NAVIGANT

# Energy Efficiency / Demand Response Plan: Plan Year 3 (6/1/2010-5/31/2011)

# Evaluation Report: Home Energy Reports

## Presented to

**Commonwealth Edison Company**

**May 16, 2012**

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


Itron

ODC OPINION DYNAMICS CORPORATION

Michaels engineering

**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@navigant.com

Jeff Erickson, Director
608.497.2322
jeff.erickson@navigant.com

**Prepared by:**

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

Bethany Glinsmann, Senior Consultant
608.497.2331
bethany.vittetoeglinsmann@navigant.com

# Table of Contents

# Section E. Executive Summary

This document presents the PY3 evaluation results for the ComEd Home Energy Reports behavioral pilot program. 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, which give customers various types of information, including: 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. ComEd 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 primary objective of the analysis in this report is to determine participants in ComEd's Home Energy Report (HER) program reduced their energy consumption due to the reports in PY3, and whether this reduction varied seasonally. Secondary questions addressed in this report concern program savings among low income households, differences in program savings between high consumption and low consumption households, and the persistence of program savings over the first two years of the program.

## *E.2 Evaluation Methods*

The HER program was implemented as an experimental design explicitly for the purpose of estimating changes in energy use due to the program. Navigant used a state-of-the-art statistical method—linear fixed effects regression—to quantify the energy savings from the pilot.

## *E.3 Key Impact Findings and Recommendations*

The impact results for PY3 are shown in Table E-1. Impacts for all seasons of PY3 are reported in Table 3-1. Savings are reported for the three groups of households defined in the initial experimental design. All three groups currently receive bimonthly Home Energy Reports. Group 1 households are high energy consumers. Households in both Groups 2 and 3 are low energy consumers relative to Group 1 households, but whereas Group 2 households received reports bimonthly since the inception of the HER program, Group 3 households started the program receiving reports monthly for the first three months, and then quarterly for the next two quarters, before switching to bimonthly reports at the start of PY3. In other words, any differences in energy savings between these two groups in PY3 are due to the persistent effects of differential reporting frequency in the first 9 months of the program (Fall 2009-Spring 2010).

In PY3, total estimated net energy savings due to the program were 13,479 MWh. Average annual household savings were 444.56 kWh (2.02% of consumption) for Group 1, 215.20 kWh (1.80%) for Group 2, and 185.54 kWh (1.55%) for Group 3. Savings for Groups 2 and 3 are *not* statistically different at the 90% confidence level, indicating that, although the *estimated* average household savings for the two groups in PY3 differ by 30 kWh, one cannot conclude with confidence that in fact their average savings in PY3 are different. Other key findings discussed in the report:

- Savings vary seasonally;
- Among Group 1 households, savings appear to be lower for households with low incomes than for households with intermediate and high incomes, though due to the small sample of households in the low income category it is not possible to assert this result with confidence.
- After controlling for differences in weather, annual program savings increased from the first year of the HER program (Fall 2009-Summer 2010) to the second (Fall 2010-Summer 2011). This indicates behavioral changes generating *increased* savings across the two program years.

Navigant recommends that the pilot study remain in its current form to the end of PY4 (May 2012). This will allow continued examination of the persistence of program effects and provide a clearer picture of the effect (if any) of income on program savings.

To investigate whether program savings persist after Home Energy Reports are terminated, Navigant recommends randomly removing from the program one-half of the households in the high consumption group (Group 1) in PY5 and replacing them with an equal number of new households. By comparing the electricity consumption of the four sets of households thereby generated –treatment households that continue in the program, treatment households removed from the program, new treatment households, and original control households—ComEd can test persistence of savings for both those households that remain in the program and those households removed from the program.

**Table E-1. *Ex Post* Program Savings – Home Energy Report Program, PY3**

| Type of Statistic | Group 1: High Use Customers (*standard error*) | Group 2: Low Use, Initially Bimonthly Reports (*standard error*) | Group 3: Low Use, Initially Monthly-to-Quarterly Reports (*standard error*) |
|---|---|---|---|
| Sample Size, Treatment Group | 18,191 | 13,496 | 13,484 |
| Sample Size, Control Group | 18,097 | 13,437 | 13,424 |
| Annual Percent Savings | 2.02% *(0.23%)* | 1.80% *(0.25%)* | 1.55% *(0.26%)* |
| Annual kWh Savings per Customer | 444.56 *(49.94)* | 215.20 *(30.19)* | 185.54 *(30.95)* |
| Total Annual MWh Savings | 8,087 *(908)* | 2,904 *(407)* | 2,488 *(417)* |

### *E.4 Cost-Effectiveness Summary*

ComEd uses DSMore™ software for the calculation of the Illinois TRC test[1]. Table E-2 summarizes the unique inputs used in the DSMore model to assess the TRC ratio for the Home Energy program in PY3. Most of the unique inputs come directly from the evaluation results presented previously in this report. Measure life estimates and program costs come directly from ComEd. All other inputs to the model, such as avoided costs, come from ComEd and are the same for this program and all programs in the ComEd portfolio.

[1] Demand Side Management Option Risk Evaluator (DSMore) software is developed by Integral Analytics.

**Table E-2. Inputs to DSMore Model for Home Energy Program**

| Item | Value Used |
|---|---|
| Measure Life | 1 |
| Utility Administration and Implementation Costs | $2,174,501 |
| Utility Incentive Costs | $0 |
| Net Participant Costs | $0 |

Based on these inputs, the Illinois societal TRC for this program is 0.39 and the program does not pass the Illinois TRC test. The Home Energy Report program was in its first full year in PY3. It is expected that the TRC will be greater than one in the future since up-front costs will moderate.

# Section 1. Introduction to the Program

## 1.1 Program Description

ComEd started the Home Energy Reports (HER) program 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 regularly 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.

### 1.1.1 Measures and Incentives

This program involves no incentives. Program measures are restricted to the mailing of Home Energy Reports at regular intervals. Originally reports were mailed at different intervals to different groups, as detailed in section 2.1.3. In PY3 all households received the reports bimonthly.

## 1.2 Evaluation Questions

The main objective of the evaluation is to verify the savings impact in the ComEd service territory in PY3.

The evaluation sought to answer the following additional questions:

Impact Questions

1. Do high consumption customers save more energy than low consumption customers?
2. Do savings vary by season?
3. Among high-use customers, are program savings for low-income customers different than for medium- and high-income customers?
4. Did the energy savings found in the first program year persist in the second program year?

# Section 2. Evaluation Methods

## 2.1 Analytical Methods

### 2.1.1 Impact Evaluation Methods

**Net Program Savings**

A significant feature of the program is that in the implementation of the program households within each group were randomly assigned between control and treatment (receiving the home energy report). So, for instance, 40,000 households were identified for Group 1, with half of these designated to receive the Home Energy Reports, and the other half serving as control households. Due to this experimental design, there are no attribution issues for this program. Net program savings are equal to gross program savings.

**Gross Program Savings**

Analysis Method

In the evaluation of the program in PY2, Navigant used two methods to estimate savings: difference-in-difference (DID) analysis and linear fixed effects regression (LFER) analysis. As these two methods generated nearly identical results, in the evaluation of program savings in PY3 Navigant focused on the linear fixed effects regression analysis. A detailed discussion of the regression analysis used to derive estimates of program savings is found in the appendix in section 5.1 of this report.

**Ex-Post Net Savings Analysis**

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 2 evaluation of this pilot.

## 2.2 Data Sources

OPOWER received the requisite billing data for the analysis period January 2008 to August 2011 from ComEd, and continues to receive this data on an ongoing basis. In turn, OPOWER linked this data to home energy report data (frequency and template type) before sending the dataset to Navigant. Navigant linked data on weather (heating and cooling degree days) and housing/household characteristics to generate the data set used in the analysis. As the set of customers did not change from the first program year to the second, it was not necessary to update the housing characteristics dataset. Descriptive statistics for the dataset are available in Table 2.1, reproduced from last year's report.

**Table 2.1. Sample descriptive statistics for housing/household characteristics (the first number is for control customers; the 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<br>25,387 | 2,402<br>2,395 | 8.94<br>8.61 | 0.58 |
| Number of Baths | 31,102<br>31,460 | 2.05<br>2.06 | 0.00808<br>0.00799 | -1.01 |
| Single Family (vs. Multi-Family) | 46,743<br>46,819 | 79.9%<br>82.0% | 0.40%<br>0.38% | -8.04 |
| Own (vs. Rent) | 38,358<br>38,428 | 92.0%<br>93.1% | 0.14%<br>0.13% | -5.79 |
| Income category (1-9) | 40,540<br>40,636 | 7.32<br>7.34 | 0.00878<br>0.00854 | -2.13 |
| Number of occupants | 40,540<br>40,642 | 4.68<br>4.69 | 0.00847<br>0.00835 | -0.46 |
| Age of Head of Household | 30,633<br>30,968 | 54.46<br>54.45 | 0.0707<br>0.0707 | 0.13 |

### 2.3 *Sampling Plan*

In the sample design developed by ComEd with OPOWER, 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 of PY2 is less than the original number by about 2,000 customers for each group, due to the loss of customers who opted out of the program or moved away, the removal of customers who do not meet selection criteria for analyses (see below), and missing data.

<u>Group 1:</u> 20,000 customers receive bimonthly reports after having started the program with six monthly reports. This group was randomly drawn from a set of 40,000 high-use customers (customers with relatively high energy consumption in the pre-program year), with the remaining 20,000 customers assigned to serve as control households for evaluating program savings.

Groups 2 and 3, and sets of control households of equal size, were randomly drawn from a set of 60,000 households with relatively low energy consumption in the pre-program year:

<u>Group 2:</u> 15,000 customers receive bimonthly reports for the duration of the program.

Group 3: 15,000 customers received monthly reports for the first three months of the program, and then switched to quarterly reports for two quarters, and then switched to bimonthly reports at the start of PY3.

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.

The estimation of all models used in the evaluation is based on only 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 through the first year of the program. 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 time frame. Navigant chose to use these criteria for deciding whether to include a household in model estimation to keep the set of households used to analyze the data as close as possible to the set used in the analysis of the program presented in last year's (PY2) impact evaluation.

### *2.4 Sampling Error*

All standard errors of the estimates of model parameters are reported with model parameter estimates in the appendix, section 5.2.

## Section 3. Program Level Results

This section presents the estimation results of the impact evaluation of the Home Energy Reports program.

### 3.1 *Impact Evaluation Results*

#### 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

All fixed effects regression models used in the impact evaluation are described in detail in the Appendix, section 5.1. Parameter estimates for the estimated models are found in the Appendix, section 5.2.

Table 5.1 in the appendix presents the parameter estimates for Model 2, which is described in section 5.1 of the appendix. This model is the source of annual and seasonal estimates of program savings. Seasons are defined as follows:

- Summer 2010: June 15-September 15
- Fall 2010: September 15-December 15
- Winter 2010-2011: December 15-March 15
- Spring 2011: March 15-June 15

Table 5.2 in the appendix presents the results of estimating Model 1 across different household incomes categories, to examine the relative savings of low income households.

Table 5.3 in the appendix presents the parameter estimates for Model 3, which allows the testing of the persistence of year-over-year program savings after adjusting for differences in weather across years.

Generally interpretation of parameter estimates is not straightforward due to the many interaction terms in the models. Estimation results are discussed in detail in Section 3.1.4.

#### 3.1.4 Gross Program Impact Results

Model 2, presented in Section 5.1 of the appendix, was used to calculate annual and seasonal program savings. Parameter estimates for the model are presented in Table 5.1 in the appendix. With reference to Model 2, the average daily savings (ADS) in PY3 is calculated by summing the coefficients of terms involving the $Treatment_k \cdot Post_t$ and $Treatment_k \cdot Post2_t$ for the relevant group:

$$ADS_{Group\ 2} = \alpha_3 + \alpha_4$$

$$ADS_{Group\ 1} = \alpha_3 + \alpha_4 + \beta_3 + \beta_4$$

$$ADS_{Group\ 3} = \alpha_3 + \alpha_4 + \gamma_3 + \gamma_4$$

Multiplying ADS by the length of the period of interest (365 days for the annual analysis) generates the average savings per customer. Multiplying this value by the number of participants generates total savings.

Savings estimates are presented in Table 3-1. Figure 3-1 graphically presents the seasonal average savings and percent savings. Estimates of total PY3 savings and seasonal savings are conservative, because we used the same conservative criteria for keeping a customer in the dataset used for the analysis as was used in the impact evaluation for PY2.

The following results emerge from Table 3-1:

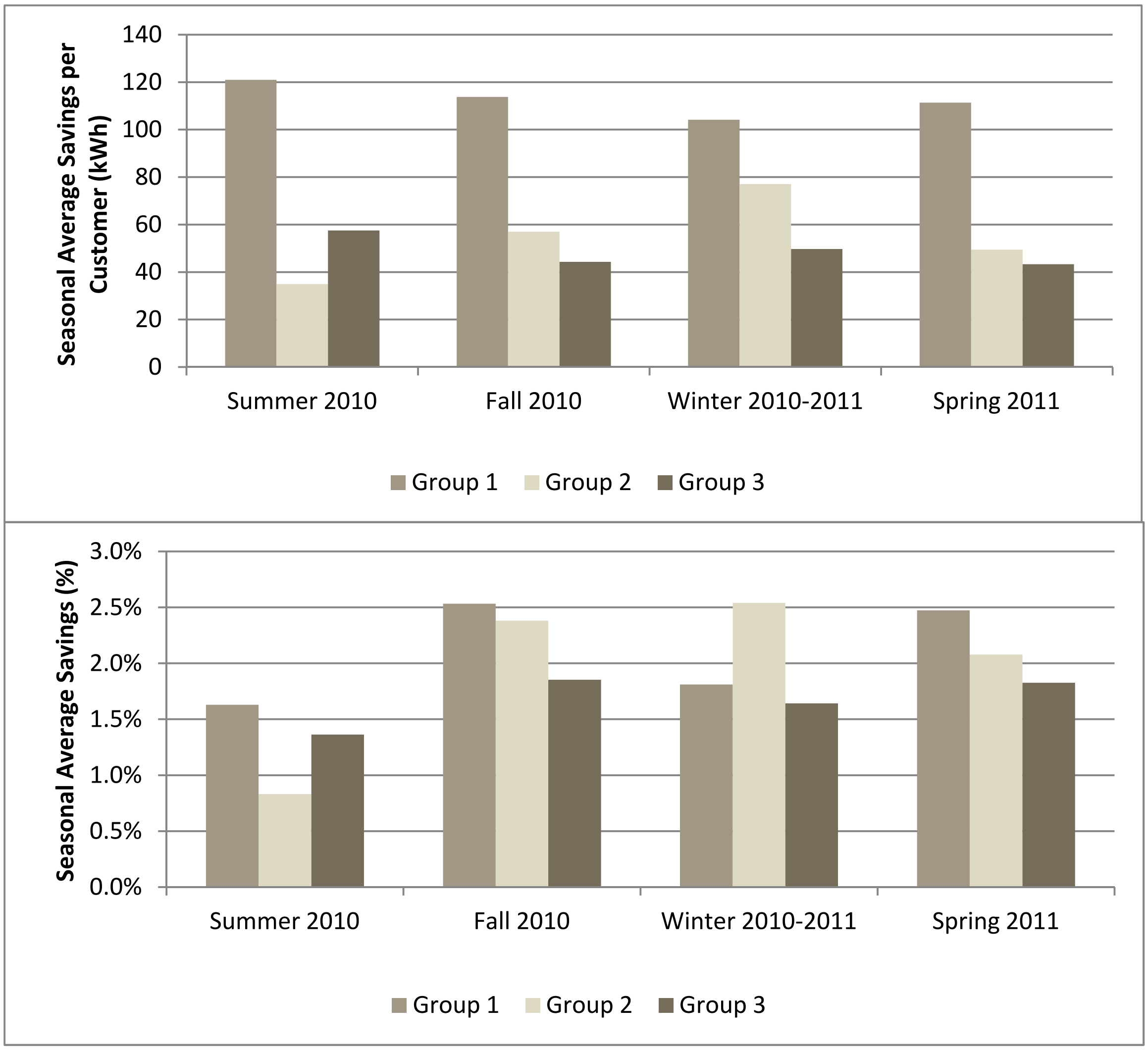
- The total annual energy savings for PY3 were 13,479 MWh.
- Among the three groups of households, PY3 savings were highest for Group 1 households (high energy users) in both absolute terms (444.56 kWh per household) and in percentage terms (2.02%).
- On an absolute basis, savings among Group 1 households were fairly consistent across the four seasons of PY3, ranging from a low of 104.15 kWh in the winter to a high of 121.00 in the summer. On a percentage basis, though, savings were highest in the fall (2.53%) and spring (2.47%).
- Savings among Group 2 households peaked in winter 2011, on both an absolute and percentage basis, at 77.05 kWh and 2.54%.
- Like Group 1 households, savings among Group 3 households were fairly constant across seasons in absolute terms, ranging from a low of 43.32 kWh in the spring to a high of 57.50 in the summer, but on a percentage basis were highest in fall (1.85%) and spring (1.83%).
- PY3 savings for Groups 2 and 3 are *not* statistically different at the 90% confidence level, indicating that, although the *estimated* average household savings for the two groups in PY3 differ by 30 kWh, one cannot conclude with confidence that their true average savings are indeed different.

**Table 3-1. Annual and Seasonal Estimates of *Ex Post* Program Savings – Home Energy Reports Program, PY3.**

| Period | Type of Statistic | Group 1: High Use Customers (*standard error*) | Group 2: Low Use, Bimonthly Reports (*standard error*) | Group 3: Low Use, Monthly-to-Quarterly Reports (*standard error*) |
|---|---|---|---|---|
| | Sample Size, Treatment | 18,191 | 13,496 | 13,484 |
| | Sample Size, Control | 18,097 | 13,437 | 13,424 |
| ANNUAL | Percent Savings | 2.02% *(0.23%)* | 1.80% *(0.25%)* | 1.55% *(0.26%)* |
| | kWh Savings per customer | 444.56 *(49.94)* | 215.20 *(30.19)* | 185.54 *(30.95)* |
| | Total MWh Savings | 8,087 *(908)* | 2,904 *(407)* | 2,488 *(417)* |
| SUMMER 2010 | Percent Savings | 1.63% *(0.27%)* | 0.83% *(0.32%)* | 1.36% *(0.32%)* |
| | kWh Savings per customer | 121.00 *(20.29)* | 34.96 *(13.52)* | 57.50 *(13.66)* |
| | Total MWh Savings | 2,201 *(369)* | 472 *(182)* | 775 *(184)* |
| FALL 2010 | Percent Savings | 2.53% *(0.35%)* | 2.38% *(0.39%)* | 1.85% *(0.41%)* |
| | kWh Savings per customer | 113.77 *(15.75)* | 56.96 *(9.37)* | 44.28 *(9.70)* |
| | Total MWh Savings | 2,069 *(287)* | 769 *(126)* | 597 *(131)* |
| WINTER 2010-2011 | Percent Savings | 1.81% *(0.35%)* | 2.54% *(0.41%)* | 1.64% *(0.42%)* |
| | kWh Savings per customer | 104.15 *(20.09)* | 77.05 *(12.46)* | 49.70 *(12.65)* |
| | Total MWh Savings | 1,894 *(365)* | 1,040 *(168)* | 670 *(171)* |
| SPRING 2011 | Percent Savings | 2.47% *(0.33%)* | 2.08% *(0.36%)* | 1.83% *(0.37%)* |
| | kWh Savings per customer | 111.35 *(14.72)* | 49.44 *(8.62)* | 43.32 *(8.74)* |
| | Total MWh Savings | 2,025 *(268)* | 667 *(116)* | 584 *(118)* |

[a]Seasonal estimates do not sum exactly to the annual estimate because the annual estimate applies to the PY3 period of June 1, 2010-May 31, 2011, whereas se4asonal estimates apply to the periods: June 15-September 14 for summer, Sept 15-Dec 14 for fall, Dec 15-March 14 for winter, and March 15-June 14 for spring.

**Figure 3.1. Average seasonal savings by customer group, in absolute and percentage terms, PY3**




### Gross Program Impact Results: Savings for Low Income Households

Navigant Consulting investigated the impact of income level on program savings in PY3. We restricted our analysis to customers in Group 1—those customers with high consumption levels receiving monthly reports. 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. The income data consists of nine brackets, which we use to create three income categories: customers with incomes of $0K-$30K (low income, brackets 1-3), $30K-$75K (medium income, brackets 4-6), and $75K+ (high income, brackets 7-9). We estimated Model 1, as described in Section 5.1 of the appendix, for each of the three income categories. Estimated regression coefficients are presented in Table 5.2 in the appendix. PY3 savings estimates are presented in Table 3-2. The following results emerge from the table:

- Savings appear to be lower for households with low incomes than for households with intermediate and high incomes, though due to the small sample of households in the low income category it is not possible to assert this result with confidence. Also due to the small sample size it is not possible to conclude that savings for low income households are different than zero.
- In both absolute and percentage terms, estimated savings in PY3 are greatest for customers in the middle income category. Due to the relatively small sample sizes of the Low Income and Middle Income categories, though, it is not possible to conclude with statistical confidence that annual savings among the three income categories differ. This is further complicated by the fact that for the set of households for which the income category is not available (3808 total households in the sample), estimates of program savings are far lower than for the other categories (180.35 kWh per year, 1.20%).

**Table 3-2. Estimates of *Ex Post* Program Savings in Group 1 by Income Category – Home Energy Reports Program, PY3[a]**

| Type of Statistic | Low Income (*standard error*) | Middle Income (*standard error*) | High Income (*standard error*) |
|---|---|---|---|
| Sample Size, Treatment | 364 | 2,465 | 13,409 |
| Sample Size, Control | 394 | 2,666 | 13,182 |
| Annual Savings (%) | 2.69% *(2.49%)* | 4.53% *(0.97%)* | 2.78% *0.33%* |
| Annual Savings (kWh per customer) | 360.72 *(333.18)* | 600.47 *(128.99)* | 466.98 *(54.70)* |

**Gross Program Impact Results: Behavioral Persistence of Savings across the Two Years of the Home Energy Report Program**

The Home Energy Report (HER) program has been in operation for two years, Fall 2009 – Summer 2011. In this section we determine whether overall program savings changed across the two years of the program due to changes in behavior.

Parameter estimates for the model used to evaluate the persistence of program savings—Model 3 in section 5.1 in the appendix—are presented in Table 5-3 in the Appendix. To calculate weather-normalized annual savings, we use the model with average daily heating and cooling degree days over the two-year program period.[2] Average weather-normalized customer savings for each year and season of the program are presented in Table 3-3, along with statistical tests on the hypothesis that the underlying behavioral model is the same in Year 2 of the HER program as in Year 1. As noted in section 5.1 of the appendix, the relevant test is based on the null hypothesis that the set of coefficients on the interaction terms involving both *Post2* and *Treatment* are all equal to zero. Figure 3-2 graphically illustrates the weather-normalized annual and seasonal average savings for each of the program years.

The following results emerge from Table 3-3:

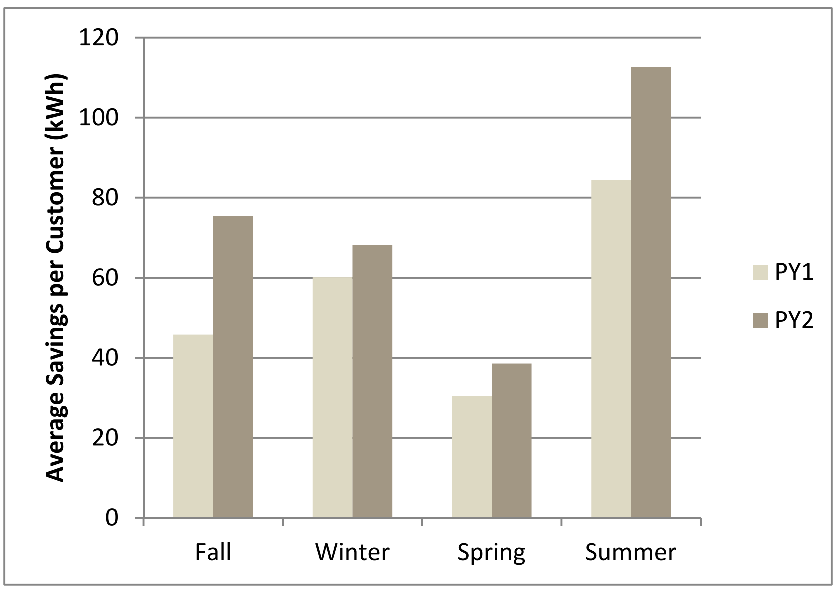
- After controlling for differences in weather, annual savings **increased** from the first program year to the second. This indicates behavioral changes conducive to increased savings across the two years of the HER program. In particular, using average values for heating and cooling degree days across the two years of the program, average weather-normalized annual savings increased from 230 to 317 kWh per customer, an increase of 38%. This increase is statistically significant.
- The increase in weather-normalized annual savings is driven by increased savings in the fall and summer seasons, for which the increase in seasonal savings is statistically significant.
- Although the weather-normalized savings increased slightly for the winter and spring seasons, this increase was small (about 8 kWh per customer), and not statistically significant. This indicates that weather-normalized winter and spring savings have not changed from the first program year to the second; that is, it indicates behavioral persistence of program effects for these seasons.

[2] The following weather values were used for the analysis, representing annual and seasonal averages over the two years of the program: ANNUAL: HDDd = 17.1 and CDDd = 3.0; FALL: HDDd=18.0, CDDd=0.4; WINTER: HDDd=38.9, CDDd=0; SPRING: HDDd=11.7, CDDd=1.7; SUMMER: HDDd=0.3, CDDd=9.9.

**Table 3-3. Weather-normalized persistence of savings results – Home Energy Report Program**

| Period | Annual Savings in Year 1(kWh) | Annual Savings in Year 2(kWh) | Difference, Y2 - Y1 (kWh) | Standard Error of Difference | Statistically Significant? |
|---|---|---|---|---|---|
| Annual | 230.21 | 316.69 | 86.48 | 19.27 | Yes |
| Fall | 45.78 | 75.40 | 29.62 | 8.81 | Yes |
| Winter | 60.10 | 68.21 | 8.12 | 9.06 | No |
| Spring | 30.42 | 38.54 | 8.13 | 7.65 | No |
| Summer | 84.45 | 112.68 | 28.23 | 9.34 | Yes |

**Figure 3-2. Weather-normalized seasonal savings for the first and second years of the HER program**




### 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 Cost Effectiveness Review

This section addresses the cost effectiveness of the Home Energy program. Cost effectiveness is assessed through the use of the Illinois Total Resource Cost (TRC) test. The Illinois TRC test is defined in the Illinois Power Agency Act SB1592 as follows:

> *'Total resource cost test' or 'TRC test' means a standard that is met if, for an investment in energy efficiency or demand-response measures, the benefit-cost ratio is greater than one. The benefit-cost ratio is the ratio of the net present value of the total benefits of the program to the net present value of the total costs as calculated over the lifetime of the measures. A total resource cost test compares the sum of avoided electric utility costs, representing the benefits that accrue to the system and the participant in the delivery of those efficiency measures, to the sum of all incremental costs of end-use measures that are implemented due to the program (including both utility and participant contributions), plus costs to administer, deliver, and evaluate each demand-side program, to quantify the net savings obtained by substituting the demand-side program for supply resources. In calculating avoided costs of power and energy that an electric utility would otherwise have had to acquire, reasonable estimates shall be included of financial costs likely to be imposed by future regulations and legislation on emissions of greenhouse gases.*[3]

ComEd uses DSMore™ software for the calculation of the Illinois TRC test.[4] The DSMore model accepts information on program parameters such as number of participants, gross savings, free ridership, program costs and $CO_2$ reductions. It then calculates a TRC that fits the requirements of the Illinois Legislation.

One important feature of the DSMore model is that it performs a probabilistic estimation of future avoided energy costs. It looks at the historical relationship between weather, electric use and prices in the PJM Northern Illinois region and forecasts a range of potential future electric energy prices. The range of future prices is correlated to the range of weather conditions that could occur, and the range of weather is based on weather patterns seen over the historical record. This method captures the impact that extreme weather has on electricity prices. Extreme weather generally results in electricity price spikes and creates a skewed price distribution. High prices are going to be much higher than the average price while low prices are going to be only moderately lower than the average. DSMore is able to quantify the weighted benefits of avoiding energy use across years which have this skewed price distribution.

[3] Illinois Power Agency Act SB1592, pages 7-8.

[4] Demand Side Management Option Risk Evaluator (DSMore) software is developed by Integral Analytics.

**Results**

Table 3-4 summarizes the unique inputs used in the DSMore model to assess the TRC ratio for the Home Energy program in PY3. Most of the unique inputs come directly from the evaluation results presented previously in this report. Measure life estimates and program costs come directly from ComEd. All other inputs to the model, such as avoided costs, come from ComEd and are the same for this program and all programs in the ComEd portfolio.

**Table 3-4. Inputs to DSMore Model for Home Energy Program**

| Item | Value Used |
|---|---|
| Measure Life | 1 |
| Utility Administration and Implementation Costs | $2,174,501 |
| Utility Incentive Costs | $0 |
| Net Participant Costs | $0 |

Based on these inputs, the Illinois societal TRC for this program is 0.39 and the program does not pass the IllinoisTRC test. The Home Energy Report program was in its first full year in PY3. It is expected that the TRC will be greater than one in the future since up-front costs will moderate.

# Section 4. Conclusions and Recommendations

## 4.1 *Conclusions*

The Home Energy Reports 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 program energy savings for PY3 was approximately 13,479 MWh.

- On a percentage basis, average energy savings for the second year of the program was 2.02% for high energy users (Group 1), 1.80% for low energy users receiving bimonthly reports since the inception of the program (Group 2), and 1.55% for low energy users who initially received monthly and then quarterly reports (Group 3).

- In PY3, high energy users (Group 1) contributed about twice as much savings on a per customer basis (445 kWh/year) as low energy users (215 kWh/year for Group 2 households, 186 kWh/year for Group 3 households).

- In PY3, savings for Groups 2 and 3 were *not* statistically different at the 90% confidence level. This indicates that, although the two groups initially received reports at different frequencies, any effects from this differential treatment has not carried over into PY3, in which both groups receive reports bimonthly.

- Among Group 1 households, the estimate for average savings in PY3 for customers in the lowest income category ($0k-$30K annual income) appear to be lower than for households with intermediate and high incomes, though due to the small sample of households in the low income category it is not possible to assert this result with confidence. Also due to the small sample size it is not possible to conclude that savings for low income households are different than zero.

- After controlling for differences in weather, annual savings increased from the first year of the HER program to the second, indicating that behavioral changes generated increased savings across the two program years. The increase in weather-controlled annual savings is driven by increased savings in the fall and summer seasons, indicating that it is in these seasons that behavioral changes have been greatest.

## 4.2 *Recommendations*

Navigant recommends that the HER program remain in its current form for another year. Program savings appear to be rising, and continuing the program for another year will allow an examination of the persistence of program effects and provide a clearer picture of the effect (if any) of income on program savings.

To investigate whether program savings persist after Home Energy Reports are terminated, Navigant recommends randomly removing from the program one-half of the Group 1 (high use) households at the start of PY5 (Summer 2012), and replacing this group with an equal number of additional high-use households. By comparing the electricity consumption of the four sets of households thereby generated –treatment households that continue in the program, treatment households removed from the program, new treatment households, and original control households—ComEd can test persistence of savings for both those households that remain in the program and those households removed from the program. We propose removing half of the Group 1 households –as opposed to removing treatment households from a different group, or removing a different fraction of households—for the following reasons:

1. Group 1 has the highest savings rate (2.02% in PY3), and the highest number of treatment households, and so the probability of statistical detection of persistence effects is greatest. Statistical detection is maximized by splitting the sample of Group 1 households evenly.

2. Based on previous simulation analysis done for ComEd, we estimate that splitting the sample in this way will allow statistical detection, at the 95% confidence level, of any difference in savings between Group 1 treatment households and Group 1 "removed" households that is 0.75% or greater. So, for instance, if Group 1 households that continue to receive the report generate savings of 2.0% in PY5, while savings for households removed from the program drop to 1.25%, statistical analysis is highly likely to detect that average savings by the removed households is indeed less than that of the continuing households.

# Section 5. Appendix

## 5.1 Linear Fixed Effects Regression (LFER) Analysis

This section of the appendix presents the regression models used to derive estimates of program savings.

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 a household-specific fixed effect constant (discussed below) and two 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; and 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. Formally,

**Model 1:**

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

Several observations about this model deserve comment. First, the coefficient $\alpha_{0k}$ captures **all** customer-specific effects on energy use that do not change over time, including those that are unobservable. Second, $\alpha_1$ captures the average increase in consumption *across all customers* during PY3 (the post-treatment period in the analysis of program impacts for PY3) compared to the pre-treatment year. Third, $\alpha_2$ is the average treatment effect; in other words, it is the average daily change in kWh consumption due to the HER program. This term is the *difference in the difference* in average daily kWh use between the treatment group and the control group across the pre-program year and PY3.

### 5.1.1 Modeling Group Differences

Model 1 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, and does not impose an independence assumption on the statistical test. It involves creating binary variables for two of the groups –the third group serves as the baseline from which differential effects are measured—and interacting these binary variables with the terms in (1) 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 3 (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,

**Model 2:**

$$ADU_{kt} = \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Post2_t + \alpha_3 Treatment_k \cdot Post_t + \alpha_4 Treatment_k \cdot Post2_t + \beta_1 G1_k \cdot Post_t + \beta_2 G1_k \cdot Post2_t + \beta_3 G1_k \cdot Treatment_k \cdot Post_t + \beta_4 G1_k \cdot Treatment_k \cdot Post2_t + \gamma_1 G3_k \cdot Post_t + \gamma_2 G3_k \cdot Post2_t + \gamma_3 G3_k \cdot Treatment_k \cdot Post_t + \gamma_4 G3_k \cdot Treatment_k \cdot Post2_t + \varepsilon_{kt}$$

For Group 2 households, average daily savings (ADS) in the second year of the program is $\alpha_3 + \alpha_4$. For Group 1 it is $\alpha_3 + \alpha_4 + \beta_3 + \beta_4$, and for Group 3 it is $\alpha_3 + \alpha_4 + \gamma_3 + \gamma_4$. It follows that a statistical test on whether PY2 savings are the same across groups involves hypothesis tests on these savings parameters. For instance, a test of whether savings in PY2 are the same for Groups 1 and 2 is a test of whether $\beta_3 + \beta_4 = 0$, and a test of whether savings in PY2 are the same for Groups 2 and 3 is a test of $\gamma_3 + \gamma_4 = 0$ .

Model 2 can be run annually and by season to obtain both annual savings by group as well as seasonal savings by group.

### 5.1.2 Modeling Behavioral Persistence of Savings

We examine the behavioral persistence of savings by comparing savings estimates annually and seasonally in the first and second years of the HER program. Not that the first and second years of the HER program **do not** correspond to the evaluation plan years. The first year of the HER program is the period Fall 2009-Summer 2010, and the second year is Fall 2010-Summer 2011. An increase in savings from the first program year to the second could be due to a change in behavior, or it could be the result of different weather conditions, and so to examine the issue of behavioral persistence it is necessary to expand Model 1 with a set of weather-related variables to control for weather effects. Speficially, we include heating degree days per day ($HDDd_t$) and cooling degree days per day ($CDDd_t$) in bill period $t$. For each of the weather variables, six terms are added to Model 1: 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 $Post_t$ and $Post2_t$ to capture differential effects of the variable due to exogenous shocks across the three years of the analysis period; and the variable interacted with the interaction terms $Treatment_k \cdot Post_t$ and $Treatment_k \cdot Post2_t$ 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 Model 1 to the following:

**Model 3:**

$$ADU_{kt} = \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Post2_t + \alpha_3 Treatment_k \cdot Post_t + \alpha_4 Treatment_k \cdot Post2_t + \beta_0 HDDd_t + \beta_1 HDDd_t \cdot Treatment_k + \beta_2 HDDd_t \cdot Post_t + \beta_3 HDDd_t \cdot Post2_t + \beta_4 HDDd_t \cdot Treatment_k \cdot Post_t + \beta_5 HDDd_t \cdot Treatment_k \cdot Post2_t + \gamma_0 CDDd_t + \gamma_1 CDDd_t \cdot Treatment_k + \gamma_2 CDDd_t \cdot Post_t + \gamma_3 CDDd_t \cdot Post2_t + \gamma_4 CDDd_t \cdot Treatment_k \cdot Post_t + \gamma_5 CDDd_t \cdot Treatment_k \cdot Post2_t + \varepsilon_{kt}$$

In this model, the average program daily savings (ADS) in the second program year is the sum of all the terms multiplying the interaction terms $Treatment_k \cdot Post_t$ and $Treatment_k \cdot Post2_t$:

$$ADS_{Year\ 2} = (\alpha_3 + \alpha_4) + (\beta_4 + \beta_5)HDDd_t + (\gamma_4 + \gamma_5)CDDd_t$$

Note, then, that the treatment effect changes across seasons because of seasonal changes in *HDDd* and *CDDd*. The coefficients on these variables indicate the effect on average savings for a day due to a 1-unit increase in heating or cooling degrees for the day. We calculate weather-normalized savings by using the average *HDDd* and *CDDd* over the two year period.

The null hypothesis $\alpha_4 = \beta_5 = \gamma_5 = 0$ is a test of weather-normalized behavioral persistence across the first and second years of the program. Failure to reject the hypothesis indicates behavioral persistence of savings.

## 5.2 *Parameter Estimates of the Linear Fixed Effects Regression Models*

This section of the appendix presents parameter estimates for the Linear Fixed Effects Regression (LFER) models estimated for the impact analysis (see Section 5.1 for a discussion of the models).

**Table 5.1. Parameter estimates for Model 2, annually and by season (dependent variable: average kWh consumption per day), PY3**

| | Group 1 interaction terms (all terms multiplied by G1) | | Group 2 terms (baseline terms) | | Group 3 interaction terms (all terms multiplied by G3) | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | t-statistic | Coefficient | t-statistic | Coefficient | t-statistic |
| *Annual Model* | | | | | | |
| Post | -1.34 | -11.86 | 1.24 | 21.01 | 0.036 | 0.42 |
| Post*Treatment | -0.63 | -3.93 | -0.59 | -7.13 | 0.084 | 0.71 |
| *Summer 2010 Model* | | | | | | |
| Post | 1.52 | 8.12 | 6.99 | 66.72 | 0.21 | 1.39 |
| Post*Treatment | -0.94 | -3.53 | -0.38 | -2.59 | -0.24 | -1.17 |

| Variable | Coefficient | t-statistic | Coefficient | t-statistic | Coefficient | t-statistic |
|---|---|---|---|---|---|---|
| *Fall 2010 Model* | | | | | | |
| Post | -3.51 | -24.79 | -2.17 | -29.55 | -0.018 | -0.17 |
| Post*Treatment | -0.62 | -3.10 | -0.62 | -6.08 | 0.14 | 0.94 |
| *Winter 2010-11 Model* | | | | | | |
| Post | -2.80 | -15.17 | -0.91 | -9.54 | -0.00092 | -0.01 |
| Post*Treatment | -0.29 | -1.15 | -0.84 | -6.18 | 0.30 | 1.54 |
| *Spring 2011 Model* | | | | | | |
| Post | -0.80 | -6.06 | 0.43 | 6.67 | 0.046 | 0.49 |
| Post*Treatment | -0.67 | -3.63 | -0.54 | -5.74 | 0.066 | 0.50 |

**Table 5.2. Parameter estimates for Model 1, by income category of Group 1 households (dependent variable: average kWh consumption per day), PY3[a]**

| | Low Income | | Middle Income | | High Income | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | t-statistic | Coefficient | t-statistic | Coefficient | t-statistic |
| Post | -2.03007 | -2.84 | -1.73851 | -7.24 | 0.445682 | 4.13 |
| Post*Treatment | -0.98827 | -1.08 | -1.64513 | -4.66 | -1.27941 | -8.54 |

[a]All households were drawn from Group 1 (high consumption) households, see discussion in section 3.1.4.

**Table 5.3. Parameter estimates for Model 3, annually and by season (dependent variable: average kWh consumption per day)**

| Variable | Coeff. | t-stat | Variable | Coeff. | t-stat |
|---|---|---|---|---|---|
| *Annual* | | | | | |
| HDDd | 0.48 | 137.12 | CDDd | 3.34 | 268.54 |
| Treatment*HDDd | -0.024 | -4.97 | Treatment*CDDd | -0.0079 | -0.46 |
| Post | -1.63 | -29.95 | Post2 | -1.77 | -26.46 |
| Post*Treatment | -0.46 | -6.10 | Post2*Treatment | -0.31 | -3.31 |
| Post*HDDd | 0.039 | 17.64 | Post2*HDDd | 0.0023 | 0.90 |
| Post*Treatment*HDDd | -0.0062 | -1.98 | Post2*Treatment*HDDd | 0.0041 | 1.15 |
| Post*CDDd | -0.012 | -1.16 | Post2*CDDd | -0.13 | -13.10 |
| Post*Treatment*CDDd | -0.021 | -1.47 | Post2*Treatment*CDDd | 0.0012 | 0.09 |
| *Summer 2010* | | | | | |
| HDDd | -1.1417 | -19.90 | CDDd | 2.4125 | 86.11 |
| Treatment*HDDd | 0.1698 | 2.11 | Treatment*CDDd | 0.0740 | 1.88 |
| Post | -7.6216 | -26.75 | Post2 | 5.2068 | 19.02 |
| Post*Treatment | 0.6913 | 1.73 | Post2*Treatment | -1.4279 | -3.79 |
| Post*HDDd | 4.0810 | 27.33 | Post2*HDDd | -3.2833 | -23.23 |
| Post*Treatment*HDDd | -0.5524 | -2.67 | Post2*Treatment*HDDd | 0.4638 | 2.38 |
| Post*CDDd | 0.7941 | 23.24 | Post2*CDDd | -0.7104 | -27.91 |
| Post*Treatment*CDDd | -0.1474 | -3.07 | Post2*Treatment*CDDd | 0.1005 | 2.86 |
| *Fall 2010* | | | | | |
| HDDd | 0.4293 | 71.37 | CDDd | 3.5587 | 113.18 |
| Treatment*HDDd | -0.0317 | -3.84 | Treatment*CDDd | -0.0415 | -0.95 |
| Post | -0.3898 | -2.37 | Post2 | -4.3309 | -22.21 |
| Post*Treatment | -0.4661 | -2.02 | Post2*Treatment | -0.4269 | -1.58 |
| Post*HDDd | -0.0459 | -4.93 | Post2*HDDd | 0.1570 | 14.56 |
| Post*Treatment*HDDd | -0.0018 | -0.14 | Post2*Treatment*HDDd | 0.0053 | 0.36 |
| Post*CDDd | 0.0686 | 1.06 | Post2*CDDd | -0.3465 | -4.78 |
| Post*Treatment*CDDd | -0.0095 | -0.11 | Post2*Treatment*CDDd | 0.0133 | 0.13 |

| Variable | Coeff. | t-stat | Variable | Coeff. | t-stat |
|---|---|---|---|---|---|
| *Winter 2010-2011* | | | | | |
| HDDd | 0.5932 | 78.23 | CDDd | - | - |
| Treatment*HDDd | -0.0173 | -1.64 | Treatment*CDDd | - | - |
| Post | -16.0029 | -31.09 | Post2 | 6.4150 | 9.84 |
| Post*Treatment | 0.8141 | 1.13 | Post2*Treatment | 0.3600 | 0.39 |
| Post*HDDd | 0.4273 | 32.62 | Post2*HDDd | -0.2324 | -14.17 |
| Post*Treatment*HDDd | -0.0381 | -2.07 | Post2*Treatment*HDDd | -0.0116 | -0.50 |
| Post*CDDd | - | - | Post2*CDDd | - | - |
| Post*Treatment*CDDd | - | - | Post2*Treatment*CDDd | - | - |
| *Spring 2011* | | | | | |
| HDDd | 0.4630 | 62.25 | CDDd | 7.0558 | 30.92 |
| Treatment*HDDd | -0.0277 | -2.71 | Treatment*CDDd | -0.2556 | -0.81 |
| Post | 1.8227 | 10.00 | Post2 | -5.1286 | -25.87 |
| Post*Treatment | -0.8881 | -3.54 | Post2*Treatment | -0.0662 | -0.24 |
| Post*HDDd | -0.1989 | -21.62 | Post2*HDDd | 0.2551 | 26.06 |
| Post*Treatment*HDDd | 0.0117 | 0.93 | Post2*Treatment*HDDd | -0.0052 | -0.38 |
| Post*CDDd | -4.1886 | -18.55 | Post2*CDDd | 0.8734 | 15.66 |
| Post*Treatment*CDDd | 0.2485 | 0.80 | Post2*Treatment*CDDd | 0.0229 | 0.29 |