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PG&E Home Energy Report (HER) Energy Savings Distribution Analysis and Trends Study

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1. Introduction

PG&E, in contract with their implementation contractor Oracle Utilities Inc., implements the HER program. The program has been implemented in a series of experimental waves, referred to as Beta, Gamma, and Waves One through Eight (Table 1). Since 2011, the HER Program uses randomized controlled trials, in which residential customer households are randomly assigned to either treatment or control conditions. Households randomly assigned to receive the treatment group are mailed reports that compare their energy usage to similar neighbors and provide energy-saving tips and suggestions. The energy savings analyses result from comparing the difference in energy consumption between the treatment and control groups. According to third-party evaluations, average evaluated savings per household is approximately 1.5% for electric usage and approximately 0.8% for gas usage. Table 1 provides an overview of each wave, start year and population size.

Table 1. PG&E's HER Program Overview

Wave	Start Year	Population in Treatment at Launch
Beta	July 2011	59,988
Gamma	Nov. 2011	189,799
Wave One	Feb. 2012	399,973
Wave Two	Jan. 2013	385,310
Wave Three	July 2013	224,982
Wave Four	Mar. 2014	199,990
Wave Five	Oct. 2014	209,986
Wave Six	Sept. 2015	311,988
Wave Seven	Mar. 2017	157,500
Wave Eight	Nov. 2017	143,000

Though the HER program is successful at generating significant energy savings today, some challenges may impact long-term program viability and effectiveness.[1] In particular, a portion of the population in treatment may not save energy. Learning more about these "negative" or "neutral" savers informs strategies for adjusting treatment in the future (e.g., framing, content, targeting). As a result, PG&E contracted with Opinion Dynamics to conduct this study to support the redesign of its HER program to increase cost-effectiveness and maximize program savings.

Opinion Dynamics used a three-phased approach to support this research. First, we characterized the distribution of individual participants' energy savings to develop energy savings groups, followed by using clustering algorithms to identify predictive characteristics of those energy savings groups. Finally, we assessed trends in attrition over time by each wave. We describe these efforts below:

[1] For a comprehensive analysis of current challenges and proposed solutions see Calas, G., K. Conley, and J. Warren. 2018. "Why Redesign a Mature Home Energy Report Program?" 2018 ACEEE Summer Study on Energy Efficiency in Buildings.

- HER Energy Savings Distribution Analysis: We employed statistical modeling (multi-level modeling)[2] to characterize the distribution of individual participants' energy savings and to understand the size and composition of savings groups over time and by wave. This effort quantified the total number of negative, neutral, and positive savers, as well as classified each participant by their savings category. Notably, these findings suggest trends that can inform program design and delivery enhancements, but are explicitly not used for claiming energy savings for any small group of participants. Results from this study can be found in Chapter 2.

- Participant Characteristics by Energy Savings Group: We identified predictive characteristics of all energy savings groups using a two-stage approach. First, we conducted a correlation analysis and linear regression modeling to identify variable importance to inform the development of groups of customers. To facilitate this stage of the research, we utilized Advanced Metering Infrastructure (AMI)[3] data to develop a set of variables identified as being predictive of energy savings for HVAC and Home Upgrade Programs.[4] Drawing on individual load curves, or individual AMI data, as well as customer information, we assessed whether factors such as income, rate (e.g., CARE), length as a PG&E customer, geographical location, or other features, are correlated to energy savings groups. Results from this study can be found in Chapter 3.

- HER Trends in Attrition Analysis: Our analyses support informed decisions to increase cost-effectiveness and maximize program savings by analyzing trends in HER program attrition. As part of this effort, Opinion Dynamics conducted descriptive statistics to identify attrition trends overall, by wave, and by attrition type (e.g., move out, move out of territory, ineligible). Results from this study can be found in Chapter 4.

We provide results for each research effort in the sections below.

[2] The team developed a multi-level model to estimate individual savings using both treatment and control group information to control for exogeneous factors that may affect energy savings or consumption within a household over time. However, because this model does not explicitly control for all non-program related changes at the individual level, we cannot state that results for any given individual are entirely attributable to the home energy reports. For instance, a change in the number of household occupants is likely to impact energy consumption, hence energy savings.

[3] Advanced metering infrastructure (AMI) data is interval data from smart meters. PG&E's residential customers have interval data with a frequency of one hour for electric consumption and of one day for gas consumption.

[4] Scheer, A., Borgeson, S., Rosendo, K. "Customer Targeting for Residential Energy Efficiency Programs: Enhancing Electricity Savings at the Meter". Whitepaper. Pacific Gas and Electric Company, Convergence Data Analytics, and Massachusetts Institute of Technology, September 2017.

2. HER Energy Savings Distribution Analysis

2.1 Research Objectives

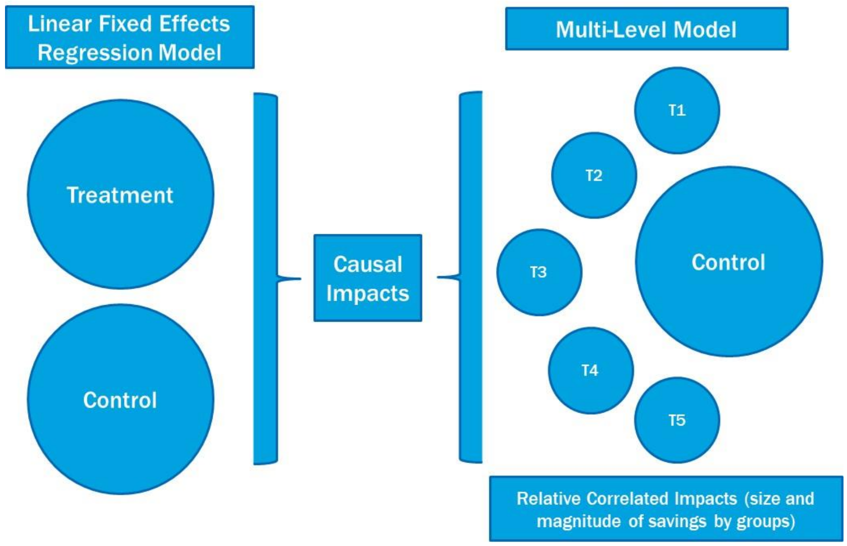
This research uses statistical modeling to characterize the distribution of individual participants' energy savings. This study addresses the following research questions:

- What is the distribution of savings groups for PG&E's HER program?
- Does the size and composition of savings groups vary by time?
- Does the distribution of savings group vary by wave?

To address these research questions, Opinion Dynamics developed regression models to estimate individual savings using PG&E treatment and control group energy consumption data to estimate the distribution of savings across individual customers. This effort quantified the total number of negative, neutral, and positive savers, as well as classified each participant by their savings category. We developed a multi-level model to estimate individual savings using both treatment and control group information to control for exogeneous factors that may affect energy savings or consumption within a household over time (see Appendix A for more details regarding the methodological approach). However, because this model does not explicitly control for all non-program related changes at the individual level, we cannot state that results for any given individual are entirely attributable to the reports. For instance, a change in the number of household occupants is likely to impact energy consumption, hence energy savings.

Importantly, results from this model do not produce causal impacts. Similarly to the classic linear fixed effects regression model used to capture and claim energy savings from HER programs, the multi-level model produces causally driven average effects, but the multi-level model also produces relative correlated impacts by size and magnitude of each savings group. This means that, on average, the savings results are consistent with typical causal models, but the energy savings groups' size and magnitude are correlations and not causally driven. This is because there is no specific control group matched to each energy savings group. As a result, the findings presented in this report produce information to derive program design and implementation decisions, but not to produce estimates of energy savings associated with each group. Figure 1 provides a visual depiction of the differences across these two types of statistical models.

Figure 1. Interpretation of Results – Differences in Modeling Approaches



2.2 Results

The following section presents the results associated with our analysis.

2.2.1 Distribution of Savings Groups

Opinion Dynamics developed a multi-level model to identify each HER participant's individual savings estimates for every year in which they received reports. We divided HER program participants into five savings groups based on the results of our model.[5] Working with PG&E, we decided to develop five groups to support identifying actionable program design revisions (i.e., to target the very positive and very negative savers differently from positive or negative savers). Distinguishing between very positive and very negative savers from the rest of the groups allows PG&E to target participants with much larger changes in energy consumption. We did this separately for the gas savings results and the electric savings results, so a dual fuel participant might be a positive gas saver and a neutral electric saver.

Based on our analysis of 2016 results, we found that HER report recipients vary in terms of their energy savings after receiving reports. In 2016, less than one quarter of participants saved energy, while nearly one quarter of participants increased their consumption, although the proportion of participants varied across electric and gas participants. This result is unsurprising given the results of third-party evaluations, which suggest that a small portion of participants have measurable savings. The following results reflect findings across all waves for 2016:

- Positive and very positive savers, those customers who save energy after receiving HERs, reflect 19% of electric participants, and 25% of gas participants.

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5 The very negative and very positive savers reflect savings more than 1.125 standard deviations, and the positive and negative savers groups reflect 0.375 standard deviations of the overall savings distribution. We selected the cut-offs for energy savings category to create groups that were actionable for program staff, and that reflected changes in energy consumption that allowed for recognizing the skewed nature of the very negative and very positive groups.

- Negative and very negative savers, those customers who increase their consumption after receiving HERs, reflect a little over a quarter of electric participants (27%), and slightly less than a third (31%) of gas participants.
- Neutral savers, those that do not change their energy consumption after receiving HERs, represent over half of the electric participant population (53%), and 43% of the gas participant population.

Table 2 presents overall average percent savings across all waves in 2016 by savings group.

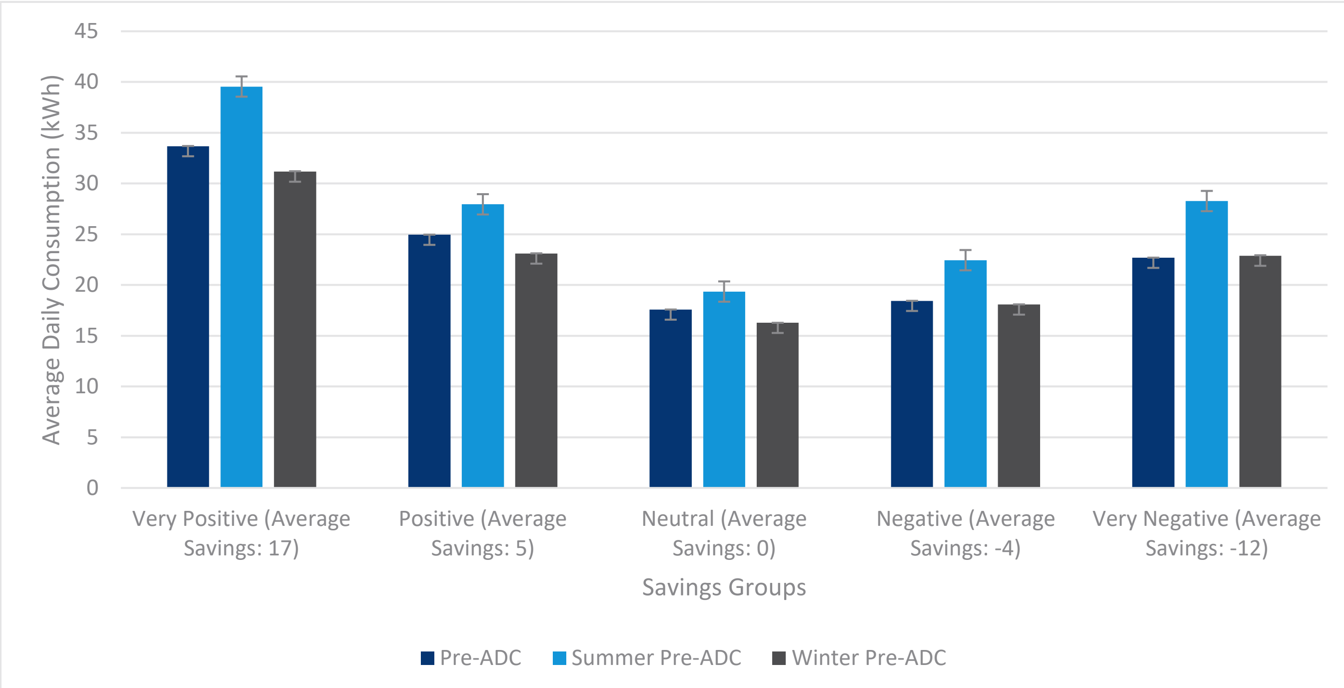
Table 2. Distribution of Savings by Savings Groups (2016)

Fuel Type	Savings Group	Number of Participants	Percent of Participants	Average Percent Savings
Electric (kWh)	Very Positive	89,421	7%	54%
	Positive	158,810	12%	21%
	Neutral	679,017	53%	0.03%
	Negative	284,018	22%	-25%
	Very Negative	61,144	5%	-59%
Gas (Therm)	Very Positive	102,438	8%	26%
	Positive	214,621	17%	13%
	Neutral	536,529	43%	0.6%
	Negative	299,091	24%	-20%
	Very Negative	86,376	7%	-48%
Results exclude 10% of customers within each wave randomly selected to validate savings. Totals may not sum due to rounding.				

As part of our analysis, we assessed whether baseline energy consumption produced any notable trends related to energy savings groups. Figure 2 shows the average kWh daily savings, and three pre-treatment average daily consumption (ADC) measures. These measures include “Pre-ADC”, which is average daily consumption prior to receiving reports for all available months in the pre-period for each wave. We also look at seasonal baseline consumption for summer and winter. Summer Pre-ADC incorporate the months of June-September in the pre-period for each wave. Winter Pre-ADC incorporate the months of December-March in the pre-period for each wave.

Very positive electric savers tend to have higher average baseline consumption (pre-ADC) than other savings groups. This is consistent with existing research that suggests that baseline consumption is correlated with larger energy savings. Further, these customers tend to have higher summer and winter baseline consumption than other savings groups as well. However, for electric participants, those with very negative savings also tend to have higher baseline consumption than neutral or positive or negative savings.

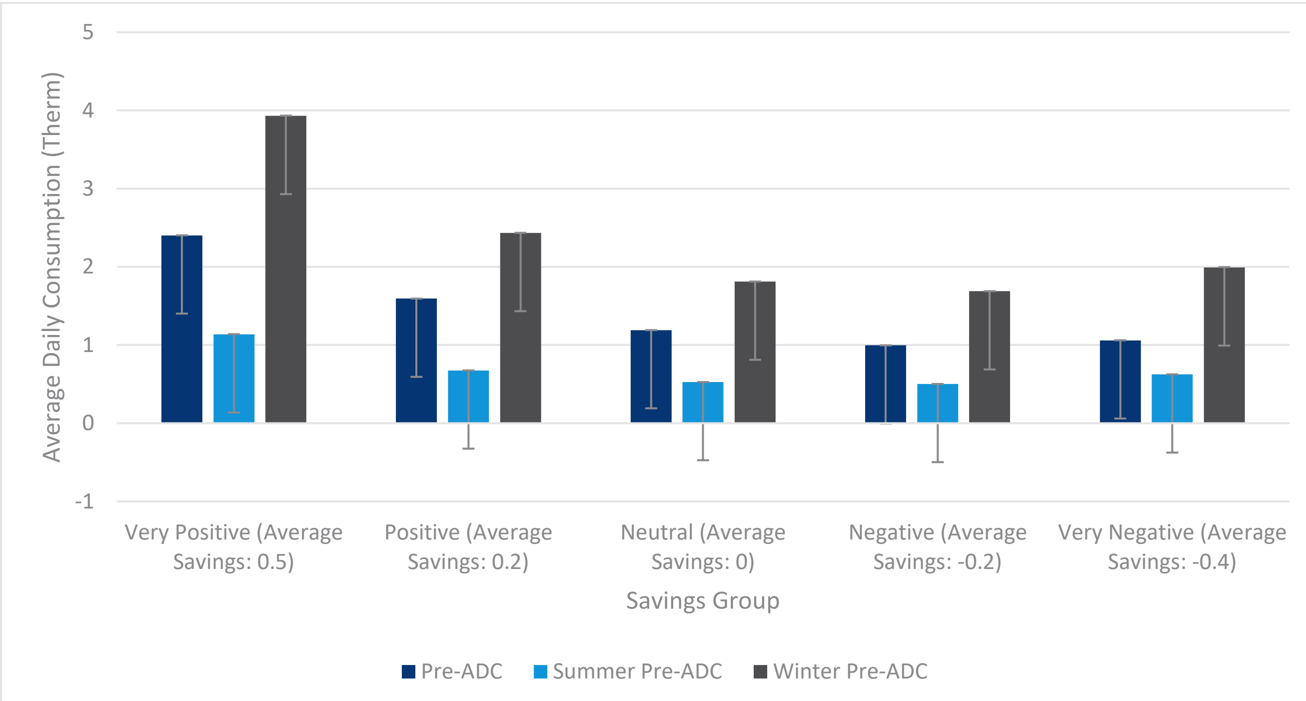
Figure 2. Electric Savings Groups by Baseline Energy Consumption (2016)



Error bars reflect modeled standard errors.

For gas participants, we find that very positive savings groups have higher than average winter baseline consumption than other groups. This finding is consistent with the type of participants who we would expect to save energy, given that the HERs are targeted for the winter heating season.

Figure 3. Gas Savings Groups by Baseline Energy Consumption (2016)



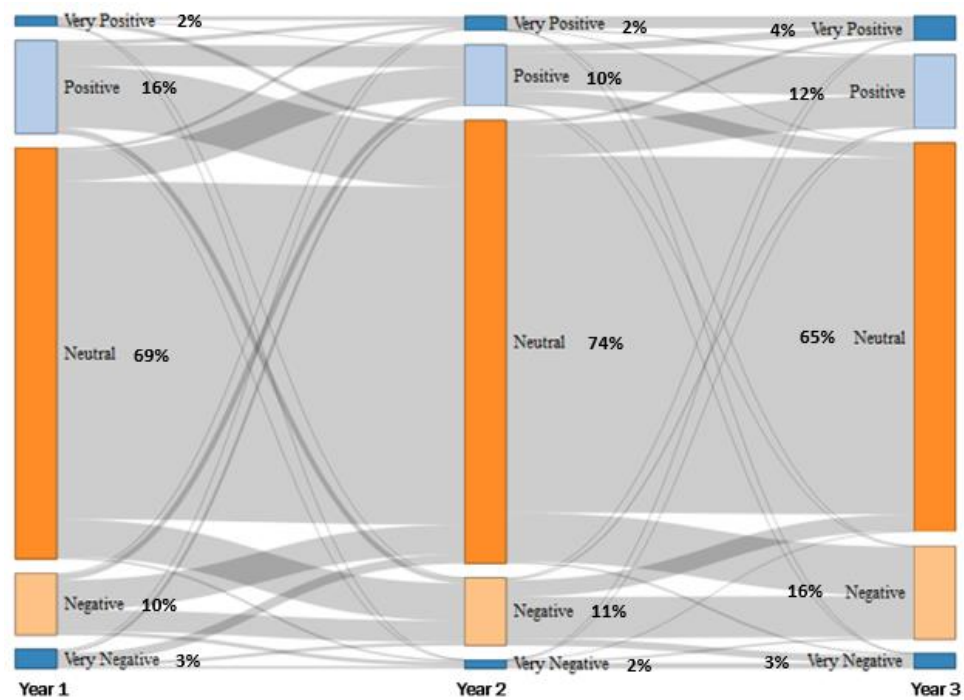
Error bars reflect modeled standard errors.

2.2.2 Variations Over Time (e.g., Inter-group Mobility)

We examined savings group mobility for the first three years of program participation to examine how participants may change from year to year, primarily to determine whether there is mobility between savings groups that is related to the amount of time in which participants receive reports. Figure 4 and Figure 5 show the temporal evolution of the proportion of participants who fall into each savings group. To compare over three years of exposure, we excluded waves that began after 2013 because they had fewer than 3 years of participation in the program.

For this analysis, we expected that savings would increase from the first year of participation to the third, as participants are able to make more program related changes over time. What we found was that this was the case for some electric participants, but some negative savers increased their usage over the years of participation with the overall proportion of negative savers increasing after each year of treatment. Approximately 52% of electric customers stayed in the same savings group over the three years. About 13% moved one group up to higher savings, while 21% moved one group down to lower savings over the three years of participation in the program. These general trends of moving to less positive savings groups reflect program participants, and not necessarily overall average savings. More specifically, the histograms provided in Appendix B suggest that the customers on the tails are moving to more extreme savings values which contribute to the overall average savings.

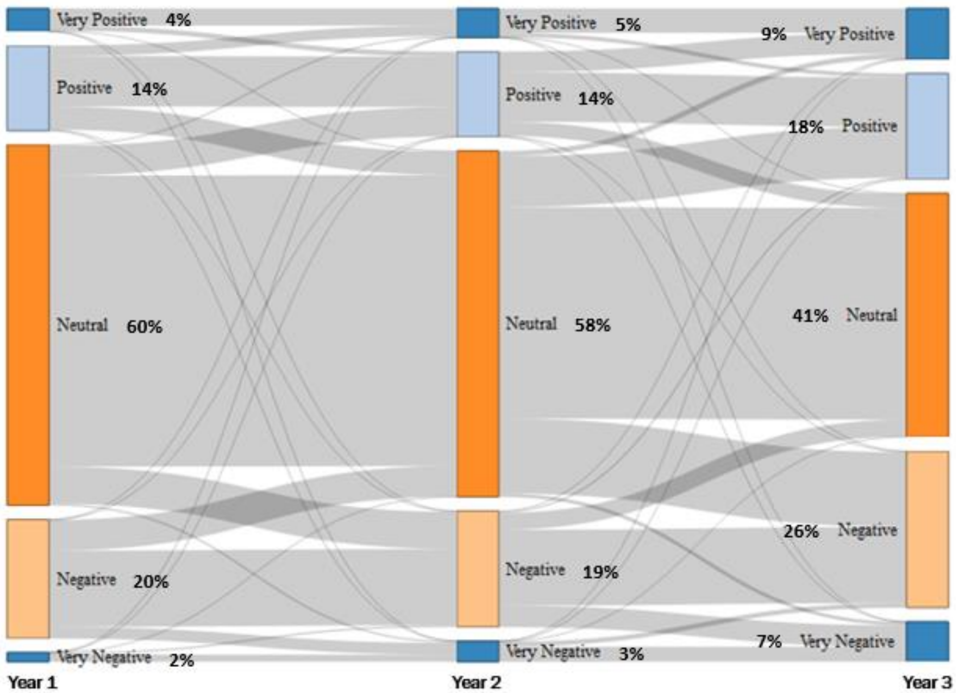
Figure 4. Electric Savings Group Evolution



Note: Each bar represents the percentage of participants in each savings group.

For gas participants, there was an increase in the size of positive and negative savers (as opposed to neutral savers) over the duration of receiving reports. Initially, nearly all gas participants fell into the middle three savings categories, and over time, some moved into the extremes. We expected to see an increasing spread of savings over time as some customers moved from lower to higher savings as they made behavioral and equipment changes. The increase in the size of the negative savings groups may mean that some participants responded to the home energy reports in ways that actually increase usage. Approximately 51% of gas customers stayed in the same savings group over the three years. About 15% of gas customers moved one group up to higher savings, while 19% of gas customers moved one group down to lower savings from the first to the third year of savings.

Figure 5. Gas Savings Group Evolution



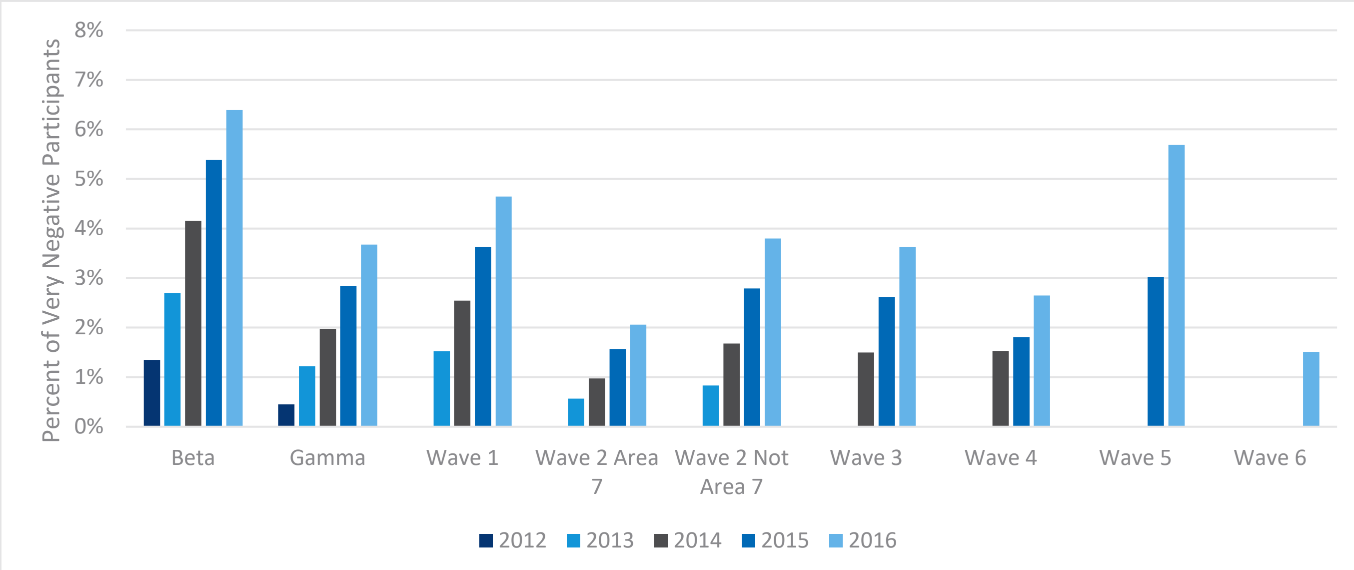
Note: Each bar represents percent of participants in each savings group.

Negative or very negative savings gas participants in the first year tended to not achieve positive savings while the opposite is true for electric participants. For instance, in the gas analysis, 70% of those participants who started as negative or very negative savers remained in the very negative or negative groups for all three years of the analysis, but this is true for only 29% of electric customers. These findings also occurred for participants who started in the positive or very positive savings groups; 70% of gas participants stayed in the positive or very positive savings groups all three years while only 24% of electric participants stayed in that group.

2.2.3 Results by Wave

We found that the percent of negative savers in each electric wave varied over time and by wave. For electric participants, the percent of negative savers appears to increase annually for all waves. For electric participants, the percent of negative savers increases with duration of treatment (Figure 6).

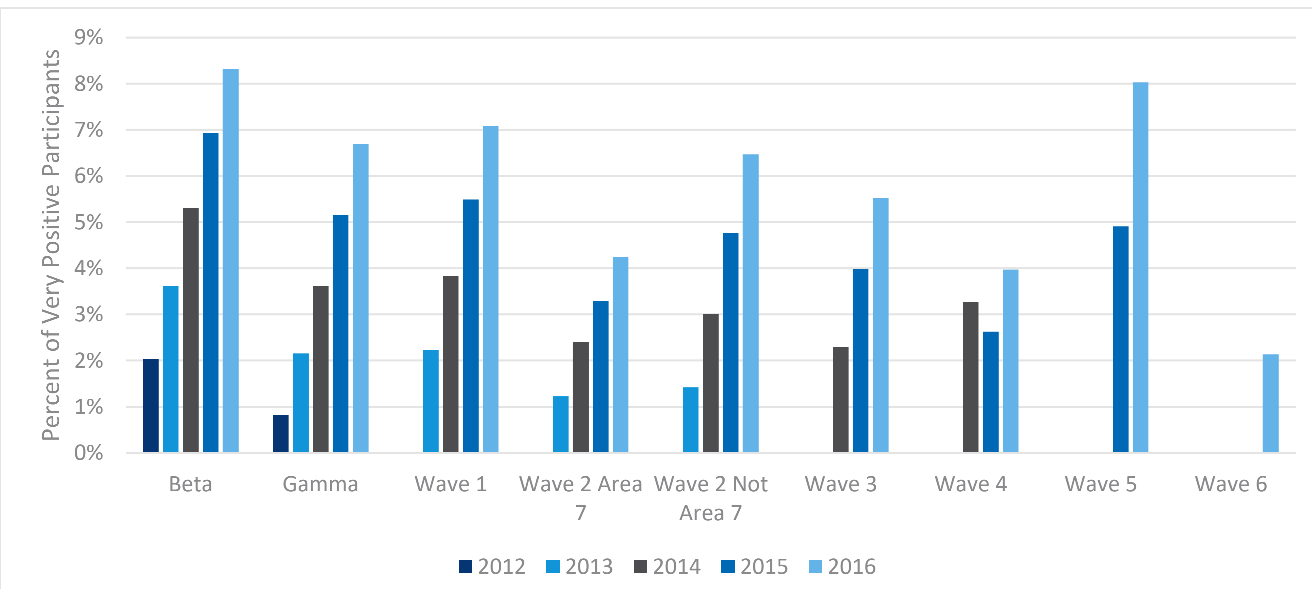
Figure 6. Percentage of Very Negative Savers by Program Year (Electric)



* The 2012 Wave 1 model exhibited poor fit, so the savings results from this model are not included.

Similarly, we see a very similar trend for very positive electric savers by program year (Figure 7).

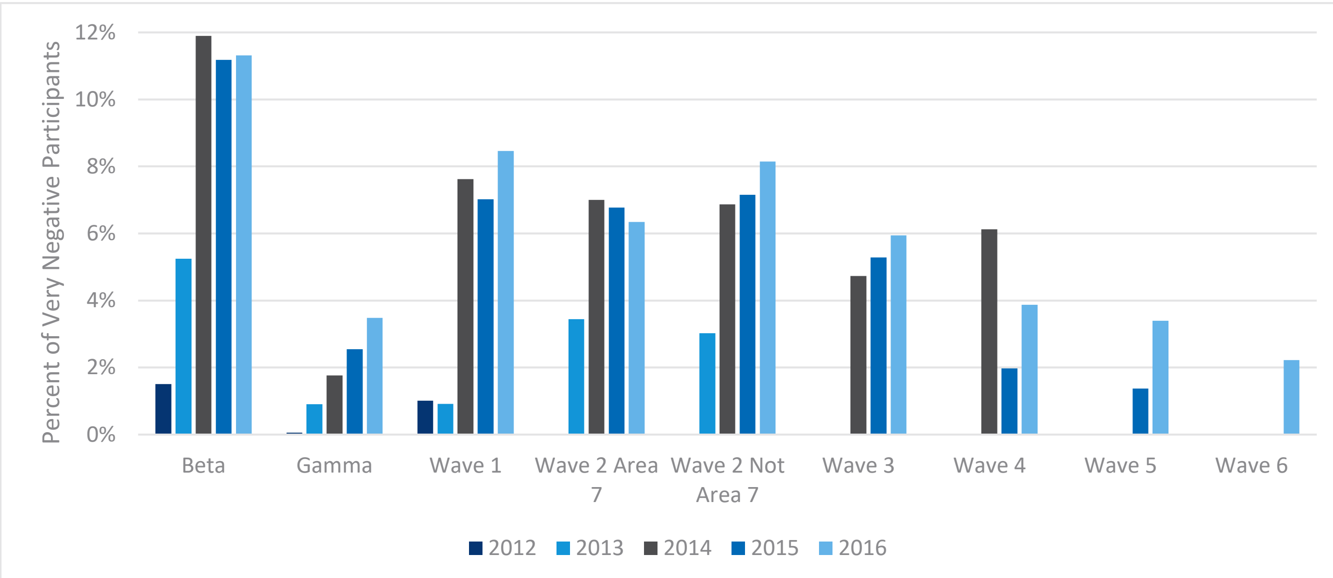
Figure 7. Percentage of Very Positive Savers by Program Year (Electric)



* The 2012 Wave 1 model exhibited poor fit, so the savings results from this model are not included.

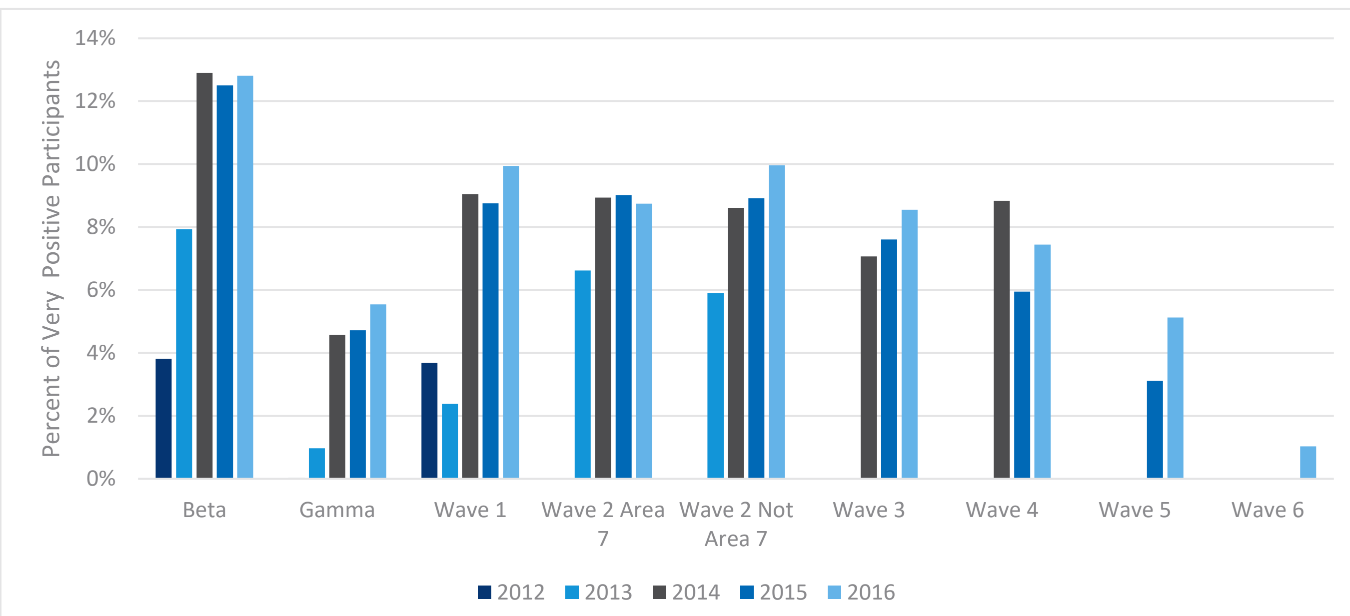
We found that the percentage of negative savers in each gas wave varied over time and by wave. More specifically, the Beta wave has the highest percent of negative savers, followed by Wave 1 and 2. Interestingly, the average pre-participation average daily consumption is much larger for Beta wave participants. Similar to electric participants, the percent of gas negative savers tend to increase or remain steady annually. Notably, gas customer savings groups tend to vary over time indicating that gas savings persistence may be lower than for electric.

Figure 8. Percentage of Very Negative Savers by Program Year (Gas)



Similarly, we see a very similar trend for very positive gas savers by year (Figure 9).

Figure 9. Percentage of Very Positive Savers by Program Year (Gas)



Our team plotted the distribution of savings by wave for each year to more closely inspect annual trends by wave. We provide those histograms, which reveal similar trends, in Appendix B. In particular, the histograms flatten over time, revealing a steady march towards the extremes (i.e., more very positive and more very negative, rather than neutral savers).

2.3 Validation

To check internal validity of the multi-level models, we used 10-fold cross validation. Cross validation re-estimates the model parameters 10 times, each with 1/10 of the data removed. If there is little variation in the parameter estimates between folds, the model is not dependent on a limited number of data points. Variation in parameter and savings estimates are very low between folds, showing that the models are stable and not sensitive to the inclusion of specific customers. The validation shows, with very high confidence, that the model is not overfit and that the savings estimates are stable.

We also compared overall multi-level model savings averages to prior evaluation results[6] and found that the multi-level model results were similar to those from the evaluation. This check is useful, but not as important as the cross validation, since the primary goal of the multi-level models is assigning participants into savings groups and not calculating overall program impacts.

2.4 Guide to Interpreting Results

The multi-level model incorporates both treatment and control group customers. As a result, the control group controls for exogenous factors that may contribute to energy consumption changes. However, because this model does not explicitly control for all non-program related changes at the individual level, we cannot state results for any given individual are entirely attributable to the reports. As a result, these findings suggest trends that can inform program design and delivery enhancements, but are explicitly not used for claiming energy savings for any small group of participants.

Based on the preliminary results, we identified several trends associated with HER program participant savings. We provide the following program design and delivery implications based on these findings:

- Finding: In 2016, less than one quarter of participants saved energy, while nearly one quarter of participants increased their consumption, although the proportion of participants varied across electric and gas participants.
  - Implication: This result suggests that a select group of participants contribute to savings. As a result, program delivery could focus on maximizing savings from positive savers through potentially increasing report delivery frequency or identifying more targeted messaging strategies, particularly for electric participants. Further, PG&E could consider removing some negative savers or reduce the frequency of reports to those participants.
- Finding: Approximately half of gas and electric participants stayed in the same savings group over three years.

[6] Nexant. 2018. "PG&E HER 2016 Energy and Demand Savings Early EM&V". Prepared for PG&E. To be published on CALMAC.

  - **Implication**: This result suggests that many participants may not change their energy consumption practices despite receiving HERs. To maximize savings for participants who will change, consider conducting customer research to identify messaging strategies that will motivate positive and negative participants to save energy. To increase cost-effectiveness, consider reducing or stopping treatment to neutral savers.

- **Finding:** Gas participants who were in the negative or very negative savings group in their first year tended to not achieve positive savings while the opposite is true for electric participants. Electric participants are more likely to move from very negative to positive than gas participants.
  - **Implication:** Very negative gas savings groups might benefit from significant modifications to the reports they receive or from stopping reports entirely.

- **Finding:** Pre-participation baseline consumption is correlated with higher energy savings. In particular, very positive electric savers tend to have higher average baseline consumption than other savings groups. For gas participants, very positive savers have higher than average winter baseline consumption than other savings groups.
  - **Implication**: Future targeting should continue to focus on high pre-participation annual and summer consumption for electric participants, and high pre-participation average daily consumption in winter periods.

3. Participant Characteristics by Savings Group

3.1 Research Objectives

This research task addresses what customer characteristics or variables are effective predictors of energy savings groups. The outcome of the analysis produces characteristics that, on average, reflect the various energy savings groups.

We utilized an array of data[7] to identify these variables. Table 3 provides a list of the types of data we included in our analysis.

Table 3. Data Incorporated within Analysis

Data Category	Example Variables
Energy Consumption Information	• Temperature-to-load correlation • Ratio of summertime (June, July, and August) electricity consumption to baseline (November, February, and March) • Total summertime or wintertime electricity usage • Average of the ratio between maximum and minimum demand for each day • Peak period ramp (i.e. average hourly increase in kWh/h during the ramp up period to the evening peak (3 p.m. to 7 p.m.) • Fraction of total summer load occurring during peak hours • Absolute range of minimum to maximum demand during the summer • Individual load curves or individual AMI consumption
Customer Characteristics	• Income[a] • Net Metering status • CARE • Geography • Climate Zone • EV or TOU rates • Length of time as a PG&E customer
Program Participation Characteristics	• Savings group • Participants who change savings groups over time • Months after receiving reports • Wave

[a] Because demographic data was not available for customers, we used American Community Survey 5-year estimates including median household income by zip code tabulation area (ZCTA).

To identify variables predictive of energy savings groups, we first conducted a correlation analysis with the variables listed above, as well as regression modeling to identify variable importance for energy savings. After conducting our correlation analysis and linear modeling, we developed a clustering architecture directionally informed by the correlation analysis. For more information see Appendix C.

[7] Our team originally sought to assess whether the chief psychographic/demographic/household characteristics were predictive. Unfortunately, the data that were provided regarding participant homeownership status (as well as other characteristics like income and education) did not have a sufficient match rate to incorporate within our analysis.

We selected nine clusters to inform HER program optimization. Drawing from a range of five to twenty clusters, we selected nine clusters as the optimal number of clusters because they represent enough clusters to differentiate customers, but few enough where it is possible to inform program changes without being excessively complex. These nine clusters vary across load, customer and participation characteristics, and meaningfully differentiate groups of customers.

Clusters were developed using customer characteristics and hourly AMI data provided by PG&E on a sample of 150,000 Home Energy Report Recipients (12% of the total HER population). We used a sample of report recipients since requiring full years of AMI data exceeded data transfer capabilities. We included individual savings estimates (participant savings categories) resulting from the multi-level model developed in Chapter 2 as a variable in the clustering model. To understand the clusters, we need to meaningfully differentiate the clusters, a task that also requires that the clustering variables make sense and create clusters that are actionable in terms of targeting, culling, or messaging.

Figure 10 provides a summary of these clusters across key characteristics, including load and energy consumption characteristics, savings, and specialized rates. The clusters purposefully vary by energy savings group, with lower numbered clusters reflecting negative savers, and higher numbered clusters reflecting positive savers. Clusters 1 and 9 reflect extreme characteristics, tending to differentiate themselves on energy consumption patterns, load shapes, and rates. These actionable features were identified through existing data to support program optimization through refining enrollment eligibility, excluding or reducing treatment, or customizing messaging to customers.

Figure 10. Overview of Clusters Across Characteristics

Characteristics	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9
Share of Sample	0.23%	3.88%	14.13%	20.92%	18.13%	10.35%	25.18%	3.77%	3.40%
Energy Savings	↓ L	↓	↓	↓	○	○	○	↑	↑ H
Energy Consumption (Summer)	↑ H	↑	↑	○	○	○	○	○	↓ L
Energy Consumption (Shoulder)	↑ H	↑	○	○	○	○	○	○	↓ L
NEM/EV/TOU	↑ H	○	○	○	○	○	○	○	↑ H
CARE	○	○	↑	○	↑ H	○	○	○	○

Below we offer a summary of key cluster features.

Figure 11. Local Capacity Requirement (LCR) Areas within the California ISO[8]

- Cluster 1 participants are primarily very negative savers with very high usage. Cluster 1 is a small cluster (0.23% of sample), but reflects substantial consumption increases in 2016. These customers are mostly located in the North Coast and Bay Area and tend to be high users at night, which may be caused by the overnight electric vehicle charging. This cluster has indeed a high percentage of customers on EV rates (11% of customers).
- Cluster 2 participants are mostly negative savers who live in areas with higher income, and have overall high consumption and especially high summer peak period consumption. A large proportion (42%) of these customers live in the Bay Area, in CEC Climate Zone 3 which extends into the East Bay.
- Cluster 3 participants are negative savers who have high summer consumption, especially during summer peak periods. A large proportion (40%) of these customers live in the Bay Area. One third of these customers are enrolled on CARE.

[8] *California Local Capacity Areas (LRA)*. February 2, 2016. California Energy Commission. https://www.energy.ca.gov/maps/reliability/Local_Reliability_Areas.pdf.

- Cluster 4 participants are slightly negative savers who live in areas with above average income. These customers appear to be less responsive to the HER program because of the relatively little change in pre- and post-consumption for this cluster. A large proportion (39%) of these customers live in the Bay Area.
- Cluster 5 participants are almost all CARE customers who have average consumption and who have not changed consumption while participating.
- Cluster 6 participants are saving energy mostly in the winter and shoulder months. These customers have been PG&E customers for longer than any of the other clusters. Their peak period consumption is similar in the summer and winter and tends to be low on average (1 kW average peak in summer and winter). A large proportion (71%) of these customers live in the Central Valley.
- Cluster 7 participants are low users who save energy in all seasons. A substantial proportion (38%) of these customers live in CEC Climate Zone 12 (e.g., Sacramento area).
- Cluster 8 participants are average and above average users with positive savings. A large proportion (86%) of these customers live in the Central Valley. This cluster is the only one to include customers that show higher savings while also having a higher than average base load (overnight load). For that reason, cluster 8 reflects potentially one of the better savings opportunities for future targeting or customizing targeted tips.
- Cluster 9 participants are almost all NEM customers with very positive savings, which is almost certainly caused by the installation of rooftop solar panels. Cluster 9 is also a small cluster (3.4% of sample), but reflects a substantial portion positive savings in 2016. Consistent with being on a NEM rate, Cluster 9 also has much lower midday consumption across seasons compared to other clusters. These customers have been dropped from the HER program because of enrollment in NEM rates. This process may take a few weeks to happen, which may explain why NEM-related savings is observed.

3.2 Detailed Results

Below we provide results by energy savings distributions, energy consumption distributions and key customer characteristics.

3.2.1 Clusters by Energy Savings Distributions

We developed clusters by savings and ordered the cluster identifiers by mean cluster savings, with Cluster 1 as very negative savers and Cluster 9 as very positive savers (Table 4).

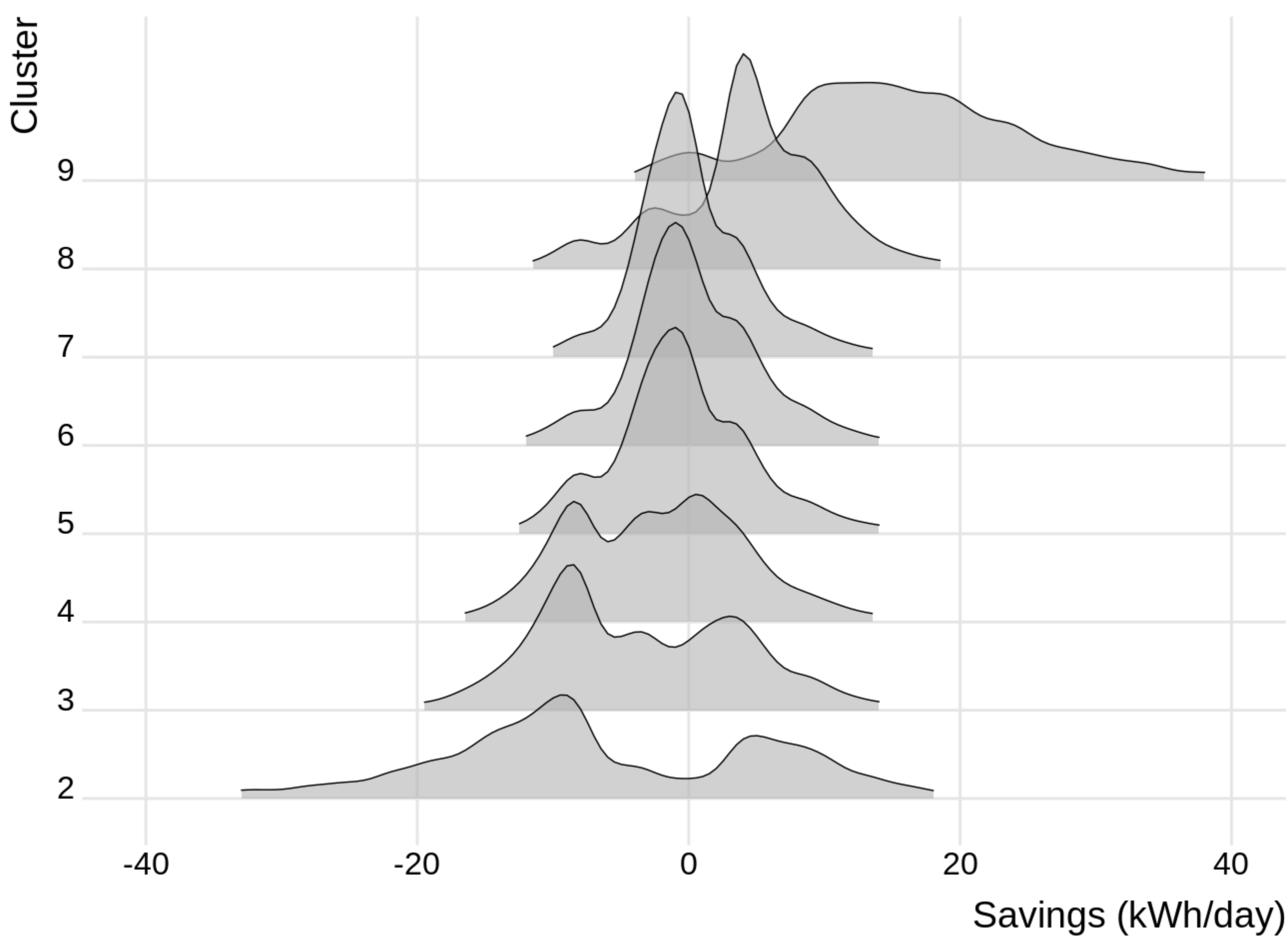
Table 4. 2016 Mean Cluster Savings

Cluster	Savings (kWh)	Customers	% of Total Population
1	-75.72	291	0.2%
2	-6.65	4,964	4%
3	-3.37	18,068	14%
4	-2.20	26,759	21%

Cluster	Savings (kWh)	Customers	% of Total Population
5	-0.19	23,188	18%
6	0.52	13,235	10%
7	0.69	32,198	25%
8	5.80	4,826	4%
9	16.36	4,354	3%

Figure 12 plots savings distributions by cluster, except Cluster 1, which has a much wider savings distribution than the other eight clusters. The savings distributions appear multimodal in that they appear to have more than one peak in their distribution, especially for the clusters with lower savings. We investigated this by plotting savings versus a range of other variables for each cluster. If we were to find a variable that exhibits similar multi-modality when compared to savings, it would signal that we should incorporate that variable into the clustering. We performed this analysis starting with variables that showed higher importance in the regression model and worked our way towards variables with lower importance, but none of the other variables produced multimodal distributions. This means that it is unlikely that we can determine the source of this multimodality with the data available.

Figure 12. Distribution of Energy Savings by Cluster



We also examined the change in consumption between the pre- and post-treatment periods for each cluster for Clusters 2-9[9], not adjusted for weather (Figure 13). This figure shows that in nearly all groups, with the exception of cluster 9, summer consumption *increased* on average between the pre- and post-periods. The *savings* were realized primarily in the shoulder months, and to a lesser extent in the winter months. Customers in Cluster 2–mostly negative and very negative savers – generally increased usage across all seasons, but increased usage much more in the summer. For Cluster 8 – primarily made up positive savers –, customers decreased energy consumption in all seasons, but much less in the summer than in the winter and shoulder months. Note that any box above zero means there was an increase in consumption, while a box below zero means a decrease in consumption in the post-period.

Boxplots help to visualize distributions; the various parts of the boxplot represent summary statistics:

Lower whisker = smallest observation greater than or equal to lower hinge - 1.5 * Inter Quartile Range (IQR)

Lower hinge = 25% quantile

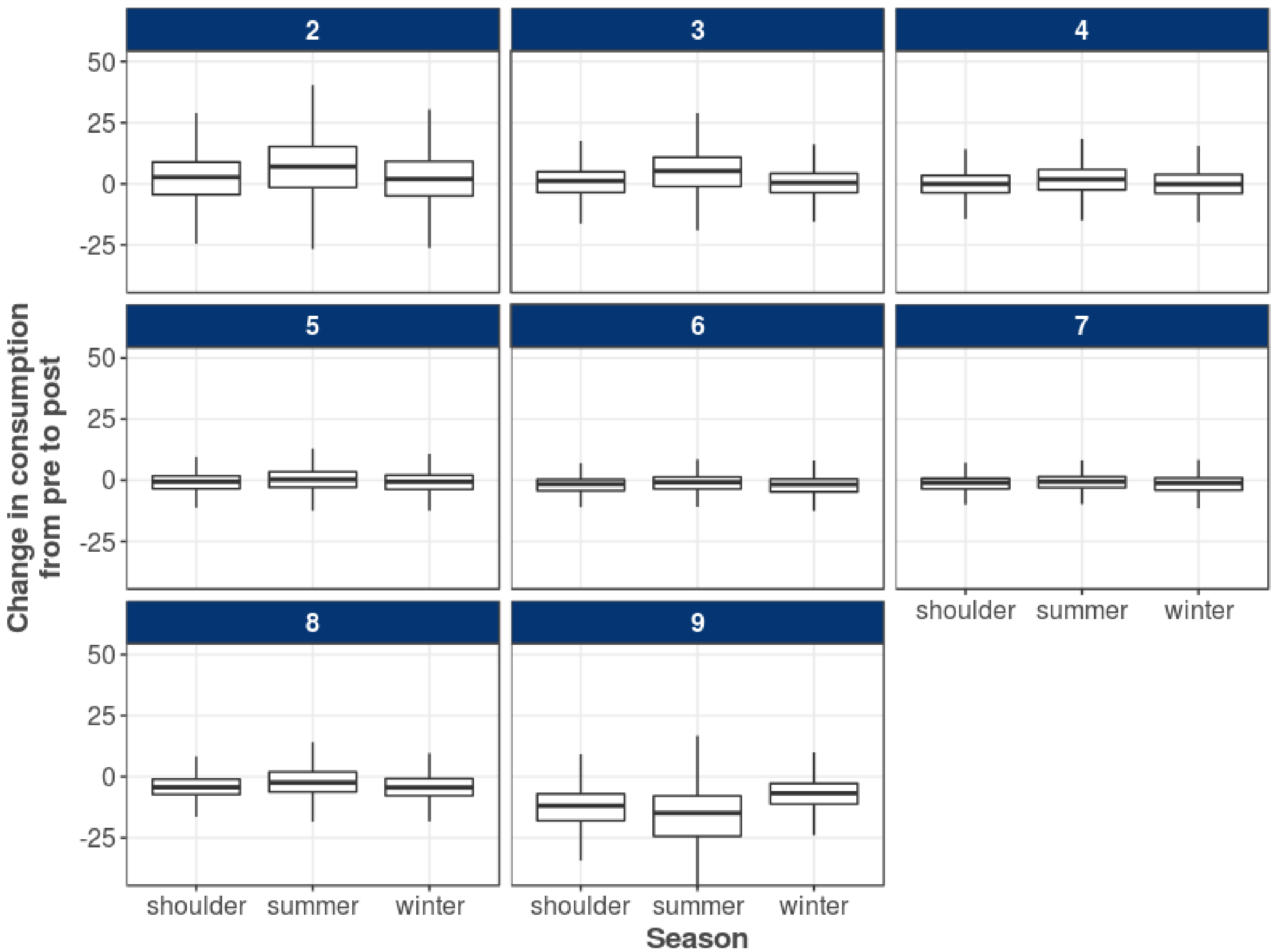
Middle = median, 50% quantile

Upper hinge = 75% quantile

Upper whisker = largest observation less than or equal to upper hinge + 1.5 * IQR

[9] Cluster 1 is not included in this figure because the change in consumption for that group was so much different than the other groups.

Figure 13. Boxplots of Change in Seasonal Average Daily kWh Consumption Between Pre- and Post-Period by Cluster



3.2.2 Clusters by Energy Consumption Distributions

To differentiate the clusters, we developed a heatmap of standardized distribution[10] for the clustering variables, with low levels marked as blue and high as red. Figure 14 shows the heatmap for the middle seven clusters. The clusters with higher consumption across the board (shown in red) have generally lower savings, while those with lower consumption (shown in blue) have neutral savings. Cluster 8 stands out since it is mostly made up positive savers that have average consumption (purple color). Note that variable descriptions are in Appendix C.

[10] To develop a normalized standard distribution, we subtracted the mean and divided by two standard deviations.

Figure 14. Heat Map of Standardized Distribution of Consumption Variables, Clusters 2-8

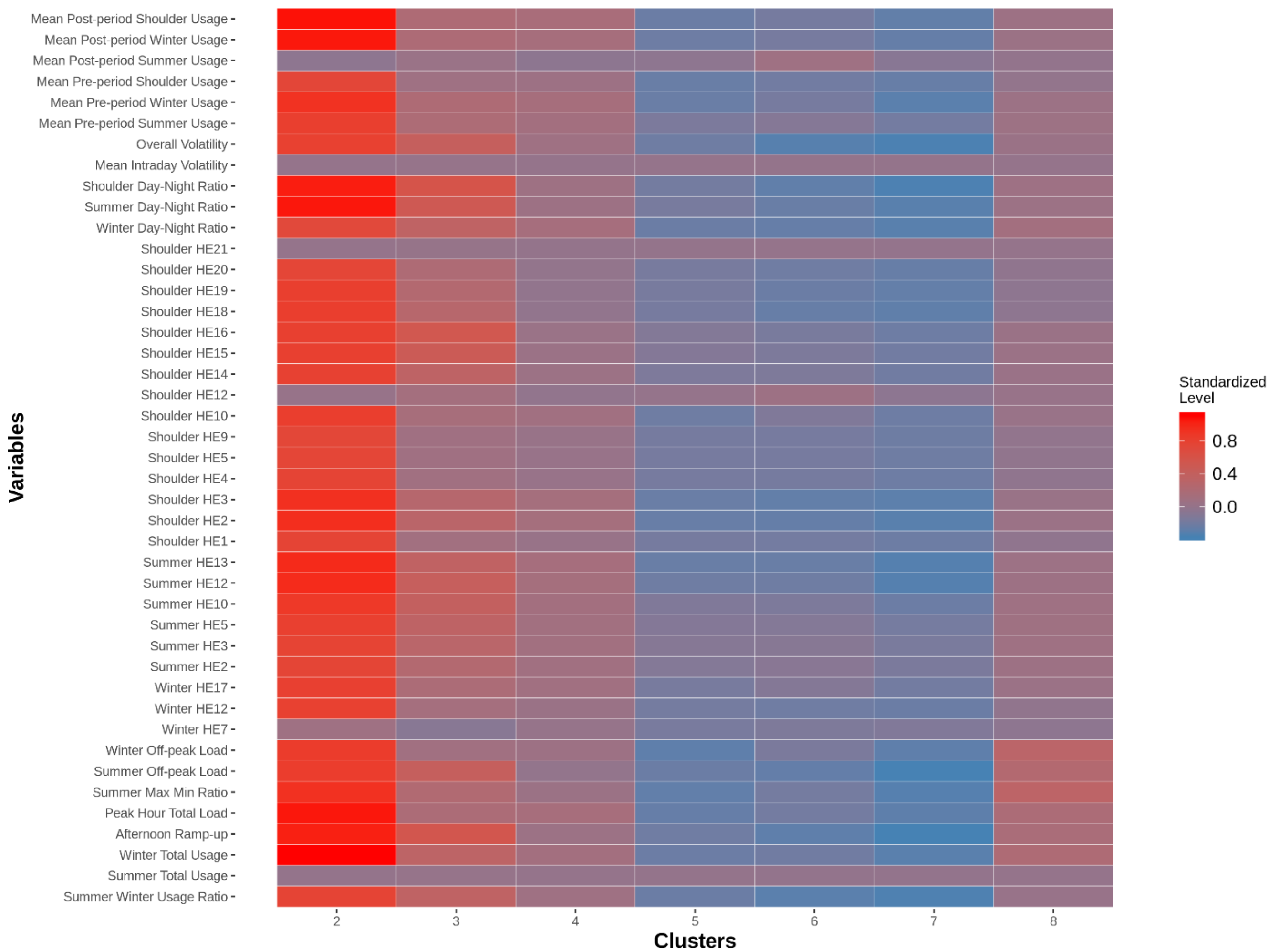
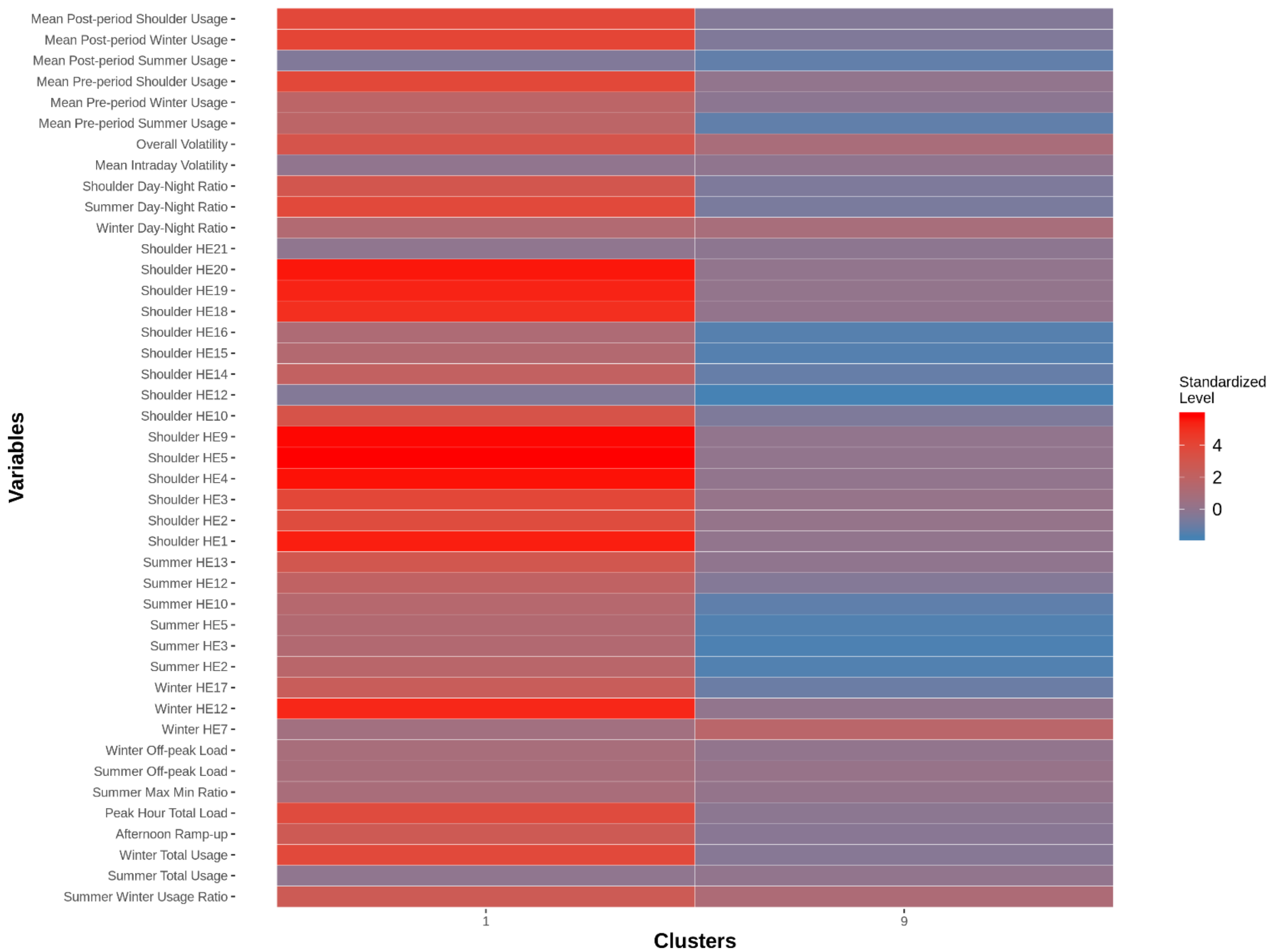


Figure 15 shows the two extreme clusters, Clusters 1 and 9, for which the standardized variable scale is much more extreme. The very positive savings cluster shows much lower midday consumption (Variables include Shoulder HE12 through Shoulder HE16) across seasons compared to other clusters, while the very negative savings cluster shows much higher overnight consumption (Shoulder HE 1 through Shoulder HE5). The very negative savers of Clusters 1 have much higher consumption than all other cohorts. This differs from findings found in other studies and evaluations.[11]

[11] Smith, B.A., Morris, L. 2014. "Neighbor Comparison Reports Produce Savings, but HOW?" 2014 ACEEE Summer Study on Energy Efficiency in Buildings.

Figure 15. Heat Map of Standardized Distribution of Consumption Variables, Clusters 1 and 8



We plotted energy consumption distributions on some variables used to generate the clusters to show the differences between clusters. This helps to explain the characteristics of the clusters and to differentiate between clusters. For instance, Figure 16 provides clusters by summer total energy consumption. This shows that there is a very substantial difference between overall summertime consumption levels in the clusters, with lower savings clusters (1-3) having much higher consumption. Some customers in Cluster 9 have negative net consumption, which reflects that those customers have some kind of generation onsite (almost certainly solar). Figure 17 shows consumption variation between midnight and 1 a.m. during shoulder months. This shows that many of the central neutral to slightly positive savings clusters (5-7) have low nighttime consumption, while cluster 2, with substantially negative savings has a high shoulder season overnight consumption that probably serves as a proxy for baseline consumption, which differs substantially across the clusters.

Figure 16. Cluster Distribution with respect to Summer Total Net Electricity Consumption

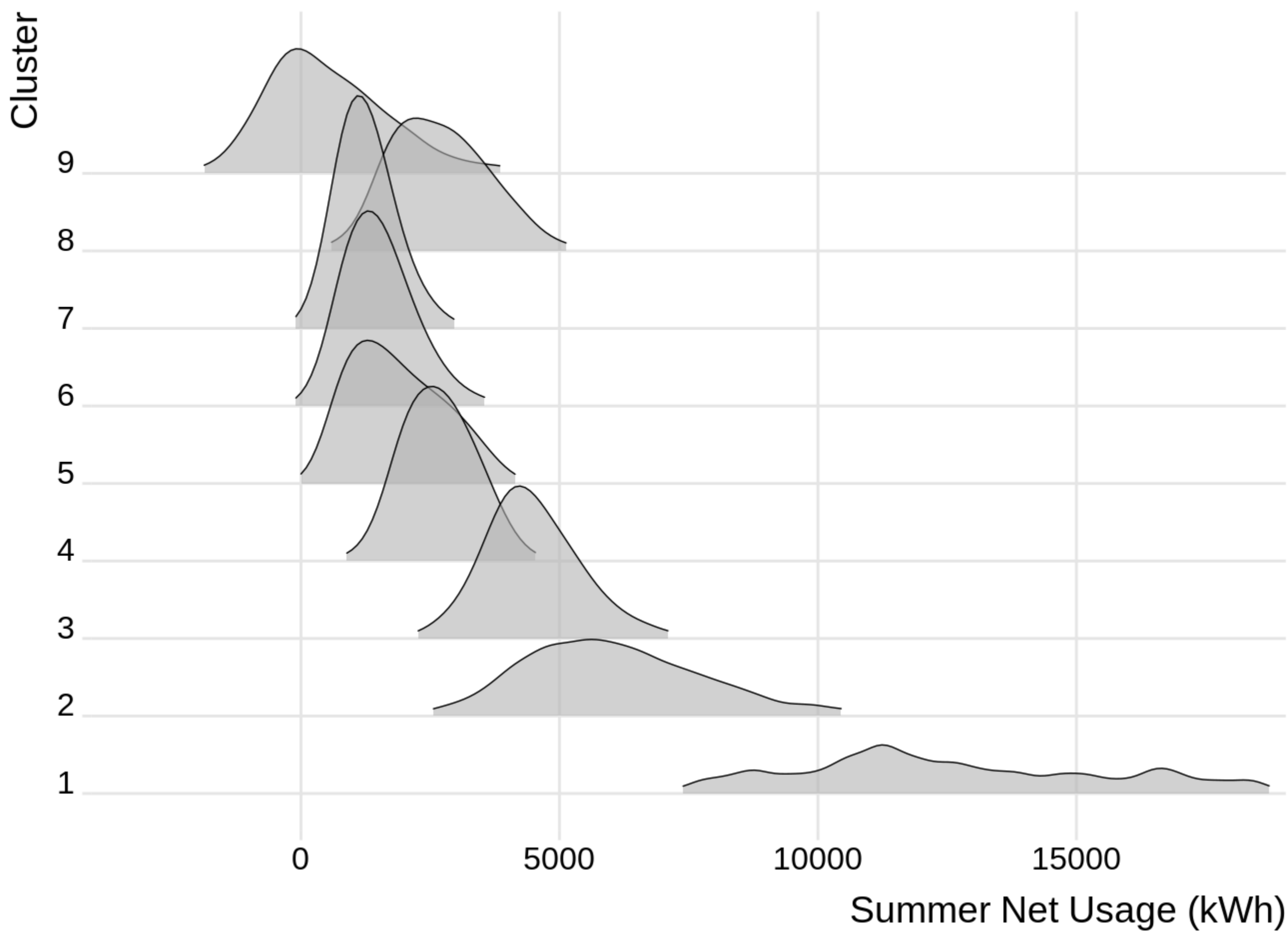
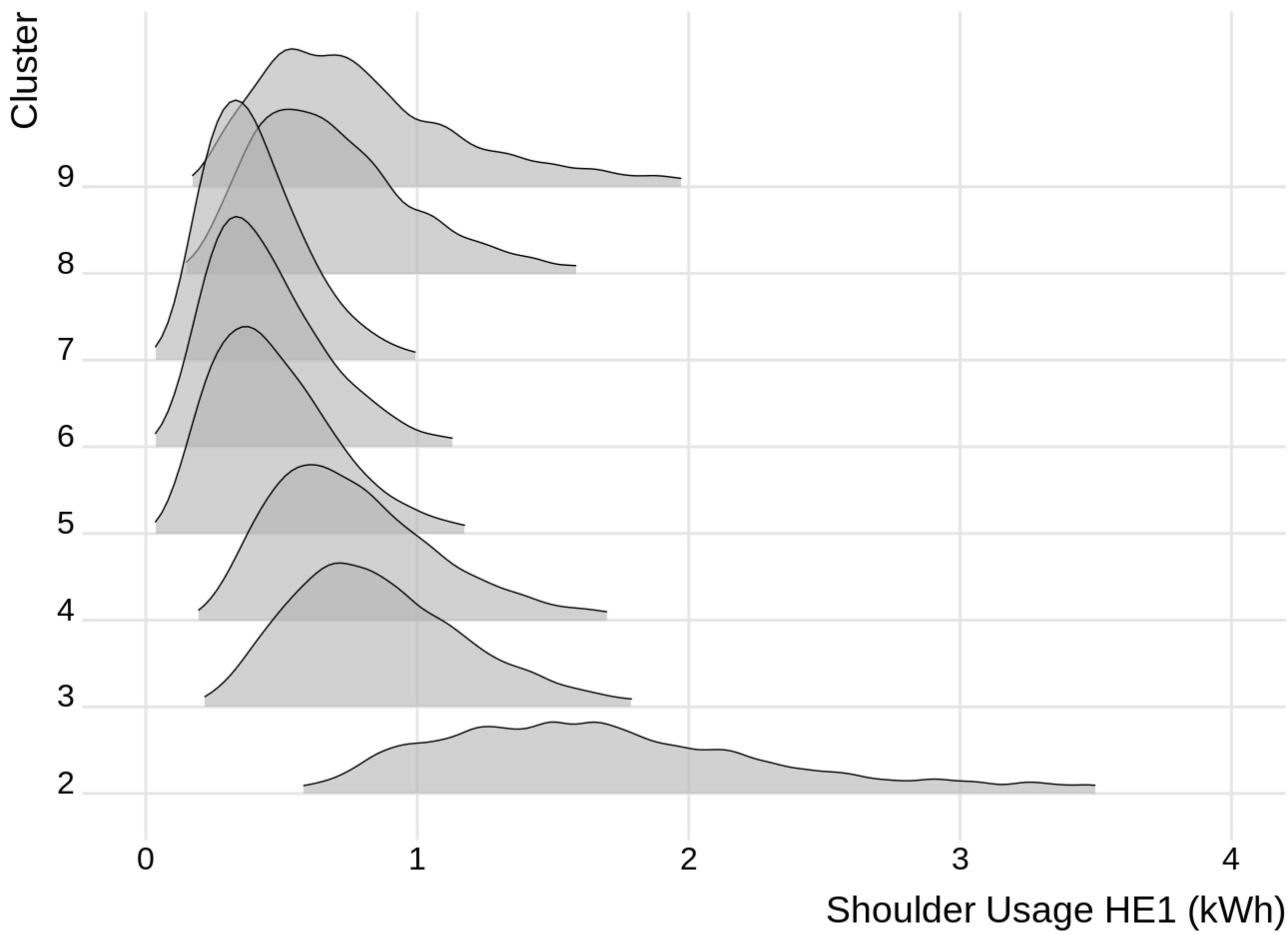


Figure 17. Cluster Distribution with respect to Shoulder Month Usage from Midnight to 1 A.M.

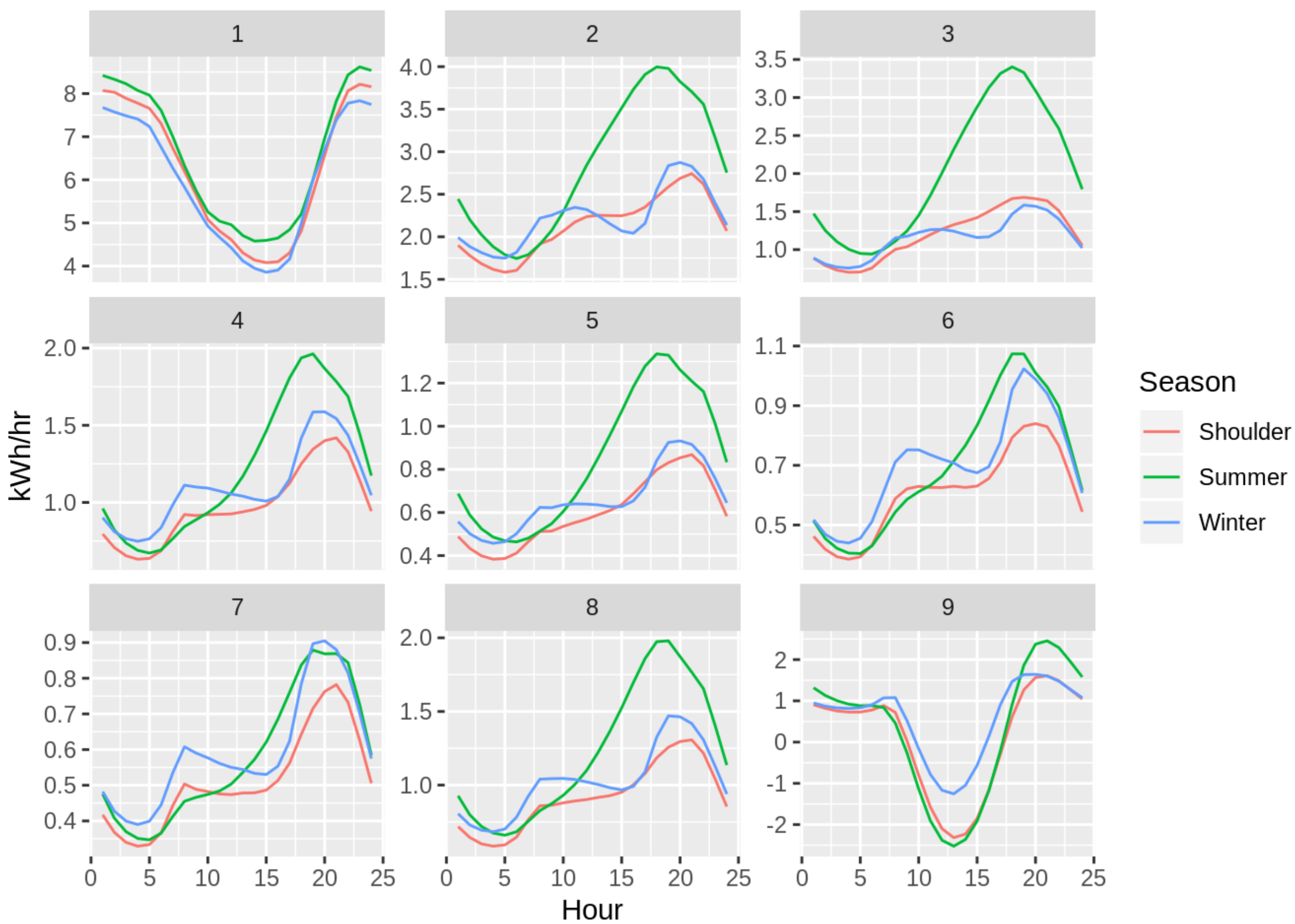


We also plotted the average seasonal load curves for each cluster (Figure 18). This figure indicates that Clusters 1 and 9 have an inversed load curve, i.e. lower energy consumption during daytime versus nighttime. Cluster 1 shows the highest baseline energy consumption, with significant energy consumption at night. We found that this cluster has the highest rate of EV customers. Cluster 9, which shows negative usage across seasons during daytime, has the highest rate of NEM customers based upon the customer rates in each segment. Summer usage of Clusters 2 and 3 is significantly greater than winter and shoulder[12] month usages. This is likely explained by a greater air conditioner usage during summer months. Cluster 6 and Cluster 7 usage may indicate that customers of these clusters have electric heat or heat pumps because electricity consumption peaks of winter and summer are close. The ability to identify customers based on their load curves builds upon existing research conducted by PG&E and can serve to characterize high potential future

[12] See Appendix C for shoulder season definition.

participants, develop residential load shape types, and characterize participants who may benefit from additional interventions (such as those with EVs).

Figure 18. Seasonal Load Curves by Cluster



3.2.3 Clusters by Customer and Participant Characteristics

We identified variation across the clusters by core customer and participant characteristics by developing a heatmap of standardized distribution[13] for the clustering variables with low levels marked as blue and high as red (Figure 19). Notably, the EV box for Cluster 1 is a standardized variable, which explains why the heat map box for this cluster is not red because the amount of variation in rates between cluster is very high, so the differences are not apparent.

[13] To develop a normalized standard distribution, we subtracted the mean and divided by two standard deviations.

Figure 19. Heat Map of Standardized Distribution of Customer Variables, Clusters 2-8

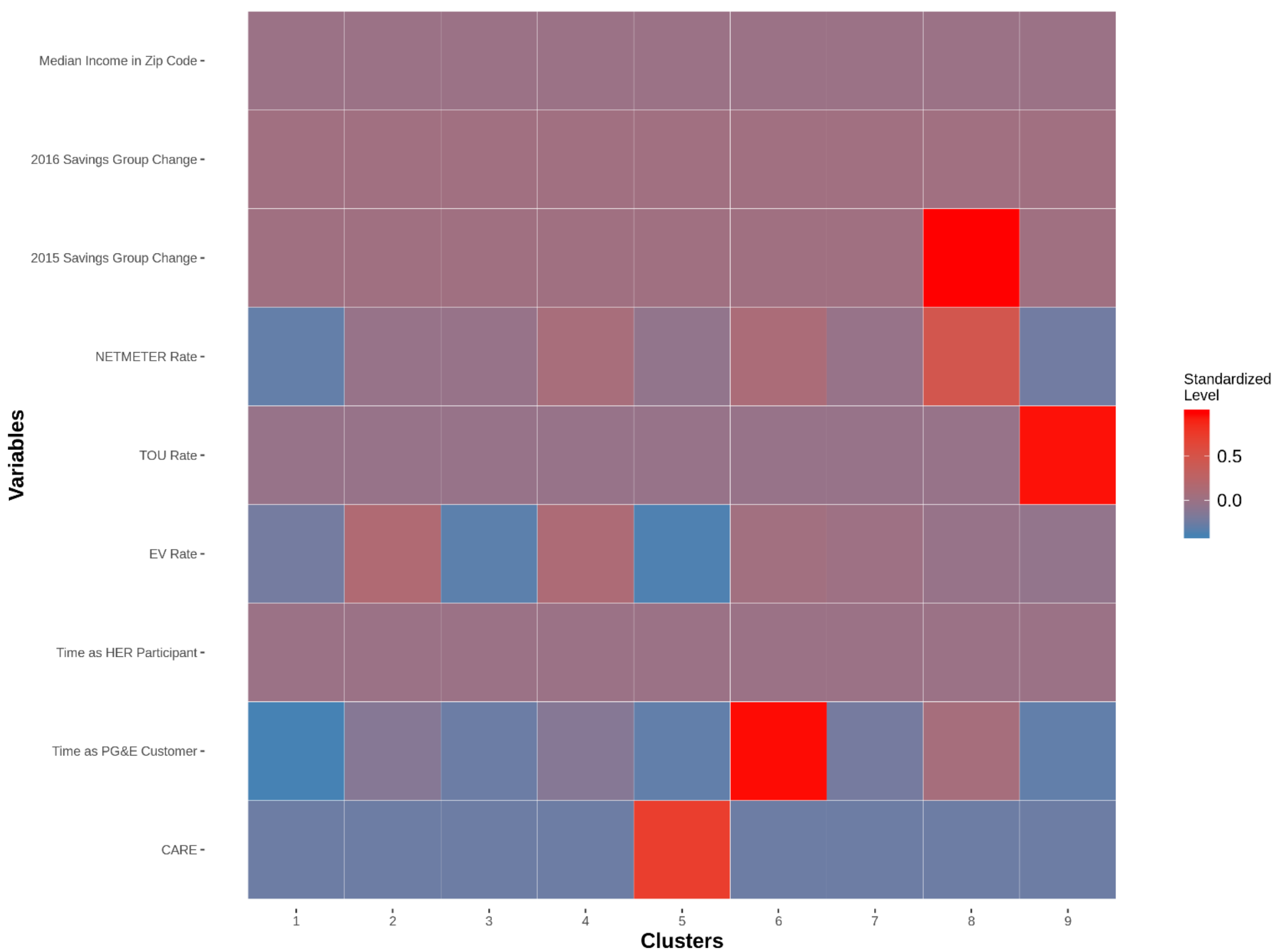


Figure 19 shows that Cluster 8 is more likely to have made a change in their savings group than other participants. As part of Section 2.2.2, we indeed examined savings group mobility between 2014 and 2015 and between 2015 and 2016 to examine how participants change from year to year. We found that for most clusters there is little change in savings groups except for participants in Cluster 8 who, on average, moved up a savings group between 2014 and 2015. Participants in Cluster 9 moved up an average of half a savings group in each of the years. Notably, in our first phase of research, we found that gas participants who were in the negative or very negative savings group in their first year tended to not achieve positive savings, while the opposite is true for electric participants. Electric participants are more likely to move from very negative to positive than gas participants, and it appears that Cluster 8 may contain many of the participants who made that change between 2014 and 2015.

The distribution for many of the customer variables in Figure 19 is shown in Table 5 below. Median income in Table 5 is the median of all the median incomes per cluster, while the other values in the table (e.g., length of time as a PG&E customer at that premise, and number of months as a customer in the post-period of the program) are the averages per cluster. Median household income ranges from $74K to $103K, with the exception of Clusters 3 ($65,891) and 5 ($59,867), which have higher adoption of CARE rates. We also categorized clusters based on how long they had been a PG&E customer. We found that Cluster 1 and 9 have the shortest tenure as PG&E customers. Finally, most of these customers also stay in the program for the same amount of months, ranging from 34 months to 55 months.

Table 5. Distribution of Customer Variables Across Clusters

Variable Name	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9
Median Income in Zip Code	$74,332	$102,659	$65,891	$96,209	$58,867	$89,145	$86,955	$87,517	$81,281
Months of Participation in HER program	34	44	42	45	40	50	41	55	40

Clusters also vary in terms of their enrollment in CARE as well as in other rates (e.g., NEM, EV and TOU). Table 6 provides the percent of customers enrolled on a given rate within each cluster. As can be seen, Cluster 1 has the greatest amount of customers on EV rates. Nearly all customers in Cluster 9 are NEM (98%), and all customers in Cluster 5 are CARE.

Table 6. Percent of Customers in Each Cluster for a Given Rate

Rate	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9
CARE	2%	8%	35%	3%	100%	11%	0.4%	16%	11%
NEM	1%	0.6%	0.2%	0.3%	0.3%	0.02%	0.5%	1%	99%
EV	11%	4%	0.3%	0%	0%	0%	0.2%	0.2%	2%
TOU	2%	1%	0.7%	0.6%	0.4%	0.6%	0.2%	0.7%	1%

Table 7 shows the proportion of participants by wave for each cluster. Notably, Cluster 1 is mostly made up of participants from the last four waves while Clusters 6 and 8 have few customers in the last three waves.

Table 7. Proportion of Participants in each Wave by Cluster

Wave	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9
BETA	3%	25%	10%	22%	3%	17%	5%	24%	9%
GAMMA	4%	10%	16%	9%	15%	13%	11%	20%	10%
WAVE 1	6%	8%	12%	11%	12%	18%	12%	18%	10%
WAVE 2 AREA 7	3%	2%	1%	3%	3%	6%	5%	4%	1%
WAVE 2 NOT AREA 7	3%	5%	7%	8%	8%	14%	10%	14%	7%
WAVE 3	15%	8%	10%	10%	14%	12%	15%	17%	13%
WAVE 4	26%	9%	10%	9%	18%	7%	16%	1%	16%
WAVE 5	11%	21%	21%	16%	12%	8%	8%	1%	17%
WAVE 6	27%	14%	13%	12%	17%	5%	18%	0%	17%

Clusters vary by climate zone and geographic distribution (Appendix C). Notably, Cluster 3 is mostly outside of the Bay Area and coastal regions, which differs from the rest of the clusters. Also, Cluster 1 has very few customers outside of the Bay Area, whereas the other clusters have a fair amount of customers surrounding cities outside of the Bay Area (e.g., Chico, Sacramento, Fresno, and Bakersfield). For details of geographic distribution of each cluster, refer to Appendix C.

3.3 Guide to Interpreting the Results

The nine clusters vary across load, customer, and participation characteristics. They also support identification of actionable customer characteristics from which to refine program delivery and design. PG&E can optimize their program design and delivery using three different strategies.

- **Strategy 1: Program customization:** Some negative savers may underperform because of life events. Others because the stimulus is not relevant (e.g., lack of understanding, lack of clarity, lack of clear next steps, difference of mindsets). Adjusting the stimulus may enable a portion of the negative savers to turn into neutral or positive savers. In this regard, we offer recommendations related to 1) developing relevant tips, 2) targeted delivery of reports that apply to clusters energy consumption patterns, and 3) program participation uplift strategies.
  - <u>Developing tips related to air conditioning usage</u>. Our analysis found that Clusters 2 and 3 have high air conditioning usage. These customers also increased their consumption, on average, between pre- and post- summer periods. These clusters reflect approximately 18% of the population of participants in the study. We recommend customizing tips related to HVAC usage in – and prior to – the summer for these customers, as well as conducting customer research to understand barriers and motivating strategies to support summer energy consumption reduction.
  - <u>Developing tips related to reducing base load</u>. Clusters 2, 3, and 4 have the highest shoulder usage (e.g., base load[14]), which also tends to be the most predictive of negative savings (this does not hold for positive savings from Clusters 8 and 9 though). Since we see base load correlated to savings, we recommend customizing tips and recommendations for reducing base load to reduce negative savings. Notably, reducing base load by 1% yields 1% savings since it applies to all hours of the day, whereas reducing peak load by 6% only saves approximately 1% because it only applies to a finite period of the day (e.g., 4 hours). Depending on how this program derives value, maximizing base load savings via tips related to plug load and other similar base load equipment could increase energy savings. However, if PG&E is interested in focusing on reducing consumption during timeframes where it may yield the most value in terms of capacity, other targeted peak load messaging may be beneficial.
  - <u>Target timing of report delivery</u>. If we hypothesize that some savings are due to behavioral changes in shoulder months, since we see that lower savings clusters, such as cluster 2, have much higher shoulder season consumption than higher savings clusters such as cluster 7, there may be untapped potential to maximize savings during that timeframe. We recommend investigating the cadence of report delivery for key clusters and targeting tips and report delivery during high yield timeframes.

[14] We use early morning shoulder month consumption as a proxy for base load. This is usually the time of lowest average load during the entire year for most participants.

- Market additional program participation. Cluster 5 may benefit from additional strategies to achieve savings. This cluster is predominantly CARE customers who are very neutral savers with consistent load shapes to other clusters that show greater energy savings. Beyond maximizing energy savings, other load shapes suggest opportunities to engage in demand response program offerings. We recommend customizing other program recommendations based on load shapes and other customer characteristics.

- **Strategy 2: Future participant targeting[15]:** Identify shared characteristics associated with negative savers to specifically identify those customers prior to program deployment through eligibility optimization.
  - Develop high potential load shape profiles to support future program targeting. We would recommend focusing on Cluster 8 as an exemplary load shape. The ability to identify customers based on their load curves can serve to characterize high potential future participants, develop residential load shape types, and characterize participants who may benefit from additional interventions.
  - Consider who to exclude based on load curves. Cluster 1 is exemplary in terms of the type of load curve to avoid. Customers in Cluster 1 have high usage across seasons. This cluster also tends to have high volatility[16] between night and day and summer and winter. Cluster 1 also has lower day time consumption and higher consumption overnight (possibly due to electric vehicle charging).

- **Strategy 3: Post-treatment exclusion:** Exclude from treatment negative savers identified based on multi-level model results. This approach is the least attractive given concerns related to nullifying the internal validity of the RCT design.

3.4 Next Steps in Research

We offer the following considerations in terms of future research:

- Identify load curve characteristics that can support tailored program design and delivery (see above) to support developing customized tips. For example, we identified residential load curve types that look promising to support dynamic pricing offerings or offering AC tips (e.g., Cluster 2, 3, and 8).

[15] Notably, this analysis uses post-period energy consumption data from 2015-2016 for a sample of customers. As a result, the information provided in this memo is informative for current, and not future participants because these customers had already received reports prior to the 2015-2016 period.

[16] We calculated volatility in two ways, as mean within-day standard deviation of consumption and as overall standard deviation of consumption

- Augment this analysis by drawing upon American Community Survey data, Clean Vehicle Rebate Project[17] data, or other secondary data by zip code to see if there are any patterns in terms of income, education, homeownership, given the poor match for existing customer demographics.
- Conduct customer survey or qualitative research to understand barriers and motivational strategies to engage particular customers across clusters.

[17] https://cleanvehiclerebate.org/eng/rebate-statistics

4. HER Trends in Attrition Analysis

Though the HER program is successful at generating significant energy savings today, some challenges may impact long-term program viability and effectiveness. In particular, PG&E's HER program is suffering from increasing attrition rates. Attrition reduces the long-term benefits of treatment directly affecting cost-effectiveness. As a result, PG&E contracted with Opinion Dynamics to conduct this study to support informed decisions to increase cost-effectiveness and maximize program savings by analyzing trends in the HER program attrition.

4.1 Research Objectives

This research identifies determinants and similarities across participants who no longer receive HERs because of program attrition. This study addresses the following research questions:

- What is the cumulative attrition since program inception for all participants as well as by wave?
- What is annual attrition by wave? Are there discernable attrition trends over time by wave?
- What are the factors driving attrition? Is it customers who move-out or are no longer eligible for the program?
- What customer characteristics are associated with attrition (e.g., energy savings groups, location)?

We present two types of attrition: cumulative and annual. We define cumulative attrition as the percent of participants who have left the program since they received reports compared to the original number of participants. Annual attrition is calculated as the total number of participants who left the program in each year, divided by the total number of participants in the wave at the start of the program year.

Attrition may be caused by four drivers: 1) customers move out of PG&E's service territory, 2) customers move to another household within PG&E territory, 3) customers become ineligible for the program, or 4) customers opt-out of the program. In conversation with PG&E, we have excluded customers who opted out of the program given that these customers are retained in their respective treatment group. Still, opt-outs represent less than 1% of participants.

As part of this effort, Opinion Dynamics conducted descriptive statistics to identify attrition trends overall, by wave, and by attrition type (e.g., move out, move out of territory, ineligible). Ineligible customers are those who have moved to an ineligible rate, such as adding solar photovoltaics or electric vehicles to their households.[18] In addition to providing descriptive statistics regarding attrition, we also integrated other available customer characteristics (e.g., energy savings groups[19], geography) and conducted a correlation analysis to examine any

[18] Ineligible PG&E rates include HE1N, HEA9, HE6N, HE7N, HETOUAN, HEVAN, H2ETOUAN, EM, HEB9, HEVB, EA9, HETOUBN, EB9, EVB, HEA7, H2ETOUBN, H2EVAN, H2E6N, EA7.

[19] Opinion Dynamics developed a multi-level model to identify each HER participant's individual savings estimates for every year in which they received reports. We divided HER program participants into five savings groups based on the results of our model.

additional trends. We developed results for participants, but also compared our results to control group customers as these trends likely reflect market trends, rather than programmatic trends.

4.1 Results

The following section presents the results associated with our analysis. The results presented reflect electric program participants only. However, we conducted similar descriptive statistics for control group customers and found results to be similar across waves, years, and drivers.

4.1.1 Attrition Rates

Table 8 presents total cumulative attrition of all participants from each wave compared to the original population of each wave. Overall, over half a million participants are no longer in the program since inception due to attrition. In addition, cumulative attrition rates vary across waves (24% to 39%), but, on average, reflect about one third of participants (34%). These average rates are consistent with rates found in the control group, suggesting market forces drive attrition rather than any program induced attrition other than opt-outs which are excluded from this analysis.

Table 8. Cumulative Attrition by Wave

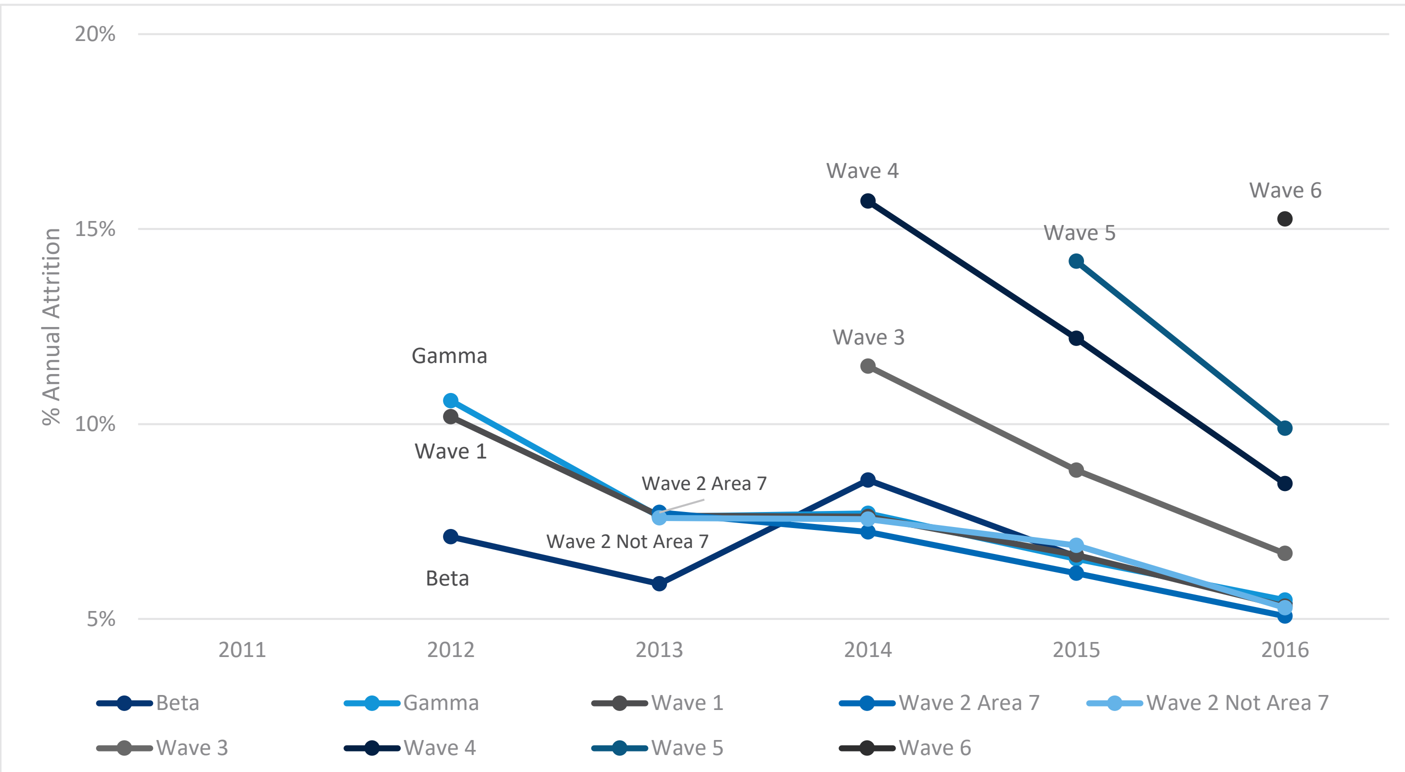
Wave	Start Year	Total Population of Participants	Cumulative Attrition [a]	% Attrition
Beta	July 2011	59,988	23,294	39%
Gamma	Nov. 2011	189,799	80,087	42%
Wave 1	Feb. 2012	399,973	149,792	37%
Wave 2 Area 7	Jan. 2013	80,047	23,638	30%
Wave 2 Not Area 7	Jan. 2013	305,263	94,486	31%
Wave 3	July 2013	224,982	80,086	36%
Wave 4	Mar. 2014	199,990	72,801	36%
Wave 5	Oct. 2014	209,986	66,216	32%
Wave 6	Sept. 2015	311,988	74,028	24%
All Waves		**1,982,016**	**664,428**	**34%**

[a] Excludes customers who opted-out of program.
The population of customers reflect all electric customers as they are the largest population of customers in the program. We do not expect these results to differ by fuel type.

The following figure (Figure 20) reflects trends in annual attrition over time by wave. We have removed the first year of participation, as most customers may not have been in the program for a full year given start dates for each wave. Except for the Beta wave, all waves have the highest rate of attrition in their first complete year (second program year) of receiving reports, with declining attrition rates in subsequent years. These results make intuitive sense – in the first case, we see high rates of attrition at the start of receiving reports because there may be classes of customers who are much more likely to leave the program (such as renters or newlyweds or some unknown feature), who will likely leave the program at a faster rate than other participants (such as homeowners or seniors or other unknown feature). Declining rates every year is also consistent with this logic, the type of customers who are more likely to attrite diminish over time as they leave the program. Unfortunately, the data that were provided regarding participant homeownership status (as well as other characteristics like income and education) did not have a sufficient match rate to be able to assess whether this was a driver of attrition.

Further, attrition rates differ by wave, with later waves, such as Waves 3, 4, and 5, having the highest overall annual attrition. In addition, waves Beta, Gamma, and Wave 2 having the lowest attrition, but the highest overall cumulative attrition for having been in the program for a longer period. This may suggest that the composition of later waves have specific customer classes with greater probability of leaving the program.

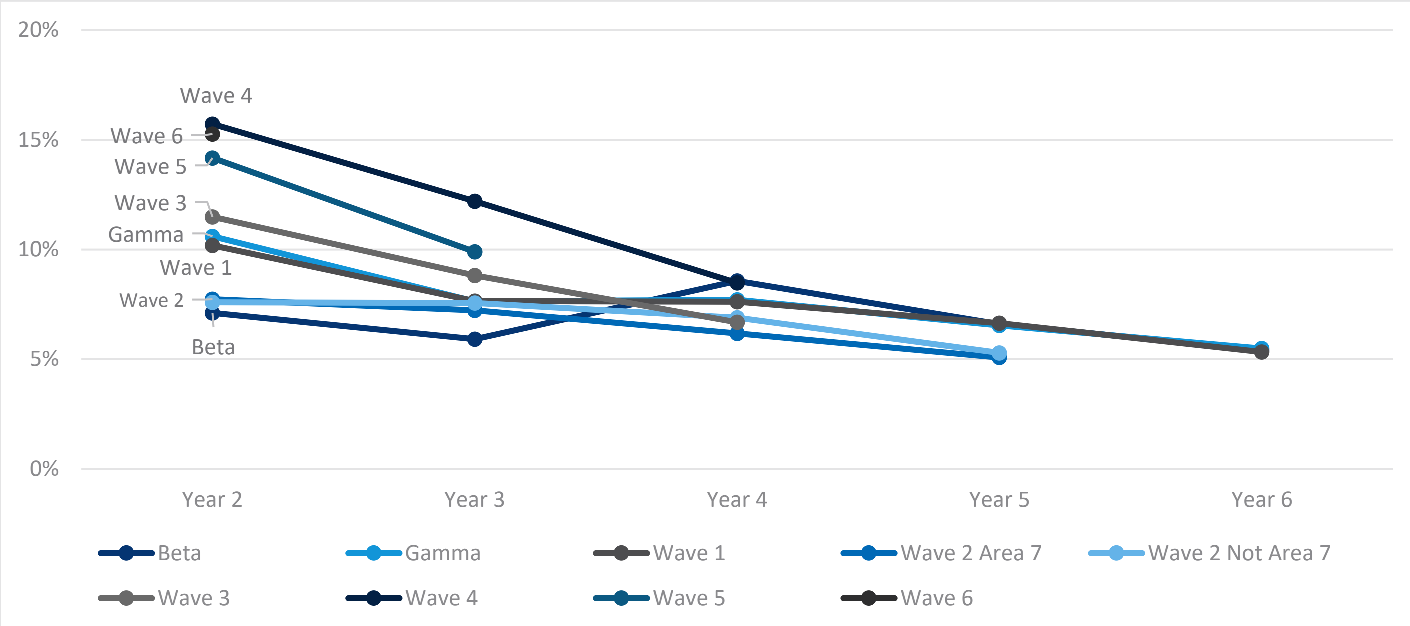
Figure 20. Annual Attrition by Wave and Year



Percentages reflect attrition in each year divided by the original population of participants at the start of the wave.

In addition to Figure 20, Figure 21 plots annual attrition with respect to duration of treatment. This table includes the same information in Figure 20, but provides comparison of attrition rates throughout the lifetime of each wave. Consistent with Figure 20, we have removed the first year of participation in Figure 21 since most customers do not enter the program at the beginning of the wave.

Figure 21. Annual Attrition by Wave and Duration of Treatment



4.1.2 Drivers of Attrition

As detailed above, our study sought to understand the drivers of attrition – including moving outside of PG&E's service territory, moving within PG&E's service territory, and customers who become ineligible for the program, such as moving to an electric vehicle rate or installing photovoltaic panels in their homes. Table 9 provides the total percent of participants by wave who left the program by each potential driver. As can be seen, the largest driver of attrition since receiving reports is moving outside of PG&E's service territory (26% of customers), while moving within and moving to ineligible rates each reflected 4% of customers. These rates are consistent with control group customer drivers of attrition.

Table 9. Drivers of Cumulative Attrition by Wave

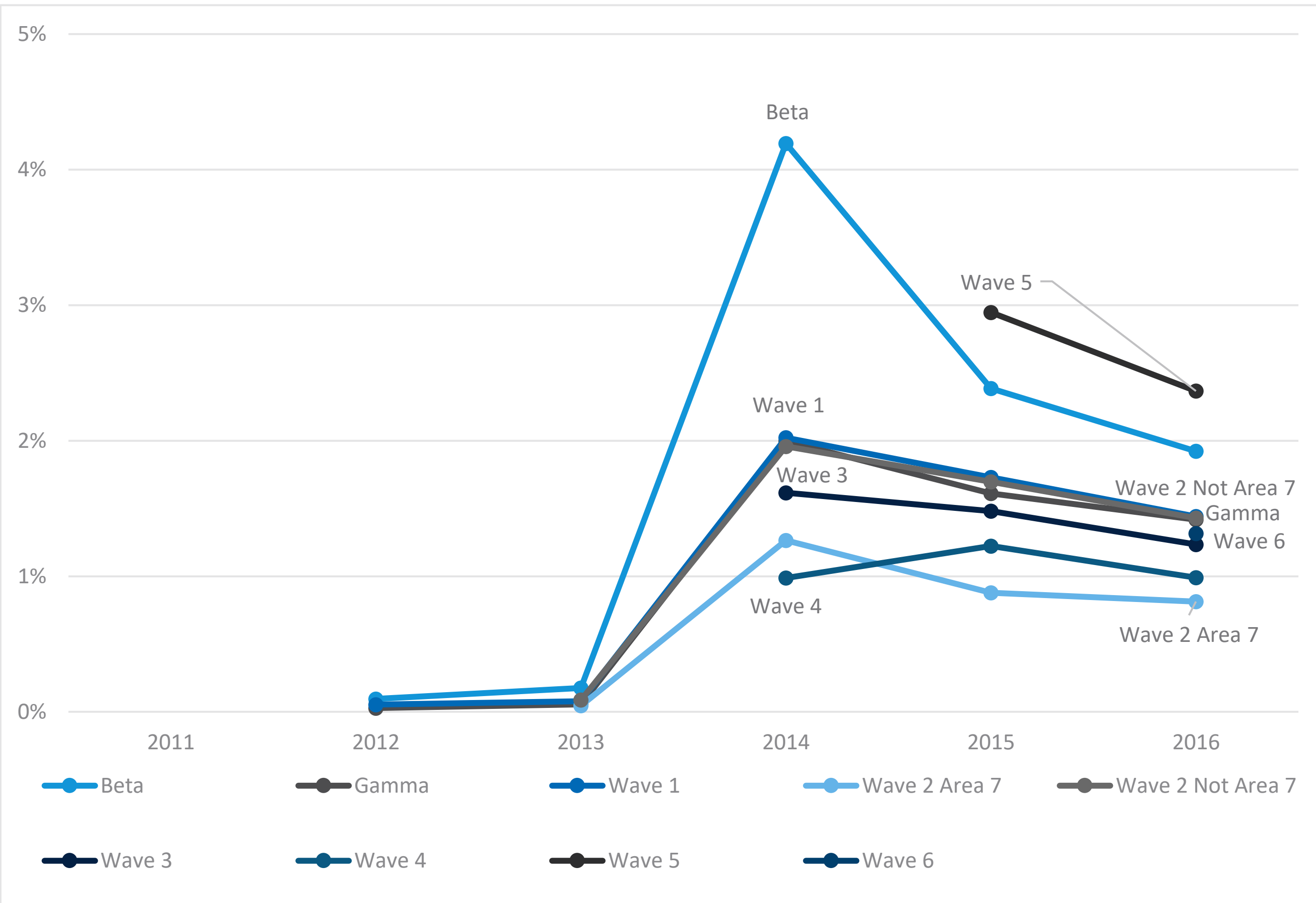
Wave	% Ineligible	% Move Outside of PG&E Territory	% Move Within PG&E Territory	Total %
Beta	8%	25%	6%	39%
Gamma	5%	31%	6%	42%
Wave 1	5%	26%	6%	37%
Wave 2 Area 7	3%	24%	3%	30%
Wave 2 Not Area 7	5%	22%	4%	31%
Wave 3	4%	27%	4%	36%
Wave 4	3%	31%	3%	36%
Wave 5	6%	25%	1%	32%
Wave 6	2%	22%	0%	24%
Total	**4%**	**26%**	**4%**	**34%**

These results suggest that there is little that PG&E can do to capture the benefits from the program on customers who attrite, particularly because they no longer are within PG&E service territory.

Figure 22 through Figure 24 provide annual attrition rates by each potential driver by wave. As can be seen, attrition due to ineligible rates increased in 2014, particularly for the Beta wave. In 2014, PG&E indeed started to exclude customers on a Net Energy Metering (NEM) rate from the HER program. Since home energy reports are based on home energy consumption comparisons, comparing NEM customers to non-NEM customers is not useful. Hence, this increase in attrition is not related to market dynamics.

These trends are consistent among control group customers as well. Overall, 98% of customers who became ineligible did so by moving to Net Energy Metering Service, and a little under 2% went to low emission electric vehicle rates. The Beta wave shows a larger increase because a greater proportion of participants switched to a NEM rate. This may be caused by two reasons: (1) the Beta wave received reports for a longer period of time and (2) the Beta wave targeted customers with higher energy consumption, who have a higher economic incentive to adopt self-generation.

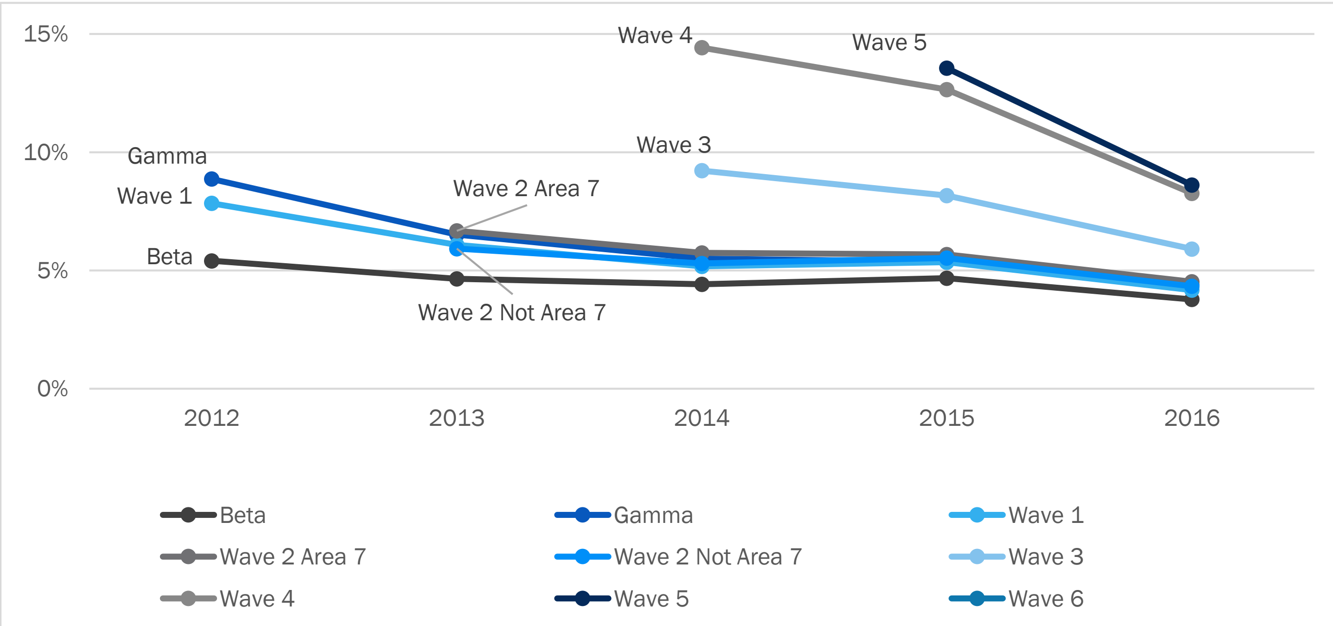
Figure 22. Annual Percent of Participants Who Became Ineligible by Wave



Percentages reflect attrition in each year divided by the total population of participants in that year by wave.

Some waves have more customers who move out of PG&E service territory, in particular, Waves 4, 5, and 6 (Figure 23). This suggests that these waves were initially composed of more transient populations than earlier waves.

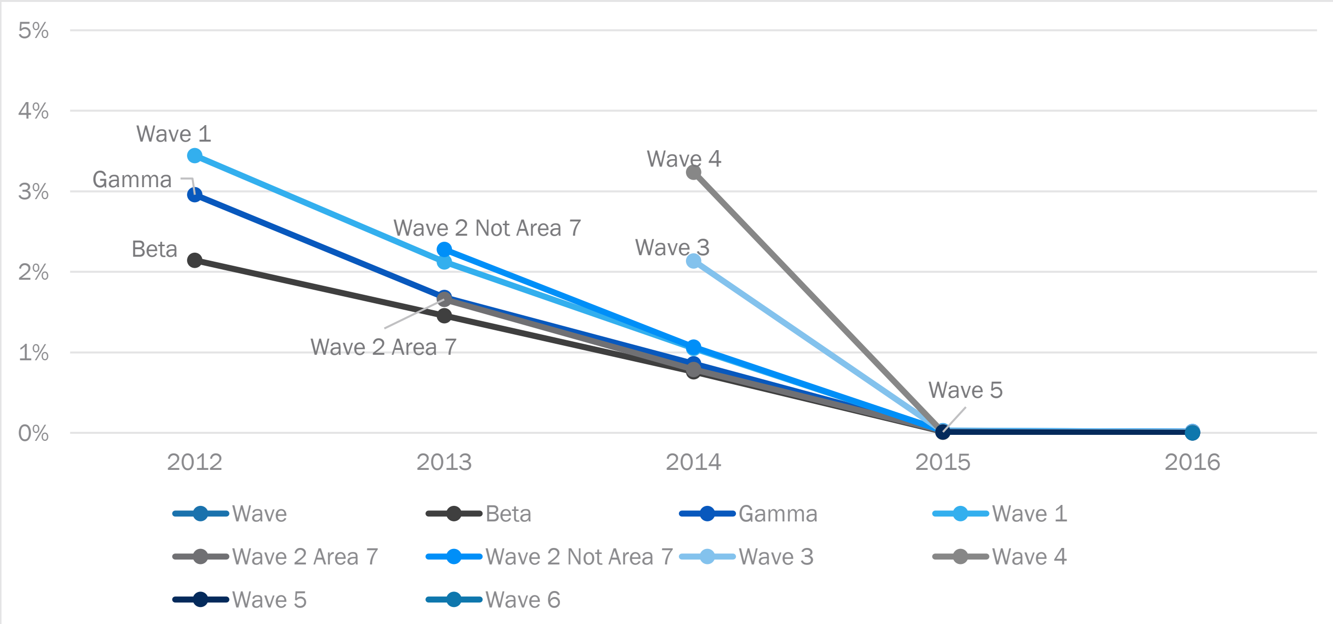
Figure 23. Annual Percent of Participants Who Move Out of PG&E Service Territory by Wave



Percentages reflect attrition in each year divided by the total population of participants in that year by wave.

Figure 24 provides annual attrition by participants who move out of homes within PG&E's service territory. We exclude 2015 and 2016 given that we do not have data for customers who moved in this time frame because we cannot know if those customers moved within or outside of PG&E territory until enough time has passed.

Figure 24. Annual Percent of Customers Who Move Out within PG&E Service Territory by Wave



Percentages reflect attrition in each year divided by the total population of participants in that year by wave.

Opinion Dynamics developed a multi-level model to identify each HER participant's individual savings estimates for every year in which they received reports. We divided HER program participants into five savings groups based on the results of our model.[20]

We compared these energy savings groups across the customers who had left the program and those who had remained. Interestingly, we found that the very negative and very positive groups tended to have higher rates of attrition than other groups. However, these groups tended to be smaller in terms of the absolute number of participants.

Table 10. Energy Savings Groups by Attrition and Remaining Electric Participants

Savings Group	Participants Who Attrited	Participants on Ineligible Rates	Participants in Program	Attrition Rate
Very Positive	30,582	20,537	56,521	54%
Positive	78,480	19,100	289,185	27%
Neutral	296,132	72,947	1,428,092	21%
Negative	60,416	19,227	244,327	25%
Very Negative	19,519	7,849	59,797	33%
NOTE: Participants counts exclude customers who were excluded from our multi-level model to validate savings results, as well as some customers who were removed from the analysis due to insufficient data.				

20 The very negative and very positive savers reflect savings more than 1.125 standard deviations, and the positive and negative savers groups reflect 0.375 standard deviations of the overall savings distribution.

4.1.3 Characteristics of Customer Attrition

We examined a range of variables in terms of whether they are related to attrition, looking at pre-period consumption of both electricity and gas overall and seasonally, and the individual savings estimates for each electric participant.[21] Table 11 shows that the correlations between attrition and these variables are all quite low. When we included these, and factors such as savings group and Local Capacity Area (LCA), we found that the attrition models had very low predictive power, so drawing conclusions about variable importance from these models is not appropriate.

Table 11. Correlations of Attrition with Numeric Variables

CARE	Electric Savings	Gas Savings	Pre-period kWh	Pre-period Summer kWh	Pre-period Winter kWh	Pre-period Therms	Pre-period Summer Therms	Pre-period Winter Therms
0.01	0.05	0.00	0.09	0.10	0.07	0.04	0.02	0.04

4.2 Guide to Interpreting Results

The results of this research seek to provide information to support approaches to mitigate attrition by identifying opportunities to keep participants within the program and potentially improve future savings and cost effectiveness. The results are presented for program participants only. However, we conducted similar descriptive statistics for control group customers and found results to be similar across waves, years, and drivers.

Our team originally sought to assess whether the chief driver of attrition had to do with renters moving to new homes or other rental homes. Unfortunately, the data that were provided regarding participant homeownership status (as well as other characteristics like income and education) did not have a sufficient match rate to be able to assess whether this was a driver of attrition.

We offer the following findings and implications related to attrition below:

- **Finding**: Participant attrition is highest for very positive and very negative savings groups.
  - **Implication:** The very negative and very positive savings groups participants may experience changes in their household, such as occupancy patterns, which may correlate both with energy consumption and moving. The multi-level model results suggest focusing on very negative and very positive savers in terms of program design enhancements. However, any program design revisions should balance the cost of making changes against the higher rate of attrition for these participants.
- **Finding**: Participant attrition is highest when the wave begins and decreases over time due to the declining size and possibly distinct rates of attrition within the population.

[21] We chose electric customers because this program provides reports to dual fuel customers, with the exception of an electric only wave. As a result, results for electric customers reflect results for both electric and gas fuel recipients.

  - **Implication**: Those participants who leave the program first likely have different characteristics than those who leave in later years. Treatment design may need to be adapted over time, initially focusing on simple actions with short payback and later on deeper energy efficiency measures.

- **Finding**: Participant attrition varies by wave, with later waves having the highest annual and absolute attrition overall.

  - **Implication**: This result suggests that there are key customer features associated with later waves that increase attrition. This may pose a threat for future program cost-effectiveness.

- **Finding**: Attrition rates follow market trends (i.e., the attrition rate is consistent by wave across treatment and control group customers). Attrition is mainly driven by participants moving in and out of the service territory.

  - **Implication:** Aside from identifying future waves who do not share characteristics with those who leave the program, there are few opportunities to mitigate the challenges associated with attrition for current waves.

A. Appendix A – Energy Savings Distribution Analysis Detailed Methods

Opinion Dynamics developed regression models to estimate individual savings using PG&E treatment and control group energy consumption data to estimate the distribution of savings across individual customers. This effort quantified the total number of negative, neutral, and positive savers, as well as classified each participant by their savings category. We developed a multi-level model to estimate individual savings using both treatment and control group information to control for exogeneous factors that may affect energy savings or consumption within a household over time. We provide detailed methods below.

4.2.1 Data Sources & Cleaning

Opinion Dynamics used the following data for this study:

- Monthly electric and gas consumption data in the pre- and post-periods for customers across waves in treatment and control groups from June 1, 2010 through December 31, 2016 cleaned by third party program evaluators. This data file included participant characteristics, such as first report date and wave.
- Half-hourly weather data for all PG&E weather stations from June 1, 2010 through December 31, 2016;
- Customer information (e.g., geographic location, CARE customer).

4.2.2 Modeling Approach

Opinion Dynamics ran three distinct types of models to verify the data, select appropriate model specifications, and produce energy savings groups: difference-in-difference model, individual regressions and a multi-level model. We describe each below.

Difference in Difference Model

Opinion Dynamics used linear fixed-effects regression (LFER) analysis to estimate program effects and verify findings from our individual regressions and multi-level model. The fixed-effects modeling approach accounts for time-invariant, household-level factors affecting energy use without entering those factors explicitly in the models. The effects of these factors are contained in a household-specific intercept or constant term in the equation. Because of the experimental design, we can assume that the treatment and control groups experienced similar historical, political, economic, and other events that had comparable effects on their energy use. The model specification is:

Equation 1. Difference in Difference Model Estimating Equation

$$ADC_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Treatment_i \cdot Post_t + \varepsilon_{it}$$

We developed this model to compare our multi-level model results to the third-party evaluation results.

Individual Regressions

Equation 2. Pre-Post Model Estimating Equation

$$ADC_t = \alpha + \beta_1 Post_t + \beta_2 HDD_t + \beta_3 CDD_t + \beta_4 HDD_t \cdot Post_t + \beta_5 CDD_t \cdot Post_t + \varepsilon_t$$

We ran individual models with the specification from Equation 2 for each participant to get a rough approximation of the distribution in savings for each wave. We do not use these estimates for reporting, but to check whether the individual savings estimates are approximately normally distributed. The multi-level model we use to make final individual savings estimates assumes that the savings is approximately normally distributed, so we use these models to quickly check that assumption. We also expect that the individual model results will have a wider distribution in savings than the multi-level model, comparing the distributions in savings gives an idea of how much the multi-level model is reducing variation in individual savings estimates.

Multi-Level Model

We used a multilevel analysis to estimate individual savings for each participating customer. We used the individual savings estimates to group customers into five categories (very positive, positive, neutral, negative, and very negative savers), and analyze the correlation of savings with demographics and household characteristics. The savings results from these multilevel models do not exactly match the savings from the impact analysis, as we have parameterized this model to understand the responses of different types of customers to the HERs rather than calculate total savings attributable to the program. The model takes into account exogenous factors, such as weather, within the model.

One method of estimating savings levels for individual households is to run individual regression models for each participant. However, in this evaluation, we used a multilevel modeling approach, which provides clear advantages over individual regression to establish individual household savings levels. These include:

- Multilevel modeling statistically controls for weather differences between pre- and post-periods for an individual household as well as across households. In contrast, individual models solely control for weather differences between pre- and post-periods for an individual household.
- Multilevel modeling allows for modeling the influence of variables that do not change over time that apply to customers and for generating appropriate standard errors and statistical tests.
- Results from multilevel regression models adjust individual savings estimates based on control group usage during the treatment period, so the savings estimates are much closer to net savings than results from individual regressions.
- Information is shared across customers in multilevel models, so the unexplained variance in individual savings across participants is much lower when we make estimates using a multilevel model.

Equation 3. Multilevel Model

$$\begin{aligned} ADC_{it} \sim N(\alpha_i + \theta_i Treatment_t + \beta_1 HDD_t + \beta_2 CDD_t + \beta_3 Post_t + \beta_4 Post_t \cdot HDD_t + \beta_5 Post_t \cdot CDD_t \\ + \beta_6 Treatment_t \cdot HDD_t + \beta_7 Treatment_t \cdot CDD_t, \sigma^2_{ADC}), \end{aligned}$$

$$for\ t = 1, \ldots, t, i = 1, \ldots, n;$$

$$\begin{pmatrix}\alpha_i\\ \theta_i\end{pmatrix} \sim N\left(\begin{pmatrix}\mu_\alpha\\ \mu_\theta\end{pmatrix}, \begin{pmatrix}\sigma_\alpha^2 & \rho\sigma_\alpha\sigma_\theta\\ \rho\sigma_\alpha\sigma_\theta & \sigma_\theta^2\end{pmatrix}\right), for\ i = 1, \dots, n$$

Where:

ADC_{it}= Average daily consumption (kWh or therms) for household i at time t

α_i= Household-specific intercept for household i

θ_i= Household-specific change in consumption for the treatment group in the post period

β_1= Coefficient for HDD

β_2= Coefficient for CDD

β_3= Coefficient for Post period

β_4= Coefficient for Post period by HDD interaction

β_5= Coefficient for Post period by CDD interaction

β_6= Coefficient for treatment group in the post period by HDD interaction

β_7= Coefficient for treatment group in the post period by CDD interaction

σ_{ADC}^2= Variance of ADC

μ_α= Mean of household-specific intercept

μ_θ= Mean of household-specific change in consumption due to treatment

σ_α^2= Variance of household-specific intercept

σ_θ^2= Variance of household-specific change in consumption due to treatment

$\rho\sigma_\alpha\sigma_\theta$= Covariance of household-specific intercept and change in consumption

N = Multivariate normal distribution

We drew data for this analysis from several sources, including program-tracking data, and customer billing data. All the calculations and modeling used R[22] statistical software, with multilevel models using the lme4[23] package.

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[22] R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

[23] Douglas Bates, Martin Maechler, Ben Bolker, Steve Walker (2015). Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software, 67(1), 1-48. doi:10.18637/jss.v067.i01.

4.2.3 Validation Methods & Results

Opinion Dynamics validated the multi-level models using 10-fold cross validation. This method assigns the customers into 10 groups and runs the model 10 times, each time with one of the groups excluded. We then examine the variation in parameter estimates to understand whether the savings estimates from the model are changing based on exclusion of a few data points. In this case, we see so little variation in parameter estimates in Figure 25, Figure 26, and Figure 27 that most of the distributions look like a single vertical line. This means that the model is not overfit and very likely to be internally valid.

Figure 25 Cross Validation Results for Electric Only Models

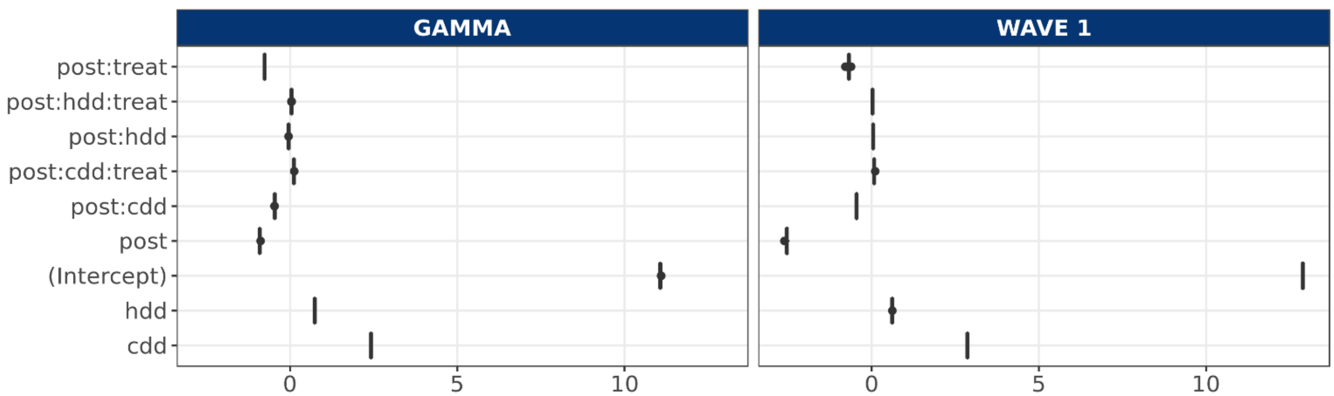


Figure 26 Cross Validation Results for Electric Models

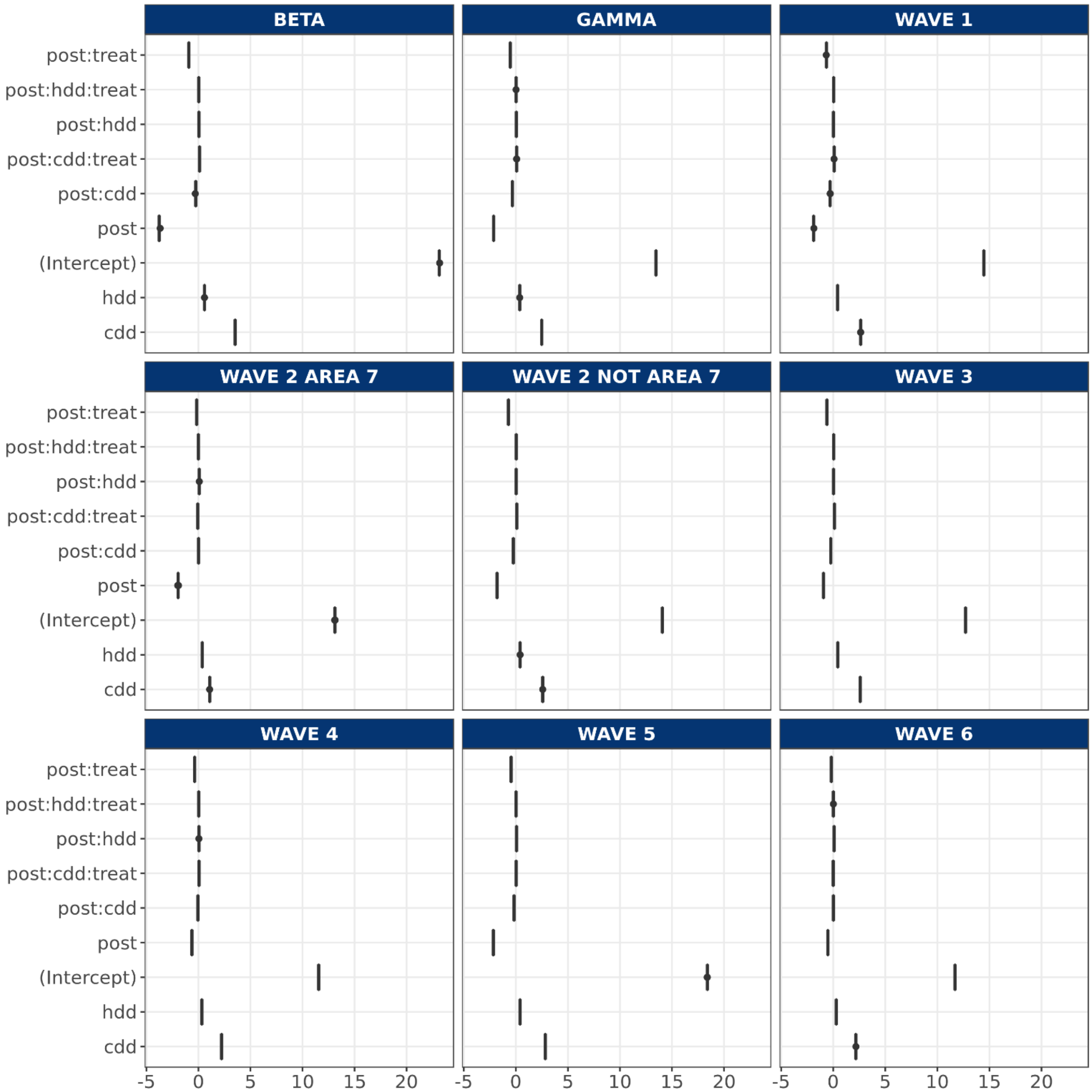
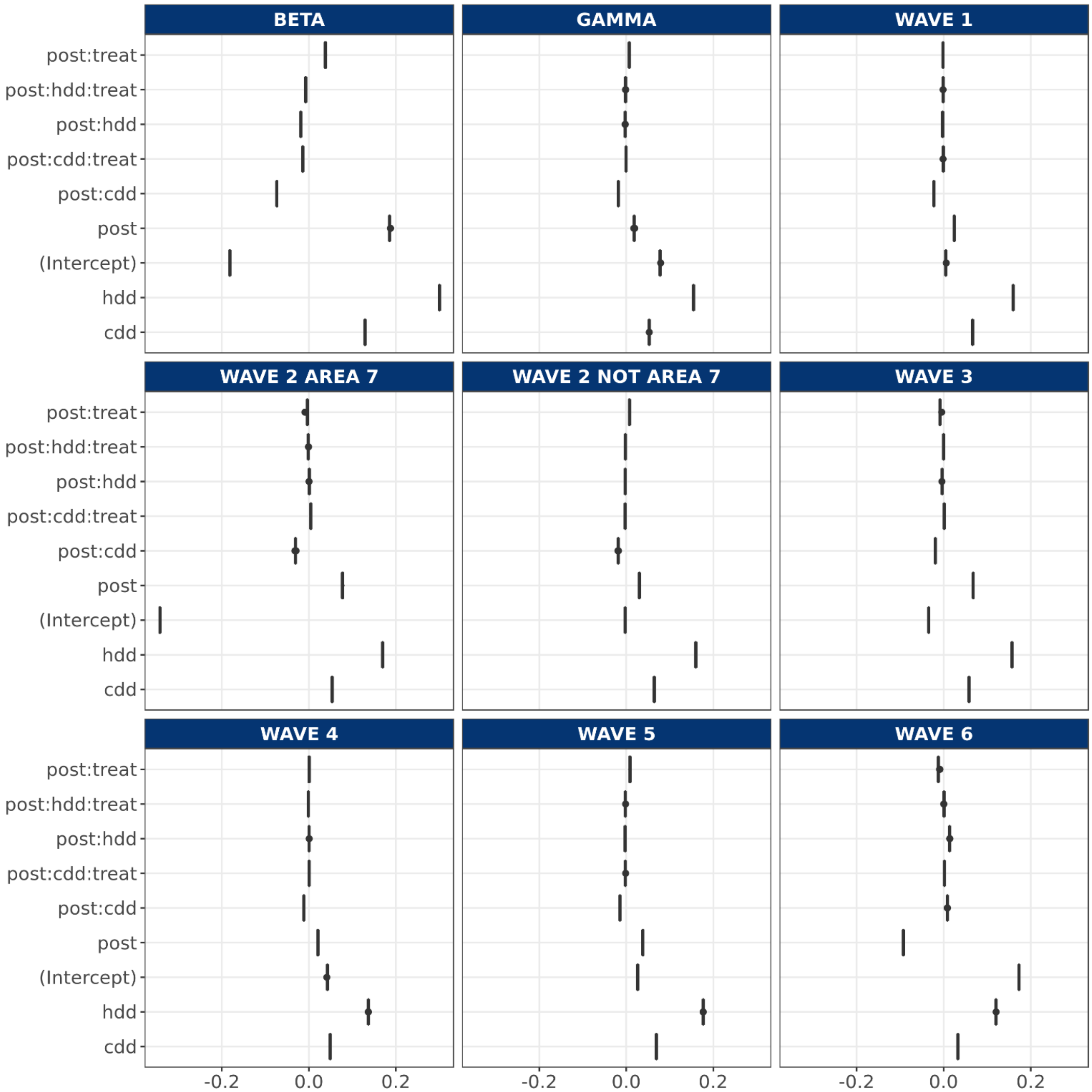


Figure 27 Cross Validation Results for Gas Models



B. Appendix B – Distribution of Energy Savings by Wave and Year

Our team plotted the distribution of savings by wave for each year to inspect annual trends by wave.

Electric Participants

Figure 28. Beta Wave Distribution of Savings by Year

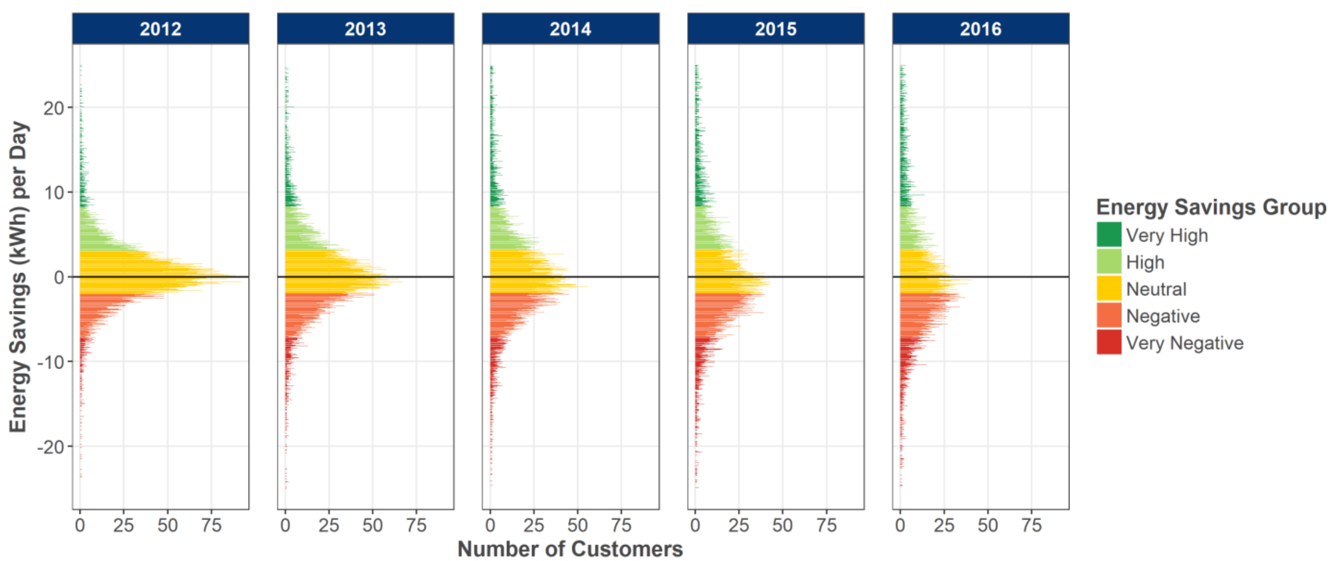


Figure 29. Gamma Wave Distribution of Savings by Year

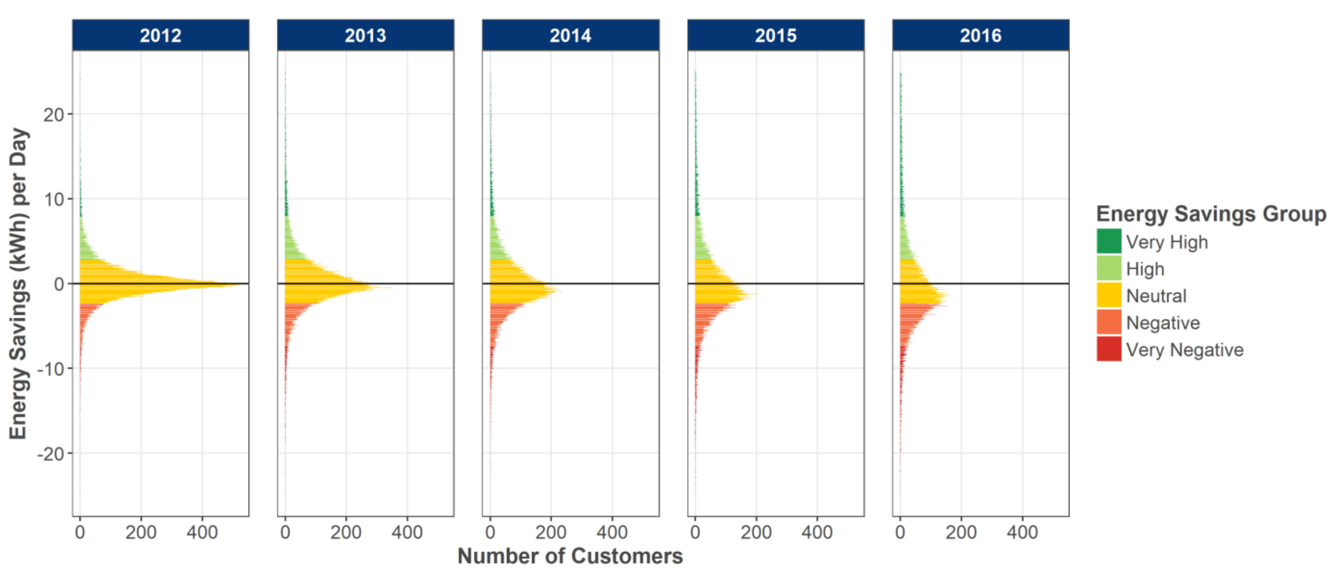


Figure 30. Wave 1 Distribution of Savings by Year

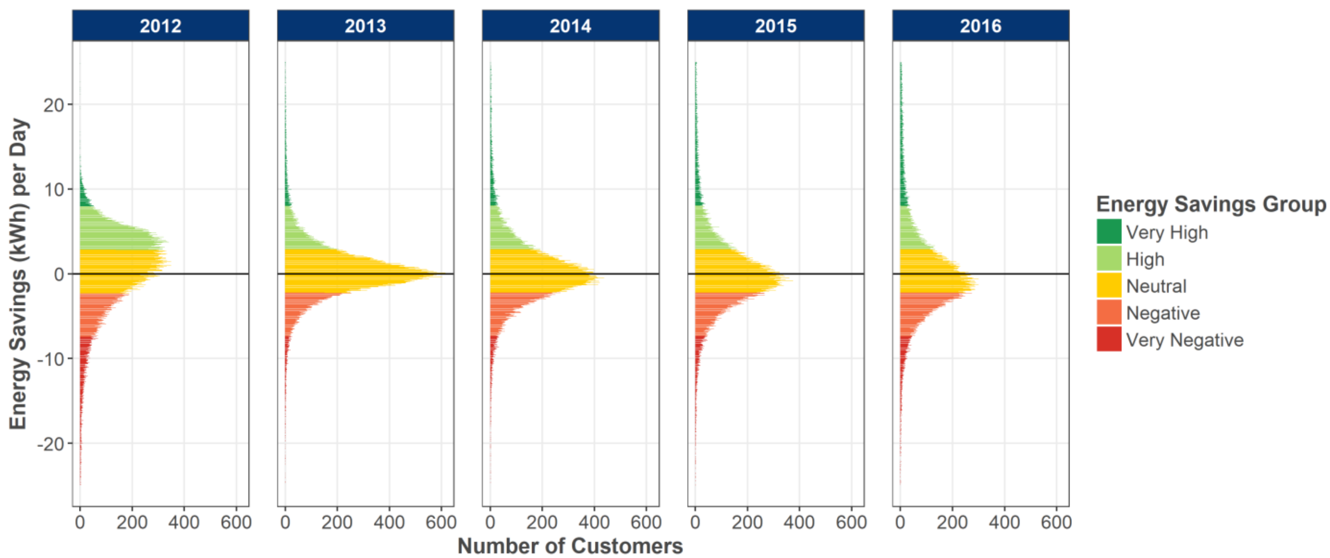


Figure 31. Wave 2 Area 7 Distribution of Savings by Year

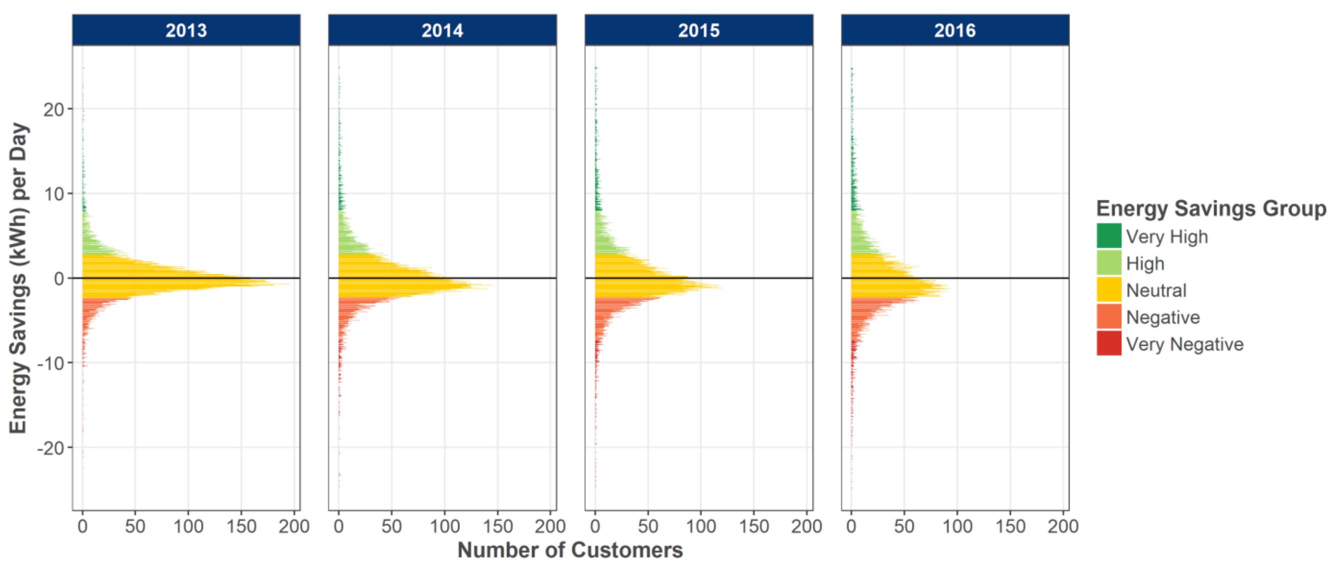


Figure 32. Wave 2 Not Area 7 Distribution of Savings by Year

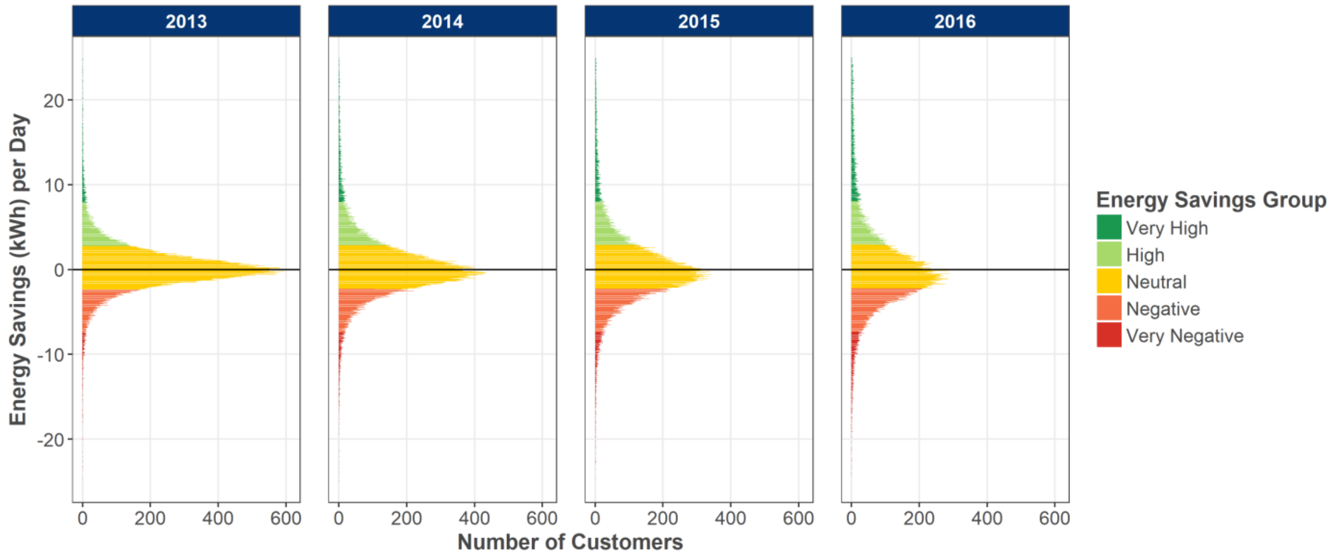


Figure 33. Wave 3 Distribution of Savings by Year

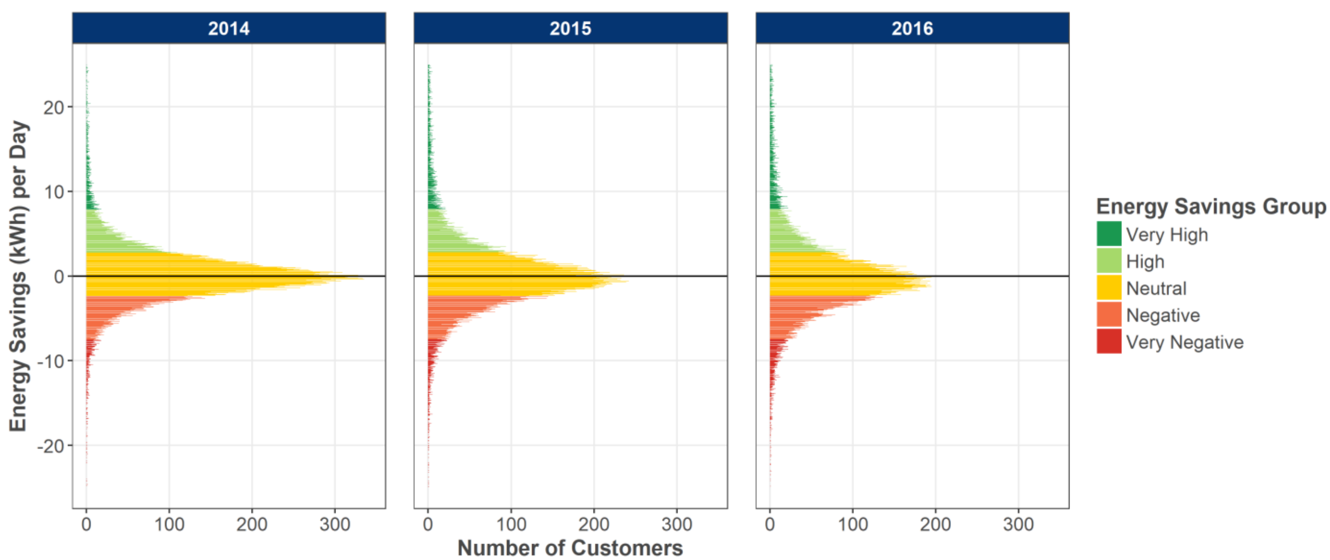
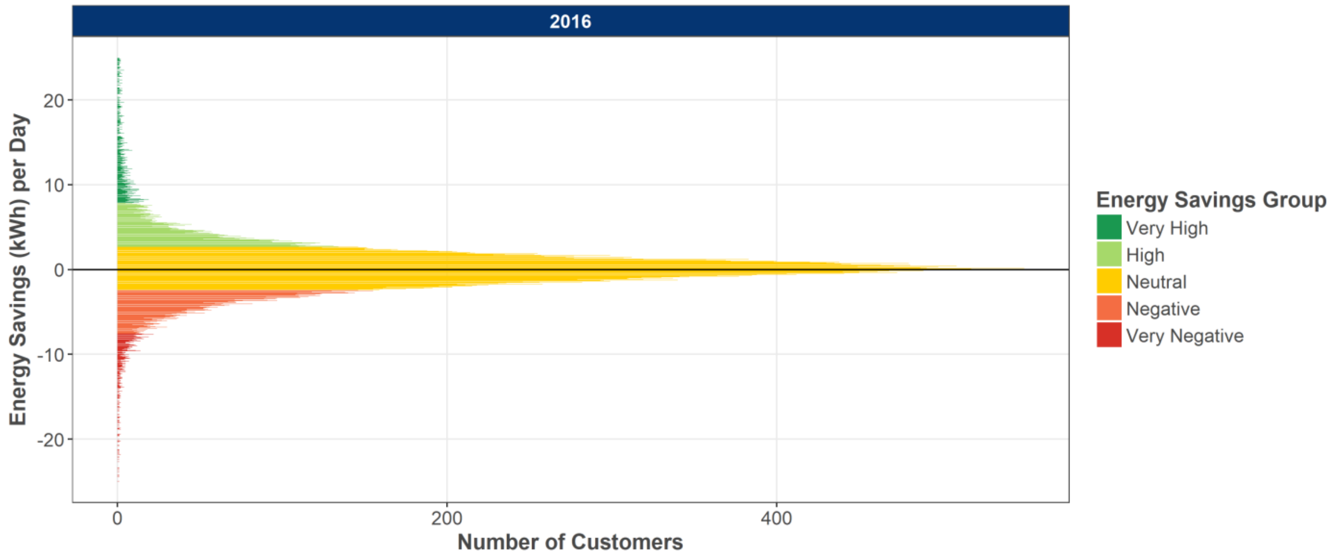


Figure 34. Wave 4 Distribution of Savings by Year

Figure 35. Wave 5 Distribution of Savings by Year

Figure 36. Wave 6 Distribution of Savings



Gas Participants

Figure 37. Beta Wave Distribution of Savings by Year

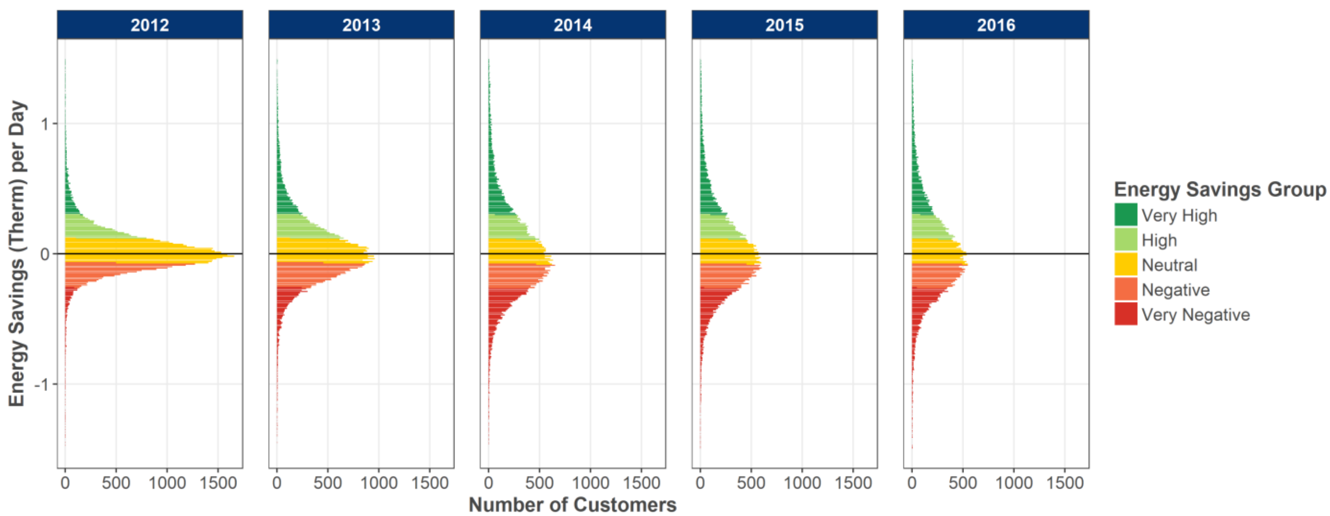


Figure 38. Gamma Wave Distribution of Savings by Year

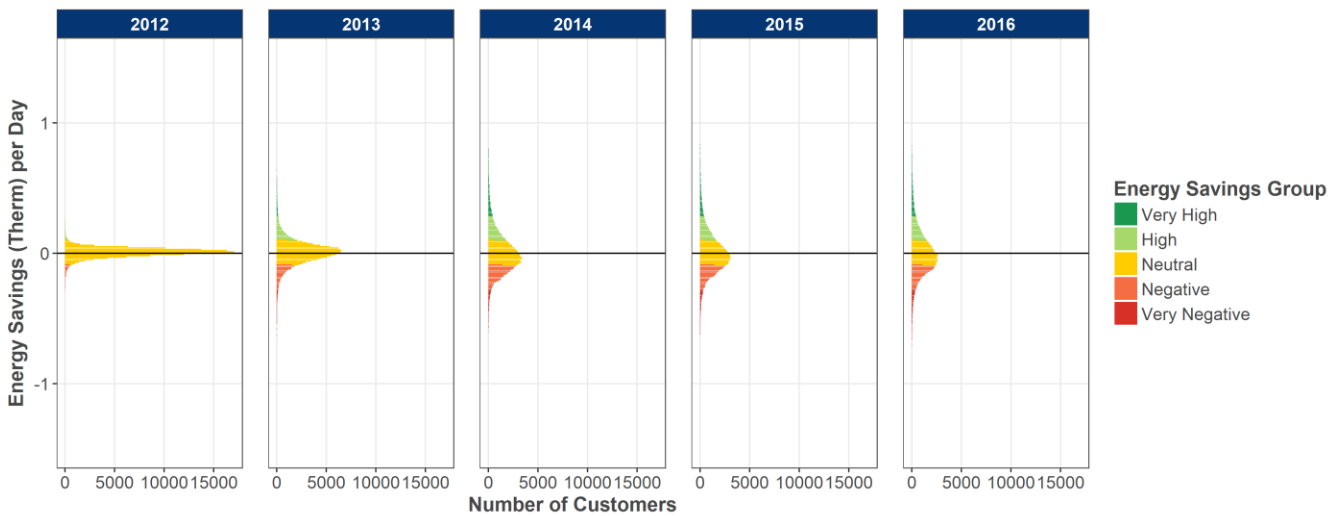


Figure 39. Wave 1 Distribution of Savings by Year

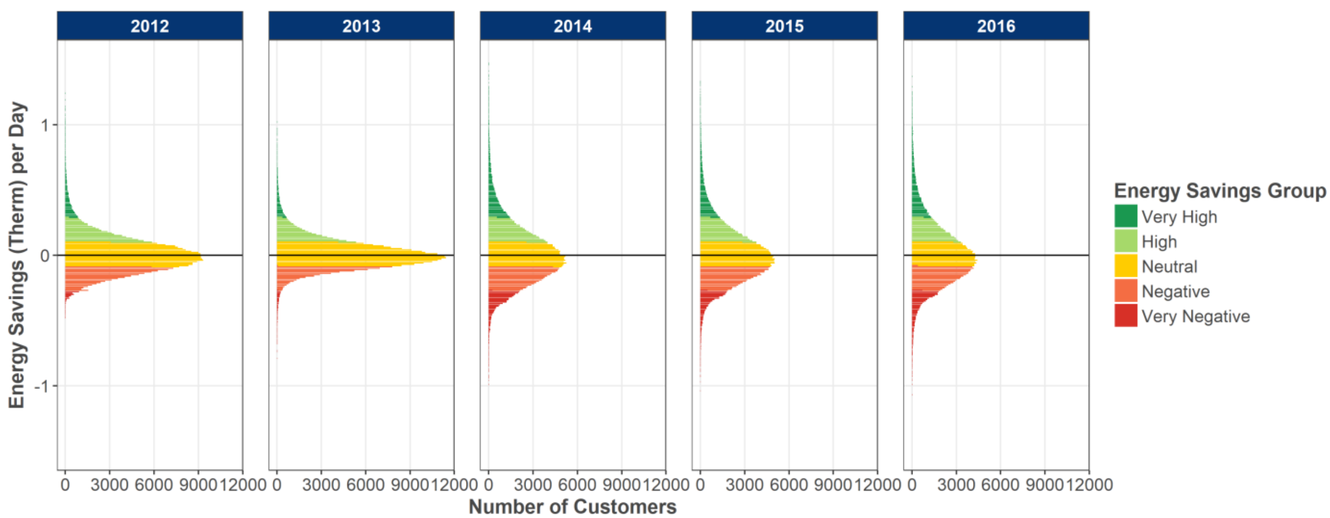


Figure 40. Wave 2 Area 7 Distribution of Savings by Year

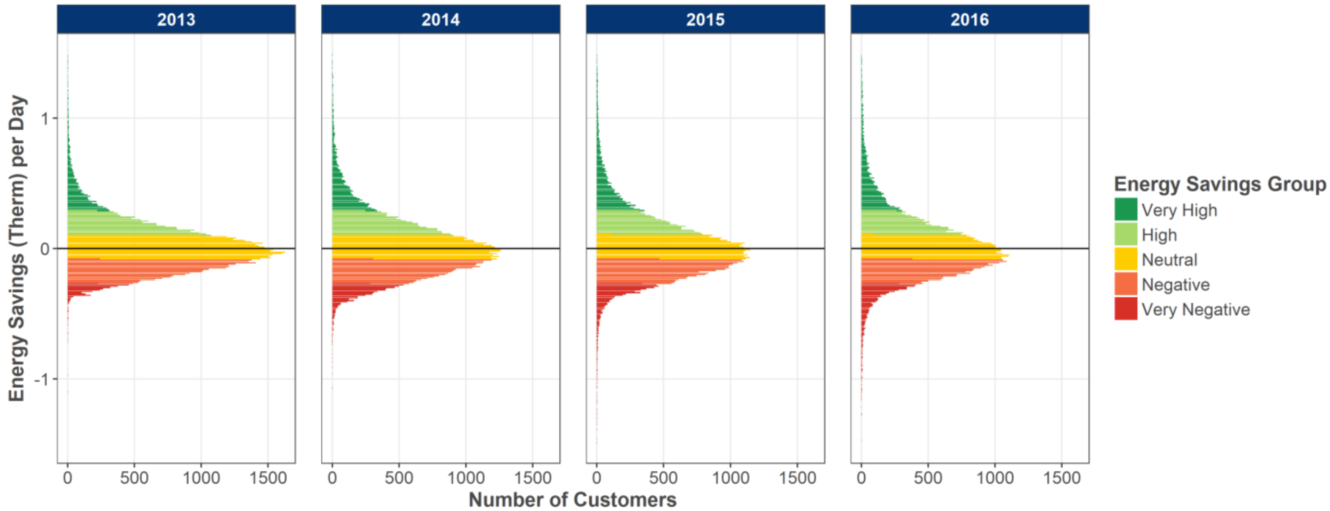


Figure 41. Wave 2 Not Area 7 Distribution of Savings by Year

Figure 42. Wave 3 Distribution of Savings by Year

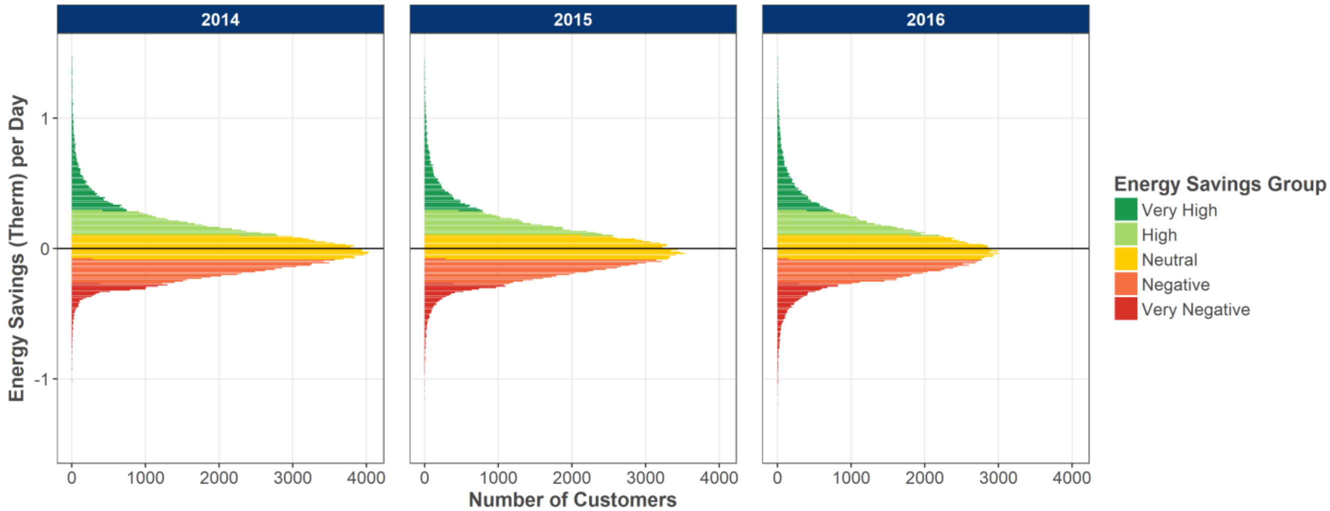


Figure 43. Wave 4 Distribution of Savings by Year

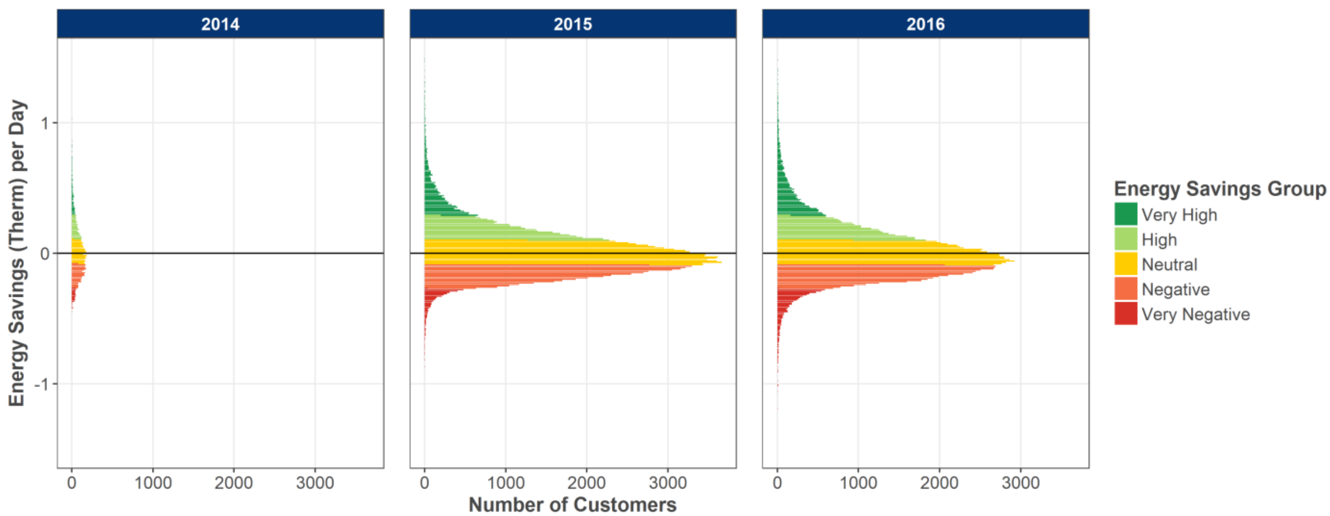


Figure 44. Wave 5 Distribution of Savings by Year

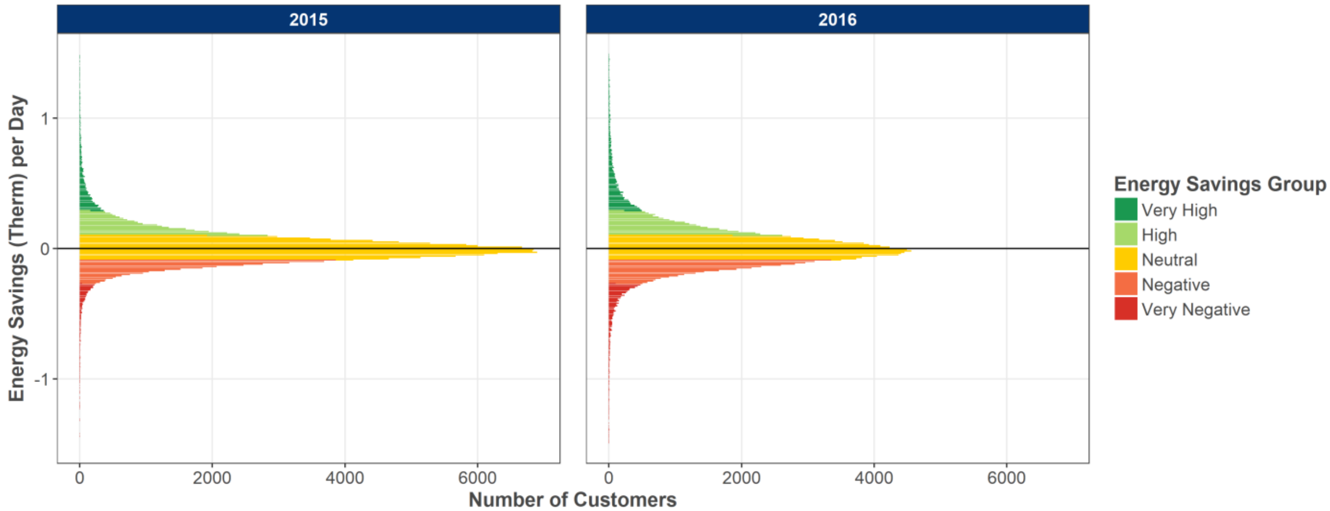
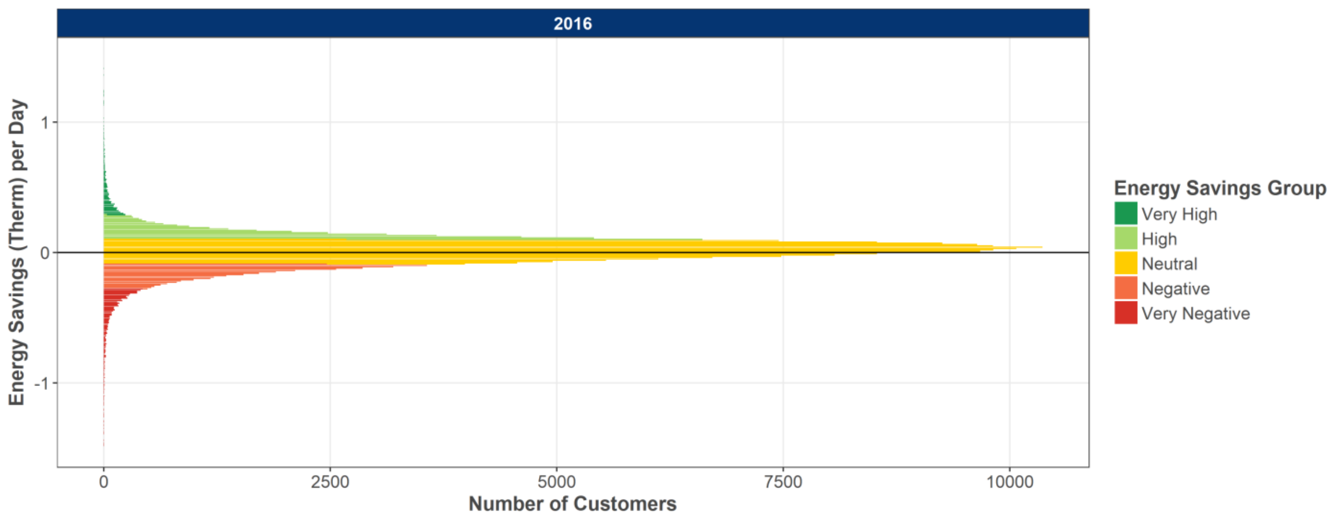


Figure 45. Wave 6 Distribution of Savings



C. Appendix C – Participant Characteristics by Savings Group Detailed Methods

Opinion Dynamics conducted descriptive statistics and correlation analysis to assess any trends related to program attrition. We provide detailed methods below.

4.2.4 Data Sources & Cleaning

Opinion Dynamics used the following data for this study:

- Electric interval data from January 1, 2015 – December 31, 2016 to support estimates of participant characteristics correlated or predictive of energy savings groups for sample of customers. As part of the research effort, we developed a stratified random sampling plan for HER participants and control customers. For the sample, we requested AMI data for 150,000 customers from 2015 and 2016 across electric treatment and control group customers stratifying on wave and savings group for treatment customers. We requested 25,000 control customers, and 125,000 treatment customers. From each wave, we randomly selected 3,125 control customers, and approximately 15,000 treatment customers. Within the treatment group population, we randomly selected approximately 3,000 treatment customers by each energy savings group. Within each wave, we ensured a sub-sample of participants who have changed energy savings group from 2015-2016. The rationale for this change is to identify if there are any changes to load curves for customers who change their energy savings group. We have combined the sub-waves: gamma and gamma reduced, and Wave 2 Area 7 and Wave 2 Not Area 7.
- Results from Section 1 (energy savings groups)
- Hourly electric consumption data in 2015 and 2016 for customers across waves in the treatment group.
- Half-hourly weather data for all PG&E weather stations from June 1, 2010 through December 31, 2016;
- Customer information (e.g., geographic location, CARE customer)
- American Community Survey data for median income by zip code

Notably, our analysis did not include Axciom and Experian customer data given the poor match quality for this data to the customers in the treatment groups.

4.2.5 Analysis Approach

Opinion Dynamics conducted two sets of analyses: 1) descriptive statistics, and 2) correlation analysis. We describe these below.

- **Descriptive Statistics**: We analyzed the customer data to produce descriptive statistics. For any comparisons of subgroups, any differences reflect true differences, because the study was conducted on the full population of participants.
- **Correlation Analysis**: We began by conducting a correlation analysis across variables of interest to see if there were differences between those participants who had remained or had left the HER program. We found that the model results had low predictive power.
- **Regression Modeling:** We built a regression model using the variables identified in our correlation analysis, as well as other key variables to identify those variables that would inform the clustering approach. We used extreme gradient boosting on regression trees to identify variables that are predictive of savings in ways that include both linear and non-linear relationships. We took the variables that were more important in the regression model as variables to include in the clustering.
- **Cluster Analysis:** We used a k-means clustering algorithm to build the clusters. We chose K-means clustering because it creates groups that are mutually exclusive and exhaustive, while tending to keep clusters close to the same size. However, it may create groupings of different sizes when a group is very different from all of the other groups. As seen above, Cluster 1 is much smaller than the other clusters, but is preserved by the k-means method. K-means can also be used to assign clusters to customers who were not originally in the model, which is very useful and not possible with all clustering algorithms.

4.2.6 Exploratory Analysis

We reduced the set of input variables using several techniques, starting with assessing the correlation of each variable with savings, and progressing to a regression model that tries to predict savings with a combination of variables. The variables that are either highly correlated with savings or are important in the regression model are candidates for inclusion in the clustering model. We then included variables that we consider to be more actionable and/or more likely to differentiate across customers. These variables are either related to program participation (‘Participation’), to customer characteristics (‘Customer’), or customer load characteristics (‘Load’). The list of clustering variable candidates is below.

Table 12. Variables Included in Analysis

Variable	Description	Group
CARE	Flag for CARE	Customer
EV	Flag for EV electric rate	Customer
Median Income by Zip Code	Median income for zipcode	Customer
LCA	Local Capacity Area	Customer
NEM	Flag for net energy metering (NEM) rate	Customer
TOU	Flag for Time Of Use (TOU) rate	Customer
Mean Intraday Volatility	Mean of daily standard deviation of load	Load
Peak Total Load	The fraction of total load during peak hours (5-9 pm) of the summer months (Jun-Aug)	Load

Variable	Description	Group
Shoulder Post Usage	Average usage for post-period during shoulder months (Mar-May, Sep-Nov)	Load
Summer Post Usage	Average usage for post-period during summer months (Jun-Aug)	Load
Winter Post Usage	Average usage for post-period during winter months (Dec-Feb)	Load
Shoulder Pre Usage	Average usage for pre-period during shoulder months (Mar-May, Sep-Nov)	Load
Summer Pre Usage	Average usage for pre-period during summer months (Jun-Aug)	Load
Winter Pre Usage	Average usage for pre-period during winter months (Dec-Feb)	Load
Usage Ramp	Average hourly usage increase during the ramp up period to the evening period (3 pm - 7 pm)	Load
Shoulder HE1	Average usage for hour 1 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE2	Average usage for hour 2 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE3	Average usage for hour 3 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE4	Average usage for hour 4 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE5	Average usage for hour 5 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE9	Average usage for hour 9 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE10	Average usage for hour 10 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE12	Average usage for hour 12 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE14	Average usage for hour 14 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE15	Average usage for hour 15 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE16	Average usage for hour 16 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE18	Average usage for hour 18 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE19	Average usage for hour 19 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE20	Average usage for hour 20 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder HE21	Average usage for hour 21 during shoulder months (Mar-May, Sep-Nov)	Load
Shoulder Day-Night Ratio	Ratio of nighttime to daytime usage during shoulder months (Mar-May, Sep-Nov)	Load
Summer HE2	Average usage for hour 2 during summer months (June-Aug)	Load
Summer HE3	Average usage for hour 3 during summer months (June-Aug)	Load
Summer HE5	Average usage for hour 5 during summer months (June-Aug)	Load
Summer HE10	Average usage for hour 10 during summer months (June-Aug)	Load
Summer HE12	Average usage for hour 12 during summer months (June-Aug)	Load
Summer HE13	Average usage for hour 13 during summer months (June-Aug)	Load
Summer Day-Night Ratio	Ratio of nighttime to daytime usage during summer months (Jun-Aug)	Load
Summer Range	Absolute range of max to min in summer	Load

Variable	Description	Group
Summer Off-peak Load	Summer total off peak load (hours 1-16 & 22-24)	Load
Summer Total Usage	Total summer usage (Jun-Aug)	Load
Summer Winter Usage Ratio	Ratio of summer to winter usage	Load
WInter HE7	Average usage for hour 7 during winter months (Dec-Feb)	Load
WInter HE12	Average usage for hour 12 during winter months (Dec-Feb)	Load
WInter HE17	Average usage for hour 17 during winter months (Dec-Feb)	Load
Winter Day-Night Ratio	Ratio of nighttime to daytime usage during winter months (Dec-Feb)	Load
Winter Off-peak Load	Winter total off peak load (hours 1-16 & 22-24)	Load
Winter Total Usage	Total winter usage (Dec-Feb)	Load
Overall Volatility	Overall standard deviation of hourly load	Load
Duration	Length of time as PG&E customer at premise	Participation
Months as HER Participant	The number of months a customer was in the post-period of the program	Participation
Savings	Individual savings estimate from Multi-Level Model	Participation
2015 Savings Group Change	Number of groups changed from 2014-2015	Participation
2016 Savings Group Change	Number of groups changed from 2015-2016	Participation

Table 13. Average by Cluster for a Subset of Variables

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9
Summer Pre Usage	67.67	59.14	41.78	26.77	20.75	18.60	15.88	36.65	35.56
Winter Pre Usage	64.01	49.30	26.97	25.53	17.37	19.60	16.85	32.96	26.04
Shoulder Pre Usage	61.09	47.29	27.72	23.04	16.02	17.30	14.76	30.82	25.65
Summer Post Usage	123.35	63.02	46.04	28.83	20.27	17.65	14.62	33.87	22.04
Winter Post Usage	120.29	51.76	27.88	26.73	16.29	17.86	15.15	28.13	20.50
Shoulder Post Usage	117.97	49.22	28.88	23.78	14.88	15.65	13.12	26.12	14.94
Months as HER Participant	33.75	43.75	42.17	44.80	39.94	49.52	40.63	55.20	40.06
Time as PG&E Customer	8.57	14.43	12.98	14.04	11.21	38.29	11.47	19.01	8.53
Median Income for Zip Code	74332	102659	65891	96209	58867	89145	86955	87517	81281
Mean Intraday Volatility	2.89	1.26	0.90	0.69	0.45	0.40	0.36	0.65	1.58
Peak Total Load	0.19	0.28	0.33	0.31	0.30	0.29	0.29	0.32	0.56
Usage Ramp	1.59	0.43	0.25	0.37	0.17	0.20	0.23	0.31	2.37
2015 Savings Group Change	-0.15	-0.09	-0.12	-0.20	-0.06	-0.06	-0.03	1.15	0.36
2016 Savings Group Change	-0.27	-0.16	-0.19	-0.09	-0.07	0.01	0.00	-0.15	0.62

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9
Shoulder HE 1	8.16	1.94	0.88	0.80	0.48	0.45	0.41	0.70	0.88
Shoulder HE 10	5.15	2.06	1.10	0.92	0.53	0.62	0.48	0.87	-0.79
Shoulder HE 12	4.65	2.22	1.25	0.93	0.56	0.62	0.47	0.89	-2.06
Shoulder HE 14	4.13	2.21	1.34	0.95	0.60	0.62	0.48	0.92	-2.19
Shoulder HE 15	4.06	2.21	1.39	0.97	0.63	0.62	0.48	0.94	-1.84
Shoulder HE 16	4.08	2.24	1.47	1.03	0.67	0.65	0.51	0.99	-1.18
Shoulder HE 18	4.70	2.44	1.63	1.24	0.78	0.78	0.64	1.17	0.55
Shoulder HE 19	5.58	2.57	1.66	1.34	0.82	0.82	0.71	1.24	1.21
Shoulder HE 2	8.14	1.82	0.79	0.71	0.43	0.41	0.36	0.63	0.80
Shoulder HE 20	6.43	2.67	1.64	1.39	0.84	0.82	0.75	1.27	1.51
Shoulder HE 21	7.28	2.73	1.61	1.40	0.85	0.81	0.77	1.28	1.55
Shoulder HE 3	7.99	1.72	0.72	0.66	0.39	0.39	0.33	0.59	0.73
Shoulder HE 4	7.89	1.65	0.70	0.63	0.38	0.38	0.32	0.57	0.71
Shoulder HE 5	7.78	1.61	0.70	0.64	0.38	0.39	0.33	0.58	0.71
Shoulder HE9	5.78	1.97	1.03	0.91	0.50	0.61	0.48	0.85	0.02
Shoulder Day-Night Ratio	0.61	1.13	1.30	1.07	1.09	1.20	1.00	1.14	-1.34
Summer HE10	5.39	2.28	1.44	0.93	0.60	0.60	0.47	0.93	-1.17
Summer HE12	4.98	2.80	2.01	1.05	0.75	0.65	0.50	1.10	-2.42
Summer HE13	4.66	3.03	2.31	1.15	0.85	0.70	0.53	1.23	-2.57
Summer HE2	8.45	2.25	1.27	0.82	0.59	0.45	0.40	0.79	1.11
Summer HE3	8.34	2.07	1.11	0.74	0.52	0.42	0.37	0.71	0.99
Summer HE5	8.06	1.82	0.95	0.67	0.47	0.40	0.34	0.65	0.86
Summer Day-Night Ratio	0.64	1.21	1.42	1.16	1.17	1.28	1.14	1.24	-1.23
Summer Range Usage	14.22	10.22	7.83	6.39	4.13	4.00	3.71	6.27	11.28
Summer Off-peak Load	11142	4118	2724	1660	1153	965	811	1661	19
Summer Total Usage	14264	6231	4489	2662	1850	1510	1257	2689	550
Summer Winter Usage Ratio	1.40	1.56	2.26	1.40	1.68	1.19	1.21	1.55	-2.15
Overall Volatility	3.86	1.63	1.20	0.88	0.60	0.52	0.48	0.85	1.74
Winter HE12	4.45	2.32	1.26	1.06	0.63	0.72	0.55	1.00	-1.20
Winter HE17	4.12	2.18	1.25	1.17	0.71	0.78	0.62	1.07	0.88
Winter HE7	6.48	2.04	1.02	0.99	0.56	0.61	0.53	0.90	1.05
Winter Day-Night Ratio	0.64	1.07	1.21	1.06	1.07	1.22	1.01	1.11	-0.37
Winter Off-peak Load	9660	3454	1712	1635	965	1020	858	1471	466
Winter Total Usage	12498	4828	2473	2386	1408	1501	1270	2152	1012

Table 14. Percent of Customers in Each Cluster for a Given Climate Zone

Climate Zone	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Total
1	3%	5%	2%	12%	28%	12%	33%	4%	1%	100%
2	1%	3%	6%	21%	16%	12%	36%	3%	2%	100%
3	0.4%	2%	2%	17%	17%	16%	41%	2%	2%	100%
4	0.1%	4%	6%	29%	13%	13%	29%	4%	3%	100%
5	0%	0%	0%	4%	52%	16%	28%	0%	0%	100%
11	0.1%	5%	26%	18%	21%	5%	14%	4%	6%	100%
12	0.1%	5%	19%	26%	16%	8%	18%	5%	4%	100%
13	0.05%	4%	35%	10%	29%	4%	8%	4%	5%	100%
16	0%	7%	13%	19%	29%	9%	21%	3%	0%	100%

Figure 46. Customer Spatial Distribution, Cluster 1 (left) and Cluster 2 (right)

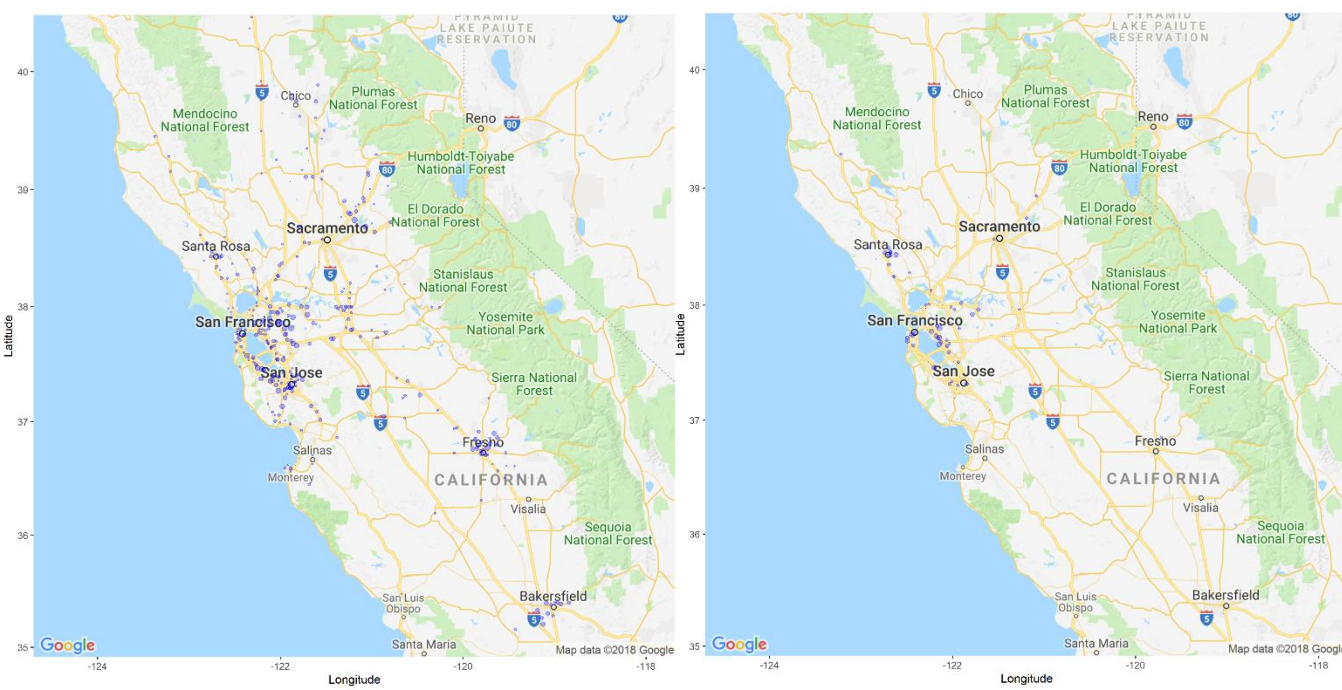


Figure 47. Customer Spatial Distribution, Cluster 3 (left) and Cluster 4 (right)

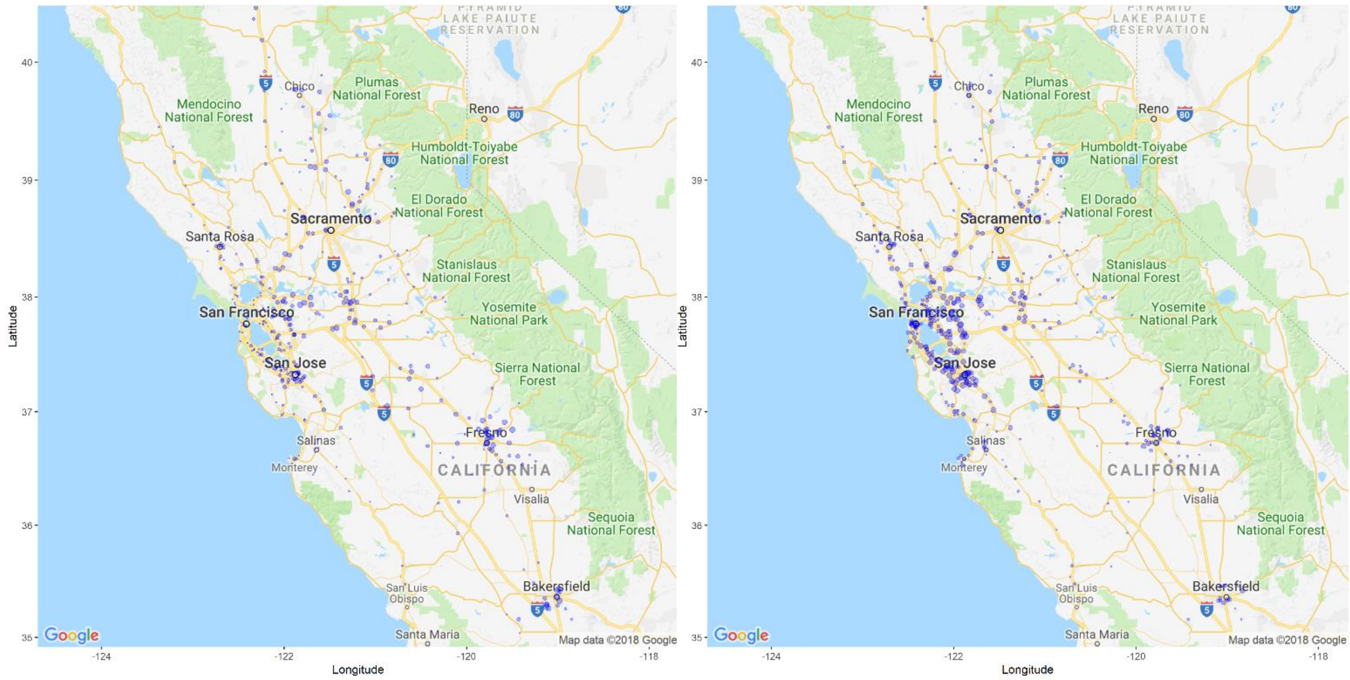


Figure 48. Customer Spatial Distribution, Cluster 5 (left) & 6 (right)

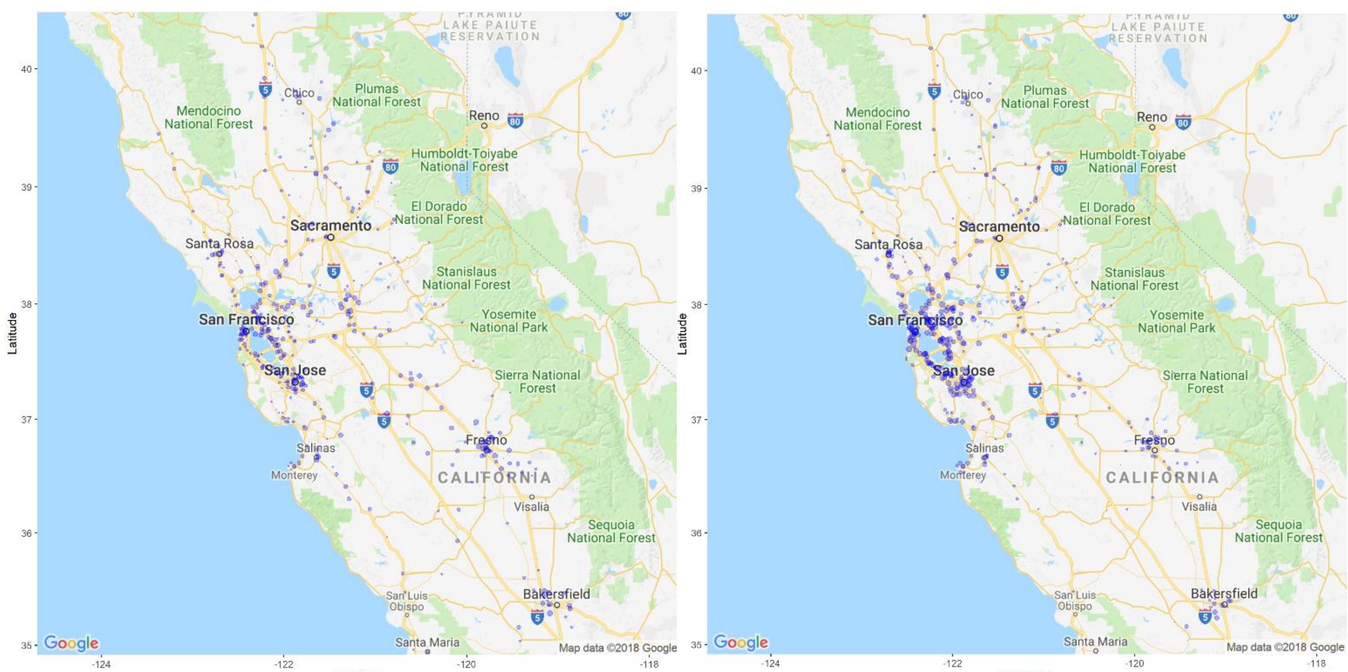


Figure 49. Customer Spatial Distribution, Cluster 7 (left) and 8 (right)

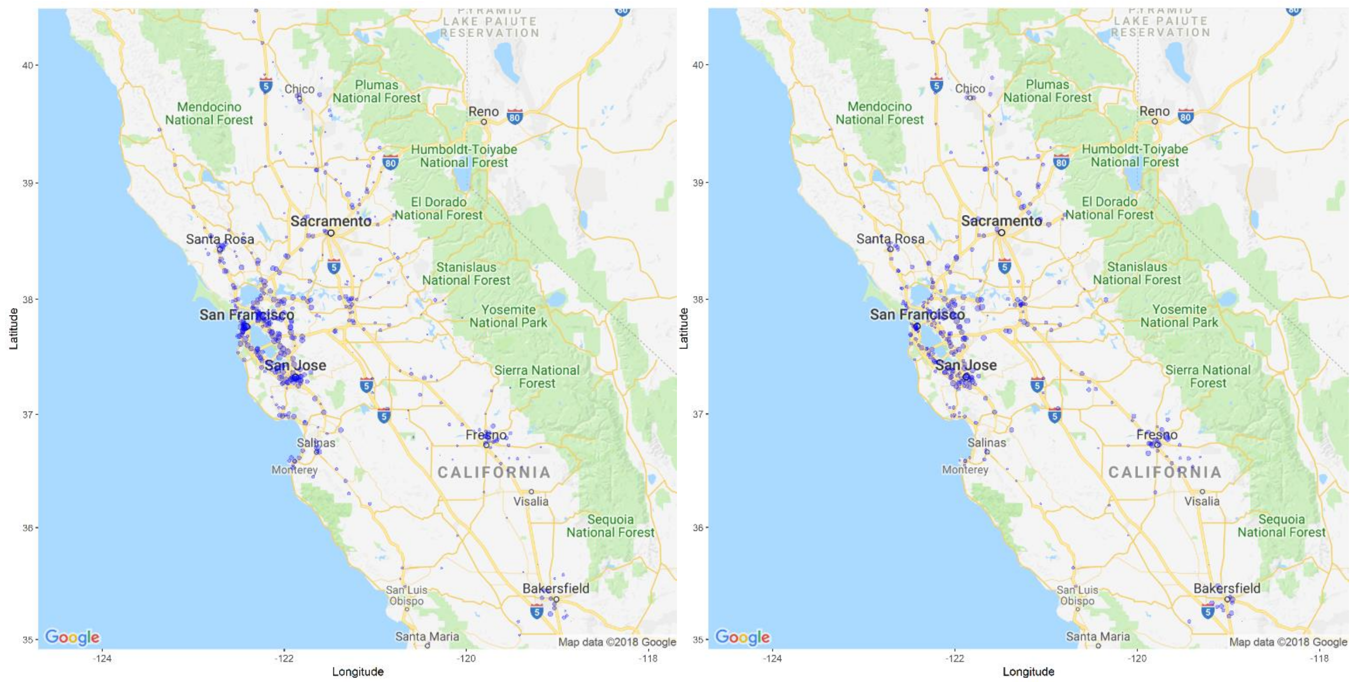
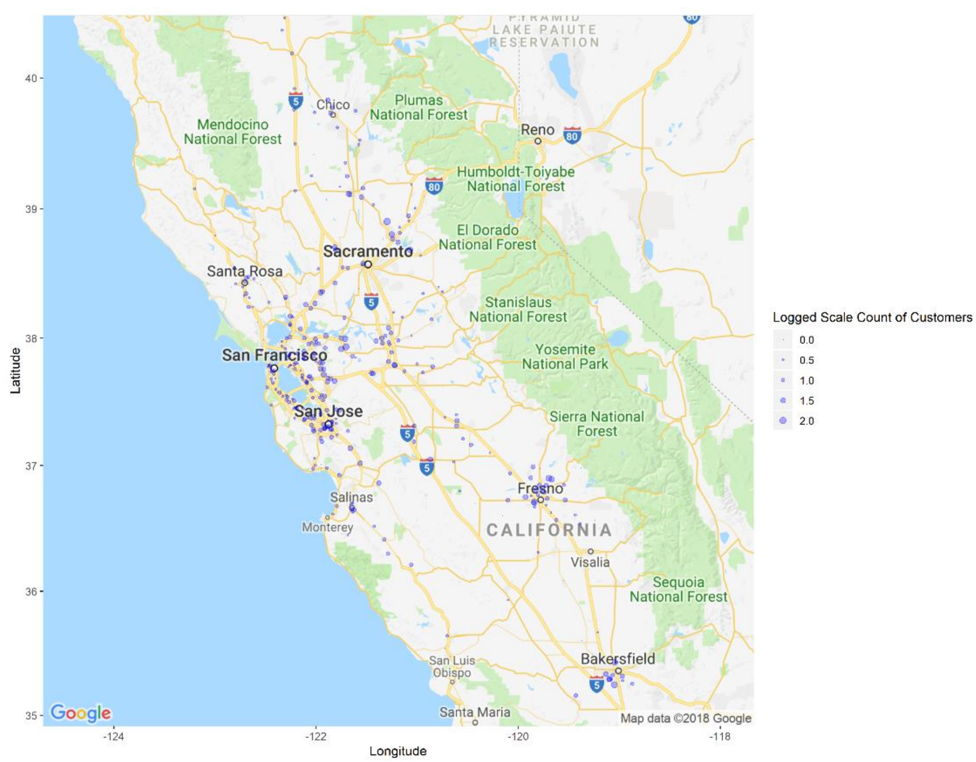


Figure 50. Customer Spatial Distribution, Cluster 9



4.2.7 Correlation Analysis and Linear Predictions

Results from our correlation analysis and regression modeling suggested the following variables were relevant to include in our clustering approach (Table 15). This table shows both importance and linear correlation. The correlation is the Pearson correlation between the variable and savings, which shows the strength of a linear relationship between the variable and individual savings. Importance, from the regression modeling standpoint, is a relative scale, with the most important variable assigned an importance of 1. Importance is related to how many times the variable appears in the set of tree-based models that make up the regression model. Important variables are more related to savings, though the relationship is not necessarily linear.

Based on these results, we found that correlations were, on average, lower than for a recent whitepaper conducted by PG&E to support customer targeting for residential energy efficiency programs using meter-based savings (Scheer 2017)[24]. This is to be expected since that study indeed focused on two energy efficiency programs targeting deep interventions on selected customers (HVAC Quality Maintenance, Whole Home Retrofit), while the HER program in this report is an opt-out program targeting small interventions, such as behaviors and low-cost actions.

Table 15. Relevant Variables from Correlation and Regression Modeling Approaches

variable	Variable Description	Importance	Correlation
Shoulder HE5	Average usage for hour 5 during shoulder months (Mar-May, Sep-Nov)	1	-0.334
Summer HE13	Average usage for hour 13 during summer months (June-Aug)	0.802	-0.361
Duration	Number of years of HER program participation	0.296	0.043
Summer HE12	Average usage for hour 12 during summer months (June-Aug)	0.296	-0.374
Summer HE4	Average usage for hour 4 during summer months (June-Aug)	0.284	-0.308
Median Income for Zip Code	Median income for zipcode	0.222	0.022
Shoulder HE2	Average usage for hour 2 during shoulder months (Mar-May, Sep-Nov)	0.188	-0.343
Summer Max_-Min	Absolute range of Summer max to min	0.188	0.001
Summer Off-peak Usage	Summer total Off Peak load (hours 1-16 & 22-24)	0.181	-0.385
Shoulder HE14	Average usage for hour 14 during shoulder months (Mar-May, Sep-Nov)	0.17	-0.401
Shoulder HE21	Average usage for hour 21 during shoulder months (Mar-May, Sep-Nov)	0.153	-0.266
Shoulder HE1	Average usage for hour 1 during shoulder months (Mar-May, Sep-Nov)	0.152	-0.338
Summer HE3	Average usage for hour 3 during summer months (June-Aug)	0.144	-0.302

[24] Scheer, A., Borgeson, S., Rosendo, K. "Customer Targeting for Residential Energy Efficiency Programs: Enhancing Electricity Savings at the Meter." Pacific Gas & Electric, October 2017. https://pda.energydataweb.com/api/view/1945/Customer_Targeting_Final_Whitepaper_ResEE.pdf

variable	Variable Description	Importance	Correlation
Summer HE14	Average usage for hour 14 during summer months (June-Aug)	0.142	-0.344
Shoulder HE16	Average usage for hour 16 during shoulder months (Mar-May, Sep-Nov)	0.139	-0.393
Shoulder HE4	Average usage for hour 4 during shoulder months (Mar-May, Sep-Nov)	0.137	-0.342
Winter HE13	Average usage for hour 13 during winter months (Dec-Feb)	0.116	-0.349
2016 Savings Group Change	Number of groups changed from 2015-2016 [-4, 4]	0.114	-0.051
Winter Off-peak Load	Winter total Off Peak load (hours 1-16 & 22-24)	0.112	-0.355
Summer Winter Usage Ratio	Ratio of summer to winter mean consumption	0.111	-0.005

We used the correlation and importance, along with professional judgment, to select the set of variables to use in the clustering model. K-means clustering does not perform well with a very large number of variables in the model, so it is necessary to reduce the set of variables from 144 to a lesser number (20, in this case) that can be used to build informative clusters.

4.2.8 Results Validation

We validated the clustering model using both cross-validation and a withheld sample of the data as a test set. Both of these methods show that the clusters are stable and there is no evidence of overfitting. Five-fold cross-validation results show that the within cluster and between cluster variation changes little across folds, while the withheld data shows that applying the clustering model to new data does not result in increased within or between cluster variation.

We assessed cluster stability by running the clustering with several sets of variables. These results show that the clusters are robust to which variables are in the model, and that a high proportion of customers are assigned to the same cluster in the various models. The final model is designed to create clusters that cover the full range of customers participating in the HER program while segmenting them by important characteristics that help to build a targeted approach to improving program savings. We selected the final model by including variables that we consider important for the clusters, such as savings, savings group mobility, and CARE, while also including the set of variables selected by the regression modeling as important for predicting savings.

D. Appendix C – HER Trends in Attrition Analysis Detailed Methods

Opinion Dynamics conducted descriptive statistics and correlation analysis to assess any trends related to program attrition. We provide detailed methods below.

4.2.9 Data Sources & Cleaning

Opinion Dynamics used the following data for this study:

- Monthly electric and gas consumption data in the pre- and post-periods for customers across waves in treatment and control groups from June 1, 2010 through December 31, 2016 cleaned by third party program evaluators. This data file included participant characteristics, such as first report date and wave.
- Half-hourly weather data for all PG&E weather stations from June 1, 2010 through December 31, 2016;
- Customer information (e.g., geographic location, CARE customer).

Notably, our analysis did not include Axciom and Experian customer data given the extremely poor match quality for this data to those customers who had left the program.

4.2.10 Analysis Approach

Opinion Dynamics conducted two sets of analyses: 1) descriptive statistics, and 2) correlation analysis. We describe these below.

- **Descriptive Statistics**: We analyzed the customer data to produce descriptive statistics. For any comparisons of subgroups, any differences reflect true differences, because the study was conducted on the full population of participants.
- **Correlation Analysis**: We began by conducting a correlation analysis across variables of interest to see if there were differences between those participants who had remained or had left the HER program. We found that the model results had low predictive power.

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