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C3-CUB Energy Saver Program
PY6 Evaluation Report

Final

Energy Efficiency / Demand Response Plan:
Plan Year 6
(6/1/2013-5/31/2014)

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E. Executive Summary

This report presents a summary of findings from the impact evaluation of the ComEd PY6 [1] C3- CUB Energy Saver program (C3-CUB program). The program is a web-based, opt-in behavioral energy efficiency program, introduced in June 2010, designed to generate energy savings by providing participants with information about their energy usage, recommendations about how participants may reduce energy consumption and reward points for saving energy that can be redeemed at local retailers. Enrollment surged at the start of the program in June 2010 and again at the program's one year anniversary in June 2011; both of these events were well-publicized and the Citizens Utility Board (CUB) made a concerted effort to enroll households during these months. In PY6, there were a total of 8,148 participants enrolled at the start of the program year and 8,793 participants enrolled at the end of the program year, the lowest annual increase in enrollment since the program's inception.

E.1. Program Savings

Table E-1 summarizes the electricity savings from the C3-CUB program. The evaluation team calculated savings using regression analysis of monthly billing data comparing participants to a matched set of nonparticipants. As discussed in this report, the analysis assumes that with respect to unobserved variables that may affect program savings, on average program enrollees are no different than customers matched to them, in which case the estimate of savings from the analysis is net savings.

Table E-1. PY6 Total Program Electric Savings

Savings Category	Energy Savings (MWh)
Verified Net Savings Prior to Uplift Adjustment*	1,572
Verified Net Savings	1,610

Source: Navigant analysis of ComEd billing data, C3 implementation data.
*The uplift adjustment reflects savings that are jointly produced by the C3-CUB program and other EE programs.

E.2. Key Findings and Recommendations

This section summarizes key impact findings and recommendations.

Finding 1. In PY6, the average percent savings per enrolled customer is 2.04 percent (Standard Error = 0.46 percent). This is an average savings of 187 kWh per customer (Standard Error = 42 kWh). Verified net program savings in PY6 is 1,572 MWh (Standard Error = 349 MWh) prior to uplift adjustment. Verified net savings is 1,610 MWh.

Finding 2. The program is performing adequately in terms of savings per customer, but as anticipated in the PY5 report, savings have dropped compared to PY5, and enrollment is decreasing compared to previous years. Overall, program energy impact savings have fallen by almost 50

[1] The PY6 program year began June 1, 2013 and ended May 31, 2014.

percent over the past year, though they remain statistically significant. There is a strong likelihood that savings will fall further in PY7 in the absence of additional interventions to recruit new participants and/or an effort to encourage participants to use the program web portal more often than they did in PY6.

> **Recommendation 1**. Given that savings per participant are similar to those of other opt-out behavioral programs, and the presumably low cost of running the program, attempts to increase enrollment should be considered, though Navigant strongly recommends that continuation of the program is contingent on the recommendations concerning self-selection bias presented below.

Finding 3. Estimated savings might be biased by customer self-selection into the program. The industry has been moving towards experimental designs, such as recruit-and-deny and recruit-and-delay, to ensure against this issue. Navigant presents preferred and alternative courses of action to address this issue.

> **Recommendation 2 (preferred)**. Ideally, the program should implement a recruit-and-deny enrollment strategy to randomize program enrollment. Customers are provided a link to the web portal but told that the program is experimental and that some customers will not be allowed access to the program. Customers denied access serve as a control group. Alternatively, a recruit-and-delay strategy denies customers access for one year.
>
> **Recommendation 3 (alternative)**. The issue of self-selection bias can be examined with the following combination of tools:
>
> - The evaluators could develop a brief questionnaire, administered by the program to new enrollees upon enrollment, which focuses on the impetus for program enrollment.
> - The evaluators could administer a survey to randomly selected PY7 participants and a matched comparison group to identify differences between them that might indicate selection bias.

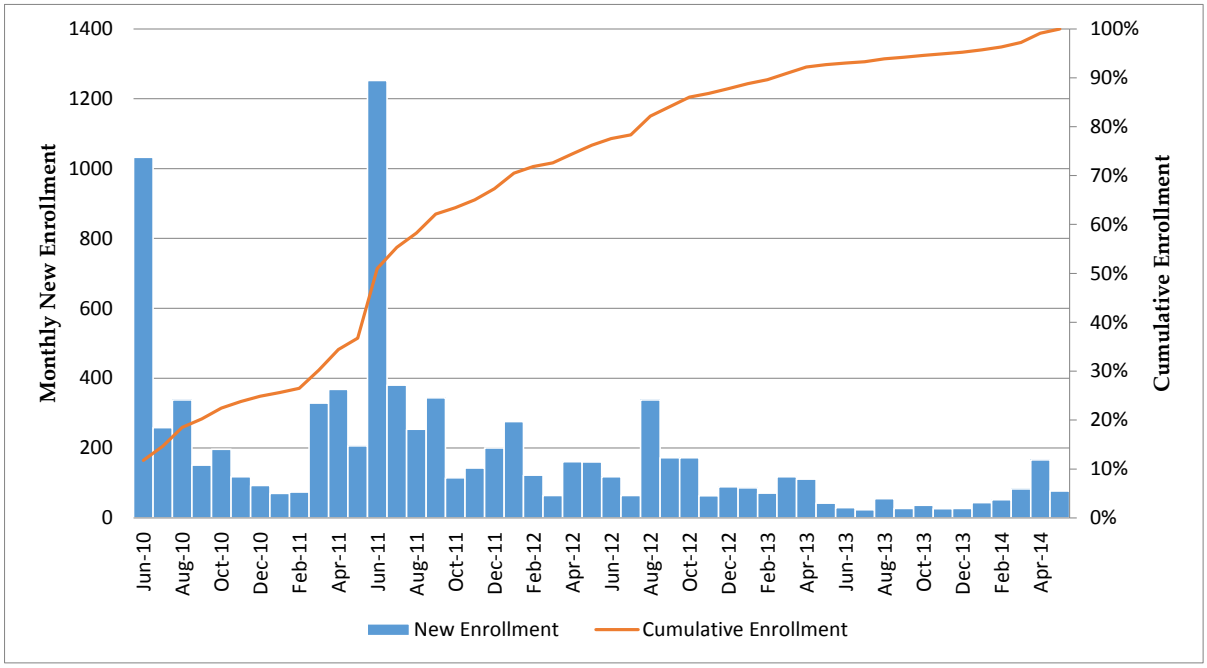
Recommendation 3 is an inferior strategy compared to the preferred approach of an experimental design from Recommendation 2, as results might be suggestive that self-selection bias is not an issue, but can never be claimed to conclusively demonstrate such bias does not exist.

1. Introduction

1.1 Program Description

The C3-CUB program is a web-based, opt-in behavioral energy efficiency program, introduced in June 2010, designed to generate energy savings by providing participants with information about their energy usage, recommendations about how participants may reduce energy consumption and reward points for saving energy that can be redeemed at local retailers. Enrollment surged at the start of the program in June 2010 and again at the program's one-year anniversary in June 2011; both of these events were well-publicized and the Citizens Utility Board (CUB) made a concerted effort to enroll households during these months. In PY6, total program enrollment increased from 8,148 to 8,793, the lowest yearly increase since the program's inception. Figure 1-1 presents monthly enrollment and cumulative enrollment since the program's inception through the end of PY6.

Figure 1-1. C3-CUB monthly enrollment, and cumulative percentage enrollment, June 2010-May 2014



Source: Navigant analysis

1.2 Evaluation Objective

The sole objective of this evaluation is to determine the PY6 energy savings generated by the C3-CUB program.

2. Evaluation Approach

This section includes Navigant's approach for evaluating this program.

2.1 Primary Data Collection

2.1.1 Overview of Data Collection Activities

Navigant received program tracking data and monthly billing data for all program participants and control customers for the period of September 2008 to May 2014. Details are provided in Table 2-1.

Table 2-1. Primary Data Collection Methods

Collection Method	Subject Data	Quantity	Net Impact	Net Impact less Joint Impact with other EE Programs
Billing Data	Program participants and matches	All	X	
Tracking Data	Program participants and matches	All	X	
Tracking Data for Other Programs	Participants in Other Programs	All		X

Source: Navigant

2.2 Statistical Approach used in the Impact Evaluation

To estimate energy savings Navigant used regression with pre-program matching (RPPM) described in Ho, Imai, King, and Stuart (2007).[2] Navigant has had good success with the RPPM method in evaluating many opt-in behavioral programs. Navigant also investigated estimating program impacts using the variation in adoption (VIA) method, the approach used by Harding and Hsiaw (2013)[3] and used by Navigant in past evaluation reports, but concluded that the maintained assumptions of the approach are violated for the program in PY6, causing estimated savings to be biased. Additional detail about the statistical approach used in this evaluation is included in Section 5.1.1.

2.2.1 Matching Algorithm and Matching Results

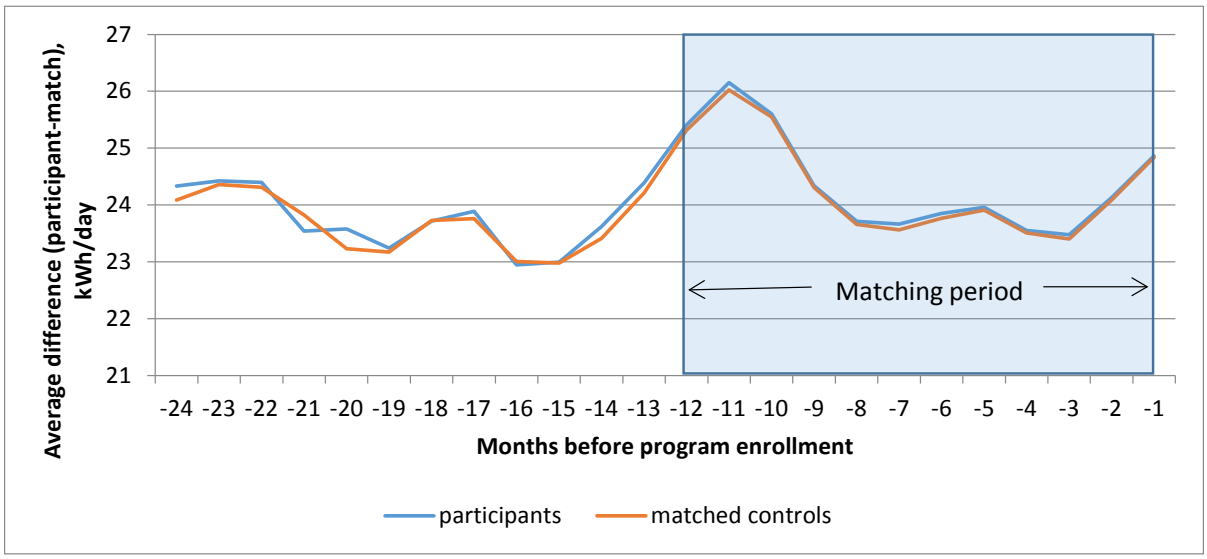
Matching methods rely on a set of matched comparison households to estimate program savings. The pool of non-participant households available for matching consisted of 356,843 ComEd residential customers. Additional detail about matching methods used for this evaluation is included in Section 5.1.2.

For each program participant with monthly billing data extending to at least twelve months before program enrollment, energy consumption in each month in the twelve months before program enrollment was compared to that of all customers in the available pool with billing data over the

[2] Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth Stuart. 2007. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis* 15(3): 199-236.
[3] Harding, M. and A. Hsiaw. Goal Setting and Energy Conservation. July 2013.

same twelve months. Figure 2-1 shows average energy use by participants and their matches for the period t_k-24 to t_k-1.

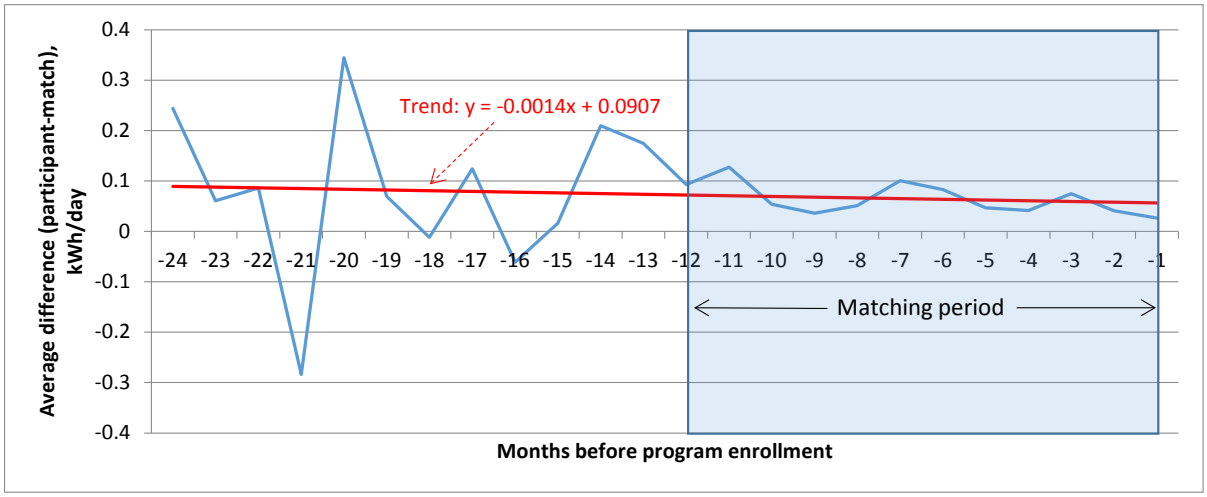
Figure 2-1. Average energy use before program enrollment, C3-CUB participants and their matches



Source: Navigant analysis

Figure 2-2 shows the average difference in energy use between participants and their matches for the period t_k-24 to t_k-1, along with a linear trend line. There is no indication of a pattern of systematic differences between participants and their matches in this period, and estimating Model 1 using this data, with and without a treatment·trend interaction, confirms this: the relevant test variables ($treatment_k$ for Model 1, $treatment_k$ and $treatment_k \cdot trend_t$ for the extended version) are not statistically significant at any reasonable confidence level, and a joint test on $treatment_k$ and $treatment_k \cdot trend_t$ also is not statistically significant.

Figure 2-2. Average difference in monthly energy use before program enrollment, C3-CUB participants and their matches



Source: Navigant analysis

2.2.2 Data Used in the Impact Analysis

In preparation for the impact analysis, Navigant combined and cleaned data provided by the program. Billing data used in the analysis extended from January 2008 (29 months before the start of the program in June 2010) to May 2014. The following customers were removed from the analysis:

- 345 customers who enrolled prior to June 2010 (customers who enrolled prior to June 2010 were identified by the implementer as test users).
- All billing data for 569 customers with fewer than 8 bills in the matching period.
- 21,752 matched pair observations with less than 20 or more than 40 days in the billing cycle.
- 6,685 matched pair observations with an outlier, defined as observations with average daily usage more than one order of magnitude from the median usage in the targeted sample for the analysis.[4]
- All observations outside of the PY6 post period (June 2013 to May 2014).

2.2.3 Accounting for Uplift in other Energy Efficiency Programs

If participation rates in other energy efficiency programs are the same on average for C3-CUB participants compared to similar non-participants, the savings estimates from the statistical analyses presented here are already "net" of savings from the other programs, as this indicates the C3-CUB program had no effect on participation in the other energy efficiency (EE) programs.[5] However, if the C3-CUB program affects participation rates in other energy efficiency programs, perhaps via the messaging in the web portal, then savings across all programs are lower than indicated by the simple summation of savings in the C3-CUB and EE programs. For instance, if the C3-CUB program increases participation in another EE program, the increase in savings may be allocated to either the C3-CUB program or the other EE program, but cannot be allocated to both programs simultaneously.[6]

As data permitted, Navigant used a difference-in-difference (DID) statistic to estimate uplift in other EE programs, in which the change in the participation rate in another EE program between PY6 and a pre-program period for enrollees was subtracted from the same change for a similar group of nonparticipants. The group of nonparticipants used in the analysis is the customers matched to the participants for the RPPM method. The designated pre-program period is June 2009-May 2010, which is the 12 month period before *any* customer enrolled in the C3-CUB program.

As an example, if the rate of participation in an EE program during PY6 is five percent for the treatment group and three percent for the matched comparison group, and the rate of participation during the 12 months before enrollment in the C3-CUB program is two percent for the treatment

[4] The median usage for participants was 20.11 kWh per day; observations with usage values greater than 201 kWh per day or less than 2.01 kWh per day were excluded from the analysis. The mean usage for participants was 24.27 kWh per day, with a standard deviation of 18.60. The median usage for matched controls was 20.42 kWh per day; observations with usage values greater than 204 kWh per day or less than 2.04 kWh per day were excluded from the analysis. The mean usage for matches was 24.54 kWh per day, with a standard deviation of 18.07.

[5] Here we assume that upon entry in the energy efficiency program the average program savings are the same for C3-CUB participants and non-participants.

[6] It is not possible to avoid double counting of savings generated by programs for which tracking data is not available, such as upstream CFL programs.

group and one percent for the matched comparison group, then the rate of uplift due to the C3-CUB program is one percent, which is reflected in the calculation (5%-2%) - (3%-1%) = 1%. The DID statistic generates an unbiased estimate of uplift when the baseline average rate of participation is the same for the treatment and control groups, or when they are different due only to differences between the two groups in time-invariant factors, such as the square footage of the residence.

An alternative statistic that generates an unbiased estimate of uplift when the baseline average rate of participation in the EE program is the same for the treatment and control groups is a simple difference in participation rates during PY6. The evaluation uses this alternative statistic (i.e. the "post-only difference" (POD) statistic) in cases where the EE program did not exist during the pre-program year.

The evaluation examined the uplift associated with four energy efficiency programs:

- The Single Family Home Energy Savings (SFHES) program, in which customers in single family homes are offered a discounted home energy assessment and free or incentivized direct install and weatherization measure recommendations and installations.
- The Complete System Replacement (CSR) program, in which education and cash incentives are offered to residential customers to encourage customer purchases of higher efficiency equipment.
- The Fridge and Freezer Recycle Rewards (FFRR) program, in which energy is saved by retirement and recycling of older, inefficient refrigerators, freezers, and room air conditioners.
- The Multi-Family Comprehensive Energy Efficiency Program (MCEEP) program, which offers direct installation of low-cost efficiency measures, such as water efficiency measures and CFLs, at eligible multifamily residences.

For only the FFRR program was it possible to use the DID statistic to calculate double-counted savings. For all other programs, the POD statistic was used. In this evaluation, the sizes of the participation group and matched comparison group are the same, and so in the presentation of results, DID and POD statistics are presented not as differences in rates of participation levels, but as differences in actual participation levels.

2.2.4 Process Evaluation

This evaluation was limited to an analysis of program impacts.

3. Gross Impact Evaluation

PY6 program verified net savings are 1,572 MWh prior to uplift adjustment. Verified net savings were 1,610 MWh. Under the maintained assumption of no selection bias, gross savings are equal to net savings. The increase in estimated savings in Table 3-1 after adjusting for uplift (i.e. joint savings with other EE programs) reflects that, on balance non-participants are *more* likely to take advantage of these other EE programs (see Section 3.3 below), and so the counterfactual they provide in the statistical analysis is slightly too high. In any event, the effect of this uplift adjustment is small representing an increase in estimated savings of 2.4 percent.

Table 3-1. PY6 Total Program Electric Savings

Savings Category	Energy Savings (MWh)
Verified Net Savings Prior to Uplift Adjustment*	1,572
Verified Net Savings	1,610

Source: Navigant analysis of ComEd billing data, C3 implementation data.
*The uplift adjustment reflects savings that are jointly produced by the C3-CUB program and other EE programs.

3.1 Model Parameter Estimates

For the RPPM model the estimated savings are derived directly from the estimate of α_2 in the model described above (Model 1), and the standard error is based on the standard error on α_2. We estimate robust standard errors with clustering of errors by customer. Regression parameter estimates for the RPPM approach are found in Table 5-1.

3.2 Verified Gross (and Net) Program Impact Results

Table 3-2 presents statistics concerning estimated savings. The savings represent a substantial reduction – close to 50 percent --from PY5. At least a partial explanation lies in the pattern of visits to the web portal presented in Figure 3-1 below; visits fell sharply in PY6.

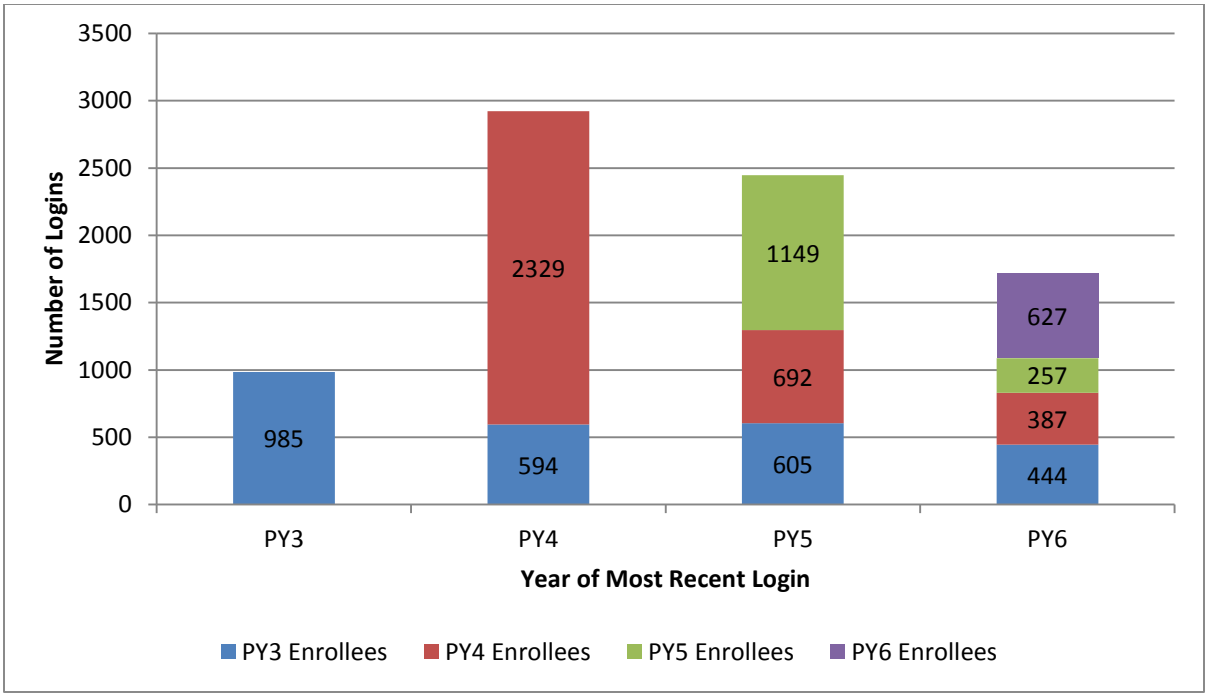
Table 3-2. C3-CUB PY6 Program Savings

Type of Statistic	Value
Number of Participants used in analysis	7,345
Average Percent Savings	2.03%
	0.46%
Average kWh savings per customer per day	0.513
	0.114
Average kWh savings per customer, PY6	187
Verified Net Savings (MWh)* (prior to uplift adjustment)	*1,572*
	349
Verified Net Savings (MWh)*	*1,610*

Source: Navigant analysis of ComEd billing data and program data.
*Total savings are pro-rated for participants that closed their accounts during PY6.

The pattern of visits to the web portal from PY3 through PY6 is presented in Figure 3-1 below. In PY6, visits to the web portal were lower than in previous years.

Figure 3-1. Frequency distribution of most recent login to the web portal, PY3-PY6, by year of enrollment



Source: Navigant analysis

3.3 Net Savings after removing Joint Savings

Program savings estimated from the statistical analysis are net savings *except* for the uplift in participation in other energy efficiency programs caused by the C3-CUB program. To avoid double-counting of savings, program savings due to this uplift must be counted towards either the C3-CUB program or the other EE programs, but not both programs. The uplift of savings in other EE programs was a small proportion of the total savings: -38 MWh, which is 2.4 percent of net savings. Subtracting these savings from net savings generates a final net savings estimate of 1,610 MWh.

Table 3-3 presents a summary of the PY6 double-counted savings due to uplift in other EE programs implied by the estimate of net savings obtained in the previous section, and the final net savings for the C3-CUB program obtained by removing these savings from the estimate of net program savings. Table 5-2 in the appendix presents the details of the calculation of the double-counted savings for each for the four ComEd energy efficiency programs considered in the analysis.

Conditional on the deemed values used in the analysis, the absolute value of the estimated interaction between the C3-CUB program and other EE programs is an *overestimate* because it presumes participation in the other EE programs occurs at the very start of the program year. Under the more reasonable assumption that participation occurs at a uniform rate throughout the year, the estimate of double-counted savings would be approximately -19 MWh, half the estimated value of -38 MWh. The main point is that double counting of savings with other ComEd energy efficiency programs is not a significant issue for the C3-CUB program.

Table 3-3. PY6 Uplift of Savings in Other EE programs

	SFHES	CSR	FFRR	MCEEP	Total
Participation uplift in other EE programs (# participants)	*41*	*11*	*-79*	*-3*	-
Savings uplift in other EE programs (MWh)	*7*	*6*	*-50*	*-1*	*-38*

Source: Navigant analysis

4. Conclusions and Recommendations

This section summarizes key impact findings and recommendations.

Finding 1. In PY6, the average percent savings per enrolled customer is 2.04 percent (Standard Error = 0.46 percent). This is an average savings of 187 kWh per customer (Standard Error = 42 kWh). Verified net program savings in PY6 is 1,572 MWh (Standard Error = 349 MWh) prior to uplift adjustment. Verified net savings is 1,610 MWh.

Finding 2. The program is performing adequately in terms of savings per customer, but as anticipated in the PY5 report, savings have dropped compared to PY5, and enrollment is decreasing compared to previous years. Overall, program energy impact savings have fallen by almost 50 percent over the past year, though they remain statistically significant. There is a strong likelihood that savings will fall further in PY7 in the absence of additional interventions to recruit new participants and/or an effort to encourage participants to use the program web portal more often than they did in PY6.

> **Recommendation 1**. Given that savings per participant are similar to those of other opt-out behavioral programs, and the presumably low cost of running the program, attempts to increase enrollment should be considered, though Navigant strongly recommends that continuation of the program is contingent on the recommendations concerning self-selection bias presented below.

Finding 3. Estimated savings might be biased by customer self-selection into the program. The industry has been moving towards experimental designs, such as recruit-and-deny and recruit-and-delay, to ensure against this issue. Navigant presents preferred and alternative courses of action to address this issue.

> **Recommendation 2 (preferred)**. Ideally, the program should implement a recruit-and-deny enrollment strategy to randomize program enrollment. Customers are provided a link to the web portal but told that the program is experimental and that some customers will not be allowed access to the program. Customers denied access serve as a control group. Alternatively, a recruit-and-delay strategy denies customers access for one year.
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> **Recommendation 3 (alternative)**. The issue of self-selection bias can be examined with the following combination of tools:
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> - The evaluators could develop a brief questionnaire, administered by the program to new enrollees upon enrollment, which focuses on the impetus for program enrollment.
> - The evaluators could administer a survey to randomly selected PY7 participants and a matched comparison group to identify differences between them that might indicate selection bias.

Recommendation 3 is an inferior strategy compared to the preferred approach of an experimental design from Recommendation 2, as results might be suggestive that self-selection bias is not an issue, but can never be claimed to conclusively demonstrate such bias does not exist.

5. Appendix

This section includes detailed impact methods used for this evaluation.

5.1 Detailed impact methodology: regression with pre-program matching (RPPM)

5.1.1 Statistical Approach used in the Impact Evaluation

As discussed in Section 2.2 above, in evaluating this program, the basic logic of matching is to balance the participant and non-participant samples by matching on the exogenous covariates known to have a high correlation with the outcome variable. Doing so increases the efficiency of the estimate and reduces the potential for model specification bias. Formally, the argument is that if the outcome variable Y is independently distributed conditional on X and D (conditional independence assumption), where X is a set of exogenous variables and D is the program variable, then the analyst can gain some power in the estimate of savings and reduce potential model specification bias by assuring that the distribution of X is the same for treatment and control observations.

In this evaluation, the outcome variable is monthly post-program period energy use, and the available exogenous covariate with by far the greatest correlation with this outcome variable is energy use in the same month of the pre-program period, $PREkWh_{kt}$, where k indexes the customer and t indexes the month; this is why the matching takes the form described in section 2.2.1. The RPPM approach can be interpreted as using regression analysis to further control for any remaining imbalance in the matching on this variable. If, for instance, after matching the participants use slightly more energy on average in the pre-program period than their matches –they are higher baseline energy users, in other words—then including $PREkWh_{kt}$ as an explanatory variable in a regression model predicting monthly energy use during the post-program period prevents this remaining slight difference in baseline energy use from being attributed to the program.

In the RPPM approach the development of a matched comparison group is viewed as a useful "pre-processing" step in a regression analysis to assure that the distributions of the covariates (i.e., the explanatory variables on which the output variable depends) for the treatment group are the same as those for the comparison group that provides the baseline measure of the output variable (see footnote 3). This minimizes the possibility of model specification bias. The regression model is applied only to the post-treatment period, and the matching focuses on those variables expected to have the greatest impact on the output variable.

5.1.2 Matching Algorithm and Matching Results

As described in section 2.2.1, we matched participant and comparison customers on energy use during the pre-treatment period, and then estimated a model for all post-program observations in which energy use in month *t* is a function of a monthly fixed effect, energy use in the same calendar month in the 1-year period before program enrollment, and whether the customer is a program participant. A shorthand version of the model is:

Model 1

$$ADU_{kt} = \alpha_{0t} \cdot M_t + \alpha_{1t} PREkWh_{kt} \cdot M_t + \alpha_2 Treatment_k + \varepsilon_{kt}$$

where:

ADU_{kt}	=	Average daily energy use by household k in month t;
M_t	=	Month/year-specific indicator variable (and thus α_{0t} is a monthly fixed effect);
$Treatment_k$	=	A 0/1 indicator variable, taking a value of 1 if customer k is a C3-CUB participant, and 0 otherwise.
$PREkWh_{kt}$	=	The average daily electricity use by household k during the most recent month before household k (or its match) enrolled in the C3-CUB program that is also the same calendar month as month t. For instance, if household k enrolled in August 2011, the value of $PREkWh_{kt}$ for June 2012 is June 2011.
ε_{kt}	=	Model error term.

In this model α_2 indicates average daily savings generated by the program in PY6. We include a monthly fixed effect to account for unobserved time-related factors, such as weather, that affect all customers, and interact the monthly dummy variable with $PREkWh_{kt}$ to account for the fact that the relationship between energy use in the year before enrollment and energy use in the program year might vary by calendar month.

For the sake of expositional clarity below, we denote by t_k as the month t in which customer k enrolled in the program, with t_k -1 denoting the month before enrollment, t_k +1 denoting the month after enrollment, and so on. Customers with more than four missing bills during the designated matching period [t_k -12, t_k -1] were not matched.

The basis of the comparison is the difference in monthly energy use between a participant and a potential match, D_{PM} (**D**ifference between **P**articipant and potential **M**atch). The quality of a match is denoted by the Euclidean distance to the participant over the twelve values of monthly D_{PM} used for matching; that is, denoting by SSD the sum of squared D_{PM} over the matching period, it is denoted by $SSD^{1/2}$. The non-participant customer with the shortest Euclidean distance to a participant was chosen as the matched comparison for the participant. Matching was done with replacement, and so, after excluding observations based on screening criteria explained in the next section, there were 8,230 participants and 7,717 unique comparison customers.

It is not possible to statistically test for self-selection bias, but Imbens and Wooldridge (2009) discuss the logic of assessing such bias by testing whether model covariates expected to be highly correlated with the outcome variable(s) of interest, but known to be *not* affected by the treatment, are revealed to be (incorrectly) affected by the treatment in the sample data.[7] As mentioned above, the covariates most strongly correlated with the outcome variables of interest (monthly energy use during program enrollment) are monthly energy use before the start of the program, and a good behavioral case can be made that if on average program participants are different than their matches in their baseline

[7] Imbens, Guido W., and Jeffrey M. Wooldridge. 2009. "Recent Developments in the Econometrics of Program Evaluation." *Journal of Economic Literature*, 47(1): 5-86.

energy use, then their energy use pattern should be different *before* program enrollment. With this in mind, in the current context a simple implementation of the assessment is to apply the RRPM model (Model 1 above) to a 24-month pre-program period –specifically, months t_k-24 to t_k-1—where, for the purpose of the assessment, months t_k-24 to t_k-13 serve as the "pre" year, and months t_k-12 to t_k-1 serve as the "post" year. The logic of the assessment is that, conditional on the assumption that the RPPM model is structurally correct, we should find no difference in how it fits participants and matches during the matching period. Finding that the coefficient on the treatment variable is not statistically significant lends support –however modest—to the conclusion that self-selection bias is not an issue. Extending Model 1 to include an interaction between the treatment variable and a time trend, $treatment_k \cdot trend_t$, where the trend variable takes a value of 1 in the first month of the "post" period (the month denoted by t_k-12), a value of 2 in the second month of the "post" period (t_k-11), and so on, allows an assessment of whether self-selection bias arises as the program enrollment month approaches.

5.1.3 Detailed impact results: parameter estimates

Parameter estimates for Model 1 are presented in Table 5-1.

Table 5-1. Parameter Estimates for RPPM Model (Model 1)

Variable	Parameter Estimate	Standard Error	t statistic
Treatment	-0.5135	0.1139	-4.5100
M(t)=June 2013	3.9993	0.2408	16.6102
M(t)=July 2013	6.0357	0.2461	24.5296
M(t)=August 2013	6.3172	0.2654	23.8039
M(t)=September 2013	9.1928	0.3822	24.0551
M(t)=October 2013	5.6675	0.2672	21.2094
M(t)=November 2013	4.9863	0.3240	15.3889
M(t)=December 2013	4.7294	0.3246	14.5693
M(t)=January 2014	5.2550	0.3439	15.2791
M(t)=February 2014	5.3254	0.3777	14.0989
M(t)=March 2014	6.0947	0.3887	15.6813
M(t)=April 2014	4.3096	0.2801	15.3859
M(t)=May 2014	4.1327	0.2530	16.3324
PREkWh*M(t)=June 2013	0.7389	0.0102	72.7392
PREkWh*M(t)=July 2013	0.7005	0.0074	94.1154
PREkWh*M(t)=August 2013	0.6071	0.0078	78.0000
PREkWh*M(t)=September 2013	0.7578	0.0149	50.7776
PREkWh*M(t)=October 2013	0.7794	0.0147	52.9294
PREkWh*M(t)=November 2013	0.7883	0.0175	45.1514
PREkWh*M(t)=December 2013	0.8311	0.0146	56.7925
PREkWh*M(t)=January 2014	0.8244	0.0139	59.4930
PREkWh*M(t)=February 2014	0.8544	0.0164	52.2415
PREkWh*M(t)=March 2014	0.8342	0.0193	43.2593
PREkWh*M(t)=April 2014	0.8061	0.0153	52.7859
PREkWh*M(t)=May 2014	0.7523	0.0137	54.9737

Source: Navigant analysis

5.1.4 Savings due to participation uplift in other EE programs

Table 5-2 presents program savings due to participation uplift in other EE programs. A dash (-) in a row concerning the change in participation from the pre-program year (2009) indicates the EE program did not exist during the pre-program year, or there was no participation by either participants or the matched comparison group in the pre-program year. In these cases, the estimate of uplift is based on a POD statistic, otherwise it is based on a DID statistic. Overall, the empirical evidence indicates that the program caused a reduction in participation in other EE programs by 37,696 kWh (approximately 38 MWh), possibly by causing participants to take actions outside of these other EE programs that obviated the value of the programs to them.

Table 5-2. Estimates of Double Counted Savings in PY6

	SFHES	CSR	FFRR	MCEEP
Average program savings (annual kWh per participant)	174	500	631	162
# C3-CUB Treatment Customers	8,231	8,231	8,231	8,231
Program participation, PY6	47	42	107	5
Change in participation from pre-program Year	-	-	-34	-
# Comparison Customers	8,231	8,231	8,231	8,231
Program participation, PY6	6	31	111	8
Change in participation from pre-program	-	-	45	-
DID/(POD) statistic	0.50%	0.13%	-0.96%	-0.04%
Participation uplift	41	11	-79	-3
Statistically Significant at the 90% Confidence Level?	Yes	No	Yes	No
Savings attributable to other programs (kWh)	7,116	5,503	-49,828	-487

Source: Navigant analysis