SCE’s Home Energy Report Program Savings Assessment

Ex-Post Evaluation Results, Program Year 2013

Final Report

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Prepared for

Southern California Edison
1515 Walnut Grove Avenue
Rosemead, CA 91770

Project Manager

Miriam Fischlein
DSM Program Measurement and Evaluation

Prepared by

Applied Energy Group
(*Formerly EnerNOC Utility Solutions Consulting*)
500 Ygnacio Valley Road
Suite 450
Walnut Creek, CA 94596

www.AppliedEnergyGroup.com

Project Manager

Patrice Ignelzi
Principal Associate
Program Evaluation and Load Analysis
Applied Energy Group

Tel. 510.982.3533
pignelzi@appliedenergygroup.com

Principal Investigators

Craig Williamson
Fuong Nguyen
Abigail Nguyen
Juan Shishido
Patrice Ignelzi

Executive Summary

Background

This report documents Applied Energy Group's evaluation of savings from the Home Energy Report (HER) pilot program that Opower operated for Southern California Edison (SCE) in 2013. Along with the savings results, the report describes the processes we used to validate the sample selection, estimate the savings, and remove savings by HER participants that were counted as part of other programs that SCE offered during the same period. We refer to this program as Opower-1 in this report.

The Opower-1 program targeted residential accounts in the San Gabriel/Rancho Cucamonga portion of SCE's service territory. The Home Energy Reports, which compare program participants' household energy use to that of similar neighbors, were sent out to customers beginning in December 2012 and continuing through December 2013. The program operated under a strict randomized control trial experimental design that was approved by the CPUC Energy Division. The approved sample of customers included 150,000 accounts, randomly assigned to one of two equal-sized groups: a treatment group (received HER reports) and control group (no HER reports). There was a group of customers that had an issue with mismatched addresses in the billing system, which caused the participants to never receive a report. This subset of customers with mismatched addresses was removed from the analysis in both the control and treatment group. This resulted in a final sample size of 65,910 control customers and 65,821 treatment customers.

The goal of this savings assessment was to provide ex-post estimates of savings for the period January-December 2013 that are attributable to the 2013 HER program, including:

- kWh savings achieved by the program participants, minus their savings claimed by other SCE programs operating during that time
- Peak kW savings calculated two ways, applying a load factor to the kWh savings based on using SCE's load research data and direct estimation from hourly interval data

Analysis Methods

We estimated per-participant energy impacts for the HER program using two methods: difference in differences and regression modeling. These analyses were based on monthly billing data, which allowed us to compare the control group of non-participants to capture variation in energy use among the program participants not due to the HER reports. The difference in differences method provided a preliminary estimate of monthly and annual energy savings that we were able to use as an initial estimate of savings. In order to estimate the savings more precisely, we also analyzed the data using a fixed effects regression approach. This allowed us to refine the savings estimate to assess the possible influence of variables related to participation and weather (in the form of heating degree days (HDDs) and cooling degree days(CDDs)) and to reduce the uncertainty of the savings estimates by accounting for more of the difference between customers with the fixed effect.

To develop the program-level savings, we applied the monthly estimates from the regression model to the active customer accounts (to account for attrition due to customer move-outs). We then subtracted the portion of savings being claimed for these participants due to their participation in SCE's other downstream (i.e., rebate) programs and upstream (price markdown) lighting program during the HER treatment period.

Once we estimated the kWh savings, we conducted two analyses to assess the peak kW impacts of the Opower-1 program. Initially, we made a simple, preliminary estimate by applying an average residential class load factor to the estimated kWh savings. Later, when interval data for the participants and control group became available, we developed a revised and improved estimate using interval data for the actual participants that was analogous to the way we estimated the energy savings. We also used the 3-day heat wave as defined by DEER for the actual year 2013 for the revised estimate, rather than from the standardized year based on calendar year of 2009 from the DEER guidelines, which we used for the preliminary estimate. The final peak kW results are from the interval data analysis.

Results

The results are the ex-post savings estimates for the HER 2013 program year. The difference in differences method provided a preliminary energy savings estimate of 144.92 kWh per year, per participant, amounting to 1.4% of their baseline usage. The regression modeling confirmed this annual savings level and provided more nuance to the estimates; the regression-based estimates were used to develop the final savings for the program.

Table ES-1 summarizes the monthly and annual energy savings for the HER program treatment period, January 2013 through December 2013 with mismatched addresses removed. It shows per-participant annual savings of 143.48 kWh or 1.4%, with monthly savings ranging from a low of 1.1% in January 2013 rising steadily to a maximum of 1.6% in the latter part of the year. The table includes the average baseline energy use based on the regression model during the treatment period. It also shows the estimated treatment customer average energy savings, percent energy savings, number of participants included in the analysis month, and total estimated savings for the population of participants. The savings are statistically significant in every single month of the program year.

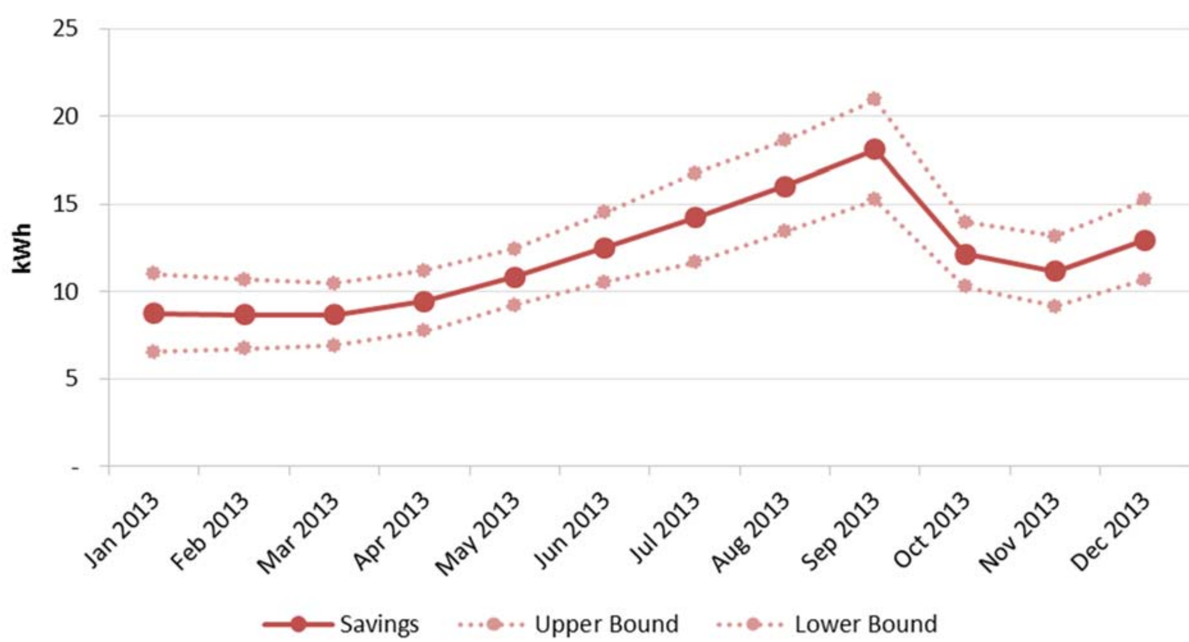
Table ES-1. Estimated HER 2013 Energy Savings

Month	Participants [a]	Average Per-Participant Savings (kWh)	% Savings	Total Savings, All Participants (kWh)
Jan-13	64,891	8.75	1.1%	568,107
Feb-13	64,554	8.69	1.2%	561,064
Mar-13	64,313	8.67	1.3%	557,793
Apr-13	64,051	9.45	1.4%	605,436
May-13	63,785	10.84	1.4%	691,119
Jun-13	63,491	12.52	1.4%	794,604
Jul-13	63,187	14.21	1.3%	898,001
Aug-13	62,916	16.01	1.5%	1,007,079
Sep-13	62,657	18.10	1.6%	1,134,000
Oct-13	62,420	12.13	1.6%	757,049
Nov-13	62,185	11.16	1.6%	693,789
Dec-13	61,975	12.96	1.6%	802,910
Total		**143.48**	**1.4%**	**9,070,952**

[a] Participant count excludes customers with address mismatches

Figure ES-1 shows these energy savings estimates graphically.

Figure ES-1. Average Per-Participant Energy Savings Estimates and 90% Confidence Band



The peak kW savings results using hourly interval data yielded per-participant savings of .0459 kW, a peak demand reduction of 1.3%. The 90% confidence interval is +/- 0.0205 kW. This represents the average savings across the nine hours 2-5 pm on September 4-6, 2013. When multiplied by the number of participants in September 2013, the total program peak load savings estimate is 2,876 kW.

Some customers included in the HER program also participated in other programs offered by SCE during 2013. To avoid double-counting of savings from multiple programs, savings estimated to have accrued to HER customers from their participation in downstream (rebate) programs and/or the upstream lighting program that were counted by those programs were removed from the total savings estimates. Table ES-2 shows the effect of removing these savings, yielding total HER program savings of 8.5 GWh and 2.8 MW.

Table ES-2. Total HER 2013 Energy Savings

	kWh	kW
Estimated Total HER Savings	9,070,952	2,876
Upstream Program Savings	(442,901)	(38)
Downstream Program Savings	(87,319)	(29)
Total Savings Attributable to 2013 HER Program	**8,540,732**	**2,809**

Key Findings

There are several key findings from the results presented above:

- **Measureable savings:** We estimate ex-post energy savings of 8,541 MWh during the 12-month treatment period. These savings estimates are statistically significant and based on a rigorous randomized control trial experimental design. We also estimate peak demand savings of 2,809 kW, based on the DEER peak hours definition.
- **Steady increase in savings:** The savings increase steadily over the treatment period, faster in the earlier months, showing a lagged and cumulative effect of the home energy reports. We infer that as a customer receives more information through the reports, they modify their behavior and energy use more.
- **Seasonal savings levels.** The kWh savings across the months show a pattern that follows seasonal consumption levels. This suggests that there is some weather sensitivity in the savings. The finding of monthly change in the savings, rather than degree-day correlation, suggests general seasonal climate sensitivity of the savings.
- **Savings comparable with other HER programs:** The results show reductions of about 1.4% in kWh usage and 1.3% in peak demand, within the 1-2% range seen in other HER programs in California and elsewhere.

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Chapter 1 – Introduction

Background

Since December 2012, Opower has operated the Home Energy Report (HER) program, a comparative energy usage and disclosure pilot program for Southern California Edison in the San Gabriel/Rancho Cucamonga portion of the service territory. This program provides SCE's residential customers feedback through reports showing household energy use and comparisons of energy use from similar neighbors. The reports also provide a personal comparison, showing the household's energy usage over time. The reports also give the recipient a number of energy efficiency tips to promote behavior modification in achieving energy savings.

The 2013 HER program, initiated in December 2012 and referred to as Opower-1 in this report, targeted residential accounts with relatively high electricity use in that area. The program operated under a strict experimental design that was approved by the CPUC Energy Division. The approved sample of customers included 150,000 accounts, assigned to one of two equal-sized groups: program participants (treatment or T group) and comparison group (control or C group). The sample was stratified by energy use, with a higher proportion of relatively high electricity use customers included, but also including users of all levels. The service area includes warmer climate zones, where households, on average, have higher usage than some other areas in SCE's service territory.

While the program ran for the full year as anticipated, there were some problems with mismatching of addresses in the initial mailing that led to the elimination of some accounts from the sample. AEG accounted for this sample attrition and other issues in estimating the program savings.

Scope of This Savings Assessment

This report describes the implementation of the 2013 program, explains our analysis methods, presents detailed energy savings results, and discusses our findings. Our evaluation employed two statistical methodologies to provide ex-post estimates of the HER program savings: First, we conducted a difference in differences analysis to gauge overall energy savings and peak load impacts achieved during the pilot. Then we used regression modeling to refine the estimate and study the effects of weather on overall energy use and program energy savings.

The goal was to provide ex-post estimates of savings for the period January-December 2013 that are attributable to the HER program, including:

- kWh savings achieved by the program participants, minus their savings claimed by other SCE programs operating during that time
- Peak kW savings calculated two ways, applying a load factor to the kWh savings based on using SCE's load research data and direct estimation from hourly interval data

Report Organization

The report is organized as follows:

- Chapter 2 describes the sample validation of the Opower-1 population.
- Chapter 3 describes the energy savings analysis methods, including the approaches we followed for the difference in differences analysis and the regression modeling.
- Chapter 4 presents results from the kWh savings analysis across the program year.
- Chapter 5 describes the methods and results of estimating the peak kW savings.
- Chapter 6 discusses the attribution of savings to the HER and SCE's downstream energy efficiency programs.
- Chapter 7 discusses the method of attributing savings to the HER and SCE's upstream lighting program.
- Chapter 8 summarizes key findings from our analysis.

Chapter 2 – Sample Validation

The estimation of savings requires that the control group provides an accurate representation of the treatment group's behavior had the home energy reports never been sent. To have confidence in this estimate, the control and treatment groups should be as similar as possible in the pre-treatment period. In combination with a large sample size, the treatment and control group assignments should be random to ensure that, on average, there were no systematic differences between the two groups. The sample population included 150,000 households, with control and treatment groups of equal size.

The sample was stratified by energy use, which enabled us to include proportionally more customers with higher usage, but also include representation at all usage levels. This allowed for the maximization of savings, since higher use customers tend to save more energy in behavioral programs, but also allows for estimation of savings for more heterogeneous groups by weighting the results by stratum as needed. The participant population was defined first, and then that group was randomly split between treatment and control groups.

To verify the randomization of the control and treatment group sample, we performed a two-sample t-test to determine if there was a significant difference between the two groups. Since the data was limited in terms of identifying characteristics for the customers, we were only able to compare the average daily use during the pre-treatment period between the two groups.

We calculated the average daily kWh use for each customer during the pre-treatment period using the cut-off date of December 10, 2012. This is the start date for generating the customer energy reports. The results of the t-test performed on the entire population are included below. Generally, p-values below 0.05 show statistically significant differences. As shown in Table 1, we found no statistically significant differences in the pre-treatment usage between the two groups, since there was a p-value of 0.481.

Table 1. Sample Validation for Full Population

Average Daily Electricity Usage (kWh/day)			
Group	**Mean**	**p-value**	*
Control	29.9045	0.481	-
Treatment	29.9581		

* Means statistically significant difference

When the program was implemented, there was an issue with mismatched addresses. When the address issue became apparent, a decision was made to not send the subsequent reports to the corrected addresses. Therefore any accounts with mismatched addresses never received any of the reports. This address mismatch condition was present in both the treatment group and the control group. It is important to note that the condition had nothing to do with the Opower-1 program – it was inherent in the SCE billing system. Because of this fact, excluding the address mismatches should not affect the randomization. However, we decided to investigate the issue further, as described below, just to be sure.

Table 2 shows the distribution of customers with and without the address mismatch in the treatment and control groups. The split is fairly similar in the treatment and control groups. We also compared the average daily energy usage on the subset of customers that did not have mismatched addresses, with the comparison shown in Table 3. As with the entire group, again we found no statistically significant differences between the treatment and control groups, with a p-value of 0.631. Because the address mismatch problem was not related to the program and affected both groups consistently, and because the removal of those with the address mismatches did not result in a difference between the treatment and control groups, we excluded the customers with mismatched addresses from both the treatment and control groups throughout the savings analysis. By doing so, we were able to get a more precise estimate of savings, since we were not mixing customers who received the reports (those with matching addresses) and those who did not receive the reports (those with mismatched addresses). Appendix A includes a comparison of the savings estimation with both the mismatched addresses removed and included in the data.

Table 2. Count of Customers with Mismatched Addresses

Group	Address Match	Customers	% of Total
Control	Different	9,090	12.1%
	Same	65,910	87.9%
Treatment	Different	9,179	12.2%
	Same	65,821	87.8%

Table 3. Sample Validation with Mismatched Addresses Removed

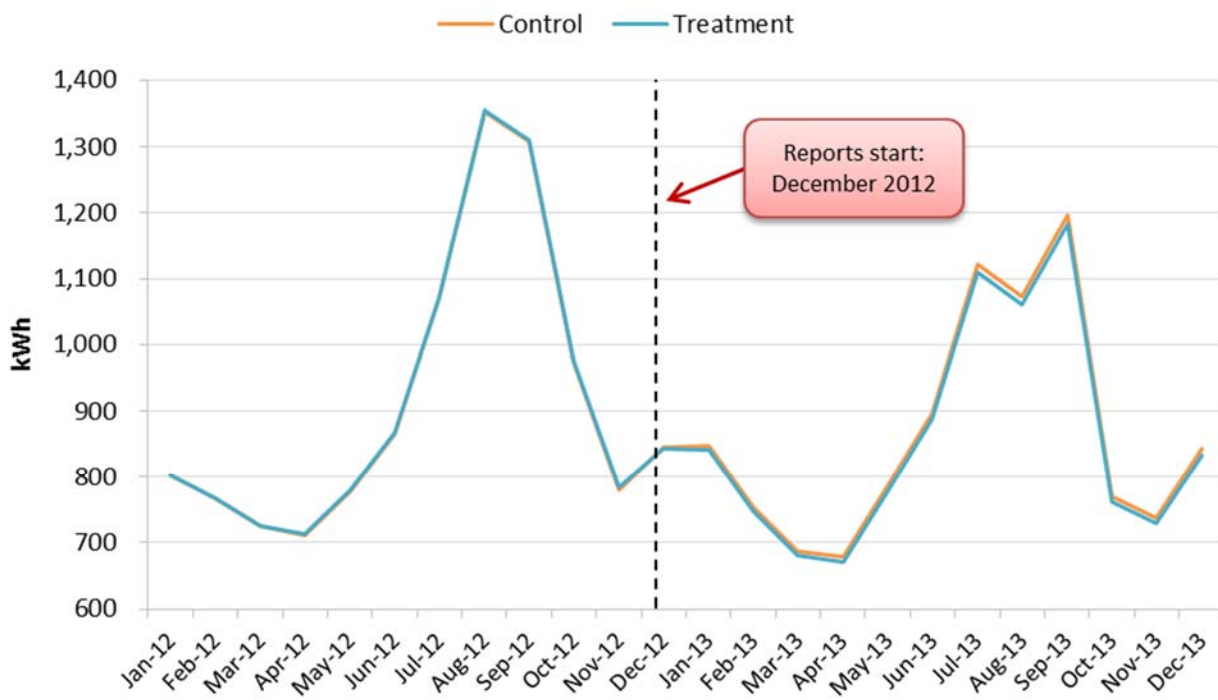
Average Daily Electricity Usage (kWh/day)			
Group	Mean	p-value	*
Control	29.5345	0.631	-
Treatment	29.5724		

* Means statistically significant difference

For the remainder of the report (with the exception of Appendix A), the results shown are based on the population without the address mismatches.

Figure 1 shows the electricity usage of the treatment and control customers over the two year period. During the pre-treatment period, the monthly electricity usage of both customer groups is nearly identical. However, once the treatment group begins to receive the HERs reports in December of 2012, there is a discernible difference in the usage of the two groups.

Figure 1. Average Usage of Population by Month



Based on this testing of pre-treatment energy use, we were able to confirm the earlier assessment of the CPUC Energy Division that the treatment and control groups in the dataset we received for the assessment of energy savings represented a valid randomized control trial experimental design.

Chapter 3 – Analysis Methods for Energy Savings

Overall Analysis Approach

To provide an independent estimate of savings from this program, we used two statistical methods: difference in differences and regression analysis. Both make use of pre-treatment and post-treatment monthly billing data for the treatment and control customers that were randomly assigned from the program population at the start of the program, with the mismatched address customers removed as described above. First, we used a difference in differences method, which directly estimates the energy savings for each month, along with a standard error and confidence intervals for those savings. Then we refined that direct estimate with a fixed effects regression model, which also incorporates actual weather data for that same period and reduces variance by accounting for different average energy use across the customers.

Both of these methods provide savings estimates by month along with the associated confidence intervals. The direct estimate from the difference in differences method provides an initial estimate of savings for each month that is not affected by the assumptions of a regression model. Because the regression model includes assumptions about the structure of the data and the nature of the residuals, it helps to have a preliminary estimate to compare with. If the regression model results are comparable to the initial estimates, we can be more confident that the results are valid. Because the regression model incorporates weather and reduces variance by using customer-specific fixed effects, it will generally provide a more precise estimate than the direct estimate. It also has the advantage that the model can be used to estimate what the savings would have been under different weather scenarios, though estimation of impacts under alternative weather scenarios is not in the scope of this project.

Difference in Differences

Equation 1 shows the mathematical calculations used in the difference in differences (DID) analysis to estimate energy savings for each month. In this case, the "before" refers to the pre-treatment month, and the control group is the group that did not receive a report.

$$\mathrm{Savings} = (\mathrm{Cntl}_{\mathrm{after}}\text{-}\mathrm{Tx}_{\mathrm{after}})\text{-}(\mathrm{Cntl}_{\mathrm{before}}\text{-}\mathrm{Tx}_{\mathrm{before}}) \quad (1)$$

Where

$\mathrm{Cntl}_{\mathrm{after}}$ is the average control group customer energy use in the treatment (after) period

$\mathrm{Tx}_{\mathrm{after}}$ is the average participant group (also referred to as the treatment group) customer energy use in the treatment (after) period

$\mathrm{Cntl}_{\mathrm{before}}$ is the average control group customer energy use in the pretreatment (before) period

$\mathrm{Tx}_{\mathrm{before}}$ is the average participant group customer energy use in the pretreatment (before) period

We also calculated standard errors and confidence intervals using the appropriate statistical formulas for the difference of two random variables (estimates).

The DID provides an initial estimate of savings for each month. We performed the analysis excluding the customers that had an issue with mismatched mailing and service addresses (who never received their home energy report). We did not eliminate the data for opt-out customers from the dataset. Given the small number of customers that opted out, the effect of excluding them was small. And since they had received at least some of the reports, they may have taken actions that resulted in savings even after they opted out, and keeping them in the analysis would capture those savings. We also included those customers when expanding the average customer results to the total population, so they were treated consistently.

Regression Modeling

We next estimated savings using a fixed-effect regression model. Both treatment and control customers are included in the model, which includes variables related to participation and weather. The model also includes a fixed effect for each customer, which is a customer-specific intercept.

The fixed-effects regression approach controls for unmeasured differences between customers that are constant over time, such as home size, vintage, major appliances, and household size, allowing us to better isolate and estimate the energy use changes associated with program participation (the savings) more precisely. We use a standard fixed-effects (also known as panel) regression, and use robust errors to reflect the correlation of the errors in the model. Again, as with the difference in differences approach, we develop a regression model based on a model that excludes the customers with the mismatched addresses.

The independent variables investigated are as follows:

- Temperature (cooling degree days and heating degree days)
- Treatment period year and month – to account for any changes in customer response
- Participation

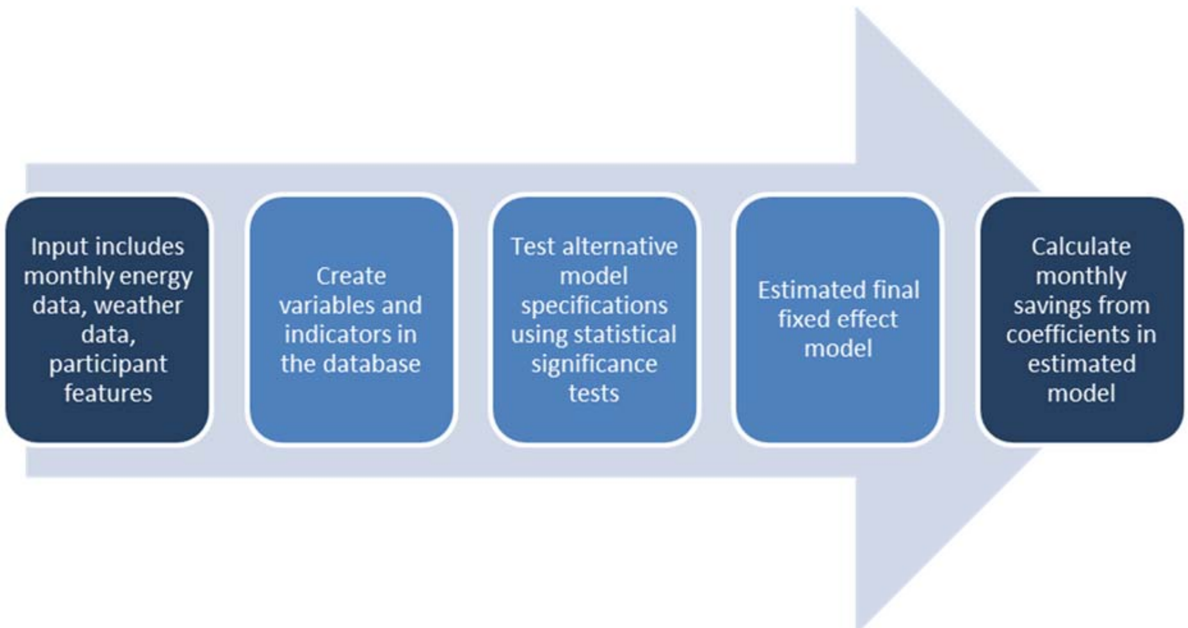
The model looks at the dependent variable (monthly energy use) as a function of the other independent or explanatory variables and then estimates the coefficients of the variables in that function.

Our regression analysis included the following general steps and assumptions (Figure 2 illustrates the approach):

- Create variables and indicators in the database. Note: The independent variables investigated include some that are related to participation, and others that are not. Conceptually, information not related to participation goes into the model to estimate the baseline energy use based on all customers (including participants and control group customers), while the participation variables (in some cases interacted with weather data) estimate the program impacts. We used the number of degree days for each month in the model, both with and without participation, so that the model quantifies any relationship between energy use and temperature as well as any relationship between savings and temperature.

- Run the fixed effects model using all treatment and control group customers (excluding those with mismatched addresses) to estimate the baseline energy use and the savings for the actual analysis period and for different scenarios (including normal weather) using the model coefficients.
- Test all the coefficients of the individual variables for statistical significance, and adjust the model as appropriate including only variables that actually influence energy use significantly. We tested numerous models during this analysis.

Figure 2. Simplified Regression Modeling Approach



Equation 2 below is the model specification we used. We tested other variables, including HDD and other interactions with weather, but this was the final model that included only statistically significant coefficients.

$$kwh_{it} = \alpha_i + [\gamma_{1t} + \gamma_{2t}P(x)]Month_t + [\gamma_{3t} + \gamma_{4t}P(x)]CDD_t + \beta_t P(x)T(x)Month_t + \varepsilon_{it} \quad (2)$$

Where the variables and their coefficients are defined as:

kwh_{it}	Consumption of customer i in month t
α_i	A fixed effect for each customer i
$[\gamma_{1t} + \gamma_{2t}P(x)]Month_t$	A vector of monthly indicator variables where $P(x)$ is an indicator variable that takes on a value of one during the treatment period
$[\gamma_{3t} + \gamma_{4t}P(x)]CDD_t$	The cooling effect of month t where $P(x)$is an indicator variable that takes on a value of one during the treatment period
$\beta_t P(x)T(x)Month_t$	A vector of monthly indicator variables where $P(x)$ is an indicator variable that takes on a value of one during the treatment period and $T(x)$ is an indicator variable that takes on a value of one if a customer i is a program participant
ε_{it}	The error for customer i during month t

Appendix B contains the output of the final regression model.

Data Used in Analysis

We conducted the energy analysis using monthly energy data for the pre-treatment and treatment periods. We used monthly billing data for the period of January 2012 through December 2013. We excluded December 2012 bills from the analysis because the first reports were sent sometime in that month, but the exact timing of when they were received by customers was uncertain. For the regression analysis, we used bills for all the remaining months. For the DID analysis, we needed to match comparable pre-treatment and treatment months. Due to the removal of the December 2012 bills, we intended to use December 2011 as the pre-treatment month as the comparison for December 2013 treatment period. However, there was not enough customer data in December 2011, and we used January 2012 (a month with similar weather) as a proxy pre-treatment month for December 2013 in the DID analysis.

We also removed from the data those customers who had a mismatched address in both the control group and treatment group, as discussed in Chapter 2 above. For participants and control group customers who moved out of their homes during 2013, we included energy data up until the time they left. Table 4 shows the number of customer accounts that were removed from the sample population during the course of our analysis.

Table 4. Count of Removed Customer Accounts

Step	Customer Accounts		
	Control	Treatment	Total
Selected sample of customer accounts	75,000	75,000	150,000
Removed mismatched addresses	9,090	9,179	18,269
Removed customers w/ missing weather station (regression model)	1	2	3
Total remaining customer accounts	**65,909**	**65,819**	**131,728**

Table 5 illustrates the customer attrition due to customers who moved out during the treatment period of the study. The table shows the count of households that had available data for the treatment and control groups by month. The number of move-outs is tracked by month and cumulatively. Though the sample included a total of 150,000 customers, the billing data for some customers was incomplete, which is the cause for the discrepancy in the customer counts with those in Table 4.

Table 5. Customer Attrition

Month	Control Group			Treatment Group		
	Open Accounts[a]	Closed Accounts		Open Accounts*	Closed Accounts	
		Monthly	Cumulative		Monthly	Cumulative
Jan 2013	64,939	0	0	64,893	0	0
Feb 2013	64,645	294	294	64,556	337	337
Mar 2013	64,436	209	503	64,315	241	578
Apr 2013	64,187	249	752	64,053	262	840
May 2013	63,902	285	1037	63,787	266	1106
Jun 2013	63,599	303	1340	63,493	294	1400
Jul 2013	63,270	329	1669	63,189	304	1704
Aug 2013	62,972	298	1967	62,918	271	1975
Sep 2013	62,704	268	2235	62,659	259	2234
Oct 2013	62,481	223	2458	62,421	238	2472
Nov 2013	62,253	228	2686	62,186	235	2707
Dec 2013	62,051	202	2888	61,976	210	2917

[a] Count of number of customer accounts vary by month due to missing billing data or account closure.

Chapter 4 – Energy Savings Results

Difference in Differences Results (Initial kWh Savings Estimates)

Table 6 summarizes the per-participant energy impacts estimated with the difference in differences approach for all program participants from January 2013 through December 2013. The table includes the number of participants included in the analysis month, average per-participant adjusted control group billing energy use, and average per-participant estimated energy savings in terms of kWh and percentage. The table also indicates whether or not the savings estimates are statistically significant based on 90% confidence for the given month.

Table 6. Monthly Ex-Post Energy Savings Estimates: Difference in Differences

Month	Average Adjusted Control Group Billing Energy (kWh)	Average Estimated Savings (kWh)	% Savings	Significant?
Jan-13	815.11	7.77	1.0%	Yes
Feb-13	734.30	7.10	1.0%	Yes
Mar-13	687.67	8.62	1.3%	Yes
Apr-13	681.48	9.29	1.4%	Yes
May-13	778.36	12.03	1.5%	Yes
Jun-13	878.24	12.70	1.4%	Yes
Jul-13	1,086.40	15.76	1.5%	Yes
Aug-13	1,069.52	16.03	1.5%	Yes
Sep-13	1,170.09	20.89	1.8%	Yes
Oct-13	740.36	11.94	1.6%	Yes
Nov-13	704.73	11.04	1.6%	Yes
Dec-13	789.90	11.74	1.5%	Yes
Total	**10,136.17**	**144.92**	**1.4%**	**Yes**

The table shows that the per-participant savings range from a minimum of 1.0% in January and February of 2013 to a maximum of 1.8% in September 2013. Overall, the analysis indicates an average savings across the program of about 1.4%, and the savings generally increase, but are somewhat "bouncy" throughout the treatment period. This is probably due in part to the fact that the direct estimation by month tends to reflect random variation inherent in energy use. The highest savings occur during the summer months. The results are statistically significant for all months.

Figure 3 and Figure 4 plot the average per-participant monthly energy results based on the difference in differences results. The first figure compares the monthly energy use for the treatment group and the adjusted control group (with the pre-treatment difference removed). The second figure shows the monthly energy savings and 90% confidence intervals. In all cases, the confidence intervals are above zero, indicating that the savings are statistically significant.

Figure 3. Difference in Differences Average Per-Participant Monthly Energy Use

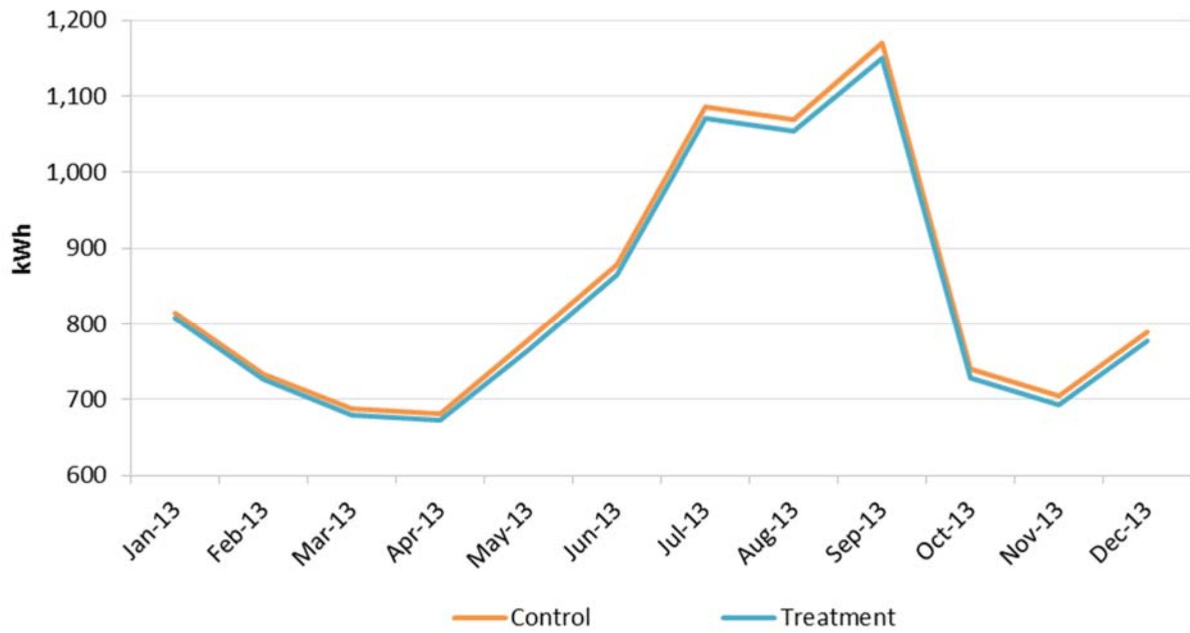
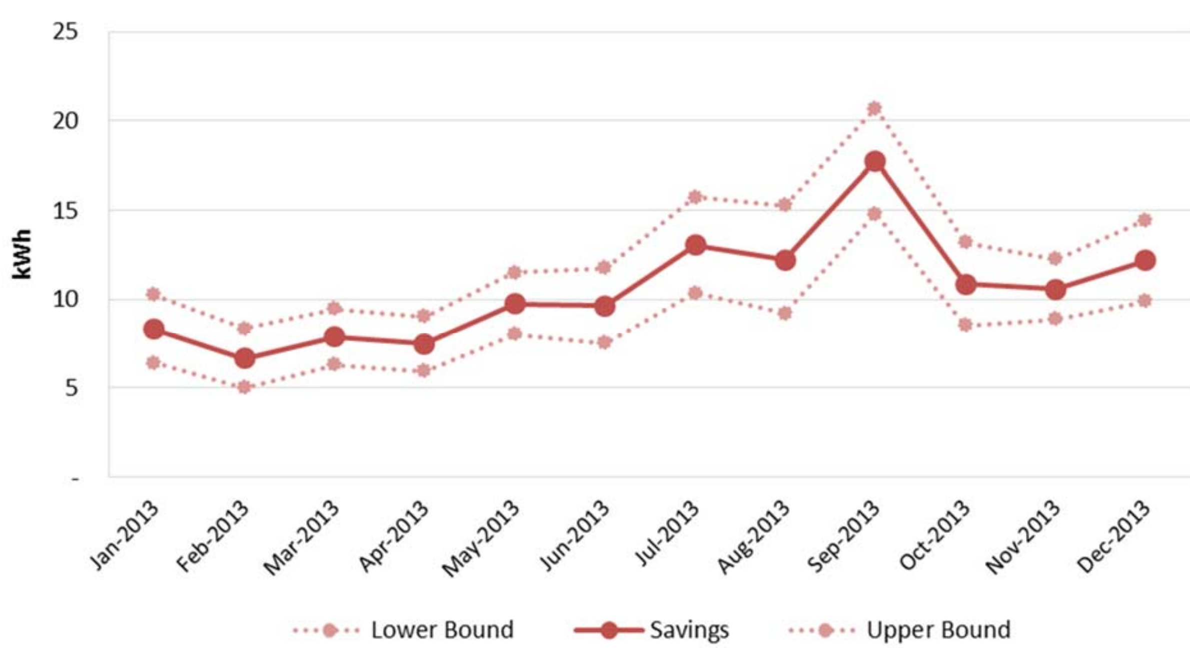


Figure 4. Difference in Differences Average Per-Participant Energy Savings Estimates



Regression Analysis (Refined kWh Savings Estimates)

After estimating the savings using a difference in differences, we then estimated the savings using a fixed-effects regression model. The first step in the assessment of the regression model was to check the results for consistency against the results from the difference in differences analysis. We found that the results were similar and, as expected, the results of from the regression model are more precise. We used the regression model results to make the final program-level estimates presented at the end of this chapter.

Table 7 summarizes the average monthly energy savings estimated with the regression model approach for the treatment period of January 2013 to December 2013. The table includes the average baseline energy use of the control group during the treatment period, less the pre-treatment difference between the two groups. It also shows the estimated treatment customer average energy savings, percent energy savings, number of participants included in the analysis month, and total estimated savings for the population of participants. The table also indicates whether or not the savings estimates are statistically significant for the given month.

The table shows the per-participant monthly savings range from a minimum of 1.1% in January 2013, rising steadily to a maximum of 1.6% in the latter part of the year. Overall, the analysis yields an average savings across the treatment period of 1.4%, almost identical to the annual result for the DID analysis. The magnitudes of these results are similar to, but steadier and more explainable than, the DID results—a trend that increases with information from more reports seems more plausible than the “bumpy” DID savings pattern. Like the difference in differences estimates, the regression estimates are statistically significant throughout the analysis period.

Table 7. Monthly Ex-Post Energy Savings Estimates: Regression Analysis

Month	Average Adjusted Control Group Billing Energy (kWh)	Average Estimated Savings (kWh)	% Savings	Significant?
Jan-13	815.50	8.75	1.1%	Yes
Feb-13	735.39	8.69	1.2%	Yes
Mar-13	687.06	8.67	1.3%	Yes
Apr-13	681.03	9.45	1.4%	Yes
May-13	776.68	10.84	1.4%	Yes
Jun-13	877.25	12.52	1.4%	Yes
Jul-13	1,084.95	14.21	1.3%	Yes
Aug-13	1,068.65	16.01	1.5%	Yes
Sep-13	1,167.41	18.10	1.6%	Yes
Oct-13	739.79	12.13	1.6%	Yes
Nov-13	703.98	11.16	1.6%	Yes
Dec-13	790.11	12.96	1.6%	Yes
Total	**10,127.80**	**143.48**	**1.4%**	**Yes**

Figure 5 and Figure 6 plot the average per-participant monthly energy results based on the regression analysis. The first figure compares the monthly energy use for the model estimates of the treatment and control groups. This figure is very similar to Figure 3. The second figure shows the monthly energy savings and 90% confidence intervals. In all cases, the lower bounds of the confidence intervals are above zero, indicating that the savings are still statistically significant.

Figure 5. Regression Analysis Average Per-Participant Monthly Energy Use

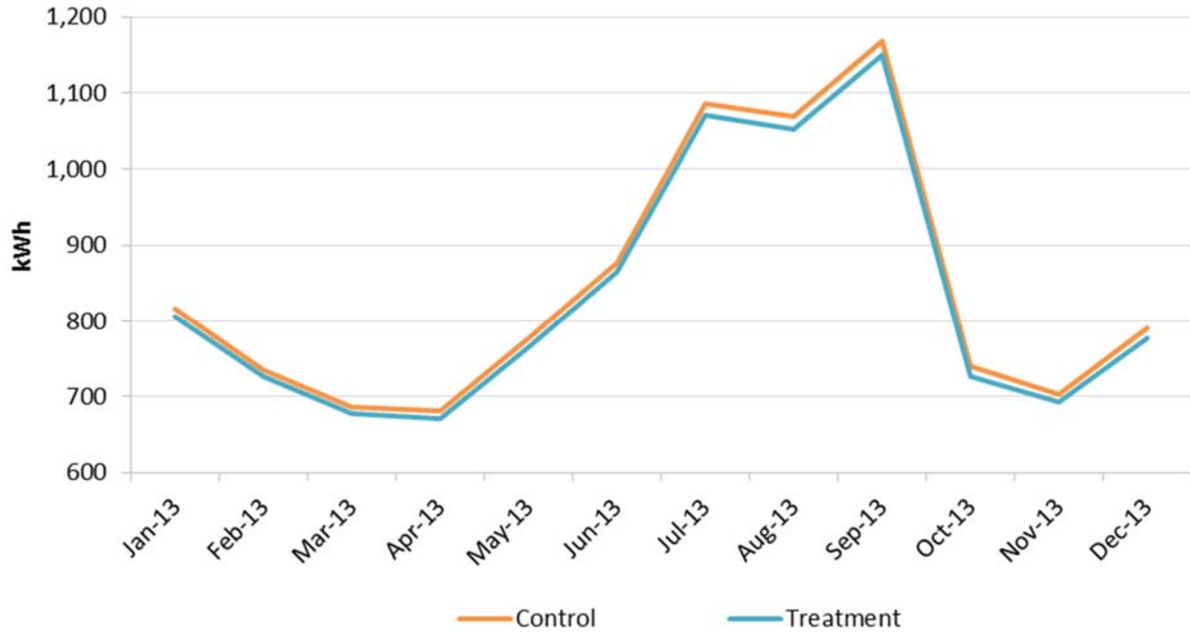


Figure 6. Regression Analysis Average Per-Participant Energy Savings Estimates

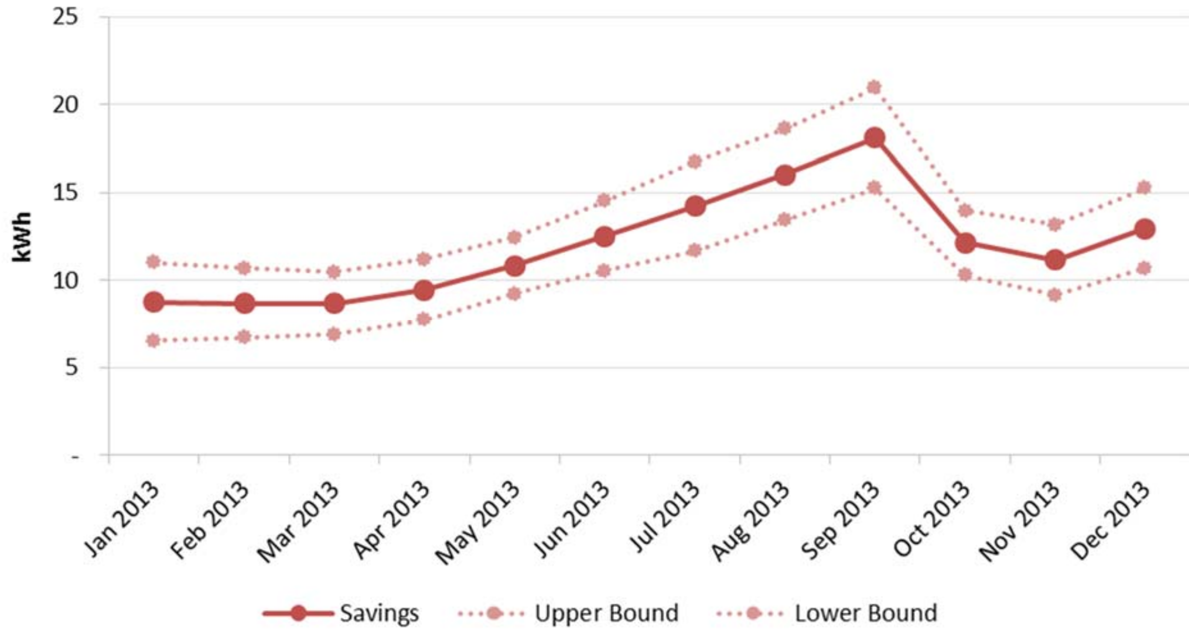


Figure 7 compares the monthly energy savings estimated with the regression model and the difference in differences approach. The energy savings are very similar across the whole treatment period. The regression model results are more stable, and reflect the structure of the savings consistently from month to month better than the difference in differences, which tend to include some random variation between months.

Figure 7. Average Per-Participant Energy Savings Estimates: Comparison of Regression and Difference in Differences Results

Figure 8 shows the monthly percentage savings estimates from the regression model across the entire treatment period. It also plots the average annual percentage energy savings achieved through the 12 months of the program based on the regression results (1.4%).

Figure 8. Monthly Energy Savings Estimates: Percentage Savings, from Final Regression Model

Program-Level Savings

The results from both the difference in differences model and the regression model show similar savings estimates. However, the results from the regression model provide more stable savings estimates with less month to month random variation. For these reasons, we used the regression model results to estimate program level savings.

Table 8 presents the total HER program savings without the adjustment for upstream and downstream program savings discussed in Chapters 6 and 7. We calculated the HER program-level savings by multiplying the average per-participant savings from the regression model by the number of active treatment accounts in each month. This gave us a total of 9.07 GWh of savings, before adjusting for the savings from other programs.

The number of active accounts is decreasing each month during the treatment period due to customer attrition, or move-outs. Again, we did not exclude the opt-out customers from this calculation, due to the small number of customers that opted-out of the program. There was an average of 63,369 program participants, which was calculated by taking the average number of monthly participants during the treatment period. We use this value when calculating the upstream savings, discussed in Chapter 7.

Table 8. Total HER Program Energy Savings (before adjustment for other program savings)

Month	Participants	Average Per-Participant Savings (kWh)	Total Savings (kWh)[a]
Jan-13	64,891	8.75	568,107
Feb-13	64,554	8.69	561,064
Mar-13	64,313	8.67	557,793
Apr-13	64,051	9.45	605,436
May-13	63,785	10.84	691,119
Jun-13	63,491	12.52	794,604
Jul-13	63,187	14.21	898,001
Aug-13	62,916	16.01	1,007,079
Sep-13	62,657	18.10	1,134,000
Oct-13	62,420	12.13	757,049
Nov-13	62,185	11.16	693,789
Dec-13	61,975	12.96	802,910
Total	**63,369[b]**	**143.48**	**9,070,952**

[a] Total savings difference due to rounding of average per-participant displayed values

[b] Average monthly customers

Chapter 5 – Peak Demand Impacts

We conducted two analyses to assess the peak kW impacts of the Opower-1 program. Initially, we made a simple, preliminary estimate by applying an average residential class load factor to the estimated kWh savings. Later, when interval data for the participants and control group became available, we developed a revised and improved estimate using interval data for the actual participants that was analogous to the way we estimated the energy savings. We also used the 3-day heat wave as defined by DEER for the actual year 2013 for the revised estimate, rather than from the standardized year based on calendar year of 2009 from the DEER guidelines, which we used for the preliminary estimate.

The revised savings estimate, based on actual customer interval data for the program year and the DEER peak definition, captures behavior at the peak period in 2013 and represents our final result for peak load savings for the Opower-1 program.

Load Factor Approach

Once we estimated the kWh savings, we then calculated a preliminary estimate of kW savings using SCE's Dynamic Load Profiles (DLP), reweighted to better reflect the makeup of the SCE HER population. We used these load profiles to develop a load factor for the peak hours, which we then applied to the kWh savings to obtain a rough estimate of the kW savings.

The dynamic load profiles were based on a stratified sample representing the entire SCE residential population, with stratification based on average monthly energy use, climate zone, and housing type (single family and multifamily). We calculated new weights based on the distribution of customers in the Opower-1 population across the strata defined by the DLP sample. By applying these alternative weights to the DLP sample interval data, SCE's Load Research department recalculated an annual 8,760-hour load shape that reflected the customers in the Opower-1 participant population.

Using this reweighted 8,760-hour load shape and the 2013 DEER-defined[1] 3-day heat wave, which is September 1-3 for the climate zones included in the participant population, we calculated the average kW for the three peak hours from 2:00-5:00 on each of the these days. Using that average peak kW, we calculated the peak load factor as the ratio of the annual consumption to the product of the peak demand and the number of hours (8,760). The peak load factor based on the reweighted dynamic load profile using this approach was 35.2%.

We then applied that load factor to the annual savings estimate from the regression analysis, with the double-counted savings removed,[2] to get the preliminary kW savings estimate of 2,770 kW, as follows:

[1] DEER2013—Codes and Standards Update for the 2013-14 Cycle. The identification of Sep 1-3 in this document actually turned out to have been the peak days from 2009, not 2013. We corrected this in the interval data analysis for the revised estimate.
[2] Removal of savings already counted in other programs is discussed in Chapters 6 and 7.

$$(Preliminary)\ Peak\ Demand\ Savings_{LF} = 2{,}770\ kW = \frac{8{,}540{,}732\ kWh}{(0.352\ \times 8{,}760)}$$

In the following section, we discuss the improved savings estimate of the peak demand impacts using actual interval data.

Interval Data Approach

When the data became available, we then developed a kW savings estimate based on the actual participant and control group customer interval data to give an improved savings estimate that more directly represents the savings for these customers. SCE provided hourly interval data for 2012 and 2013, for both participants and control group customers.

Before estimating the peak demand savings, we processed the data and validated the sample. While we previously checked the randomization for the kWh analysis by performing a two-sample t-test on average daily energy using the billing data, we decided to validate once more using the pre-treatment[3] interval data. In addition to checking average daily energy in 2012, we compared average daily energy at the monthly level. The tests confirm that the sample is well balanced and that there are no systematic differences between the treatment and control group in terms of pre-treatment energy. On average, the treatment group used 30.09 kWh per day while the control group used 30.04 kWh. The difference is not statistically significant, with a t-statistic of -0.67 and a p-value of 0.5000. The table below shows the comparisons for each month.

Table 9. Comparison of Average Daily Usage, by Month

Month	Treatment kWh	Control kWh	t-statistic	p-value
Jan-12	25.66	25.62	-0.67	0.5019
Feb-12	25.05	25.04	-0.22	0.8297
Mar-12	24.27	24.23	-0.60	0.5498
Apr-12	24.15	24.11	-0.60	0.5480
May-12	25.89	25.83	-0.91	0.3615
Jun-12	28.94	28.88	-0.61	0.5411
Jul-12	35.63	35.60	-0.25	0.8002
Aug-12	47.08	47.05	-0.25	0.7994
Sep-12	41.76	41.65	-0.97	0.3297
Oct-12	27.36	27.29	-0.95	0.3401
Nov-12	24.79	24.74	-0.66	0.5090
Dec-12	26.14	26.12	-0.39	0.6961

In addition to the sample validation, we cleaned the 2013 interval data by checking for missing values, zeroes, negatives, and outliers. In a given day, if there were more than three missing

[3] Using the cut-off date of December 10, 2012.

hours[4] or more than three zeroes, we considered it an unusable day. In addition, if a day had more than one negative hourly value, we omitted the day.[5] We used two separate processes to identify outliers. First, for each season[6] and day type,[7] we calculated average daily energy and the associated standard deviation. Days that were more than four standard deviations away from the season and day type mean (in either direction) were considered unusable. The second approach to identifying outliers was to examine the maximum daily kW and compare it to the preceding day's value. We excluded records if the current day's value was more than six times larger than or less than 1/6th the size of the previous day's max. Finally, we omitted customers with more than 20% of their days flagged as unusable. We also cleaned the 2012 interval data prior to validating the sample using the exact conditions listed above. However, the two years were cleaned independently of one another. That is, the results of 2012 did not carry over to 2013 or vice versa. The 2012 interval data was cleaned for sample validation purposes while the 2013 interval data was cleaned for analysis purposes. Overall, the SCE data were quite clean. In total, the exclusions from the cleaning amounted to just over 1% of the records.

Consistent with the kWh analysis, we also excluded accounts from both the participants and control group that had the mismatched address problem. This reduced the analysis group by about 12%. Table 10 below shows the final number of customer accounts included in the analysis. It also shows the average demand during the peak weather hours in 2013.

Table 10. Customer Accounts Included in the Interval Data Analysis

Group	Number of Accounts	Average Peak Day Demand (kW)
Control	62,090	3.5125
Treatment	62,014	3.4665

The load factor approach described earlier used a 3-day heat-wave of September 1-3, defined using the 2013 updated DEER documentation, which apparently used a 2009 calendar. For the interval data approach, we revised this estimate to use the 2013 weather data for climate zones included in our sample. We determined that the three hottest, consecutive weekdays (excluding holidays) occurred on September 4-6, 2013 for all weather stations represented in the participant group. The average peak day demand in the table above is for these hours.

Using hours 2-5 pm on September 4-6 for each customer, we estimated the peak demand impacts by calculating the difference between the average demand for the treatment and control group. We calculated the savings across these nine hours. For each customer, we calculated the average demand during this nine-hour period. Then, we calculated the average by group—treatment versus control. We checked whether the differences were statistically significant and

[4] The exception is for the beginning of Daylight Saving Time (March 11, 2012), which allowed four missing values or less.
[5] We did not find any negative values, but included the condition as part of our standard cleaning practice.
[6] Summer (June-September) versus winter.
[7] Weekday versus weekend.

found a t-statistic of 3.68 and a p-value of 0.0002, indicating that the difference is, indeed, statistically significant.

The average per-participant peak savings is 0.0459 kW. This is a savings of 1.3% from baseline demand. The 90% confidence interval is +/- 0.0205 kW.

Finally, we assessed the aggregate (program-level) kW impact. We did this by taking the average per-participant savings estimate and multiplying it by the number of participants in September 2013, which was 62,657. To calculate the final peak demand savings estimate, we removed the savings associated with and already counted in other programs, 28.55 kW from downstream and 38.38 kW from upstream programs, to avoid double counting.[8] Thus, the interval data approach yields a kW impact estimate of 2,809 kW.

$$(Revised)\ Peak\ Demand\ Savings_{ID} = 2{,}809\ kW$$
$$= (0.0459\ kW \times 62{,}657) - (already\ counted\ savings\ from\ other\ programs)$$
$$= 2{,}876\ kW - (28.55\ kW + 38.38\ kW)$$

The result from the analysis of interval data is our final estimate of the kW savings associated with the HER pilot program.

[8] Calculation of savings from the downstream and upstream programs is discussed in the following chapters. The values are included here to allow direct comparison of kW savings estimates using the load factor and interval data approaches.

Chapter 6 – Attributing Savings to Downstream Programs

SCE provided AEG with the annual per-measure savings estimates for HER participant and control group customers' participation in other energy efficiency programs the company offered in 2013, based on the official program tracking data submitted to CPUC. These programs are referred to as downstream programs because incentives are offered directly to the end-users of energy and their participation and expected savings are tracked by individual households.

There are a wide range of energy efficiency measures that are rebated through these programs, such as the purchase of energy efficient refrigerators, clothes washers or pool pumps. Because SCE receives credit for the savings achieved through these programs, it is possible that part of the total 2013 HER savings estimated and reported in the previous chapter are attributable to and will be counted as part of those downstream programs' savings. Note that it is only the incremental difference between the treatment and control group customers that are at risk of double counting – the control group accounts for a "baseline" level of participation that would have happened in the absence of the program.

Table 11 shows the kWh savings attributed to the downstream programs for the Opower-1 control and treatment customers, and the incremental difference between the two groups. We calculated the kWh difference by prorating the annual kWh for each measure to the numbers of days in the treatment period after that measure was installed. This represents the savings resulting from the measures installed. Next, we subtracted the prorated kWh savings of the control customers from the prorated kWh savings of the treatment group to get the difference in savings during the treatment period. This represents the incremental kWh savings for the treatment group over and above the savings for the control group. These incremental savings were included in savings we estimated for the Opower-1 program, but were also counted as part of the downstream programs. In order to eliminate this double counting of savings, these savings were removed from the Opower-1 program savings estimate. Because the savings estimates provided by SCE for the downstream programs were already net savings, they are already corrected for attribution to the program.

Table 12 shows the analogous information for the kW savings associated with the downstream programs. We calculated kW difference by including the measures and kW savings for only those customers in each group who had installed their measures by September 4, 2013, the first day of the DEER-defined heat wave period. That is why the Customer Measure Count is different from Table 12. The individual kW values for each customer with peak day installations were not adjusted since they reflect the demand savings on the peak day.

During the treatment period of January 2013 to December 2013, a total of 2,175 energy efficiency measures were installed by customers assigned to the control group, 1,315 of them by September 4. The total prorated savings achieved by the control group through downstream measures for that period was 373,337 kWh and 141.39 kW. This is compared to a total of 2,559 energy efficiency measures installed by customers who received HER reports, 1,543 of them by September 4. The total prorated downstream savings from the treatment group for that period was 460,656 kWh and 169.94 kW. The difference between the two groups, the incremental savings resulting from HERs that would be counted elsewhere, are 87,319 kWh and 28.55 kW.

Table 11. Downstream Program Savings (kWh)

Measure	Control		Treatment		kWh Difference
	Customer Measure Count	kWh Savings	Customer Measure Count	kWh Savings	
Central AC	60	13,343	80	16,408	3,064
Evaporative Cooler	1	528	-	-	-528
Whole House Fan	18	113	18	60	-53
Lighting	54	3,960	64	25,149	21,189
In Home Survey	8	1,197	18	3,501	2,305
Mail Survey	801	54,250	881	57,854	3,604
Online Survey	195	5,724	228	6,746	1,022
Phone Survey	1	115	8	1,521	1,406
Clothes Washer	2	79	-	-	-79
Pool Pump	185	55,559	265	82,676	27,116
Refrigerator	819	224,814	961	251,261	26,447
Whole House Retrofit	31	13,654	36	15,481	1,827
Total	**2,175**	**373,337**	**2,559**	**460,656**	
	Total Difference in Savings (kWh)				**87,319**

Difference in total savings shown is due to rounding.

Table 12. Downstream Program Savings (kW)

Measure	Control		Treatment		kW Difference
	Customer Measure Count *	kW Savings	Customer Measure Count *	kW Savings	
Central AC	31	18.16	48	25.20	7.04
Evaporative Cooler	1	1.31	-	-	-1.31
Whole House Fan	15	0.06	17	0.07	0.01
Lighting	54	0.79	64	6.15	5.36
In Home Survey	5	0.34	12	0.82	0.48
Mail Survey	246	25.09	251	25.60	0.51
Online Survey	195	3.32	228	3.88	0.56
Phone Survey	1	0.06	8	0.48	0.42
Clothes Washer	1	0.06	-	-	-0.06
Pool Pump	159	5.41	237	8.06	2.65
Refrigerator	589	61.88	650	64.73	2.84
Whole House Retrofit	18	24.92	28	34.97	10.04
Total	**1,315**	**141.39**	**1,543**	**169.94**	
	Total Difference in Savings (kW)				**28.55**

* Reflects measures installed by September 4, 2013.

Chapter 7 – Attributing Savings to Upstream Programs

Upstream program savings are not tracked at the customer level, but are also a source of savings that can potentially be double counted. SCE runs programs that provide incentives to manufacturers and retailers to change stocking practices of energy efficient CFLs (Upstream Lighting Program or ULP) and TVs (Business and Consumer Electronics Program or BCE). Since it is not possible to track which customers purchased CFLs and TVs at reduced prices, we used a proxy method to determine the savings that are potentially double-counted.[9]

PG&E recently conducted in-home surveys[10] that assess the uptake of upstream measures (mainly, CFLs and flat screen TVs). The surveys included samples of treatment and control customers from PG&E's HER program. Rather than duplicate that very costly and time-consuming study, we assumed a similarity between the change in CFL ownership resulting from HERs participation for SCE and PG&E, and used the results from that study as the basis for an estimate of the SCE upstream savings.

To estimate the double-counted or incremental savings in terms of energy (kWh), we use the following formula:

$$\begin{aligned} kWh\ attributable\ to\ both\ program \\ &= (CFLs\ installed\ due\ to\ HERs) \times (customer - years\ CFLs\ have\ been\ installed) \\ &\times \left(\frac{rebated\ CFLs}{total\ CFLs}\right) \times \left(\frac{CFLs\ attributable\ to\ ULP}{rebated\ CFLs}\right) \times (CFL\ savings\ per\ year) \end{aligned}$$

In the PG&E survey report, the analysis identified that, on average, treatment households installed an additional 0.95 bulbs[11] per household more than the control group. As with the downstream savings described in the previous chapter, it is only the incremental difference between the treatment and control groups that would potentially be double counted. To reiterate, the assumption made in the use of the PG&E study is that the increase in per customer CFL ownership resulting from receiving HERs is about the same for the programs at the two different utilities. The additional 0.95 bulbs per customer represent savings that could be potentially be counted by both the ULP and the SCE Opower-1 program.

To calculate the customer-years that the CFLs have been installed, we made the additional assumption that the CFLs were installed uniformly throughout the year, with 1/365 of them first installed on each day. Conceptually, if we plotted the cumulative number of CFLs installed by date throughout the year, we would see a triangle, with dates along the bottom and number of installations along the upward-sloping hypotenuse. This triangle is half what the total number would be if we assumed all were installed on January 1 and remained throughout the year

[9] SCE deactivated the BCE in 2013, so we did not address removing any possible BCE savings in this assessment.
[10] Evaluation of Pacific Gas and Electric Company's Home Energy Report Initiative for the 2010–2012 Program; Freeman, Sullivan & Co., April 25, 2012.
[11] Ibid, Table 7-3, p. 46. Surveys conducted in PG&E service territory; no data for SCE service territory available.

(which would instead be represented by a full rectangle, each day having the same number of installations). Therefore, the total customer-years of CFLs is simply the average number of participant customers for the year divided by two. With the average number of treatment customers in the Opower-1 program being 63,369, dividing by two gives us 31,684.5 customer-years for the installed CFLs.

The next step was determining what fraction of the savings for the excess CFLs are also counted as part of the ULP. According to the most recent ULP evaluation, 0.74[12] of CFLs received rebates statewide through the ULP, calculated as the total rebated CFLs divided by the total CFLs sold. Next, we determined the fraction of rebated CFLs attributable to the ULP using the applicable net-to-gross ratio (NTGR). For the SCE territory, the most recent, approved upstream lighting NTGR is 0.64.[13]

The final step was determining the expected total energy savings per year, based on the average hours of use per day and the average wattage saved per CFL. Based on information for SCE in the ULP report, the typical ULP CFL is in use for 1.9 hours per day, with a savings of 44.8 watts per bulb.[14] This results in a savings of: 1.9×365×44.8÷1000=31.0688 kWh per year per CFL.

Multiplying all of these values together (shown below) gives us the incremental savings that need to be deducted from the total annual kWh savings estimate:

	0.95	CFLs installed due to HER program (based on PG&E Home Inventory)
×	**31,684.50**	Customer-years CFLs have been installed (average monthly SCE HER program participants × 0.5)
×	**0.74**	Proportion of CFLs that are rebated (statewide)
×	**0.64**	Proportion of CFLs attributable to upstream program (SCE specific)
×	**31.0688**	Per CFL savings per year (SCE specific) (1.9×365×44.8÷1000)
=	**442,901**	kWh of savings attributable to both programs

In order to determine the incremental demand savings, we modified two of the values in the above calculation.

First, we adjusted the value used for customer-years the CFLs have been installed by using the number of participants in September and updating our assumption about the number of CFLs installed at that time. The kW analysis involved estimating the kW savings at the three peak hours on the three hottest, consecutive non-holiday weekdays. For the climate zones included in this study, those dates were September 4-6, 2013. The number of participants in September

12 Final Evaluation Report: Upstream Lighting Program; KEMA, Inc., February 8, 2010, Table 23, p. 49.
13 Ibid, Table 25, p. 54.
14 Ibid, Table 18, p. 42.

was 62,657 and the number of CFLs installed at that time was 0.6767. The latter is calculated as the ratio of the number of days of the year elapsed on September 4 divided by the total number of days in the year: 247/365, assuming that the 0.95 CFLs that were installed per customer were installed uniformly across the year (the same assumption used for the kWh estimate). Taken together, the estimated total number of customers with CFLs installed is 42,400.8.

Second, we modified the CFL savings per year value. This involved replacing the value for CFL savings per year with the CFL demand savings at peak. This value represents the estimated demand savings per CFL during the three peak hours on a heat wave lasting three days, falling on non-holiday weekdays. It is the product of the kW savings per CFL and the coincidence diversity factor for CFLs. The coincidence diversity factor used was the weighted average of the coincidence diversity for the climate zones with participants, weighted by the number of participants in those climate zones. The diversity factor provided by the SCE engineers was 0.0449.

The calculation of incremental savings that need to be deducted from the peak kW savings estimates are shown below:

	0.95	CFLs per customer installed due to HER program (based on PG&E Home Inventory)
×	**42,400.8**	Customers in September (SCE HER program participants × 0.6767)
×	**0.74**	Proportion of CFLs that are rebated (statewide)
×	**0.64**	Proportion of CFLs attributable to upstream program (SCE specific)
×	**0.0020**	Per CFL kW savings at the peak (SCE specific) (44.8×0.0449÷1000)
=	**38.38**	kW savings at the peak attributable to both programs

Chapter 8 – Final Results and Conclusions

Final 2013 HER Savings Results

The total estimated program Opower-1 program savings, showing the removal of upstream and downstream program savings are shown in Table 13:

Table 13. Total SCE Opower-1 HER Program Savings

	kWh	kW
Opower-1 Savings	9,070,952	2,876
Upstream Program Savings	(442,901)	(38)
Downstream Program Savings	(87,319)	(29)
Total Program Savings	**8,540,732**	**2,809**

Key Findings

Key findings and conclusions from the analysis:

- **Measureable savings:** We estimate ex-post energy savings of 8,541 MWh during the 12-month treatment period. These savings estimates are statistically significant and based on a rigorous randomized control trial experimental design. We also estimate peak demand savings of 2,809 kW, based on the DEER peak hours definition.
- **Steady increase in savings:** The savings increase steadily over the treatment period, faster in the earlier months, showing a lagged and cumulative effect of the home energy reports. We infer that as a customer receives more information through the reports, they modify their behavior and energy use more.
- **Seasonal savings levels.** The kWh savings across the months show a pattern that follows seasonal consumption levels. This suggests that there is some weather sensitivity in the savings. The finding of monthly change in the savings, rather than degree-day correlation, suggests general seasonal climate sensitivity of the savings.
- **Savings comparable with other HER programs:** The results show reductions of about 1.4% in kWh usage and 1.3% in peak demand, within the 1-2% range seen in other HER programs in California and elsewhere.

Appendices

Appendix A – Mismatched Addresses

Due to an issue regarding mismatched addresses in SCE's billing system, there were a number of participants that did not receive a home energy report. This included customers in both the control and treatment groups of the sample. We did an analysis of the Difference in Difference results with two datasets, one with the customers that had mismatched addresses removed, and one that had those customers included.

Table A-1 shows the monthly percentage savings results of the two datasets. As expected, the monthly savings are slightly higher when the mismatched addresses were removed, since this is an average of only customers who received the reports. This is because the overall amount of savings remained the same, but the number of customers that the savings is distributed between (or the denominator) is smaller once the mismatched addresses were removed. Figure A-1 illustrates this expected finding.

Table A-2. quantifies and Figure A-2 illustrates the total program level savings when we multiply the average monthly savings by the respective number of participants in each month. The total HER program savings with the mismatched addresses included is about 9.0 GWh, compared to 9.2 GWh when the customers with mismatched addresses were removed.

NOTE: The results in this section are for purposes of comparing the effect of removing versus including accounts with mismatched addresses using the difference in differences approach. They are not the final results of the analysis. The final savings are based on the regression analysis.

Tables and figures are on the following pages.

Table A-1. Comparison of Monthly Percentage Savings with Mismatched Addresses Removed

Month	Monthly Savings (mismatches included)	Monthly Savings (mismatches removed)
Jan 2013	1.0%	1.0%
Feb 2013	0.8%	1.0%
Mar 2013	1.1%	1.3%
Apr 2013	1.2%	1.4%
May 2013	1.3%	1.5%
Jun 2013	1.2%	1.4%
Jul 2013	1.2%	1.5%
Aug 2013	1.2%	1.5%
Sep 2013	1.5%	1.8%
Oct 2013	1.4%	1.6%
Nov 2013	1.4%	1.6%
Dec 2013	1.4%	1.5%

Figure A-1. Comparison of Savings after Removing Customers with Mismatched Address

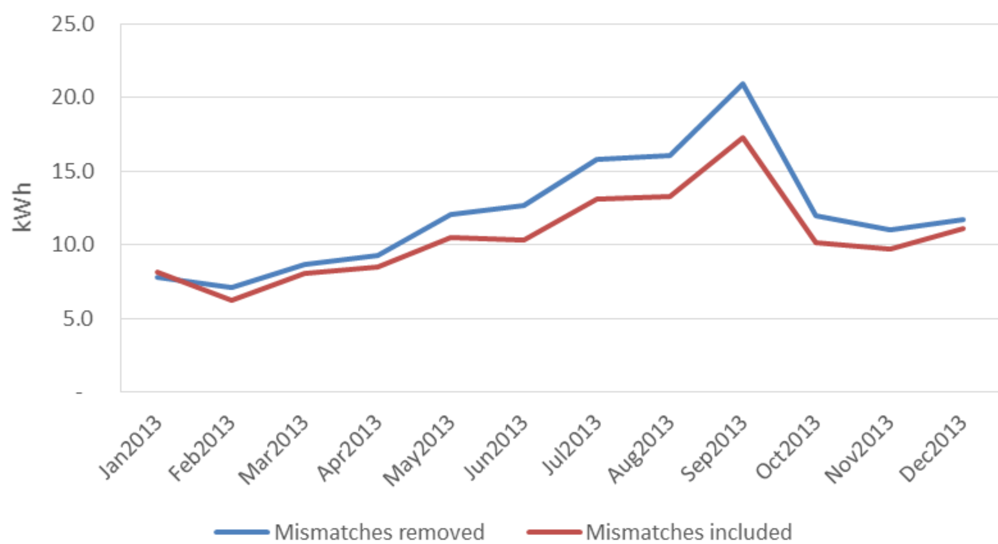
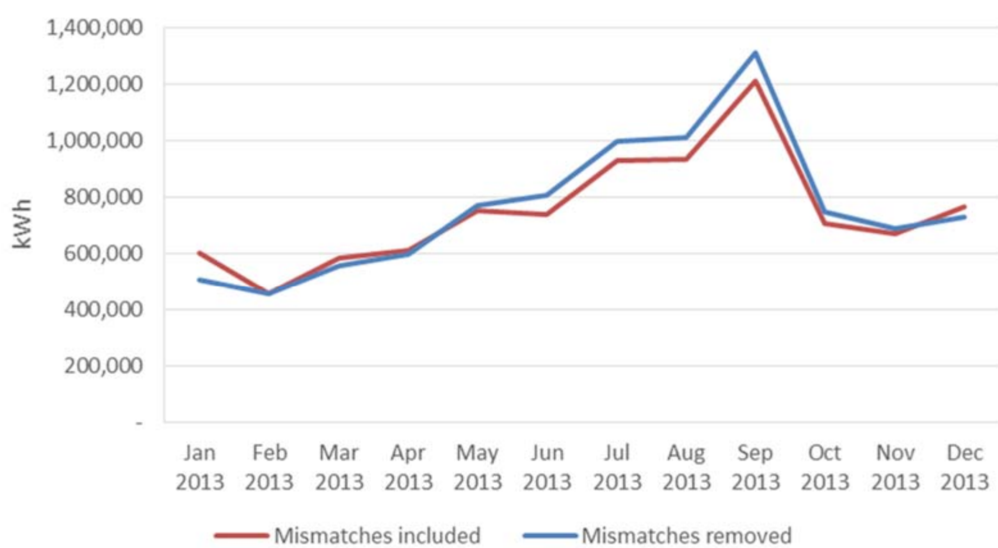


Table A-2. Total Program Savings with Mismatched Addresses Removed and Included

Month	Mismatches Included			Mismatches Removed		
	Participants	Average Per-Participant Savings (kWh)	Total Savings (kWh)	Participants	Average Per-Participant Savings (kWh)	Total Savings (kWh)
Jan 2013	73,569	8.1	599,423	64,893	7.8	504,349
Feb 2013	73,101	6.2	454,148	64,556	7.1	458,397
Mar 2013	72,734	8.0	582,276	64,315	8.6	554,636
Apr 2013	72,335	8.4	610,799	64,053	9.3	594,996
May 2013	71,921	10.5	753,455	63,787	12.0	767,567
Jun 2013	71,448	10.4	739,611	63,493	12.7	806,052
Jul 2013	70,970	13.1	930,293	63,189	15.8	995,934
Aug 2013	70,523	13.3	934,503	62,918	16.0	1,008,868
Sep 2013	70,133	17.3	1,211,883	62,659	20.9	1,308,749
Oct 2013	69,776	10.2	708,335	62,421	11.9	745,494
Nov 2013	69,419	9.7	671,823	62,186	11.0	686,488
Dec 2013	69,105	11.1	763,878	61,976	11.7	727,381
	Total Program Savings		**8,960,429**	**Total Program Savings**		**9,158,911**

Figure A-2. Comparison of Total Program Savings, With and Without Mismatched Address Accounts



Appendix B – Regression Model Output

Fixed-effects (within) regression	Number of obs = 2943926
Group variable: account_id	Number of groups = 131728
R-sq: within = 0.4927	Obs per group: min = 6
between = 0.0082	avg = 22.3
overall = 0.1647	max = 23
	F(36,131727) = 10895.26
corr(u_i, Xb) = -0.0009	Prob > F = 0
(Std. Err. adjusted for 131728 in account_id)	

Norm kWh	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
m2	-33.882	0.402585	-84.16	0	-34.671	-33.0929
m3	-53.2859	0.435742	-122.29	0	-54.1399	-52.4318
m4	-63.8896	0.518681	-123.18	0	-64.9063	-62.873
m5	-22.9354	0.675215	-33.97	0	-24.2588	-21.612
m6	53.76374	0.826101	65.08	0	52.1446	55.38289
m7	164.8543	1.099342	149.96	0	162.6996	167.009
m8	244.7991	2.15818	113.43	0	240.5691	249.0291
m9	164.1751	2.18729	75.06	0	159.888	168.4621
m10	11.24025	1.037722	10.83	0	9.206333	13.27417
m11	-45.459	0.602249	-75.48	0	-46.6394	-44.2786
norm_cdd	1.825756	0.010891	167.65	0	1.804411	1.847102
postxm1	38.35141	0.931158	41.19	0	36.52636	40.17647
postxm2	-7.82535	0.79508	-9.84	0	-9.38369	-6.26701
postxm3	-37.5951	0.727865	-51.65	0	-39.0217	-36.1685
postxm4	-35.2518	0.703345	-50.12	0	-36.6303	-33.8732
postxm5	-18.4417	0.726542	-25.38	0	-19.8657	-17.0177
postxm6	-10.212	0.868759	-11.75	0	-11.9147	-8.50922
postxm7	-11.299	1.149842	-9.83	0	-13.5527	-9.04537
postxm8	-115.008	1.935776	-59.41	0	-118.802	-111.214
postxm9	-40.5478	1.835547	-22.09	0	-44.1454	-36.9502
postxm10	-64.8112	1.028023	-63.04	0	-66.8261	-62.7963
postxm11	-31.581	0.774542	-40.77	0	-33.0991	-30.0629
postxm12	12.71696	0.984227	12.92	0	10.78789	14.64602
postxcdd	0.357971	0.008755	40.89	0	0.340812	0.375131
postxtrtxm1	-8.7548	1.360743	-6.43	0	-11.4218	-6.08777
postxtrtxm2	-8.69139	1.199168	-7.25	0	-11.0417	-6.34104
postxtrtxm3	-8.6731	1.091489	-7.95	0	-10.8124	-6.5338
postxtrtxm4	-9.4524	1.054677	-8.96	0	-11.5196	-7.38525
postxtrtxm5	-10.8351	0.982251	-11.03	0	-12.7603	-8.90994
postxtrtxm6	-12.5152	1.206336	-10.37	0	-14.8796	-10.1508
postxtrtxm7	-14.2118	1.545545	-9.2	0	-17.241	-11.1826
postxtrtxm8	-16.0067	1.571708	-10.18	0	-19.0872	-12.9262
postxtrtxm9	-18.0985	1.732881	-10.44	0	-21.495	-14.7021
postxtrtxm10	-12.1283	1.115036	-10.88	0	-14.3138	-9.94286
postxtrtxm11	-11.1569	1.214528	-9.19	0	-13.5373	-8.7764
postxtrtxm12	-12.9554	1.392715	-9.3	0	-15.6851	-10.2257
Intercept	777.0984	0.603412	1287.84	0	775.9157	778.2811

sigma u | 419.29546

sigma e | 212.18102

rho | 0.79612872 (fraction of variance due to u_i)