IMPACT EVALUATION OF POSITIVE ENERGY SMUD PILOT STUDY

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FINAL REPORT

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1 EXECUTIVE SUMMARY

Information technologies designed to assist and encourage customers to use less energy are increasing in the industry. Positive Energy offers an information program to help customers manage their energy use by providing reports comparing their energy use to the energy use of other similar households. These energy reports provide customers with normative comparisons of their current energy use compared to their neighbors and suggest actions that they can take to reduce their electric use. It is believed that there is a social driver at work in the presentation of energy use in this comparative fashion. If households learn they use more energy than their neighbors, it is assumed they will be motivated to reduce energy use and possibly do more than their neighbors.

Positive Energy put this theory to the test with an aggressive experimental design across the Sacramento Municipal Utility District (SMUD). Census blocks were randomly assigned to treatment and control groups. Thirty-five thousand single-family residential customers in the treatment group received regular reports over the period of a year on how their energy use compared to their neighbors' energy use. Fifty thousand single-family customers in the control group did not receive any reports. The pilot began in April 2008. Billing data was collected for all customers for two years, starting one year before the test began, to support the impact evaluation of the program.

This report presents Summit Blue's independent third-party impact evaluation of the SMUD experimental design pilot conducted by Positive Energy. The impact evaluation focuses on answering three research questions:

1. Does receiving the reports lead to energy savings?
2. Can the characteristics of large savers be identified?
3. What is the distribution of savings across customers?

Does receiving the reports lead to energy savings?

Three different statistical methods were used to estimate savings from the program based on analysis of billing data. Table 1 shows that all three methods provided similar results, leading to the conclusion that the reports did indeed encourage customers to reduce their energy use. The estimate of annual savings from each of the three methods ranged from 2.1% to 2.2% showing strong robustness of results. The range around each of these estimates is tight, providing good reliability and precision.

The strength of these estimates rests on the clean design of the experiment and the very large sample sizes that were used. It is often difficult to accurately assess a program savings of 2% from billing analysis because of the wide range of variability in customer bills, but the large scale of this experiment allowed for accurate assessment of savings from this program. Given the consistent estimate of savings found across several methods and the tight range of precision around each estimate, it is clear that the Positive Energy reports did encourage a reduction in energy use among customers who received them.

Table 1. Comparison of Savings Estimates from Three Statistical Methods

Method	*Average annual kWh savings*	*95% Confidence interval on avg. annual savings*	*Average annual percent savings*	*95% Confidence interval on avg. percent savings*
Method 1: Difference-in-Difference Statistic	257	-	2.20%	-
Method 2: Baseline OLS Linear Model	253.75	{216.81, 290.69)	2.24%	{1.91%, 2.56%}
Method 3: Baseline Differenced Linear Fixed Effects Model	240.88	{222.81, 258.95)	2.13%	{1.97%, 2.28%}

While annual savings were consistently estimated between 2.1% and 2.2%, this is an average of savings that actually varied by season across the year. Table 2 uses the difference in difference method to show that savings were the greatest during the summer at 2.6%, followed by a savings of 2.2% during the winter and 1.7% during the other shoulder months. Differences by season are reasonable and expected given that customers use electricity for different purposes during each season. Summer electric use and savings are the highest due to air-conditioning load. Winter use reflects additional lighting and some space heating. The shoulder months have the lowest overall use and savings.

Table 2. Savings by Season

Season	*Group*	*2007 KWH/Day*	*2008 KWH/Day*	*Difference KWH/Day*	*Percent Difference*
Summer: July, Aug, Sept Billing Months	Participants	37.53	37.10	-0.43	
	Control Group	37.83	38.37	+0.54	
				-0.97	-2.6%
Winter: Dec, Jan, Feb, Mar, Apr Billing Months	Participants	33.19	31.56	-1.63	
	Control Group	33.34	32.45	-0.89	
				-0.74	-2.2%
Shoulder Months: May, June, Oct, Nov	Participants	26.58	26.73	+0.15	
	Control Group	26.91	27.52	+0.61	
				-0.46	-1.7%

Participants with low electric use (less than 21.863 kWh/day) received reports quarterly while most participants received reports monthly

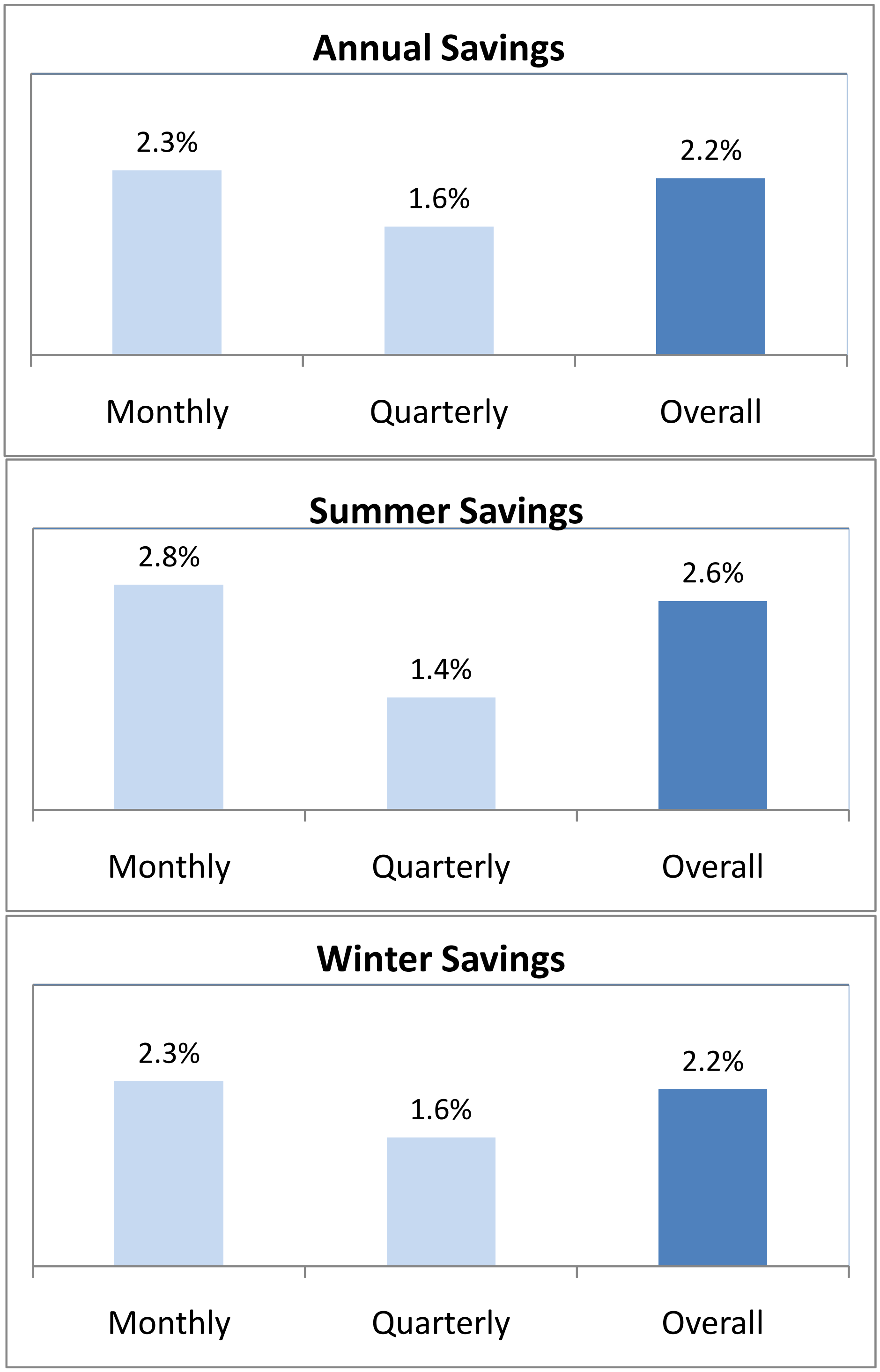
Table 3 shows that the high use customers receiving monthly reports achieved greater savings than low use customers receiving quarterly reports. However, both groups achieved savings in each season. Summer was the season showing the greatest savings for high use customers, while low use customers showed relatively consistent savings across all of the seasons.

Table 3. Comparison of Savings for Quarterly vs. Monthly Report Recipients

Method	***Summer Impact***	***Winter Impact***	***Shoulder Months Impact***	***Annual Impact***
Monthly Reports (High Use Customers)	-2.8%	-2.3%	-1.9%	-2.3%
Quarterly Reports (Low Use Customers)	-1.4%	-1.6%	-1.4%	-1.6%
Overall	-2.6%	-2.2%	-1.7%	-2.2%

These seasonal differences for the different report frequencies are illustrated in Figure 1.

Figure 1. Comparison of Savings for Monthly vs. Quarterly Report Recipients



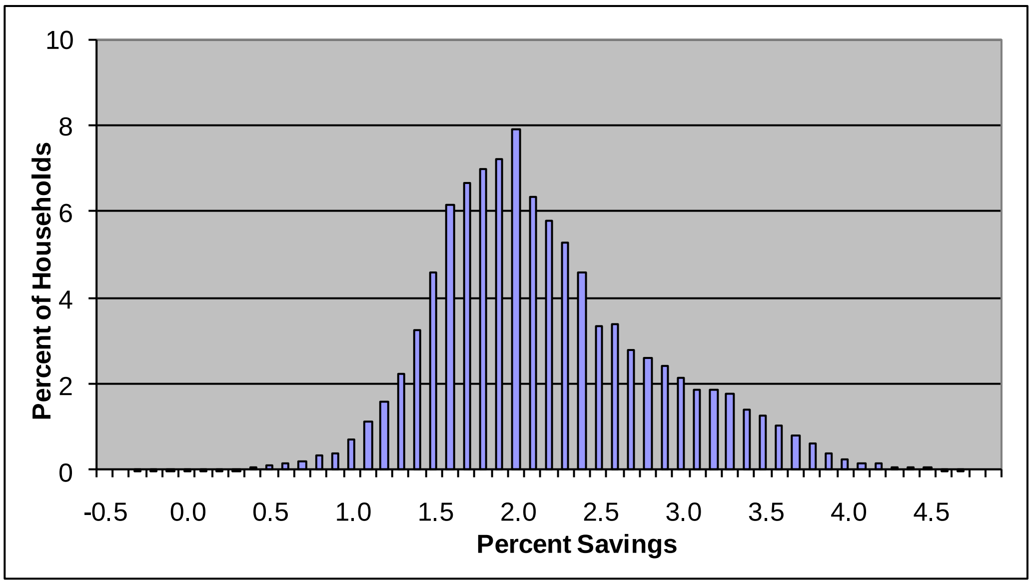
Can the characteristics of large savers be identified?

[The information in this section is the intellectual property of Positive Energy and has been removed since it is confidential. For details on program impact for various customer segments, including analysis of the most significant demographic attributes, please contact Positive Energy.]

What is the distribution of savings across customers?

The method 2 linear regression model was used to predict the distribution of savings within the participant group. Figure 2 shows that savings were predicted for nearly all customers. As noted previously, the average savings is about 2.2%. Predicted percent savings for 50% of all households lie in the interval {1.6, 2.2}, predicted savings for 80% of all households lie in the interval {1.4, 2.9}, and predicted savings for 95% of all households lie in the interval {1.1, 3.5}.

Figure 2. Frequency distribution of predicted percent annual energy savings (2007 as base year) within the treatment group



This distribution curve shows that savings are predicted for virtually all individuals, rather than being possible for just a small subset of customers with particular characteristics.

2 BACKGROUND AND OBJECTIVES

Information technologies designed to assist and encourage customers to use less energy are increasing in the industry. There are a wide variety of information technology options available for accomplishing this purpose. Some focus on hardware solutions that put devices into a customer's home to give them information on current energy use. These devices can be expensive.

Positive Energy offers an alternative low cost information program to help customers manage their energy use by providing reports comparing their energy use to the energy use of other similar households. These energy reports provide customers with normative comparisons of their current energy use compared to their neighbors and suggest actions that they can take to reduce their electric use.

It is believed that there is a social driver at work in the presentation of energy use in this comparative fashion. If households learn they use more energy than their neighbors, it is assumed they will be motivated to reduce energy use and possibly do more than their neighbors.

Positive Energy put this theory to the test with an aggressive experimental design across the Sacramento Municipal Utility District (SMUD). Census blocks were randomly assigned to treatment and control groups. Thirty-five thousand single-family residential customers in the treatment group received regular reports over the period of a year on how their energy use compared to their neighbors' energy use. Fifty thousand single-family customers in the control group did not receive any reports. The pilot began in April 2008. Billing data was collected for all customers for two years, starting one year before the test began, to support the impact evaluation of the program.

Evaluation Objectives

The impact evaluation which is the focus of this report has both primary and secondary evaluation objectives related to the Positive Energy customer reports that were tested in the SMUD pilot.

The primary objective is to answer the basic question:

> Does receiving the reports lead to energy savings?

Additional secondary objectives were also identified. These include:

1. What is the distribution of savings across customers?
2. Can the characteristics of large savers be identified?

The remainder of this report will present the findings to these key evaluation questions.

3 ANALYSIS METHODS

A large set of data generated by a well-constructed experimental design was provided for estimation of impacts of the SMUD Pilot Study. We estimated program impacts using three distinct statistical approaches. Each approach is presented below. Results are presented in section 4.

3.1 Method 1: Difference-in-Difference Statistic

Assuming random assignment of a large number of treatment and control households, a simple difference-in-difference statistic provides a good estimate of the average annual household savings in energy use (measured in kwh) from the treatment.

Denote by $\overline{E}_{pg}$ the average annual rate of kwh use in period *p* (*p*=0 for the pre-treatment period, *p*=1 for the post-treatment period) by households in group *g* (*g*=0 for the treatment group, *g*=1 for control group). The difference-in-difference 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,

$$\begin{aligned} \Delta E &= \left(\overline{E}_{11} - \overline{E}_{01}\right) - \left(\overline{E}_{10} - \overline{E}_{00}\right) \\ &= \Delta \overline{E}_1 - \Delta \overline{E}_0 \end{aligned} \quad . \qquad (1)$$

Dividing the difference-in-difference statistic by the average energy use of the control group in the pre-treatment period gives the proportional reduction from treatment,

$$\text{Prop reduction} = \frac{\Delta E}{\overline{E}_{01}} \quad . \qquad (2)$$

3.2 Method 2: Linear Regression (LR) Models

A second approach is to cast household energy use as a function of a variety of explanatory variables including: a) group membership (treatment vs. control); b) observation period (pre- versus post-treatment); c) relevant weather-related variables such as heating degree days; d) observable housing/household characteristics such as square footage of the residence and the number of household members; and e) an error term reflecting unobservable variables (or alternatively, variables that are not included in the available data set).

The simplest version convenient for exposition is a linear specification in which average daily use (*ADU*) of kilowatt-hours by household *k* in month t (where months are assigned consecutively throughout the study period), is a function of three variables: the binary variable $Treatment_k$, taking a value of 0 if household *k* is assigned to the control group, and 1 if assigned to the treatment group; the binary variable $Post_t$, taking a value of 0 if month *t* is in the pre-treatment period, and 1 if in the post-treatment period; and the interaction between these variables, $Treatment_k \cdot Post_t$. Formally,

$$ADU_{kt} = \alpha_0 + \alpha_1 Treatment_k + \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t + \varepsilon_{kt} \qquad (3)$$

Three observations about this specification deserve comment. First, the treatment response is captured by the coefficient α_3. This term captures the *difference in the difference* in average daily kwh use between the treatment group and the control group across the pre- and post-treatment periods. In other words, whereas the coefficient α_2 captures the change in average daily kwh use across the pre- and post-treatment for the *control* group, the sum $\alpha_2 + \alpha_3$ captures this change for the treatment group.

Second, given assignment of households to the treatment group via random assignment of census blocks, the effect of the treatment group on energy use will approach zero ($\alpha_1 \to 0$) as the sample of *census blocks* grows large. In small samples the estimated value of α_1 may differ from zero.

Third, if the error term ε_{kt} is independent and identically distributed across observations, ordinary least squares (OLS) regression will generate unbiased and efficient estimates. As noted in section 3.3, if the error term includes unobservable housing/household characteristics, then errors are temporally correlated, and ordinary least squares (OLS) regression will generate inefficient parameter estimates. Moreover, if these unobservable characteristics are correlated with treatment assignment $Treatment_k$, the estimate of the treatment effect will be biased. Nonetheless, OLS regression is a useful benchmark, will give good estimates if unobserved household-level effects are negligible, and the method discussed in section 3.3 addresses the case when they are not.

The model can be expanded to include three other types of variables. weather-related variables, housing/household characteristics, and treatment variables reflecting differences in the particular treatment of treatment households. For each of the weather variables and housing characteristics included in estimation, four terms are added: the variable itself; the variable interacted with $Treatment_k$ to capture differential effects due to treatment category; the variable interacted with $Post_t$ to capture differential effects of the variable due to exogenous shocks across the two study periods; and the variable interacted with the interaction $Treatment_k \cdot Post_t$ to capture the effect of the variable on the treatment response.

For each of the treatment variables included in estimation, three terms are added to the model: the variable interacted with $Treatment_k$, the variable interacted with $Post_t$, and the variable interacted with $Treatment_k \cdot Post_t$. This last interaction term captures the effect of the differential treatment on the treatment response.

Formally, defining $\mathbf{V}_k$ as a vector of treatment variables, $\boldsymbol{W}_t$ as a vector of weather characteristics in month *t*, and $\boldsymbol{Z}_k$ as a vector of housing/household characteristics for household *k*, we have the expanded linear model,

$$\begin{aligned} ADU_{kt} = {} & \alpha_0 + \alpha_1 Treatment_k + \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t \\ & + \lambda_1 \mathbf{V}_k \cdot Treatment_k + \lambda_2 \mathbf{V}_k \cdot Post_t + \lambda_3 \mathbf{V}_k \cdot Treatment_k \cdot Post_t \\ & + \beta_0 \mathbf{W}_t + \beta_1 \mathbf{W}_t \cdot Treatment_k + \beta_2 \mathbf{W}_t \cdot Post_t + \beta_3 \mathbf{W}_t \cdot Treatment_k \cdot Post_t \\ & + \delta_0 \mathbf{Z}_k + \delta_1 \mathbf{Z}_k \cdot Treatment_k + \delta_2 \mathbf{Z}_k \cdot Post_t + \delta_3 \mathbf{Z}_k \cdot Treatment_k \cdot Post_t + \varepsilon_{kt} \end{aligned} , \tag{4}$$

where the coefficients λ_i, β_i and δ_i are vector-valued of conformable dimension. In this model, the average daily treatment effect (ADTE) is the sum of all terms multiplying the interaction term $Treatment_k \cdot Post_t$:

$$ADTE_{kt} = \alpha_3 + \lambda_3 \mathbf{V}_k + \beta_3 \mathbf{W}_t + \delta_3 \mathbf{Z}_k \ . \tag{5}$$

3.3 Method 3: Differenced Linear Fixed Effects (DLFE) Model

The linear regression (LR) models of section 3.2 will generate biased estimates of treatment response *if* the household-specific error ε_{kt} is correlated with the treatment assignment variable $Treatment_k$. Given the careful experimental design of the study, this seems highly unlikely. However remote the possibility, it can be avoided by estimating a fixed effects model in which a household fixed effects parameter α_{0k} captures all household-specific effects on energy use that do not change over time, including those that are unobservable. With reference to section 3.2 above, and defining φ_k as the household-specific portion of the error, the fixed effects parameter is defined as:

$$\alpha_{0k} = \alpha_0 + \alpha_1 Treatment_k + \lambda_1 \mathbf{V}_k \cdot Treatment_k + \delta_0 \mathbf{Z}_k + \delta_1 \mathbf{Z}_k \cdot Treatment_k + \varphi_k \quad , \tag{6}$$

and the fixed effects model is the corresponding modification of (4):

$$\begin{aligned} ADU_{kt} &= \alpha_{0k} + \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t \\ &+ \lambda_2 \mathbf{V}_k \cdot Post_t + \lambda_3 \mathbf{V}_k \cdot Treatment_k \cdot Post_t \\ &+ \beta_0 \mathbf{W}_t + \beta_1 \mathbf{W}_t \cdot Treatment_k + \beta_2 \mathbf{W}_t \cdot Post_t + \beta_3 \mathbf{W}_t \cdot Treatment_k \cdot Post_t \\ &+ \delta_2 \mathbf{Z}_k \cdot Post_t + \delta_3 \mathbf{Z}_k \cdot Treatment_k \cdot Post_t + \varepsilon_{kt} \end{aligned} \tag{7}$$

In the fixed effect model, estimation of the set of parameters $\{\alpha_0, \alpha_1, \delta_0, \delta_1\}$ in the LR model (4) is replaced by estimation of the fixed effects parameter α_{0k} for *each* household in the sample; in the current study of approximately 85,000 households, this is not a feasible exercise. We instead take advantage of the favorable properties of the fixed effects model—in particular the elimination of the aforementioned potential bias—while avoiding the estimation of the fixed effects parameters, as follows. First, the average of monthly *ADU* is modeled for each household using (7), by taking the average over all variables (this includes the average of variables that are interactions). Using (7) to average across all such monthly observations for a household gives (where "bars" on variables indicate means):

$$\begin{aligned} \overline{ADU}_k &= \alpha_{0k} + \alpha_2 \overline{Post}_t + \alpha_3 \left(\overline{Treatment_k \cdot Post_t} \right) \\ &+ \lambda_2 \left(\overline{\mathbf{V}_k \cdot Post_t} \right) + \lambda_3 \left(\overline{\mathbf{V}_k \cdot Treatment_k \cdot Post_t} \right) \\ &+ \beta_0 \bar{\mathbf{W}}_t + \beta_1 \left(\overline{\mathbf{W}_t \cdot Treatment_k} \right) + \beta_2 \left(\overline{\mathbf{W}_t \cdot Post_t} \right) + \beta_3 \left(\overline{\mathbf{W}_t \cdot Treatment_k \cdot Post_t} \right) \\ &+ \delta_2 \left(\overline{\mathbf{Z}_k \cdot Post_t} \right) + \delta_3 \left(\overline{\mathbf{Z}_k \cdot Treatment_k \cdot Post_t} \right) + \bar{\varepsilon}_{kt} \end{aligned} \quad . \tag{8}$$

Equation (8) is then subtracted from (7) for each household. This generates deviations in monthly household ADU from the household's average monthly ADU. Defining deviations by the symbol "□" (so, for instance, the deviation in the dependent variable is $□ADU_{kt} = ADU_{kt} - \overline{ADU}_k$), we have,

$$
\begin{aligned}
\Delta ADU_k = {} & \alpha_2 \Delta Post_t + \alpha_3 \Delta \left(Treatment_k \cdot Post_t \right) \\
& + \lambda_2 \Delta \left(\mathbf{V}_k \cdot Post_t \right) + \lambda_3 \Delta \left(\mathbf{V}_k \cdot Treatment_k \cdot Post_t \right) \\
& + \beta_0 \Delta \mathbf{W}_t + \beta_1 \Delta \left(\mathbf{W}_t \cdot Treatment_k \right) + \beta_2 \Delta \left(\mathbf{W}_t \cdot Post_t \right) + \beta_3 \Delta \left(\mathbf{W}_t \cdot Treatment_k \cdot Post_t \right) \\
& + \delta_2 \Delta \left(\mathbf{Z}_k \cdot Post_t \right) + \delta_3 \Delta \left(\mathbf{Z}_k \cdot Treatment_k \cdot Post_t \right) + \Delta \varepsilon_{kt}
\end{aligned}
\tag{9}
$$

Note that because the fixed effect α_{0k} is the same in every observation period, $\bar{\alpha}_{0k} = \alpha_{0k}$, it is eliminated from (9). Moreover, if ε_{kt} in (7) is an independent and identically distributed normal random variable, then so too is $\Delta \varepsilon_{kt}$, and unbiased parameter estimates are obtained via OLS regression. Finally, the equation generating the estimate of the average daily treatment effect is the same as in the LR model, equation (5).

3.4 Summary of Methods: Relative Strengths and Weaknesses

The difference-in-difference statistic (method 1) has the advantage of simplicity. However, if the assignment of households to the treatment and control groups is not random, or the sample is small, it may deviate substantially from the true treatment effect. Moreover, it provides no information about the effect of household characteristics and treatment variables on program efficacy.

The LR models of method 2 allow examination of the effect of housing/household characteristics on the treatment effect. The main potential disadvantage of these models is that if unobservable housing/household characteristics affecting the treatment response are correlated with assignment to the treatment group—highly unlikely given the careful experimental design of the study—the estimated effect of the average treatment response will be biased.

The DLFE models of method 3 forego the opportunity to estimate the effect of housing/household characteristics on average daily use of kwh in exchange for assuring no bias in estimates of the average treatment response due to correlation between housing/household characteristics and household assignment across the treatment and control groups. All housing/household characteristics that do not change over time—observable and unobservable characteristics alike—are embedded in the fixed effect, which in turn is eliminated from estimation by differencing. It is important to emphasize, though, that estimating the effect of housing characteristics and treatment variables on treatment response *is* possible, because the variables used to measure this effect—interactions involving the variable $Post_t$—do change over time.

4 FINDINGS

The calculation of the difference-in-difference statistic from (1) is straightforward, but the calculation of energy savings from the LR model (method 2) and the DLFE model (method 3) depends on the particular specification of the models. In the next section we provide the average annual savings generated by the difference-in-difference statistic and the *baseline* LR and DLFE models. In section 4.2, we discuss the baseline LR and DLFE models in more detail, and in section 4.3 we expand the LR model to examine the effect of household characteristics on the treatment response. In section 4.4, we examine the distribution of savings in the population, including the difference in savings between households contacted monthly and those contacted quarterly.

4.1 Estimates of Average Annual Savings

As discussed in the previous section, three different methods were used to estimate average annual savings from the program. Results from each method will now be presented.

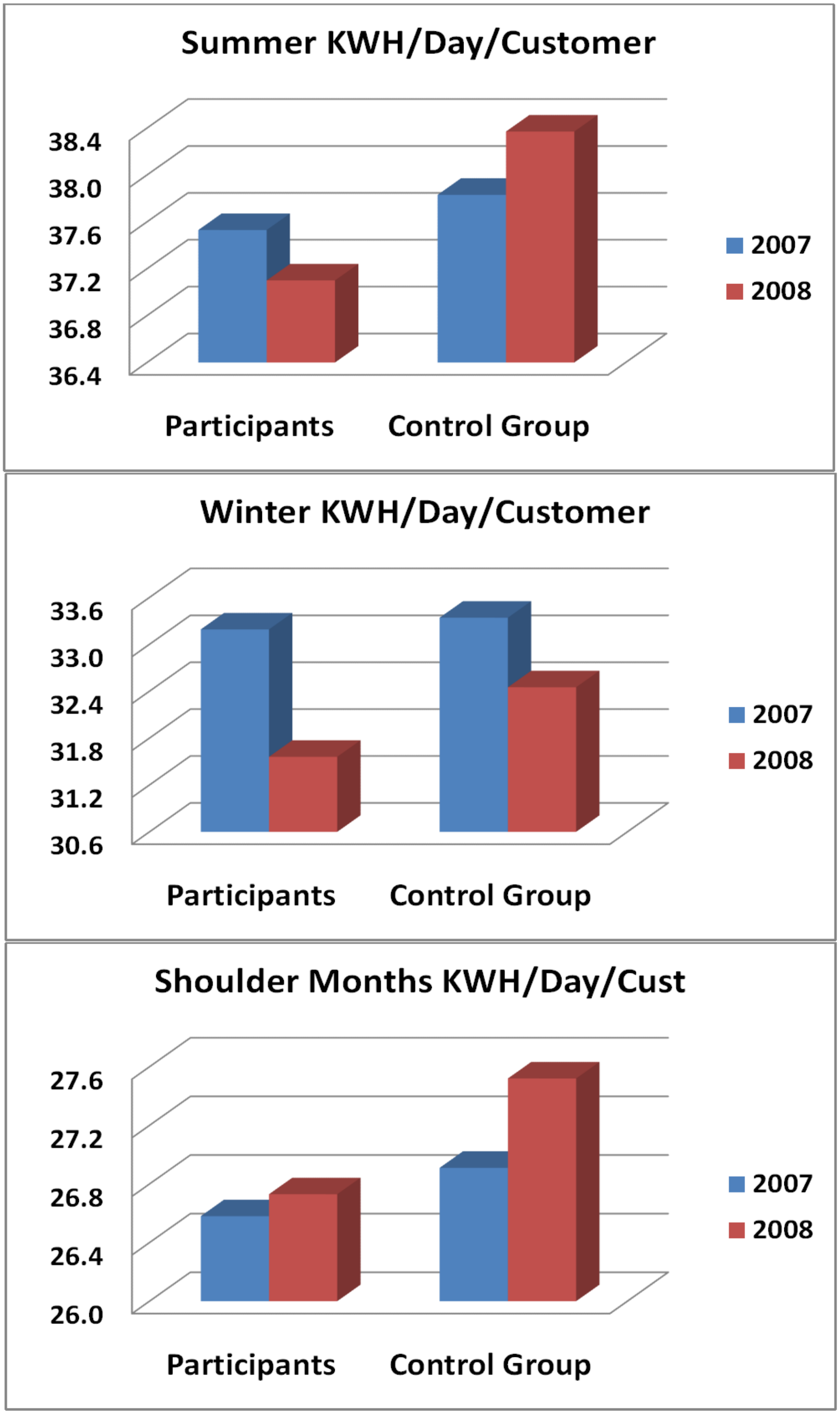
Table 4 summarizes the estimation of savings by season using method 1, the difference in differences approach. It shows that savings were the greatest during the summer at 2.6%, followed by a savings of 2.2% during the winter and 1.7% during the other shoulder months. Differences by season are reasonable and expected given that customers use electricity for different purposes during each season. Summer electric use, and savings, are the highest due to air-conditioning load. Winter use reflects additional lighting and some space heating. The shoulder months have the lowest overall use and savings.

Table 4. Savings by Season from Difference in Differences Method

Season	*Group*	*2007 KWH/Day*	*2008 KWH/Day*	*Difference KWH/Day*	*Percent Difference*
Summer: July, Aug, Sept Billing Months	Participants	37.53	37.10	-0.43	
	Control Group	37.83	38.37	+0.54	
				-0.97	-2.6%
Winter: Dec, Jan, Feb, Mar, Apr Billing Months	Participants	33.19	31.56	-1.63	
	Control Group	33.34	32.45	-0.89	
				-0.74	-2.2%
Shoulder Months: May, June, Oct, Nov	Participants	26.58	26.73	+0.15	
	Control Group	26.91	27.52	+0.61	
				-0.46	-1.7%

The consistent savings behavior of the participants across all of the seasons can be clearly seen in Figure 3. This is most dramatic during the summer when participants reduce their use while control group use increases.

Figure 3. Savings by Season from Difference in Differences Method



The observed savings per day by season can be used to estimate the annual savings from the program. Table 5 shows that the estimated annual savings is 257 kWh per customer which represents a 2.2% reduction in use for participants.

Table 5. Annual Savings from Difference in Difference Method

Method	*KWH per Day per Customer Difference*	*Days per Year*	*Annual KWH Savings per Customer*	*Percent Savings*
Summer	-0.97	92	-89	
Winter	-0.74	151	-112	
Shoulder Months	-0.46	122	-56	
Annual			-257	-2.2%

Estimated savings from methods 2 and 3 are based on a baseline model specification in which the only terms added beyond those in the simplest model (3) concern heating and cooling degree days. In particular, the baseline LR model is,

$$\begin{aligned} ADU_{kt} &= \alpha_0 + \alpha_1 Treatment_k + \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t \\ &+\beta_{H0} HDDd_t + \beta_{H1} HDDd_t \cdot Treatment_k + \beta_{H2} HDDd_t \cdot Post_t + \beta_{H3} HDDd_t \cdot Treatment_k \cdot Post_t \\ &+\beta_{C0} CDDd_t + \beta_{C1} CDDd_t \cdot Treatment_k + \beta_{C2} CDDd_t \cdot Post_t + \beta_{C3} CDDd_t \cdot Treatment_k \cdot Post_t + \varepsilon_{kt} \end{aligned} \quad ,(10)$$

where $HDDd_t$ is heating degree days per day in month t, and $CDDd_t$ is cooling degree days per day in month t. Similarly, the baseline DLFE model is,

$$\begin{aligned} ADU_{kt} &= \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t \\ &+\beta_{H0} HDDd_t + \beta_{H1} (HDDd_t \cdot Treatment_k) + \beta_{H2} (HDDd_t \cdot Post_t) + \beta_{H3} (HDDd_t \cdot Treatment_k \cdot Post_t) \\ &+\beta_{C0} CDDd_t + \beta_{C1} (CDDd_t \cdot Treatment_k) + \beta_{C2} (CDDd_t \cdot Post_t) + \beta_{C3} (CDDd_t \cdot Treatment_k \cdot Post_t) + \varepsilon_{kt} \end{aligned} \quad . (11)$$

From (5), for both models the effect of treatment on average daily Kwh use—the average daily treatment effect (ADTE)— is,

$$ADTE_t = \alpha_3 + \beta_{H3} HDDd_t + \beta_{C3} CDDd_t \ . \quad (12)$$

Expanding (12) by using 2007 values of $HDDd_t$ and $CDDd_t$ generates the equation used in the calculation of annual savings due to the treatment effect (*AnnTE*) reported in Table 6:

$$AnnTE = \alpha_3 \cdot 365 + \beta_{H3} \cdot 2622 + \beta_{C3} \cdot 853 \quad (13)$$

Table 6 compares the estimated annual savings from each of the three methods. Two results deserve comment. First, all three methods give approximately the same result of an annual savings of about 2.1-2.2%. We found this result to hold across a wide variety of model specifications. Second, these estimates are very reliable, having a range of 1.9 to 2.6% at the 95% confidence level. The confidence intervals for methods 2 and 3 were calculated using the delta method (Greene 2002). They reflect the degree of precision in model parameter estimates, and are based on energy use in the sample in 2007 (the pre-treatment period), and thus on heating and cooling degree days in 2007. Along with the mean savings, these intervals would expand or contract somewhat depending on annual weather.

Table 6. Summary of Average Annual KWH Savings

Method	*Average annual kWh savings*	*95% Confidence interval on avg. annual savings*	*Average annual percent savings*	*95% Confidence interval on avg. percent savings*
Method 1: Difference-in-Difference Statistic:	257	-	2.20%	-
Method 2: Baseline OLS Linear Model	253.75	{216.81, 290.69)	2.24%	{1.91%, 2.56%}
Method 3: Baseline Differenced Linear Fixed Effects Model	240.88	{222.81, 258.95)	2.13%	{1.97%, 2.28%}

4.2 Differential Effect of Heating/Cooling Degree Days on Treatment and Control Households

Parameter estimates derived from the baseline LR model (10) are presented in Table 7, and estimates of the same parameters derived from the baseline DLFE model (11) are presented in Table 8.

Parameter estimates are interpreted as the marginal effect of a change in the variable on energy use. So, for instance, the LR model indicates that a 1-unit increase in heating degrees days per day increases average daily consumption of energy by .739 Kwh, while the DLFE model indicates such a change would increase average daily consumption by .730 Kwh.

The models are in good agreement with regard to the average daily treatment effect (see equation (12)). The LR model indicates that on a day free of heating and cooling degree days, the treatment reduces consumption of energy by 0.448 Kwh; each heating degree day adds 0.0182 to the savings, and each cooling degree day adds 0.0498 to the savings. These figures for the DLFE model are 0.326, 0.0245, and 0.0675, respectively. In the DLFE model, all treatment terms are significant at the .01 level. Estimates of the treatment effects in the LR model are less precise; the treatment terms $Treatment_k \cdot Post_t$ and $CDDd_t \cdot Treatment_k \cdot Post_t$ are significant at the .05 level, and the treatment term $HDDd_t \cdot Treatment_k \cdot Post_t$ is significant at the .08 level.

Table 7. Parameter estimates using the baseline Linear Regression (LR) Model (Dependent variable: Average daily Kwh; treatment terms shaded)

Variable	*Parameter estimate*	*Standard error*	*t-statistic*
Intercept	20.03454	0.05397	371.24
$Treatment_k$	-0.34995	0.08422	-4.16
$Post_t$	1.01504	0.08935	11.36
$Treatment_k \cdot Post_t$	-0.44838	0.13928	-3.22
$HDDd_t$	0.73943	0.00393	188.39
$HDDd_t \cdot Post_t$	-0.06662	0.00664	-10.04
$HDDd_t \cdot Treatment_k$	0.00277	0.00612	0.45
$HDDd_t \cdot Treatment_k \cdot Post_t$	-0.01815	0.01036	-1.75
$CDDd_t$	2.49685	0.01061	235.42
$CDDd_t \cdot Post_t$	-0.30645	0.01588	-19.3
$CDDd_t \cdot Treatment_k$	-0.03342	0.01652	-2.02
$CDDd_t \cdot Treatment_k \cdot Post_t$	-0.04983	0.0247	-2.02

Table 8. Parameter estimates using the baseline Differenced Linear Fixed Effects (DLFE) model (Dependent variable: Average daily Kwh)

Variable	*Parameter estimate*	*Standard error*	*t-statistic*
$Post_t$	-0.13361	0.04369	-3.06
$Treatment_k \cdot Post_t$	-0.32591	0.0681	-4.79
$HDDd_t$	0.73034	0.00192	380.76
$HDDd_t \cdot Post_t$	-0.01074	0.00324	-3.31
$HDDd_t \cdot Treatment_k$	0.0041	0.00299	1.37
$HDDd_t \cdot Treatment_k \cdot Post_t$	-0.02453	0.00506	-4.85
$CDDd_t$	2.44219	0.00518	471.24
$CDDd_t \cdot Post_t$	-0.16486	0.00776	-21.24
$CDDd_t \cdot Treatment_k$	-0.02305	0.00807	-2.86
$CDDd_t \cdot Treatment_k \cdot Post_t$	-0.06754	0.01208	-5.59

4.3 Extending the Analysis: The Effect of Housing Characteristics and Treatment Variables on Energy Savings

To the baseline models we added the following housing characteristics to examine the effect of these characteristics on energy savings under treatment:

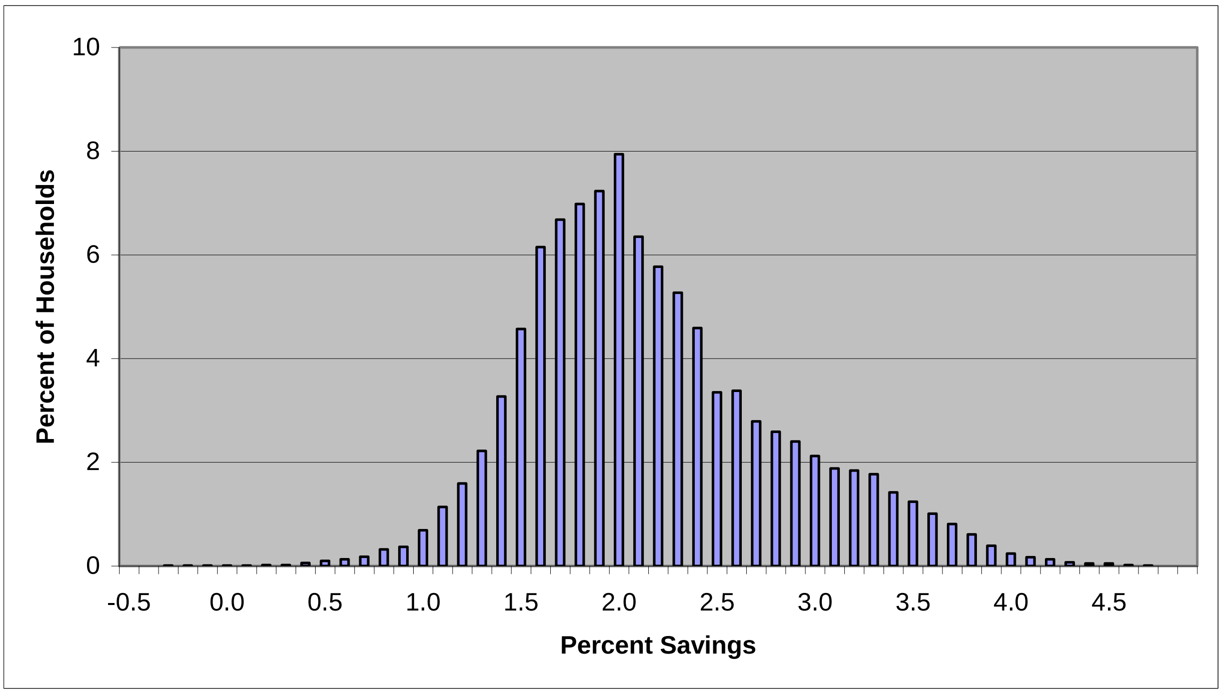
- A binary variable indicating the presence of a pool ($Pool_k$ takes a value of 1 if household k has a pool, and 0 otherwise;
- A binary variable indicating the presence of a spa (Spa_k takes a value of 1 if household k has a spa, and 0 otherwise;
- An interaction term multiplying a binary variable indicating the presence of electric heat ($Eheat_k$ takes a value of 1 if household k has electric heat, and 0 otherwise) by the heating degree days per day, $HDDd_t$;
- Square footage of the residence ($Sqft_k$), measured in units of 100 square feet;
- Age of the residence (Age_k) measured in years; and
- The assessed value of the property ($Value_k$) measured in $10,000 of assessed value.

[The rest of the information in this section is the intellectual property of Positive Energy and has been removed since it is confidential. For details on program impact for various customer segments, including analysis of the most significant demographic attributes, please contact Positive Energy.]

4.4 Predicted Distribution of Savings in the Treatment Group

Using the LR model of the previous section, the predicted distribution of savings within the treatment group is presented in Figure 4. As noted previously, the average savings is about 2.2%. Predicted percent savings for 50% of all households lie in the interval {1.6, 2.2}, predicted savings for 80% of all households lie in the interval {1.4, 2.9}, and predicted savings for 95% of all households lie in the interval {1.1, 3.5}.

Figure 4. Frequency distribution of predicted percent annual energy savings (2007 as base year) within the treatment group



This distribution curve shows that savings are predicted for virtually all individuals, rather than being possible for just a small subset of customers with particular characteristics.

4.5 Energy Savings of Treatment Households Receiving Monthly Versus Quarterly Reports

A treatment variable not included in the above analysis was the frequency of reports (monthly vs. quarterly) sent to treatment households. This is because the experimental design targeted households with relatively high energy use for monthly reports, and so including this variable would confound the estimated effects of housing characteristics correlated with high energy use.

To examine seasonal impacts by frequency of reporting, we ran the seasonal difference in difference model of Table 4 separately for households receiving monthly reports and households receiving quarterly reports. Control households were designated for the different report frequencies based on their level of use to properly match the participant groups. Results are presented in Table 9.

Table 9. Comparison of Impacts by Season and Frequency of Reports

Method	*Summer Impact*	*Winter Impact*	*Shoulder Months Impact*	*Annual Impact*
Monthly Reports (High Use Customers)	-2.8%	-2.3%	-1.9%	-2.3%
Quarterly Reports (Low Use Customers)	-1.4%	-1.6%	-1.4%	-1.6%
Overall	-2.6%	-2.2%	-1.7%	-2.2%

Low use customers receiving quarterly reports show relatively consistent savings throughout the seasons, with slightly higher savings in winter. High use customers receiving monthly reports reflect the overall pattern of savings, showing greatest savings in summer and lowest savings in the shoulder months.

5 AUTHOR BIOGRAPHIES

Daniel Violette, Ph. D. -- Dr. Violette is a Principal with Summit Blue Consulting who has over 20 years of experience in the energy industry. He is a founder and former CEO of Summit Blue and also served as a Vice President and Director with Hagler Bailly Consulting for over 10 years. He has also held officer-level positions with other major companies including serving as a Sr. Vice President with XENERGY, Inc., an energy services company, and with the Management Consulting Services Business Unit of Electronic Data Systems (EDS), one of the largest worldwide management services and technology companies.

Dr. Violette has managed many complex projects resulting in recommendations to senior management regarding actions to be taken related to demand response (DR), pricing and rates, resource planning, and energy efficiency. Current projects include several multi-year efforts examining the role of energy efficiency (EE) and DR in resource planning and development of integrated resource plans that address risk and uncertainty. He also has completed projects for the International Energy Agency on the value of EE and DR in resource planning including hedge/option values and risk management of system costs with a dozen US utilities and 20 countries, and he has authored a report for the Demand Response Research Center (CEC) on an integrated framework for assessing energy efficiency and DR. He is well known for his years of work on demand-side issues including planning, design, evaluation and integration. Dr. Violette has presented testimony and served on expert panels in over 25 regulatory jurisdictions in North America.

Bill Provencher, Ph.D. – Dr. Provencher serves as a full professor in the Department of Agriculture and Applied Economics at the University of Wisconsin-Madison. His published work has two distinct emphases: the dynamic allocation of resources and the valuation of nonmarket goods and services. His current research program focuses on three areas: a) the development of discrete choice models of the consumption of nonmarket goods and services; b) the interaction between socioeconomic and ecological systems; and c) dynamic issues in resource allocation, with attention focused mainly on using statistical methods to recover the dynamic behavior of resource owners. He has served on the board of the Association of Environmental and Resource Economists (AERE), co-edited and served on the editorial council of the *Journal of Environmental Economics and Management* (JEEM), and is currently on the editorial board of *Land Economics*. Dr. Provencher received an undergraduate degree in natural resources at Cornell University, an M.S. degree in forestry at Duke University in 1985, and a Ph.D. in agricultural economics from UC-Davis in 1991.

Mary Klos – Ms. Klos is a Senior Consultant at Summit Blue and has over 20 years of experience in the energy industry. Currently, she leads projects focused on impact analysis of energy efficiency and demand response programs. In her time at the Wisconsin Public Service Corporation, Ms. Klos worked consistently with energy efficiency and demand response issues from a variety of positions, including load forecasting, market research and demand-side management planning. She has worked with generation planners, transmission and distribution planners, rate design experts and marketing professionals to develop an integrated view of the entire DSM effort, and she has testified in rate proceedings and integrated resource planning dockets. Ms. Klos earned a BA in Economics from Beloit College and a Masters in Business Administration from the University of Wisconsin. Ms. Klos is also a certified Statistical Analysis System (SAS) Base Programmer.

APPENDIX A:

DETAILED MODEL RESULTS

Method 2: Linear Regression Base Model

The REG Procedure
Model: OrigOLS
Dependent Variable: AveDailyKWH

Number of Observations Read	2029885
Number of Observations Used	2029885

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	46553310	4232119	14082	<.0001
Error	2.03E+06	610043717	300.53295		
Corrected Total	2.03E+06	656597027			

Root MSE	17.33589	**R-Square**	0.0709
Dependent Mean	31.07693	**Adj R-Sq**	0.0709
Coeff Var	55.78378		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	**1**	20.03454	0.05397	371.24	<.0001
hddD	**1**	0.73943	0.00393	188.39	<.0001
cddD	**1**	2.49685	0.01061	235.42	<.0001
Post	**1**	1.01504	0.08935	11.36	<.0001
PosthddD	**1**	-0.06662	0.00664	-10.04	<.0001
PostcddD	**1**	-0.30645	0.01588	-19.3	<.0001
ParticPost	**1**	-0.44838	0.13928	-3.22	0.0013
ParticPosthddD	**1**	-0.01815	0.01036	-1.75	0.0796
ParticPostcddD	**1**	-0.04983	0.0247	-2.02	0.0437
Partic	**1**	-0.34995	0.08422	-4.16	<.0001
PartichddD	**1**	0.00277	0.00612	0.45	0.6505
ParticcddD	**1**	-0.03342	0.01652	-2.02	0.0431

Method 3: Fixed Effects Base Model

The REG Procedure
Model: base
Dependent Variable: diffaveDailykWh

Number of Observations Read	2029885
Number of Observations Used	2029885

Note: No intercept in model. R-Square is

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	10	46287941	4628794	64523.2	<.0001
Error	2.03E+06	145619983	71.7384		
Uncorrected Total	2.03E+06	191907924			

Root MSE	8.46985	**R-Square**	0.2412
Dependent Mean	1.80E-17	**Adj R-Sq**	0.2412
Coeff Var	4.71E+19		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
diffcddD	**1**	2.44219	0.00518	471.24	<.0001
diffhddD	**1**	0.73034	0.00192	380.76	<.0001
diffPost	**1**	-0.13361	0.04369	-3.06	0.0022
diffPosthddD	**1**	-0.01074	0.00324	-3.31	0.0009
diffPostcddD	**1**	-0.16486	0.00776	-21.24	<.0001
diffParticPost	**1**	-0.32591	0.0681	-4.79	<.0001
diffParticPosthddD	**1**	-0.02453	0.00506	-4.85	<.0001
diffParticPostcddD	**1**	-0.06754	0.01208	-5.59	<.0001
diffParticHDDd	**1**	0.0041	0.00299	1.37	0.1704
diffParticCDDd	**1**	-0.02305	0.00807	-2.86	0.0043

Base Model for Quarterly Report
Group

The REG Procedure
Model: Qtrly
Dependent Variable: diffaveDailykWh

Number of Observations Read	240168
Number of Observations Used	240168

Note: No intercept in model. R-Square is redefined.

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	5	1901600	380320	19722.3	<.0001
Error	240163	4631247	19.28376		
Uncorrected Total	240168	6532846			

Root MSE	4.39133	**R-Square**	0.2911
Dependent Mean	-4.51E-18	**Adj R-Sq**	0.2911
Coeff Var	-9.73E+19		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
diffPost	**1**	0.30321	0.05111	5.93	<.0001
diffcddD	**1**	1.39007	0.00593	234.31	<.0001
diffPostcddD	**1**	-0.09566	0.00897	-10.66	<.0001
diffhddD	**1**	0.34707	0.0022	157.56	<.0001
diffPosthddD	**1**	-0.00083494	0.00378	-0.22	0.8253

Covariance of Estimates					
Variable	**diffPost**	**diffcddD**	**diffPostcddD**	**diffhddD**	**diffPosthddD**
diffPost	0.002612615	0.000141865	-0.000385561	5.94168E-05	-0.000172727
diffcddD	0.000141865	3.51952E-05	-0.000035206	9.21E-06	-9.21E-06
diffPostcddD	-0.000385561	-0.000035206	8.04653E-05	-9.21E-06	2.53404E-05
diffhddD	5.94168E-05	9.21E-06	-9.21E-06	4.85E-06	-4.86E-06
diffPosthddD	-0.000172727	-9.21E-06	2.53404E-05	-4.86E-06	1.43038E-05

Base Model for Monthly Report
Group

The REG Procedure
Model: Month
Dependent Variable: diffaveDailykWh

Number of Observations Read	586698
Number of Observations Used	586698

Note: No intercept in model. R-Square is redefined.

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	5	18214496	3642899	40555.2	<.0001
Error	586693	52700128	89.82573		
Uncorrected Total	586698	70914624			

Root MSE	9.47764	**R-Square**	0.2569
Dependent Mean	3.17E-17	**Adj R-Sq**	0.2568
Coeff Var	2.99E+19		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
diffPost	**1**	-0.56019	0.06894	-8.13	<.0001
diffcddD	**1**	2.84333	0.00824	345.22	<.0001
diffPostcddD	**1**	-0.31349	0.01225	-25.59	<.0001
diffhddD	**1**	0.89418	0.00305	292.81	<.0001
diffPosthddD	**1**	-0.0613	0.00514	-11.93	<.0001

Covariance of Estimates					
Variable	**diffPost**	**diffcddD**	**diffPostcddD**	**diffhddD**	**diffPosthddD**
diffPost	0.004752634	0.000276504	-0.000708873	0.000114856	-0.000314899
diffcddD	0.000276504	6.78382E-05	-0.000067851	1.77594E-05	-0.000017764
diffPostcddD	-0.000708873	-0.000067851	0.000150131	-0.000017762	4.66113E-05
diffhddD	0.000114856	1.77594E-05	-0.000017762	9.33E-06	-9.33E-06
diffPosthddD	-0.000314899	-0.000017764	4.66113E-05	-9.33E-06	2.63913E-05