Lawrence Berkeley National Laboratory
Environmental Energy Technologies Division **Behavior Analytics**
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Insights from Smart Meters: The Potential for Peak-Hour Savings from Behavior-Based Programs

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Smart Meter Data: the Opportunity

The rollout of smart meters in the last several years has opened up new forms of previously unavailable energy data. Many utilities are now able in real-time to capture granular, household level interval usage data at very high-frequency levels for a large proportion of their residential and small commercial customer population. This can be linked to other time and location-specific information, providing vast, constantly growing streams of rich data (sometimes referred to by the recently popular buzz word, "big data"). Within the energy industry there is increasing interest in tapping into the opportunities that these data can provide.

What can we do with all of these data? The richness and granularity of these data enable many types of creative and cutting-edge analytics. Technically sophisticated and rigorous statistical techniques can be used to pull interesting insights out of this high-frequency, human-focused data. We at LBNL are calling this "behavior analytics". This kind of analytics has the potential to provide tremendous value to a wide range of energy programs.

For example, highly disaggregated and heterogeneous information about actual energy use would allow energy efficiency (EE) and/or demand response (DR) program implementers to target specific programs to specific households; would enable evaluation, measurement and verification (EM&V) of energy efficiency programs to be performed on a much shorter time horizon than was previously possible; and would provide better insights in to the energy and peak hour savings associated with specifics types of EE and DR programs (e.g., behavior-based (BB) programs).

In this series, "Insights from Smart Meters", we will present concrete, illustrative examples of the type of value that insights from behavior analytics of these data can provide (as well as pointing out its limitations). We will supply several types of key findings, including:

- **Novel results**, which answer questions the industry previously was unable to answer;
- **Proof-of-concept analytics tools** that can be adapted and used by others; and
- **Guidelines and protocols** that summarize analytical best practices.

The goal of this series is to enable evidence-based and data-driven decision making by policy makers and industry stakeholders, including program planners, program designers, program administrators, utilities, commissioners, regulators, and evaluators. This series is one of the products we are employing to achieve this goal.

Focus on: The Potential for Peak Hour Savings from Behavior-Based Programs

This report focuses on one example of the kind of value that analysis of this data can provide: insights into whether behavior-based (BB) efficiency programs have the potential to provide peak-hour energy savings. This is important because there is increasing interest in using BB programs as a stand-alone peak reduction program, as well as integrating behavior-based strategies into residential incentive-based demand response (DR) programs and time-based retail rates as a way to augment peak hour energy savings.

There are many studies that use hourly data estimate the hour-by-hour savings from time-based rate or load control programs, and many studies that use billing data to estimate the annual or monthly energy savings from BB programs.[1] However, few, if any, studies have looked at the hour-by-hour savings from BB programs.[2] The potential for BB strategies as a peak hour energy savings resource is therefore currently largely unknown. Estimating the hour-by-hour savings can help identify whether households in BB programs are saving energy when the energy savings are most valuable (i.e., during peak hours), or if the savings are occurring primarily during off-peak hours.

Why does this matter?

If these programs result in peak hour energy savings, and hourly interval data is available to precisely and credibly estimate these savings, then load forecasts can be improved to more accurately represent the impacts of these programs on actual usage. As such, these programs can help utilities by:

- **Reducing short-run supply costs through avoided energy** by reducing the quantity of energy procured either through forward contracts or spot market purchases;
- **Reducing long-term capital expenditures through avoided capacity** by deferring investments in infrastructure needed to otherwise meet additional peak demand in order to maintain a reliable system, if these savings are shown to persist over time; and

[1] There are many examples; we only list a few here. For an example of hourly savings estimates from a control load program, see Freeman, Sullivan & Co. (2012). For an example of hourly savings estimates from a time-based rate program, see SMUD (2013) or EPRI (2011). For an example of monthly and annual savings estimates from a BB program, see KEMA (2010).

[2] Stewart (Work in progress, 2013) examines the peak-coincident demand savings from behavior-based programs.

- **Increasing the cost effectiveness of these programs** by allowing program administrators to more successfully plan for and achieve peak savings goals at lowest cost.

We use data from one particular program rollout as a test-case: we draw upon electricity data from the Pacific Gas & Electric (PG&E) AMI system to analyze the hour-by-hour impacts of a Home Energy Reports (HERs) behavior-based program.

HERs are letters that are mailed to households on a monthly or bi-monthly basis. The letters provide information about the household's own energy use in addition to how their energy use compares to their neighbors. The letters also include some energy savings tips. These programs are designed as randomized controlled trials (RCTs): households are randomly assigned to either the treatment group that receives the letters, or the control group that does not. A well-designed RCT is the "gold standard" of program evaluation design, and thus allows us to produce valid and unbiased estimates of the energy savings during each hour.[3]

We analyze hourly interval electricity consumption data for one particular HER program pilot rollout (called "Wave One" by PG&E). It includes 500,000 households in the top three quartiles of energy use, drawn from most geographic regions in PG&E's service territories.[4] Although it was not a full scale rollout, this large-scale pilot may be representative of households targeted in a full scale rollout.[5] The PG&E rollout began on February 2012, but only three months of data were made available for this analysis: August 1st - October 31st 2012. This period includes 6 of the 10 highest hourly consumption levels of 2012.

We provide a prototype for analysis and insights from this test-case. We use it to develop analytical techniques for estimating hourly savings patterns (heretofore untried in this context), and provide novel results with some very interesting insights that answer questions the industry was previously unable to address. However,

[3] Although RCTs are the main component of producing valid energy savings estimates, there are many other factors that also matter; see "Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-Based Energy Efficiency Programs: Issues and Recommendations."

[4] There were also two additional pilot "waves" of HERs that went out to different portions of the PG&E residential population previous to Wave One: Beta Wave and Gamma Wave. Wave One was the most representative of what a full scale HER program rollout would be. The Gamma Wave includes fewer households (~150,000), in all quartiles of energy use in a smaller geographic region, and the Beta Wave includes even fewer households (~120,000) in only the top quartile of energy use in an even smaller geographic region. For other reports we will use other data.

[5] A full scale rollout would likely also exclude the lowest energy use households because they typically yield lower savings that may not result in a cost-effective program offering to such customers.

because these are some of the first results looking at hour-by-hour electricity savings patterns from BB programs, and because we only have data from one utility (with a limited set of data), replication of these results needs to be performed in order to draw more definitive widespread conclusions about the impacts of BB programs on peak hour electricity consumption in different regions of the country.

Key Findings: Insights from the data

Previous to the rollout of smart meters, monthly utility billing data was used to estimate monthly and annual energy savings for BB programs. Without higher-frequency electricity consumption data, it was it was not possible to determine when during the day that these savings occurred. The analysis in this report is the one of the first to estimate the hourly profile of these savings.

New types of analysis enabled by investments in smart meters AMI allow us to examine hourly patterns of electricity usage and savings by customers participating in BB programs and perform statistical tests of whether savings during peak hours are higher than other hours. We employed a regression technique that compares the electricity use of the treatment group to the electricity use of the control group jointly for each hour of the day.[6] In addition, we used similar techniques to estimate the savings during all of the peak hours (which allows us to test whether or not the peak hours showed savings that were statistically significantly higher than savings during other hours), and the savings on the highest system peak days.

New kinds of results from the hour-by-hour electricity savings estimates are shown in Figure 1 (along with the 95% confidence intervals). The savings are shown with three different scales: first, *kWh savings* (left-hand y-axis on the top graph); second, *normalized savings* (right-hand y-axis on the top graph) as a percent of the total average energy usage of the control group across all hours (in order to give a sense as to how large the kWh savings are); and third, *proportional savings* (y-axis on the bottom graph) as a percentage of each hour's average energy usage for the control group (in order to show the proportional savings relative to the energy consumed for each hour).

[6] More details about the analysis specification are in the Appendix. We used difference-in-averages estimators with dummy variables that indicated treatment during each hour of the day. To account for correlation within customers but across days and hours, the standard errors are robust and clustered at the household level. Because of computing limitations, we maintained unique observations for each customer, but we aggregated all weekday data within a week for each hour, so that there were 24 hourly observations per week for each customer. To test peak vs. off peak, we used a similar approach but with dummy variables that indicated treatment during peak hours.

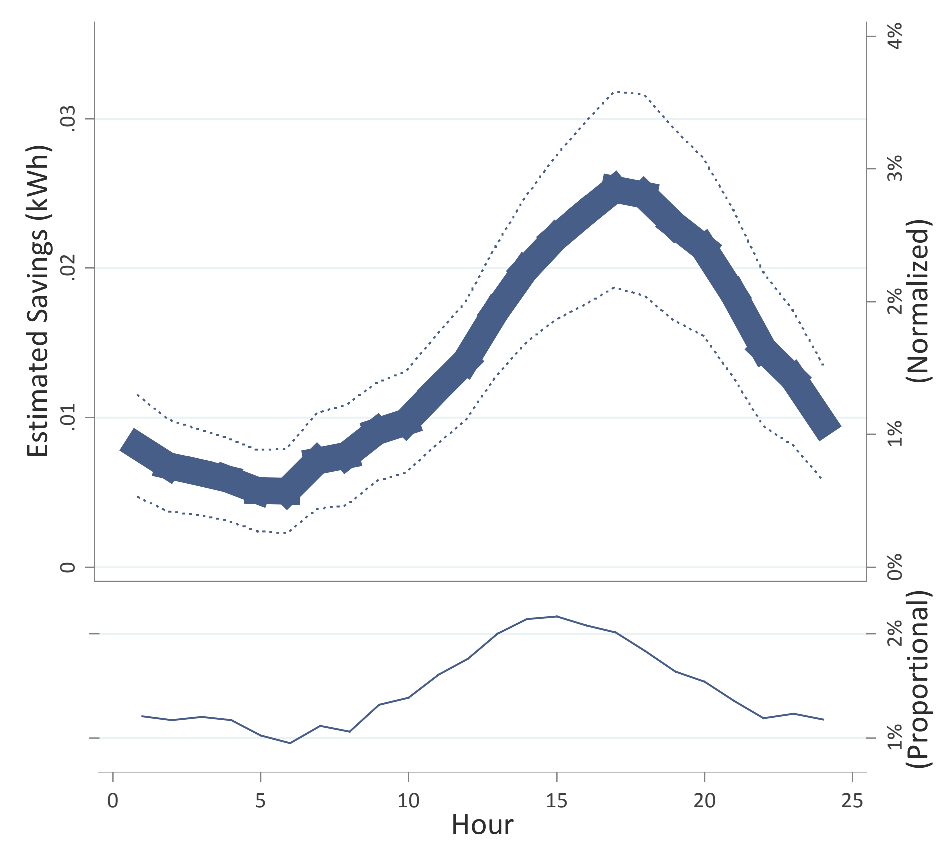

Figure 1. Hour-by-hour electricity savings

For analysis of the particular program rollout that we are using as our test-case (shown in Figure 1), we find:[7]

- **Statistically significant electricity savings during every hour;**
- **Higher kWh savings during peak hours; and**
- **A higher percentage of savings during peak hours, relative to the energy usage in each hour.**

These results show that this pilot program rollout resulted in savings that are higher during peak hours. It is particularly interesting because the savings disproportionately *increase* during the peak hours. Without hourly data, one assumption that was commonly used (based on anecdotal evidence) was that this was not the case; that either the savings are spread out evenly in proportion to the electricity usage, or that savings are actually harder to achieve

[7] Electricity savings during each hour are statistically significant. Peak savings vs. off-peak kWh savings are statistically significantly different. Results and standard errors for all analyses are shown in the Appendix.

during peak hours.

Figure 2 displays hour-by-hour savings, but for only the ten highest and ten lowest system peak days included in our dataset. The X and Y-axis scales are similar to the previous graph: first, *kWh savings*; second, *normalized savings* as a percent of the total average energy usage of the control group across all hours; and third, *proportional savings* as a percentage of each hour's average energy usage for the control group during the ten highest and ten lowest system peak days. For reference, Figure 2 also includes the savings during all days from Figure 1.

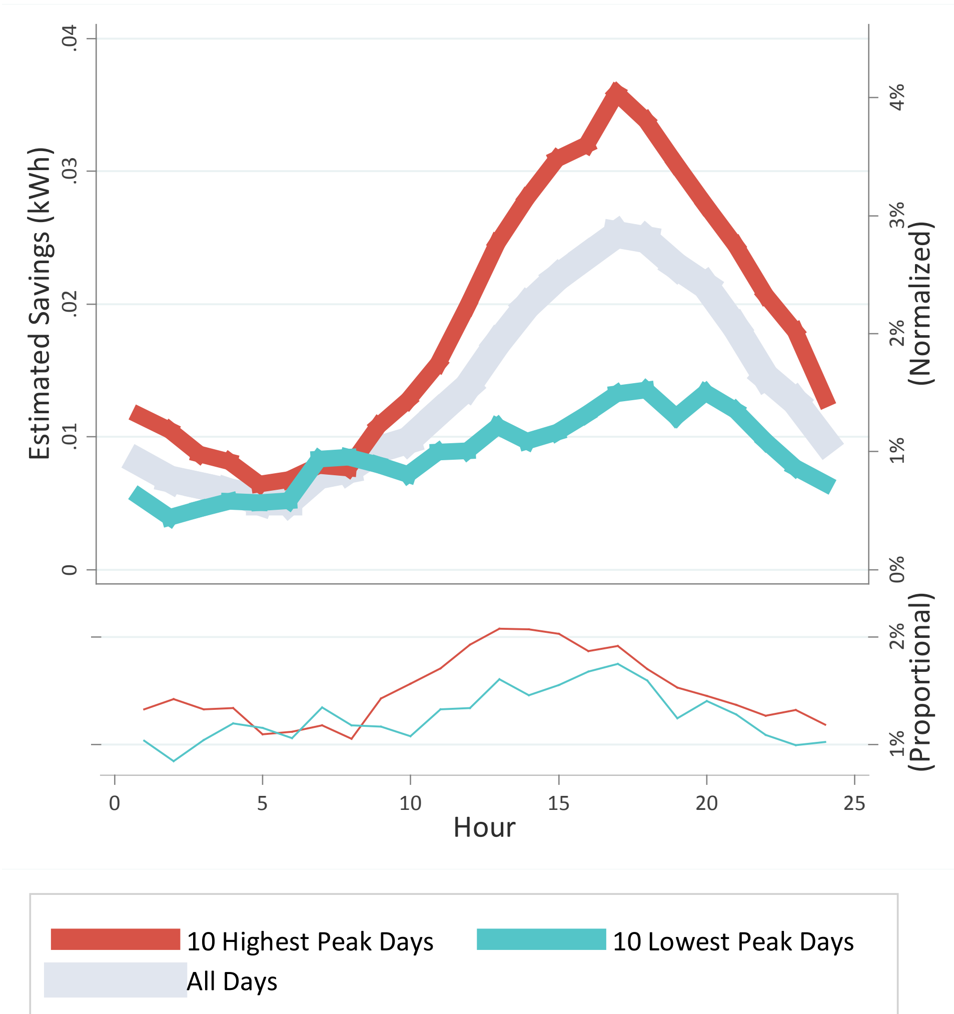

Figure 2. Hour-by-hour savings for the 10 highest and 10 lowest system peak days

Figure 2 shows additional key findings: [8]

- **Higher peak savings during the ten highest system peak days and**
- **Slightly higher proportional peak savings during the ten highest system peak days**

Together with the findings from Figure 1, this implies that BB programs have the potential to induce electricity savings exactly when they are most needed; the savings are disproportionately high during peak hours on peak days.

Key Finding 1: Proof-of-concept analytics tool

High-frequency data from smart meters enable new forms of analysis techniques that allow us to examine hourly usage patterns and determine when during the day households in BB programs are actually saving. This includes hour-by-hour savings estimates and rigorous peak versus off-peak statistical tests.

Implication: This allows measurement of the effectiveness of BB programs in producing peak-hour savings and improves the prediction accuracy of load forecasts.

Key Finding 2: Novel result

Our results show an example of one rollout of a BB program that provides savings during every hour, with disproportionally high savings during peak hours and during high system peak days.

Implication: BB programs have the potential to provide peak-hour savings, and should be considered as a potential (non-dispatchable) resource for improving short-run reliability. If the peak hour energy savings can be maintained and accurately predicted over time, system planners can assess whether this type of program is treated as a planning capacity resource.

While we show that it is feasible for such BB programs to provide peak-hour savings, these results may be specific to this particular program in this specific situation. Because this is only

[8] Savings during each hour are statistically significant for both the 10 highest and 10 lowest system peak days. Peak savings during high system peak days versus during low system peak days are statistically significantly different. Results and standard errors for all analyses are shown in the Appendix.

one example of a BB program that provides peak-hour savings, this does not imply that these results can be generalized and that all BB programs can provide this kind of savings.[9] Until we have a better understanding of what is driving these savings levels and their differences across different populations and under different circumstances, it is not possible at this time to definitively conclude that all BB programs will produce peak hour savings.

[9] In other words, even though the RCT design ensures that the results are *internally valid* (e.g., unbiased for a particular program, with a given participant population and a given time frame) does not mean that the results are *externally valid* (e.g., can be generalized and applied to new populations, circumstances, and future years).

Next Steps & Future Research

In this report, we presented illustrative examples of some of the new types of analyses and valuable insights that smart meter data enable. Using one test-case BB program rollout, we show that BB programs have the potential to provide peak-hour savings.

More research is needed in the future to better understand how BB programs can be considered as a resource capable of providing dependable and predictable peak-hour electricity savings. In order to determine whether this finding is common in all kinds of contexts, this analysis will have to be replicated across many different BB programs, in many different situations and with many different customer populations. In order for system planners to be able to rely on these peak hour savings, this analysis will need to be replicated over time to understand the degree to which these savings are maintained or degrade over time, and to understand if that happens in a predictable manner. In order for utilities to be able to claim capacity credit for these resources, new EM&V protocols would also have to be developed and adopted. Fortunately, the ability to perform this type of analysis and see if the results are replicable across a variety of different BB program offerings should become easier and more commonplace as the availability of AMI data continues to expand.

There are also several other novel types of analyses enabled by smart meter data that might provide additional valuable insights. Savings during peak hours and high system peak days hint at a relationship of temperature to electricity savings; exploring this may help us understand what is driving these savings. Examining the hourly savings over time may allow us to better understand how households respond to BB programs.

This series will continue to explore the kinds of insights which can be pulled from the newly available data captured by smart meters and other sources, and to report our key findings in this series *Insights from Smart Meters*.

References

EPRI. 2011. "The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 1." EPRI, Palo Alto, CA: 2011. 1022703.

Freeman, Sullivan & Co. 2012. "2011 Load Impact Evaluation for Pacific Gas and Electric Company's SmartAC Program," San Francisco, CA.

KEMA. 2010. "Puget Sound Energy's Home Energy Reports Program: 20 Month Impact Evaluation." Madison, WI.

SMUD. 2013. "SmartPricing Options Interim Evaluation: An interim evaluation of the pilot design, implementation, and evaluation of the Sacramento Municipal Utility District's Consumer Behavior Study."

State and Local Energy Efficiency Action Network. 2012. "Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-Based Energy Efficiency Programs: Issues and Recommendations." Prepared by A. Todd, E. Stuart, S. Schiller, and C. Goldman, Lawrence Berkeley National Laboratory. http://behavioranalytics.lbl.gov.

Stewart, James. Work in progress, Nov 2013. "Peak-Coincident Demand Savings from Residential Behavior-Based Programs: Evidence from PPL Electric's Opower Program."

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Appendix
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Appendices

These Appendices provide detailed descriptions as an addendum to the paper: "Insights from Smart Meters: The Potential for Peak Hour Savings from Behavior-Based Programs". In Appendix A, we provide a detailed description of Home Energy Reports (HERs) and the experimental design (a Randomized Controlled Trial, (RCT)). Appendix B describes the data used in the analysis, and Appendix C provides summary statistics and a validation of the randomization. In Appendix D we describe our analytical approach and present the results in a table format (graphical representations are available in the main body of the paper).

Appendix A: Program description and experimental design

In this section we provide an overview of Opower's Home Energy Reports program that was implemented at PG&E, the program design employed, and a general overview of our analysis methods and the available data.

A.1 Description of Home Energy Reports

Opower worked with PG&E to provide its residential customers with periodic Home Energy Reports (HERs) by mail that contain energy usage feedback and behavioral suggestions (see Figure A-1 for an example). Specifically, the HER compares a customer's monthly electric and/or gas usage to an average of similar homes' usage as well as to an average of the most efficient 20% of similar homes' usage. These "neighbor comparisons" are based on a variety of customer characteristics, including location, home square-footage, presence of high energy consuming devices (e.g., pool), and type and number of air conditioning and/or heating units.

The neighbor comparison is used to give the customer one of three ratings:

- *Great* – the customer is more efficient than both average neighbors and efficient neighbors
- *Good* - the customer is more efficient than average neighbors but less efficient than their efficient neighbors
- *Using More than Average* - the customer is less efficient than both average and efficient neighbors

If a customer receives a rating of "Good" or "More than Average," the HER will include a dollar amount of savings that the customer could realize on their annual energy bills by matching their efficient neighbors' usage. A HER also provide a list of several simple energy savings tips and their potential annual dollar savings. For customers receiving reports on their electric usage, the reports include a graph of their load shape by hour for an average day from the last month of usage. Load shapes are not provided for natural gas usage because gas usage data are generally not collected hourly.

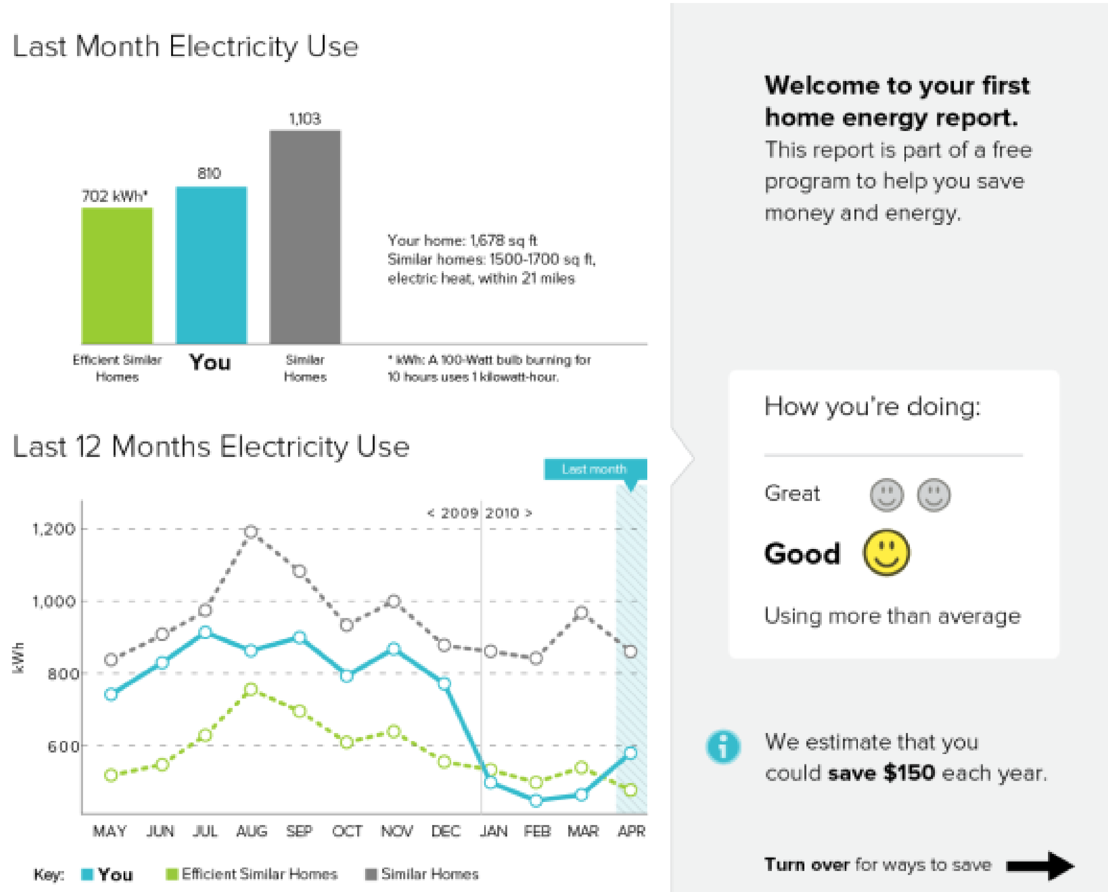

Figure A-1. Example of a Home Energy Report

A.2 Experimental Design

Opower's HER program in PG&E's service territory was designed as a field experiment that employed a randomized controlled trial (RCT). An RCT is a type of experimental design in which households in a given population are randomly assigned to two groups: a treatment group that receives the reports and a control group that does not.

The HER program utilizes an opt-out recruiting process. HERs are sent out to customers assigned to the treatment group without their prior knowledge or approval. These customers can elect to opt-out of receiving future HERs, if they wish by contacting PG&E.[1] Customers in the treatment group can then decide for themselves if and how to best respond to the energy usage feedback and behavioral suggestions contained in the HER. Customers in the control group are likely not aware that an experiment is occurring, since they are likely unaware their

[1] PG&E reports that the HERs generate very few complaints and opt-outs.

peers in the treatment group are receiving HERs, and are therefore unlikely to become dissatisfied.

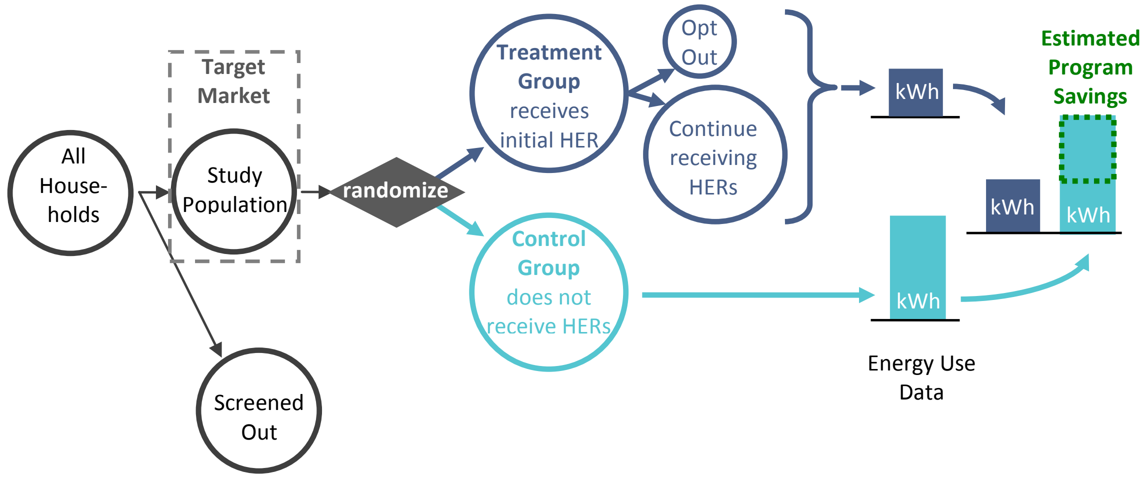

Figure A-2. Experimental design of HER program: opt-out randomized controlled trial

Because HERs are designed as RCTs, we can readily compare energy use data from customers in the treatment group to those in the control group in order to produce valid and unbiased statistical estimates of the total electricity savings, the peak demand savings, and the hour-by-hour electricity savings.

A.3 Screening criteria

PG&E's residential customers were screened into the study population using certain required inclusion criteria (in addition to satisfying geographic or energy usage criteria discussed in Appendix B). Customers must: have a full year of bills (to provide pre-treatment data for savings estimation); have had a functioning smart meter for greater than one year; be on selected rate schedules—either PG&E's standard residential rate schedule or one of its residential time-of-use rates; neither be on a medical baseline rate, nor flagged as "vulnerable or disabled" in PG&E databases; not be master metered;[2] not be net metered;[3] not live in a mobile home; not be on an electric vehicle rate; not be on a natural gas vehicle rate; not be in another HER pilot program; not live in a multifamily dwelling; not be billed by a municipality; and have not previously requested that PG&E cease sending them any and all marketing materials.

[2] Master metered means that several homes share one meter—such as in a trailer park.

[3] Net metered homes have the ability to generate as well as consume power.

Appendix B: Data description

In this study, we analyze hourly interval electricity consumption data for one particular HER program pilot rollout within the broader set of HER programs implemented in PG&Es service territory (called "Wave One" by PG&E; see Table B-1).[4] It includes 500,000 households in the top three quartiles of energy use[5], drawn from most geographic regions in PG&E's service territories (see Figure B-1 for more information about PG&E's geographic territories). The Wave One rollout began on February 2012, but only three months of data were made available for this analysis: August 1st - October 31st 2012. This period includes 6 of the 10 highest hourly consumption levels of 2012.[6]

Table B-1. Overview of the Wave One dataset

	# Treat	# Control	Launch Date	Hourly interval data available	PG&E territory	Quartile of energy use	Service received from PG&E
Wave One	400,000	100,000	Feb 2012	Aug 1, 2012-Oct 31, 2012	**P, Q**, R, S, T, **V**, W, X, **Y**	Top 3 quartiles	Electric & gas service, and electric-only service

[4] There were also two additional pre-pilot "waves" of HERs that went out to different portions of the PG&E residential population previous to Wave One: Beta Wave and Gamma Wave. The Gamma Wave includes fewer households (~150,000), in all quartiles of energy use in a smaller geographic region, and the Beta Wave includes even fewer households (~120,000) in only the top quartile of energy use in an even smaller geographic region. No member of the treatment or control group of any wave is also a member of a treatment or control group of another wave. Future research will examine the data from these pre-pilots.

[5] The top (4th or highest) quartile refers to the 25% of energy users who use the most total annual energy on average (using the most energy as compared to the rest of the population). The quartiles were determined based on a combined electric and gas usage index.

[6] The highest consumption levels were determined based on ranking the hourly system retail load for 2012.

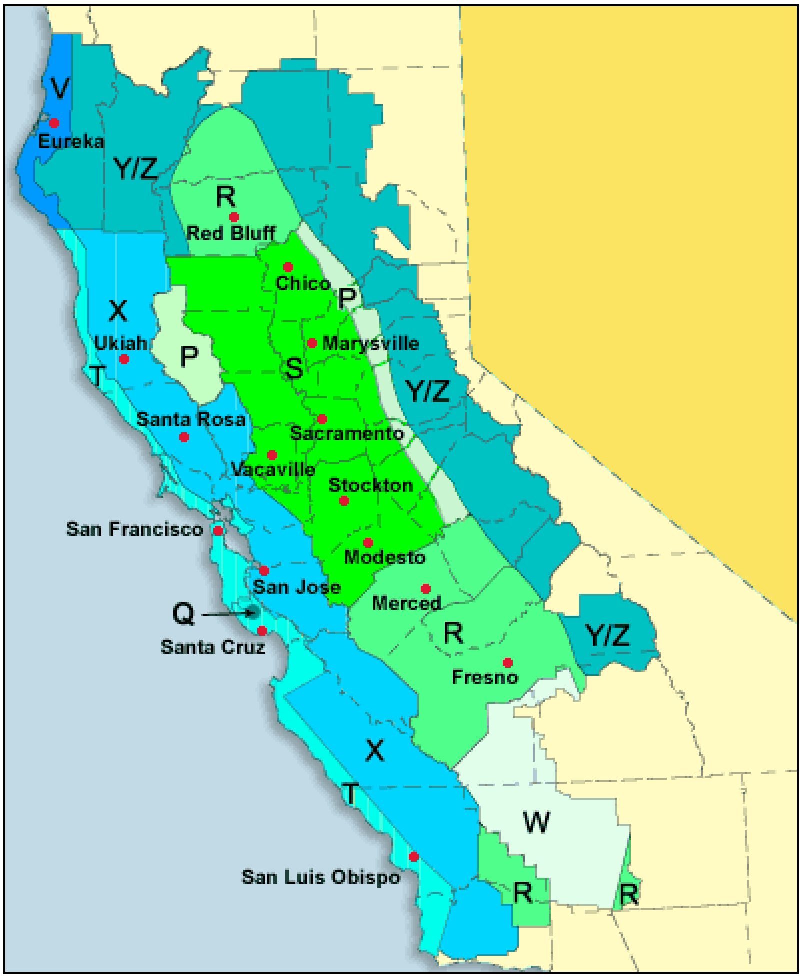

Figure B-1. PG&E Territory Map

Appendix C: Descriptive statistics and validation of randomization

In this section we present descriptive statistics of the pilot and pre-pilot study waves, and validate the comparability between the control and treatment groups through randomization. Figure C-1 presents the weekday hourly load profiles of control group customers in Wave One for the time period included in our dataset.

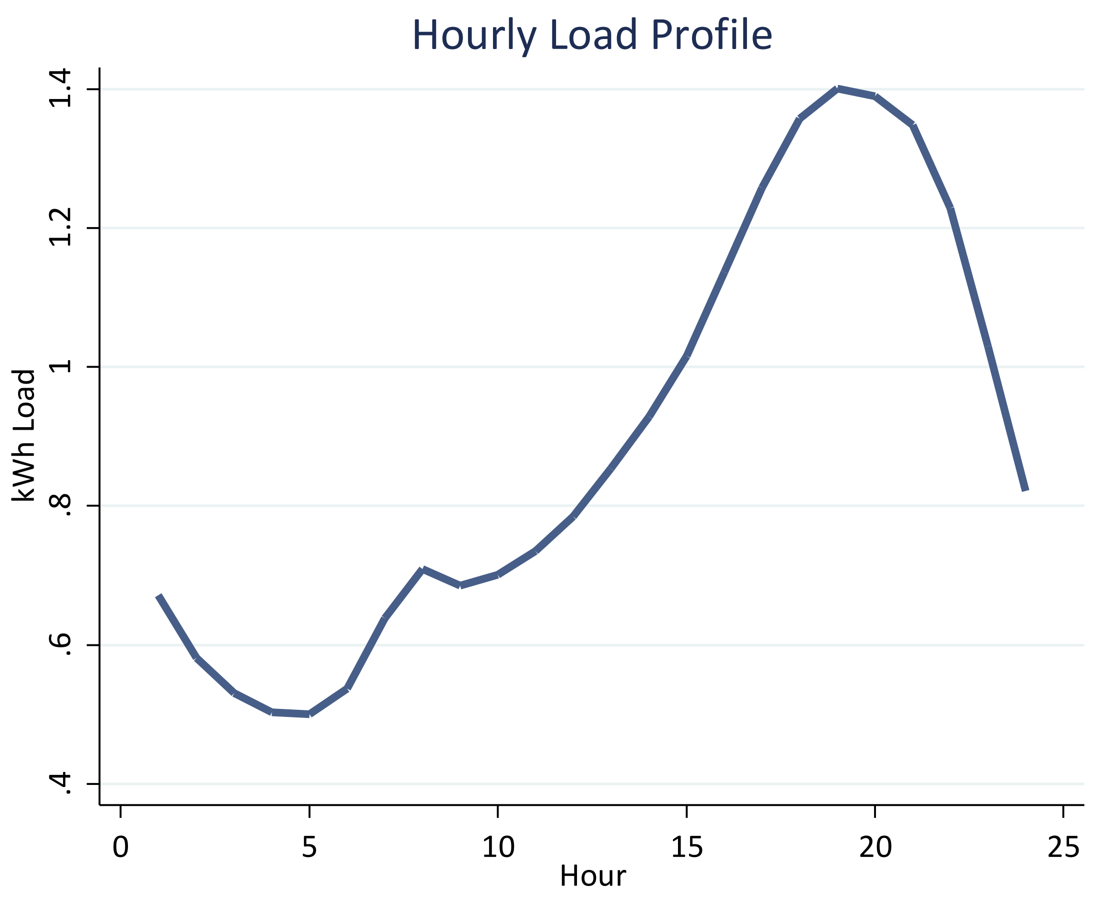

Figure C-1. Hourly control group weekday load profiles for Wave One

Table C-1 demonstrates the successful randomization of customers onto control and treatment groups, as well as showing basic summary statistics. The table shows both the percentage of customers with observed characteristics as well as mean values for quantitative variables.[7] The

[7] Data for tables 2-1 through 3-3 come from a combination of PG&E and third party databases licensed by PG&E.

observed characteristics in the table include baseline territory, CARE status (a program for low-income households offering subsidized rates), income level as estimated by a third party, homeownership status as estimated by a third party, home attributes, and monthly electricity usage prior to treatment. As the table shows, the distribution of each characteristic is similar across treatment and control groups.

The table also shows the results of statistical tests that tell us whether there is any evidence that the distribution of a given characteristic is correlated with treatment status. For binary variables, a z-test on the difference in means was used and the p-value for equality of means is shown. For metrics with more than two categories, the test used was Fisher's exact test and the p-value for independence of category with respect to treatment and control is shown.

Table C-2 shows the number of customers who were sent the first mailing in each wave; the number of months since wave inception through December 2012; and the average monthly attrition rate due to account closure from the beginning of the wave through December 2012. It is our understanding that account closure occurs almost primarily due to customers moving. In our analysis, we assume that moving (and any other source of account closure) is independent of being in the treatment or control groups. As the table shows, the Wave One control group was roughly four times smaller than the treatment group.

Table C-1. Distributions of Characteristics across Treatment and Control Groups (Wave One)

Metric	Category	Unit	Treatment	Control	P-value
Baseline Territory	P	(% of group)	1.1%	1.1%	0.36
	Q	(% of group)	0.0%	0.0%	
	R	(% of group)	11.3%	11.4%	
	S	(% of group)	23.9%	23.9%	
	T	(% of group)	12.2%	12.0%	
	V	(% of group)	0.0%	0.0%	
	W	(% of group)	6.0%	6.0%	
	X	(% of group)	45.4%	45.5%	
	Y	(% of group)	0.1%	0.1%	
Dual-fuel		(% of group)	90.1%	90.0%	0.60
CARE Rate		(% of group)	29.7%	29.8%	0.43
Estimated Household Income	<$30k	(% of group)	12.8%	12.8%	0.79
	$30k-$50k	(% of group)	13.3%	13.5%	
	$50k-$80k	(% of group)	29.6%	29.4%	
	>$80k	(% of group)	44.3%	44.3%	
Renter Status		(% of group)	5.4%	5.4%	0.98
Presence of Pool or Spa		(% of group)	13.4%	13.5%	0.47
Estimated Number of Residents		(number of residents)	2.8	2.9	0.16
Living Space		(square feet)	1734.3	1702.8	0.61
Year Home Built		(year)	1972.1	1972.1	0.93
Estimated Age of Head of Household		(years)	52.2	52.4	0.05

Pre-HER Usage	**Jan-11**	**(monthly kWh)**	637	638	0.29
	Feb-11	**(monthly kWh)**	598	598	0.84
	Mar-11	**(monthly kWh)**	558	558	0.68
	Apr-11	**(monthly kWh)**	535	536	0.64
	May-11	**(monthly kWh)**	521	521	0.93
	Jun-11	**(monthly kWh)**	664	666	0.32
	Jul-11	**(monthly kWh)**	728	729	0.24
	Aug-11	**(monthly kWh)**	722	725	0.10
	Sep-11	**(monthly kWh)**	690	692	0.38
	Oct-11	**(monthly kWh)**	549	550	0.29
	Nov-11	**(monthly kWh)**	593	594	0.16
	Dec-11	**(monthly kWh)**	662	663	0.15
	Jan-12	**(monthly kWh)**	638	639	0.38

Table C-1. Monthly Attrition Rate by Wave and Fuel Type

Wave		**Wave One**	
		Dual	**Electric-only**
# of Customers at Launch of Wave	Control	89,026	9,825
	Treatment	356,419	39,124
# of Months of HERs*		11	11
Monthly Rate of Attrition (%)	Control	0.9%	1.4%
	Treatment	0.9%	1.4%

Appendix D: Analysis and results

In this section, we describe our analytical approach used to estimate the total overall savings, the savings during each hour, the peak versus off-peak savings, and the savings during the 10 highest and 10 lowest system peak days. Here, we present the results in a table format (a graphical representation of the results is in the main body of the paper).

We only estimate savings for the time period during which we have data: Aug 1, 2012-Oct 31, 2012. We chose to include only weekdays for the analyses in this section because those are typically the times when electricity is most likely to have large demand spikes and corresponding price spikes. Weekends also tend to have noticeably different usage patterns.

To account for correlation within customers across days and hours, the standard errors for all specifications in this report are robust and clustered at the household level unless explicitly stated. Because of computing limitations, we maintained unique observations for each customer, but we aggregated all weekday data within a week for each hour, so that there were 24 hourly observations per week for each customer.

D.1 Overall savings

First, we estimate the total overall electricity savings, using the following specification:[8]

$$kwh_{it} = a + bT_i + e_{it} \qquad (0.1)$$

Where:

- kwh_{it} indicates energy use per hour, averaged across days within a season;
- t indicates each hour;
- T_i is an indicator variable for customers in the treatment group; and
- b is the estimated average treatment effect (i.e., the estimated overall savings).

Table D-1 displays the results; note that the total overall savings is statistically significant.

[8] Pre-treatment data was not available and thus we could not perform a difference-in-differences approach. Because this is a randomized controlled trial, we would expect that adding pre-treatment data for a difference-in-difference analysis would increase the precision but not affect the estimates of savings.

Table D-1. Overall savings estimates

	Wave One
Treatment	-0.0136***
	(.0018)
Constant	0.6866***
	(.0016)
Hour of Day FE	No
Week FE	Yes
R-squared	.0334373
Number of hh	493,416
Dates	Aug 1 - Oct 31

Standard errors in parentheses
Note: SE clustered at household level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.2 Savings during each hour

Next, we estimate the electricity savings for each weekday hour. Our specification compares electricity use of the control group to that of the treatment group in each hour:

$$kwh_{it} = \sum_{h=1}^{24} b_h H_h T_i + n_h + e_{it} \tag{0.2}$$

Where:

- kwh_{it} indicates energy use per hour;
- h indicates the hour;
- H_h is an indicator variable for each hour;
- T_i indicates customers in the treatment group;
- n_h is a set of hourly fixed effects; and
- b_h is the estimated average treatment effect (i.e., the estimated savings) for each hour.

Table D-2 displays the numerical results (graphical results are shown in the main body of the report). The results show statistically significant savings for each weekday hour.

Table D-2. Savings estimates for each hour

	Wave One –
Treat X Hour 1	-0.0081***
	(.0017)
Treat X Hour 2	-0.0068***
	(.0016)
Treat X Hour 3	-0.0064***
	(.0015)
Treat X Hour 4	-0.0059***
	(.0014)
Treat X Hour 5	-0.0051***
	(.0014)
Treat X Hour 6	-0.0051***
	(.0014)
Treat X Hour 7	-0.0071***
	(.0016)
Treat X Hour 8	-0.0075***
	(.0017)
Treat X Hour 9	-0.0091***
	(.0017)
Treat X Hour 10	-0.0097***
	(.0017)
Treat X Hour 11	-0.0118***
	(.0019)
Treat X Hour 12	-0.0137***
	(.002)
Treat X Hour 13	-0.0171***
	(.0022)
Treat X Hour 14	-0.0198***
	(.0025)
Treat X Hour 15	-0.0219***
	(.0028)
Treat X Hour 16	-0.0235***
	(.0031)
Treat X Hour 17	-0.0251***
	(.0033)
Treat X Hour 18	-0.0246***
	(.0034)
Treat X Hour 19	-0.0226***
	(.0033)
Treat X Hour 20	-0.0211***
	(.003)
Treat X Hour 21	-0.0181***

	(.0028)
Treat X Hour 22	-0.0145***
	(.0026)
Treat X Hour 23	-0.0125***
	(.0023)
Treat X Hour 24	-0.0095***
	(.002)
Hour of Day FE	Yes
Week FE	Yes
R-squared	.1558469
Number of hh	493416
Dates	Aug 1 - Oct 31

Standard errors in parentheses
Note: SE clustered at household level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.3 Peak versus off-peak savings

We also explicitly estimate the electricity savings during peak hours, defined as 3-8pm during weekdays, and during off-peak hours, defined as all other hours in a weekday. Our specification compares electricity use of the control group to that of the treatment group, using an indicator for peak hours and an indicator for off-peak hours:

$$kwh_{it} = b_{peak}H_{peak}T_i + b_{off-peak}H_{off-peak}T_i + n_h + e_{it} \tag{0.3}$$

Where:

- kwh_{it} indicates energy use per hour, averaged across days within a season;
- h indicates each hour;
- H_{peak} and H_{peak} are indicator variables for on and off-peak hours;
- T_i is an indicator variable for customers in the treatment group, n_h is a set of hourly fixed effects, and b_h is the estimated average treatment effect for each hour.

Results are displayed in Table D-3. The results show statistically significant peak savings, and a t-test shows that the peak savings are also statistically significantly different than off-peak savings.

Table D-3.

	Wave One
Treat X Peak	-0.0231***
	(.003)
Treat X Off Peak	-0.0104***
	(.0016)
Hour of Day FE	Yes
Week FE	Yes
R-squared	.1558435
Number of hh	493416
Dates	Aug 1 - Oct 31

Standard errors in parentheses
Note: SE clustered at household level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix E: References

EPRI. 2011. “The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 1.” EPRI, Palo Alto, CA: 2011. 1022703.

Freeman, Sullivan & Co. 2012. “2011 Load Impact Evaluation for Pacific Gas and Electric Company’s SmartAC Program,” San Francisco, CA.

KEMA. 2010. “Puget Sound Energy’s Home Energy Reports Program: 20 Month Impact Evaluation.” Madison, WI.

SMUD. 2013. “SmartPricing Options Interim Evaluation: An interim evaluation of the pilot design, implementation, and evaluation of the Sacramento Municipal Utility District’s Consumer Behavior Study.”

State and Local Energy Efficiency Action Network. 2012. “Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-Based Energy Efficiency Programs: Issues and Recommendations.” Prepared by A. Todd, E. Stuart, S. Schiller, and C. Goldman, Lawrence Berkeley National Laboratory. http://behavioranalytics.lbl.gov.

Stewart, James. Work in progress, Nov 2013. “Peak-Coincident Demand Savings from Residential Behavior-Based Programs: Evidence from PPL Electric’s Opower Program.”