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Evaluation Report: OPOWER SMUD Pilot Year2

Presented to

OPOWER , Inc.

February 20, 2011

Presented by:

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February 20, 2011

Re: OPOWER 2 ½ Year Results at Sacramento Municipal Utility District

To Whom it May Concern:

OPOWER is pleased to share the latest analysis of the nation's longest running behavioral energy program, our 35,000 household Home Energy Report deployment with Sacramento Municipal Utility District (SMUD). The analysis was led by Bill Provencher, Associate Director of the Navigant Consulting Energy Practice, and reviews data from April 2008 to October 2010.

Navigant confirms the persistence, and even increase, of savings over the program's lifetime.

The key findings of the updated report are:

- Year 2 savings = 2.89%, a 22% increase over Year 1
- Highest savings occur during the peak season: 3.56% savings in July and August of 2009
- **No sign of impact deterioration** over 30 months

This independent analysis validates OPOWER's internal assessment of the Home Energy Reports, and confirms the persistence and predictability of the Home Energy Reporting platform. This same M&V methodology is currently being employed to verify the impact of our program at 47 other utilities across the nation, where OPOWER is observing similar savings.

For more information about the SMUD analysis, or the impact of Home Energy Reports at other utilities, please contact results@opower.com.

Sincerely,

Ogi Kavazovic
VP, Strategy and Marketing

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Executive Summary

Information technologies designed to assist and encourage customers to use less energy are increasing in the industry. OPOWER, Inc. offers an information program to help residential customers manage their electricity use by providing regular reports –called Home Electricity Reports—about the customer's electricity consumption. Along with other information, these reports compare a household's electricity use to that of its neighbors and suggest actions the household can take to reduce its electricity use. It is hypothesized that presentation of energy use in this comparative fashion creates a "social nudge" that induces households to reduce their electricity use.

This hypothesis is being tested in a three-year pilot of the OPOWER program in the Sacramento Municipal Utility District (SMUD) that began in spring 2008. The program consists of an experimental design across Census blocks in which blocks were randomly assigned to treatment and control groups. 35,000 single-family residential customers in the treatment group receive regular reports on how their energy use compares to their neighbors' energy use. Treatment households with high consumption in 2007 receive monthly reports, and households with low consumption receive quarterly reports. 50,000 single-family customers in the control group did not receive any reports. Billing data has been assembled for all customers beginning the year prior to the start of the program.

Several studies have examined the results of the first year of the SMUD OPOWER pilot program, including an analysis done by Summit Blue Consulting (now part of Navigant Consulting). All studies concluded that program savings in the first year was about 2.1%. The robustness of the savings estimates across studies is due largely to the experimental design of the program. The experimental design makes the identification of program savings robust to the specification of the econometric model used to estimate savings.

This report presents an evaluation of the first 29 months of the program, with an emphasis on the second year of the program. The main research questions addressed in the evaluation and presented in this report are the following:

A. Does the program continue to generate savings?
B. What is the trend in program savings? Is there a ramp-up period to savings? If so, for how long? Are savings now relatively stable, increasing, or falling?
C. Do program savings increase with usage?

A. Does the program continue to generate savings?

The program continues to generate savings:

- Average savings in program Year 2 were 2.89% for high consumption (HC) households receiving monthly reports, and 1.70% for low consumption (LC) households receiving quarterly reports.
- Year 2 average household savings is 381 kWh for HC households and 104 kWh for LC households.
- Average household savings through the first 29 months of the program is 878 kWh for HC households and 234 kWh for LC households.

B. What is the trend in program savings?

Program savings are characterized by temperature-driven seasonal fluctuations around a baseline trend. For HC households, the baseline trend ramped up through the first 10-12 months and appears to have remained fairly constant since then:

- Average percent savings in program Year 2 are higher than in Year 1, 2.89% compared to 2.37%, which is a 22% increase in savings in the second year. The increase is statistically significant.
- Statistical analysis indicates that the long term trend for savings leveled off at about 10-12 months, and has remained fairly constant since then. In other words, after the first year of the program the fundamental effectiveness of the program does not appear to have changed substantially.
- Statistical analysis supports a long term savings trend of about 380 kWh per year, approximately 2.9% per year.
- Additional analysis after the program has been in place for a full three years, with data for at least three occurrences of each season, should give a better indication of whether the long term trend in savings is indeed constant or instead showing signs of rising or falling.

For LC households, program savings continue to trend upward:

- Average percent savings in program Year 2 are higher than in Year 1, 1.70% compared to 1.25%, which represents a 36% increase in savings.
- Statistical analysis indicates that program savings continue to trend upward through the first 29 months of the program.

C. Do program savings increase with electricity use?

For both HC and LC households, program savings reveal strong seasonal effects, with savings highest in the seasons of highest electricity use, summer and winter. For instance, in Year 2 (spring 2009-winter 2010) the average kWh savings for HC households in the seasonal sequence spring-summer-fall-winter was 80-123-84-97 kWh. The same sequence for LC households was 13-36-20-33 kWh.

The seasonality of savings is especially apparent in the pronounced rise in savings in the months of July and August. For HC households the percent savings for these months is 3.56% in summer 2009 and 3.27% in summer 2010. The difference between these percent savings is not statistically significant at any reasonable level of significance (the t-statistic on the difference is 1.2).

D. Graphical summary

Figures E1 and E2 present the trends in annual program savings for HC and LC households over months 6-29 of the OPOWER program. The figures abstract from seasonal fluctuations in program savings by setting heating and cooling degree days at their annual averages. The figures illustrate several of the points made above:

- For HC households, program savings appear to have remained constant on an annual basis after an initial ramp-up period of about 10-12 months; the tail end of the ramp-up period is apparent in months 6-12 of figure E1. The long run annual savings of about 380 kWh is a savings of approximately 2.9% per year.
- For LC households, program savings continue to trend upward.

Figure E3 presents monthly fluctuations in program savings directly attributable to fluctuations in temperatures during the program period. The figure illustrates that:

- Program savings are highest in the summer and winter months, with the summer response especially pronounced for HC households;
- Fluctuations follow the same pattern for HC and LC households, with fluctuations for HC household scaled up by a factor of about 2.5 relative to LC households.

Figure E1. Trend in annual program savings, HC households, program months 6-29 (September 2009-August 2010).

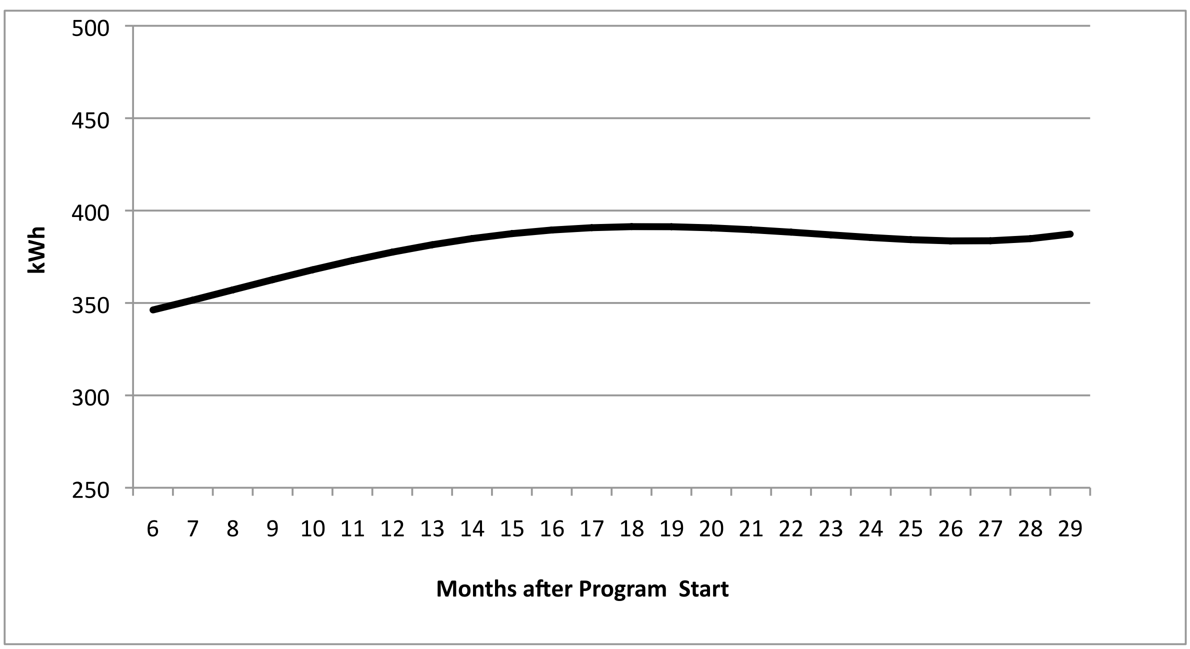


Figure E2. Trend in annual program savings, LC households, program months 6-29 (September 2009-August 2010).

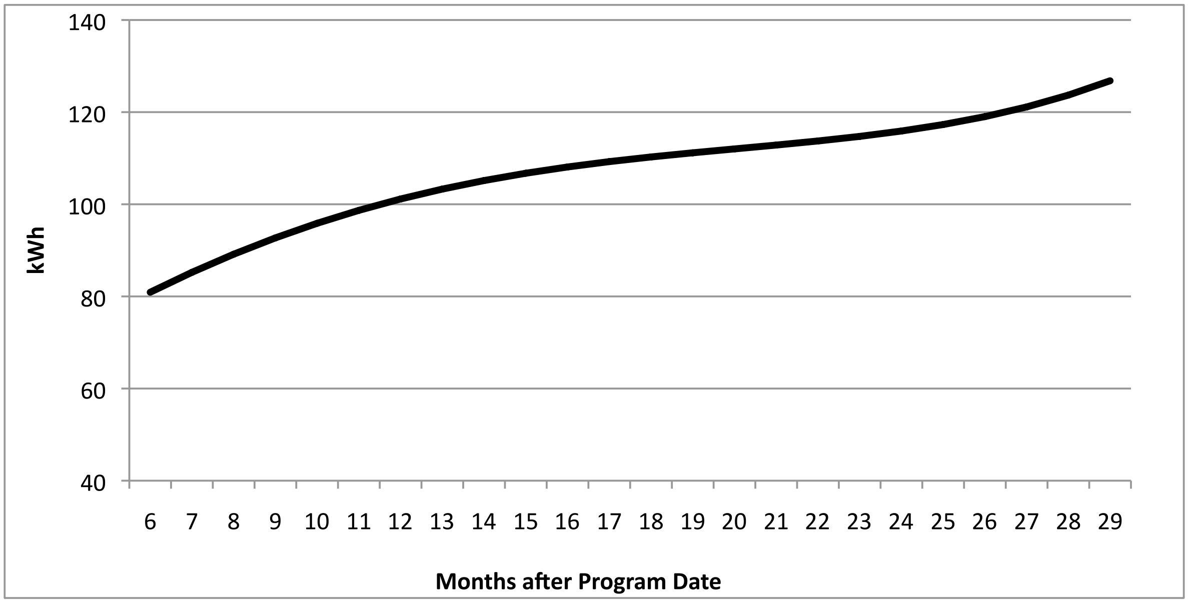
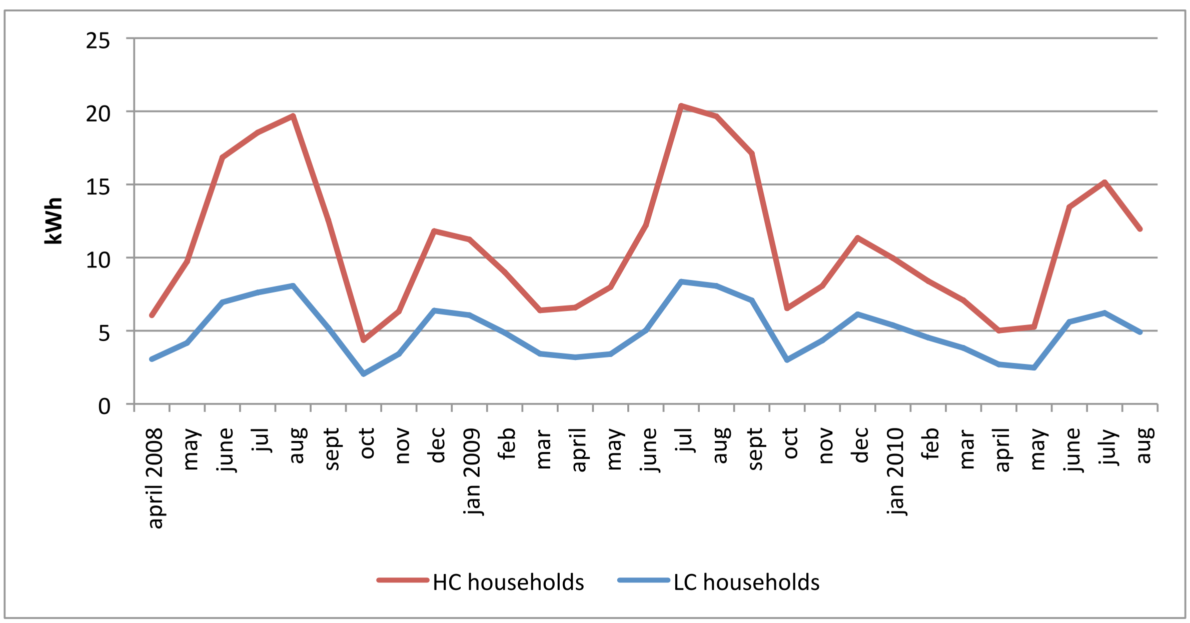


Figure E3. Estimate of temperature-related monthly program savings



I. Program Description and Evaluation Objectives

OPOWER, Inc. offers an information program to help residential customers manage their electricity use by providing regular reports –called Home Electricity Reports—about the customer's electricity consumption. Along with other information, these reports compare a household's electricity use to that of its neighbors and suggest actions the household can take to reduce its electricity use. It is hypothesized that presentation of energy use in this comparative fashion creates a "social nudge" that induces households to reduce their electricity use.

This hypothesis is being tested in a three-year pilot of the OPOWER program in the Sacramento Municipal Utility District (SMUD) that began in spring 2008, with initial reports mailed between March 14 and April 30. The objective of the pilot is to test whether, and to what extent, the OPOWER program reduces residential electricity consumption. The reports give customers three types of information: a) how their recent electricity use compares to their energy use in the past; b) tips on how to reduce electricity consumption, some of which are tailored to the customer's circumstances (e.g. customers with electric heat receive information on how to reduce electricity consumption by electric heating systems); and c) most strikingly, information on how their electricity use compares to that of neighbors with similar homes.

Importantly, the program was set up as an experimental design. Households were randomly assigned between those that receive the Home Electricity Reports (treatment group) and those that do not receive them (control group), by census block. In particular, sets of 5 contiguous census blocks were randomly assigned in turn to the treatment and then the control group until the threshold 35,000 households in the treatment group was reached, at which point the remaining census blocks were assigned to the control group, generating about 50,000 control households. Ayres et al. established that treatment households generally are not different than control households, either statistically or substantively, on a number of characteristics, including house value, heat type (gas vs. electric), square footage (statistically significant, but with an average of 1,737 sq. ft. for treatment households and 1,753 sq. ft. for control households), and quartile income group.[1]

Most treatment households (24,761) received reports on a monthly basis, and the remainder (9,903) received the reports on a quarterly basis. Assignment to monthly vs. quarterly reports was not random; households receiving monthly reports were generally higher energy consumers than households receiving quarterly reports. For instance, among the treatment households examined in the analysis presented in this report, 98.8% of those receiving monthly reports consumed more than 20 kWh per day in 2008, whereas only 16.6% of those receiving quarterly reports consumed more than 20 kWh per day.

Several studies have examined the results of the first year of the OPOWER program, including an analysis done by Summit Blue Consulting (now part of Navigant Consulting).[2] All studies

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[1] Ayres, Raseman and Shih, 2009, Table A1, pg. 29. See footnote 2 for full citation.
[2] These studies include:

Ayres, I., S. Raseman and A. Shih. "Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage", NBER working paper no. 15386, September 2009.

Costa, D.L. and M.E. Kahn. "Energy Conservation "Nudges" and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment", NBER working paper no. 15939, April 2010.

concluded that program savings in the first year was about 2.1%. The robustness of the savings estimates across studies is due largely to the experimental design of the program. The experimental design makes the identification of program savings robust to the specification of the econometric model used to estimate program savings.

This report presents an evaluation of the first 29 months of the program, with an emphasis on the second year of the program. The main research questions addressed in the evaluation, and presented in this report, are the following:

D. Does the program continue to generate savings?
E. What is the trend in program savings? Is there a ramp-up period to savings? If so, how long? Are savings now relatively stable, increasing, or falling?
F. Do program savings increase with usage?

Summit Blue Consulting (now a part of Navigant Consulting). "Impact Evaluation of OPOWER SMUD Pilot Study". September 2009, unpublished.

II. Impact Evaluation Methods

Two statistical analyses were used to estimate savings during the first year of the program. These methods are a) difference-in-difference (DID) analysis, and b) linear fixed effects regression(LFER) analysis. Below we describe these methods, emphasizing that the DID estimate of program savings can be recovered using a simple LFER analysis.

A. Difference-in-Difference (DID) analysis

Assuming random assignment of treatment and control customers, a simple difference-in-difference (DID) statistic provides an unbiased estimate of the average customer savings in energy use (measured in kWh) from the treatment for a given period, such as a year or a season. The basic logic of the estimator is that the average difference among treatment customers in energy consumption before treatment and after treatment is due in part to the treatment and in part to unobserved temporal factors affecting energy consumption. A set of control customers is used to isolate the part that is due to unobserved temporal factors. Calculating this same difference for the set of control customers and subtracting this value from that obtained for treatment customers isolates the portion of the change in consumption among treatment customers that is due to the treatment (i.e., the OPOWER program).

Formally, we denote by $\overline{kWh}_{pg}$ the average daily kWh use in period *p* (*p*=0 for the pre-treatment period, *p*=1 for the post-treatment period) by customers in group *g* (*g*=0 for the control group, *g*=1 for the treatment group).[3] The length of time over which average daily kWh is measured depends on the question being asked; for instance, the period could be a year or a season. The DID statistic is the difference between the control and treatment groups in the *change* in their annual rate of kWh use across the pre- and post-treatment periods. Formally,

$$\begin{aligned} Treatment\ Effect &= DID = \left(\overline{kWh}_{11} - \overline{kWh}_{01}\right) - \left(\overline{kWh}_{10} - \overline{kWh}_{00}\right) \\ &= Dif\left(\overline{kWh}_{1}\right) - Dif\left(\overline{kWh}_{0}\right) \end{aligned}, \qquad (1)$$

where $Dif\left(\overline{kWh}_{g}\right)$ is the *difference* in average daily kWh consumption across periods for customers in group g. Dividing the DID statistic by the average daily kWh consumption of the treatment group in the post-treatment period gives the proportional reduction from treatment,

$$Proportional\ Treatment\ Effect = \frac{Dif\left(\overline{kWh}\right)}{\overline{kWh}_{11}}. \qquad (2)$$

B. Linear Fixed Effects Regression (LFER) model

The simplest version of a linear fixed effects regression (LFER) model convenient for exposition is one in which average daily consumption of kWh by customer *k* in bill t, denoted by ADU_{kt}, is a function of three terms: the binary variable $Treatment_k$, taking a value of 0 if customer *k* is

[3] Both the control and treatment groups could be subsets, such as the set of high consumption households.

assigned to the control group, and 1 if assigned to the treatment group; the binary variable $Post_t$, taking a value of 0 if bill t is before the customer's *program start date* and 1 if the bill is received on or after the program start date; and the interaction between these variables, $Treatment_k \cdot Post_t$. Formally,

$$ADU_{kt} = \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t + \varepsilon_{kt} \tag{3}$$

We refer to this model as the "Basic LFER model". Three observations about this specification deserve comment. First, the coefficient α_{0k} captures *all* customer-specific effects on electricity use that do not change over time, including those that are unobservable. Second, α_1 captures the average effect *among control customers* of being in the post-treatment period. In other words, it captures the effects of exogenous factors, such as an economic recession, that affect all customers in the post-treatment period but not in the pre-treatment period. Third, $\alpha_1 + \alpha_2$ captures the average effect *among treatment customers* of being in the post-treatment period, and so the effect directly attributable to the OPOWER program is captured by the coefficient α_2. In other words, this coefficient captures the *difference-in-difference* in average daily kWh use between the treatment group and the control group across the pre- and post-treatment periods. Consequently the DID statistic can be estimated by simply estimating equation (3).

Expanding the basic LFER model to account for degree days

In a second model the simple LFER model described above is expanded to include two weather-related variables: heating degree days per day ($HDDd_t$) in bill period t, and cooling degree days per day, $CDDd_t$. For each of these, four terms are added to the model: the variable itself; the variable interacted with $Treatment_k$ to capture differential effects of the variable specific to the treatment group; the variable interacted with $Post_t$ to capture differential effects of the variable due to exogenous shocks across the pre- and post-treatment periods; and the variable interacted with the interaction $Treatment_k \cdot Post_t$ to capture the effect of the variable on the treatment response (that is, how the variable affects program savings).

Formally, we expand our basic LFER model to the following:

$$\begin{aligned}ADU_{kt} &= \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t \\ &+ \beta_0 HDDd_t + \beta_1 HDDd_t \cdot Treatment_k + \beta_2 HDDd_t \cdot Post_t + \beta_3 HDDd_t \cdot Treatment_k \cdot Post_t \\ &+ \gamma_0 CDDd_t + \gamma_1 CDDd_t \cdot Treatment_k + \gamma_2 CDDd_t \cdot Post_t + \gamma_3 CDDd_t \cdot Treatment_k \cdot Post_t + \varepsilon_{kt}\end{aligned} \tag{4}$$

We refer to this model as the "degree day model". In this model, the average daily treatment effect (ADTE) is the sum of the terms involving the variable $Treatment_k$:

$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3 CDDd_t \,. \tag{5}$$

Note, then, that the treatment effect changes across seasons because of seasonal changes in *HDDd* and *CDDd*. The coefficients on these variables in (5) indicate the average effect on a customer's program savings of a 1-unit increase in heating or cooling degree days.

Expanding the degree day model to examine savings trends

The second objective of the evaluation (see page 7) is to determine the length of a ramp-up period and whether the trend in program savings is increasing, decreasing, or remaining steady. We address this objective by including in the LFER model trend variables involving the root variable $PostTrend_t$, which takes a value of 0 in the period before the customer's program start date and increases by 1 with each bill received by the customer beginning with the program start date. Consider, for instance, the following linear trend:

$$
\begin{aligned}
ADU_{kt} = {} & \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t \\
& + \beta_0 HDDd_t + \beta_1 HDDd_t \cdot Treatment_k + \beta_2 HDDd_t \cdot Post_t + \beta_3 HDDd_t \cdot Treatment_k \cdot Post_t \\
& + \gamma_0 CDDd_t + \gamma_1 CDDd_t \cdot Treatment_k + \gamma_2 CDDd_t \cdot Post_t + \gamma_3 CDDd_t \cdot Treatment_k \cdot Post_t \\
& + \lambda_0 PostTrend_t + \lambda_1 Treatment_k \cdot PostTrend_t + \varepsilon_k
\end{aligned}
\tag{6}
$$

Note that in this specification the root variable $PostTrend_t$ appears both separately and interacted with the treatment variable $Treatment_k$. This specification recognizes that energy consumption in the post-treatment period may be trending quite apart from the program effect, and uses the interaction with the treatment variable to identify whether the program is causing a divergence from this general trend.

The problem with a linear trend is that it is not sufficiently flexible to allow for a period of stasis in the treatment effect, whereby, after correcting for heating and cooling degree days, the program settles down into a fairly constant rate of program savings. With a linear trend the program effect is constrained to be always increasing, always decreasing, or always constant. This is not a sensible model for analyzing long term trends given that the program quite likely involves an initial ramp-up period.

A quadratic specification would provide greater flexibility –it allows savings to rise and then fall—but it too is not flexible enough to account for periods of stasis. With this in mind, we estimate LFER models with polynomial trends ranging from 1st order (linear) to 4th order (quartic). Increasing the polynomial trend increases the size of the LFER model by two terms involving the root variable $PostTrend_t$. For instance, the LFER model with a quadratic trend takes the form,

$$
\begin{aligned}
ADU_{kt} = {} & \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t \\
& + \beta_0 HDDd_t + \beta_1 HDDd_t \cdot Treatment_k + \beta_2 HDDd_t \cdot Post_t + \beta_3 HDDd_t \cdot Treatment_k \cdot Post_t \\
& + \gamma_0 CDDd_t + \gamma_1 CDDd_t \cdot Treatment_k + \gamma_2 CDDd_t \cdot Post_t + \gamma_3 CDDd_t \cdot Treatment_k \cdot Post_t \\
& + \lambda_0 PostTrend_t + \lambda_2 Treatment_k \cdot PostTrend_t + \lambda_3 PostTrend_t^2 + \lambda_4 Treatment_k \cdot PostTrend_t^2 + \varepsilon_k
\end{aligned}
\tag{7}
$$

The treatment effect for the linear trend model in (6) is the following:

$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3 CDDd_t + \lambda_1 \cdot PostTrend_t. \tag{8}$$

Note that the treatment effect depends on the time elapsed since the beginning of the program. Similarly, the treatment effect for the quadratic trend is,

$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3\, CDDd_t + \lambda_2 \cdot PostTrend_t + \lambda_4\, PostTrend_t^2 . \quad (9)$$

Following this pattern, the treatment effects for the cubic and quartic trend models are:

$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3\, CDDd_t + \lambda_2 \cdot PostTrend_t + \lambda_4\, PostTrend_t^2 + \lambda_6\, PostTrend_t^3$$
$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3\, CDDd_t + \lambda_2 \cdot PostTrend_t + \lambda_4\, PostTrend_t^2 + \lambda_6\, PostTrend_t^3 + \lambda_8\, PostTrend_t^4$$

(10)

Increasing the size of the polynomial provides great flexibility in fitting the model to the program effect, though at the cost of increasing the number of "turning points" in the fit. For this reason the observation of a turning point, especially at the edge of the data range, should be interpreted with considerable caution. A turning point could be an artifact of the parametric form of the model used to fit the data, rather than an actual change in the trend in program savings. We limited the analysis to polynomial trends of 4^{th} order and lower because for polynomial fits up to the fourth order, all terms of the polynomial involving the interaction with $Treatment_k$ were statistically significant. Higher-order polynomials generated nonsignificant terms.

III. Impact Evaluation Results

A. Results of DID estimation

Results for the DID estimation are presented in Table 3.1. Results are graphically summarized in Figure 3.1-3.4. Relevant baseline consumption and heating and cooling degree days for the various periods of the analysis are presented in Table A.1 in Appendix A.

For the analysis of annual savings the sample of treatment and control customers was restricted to those with:

- 12 bills in the 375 days before the customer's program start date;
- 12 bills in the 355 days after the customer's program start date, the program start date inclusive (first year of the program); and
- 12 bills in the subsequent 375 days (second year of the program).

A customer's program start date was the date of the first bill *after* the bill in which the first report was included. The appropriate point of reference for evaluating the program is the program start date, rather than the bill date of first receipt of the report, because it is the former date that includes the initial response of the customer to the report information. The departure from exactly 365 days before and after the program start date in the specification of the pre- and post-treatment periods is to account for small deviations in the actual delivery dates for bills.

The analysis of seasonal effects restricted the data to bills falling within season dates.[4] To be included in a seasonal analysis a customer must have received 2-4 bills in both the pre-treatment and post-treatment seasons. The pre-treatment periods for seasonal analyses were summer 2007, fall 2007, winter 2007-08, and spring 2008.

The following results emerge from Table 3.1 and Figures 3.1-3.4:

- *Over the 30-month period, savings averaged about 2.6% for high consumption (HC) households and about 1.5% for low consumption (LC) households;*

- *For both HC and LC households, second year savings were greater than first year savings. For HC households, savings were 2.32% in the first year and 2.85% in the second year, and for LC households savings were 1.30% in the first year and 1.79% in the second year.*[5]
- *Over the past year the percent savings for HC households has remained constant at about 2.7% per year;*

- *The percent savings for LC households appears still to be trending upwards after 30 months.*

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[4] Season dates were Fall: September 15-December 14; Winter: December 15-March 14; Spring: March 15-June 14; Summer: June 15-September 14.
[5] Recent studies of the first year of the SMUD OPOWER program, including the one conducted by Summit Blue/Navigant, report savings of roughly 2.1%. This figure applies to HC and LC households combined. In our analysis, combining HC and LC households generates first year savings of 2.1%. The heavy weighting towards the HC estimate reflects the greater number of HC households and their high consumption levels.

Extension of DID results: Examination of the summer months July-August

As requested we conducted a DID analysis of the two summer months July and August. Before presenting these results we use the illustration in Figure 3.5 to emphasize several important caveats about examining treatment effects using billing data over very short time horizons (one or two months). The figure considers a one-month billing period (July) and assumes that the billing of these households is uniformly distributed over the month –a good approximation of the billing data in this evaluation. The dates of June 1 and July 31 are covered by only one out of every 31 July bills (about 3.2%); the dates of June 2 and July 30 covered by two out of every 31 July bills (about 6.4%); June 3 and July 29 are covered by three out of every 31 July bills; and so on, with July 1 covered by *all* bills. This pyramidal sampling has several implications:

1. An analysis of bills at the monthly level is not an analysis of the treatment effect for the month per se, but rather is an analysis of the treatment effect *centered on the first day of the month*.
2. The estimate of the treatment effect is much more heavily influenced by unobserved events around the 1st of the month than by unobserved events late in the month or early in the previous month, suggesting correlated errors across households according to bill dates;
3. Analysis of the treatment effect on a monthly basis will exhibit greater volatility than truly applies on a monthly basis (where each day of the month receives an equal number of observations), because of the "center-weighting " illustrated in Figure 3.5.

The first point above—that analyzing data by the bill month does not give the treatment effect for the month, but rather a weighted estimate for the effect centered on the first of the month—is especially salient in the case of July because July 4th weekends can be 3 or 4 days long, and thus behavior during this period has an inordinate effect –inordinate if the analyst falsely believes that the measurement applies to average July behavior—on the estimate of the treatment effect.

Extending the analysis period serves to eliminate or at least substantially reduce the sampling issues raised above. Figure 3.6 considers the probability that a date is represented in a household's bills dated between July 15 and September 15, the bill dates that best cover the period July-August. Every household has a bill covering July 15-August 15. The 30-day plateau implies lower correlation of errors across households and reduced volatility. The plateau is centered on August 1.

Figures 3.7-3.8 present DID estimation results for July-August 2008, 2009, and 2010 for high consumption (HC) and low consumption (LC) households, respectively. Relevant baseline consumption and heating and cooling degree days are presented in Table A.1 in Appendix A. In the analysis we used bill dates between July 15 and September 15. If instead we had used bills in the period July 1- August 31 –the intuitive selection criterion for a July-August analysis—the analysis would have involved a 30-day plateau extending from *July 1 –July 30* and centered on July 15. Results are presented in terms of the percent of the average household kWh consumption for the time period, with actual kWh savings indicated in the figures. For HC households the percent savings rises from 2.97% in summer 2008 to 3.56% in summer 2009, before falling to 3.27% in summer 2010. The difference between percent savings in the summers of 2009 and 2010 is not statistically significant at any reasonable level of significance (t-statistic on the difference =1.2).

For LC households the percent savings rises from 1.31% in summer 2008 to 2.28% in summer 2009 to 2.66% in summer 2010. As with HC households, the difference between percent savings in the summers of 2009 and 2010 is not statistically significant (t-statistic on the difference =0.85).

Table 3.1. DID Seasonal Estimates of Program Savings[a]

Period	Statistic	Estimate for HC Households (standard error)	Estimate for LC Households (standard error)
First Year (April 2008- March 2009)	Average percent savings	2.37% (0.11%)	1.25% (0.18%)
	Average savings per customer (kWh)	317 (15)	76 (25)
Second Year (April 2009- March 2010)	Average percent savings	2.89% (0.11%)	1.70% (0.18%)
	Average savings per customer (kWh)	381 (14)	104 (11)
Summer 2008 (June 15-Sept 14)	Average percent savings	2.63% (0.12%)	0.94% 0.21%)
	Average savings per customer (kWh)	105 (5)	18 (4)
Fall 2008 (Sept 15-Dec 14)	Average percent savings	2.30% (0.14%)	1.31% (0.27%)
	Average savings per customer (kWh)	69 (4)	18 (4)
Winter 2008-09 (Dec 15 - March 15)	Average percent savings	2.65% (0.12%)	1.82% (0.23%)
	Average savings per customer (kWh)	95 (4)	28 (4)
Spring 2009 (March 15 -June 14)	Average percent savings	2.81% (0.15%)	1.02% (0.22%)
	Average savings per customer (kWh)	80 (4)	13 (3)
Summer 2009 (June 15 -Sept 14)	Average percent savings	3.27% (0.13%)	2.00% (0.24%)
	Average savings per customer (kWh)	123 (5)	36 (4)
Fall 2009 (Sept 15-Dec 14)	Average percent savings	2.70% (0.14%)	1.42% (0.29%)
	Average savings per customer (kWh)	84 (4)	20 (4)

Period	Statistic	Estimate for HC Households (standard error)	Estimate for LC Households (standard error)
Winter 2009-10 (Dec 15 - March 14)	Average percent savings	2.81% (0.12%)	2.11% (0.26%)
	Average savings per customer (kWh)	97 (4)	33 (4)
Spring 2010 (March 15 -June 14)	Average percent savings	2.73% (0.15%)	1.16% (0.23%)
	Average savings per customer (kWh)	75 (4)	15 (3)
Summer 2010 (June 15 -Sept 14)	Average percent savings	2.99% (0.18%)	2.29% (0.33%)
Sample Treatment= 18,554 *Sample Control= 27,346*	Average savings per customer (kWh)	105 (6)	39 (5)

[a]Except for minor variations, sample size for all seasons except summer 2010 is 20,200 for high consumption (monthly reports) treatment households, 29,800 for high consumption control households, 8,300 for low consumption (quarterly reports) treatment households, and 12,200 for low consumption control households. In summer 2010, SMUD reduced the number of treatment households by 10,000, and so in the analysis of summer 2010 the samples are 13,148 HC treatment households and 19,385 HC control households, 5,406 LC treatment households, and 7,961 LC control households. The reduction was done to examine the persistence of effects after discontinuation of the Home Electricity Reports, and was done by random assignment.

Figure 3.1. DID Estimates of Average Household Seasonal Savings (kWh) with 95% Confidence Intervals; *HC households (monthly reports)*

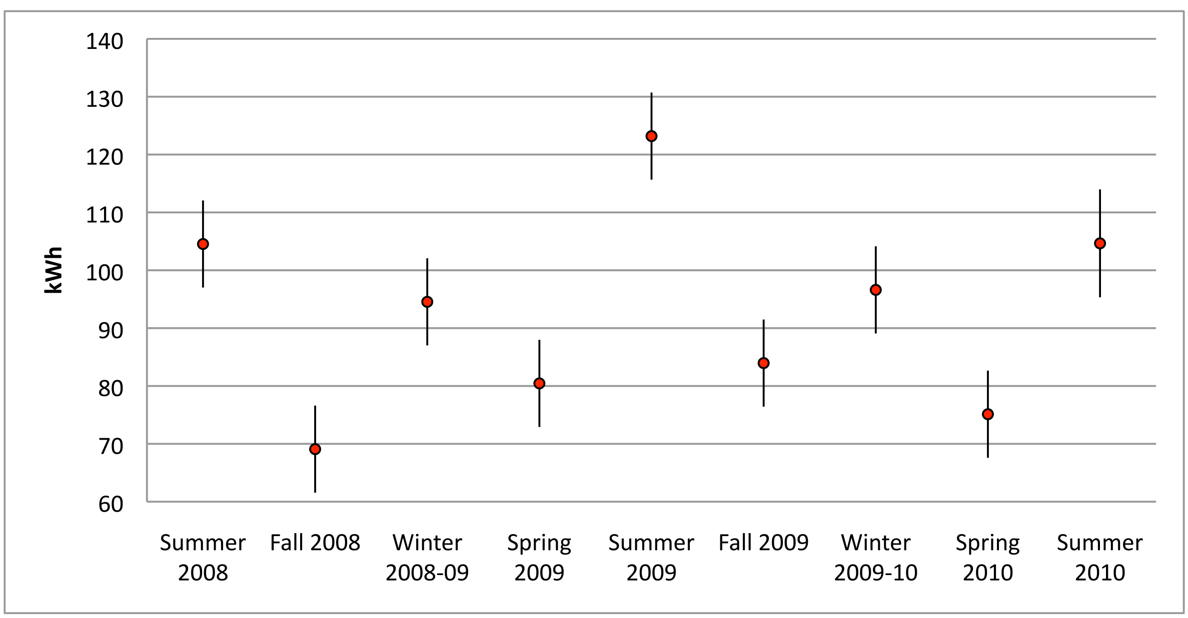


Figure 3.2. DID Estimates of Percent Seasonal Savings with 95% Confidence Intervals; *HC households (monthly reports)*

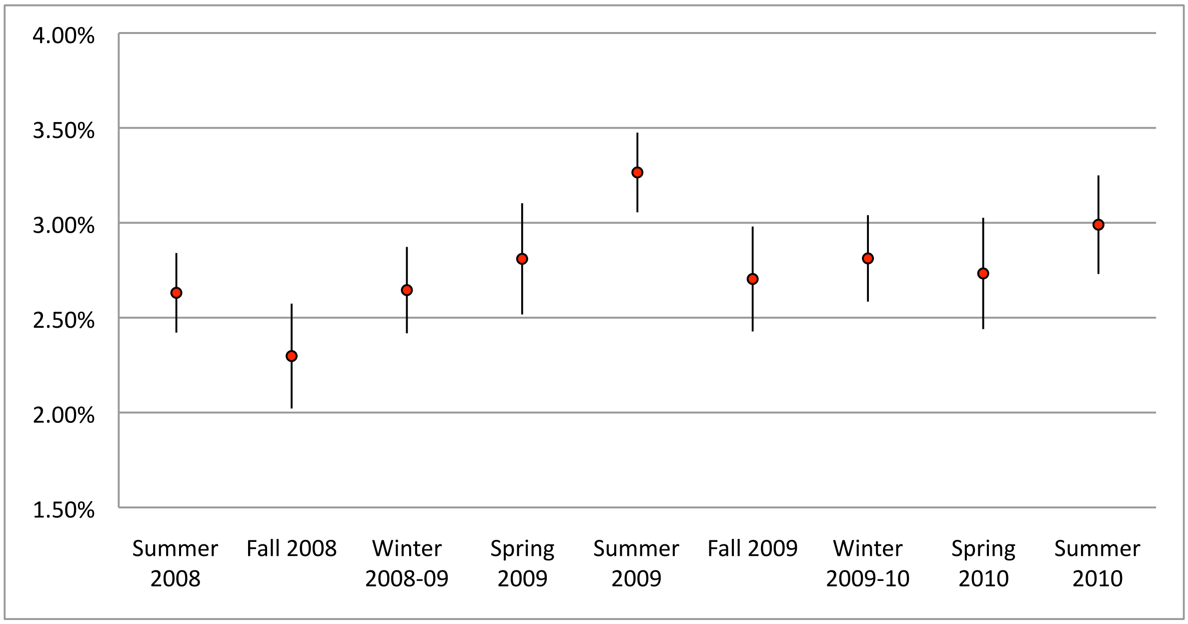


Figure 3.3. DID Estimates of Average Household Seasonal Savings with 95% Confidence Intervals; *LC households (quarterly reports)*

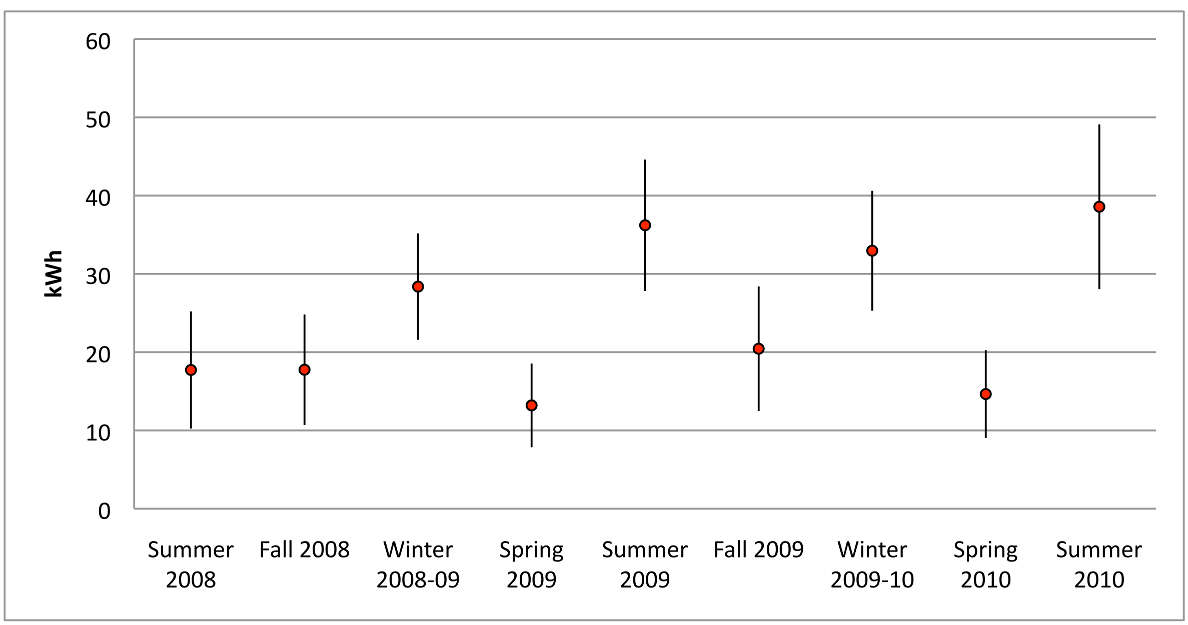


Figure 3.4. DID Estimates of Seasonal Percent Savings with 95% Confidence Intervals; *LC households (quarterly reports)*

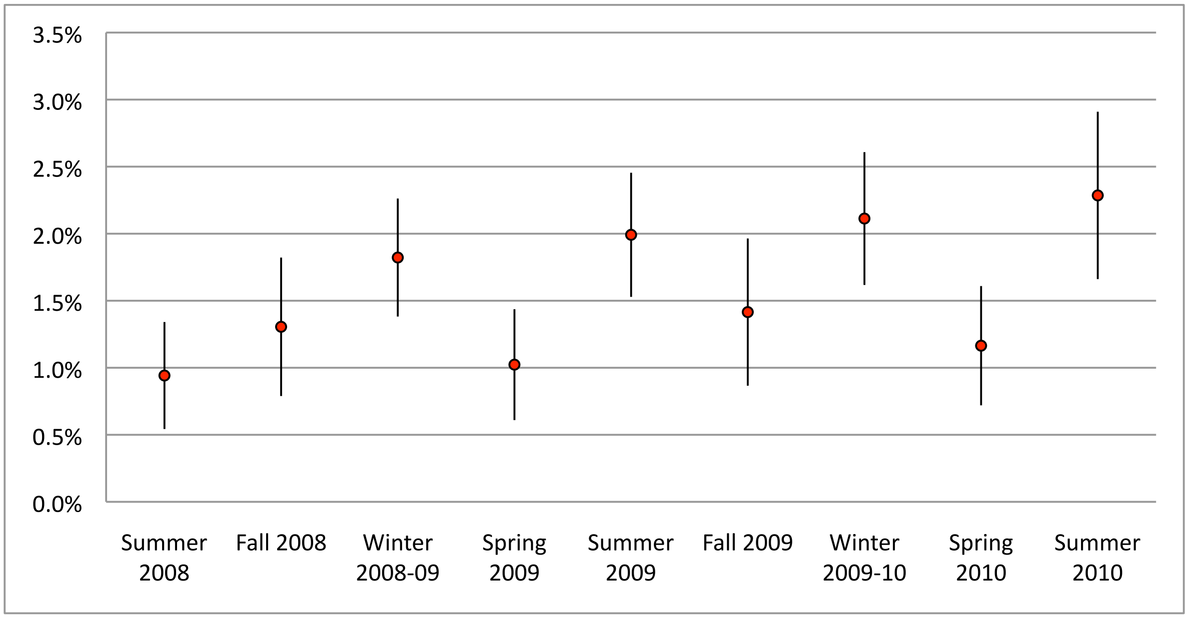


Figure 3.5. Probability that a Date is Represented in a July Bill

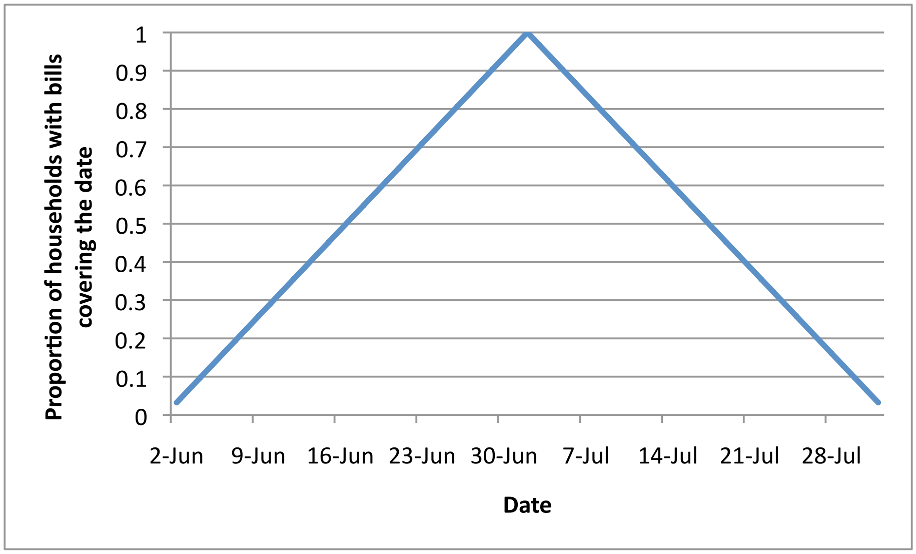


Figure 3.6. Probability that a Date is Represented in a Household's Bills Dated between July 15 and September 15

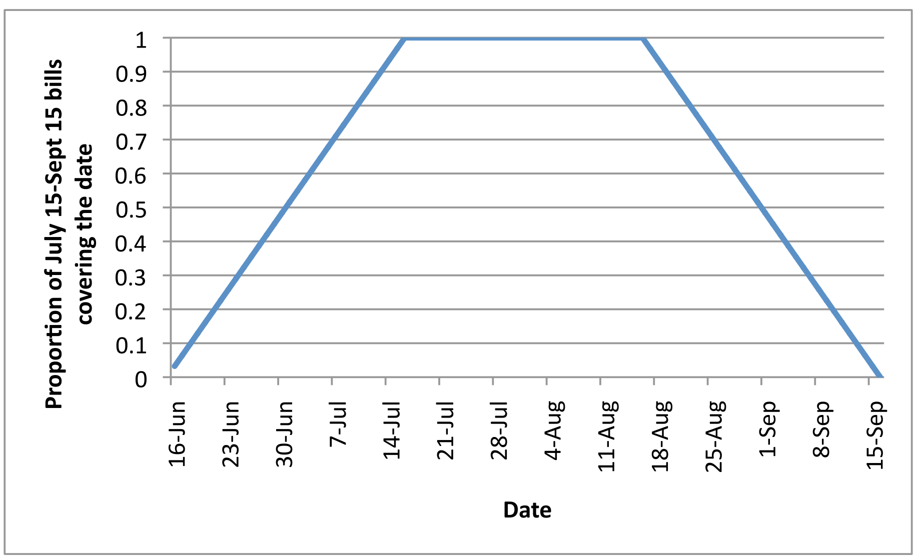


Figure 3.7. DID Estimates of July-August Average Household Percent Savings with 95% Confidence Intervals, with kWh savings indicated, *HC households (monthly reports)*

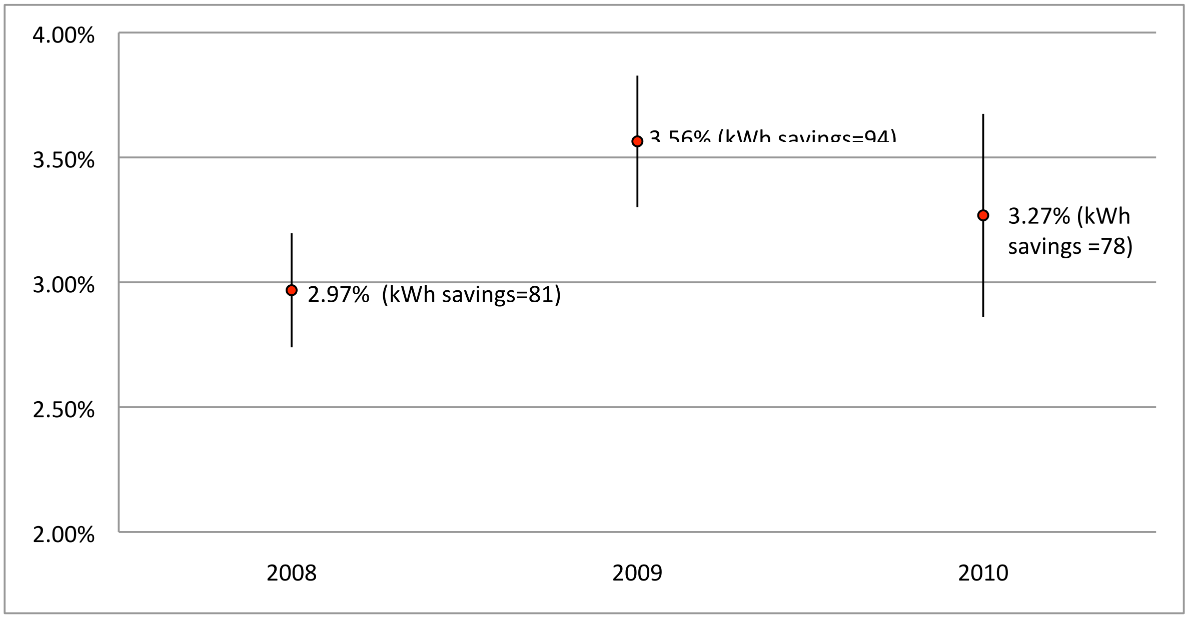
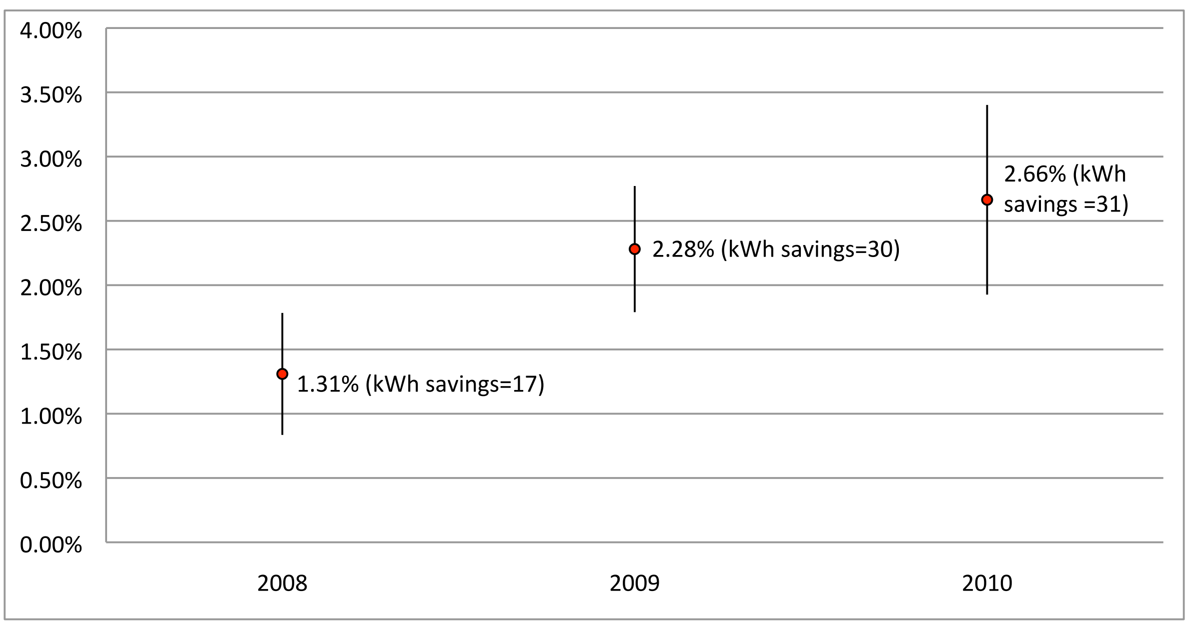


Figure 3.8. DID Estimates of July-August Average Household Percent Savings with 95% Confidence Intervals, with kWh savings indicated, *LC households (quarterly reports)*



B. Results of Linear Fixed Effects Regression (LFER) Analysis

The difference between the estimated savings for high consumption households in summer 2009 and summer 2010 presented in Figures 3.1-3.2 and 3.7 can lead one to conclude that the effectiveness of the program is waning over time, and so we arrive at a cautionary note about DID analysis: because the basic DID statistic is not conditioned on variables that change over time, such as weather variables, it is not a good basis for evaluating persistence of program effectiveness, where we define program effectiveness as program savings after accounting for random fluctuations in factors that change over time, such as weather and the overall state of the economy. In other words, *program effectiveness reflects the behavioral fundamentals of the program*.

Consider, for instance, that the summer of 2010 was about 25% cooler than the summer of 2009. To the extent that the treatment effect is greater on hotter days –a quite reasonable hypothesis— the difference in the treatment effect between the summer of 2009 and 2010 can be explained without resorting to discussions about changes in behavioral fundamentals. LFER analysis permits the analyst to condition the treatment effect on a variety of variables that change over time, thereby providing insight about the explanation for relatively low program savings in Summer 2010, and more generally, long term trends in program savings.

We estimated the degree day model and extensions involving linear, quadratic, cubic, and quartic trends for both HC and LC households to get a broad sense of ramping and persistence in program savings. Models were fit to the 12-month pre-program period and the 29-month program period for which we had sufficient data (April 2008-August 2010). Regression results for these models are presented in Tables B.1-B.5 in Appendix B. For all models the shaded rows in the tables indicate regression terms that impact estimates of program savings. In the discussion below we use these models to first examine the long term trend in program savings, and to then take up the issue of fluctuations around the long trend due to interseasonal temperature fluctuations.

Long term trend in program savings

Using the LFER results for the degree day model and its polynomial trend extensions, we developed annualized savings trends –trends scaled up to annual average savings—by using average annual heating and cooling degree days per day in the estimate of the ADTE's in (5) and (8)-(10), and then multiplying the ADTE's by 365. These annualized trends are presented in Figures 3.9 and 3.10.[6] It must be remembered that the peaks and valleys in the polynomial trends in the figures do not necessarily reflect actual behavioral changes over time, but may instead reflect the attempt to capture the overall trend in program savings with flexible functional forms that are inclined to undulate. To correct for this possibility, we average the trends produced by the four polynomial specifications, with results presented in Figures 3.11 and 3.12, with annualized savings for the degree day model (no trend) for comparison. Results appear to indicate that program savings for HC households involves a ramp-up period of about 10-12 months followed by fairly constant annual savings of about 390-400 kWh, and that program savings for LC households continue to trend upward.

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[6] Average annual heating and cooling degree days used in the figures are those for Sacramento, CA as reported by the National Climate Data Center, NOAA-USDC at
http://www.ncdc.noaa.gov/oa/climate/online/ccd/nrmcdd.html
and http://www.ncdc.noaa.gov/oa/climate/online/ccd/nrmhdd.html .

It is possible that the polynomial fits to the long-term trend for HC households is distorted by the attempt of the polynomial forms to capture the ramp-up period. With this in mind we re-estimated the four polynomial trend models for the program period 6-29 months—that is, we dropped the first 5 months of the program period from the analysis. Trend results for this model are shown in Figure 3.13, and averaging the trends generates Figure 3.14. These results support the conclusion of a ramp-up period of about 10-12 months, followed by an 18- month period to the end of the available data (September 2008 –August 2010) over which there is neither an upward nor downward trend in program savings. The steady-state annual savings appears to be closer to 380 kWh rather than the 390-400 kWh indicated in Figure 3.11.

In summary:

- *For HC households, program savings ramped up for 10-12 months and are now on trajectory of relatively constant annual savings of about 390 kWh per household;*
- *For LC households, program savings continue to trend upward.*

Temperature-related fluctuations around the long term trend

The foregoing analysis considers the long term trend in annual savings, with interseasonal, temperature-related fluctuations around the trend suppressed by using average annual heating and cooling degree days per day for the variables $HDDd_t$ and $CDDd_t$ in equations (5) and (8)-(10). We now turn to analyzing these fluctuations. For each of the coefficients β_3 and γ_3—the coefficients capturing the effect of $HDDd_t$ and $CDDd_t$ on program savings—we averaged coefficient estimates across the degree day model and the four trend models, and then used these averaged coefficient estimates with appropriate monthly degree day data to estimate the *actual effect* of temperature over the 29-month program period, and to predict the long-run average effect of temperature on program savings.[7] Figures 3.15 and 3.16 present the results of this exercise. The average monthly temperature-related savings reflect average annual heating and cooling degree days, and are the values used in the annualized trend analysis just presented. The estimates of actual temperature-related monthly program savings are based on actual heating and cooling degree days during the course of the program (April 2008-August 2010), and the horizontal axis is labeled to reflect the program period. Long-term average values are based on long run heating and cooling degree days, as reported by the National Climate Data Center, NOAA-USDC (see footnote 8 above). The figure generates the following conclusions:

- *Temperature-related savings are highest in summer;*

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[7] This averaging was done separately for the HC and LC household models. The coefficient estimates for β_3 and γ_3 were strongly significant in the degree day model and all four trend regressions, for both the HC and LC models. Moreover, because these coefficient estimates were fairly stable across the five models, the averaged estimates are reasonably close to the estimates in each of the equations. For instance, as seen in Tables A.1-A.5, the estimates of β_3 across the degree day model and the four trend models for HC households, were -.02729, -0.02674, -0.01989, -0.02111, and -0.01865, which averages to -.02274. The coldest month of the year, January, has a long term average value of HDD=580, and so the estimated program savings due to heating degree days in January varies from a high of 580·.02729=15.8 kWh for the linear trend, to a low of 10.8 kWh for the quartic trends, with an average estimate of 13.2 kWh.

- *Temperature-related fluctuations in program savings follow the same pattern for high consumption and low consumption households, with the savings for high consumption households scaled up.by a factor of about 2.5;*
- *Recent summers have been cool, with temperatures especially cool in summer 2010. This appears to largely explain the relatively low savings reported for HC households in summer 2010 compared to summer 2009 (see Table 3.1 and Figure 3.2). In particular, the cooler summer in 2010 compared to 2009 accounts for a difference of about 12 kWh in program savings.*

Figure 3.9. Annualized Savings Trend for High Consumption (HC) Households

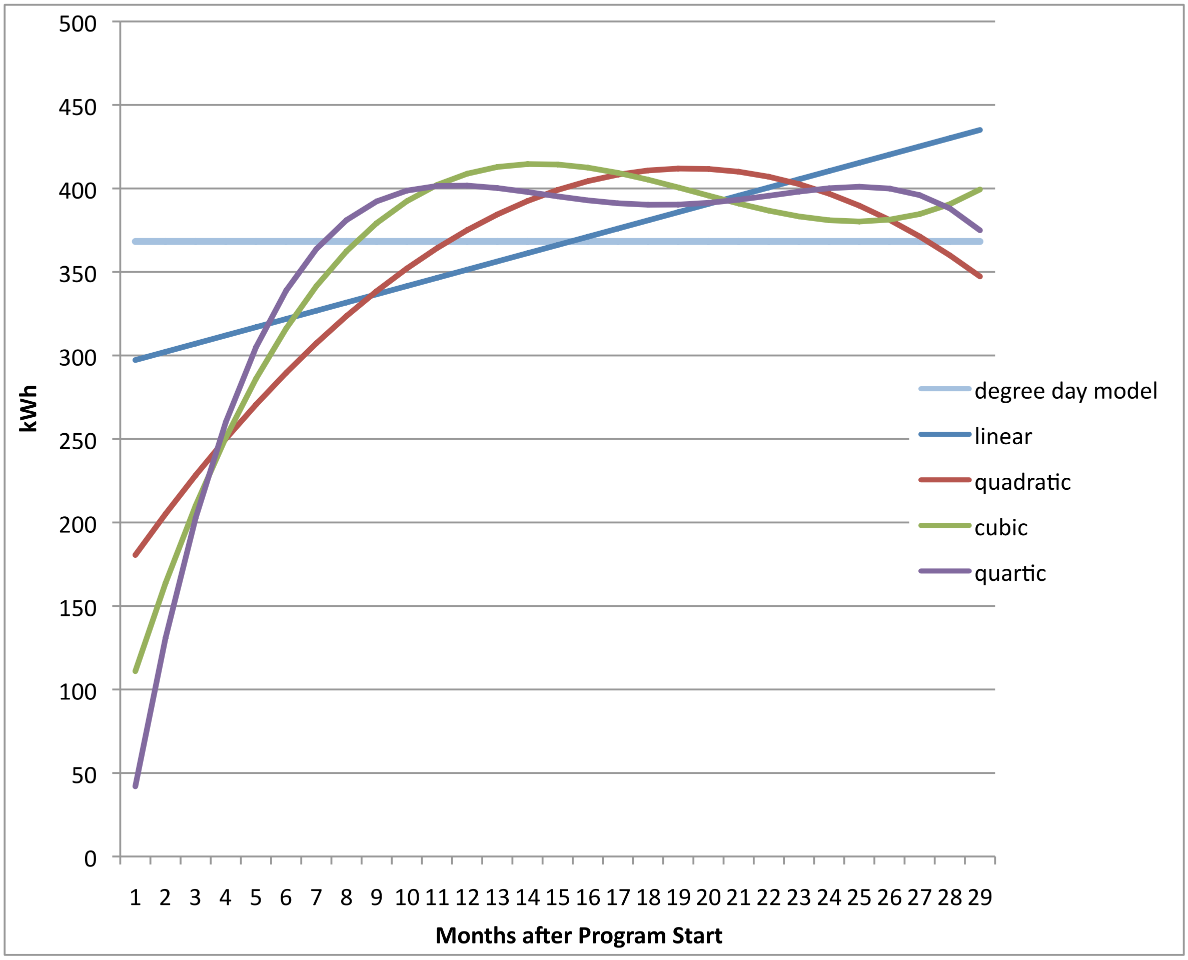


Figure 3.10. Annualized Savings Trend for Low Consumption (LC) Households

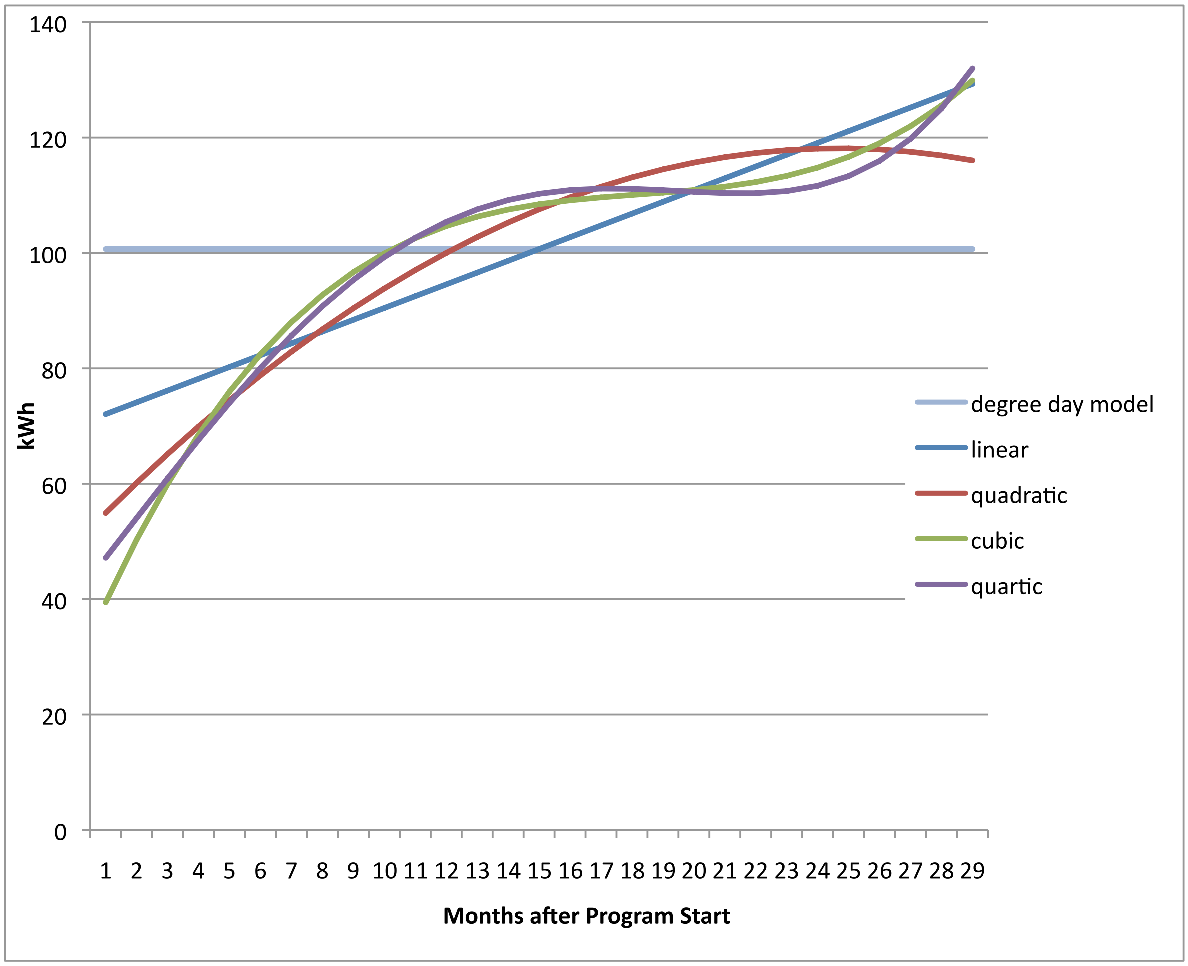


Figure 3.11. Annualized savings trend average, HC households

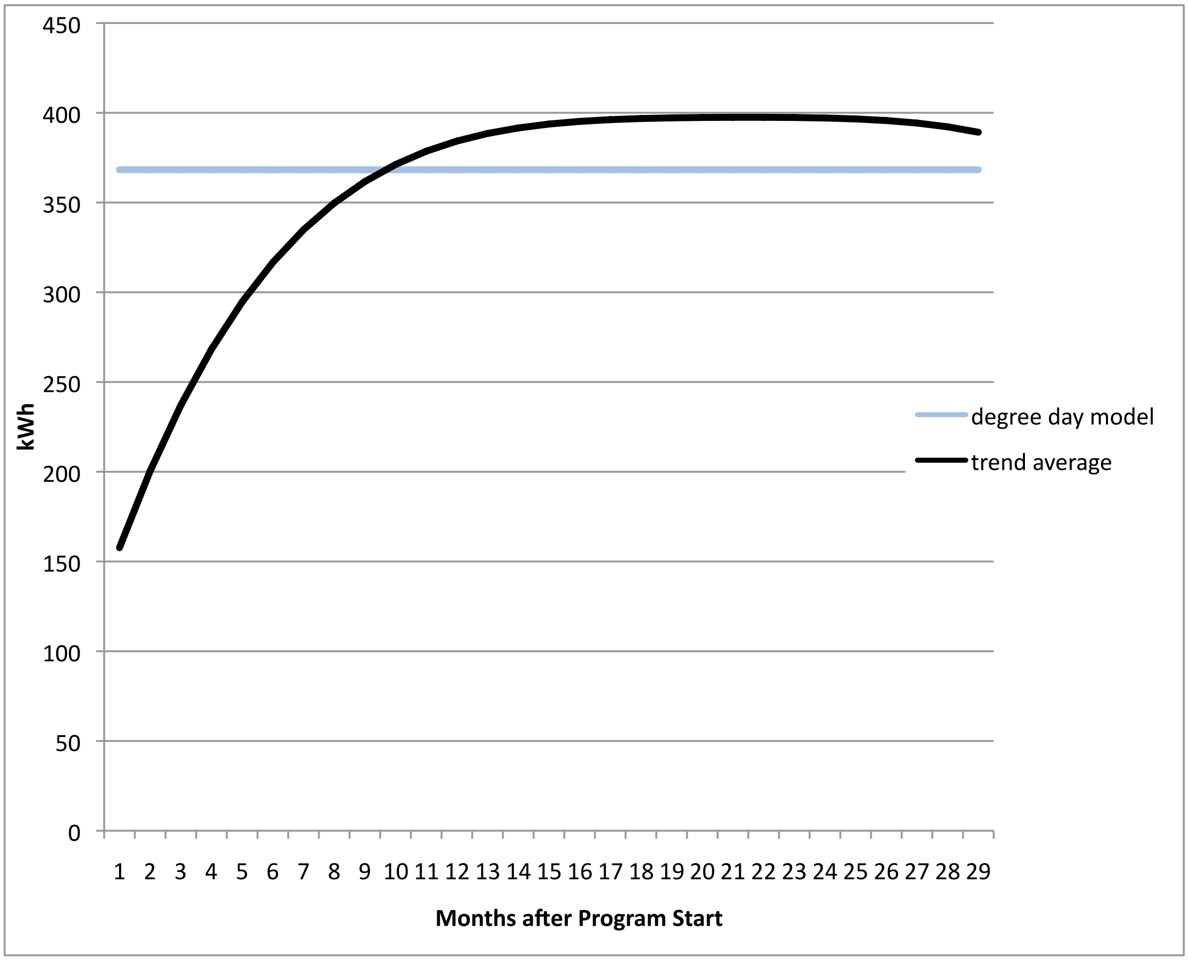


Figure 3.13. Annualized savings trend average, LC households

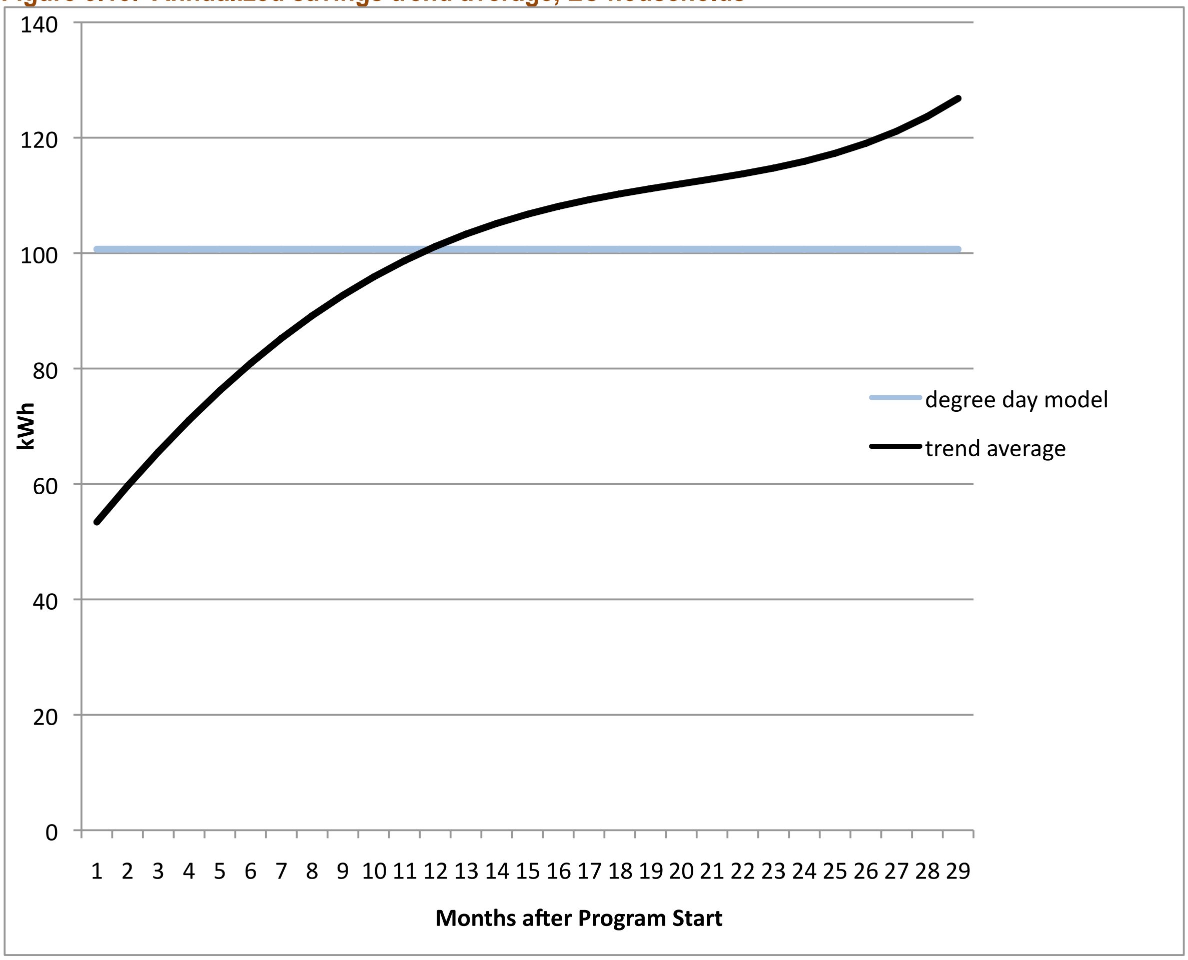


Figure 3.13. Annualized savings trend after first 5 months of the program, HC households

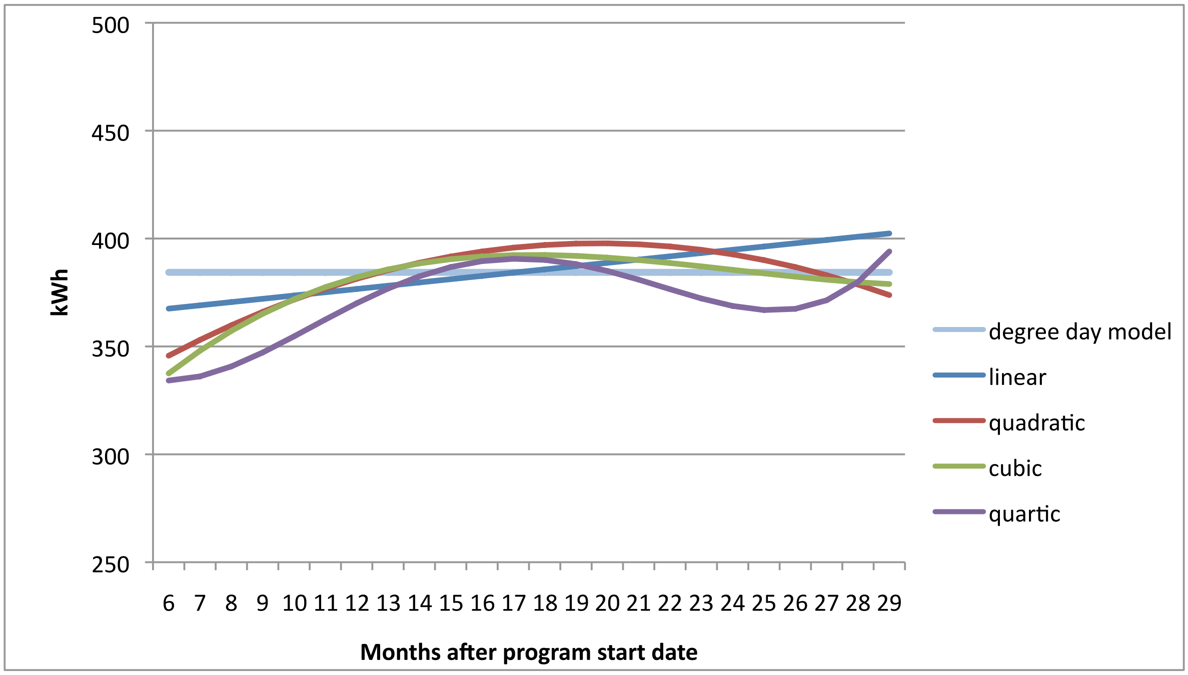


Figure 3.14. Annualized savings trend average after first 5 months of the program, HC households

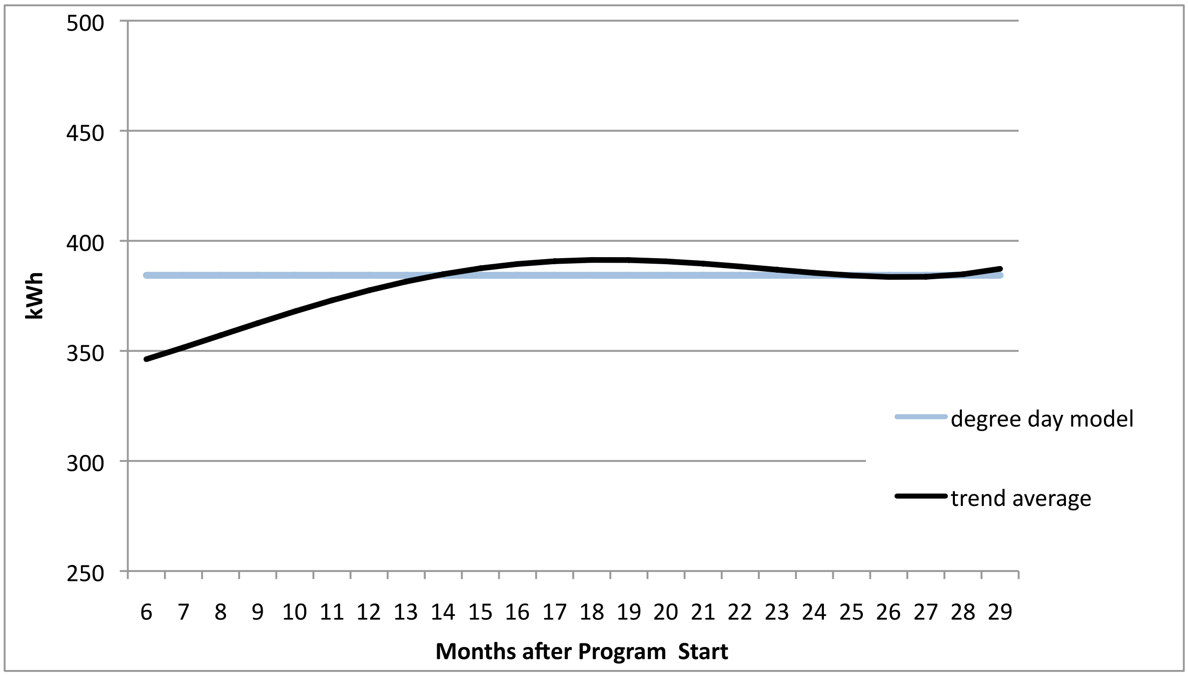


Figure 3.15. Temperature-related monthly program savings, HC households

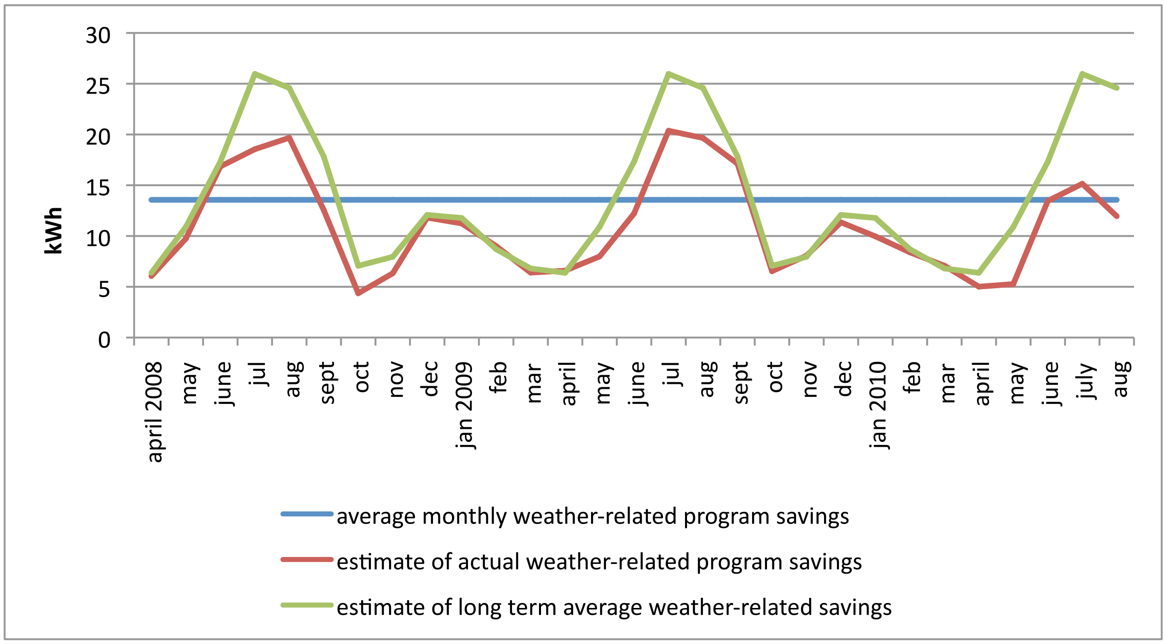
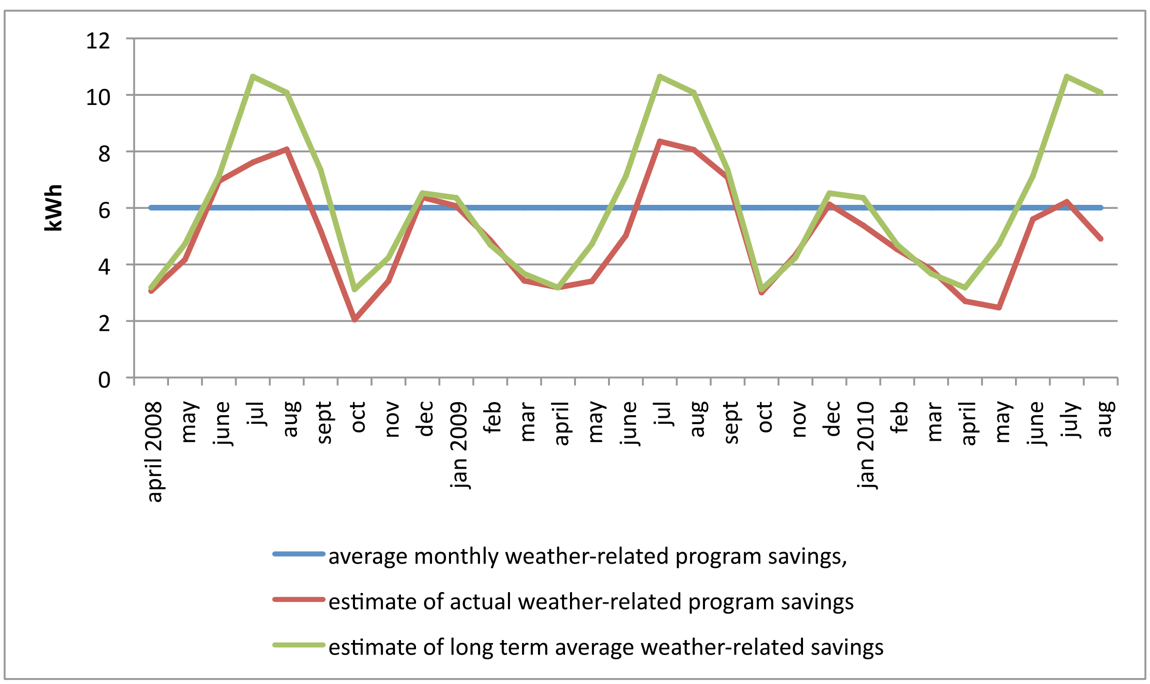


Figure 3.16. Temperature-related monthly program savings, LC households



IV. Conclusion

The analysis presented in this report generates the following overall conclusions:

A. The program continues to generate savings

- Average savings in program Year 2 were 2.89% for high consumption (HC) households receiving monthly reports, and 1.70% for low consumption (LC) households receiving quarterly reports.
- Year 2 average household savings is 381 kWh for HC households and 104 kWh for LC households.
- Average household savings through the first 30 months of the program is 878 kWh for HC households and 234 kWh for LC households.

B. The trend for high consumption households

Program savings are characterized by temperature-driven seasonal fluctuations around a baseline trend. For HC households, the baseline trend ramped up through the first 10-12 months and has remained fairly constant since then:

- Average percent savings in program Year 2 are higher than in Year 1, 2.89% compared to 2.37%, which is a 22% increase in savings in the second year. The increase is statistically significant.
- Statistical analysis indicates that the long term trend for savings leveled off at about 10-12 months, and has remained constant since then. In other words, after the first year of the program the fundamental effectiveness of the program does not appear to have changed substantially.
- Statistical analysis supports a long term savings trend of about 380 kWh per year, approximately 2.9% per year.
- Additional analysis after the program has been in place for a full three years, with data for at least three occurrences of each season, should give a better indication of whether the long term trend in savings is indeed constant or instead showing signs of rising or falling.

C. The trend for low consumption households

For LC households, program savings continues to trend upward:

- Average percent savings in program Year 2 are higher than in Year 1, 1.70% compared to 1.25%, which represents a 36% increase in savings.
- Statistical analysis indicates that program savings continue to trend upward through the first 29 months of the program.

D. Program savings increase with electricity use

For both HC and LC households, program savings reveal strong seasonal effects, with savings highest in the seasons of highest electricity use, summer and winter. For instance, in Year 2 (spring 2009-winter 2010) the average kWh savings for HC households in the seasonal sequence spring-summer-fall-winter was 80-123-84-97 kWh. The same sequence for LC households was 13-36-20-33 kWh.

The seasonality of savings is especially apparent in the pronounced rise in savings in the months of July and August. For HC households the percent savings for these months is 3.56% in summer 2009 and 3.27% in summer 2010. The difference between these percent savings is not statistically significant at any reasonable level of significance (the t-statistic on the difference is 1.2).

E. Graphical summary

Figures 4.1 and 4.2 present the trends in annual program savings for HC and LC households over months 6-29 of the OPOWER program. The figures abstract from seasonal fluctuations in program savings by setting heating and cooling degree days at their annual averages. The figures illustrate several of the points made above:

- For HC households, program savings appear to have remained constant on an annual basis after an initial ramp-up period of about 10-12 months; the tail end of the ramp-up period is apparent in months 6-12 of the figure. The long run annual savings of about 380 kWh is a savings of approximately 2.9% per year.
- For LC households, program savings continue to trend upward.

Figure 4.3 presents monthly fluctuations in program savings directly attributable to fluctuations in temperatures during the program period. The figure illustrates that:

- Program savings are highest in the summer and winter months, with the summer response especially pronounced for HC households;
- Fluctuations follow the same pattern for HC and LC households, with fluctuations for HC household scaled up by a factor of about 2.5 relative to LC households.

Figure 4.1. Trend in annual program savings, HC households, program months 6-29 (September 2009-August 2010).

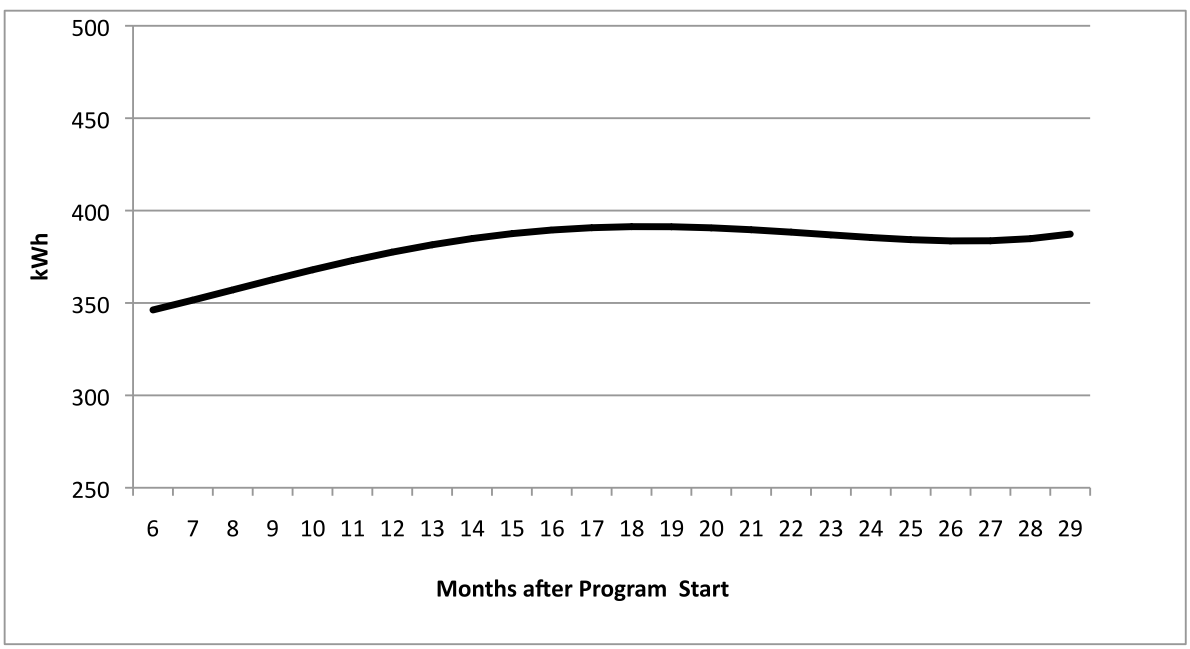


Figure 4.2. Trend in annual program savings, LC households, program months 6-29 (September 2009-August 2010).

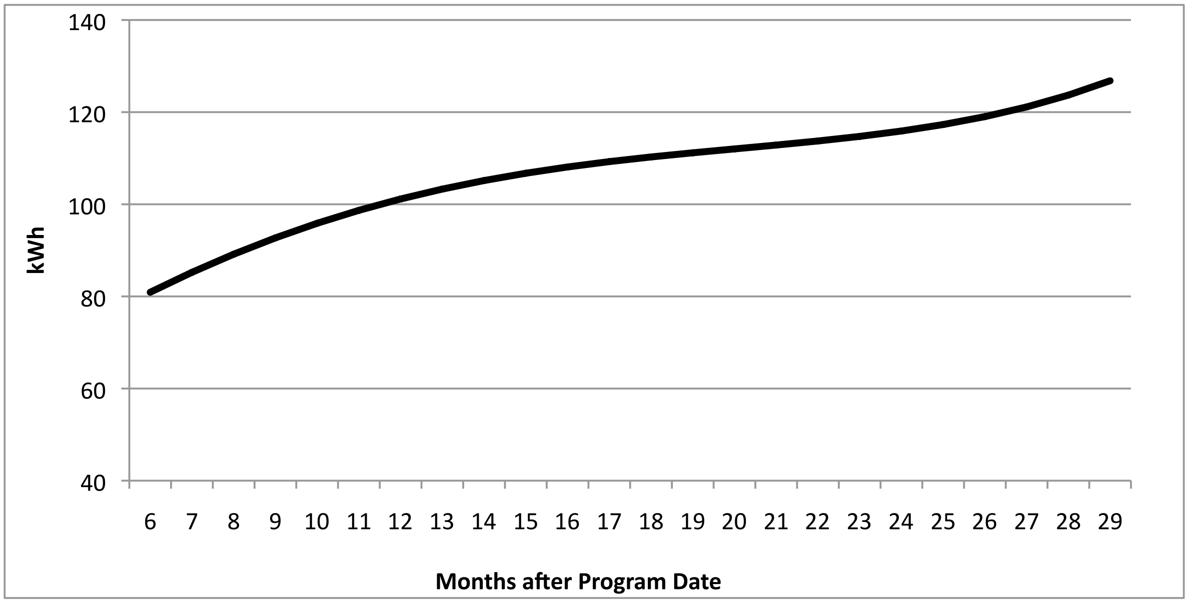
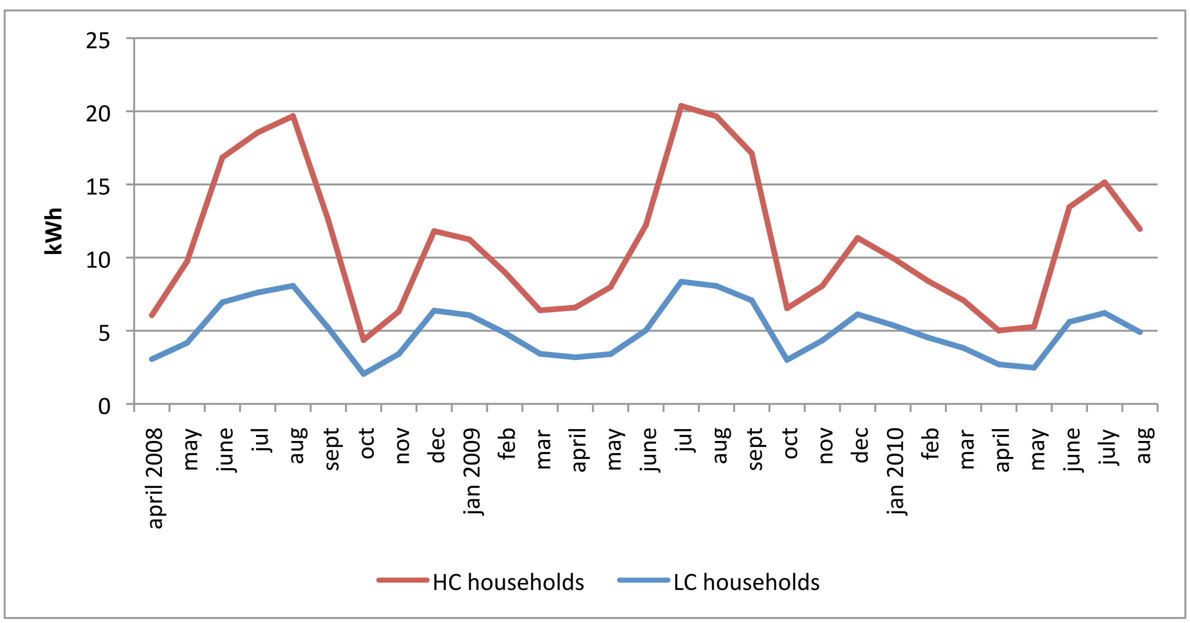


Figure 4.3. Estimate of temperature-related monthly program savings



Appendix A. Baseline Statistics Used in Analysis

Table A.1. Baseline Statistics: Average Daily kWh Consumption, Heating Degree Days, and Cooling Degree Days, by Period[a]

Period	kWh Average Daily Consumption HC Control Households	kWh Average Daily Consumption HC Treatment Households	kWh Average Daily Consumption LC Control Households	kWh Average Daily Consumption LC Treatment Households	Heating Degree Days per Day	Cooling Degree Days per Day
First Year	37.35	35.87	16.60	16.43	7.32	2.18
Second Year	36.69	35.03	16.75	16.50	7.05	2.63
Summer 2008	44.16	42.51	20.61	20.48	0.11	6.65
July-August 2008	45.73	43.79	21.53	21.32	0.05	7.72
Fall 2008	33.98	32.28	15.02	14.75	4.51	1.83
Winter 2008-2009	39.79	38.24	16.97	16.80	17.45	0.00
Spring 2009	32.00	30.58	14.21	14.03	6.23	1.25
Summer 2009	41.96	40.10	19.91	19.58	0.07	6.83
July-August 2009	44.49	42.39	21.31	20.92	0.00	8.01
Fall 2009	35.07	33.20	15.94	15.64	5.71	2.81
Winter 2009-10	38.27	36.69	16.99	16.78	16.01	0.00
Spring 2010	30.75	29.38	13.86	13.66	8.25	0.24
Summer 2010	40.43	37.31	18.53	18.12	0.47	5.27
July-August 2010	40.43	38.46	19.23	18.74	0.05	5.48

aThe first year applies to bill dates in the period April 2008-March 2009; the second year applies to bill dates in the period April 2009-March 2010; spring season applies to bill dates in the interval March 15-June 14; summer season applies to bill dates in the interval June 15-September 14; fall season applies to bill dates in the interval September 15-Dec 14; winter season applies to bill dates in the interval Dec 15-March 14; July-August period applies to bill dates in the interval July 15-September 15.

Appendix B. LFER Regression Results

Table B.1 LFER Analysis Result: Degree Day Model

Variables	Coefficient Estimates			
	High Consumption (HC) Households		**Low Consumption (LC) Households**	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.8913	338.41	0.3380	173.83
CDDd	2.8816	404.41	1.3812	263.60
Treatment*HDDd	-0.0027	-0.66	0.0089	2.93
Treatment*CDDd	-0.0384	-3.45	0.0056	0.69
Post	-0.4010	-8.59	0.2547	7.39
Post*HDDd	-0.0394	-11.03	0.0246	9.30
Post*CDDd	-0.3057	-35.02	-0.0801	-12.41
Treatment*Post	-0.5106	-6.98	-0.0778	-1.44
Treatment*Post*HDDd	-0.0273	-4.87	-0.0119	-2.85
Treatment*Post*CDDd	-0.0883	-6.47	-0.0329	-3.25

Table B.2. LFER Analysis Results: Degree Day Model with Linear Trend

Variables	Coefficient Estimates			
	High Consumption (HC) Households		**Low Consumption (LC) Households**	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.89122	338.5	0.33807	173.88
CDDd	2.88097	404.47	1.38145	263.68
Treatment*HDDd	-0.00273	-0.66	0.00891	2.92
Treatment*CDDd	-0.03868	-3.48	0.00551	0.67
Post	0.12313	2.41	0.04192	1.10
Post*HDDd	-0.03871	-10.83	0.0246	9.29
Post*CDDd	-0.31576	-36.15	-0.07462	-11.54
PostTrend	-0.03214	-25.47	0.01293	13.27
Treatment*Post	-0.29446	-3.68	0.01482	0.25
Treatment*Post*HDDd	-0.02674	-4.78	-0.01189	-2.86
Treatment*Post*CDDd	-0.09189	-6.73	-0.03537	-3.49
Treatment*PostTrend	-0.01348	-6.79	-0.0056	-3.66

Table B.3. LFER Analysis Results: Degree Day Model with Quadratic Trend

Variables	Coefficient Estimates			
	High Consumption (HC) Households		Low Consumption (LC) Households	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.89108	338.5	0.33794	173.81
CDDd	2.88007	404.47	1.38088	263.54
Treatment*HDDd	-0.0029	-0.66	0.00887	2.91
Treatment*CDDd	-0.0398	-3.48	0.00532	0.65
Post	0.33371	2.41	0.16569	3.86
Post*HDDd	-0.03343	-10.83	0.02761	10.25
Post*CDDd	-0.30978	-36.15	-0.07216	-11.14
PostTrend	-0.07777	-25.47	-0.01359	-3.10
$PostTrend^2$	0.00144	-25.47	0.000853	6.21
Treatment*Post	-0.01816	-3.68	0.05973	0.89
Treatment*Post*HDDd	-0.01989	-4.78	-0.01078	-2.55
Treatment*Post*CDDd	-0.08447	-6.73	-0.03441	-3.39
Treatment*PostTrend	-0.07302	-6.79	-0.01524	-2.22
$Treatment*PostTrend^2$	0.00189	-6.79	0.000309	1.43

Table B.4. LFER Analysis Results: Degree Day Model with Cubic Trend

Variables	Coefficient Estimates			
	High Consumption (HC) Households		Low Consumption (LC) Households	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.89292	339.43	0.33912	174.46
CDDd	2.89298	406.25	1.38616	264.46
Treatment*HDDd	-0.0032	-0.78	0.00875	2.87
Treatment*CDDd	-0.04182	-3.76	0.00484	0.59
Post	-1.83376	-25.82	-0.6147	-11.47
Post*HDDd	-0.02751	-7.58	0.02852	10.59
Post*CDDd	-0.3281	-37.44	-0.07662	-11.83
PostTrend	0.62417	42.00	0.24206	21.23
$PostTrend^2$	-0.05213	-49.00	-0.01893	-22.91
$PostTrend^3$	0.00114	51.05	0.000426	24.28
Treatment*Post	0.28938	2.60	0.1217	1.45
Treatment*Post*HDDd	-0.02111	-3.71	-0.0109	-2.58
Treatment*Post*CDDd	-0.08247	-6.02	-0.03448	-3.39
Treatment*PostTrend	-0.17145	-7.34	-0.03519	-1.97
$Treatment*PostTrend^2$	0.00941	5.63	0.00187	1.44
$Treatment*PostTrend^3$	-0.00016	-4.56	-3.4E-05	-1.24

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Table B.5. LFER Analysis Results: Degree Day Model with Quartic Trend

Variables	Coefficient Estimates			
	High Consumption (HC) Households		**Low Consumption (LC) Households**	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.89238	339.11	0.33939	174.38
CDDd	2.88935	404.76	1.38734	263.79
Treatment*HDDd	-0.00356	-0.87	0.00881	2.89
Treatment*CDDd	-0.04436	-3.98	0.00515	0.62
Post	-1.43528	-16.03	-0.73206	-10.66
Post*HDDd	-0.0241	-6.59	0.02734	10.03
Post*CDDd	-0.32361	-36.84	-0.07761	-11.96
PostTrend	0.41861	13.15	0.30254	12.16
$PostTrend^2$	-0.0253	-6.61	-0.0269	-8.88
$PostTrend^3$	-0.00016	-0.88	0.000816	5.69
$PostTrend^4$	2.06E-05	7.30	-6.3E-06	-2.74
Treatment*Post	0.58517	4.16	0.08913	0.83
Treatment*Post*HDDd	-0.01865	-3.25	-0.01121	-2.62
Treatment*Post*CDDd	-0.07949	-5.79	-0.03477	-3.42
Treatment*PostTrend	-0.32305	-6.45	-0.01843	-0.47
$Treatment*PostTrend^2$	0.02917	4.85	-0.00033	-0.07
$Treatment*PostTrend^3$	-0.00111	-3.96	7.28E-05	0.32
$Treatment*PostTrend^4$	1.51E-05	3.42	-1.7E-06	-0.48