NAVIGANT

Energy Efficiency / Demand Response Plan: Plan Year 2 (6/1/2009-5/31/2010)

Evaluation Report: OPOWER Pilot

Presented to

Commonwealth Edison Company

December 16, 2010

Presented by

Randy Gunn
Managing Director

Navigant Consulting
30 S. Wacker Drive, Suite 3100
Chicago, IL 60606

phone 312.583.5700
fax 312.583.5701

www.navigantconsulting.com

Submitted to:

ComEd
Three Lincoln Centre
Oakbrook Terrace, IL 60181

Submitted by:

Navigant Consulting, Inc.
30 S. Wacker Drive, Suite 3100
Chicago, IL 60606
Phone 312.583.5700
Fax 312.583.5701

Contact:

Randy Gunn, Managing Director
312.938.4242
randy.gunn@navigantconsulting.com

Jeff Erickson, Associate Director
608.497.2322
jeff.erickson@navigantconsulting.com

Prepared by:

Bill Provencher, Associate Director
608.497.2327
bill.provencher@navigantconsulting.com

Table of Contents

Section E. Executive Summary

This document presents the evaluation results for the first year of the OPOWER behavioral pilot at Com Ed. The objective of the pilot is to determine if residential customer energy use can be altered by providing particular sets of information about customer energy use and energy conservation. The information is provided in the form of Home Energy Reports on a regular basis over a three-year period. The Home Energy Reports give customers three types of information: a) how their recent energy use compares to their energy use in the past; b) tips on how to reduce energy consumption, some of which are tailored to the customer's circumstances (e.g. customers with pools receive information on how to reduce energy use by pools); and c) information on how their energy use compares to that of neighbors with similar homes. This set of information has been shown in other studies to stimulate customers to reduce their energy use, creating average energy savings in the 1% to 3% range, depending on local energy use patterns. Com Ed started the pilot for 50,000 residential customers on July 14, 2009. Initial reports were received by the vast majority of participating customers in the six-week period ending on August 31, 2009.

E.1 Evaluation Objectives

The objective of the evaluation is to verify the savings impact in the Com Ed service territory of the OPOWER behavioral pilot during each year of the three year pilot.

The primary research question addressed in this report is whether customers receiving the reports reduced their energy consumption due to the reports over the past year, and whether this reduction varied seasonally. Secondary research questions addressed in this report are designed to improve program cost-effectiveness.

E.2 Evaluation Methods

The OPOWER pilot was implemented as an experimental design explicitly for the purpose of estimating changes in energy use due to the program. Navigant Consulting used two state-of-the-art statistical methods to quantify the energy savings from the pilot: Difference-in-Difference (DID) estimation and linear fixed effects regression. As expected the methods gave essentially the same results.

E.3 Key Findings

The impact results for the OPOWER pilot are shown in Table E- 1 for the first year of the program and for summer 2010. Impact for all seasons are reported in Table 3.4. Average annual savings was 1.54% for high energy users, and was 1.27% for low energy users. Other key findings:

- Savings vary seasonally;
- We found no statistical difference in annual program effect across two groups of low energy users that received reports at different frequencies (groups 2 and 3 in Table E-1);
- Among high energy users, savings appear to be higher for households with intermediate incomes than for households with relatively low and high incomes.

Table E- 1. *Ex Post* Program Savings – OPOWER Pilot[a]

Period	*Type of Statistic*	*Group 1: High Energy Users (standard error)*	*Group 2: Low Energy Users, Bimonthly Reports (standard error)*	*Group 3: Low Energy Users, Monthly-to-Quarterly Reports (standard error)*
ANNUAL, (Fall 2009-Summer 2010)	*Sample size of treatment group* *Sample size of control group*	*17,827* *17,708*	*13,132* *13,101*	*13,201* *13,083*
	Annual (Sept 2009-August 2010) percent savings	*1.54%* *(0.18%)*	*1.17%* *(0.21%)*	*1.37%* *(0.22%)*
	Annual savings per customer (kWh)	*330.5* *(38.9)*	*130.9* *(23.7)*	*153.1* *(23.9)*
	Total Annual savings (mWh)	*5,892* *(693)*	*1,719* *(311)*	*2,021* *(316)*
SUMMER 2010 (June 15-September 15 bill dates)	*Sample size of treatment group* *Sample size of control group*	*16,938* *16,848*	*12,565* *12,660*	*12,612* *12,605*
	Summer 2010 percent savings	*2.23%* *(0.45%)*	*0.44%* *(0.55%)*	*0.81%* *(0.55%)*
	Summer 2010 savings per customer (kWh)	*124.1* *(24.9)*	*12.7* *(15.9)*	*23.4* *(15.9)*
	Total Summer 2010 savings (mWh)	*2101* *(422)*	*160* *(199)*	*295* *(200)*

[a] *Full results and discussion are found in section 3, Tables 3.3-3.4.*

Section 1. Introduction to the Program

1.1 *Program Description*

Com Ed started the OPOWER pilot for 50,000 residential customers on July 14, 2009. The objective of the pilot is to determine if residential customer energy use can be altered by providing particular sets of information. The information is provided in the form of Home Energy Reports on a regular basis over a three year period. The Home Energy Reports give customers three types of information: a) how their recent energy use compares to their energy use in the past; b) tips on how to reduce energy consumption, some of which are tailored to the customer's circumstances (e.g. customers with electric heat receive information on how to reduce energy use by electric heating systems); and c) information on how their energy use compares to that of neighbors with similar homes. This set of information has been shown in other studies to stimulate customers to reduce their energy use, creating average energy savings in the 1% to 3% range, depending on local energy use patterns.

1.2 *Evaluation Questions*

The objective of the evaluation is to verify the savings impact in the Com Ed service territory during each year of the three year pilot.

The primary research question addressed in this report is whether customers receiving the reports reduced their energy consumption due to the reports over the past year, and whether this reduction varied seasonally.

Secondary research questions addressed in this report, and designed to improve program cost-effectiveness are the following:

- Do high consumption customers save more energy than low consumption customers?
- Do savings vary by season?
- Does the frequency of report delivery impact the energy savings?
- Do participants show greater participation in Com Ed's other energy efficiency programs due to the information they receive?
- Among high-use customers, are program savings for low-income customers different than for medium- and high-income customers?

Section 2. Evaluation Methods

This section describes the analytical methods used for the evaluation. Impact evaluation methods will be presented in detail. There was no process evaluation for the Year 1 evaluation of this pilot.

2.1.1 Impact Evaluation Methods

Gross Program Savings

Estimation of gross program savings over the past year is the primary research objective of this evaluation. In this section we discuss the steps taken to obtain gross program savings: data collections methods, sampling approach, and the methods used for analysis.

Data collection methods, sample design and sample data

OPOWER received the requisite billing data for the analysis period January 2008 to August 2010 from ComEd, and continues to receive this data on an ongoing basis. In turn, OPOWER linked this data to data on weather (heating and cooling degree days), housing/household characteristics, and home energy report data (frequency and template type) before sending finished dataset to Navigant for analysis. Several descriptive statistics for the current data set are available in Table 2.1. As expected, treatment and control customers are very similar on average.

Table 2.1. Sample descriptive statistics for housing/household characteristics (first number is for control customers, second number is for treatment customers)

Variable	Sample Size	Mean (proportion with feature)	Standard Error of the Mean	t-statistic on difference
Square Footage of Home	24,711 25,387	2,402 2,395	8.94 8.61	0.58
Number of Baths	31,102 31,460	2.05 2.06	0.00808 0.00799	-1.01
Single Family (vs. Multi-Family)	46,743 46,819	79.9% 82.0%	0.40% 0.38%	-8.04
Own (vs. Rent)	38,358 38,428	92.0% 93.1%	0.14% 0.13%	-5.79
Income category (1-9)	40,540 40,636	7.32 7.34	0.00878 0.00854	-2.13
Number of occupants	40,540 40,642	4.68 4.69	0.00847 0.00835	-0.46
Age of Head of Household	30,633 30,968	54.46 54.45	0.0707 0.0707	0.13

In the sample design the treatment customers are distributed across three groups. Each group is described below along with the original number of customers in the group. The actual number of customers used in the analyses is less than the original number by about 2,000 customers for each group, due to a small number of customers who opted out of the program or moved away, the removal of customers who do not meet selection criteria for analyses, and missing data.

Group 1: 20,000 customers receive monthly reports for a period of six months, then switch to bimonthly reports. This group consists of the highest use customers, where more frequent reports can have a greater impact.

Group 2: Nominal 15,000 customers receive bimonthly reports for the duration of the program. This group is randomly assigned from the remaining customers of the original 50,000 (after choosing Group 1).

Group 3: Nominal 15,000 customers receive monthly reports for a period of three months, then switch to quarterly reports. This group is randomly assigned from the remaining customers of the original 50,000 (after choosing Group 1).

Differences in savings between Group 1 and Groups 2 and 3 provide information on the joint effect on program savings of high report frequency and initially high energy use. Differences in savings between Groups 2 and 3 provide information on the effect of report frequency on program savings.

Analysis 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. In theory these methods should generate very similar results, and so using both methods provides a strong check on results.

Difference-in-Difference 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. Calculating this same difference for a 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.

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).[1] 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 difference-in-difference statistic is the difference between the control and treatment groups in the *change* in their annual rate of energy use across the pre- and post-treatment periods. Formally,

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

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 pre-treatment period gives the proportional reduction from treatment,

$$Proportional\ Treatment\ Effect = \frac{Dif\left(\overline{kWh}\right)}{\overline{kWh}_{01}} . \quad (2)$$

Linear Fixed Effects Regression Analysis

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 period 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 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,

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

Three observations about this specification deserve comment. First, the coefficient α_{0k} captures **all** customer-specific effects on energy use that do not change over time, including those that are unobservable. Second, α_1 captures the average effect *across all customers* of being in the post-treatment period. In other words, the effects of exogenous factors, such as an economic recession, that affect all customers in the post-treatment period are absorbed in the *Post*

[1] Both the control and treatment groups could be subsets, such as the set of customers with pools.

variable. ***Third, the effect of being both in the treatment group and in the post period –the effect directly attributable to the program—is captured by the coefficient*** α_2**.** 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_1 captures the change in average daily kWh use across the pre- and post-treatment periods for the *control* group, the sum $\alpha_1 + \alpha_2$ captures this change for the treatment group, and so α_2 is the coefficient analogous to the DID statistic indicating the effect on the program on average monthly customer energy use.

Expanding the Basic LFER Model

The simple LFER model described above can be expanded to include two other types of variables: those that change over time, such as weather-related variables or dummy variables indicating the report frequency, and those that are fixed over time but change across customers, such as housing/household characteristics. In the modeling conducted for this analysis, we limit additional variables to the two weather-related variables, heating degree days per day ($HDDd_t$) in bill period *t*, and cooling degree days per day, $CDDd_t$, and group membership in the sample design.

For each of the weather variables, 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 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 (that is, how the variable affects the effect of the program on customer energy consumption).

Formally, we expand our model to the following:

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

In this model, the average daily treatment effect (ADTE) is the sum of all the terms multiplying the interaction term $Treatment_k \cdot Post_t$:

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

Note, then, that the treatment effect changes across seasons because of seasonal changes in *HDDd* and *CDDd*. The coefficients on these variables indicates the effect on savings per day for a billing period (approximately 1 month) due to a 1-unit increase in the average heating or cooling degree days for the period (in other words, due to an approximate increase of 30 heating or cooling degree days for the period).

As discussed in the next section, The LFER model (4) can be estimated separately for each of the three groups in the analysis, or these groups can be combined in a single regression. The advantage of the latter approach is that it allows the analyst to formally test whether program savings varies across groups. It involves creating dummy variables for two of the groups –the third group serves as the baseline from which differential effects are measured—and interacting these dummy variables with the terms in (4) that change over time. Formally, we let the dummy variable $G1_k$ take a value of 1 if sample customer k is in group 1 (high energy users) and 0 otherwise, and we let the dummy variable $G3_k$ take a value of 1 if sample customer k is in group 2 (low energy users, monthly-to-quarterly reports), and 0 otherwise. In this case the baseline comparison group is Group 2, the low energy users receiving bimonthly reports, and our regression model becomes,

$$
\begin{aligned}
ADU_{kt} = {} & \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t \\
& + \alpha_3 G1_k \cdot Post_t + \alpha_4 G3_k \cdot Post_t \\
& + \alpha_5 G1_k \cdot Treatment_k \cdot Post_t + \alpha_6 G3_k \cdot Treatment_k \cdot Post_t \\
& + \beta_0 HDDd_t + \beta_1 HDDd_t \cdot Treatment_k + \beta_2 HDDd_t \cdot Post_t + \beta_3 HDDd_t \cdot Treatment_k \cdot Post_t \\
& + \beta_4 G1_k \cdot HDDd_t + \beta_5 G1_k \cdot HDDd_t \cdot Treatment_k + \beta_6 G1_k \cdot HDDd_t \cdot Post_t + \beta_7 G1_k \cdot HDDd_t \cdot Treatment_k \cdot Post_t \\
& + \beta_8 G3_k \cdot HDDd_t + \beta_9 G3_k \cdot HDDd_t \cdot Treatment_k + \beta_{10} G3_k \cdot HDDd_t \cdot Post_t + \beta_{11} G3_k \cdot HDDd_t \cdot Treatment_k \cdot Post_t \\
& + \gamma_0 CDDd_t + \gamma_1 CDDd_t \cdot Treatment_k + \gamma_2 CDDd_t \cdot Post_t \quad + \gamma_3 CDDd_t \cdot Treatment_k \cdot Post_t \\
& + \gamma_4 G1_k \cdot CDDd_t + \gamma_5 G1_k \cdot CDDd_t \cdot Treatment_k + \gamma_6 G1_k \cdot CDDd_t \cdot Post_t + \gamma_7 G1_k \cdot CDDd_t \cdot Treatment_k \cdot Post_t + \varepsilon_{kt} \\
& + \gamma_8 G3_k \cdot CDDd_t + \gamma_9 G3_k \cdot CDDd_t \cdot Treatment_k + \gamma_{10} G3_k \cdot CDDd_t \cdot Post_t + \gamma_{11} G3_k \cdot CDDd_t \cdot Treatment_k \cdot Post_t + \varepsilon_{kt}
\end{aligned}
\tag{6}
$$

As with the other models, the program effect (ADTE) is the sum of terms involving the interaction $Treatment_k \cdot Post_t$. Differences in ADTE between the groups are indicated by statistically significant coefficients on the ADTE terms that include *G1* or *G3*.

Net Program Savings

There are no program attribution issues related to this type of behavioral program. Customers would not receive this type of personal energy use comparison information in the absence of the program, so net program savings are equal to gross program savings.

2.1.2 Process Evaluation Methods

A process evaluation was not included in the Year 1 evaluation of this pilot.

Section 3. Program Level Results

3.1 *Impact Evaluation Results*

This section will present the parameter estimate results from the analysis methods, as well as total pilot savings for Year 1 based on participation numbers and the parameter estimates.

3.1.1 Verification and Due Diligence

There were no verification and due diligence reviews related to this pilot.

3.1.2 Tracking System Review

There was no tracking system for this pilot.

3.1.3 Gross Program Impact Parameter Estimates

The DID analysis does not involve estimation of parameters. Here we present parameter estimates for the linear fixed effects regression (LFER) model.

All LFER models are based only on those customers with 22-26 billing records over the 2-year period beginning one year period *before* the program date for the customer, and extending one year after the program date. The program date is the date of the bill *following* the first bill in which a home energy report was received. It is the first bill, in other words, after the customer had a chance to respond to the information contained in the home energy report. In the random assignment of customers, the date the control customers would have received the first home energy report was recorded, and so the inclusion of control customers in the analysis was also conditioned by the requirement of 22-26 bills in the same timeframe.

We first estimated model (6) for this two-year period, results of which are in Table 3.1 in the model entitled "Encompassing model", so-named because the model includes all groups. Terms involving program effects are indicated in the first column. In the encompassing model, the lightly-shaded "A" terms pertain to the baseline group, Group 2 (low energy users, bimonthly report frequency); the medium-shaded "B" terms (G1 terms) pertain to Group 1 (high energy users), and indicate whether Group 1 households are different than Group 2 households in their average response to the program; and the darkest-shaded "C" terms (G3 terms) pertain to Group 3 (low energy users, monthly-to-quarterly report frequency), and indicate whether Group 3 households are different than Group 2 in their average response to the program.

Two important conclusions can be drawn from comparisons of the A, B, and C terms:

- Program effects for the low energy users receiving the home energy reports bimonthly are not statistically different than for the low energy users receiving the reports quarterly. This is indicated by the low t-statistics (all less than 1.96) for all of the G3 terms.

- Program effects for the high energy users are indeed statistically different than for the baseline group. This is indicated by the high t-statistics (over 1.96) for several of the G1 terms.

- In light of these two results, we conclude more generally that the effect of the program on energy consumption by high energy users is different than the effect on consumption by low energy users.

Given these results for the encompassing model, we estimated two other regression models using the annual data. The first was a model for the high energy users, and the second was a model for the low energy users, combining Groups 2 and 3. Results for these models are also reported in Table 3.1, and form the basis for annual savings estimates from the LFER analysis reported in section 3.1.4.

Because of the close match between estimated annual savings for the DID and LFER annual analyses (as reported in the next section), we restricted seasonal analysis of program effects using an LFER regression model to the summer of 2010 (bill dates between June 15 and September 15), because under the DID analysis it generated the most surprising result: a low percent saving for low energy users compared to other seasons. In light of the results for the annual encompassing model, separate regression equations were estimated for high energy users and low energy users (Groups 2 and 3 combined). Moreover, preliminary analysis revealed no statistically significant effect of either heating degree days per day (*HDDd*) or cooling degree days per day (*CDDd*) during the summer months, most likely because the time period involved provides little variation in these variables—monthly bills during the summer tend to have roughly similar values for *CDDd* and *HDDd*, and so the analysis is restricted to the simplest model, equation (3). For this model, the average daily treatment effect (ADTE) is simply the coefficient on the interaction $Treatment_k \cdot Post_t$.

Regression results for the summer analysis are reported in Table 3.2. Coefficient estimates indicate that the program effect is statistically significant for both high and low energy users. High energy users saved an average of 1.279 per day during the summer; low energy users saved an average of 0.345 per day.

Table 3.1. Linear fixed effects regression model for the program period Fall 2009-Summer 2010 (dependent variable: average kWh consumption per day).

		Models					
		Encompassing Model		High Energy Users Only (Group 1)		Low Energy Users (Groups 2 and 3 combined)	
	Variables	*Coefficient*	*t-statistic*	*Coefficient*	*t-statistic*	*Coefficient*	*t-statistic*
	HDDd	0.3305	95.25	0.6862	160.12	0.3314	209.11
	CDDd	2.7014	133.24	4.8470	185.96	2.7011	277.4
	Treatment*HDDd	-0.0003	-0.07	-0.0557	-9.2	-0.0020	-0.9
	Treatment*CDDd	0.0463	1.8	-0.0958	-2.6	0.0528	3.84
	Post	-0.8667	-6.53	-1.7369	-10.14	-0.8483	-13.41
	Post*HDDd	0.0286	5.7	0.0209	3.31	0.0287	12.31
	Post*CDDd	-0.0082	-0.35	-0.2239	-6.9	-0.0039	-0.32
A	Treatment*Post	-0.0229	-0.13	-1.0377	-4.29	-0.1027	-1.15
A	Treatment*Post*HDDd	-0.0153	-2.3	0.0022	0.24	-0.0119	-3.6
A	Treatment*Post*CDDd	-0.0429	-1.56	0.0513	1.12	-0.0427	-2.51
	G1*HDDd	0.3557	76.45				
	G1*CDDd	2.1456	77.49				
	G1*Treatment*HDDd	-0.0554	-8.62				
	G1*Treatment*CDDd	-0.1421	-3.84				
	G1*Post	-0.8702	-4.79				
	G1*Post*HDDd	-0.0077	-1.13				
	G1*Post*CDDd	-0.2157	-6.46				
B	G1*Treatment*Post	-1.0148	-4.16				
B	G1*Treatment*Post*HDDd	0.0175	1.88				
B	G1*Treatment*Post*CDDd	0.0942	2.19				
	G3*HDDd	0.0018	0.38				
	G3*CDDd	-0.0006	-0.02				
	G3*Treatment*HDDd	-0.0034	-0.56				
	G3*Treatment*CDDd	0.0130	0.49				
	G3*Post	0.0368	0.22				
	G3*Post*HDDd	0.0002	0.03				
	G3*Post*CDDd	0.0087	0.32				
C	G3*Treatment*Post	-0.1597	-0.88				
C	G3*Treatment*Post*HDDd	0.0068	0.85				
C	G3*Treatment*Post*CDDd	0.0003	0.05				

Table 3.2. Linear fixed effects regression model for Summer 2010 (dependent variable: average kWh consumption per day)

Variables	Models			
	High Energy Users Only (Group 1)		Low Energy Users (Groups 2 and 3 combined)	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
Post	17.42	112.59	11.35	163.78
Treatment*Post	-1.279	-5.85	-0.345	-3.53

3.1.4 Gross Program Impact Results

Gross Program Impact Results: Difference-In-Difference Estimation

Results for the DID estimation are presented in Table 3.3. As would be expected given the results of the LFER encompassing model, we found no statistically significant difference in program savings between the two low usage consumer groups, Groups 2 and 3. There is a statistically significant difference in savings between Group 1 and Groups 2 and 3, but in light of the experimental design it is not possible to determine whether this difference is due to differences in energy consumption in the pre-treatment period, or due to the frequency with which reports are received.

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 bill date", and 12 bills in the 355 days after the customer's program bill date, the program bill date inclusive. A customer's program bill 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 bill 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 bill in the specification of the pre- and post-treatment periods is to account for small deviations in the actual delivery dates for bills.

Bills falling within season dates were included in the analysis for the particular season.[2] 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 2008, fall 2008, winter 2008-09, and spring 2009.

[2] Season dates were Fall: September 15-December 15; Winter: December 15-March 15; Spring: March 15-June 15; Summer: June 15-September 15.

The following results emerge from Table 3.3:

- Total annual energy savings for one year of the program was approximately 9600 MWh.
- On a percentage and actual basis, savings among high energy users peaked in the last quarter of the program (summer 2010), though savings estimates for this quarter are preliminary because not all of the summer data was available when program evaluation began. Savings among high users for summer 2010 is estimated at 2.23%, or about 124kWh per customer.
- On the other hand, on a percentage and actual basis savings among low energy users were lowest in the last quarter of the program (summer 2010), at 0.44% and 0.81% for Groups II and III, respectively. These figures denote savings of only 12.7 and 23.4 kWh per customer for the summer.
- High energy users contributed about twice as much savings on a per customer basis (330 kWh/year) than did low energy users (131 kWh/year and 153 kWh/year for Groups II and III, respectively).
- There is no statistical evidence that customers receiving quarterly reports generated lower or higher savings than customers receiving bimonthly reports.

Table 3.3. DID Estimates of First Year *Ex Post* Program Savings – OPOWER Pilot

Period	Type of Statistic	Group 1: High Use Customers (standard error)	Group 2: Low Use Frequency 1 (standard error)	Group 3: Low Use Frequency 2 (standard error)
ANNUAL (Fall 2009-Summer 2010)	Sample size of treatment group Sample size of control group	17,827 17,708	13,132 13,101	13,201 13,083
	Annual (Sept 2009-August 2010) percent savings	1.54% (0.18%)	1.17% (0.21%)	1.37% (0.22%)
	Annual savings per customer (kWh)	330.5 (38.9)	130.9 (23.7)	153.1 (23.9)
	Total Annual savings (mWh)	5,892 (693)	1,719 (311)	2,021 (316)
FALL 2009 (September 15-December 15 bill dates)	Sample size of treatment group Sample size of control group	18,660 18,581	13,920 13,954	13,938 13,942
	Fall 2009 percent savings	1.46% (0.27%)	0.90% (0.40%)	1.51% (0.30%)
	Fall 2009 savings per customer (kWh)	72.1 (13.2)	23.0 (10.2)	38.4 (7.7)
	Total Fall 2009 savings (mWh)	1346 (246)	319 (142)	535 (107)
WINTER 2009-10 (December 15-March 15 bill dates)	Sample size of treatment group Sample size of control group	18,632 18,556	13,898 13,929	13,913 13,915
	Winter 2009-10 percent savings	1.22% (0.306%)	1.63% (0.364%)	1.14% (0.364%)
	Winter 2009-10 savings per customer (kWh)	74.0 (18.6)	50.2 (11.2)	35.1 (11.2)
	Total Winter 2009-	1378	697.8	488

Period	Type of Statistic	Group 1: High Use Customers (standard error)	Group 2: Low Use Frequency 1 (standard error)	Group 3: Low Use Frequency 2 (standard error)
	10 savings (mWh)	(346)	(155.7)	(156)
SPRING 2010 (March 15-June 15 bill dates)	Sample size of treatment group Sample size of control group	18,558 18,479	13,848 13,858	13,857 13,854
	Spring 2010 percent savings	1.89% (0.32%)	1.07% (0.35%)	1.41% (0.36%)
	Spring 2010 savings per customer (kWh)	83.3 (13.9)	24.2 (8.0)	31.7 (8.15)
	Total Spring 2010 savings (mWh)	1545 (258)	335 (111)	439 (113)
SUMMER 2010 [a] (June 15-September 15 bill dates)	Sample size of treatment group[b] Sample size of control group	16,938 16,848	12,565 12,660	12,612 12,605
	Summer 2010 percent savings	2.23% (0.45%)	0.44% (0.55%)	0.81% (0.55%)
	Summer 2010 savings per customer (kWh)	124.1 (24.9)	12.7 (15.9)	23.4 (15.9)
	Total Summer 2010 savings (mWh)	2101 (422)	160 (199)	295 (200)

[a]Summer 2010 savings are preliminary; at the time of the evaluation not all summer 2010 data were available.

[b]Relatively low summer sample sizes reflect that only customers with 2-4 bills during the summer period are included in the analysis, and at the time of the analysis not all summer 2010 data were available.

Gross Program Impact Results: Linear Fixed Effects Regression (LFER) Analysis

As expected, linear fixed effects regression (LFER) analysis generated virtually the same estimates of annual savings as obtained in the DID analysis. This being the case, we restricted the fixed effects analysis to annual savings and savings for summer 2010 because the results are so close to those obtained for the DID analysis that analysis of the other seasons was not deemed cost effective. We chose to analyze the summer season over the other seasons because we wanted to check the robustness of the surprising result in the DID analysis that savings among low energy users was lower in the summer of 2010 than in the previous three seasons.

Estimates of annual savings from the LFER analysis

The LFER model used to calculate annual program savings is presented in (4), with estimated regression coefficients presented in Table 3.1, one set for high energy users (Group 1) and one set for low energy users (Groups 2 and 3). With reference to equation (5), and denoting by $\overline{CDDd}$ the annual average cooling degree days per day, and by $\overline{HDDd}$ the annual average heating degree days per day, the average daily treatment effect (ADTE) for the year following program implementation is:

$$ADTE = \alpha_2 \cdot + \beta_3 \overline{HDDd} \alpha_1 + \gamma_3 \overline{CDDd} \; . \tag{7}$$

Multiplying this value by the length of the period in question (365 days for the annual analysis) generates average savings per customer. Multiplying this by the number of participants generates total savings for the period. Drawing on data for the two years of the analysis, we set $\overline{CDDd}$ =2.05 and $\overline{HDDd}$ =16.56 for the annual analysis.

Annual program savings are reported in Table 3.4. Highlights:

- Total annual program savings are estimated to be 9,761 mWh, compared to the estimate of 9,632 for the DID analysis;
- Average annual percent savings is 1.52% for high energy users and 1.27% for low energy users; this compares to 1.54% and 1.27% (weighted average) for the DID analysis.

Estimates of summer 2010 savings from the LFER analysis

The LFER analysis for Summer 2010 is based on the simplest model(3), because the lack of variation in cooling degree days across bills caused the parameters on *HDDd* and *CDDd* to be nonsignificant. Mean daily savings is simply the coefficient on $Partic \cdot Post$, α_2 . The standard error of the estimate is simply the standard error on this parameter. Regression results—estimates of α_2 and its standard error for the models of high energy and low energy users—are reported in Table 3.2. Multiplying α_2 by the length of the summer (91 days) generates savings per customer, and in turn multiplying this by the number of participants in the analysis generates the estimate of program savings for the summer.

As with our estimate of program savings from the DID analysis, we consider the estimate derived from the fixed effects regression analysis to be conservative because we were fairly restrictive in setting conditions for keeping a customer in the analysis. In particular, customers without 22-24 total bills over the 2-year period were not included in the annual or summer analysis.

Saving estimates are presented in Table3.4. The key result:

- As with the DID analysis, summer 2010 savings were much *higher* than average for the high energy users (2.09%), and lower than average for the low energy users (1.08%), though the value for the low energy users was actually higher than found in the DID analysis. Still, this latter result is surprising, and the performance of the program among low energy users bears monitoring in future evaluations.

For none of the program savings statistics that we examined were the values derived from the DID analysis and the LFER analysis statistically different.

Table 3.4. LFER Estimates of First Year *Ex Post* Program Savings – OPOWER Pilot

Period	Type of Statistic	Group 1: High Use Customers (standard error)	Groups 2-3: Low Use Customers (standard error)
ANNUAL, Fall 2009-Summer 2010	Sample size of treatment group[a] Sample size of control group	18,191 18,097	26,981 26,861
	Annual (Sept 2009-August 2010) percent savings	1.52% (0.18%)	1.27% (0.21%)
	Annual savings per customer (kWh)	327.2 (37.6)	141.2 (13.9)
	Total Annual savings (mWh)	5,952 (685)	3,809 (375)
SUMMER 2010 (June 15-September 15 bill dates)	Sample size of treatment group Sample size of control group	18,191 18,097	26,981 26,861
	Summer 2010 percent savings	2.09% (0.36%)	1.08% (0.42%)
	Summer 2010 savings per customer (kWh)	116.4 (19.9)	31.4 (8.9)
	Total Summer 2010 savings (mWh)	2118 (362)	572 (162)

Gross Program Impact Results: DID Analysis Results for Low Income Customers

The evaluation plan also calls for the evaluation of program savings for a pre-selected subset of 381 low income customers. This was not feasible for the following reasons:

1. The dataset of pre-selected customers is too small a sample to obtain reasonable estimates of savings. Even if the effect for these customers was similar to that for

customers generally, an analysis would not generate the conclusion that the effect is statistically different than zero.

2. All of the customers in the pre-selected low income dataset are treatment customers (received the home energy reports). A properly conducted analysis would require a comparison group of control customers that meet the same selection criteria.

With these limitations in mind, we did not restrict the analysis to the pre-selected low income households, and instead grouped customers in the main dataset into three income brackets and conducted the DID analysis for each bracket, limiting the analysis to the original Group 1 customers (high energy users).[3] The income brackets corresponded to income categories in the data set: incomes of $0K-$30K in Income Bracket I, $30K-75K in Income Bracket II, and $75K+ in Income Bracket III.[4]

Estimation results are presented in Table 3.5. Key results:

- The estimate for average annual program savings for customers in the lowest income class (Income Bracket I) is only 0.53%, and not statistically different than zero, though the sample size is quite small. This compares to an average annual program savings of 1.54% for Group I customers generally.

- Perhaps the most interesting finding is that in both absolute and percentage terms, program savings appear to be greatest for customers in the middle income bracket. The estimate for average annual program savings for these customers is 2.21%, which is greater than for customers in the top bracket (1.57%). Moreover, this difference even applies in absolute terms: Bracket II customers saved an average of 431 kWh for the year, whereas Bracket III customers saved 341 kWh per year. Though the statistical significance of this difference is low, it bears additional study in the future.

---

[3] The analysis was limited to Group 1 customers in part because *all* of the customers in the selected low-income dataset received home energy reports on a monthly basis, the same frequency reports were received by Group 1 customers, and in part because Group 1 customers showed the greatest savings response to the program, and so provided the best opportunity to benchmark the effect of income on program savings.

[4] Of the 234 customers in the pre-selected low income group that reported incomes, 101 (43% of reporting) were in Income Bracket I, 116 (50%) were in Income Bracket II, and 17 (7%) were in Income Bracket III. By comparison, among the treatment customers in Group 1 (high energy users) in the general data set for which the income variable is reported, and which met other conditions for analysis (in particular, 24 bills in the two-year analysis period), 2.2% were in Income Bracket I, 15.1% were in Income Bracket II, and the remainder (82.7%) were in Income Bracket III.

Table 3.5. DID Estimates of First Year Program Energy Savings – OPOWER Pilot, by Customer Income.

Period	Statistic	Income Bracket I (standard error)	Income Bracket II (standard error)	Income Bracket III (standard error)
ANNUAL, (Fall 2009-Summer 2010)	Sample size of treatment group Sample size of control group	354 382	2,410 2,595	13,166 12,928
	Annual (Sept 2009-August 2010) percent savings	0.53% (1.47%)	2.21% (0.54%)	1.57% (0.20%)
	Annual savings per customer (kWh)	111.2 (304.1)	430.8 (102.4)	340.6 (42.5)
	Total Annual savings (mWh)	39 (108)	1,038 (247)	4485 (560)

Gross Impact Results: The effect of participation in the OPOWER behavioral program on participation in other energy efficiency programs

The experimental design of the OPOWER program allows an examination of the effect of the program on participation in other programs. The logic of such an examination is straightforward: because customers are randomly assigned to the program, the effect of the OPOWER program on participation in another energy efficiency program is the difference during the post-treatment period between enrollment in the other program among control customers and treatment customers.

At this stage in the evaluation we considered two energy efficiency programs: the Appliance Recycling program and the Multi-family Direct Install program. Additional programs will be evaluated in the second year. The Multi-family Direct Install program had only six cases after the start of the OPOWER program, and so we did not analyze this program due to the lack of data. For the evaluation of the Appliance Recycling program the analysis was conducted separately for high-use customers (Group 1) and low-use customers (Groups 2 and 3 combined). Results are presented in Table 3.6 and reveal the following:

- Among high-use customers there is a statistically significant difference in the probability of enrollment in the applied recycling program. We found that 0.90% of the treatment customers enrolled in the program, while 0.62% of control customers did. As a practical matter, though, this difference is small, representing an enrollment difference of 2.8 per 1000 customers.

- Among low-use customers we found no statistical or practical difference in the enrollment between treatment and control customers.

Table 3.6. Participation by the OPOWER sample in the ComEd appliance recycling program

	Program Appliance Recycling	
	High Energy Users (Group 1)	Low Energy Users (Groups 2 and 3)
Number of OPOWER treatment customers:	18,307	27,124
Number of OPOWER control customers:	18,209	27,026
Treatment customers in the program:	164	238
Control customers in the program:	112	220
Difference in enrollment in program:	52	18
Percentage of treatment customers in the program	0.896%	0.877%
Percentage of control customers in the program	0.615%	0.814%
Percentage difference:	0.281%	0.063%
t-statistic on the percent difference	3.10	0.81

3.1.5 Net Program Impact Results

Due to the experimental design of the program, net program impacts are the same as gross program impacts.

3.2 *Process Evaluation Results*

There was no process evaluation of this pilot in Year 1.

Section 4. Conclusions and Recommendations

4.1 Conclusions

The OPOWER behavioral program appears to be performing at a level comparable to what has been found in published analyses of other applications of the program. Key findings:

- Total annual energy savings for one year of the program was approximately 9600 mWh.
- On a percentage basis, average energy savings for the first year of the program was about 1.54% for high energy users and 1.27% for low energy users. (LFER analysis)
- Over the first year of the program, high energy users contributed about twice as much savings on a per customer basis (327 kWh/year) as low energy users (141 kWh/year). (LFER analysis)
- There is no statistical evidence that low energy users receiving monthly-to-quarterly reports generated lower or higher savings than low energy users receiving bimonthly reports.
- On a percentage and actual basis, savings among high energy users peaked in the last quarter of the program (summer 2010), though savings estimates for this quarter are preliminary because not all of the summer data was available when program evaluation began. Savings among high users for summer 2010 is estimated at 2.09%, or about 116kWh per customer. (LFER analysis)
- On the other hand, on a percentage and actual basis savings among low energy users were lowest in the last quarter of the program (summer 2010), at 1.08%. This figure denotes savings of only 31 kWh per customer for the summer. (LFER analysis)
- Among high energy users, the estimate for average annual program savings for customers in the lowest income class ($0k-$30K annual income) is only 0.53%, and not statistically different than zero, though the sample size is quite small. This compares to an average annual program savings of 1.54% for high energy users generally.
- Among high energy users, program savings appear to be greatest for customers in the middle income class ($30K-$75K annual income). The estimate for average annual percent program savings for these customers is 2.21%, which is greater than for customers in the top income bracket (1.57%; the top income bracket is >$75k per year). Moreover, this difference even applies in absolute terms: middle income customers saved an average of 431 kWh for the year, whereas high-income customers saved 341

kWh per year. Though the statistical significance of this difference is low, it bears additional study in the future.

- Among high energy users there is a statistically significant difference in the probability of enrollment in the ComEd appliance recycling program. 0.90% of the treatment customers enrolled in the program, while 0.62% of control customers did. As a practical matter, though, this difference is small, representing an enrollment difference of 2.8 per 1000 customers.

- Among low energy users we found no statistical or practical difference between treatment and control customers in enrollment in the ComEd appliance recycling program.

4.2 Recommendations

The pilot study should remain in its current structure for another year. This will allow an examination of the persistence of program effects and provide a clearer picture of the effect (if any) of income and report frequency on program savings.

Section 5. Appendices

5.1 Calculation of standard errors on annual savings, LFER analysis

The estimate of average daily treatment effect in (7) is a linear function of three random variables: α_2, β_3, and γ_3. The standard error of the estimate is computed using the delta method. In particular, the standard error on mean daily savings is the value:

$$SE = \begin{bmatrix} 1 & \overline{CDDd} & \overline{HDDd} \end{bmatrix} \begin{bmatrix} \operatorname{var}(\alpha_0) & \operatorname{cov}(\alpha_0,\alpha_1) & \operatorname{cov}(\alpha_0,\alpha_2) \\ \operatorname{cov}(\alpha_0,\alpha_1) & \operatorname{var}(\alpha_1) & \operatorname{cov}(\alpha_1,\alpha_2) \\ \operatorname{cov}(\alpha_0,\alpha_2) & \operatorname{cov}(\alpha_1,\alpha_2) & \operatorname{var}(\alpha_2) \end{bmatrix} \begin{bmatrix} 1 \\ \overline{CDDd} \\ \overline{HDDd} \end{bmatrix}, \tag{8}$$

where variances and covariances in (8) refer to the regression estimates of the indicated parameters.

5.2 *Memo on Savings after First Six Months of Pilot Implementation*

To: **Louis Lampley, Michael Brandt, David Nichols, Jeff Erickson, Randy Gunn**

From: **Mary Klos, Lakin Garth, Bill Provencher**

Date: **March 25, 2010**

Re: **ComEd OPower Impact Analysis Update**

Summary Findings

The purpose of this memo is to summarize preliminary findings of estimated savings for participants in ComEd's OPower program. Nearly 50,000 participants have received comparison reports of their monthly kWh usage beginning on July 14th, 2009. The post period usage data included in this analysis ends with bills and reports received in February of 2010, providing a window of pre and post analysis of roughly 7 months.

Navigant consultants have employed various billing analysis estimation methods to attempt to determine the early impacts of this program. These results are given in the Table 1 below.

Table 1: Comparison of Savings Estimates from Two Statistical Methods

% of Pre Participant Period Usage	Diff in Diff Statistic	DLFE
Group 1: High Users, Monthly	-1.25%	-1.40%
Group 2: Bi-Monthly	-1.05%	-0.98%
Group 3: Monthly to Quarterly	-1.22%	-1.24%

Table 1 provides a summary comparison of the overall impacts to participants in the program using two separate statistical techniques. As will be discussed later, several other methods have been employed but are not reported either due to redundancy or timing issues.

The percentage savings levels presented in the table are not based upon annual numbers; the percentage of savings in Table 1 are based upon the 7 month pre period usage data beginning in August 2008 and ending in February 2009. Due to changes in patterns of kWh usage due to seasonality, it is not reasonable to extrapolate these percentages based upon annual numbers until an entire year of post program introduction data has been completed. Therefore, these numbers can easily change between now and the end of the first year of the program.

The estimate of savings range from 0.98% to 1.40% based upon the statistical technique employed and the group of participants analyzed. It is necessary to report the Groups separately, as Group 1, comprised of "high-use" customers" was not randomly selected, therefore potentially biasing any extrapolation to a greater population. In addition, for this memo, Groups 2 and 3, which have been randomly selected to participate, are split in order to maintain consistency in analysis and reporting.

Overall Methodology

Of the 98,959 combined participants and non-participants in the original customer file, 90,666 remained after removing those who were included in the later vintage (2,695), those who opted out (2,748), moved out (2,806), and those who were otherwise flagged (44) for other reasons as indicated by the 'include flag' variable in the customer file that was provided.

The first initial report date was July 14th and the last was August 14th. Of the 45,431 participants remaining in the data used for the analysis, about 32% received reports on or after August 1st.

There were 18,307 participants who were deemed high use (Group 1) and received monthly reports for the first six months before being switched to bi-monthly reports. Group 2 participants include 13,565 customers who have and will receive bi-monthly reports for the duration of the program. Lastly, there are 13,559 Group 3 participants who receive monthly reports for the first three months, and then will switch to quarterly reports.

Since an entire year has not passed since the last of the initial reports have been received, it was necessary to clearly distinguish the pre and post periods of usage for comparison purposes. This post period will also serve as the main 'season,' as trying to analyze the seasonal effects of this program is not feasible until an entire year has passed.

Given that the majority (68%) of the initial reports were received in July 2009, the months included in the pre and post analysis begin with August (2008 and 2009 respectively) and conclude with the most recent data provided for the month of February. Therefore, there are roughly 7 months of pre and post usage data available for both the participant and non-participant groups.

Difference in Difference Statistic

Assuming random assignment of a large number of treatment and control customers, a simple difference-in-difference statistic provides a good estimate of the average annual customer savings in energy use (measured in kWh) from the treatment. The difference in difference statistic is the difference between the nonparticipant and participant groups in the *change* in their rate of kWh use across the pre and post periods. Dividing the difference-in-difference statistic by the average energy use of the participant group in the pre period gives the proportional reduction from the treatment.

The pre and post average kWh per customer per group usage values given in the tables below are not annual numbers, but are values from the seven months in each period. Tables 2 through 4 give the difference in difference statistic in the last column. N is simply the number of customers in each participant or nonparticipant group for that group's frequency. Tables 5 through 7 give values based upon average kWh/day and instead of a difference in difference statistic in the last column, these tables show a daily average kWh reduction for the program participants in each frequency group.

Table 2: High Use Group. Monthly reports for first six months, bi-monthly thereafter.

Group 1	N	Pre Avg kWh	Post Avg kWh	% Change	Difference
Participant	18307	13905	12571	-9.59%	-1.25%
Non-participant	18209	14256	13066	-8.34%	

Table 3: Randomly assigned. Bi-monthly frequency.

Group 2	N	Pre Avg kWh	Post Avg kWh	% Change	Difference
Participant	13565	7207	6606	-8.34%	-1.05%
Non-participant	13513	7175	6652	-7.30%	

Table 4: Randomly assigned. Monthly reports for first three months, quarterly thereafter.

Group 3	N	Pre Avg kWh	Post Avg kWh	% Change	Difference
Participant	13559	7196	6592	-8.39%	-1.22%
Non-participant	13513	7165	6651	-7.18%	

The pre and post average kWh/day per customer per group usage values given in the tables below are not annual numbers, but are values from the seven months in each period.

Table 5: High Use Group

Group 1	Pre Avg kWh/day	Post Avg kWh/day	Change	Difference
Participant	63.9	58.7	-5.2	-0.692
Non-participant	65.5	61.0	-4.5	

Table 6: Randomly assigned. Bi-monthly frequency.

Group 2	Pre Avg kWh/day	Post Avg kWh/day	% Change	Difference
Participant	33.1	30.8	-2.3	-0.346
Non-participant	33.0	31.0	-2.0	

Table 7: Randomly assigned. Received monthly reports for first three months, then quarterly.

Group 3	Pre Avg kWh/day	Post Avg kWh/day	% Change	Difference
Participant	33.1	-30.8	-2.3	-0.411
Non-participant	32.9	-31.0	-1.9	

Baseline Differenced Linear Fixed Effects Model

In addition to the Baseline Differenced Linear Fixed Effects Model (DFLE), an OLS Linear Regression model and a DLFE with time effects model were also used to come up with parameter estimates of the average daily kWh effects due to participation in the program. The results of the OLS model closely resemble those of the DLFE model and are not presented here due to redundancy. At this point in the program's evolution, there does not appear to be enough evidence to support a DLFE with time effects, though that may change as the program ages.

The main advantage of the difference in difference statistic is its simplicity. However, if customers are not randomly assigned to their respective groups, then the statistic may not provide reasonable estimation of the true effects of the program. This is particularly the case for Group 1, as these participants and nonparticipants were chosen from the overall population based upon their high usage, even though their assignment to the participant or nonparticipant groups is random. Thus, the clear advantage of the DLFE model over that of the difference in difference is that the DLFE assures no bias due to unobservable customer level characteristics that may be correlated either across time or customers. These unobservable characteristics that do not change over time are captured in the fixed effect, and then removed by the differencing.

In Tables 8 through 10 below, the key variables to the analysis are highlighted. Through an algebraic formula presented and explained below, we can combine these variables to estimate the DLFE statistic for comparative purposes to that of the difference in difference statistics previously shown. In essence, what these variables have in common is the capture effect of participant participation in the program during the post period. Here, the "cddD" and "hddD" designations simply stand for cooling and heating degree days *per day*. It is necessary to include these terms in order to capture the change in energy consumption due to weather.

Table 8: Group 1 DLFE. Dependent variable is Average Daily kWh.

Variable	Parameter	SE	t-stat
diffcddD	4.30907	0.03091	139.42
diffhddD	0.63969	0.00538	118.96
diffPost	-3.21929	0.24823	-12.97
diffPosthddD	0.09951	0.00807	12.34
diffPostcddD	0.55535	0.05482	10.13
diffParticPost	-0.80716	0.35054	-2.30
diffParticPosthddD	-0.00620	0.01139	-0.54
diffParticPostcddD	0.00507	0.07741	0.07
diffParticHDDd	-0.05343	0.00759	-7.04
diffParticCDDd	-0.04892	0.04363	-1.12

In order to interpret the values in the regression table above, it is also necessary to have the number of days in the period (212) and both the number of average Heating (4,044) and Cooling (297) degree days as well. The calculation to determine the predicted average kWh per day saved by the program participants is given below:

*(diffParticPost * #days) + (diffParticPosthddD * #HDD) + (diffParticPostcddD * #CDD) = Avg kWh*

So, for Group 1, the predicted average kWh savings for participants in the program is 194.7. The pre period average kWh usage for participants is 13,905 kWh, which results in predicted savings of 1.40%.

In addition to the predicted savings for Group 1, the DLFE model has also been used to come up with predicted savings for Group 2 and Group 3.

Table 9: Group 2 (Bi-Monthly) DLFE. Dependent variable is Average Daily kWh.

Variable	Parameter	SE	t-stat
diffcddD	2.44458	0.01584	154.37
diffhddD	0.30180	0.00274	109.96
diffPost	-1.45278	0.12705	-11.43
diffPosthddD	0.06752	0.00413	16.35
diffPostcddD	0.29664	0.02838	10.45
diffParticPost	0.09891	0.17955	0.55
diffParticPosthddD	-0.02108	0.00584	-3.61
diffParticPostcddD	-0.02023	0.04003	-0.51
diffParticHDDd	0.00214	0.00388	0.55
diffParticCDDd	0.06256	0.02243	2.79

Interestingly, the estimated parameter for the participant group in the post period has a positive coefficient that is not significant. However, that term's interaction with the number of heating degree days per day is negative and highly significant. Following the same calculation to determine predicted savings for Group 1 above, the results of the regression for Group 2 participants gives an estimated savings of 70.5 kWh in the post period. This estimation is equal to 0.98 percent of the average Group 2 participant's usage of 7,207 kWh from the pre period.

Table 10: Group 3 (Monthly to quarterly) DLFE. Dependent variable is Average Daily kWh.

Variable	Parameter	SE	t-stat
diffcddD	2.45468	0.01601	153.35
diffhddD	0.30588	0.00277	110.50
diffPost	-1.28565	0.12801	-10.04
diffPosthddD	0.06239	0.00416	15.00
diffPostcddD	0.29634	0.02853	10.39
diffParticPost	-0.32750	0.18082	-1.81
diffParticPosthddD	-0.00452	0.00588	-0.77
diffParticPostcddD	-0.00538	0.04019	-0.13
diffParticHDDd	-0.00577	0.00391	-1.47
diffParticCDDd	0.04609	0.02266	2.03

For Group 3, the estimated parameter for the participant group in the post period has the expected negative coefficient that is significant at the .07 level. That term's interaction with the number of heating degree days per day is negative and not significant. The results of the regression for Group 3 participants give an estimated savings of 89.3 kWh in the post period. This estimation is equal to 1.24 percent of the average Group 3 participant's usage of 7,196 kWh from the pre period.

In addition to the regression results for Groups 2 and 3 above, two other regressions that combined all the data from these two groups, which were randomly assigned, were also run. The first of these regressions was set up just like the ones presented above, whereas the second regression also included an additional three dummy variables for Group 2, interacted with the *diffParticPost*, *diffParticPosthddD*, and *diffParticPostcddD* terms.

The purpose of this second regression was to allow for a statistical test of joint significance on the three interacted dummy variables representing Group 2. If these three variables were found to be jointly significant, then one could postulate that any difference in predicted savings between Groups 2 and 3 was due to the frequency of the reports received by each group. However, the result of this test shows that the difference in savings estimates between Groups 2 and 3 is not statistically significant.

This result could be explained by a number of factors. The first could be that other factors not introduced in these models are responsible. There are certainly some housing characteristic variables that, if available for all participants and non-participants, could possibly allow for more insight. Other behavioral factors could also play a role.

Another possible explanation is that, simply, not enough time has elapsed to notice any appreciable difference in usage due to the reporting frequencies. It is not entirely surprising that the Group 3, who received monthly reports for the first three months before switching to quarterly reports, has a higher level of predicted savings than Group 2 who has received bi-monthly reports throughout the program. In a six month period, Group 3 should receive 4 reports, whereas Group 2 would only receive 3. After the completion of the first year of the program, when all participants in this program in Groups 2 and 3 have received the same number of reports (6), then perhaps any difference in estimated savings could be better explained by the frequency of reporting.

Preliminary Messaging Results

The primary focus of this memo update was to analyze overall predicted levels of savings for participants in different groups by a variety of methods. In addition to analyzing the effects of the frequency of reporting methods, a secondary focus to be analyzed is that of the type and intensity of the messaging employed in the reports themselves. The table below shows results of a regression used to analyze any potential difference in predicted savings between the groups of participants that receive a message comparing their usage to "Similar Homes" versus the group of participants that receive a message comparing usage to "Neighbors."

In the results presented below, it is important to note that the data used contains only participants in the program and is not segmented by reporting frequency. The variable in the last row of the table is an interaction term for participants that receive the "Similar Homes" message. This allows for a direct comparison to those who receive a "Neighbors" message about usage.

Table 11: Normative messaging results. Dependent variable is average daily kWh.

Variable	Parameter	SE	t-stat
diffPost	-0.86515	0.07435	-11.64
diffcddD	3.35480	0.01172	286.25
diffPostcddD	0.01645	0.01313	1.25
diffhddD	0.44178	0.00199	222.33
diffPosthddD	0.01143	0.00176	6.49
diffPostSHM	**0.13675**	**0.08988**	**1.52**

There are two main point of interest with respect to the table above. The first is to note that the coefficient of the post period dummy variable is both negative and highly significant. The second is that the estimated coefficient of the interaction term for the post period and the participants who received a "Similar Homes" message is positive. This means, all other things equal, the participants receiving a "Similar Homes" message would consume, on average, 0.13675 kWh per day (~ 29 kWh overall) more than those participants receiving a "Neighbors" message during the post period. The "Neighbors" message appears to be a bit more effective. This predicted difference is statistically significant at the 87% probability level.

An additional regression was run in an attempt to compare any potential estimated savings difference between participants receiving gentle or standard messaging. Again, the data used contains only participants in the program and is not segmented by reporting frequency. The variable in the last row of the table is an interaction term for participants in the post period who received a "Standard" message versus those who received a "Gentle" message.

Table 12: Intensity of messaging results. Dependent variable is average daily kWh.

Variable	Parameter	SE	t-stat
diffPost	-0.77055	0.07443	-10.35
diffcddD	3.35481	0.01172	286.25
diffPostcddD	0.01645	0.01313	1.25
diffhddD	0.44178	0.00199	222.33
diffPosthddD	0.01143	0.00176	6.49
diffPostSM	**-0.05248**	**0.08988**	**-0.58**

The estimated parameter for participants in the post period is again both negative, as expected, and highly significant. Although the interaction term representing participants who received a "Standard" message in the post period has a negative sign, meaning less usage versus those receiving a "Gentle" message, the value is not remotely significant and thus statistically not different from zero.