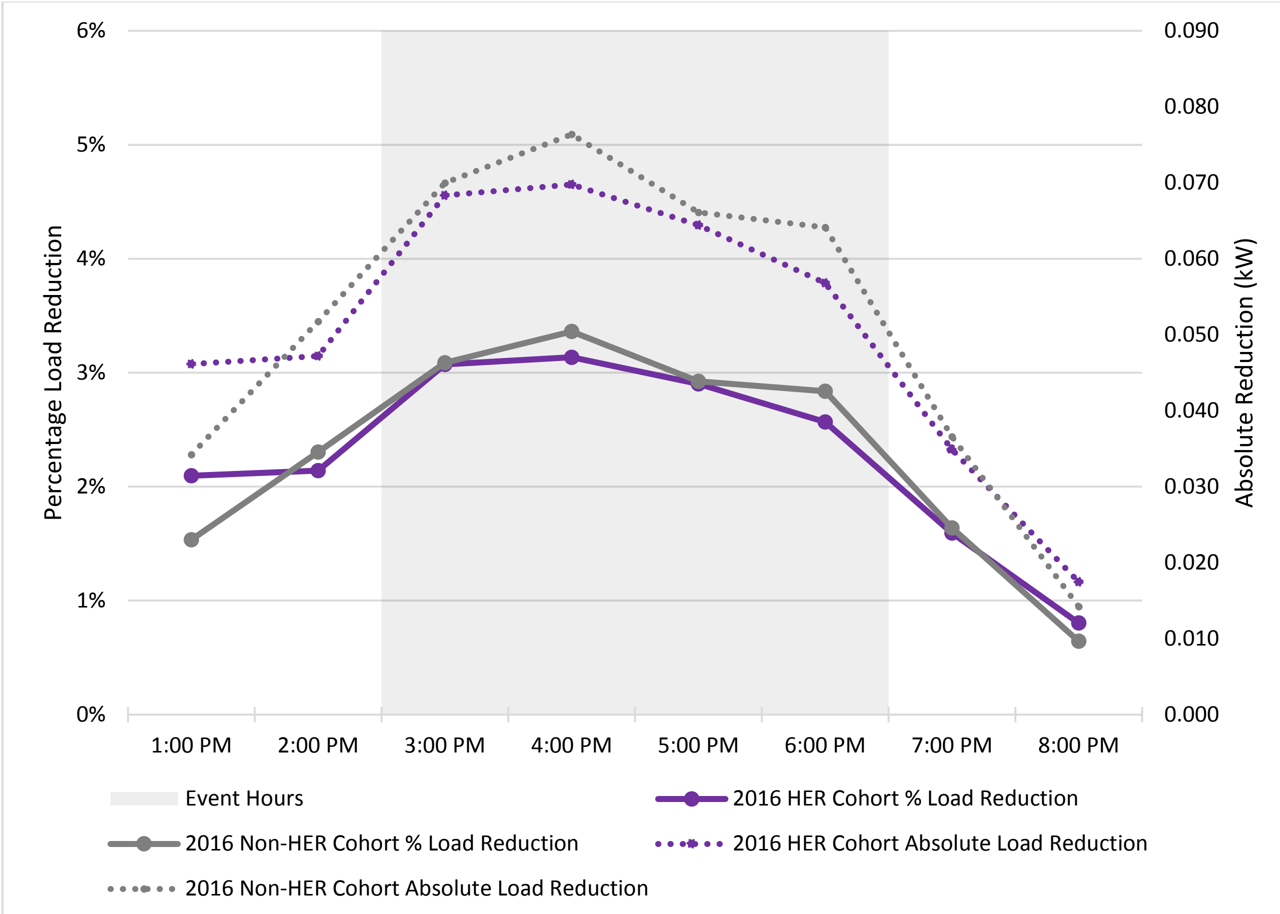

Figure 2. 2016 savings estimates (HER overlap) *Source:* Navigant.

Table 5 presents average hourly event impacts for the 2016 HER and non-HER cohorts.

Table 5. Average hourly event impacts (2016 HER and non-HER cohorts)

Event Hour	2016 Non-HER Cohort in 2016	2016 HER Cohort in 2016
3 PM	3.1%	3.1%
4 PM	3.4%	3.1%
5 PM	2.9%	2.9%
6 PM	2.8%	2.6%
Event Average	3.1%	2.9%

Source: Navigant.

Conclusion

DTE Energy began offering a BDR pilot program in 2015 with the objective of determining whether BDR can offer a reliable demand resource with savings that persist year-over-year. In 2016, DTE Energy re-designed their pilot with the objective of testing whether BDR savings were different when the participant is an HER recipient. Using regression analysis of AMI data, this study finds statistically significant BDR demand savings ranging from 2.3% to 4.4%. These savings extend into the hours leading up to and following a BDR event, and do not consistently degrade over the course of the event. Finally, customers with higher baseline energy usage appear to have higher demand savings. Utilities can use these results to strategically target high users for both HER and BDR programs as being an HER recipient does not influence BDR demand savings.

References

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