NAVIGANT

C3-CUB Energy Saver Program
EPY5 Evaluation Report

Final

Energy Efficiency / Demand Response Plan:
Plan Year 5
(6/1/2012-5/31/2013)

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Prepared by:

Bill Provencher
Navigant Consulting

Carly McClure
Navigant Consulting

www.navigant.com

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NAVIGANT

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

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E. Executive Summary

This report presents a summary of the findings and results from the Impact and Process Evaluation of the EPY5[1] C3- CUB Energy Saver program (hereafter called "C3-CUB program"). The program is a web-based, opt-in program, introduced in June 2010, designed to generate energy savings by providing customers with information about their energy savings, tips on how to reduce energy consumption, and reward points for saving energy that can be redeemed at local retailers. Each month participants receive emails indicating the amount of energy they saved and the reward points earned by the customer for the savings. Reward points are strictly positive; if savings are negative, reward points are not deducted from the customer's "Rewards Account". An independent analysis of the program savings for the first year and a half of the program (June 2010-December 2011) estimated average annual savings of 4.4% prior to becoming a program in ComEd's portfolio.[2]

In EPY5, there were a total of 5, 913 customers enrolled at the start of the program year and 6,656 customers enrolled at the end of the program year. An important aspect of the program in EPY5 was a marketing campaign designed as a randomized controlled trial (RCT) involving 115,000 targeted treatment households and 63,151 targeted control households, with the treatment households receiving a single mailer encouraging energy savings and participation in the program. It is not possible to conclude at any reasonable level of statistical confidence that the average customer savings due to the mailer was different than zero. Only 339 of the treatment customers opted into the program before the end of EPY5 (0.29%). These 339 treatment customers were included in a quasi-experimental analysis of savings by all opt-in customers.

E.1. Program Savings

As discussed in this report, the analysis assumes that with respect to unobserved variables that may affect program savings, on average late enrollees in the program are the same on average as early enrollees, in which case the estimate of savings from the analysis is net savings. Table E-1 summarizes the electricity savings from the C3-CUB program.

Table E-1. EPY5 Total Program Electric Savings

Savings Category †	Energy Savings (MWh)
Verified Net Savings Prior to Uplift Adjustment	2,916
Verified Net Savings	2,914

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

[1] The EPY5 program year began June 1, 2012 and ended May 31, 2013.
[2] Harding, M. and A. Hsiaw. Goal Setting and Energy Conservation. July 2013. Available at: http://www.stanford.edu/~mch/resources/Harding_Goals.pdf.

E.2. Conclusions and Recommendations

The program appears to generate savings, with the key findings that:

1. Average percent savings per enrolled customer in EPY5 is 3.81% (Standard Error = 0.59%). This is an average savings of 360 kWh per customer (SE=56); and

2. Total program savings in EPY5 is 2,914 MWh (SE=449 MWh).

The program is performing well in terms of savings per customer, but is lagging in enrollment. With this in mind, major recommendations are limited:

1. **Recommendation.** Continue the program in its current form. There is a possibility that savings will diminish after 3 years; this will warrant investigation in the PY6 evaluation.

2. **Recommendation.** Given the relatively high savings per participant compared to other behavioral programs, and the presumably low cost of running the program, attempts to increase enrollment should be considered, though only if such attempts also address the recommendation below.

3. **Recommendation**. In the future the program should take proactive steps to investigate the issue of selection bias. For instance, a brief questionnaire to discern selection bias could be developed and administered to new enrollees upon enrollment. Navigant can assist in the development of the questionnaire.

1. Introduction

1.1 Program Description

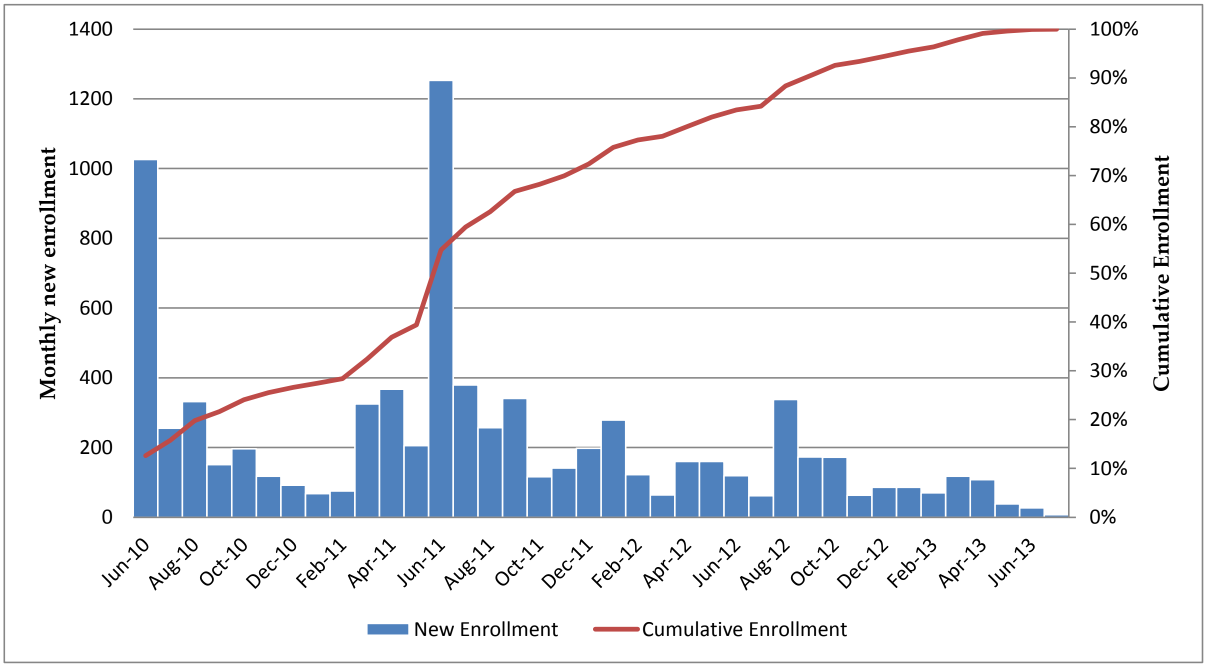
The C3-CUB program is a web-based, opt-in behavioral energy efficiency program, introduced in June 2010, designed to generate energy savings by providing customers with information about how their energy use is changing over time, tips on how to reduce energy consumption, and reward points for saving energy that can be redeemed at local retailers. Each month participants receive emails indicating the amount of energy they saved and the reward points earned by the customer for the savings. Reward points are strictly positive; if savings are negative, reward points are not deducted from the customer's "Rewards Account". An independent analysis of the program savings for the first year and a half of the program (June 2010-December 2011) estimated average annual savings of 4.4% (see footnote 2). In EPY5, total program enrollment increased from 6,680 to 8,113.

An important aspect of the program in EPY5 was a marketing campaign formulated as a randomized controlled trial involving 115,000 targeted treatment households and 63,151 targeted control households, with the treatment households receiving a single mailer encouraging energy savings and participation in the program. It is not possible to conclude at any reasonable level of statistical confidence that the average customer savings due to the mailer was different than zero, and so this report is restricted to the analysis of savings by customers who activated the Web UI.[3] Only 339 of the treatment households opted into the program before the end of EPY5 (0.29%). These 339 treatment customers were included in a quasi-experimental analysis of savings by all opt-in customers.

Figure 1-1 presents monthly enrollment and cumulative enrollment since the program's inception. Enrollment surged at the start of the program in June 2010 and again at the program's 1-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.

[3] We used a linear fixed effects regression model to estimate average savings by customers receiving the mailer. The model generated a point estimate of *negative* savings (-0.0167 kWh/day per customer, or an average of -6.0955 kWh per year per customer), with a standard error of 0.0228 (t-statistic=-0.73).

Figure 1-1. C3-CUB monthly enrollment, and cumulative percentage enrollment, June 2010-July 2013



Source: Navigant analysis

1.2 Evaluation Objective

The sole objective of the analysis in this report is to determine the EPY5 energy savings generated by the C3-CUB program.

2. Evaluation Approach

Navigant used three evaluation approaches to estimate energy savings. The first is the variation in adoption (VIA) method used by Harding and Hsiaw (2013; see footnote 2) to estimate energy savings in the first year of the C3-CUB program. The second and third are matching methods that draw on the same set of program enrollees and their 1:1 non-program matches, but are distinguished by the statistical analysis used to estimate program impacts. The first of these is regression with pre-program matching (RPPM) described in Ho, Imai, King, and Stuart (2007).[4] The other is matching with bias correction (MBC) introduced by Abadie and Imbens (2011).[5] The three methods have different strengths and potential weaknesses, but generated very similar estimates of program savings. We present results for all three methods, but in reporting total savings we use results from the VIA approach because of its past use to evaluate the program by independent researchers, and some concern about selection bias in the matching methods.

2.1 Primary Data Collection

2.1.1 Overview of Data Collection Activities

From the program implementer Navigant received tracking data and monthly billing data for all program participants and control customers for the period of September 2008 to August 2013. 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	Process
Billing Data	Program participants and matches	All	X		N/A
Tracking Data	Program participants and matches	All	X		N/A
Tracking Data for Other Programs	Participants in Other Programs	All		X	N/A

[4] 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.
[5] Abadie, Alberto, and Guido Imbens. 2011. Bias-corrected matching estimators for average treatment effects. *Journal of Business and Economic Statistics* 29(1): 1-11.

2.1.2 Sampling Plan

The VIA approach used data for all 8,138 C3-CUB customers who were active at some time during the program. The matching methods used 6,973 program enrollees, and 6,551 unique matched customers, with the reduction in the number of program enrollees due to conditions necessary for proper matching.

2.1.3 Matching Algorithm and Matching Results

The matching methods rely upon a set of matched comparison households to estimate program savings. The pool of non-participant households available for matching consisted of 160,573 ComEd residential customers whose billing data were already accessible by Navigant.

For each program participant with monthly billing data extending to at least 14 months before program enrollment, energy consumption in each month in the period spanning 3-14 months before program enrollment (a twelve month period) was compared to that of all customers in the available pool with billing data over the same 12 months. For the sake of expositional clarity below, we denote by t_k=0 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 missing bills during the designated matching period [t_k -14, t_k -3], but whose billing data extended past 14 months before program enrollment, were matched based on their most recent 12 bills before t_k -2 (that is, starting three months before enrollment and working backwards in time).

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 12 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 6,973 participants and 6,551 unique comparison customers.

It is not possible to statistically test for selection bias, but Imbens and Wooldridge (2009) present a test that is suggestive (hereafter called the "IW test").[6] In the current context the logic of the test is that in the absence of selection bias there should be no difference between participants and matches in average energy use outside of the matching period and outside of the program period. A simple implementation of the test is to determine whether, given matching based on months t_k-3 to t_k-14, average D_{PM} in the two months before program enrollment, months t_k-1 and t_k-2, is practically or statistically different than zero.

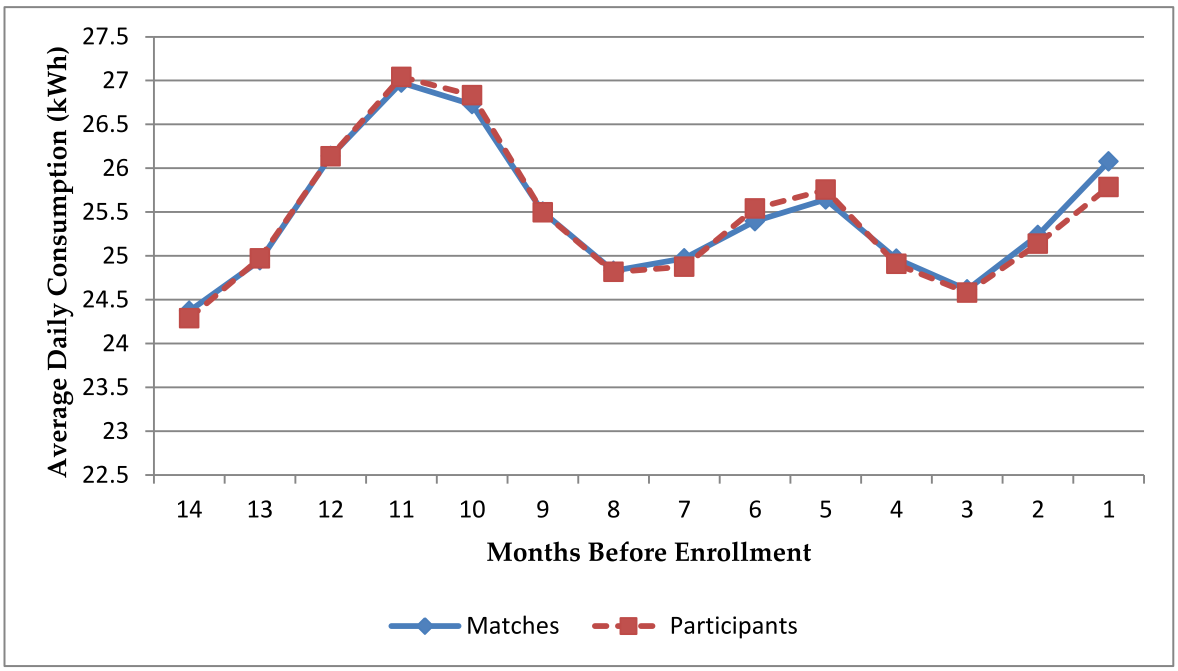
Figure 2-1 presents the average energy use of participants and their matches over the period t-14 to t-1, and Figure 2-2 amplifies differences between the two groups by presenting the average *difference* in energy use between participants and their matches in percentage terms, with 90% confidence intervals. The figure illustrates two important points:

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

- On average the energy use by matches is very similar to that of program participants. Mean differences in energy use during the 12-month matching period generally are not statistically or practically different than zero.

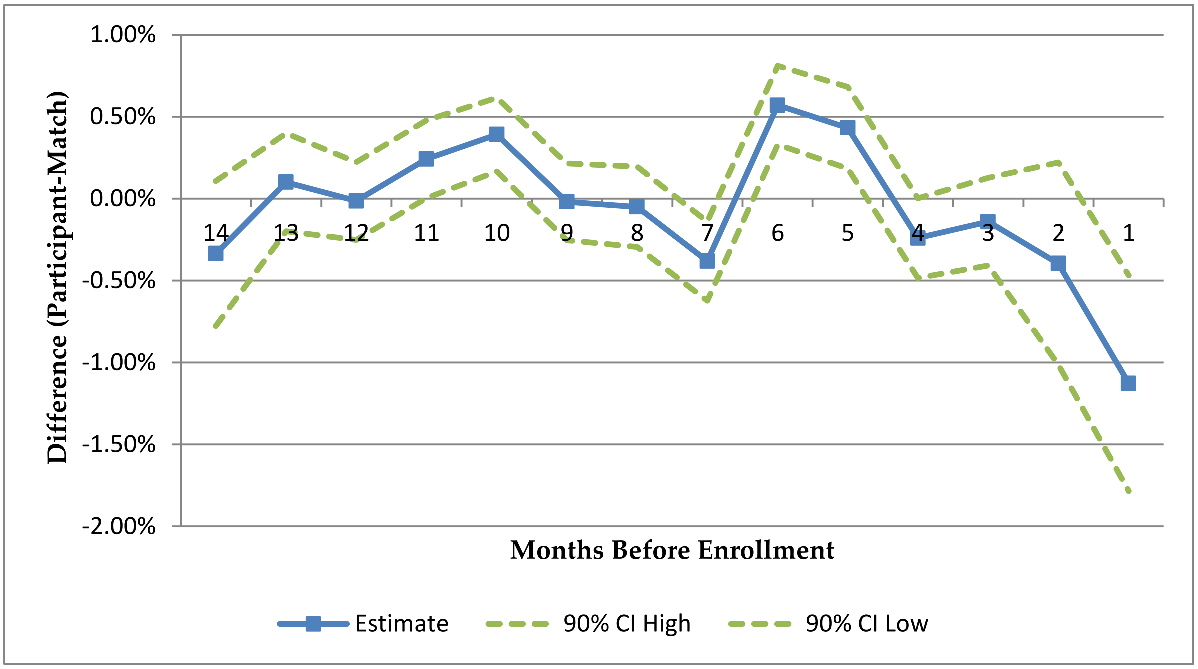
- The mean difference in energy use is not statistically different than zero in test period t-2 (90% confidence level), but is statistically different than zero in test period t-1, leaving ambiguous the issue of selection bias in the sample. In other words, in period t-1 there is statistical evidence that participants used less energy than their matches, which could be due to discrepancies in the program start date for some participants, but also raises the possibility that on average participants were already more inclined than their matches to reduce energy as they entered the program (that is, energy savers were self-selecting into the program), in which case the estimate of program savings would be biased upwards.

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



Source: Navigant analysis

Figure 2-2. Average difference in monthly energy use before program enrollment, C3-CUB participants and their matches, with 90% confidence intervals



Source: Navigant analysis

2.1.4 Data Used in the Impact Analysis

In preparation for the impact analysis, Navigant combined and cleaned the data provided by the implementer. Billing data used in the analysis extended from January 2008 (29 months before the start of the program) to August, 2013.

Both the VIA approach and the matching methods involved the removal of the following customers:

- 143 customers with no created date.
- 331 customers who enrolled prior to June 2010 (customers who enrolled prior to June 2010 were identified by the implementer as test users).
- 1 customer labeled as invalid account.

The VIA approach also involved the removal of the following billing data:

- 1,233 bills with insufficient bill date information.
- 1,503 bills with less than 20 or more than 40 days in the billing cycle.
- 4,195 outliers, defined as observations with average daily usage more than one order of magnitude from the median usage in the targeted sample for the analysis.[7]

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[7] The median usage was 20.35 kWh per day; observations with usage values greater than 203.50 kWh per day or less than 2.04 kWh per day were excluded from the analysis. Mean usage was 24.74 kWh per day, with a standard deviation of 18.98.

The matching methods involved the removal of the following additional billing data:

- All billing data for 608 customers with fewer than 12 bills in the matching period.
- 1,233 participant bills with insufficient bill date information.
- 819 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.[8]
- 2,572 matched pair observations with less than 20 or more than 40 days in the billing cycle.

2.1.5 Statistical Approaches used in the Impact Evaluation

Navigant used three methods –the VIA, MBC, and RPPM methods briefly described above–to estimate program savings. Final estimates of program savings are based on the VIA approach because the assumption necessary to claim that the estimate of program impacts is not confounded by selection bias is weaker than the assumption necessary to make the same claim in the matching method, and because the IW test for bias in the selection of matches is not unambiguously supportive of the conclusion of no bias. All three models generate very similar estimates of savings.

Details of the VIA approach are presented in the appendix in Section 6. The method uses only program participants to estimate savings, with late enrollees essentially serving as controls for early enrollees. It relies on the assumption that, controlling for both customer and monthly fixed effects, neither energy use in month t, nor energy savings s months into the program, is correlated with the timing of program entry.

Details of the MBC and RPPM approaches are presented in the appendix in Section 6. They draw on the same set of matches for the comparison group, but differ in their use of a structural model to estimate program savings. The MBC approach is less parametric, using regression analysis to correct for bias in differences between participants and their matched comparisons. The RPPM method, by contrast, treats matching as a “pre-processing” stage of the analysis and assumes that monthly energy use in the post-program period can be modeled as a linear regression function involving participants and matches.

[8] The median usage for participants was 20.94 kWh per day; observations with usage values greater than 209.40 kWh per day or less than 2.09 kWh per day were excluded from the analysis. The mean usage for participants was 25.40 kWh per day, with standard deviation of 18.80. The median usage for matched controls was 21.48 kWh per day; observations with usage values greater than 214.80 kWh per day or less than 2.15 kWh per day were excluded from the analysis. The mean usage for matches was 26.32 kWh per day, with standard deviation 19.6.

2.1.6 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.[9] 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.[10]

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 EPY5 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 MBC and RPPM methods. 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 EPY5 is 5% for the treatment group and 3% for the matched comparison group, and the rate of participation during the 12 months before enrollment in the C3-CUB program is 2% for the treatment group and 1% for the matched comparison group, then the rate of uplift due to the C3-CUB program is 1%, 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 EPY5. Navigant uses this alternative statistic –the "post-only difference" (POD) statistic –in cases where the EE program did not exist during the pre-program year.

Navigant examined the uplift associated with five energy efficiency programs:

- The Residential 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.

[9] 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.
[10] 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.

- The Complete System Replacement (CSR) program, in which education and cash incentives are offered to ComEd's, Nicor Gas', North Shore Gas', and Peoples Gas' residential customers to encourage customer purchases of higher efficiency equipment.
- 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 Multi-Family Home Energy Savings (MFHES) program, which offers direct installation of low-cost efficiency measures, such as water efficiency measures and CFLs, at eligible multifamily residences.
- The Clothes Washer (CW) program, which offers point-of-sale discounts for qualified energy efficient clothes washers.

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.

2.1.7 Process Evaluation

The evaluation of the HER program involved no process evaluation.

3. Gross Impact Evaluation

As detailed below, the three methods used in the analysis generated very similar results for program savings; the small differences in savings are not statistically significant. In reporting savings estimates we use results from the VIA approach because it was previously used in an independent analysis (see footnote 2), and was judged to be less susceptible to selection bias.

Overall gross program savings for EPY5 are 2,916 MWh. Under the maintained assumption of no selection bias, gross savings are equal to net savings.

3.1 Model Parameter Estimates

Regression parameter estimates for the VIA approach are found in Table 6-1 in the appendix in Section 6. Regression parameter estimates for the RPPM approach are found in Table 6-2. The regression parameter estimates for the bias correction for the MBC approach are reported in Table 6-3.

3.2 Verified Gross Program Impact Results

Table 3-1 presents the estimated savings for the three methods used in the evaluation. Results are quite similar across the methods.

For the VIA approach estimated savings in EPY5 were derived by identifying each customer's months of program enrollment in EPY5, and using the estimated values of γ in Model 1 in the appendix to calculate the customer's total savings. Standard errors are calculated analytically using the covariance matrix of the estimated values of γ.

For the RPPM approach the estimated savings are derived directly from the estimate of α_2 in Model 2 in the appendix, and the standard error is based on the standard error on α_2. We estimate robust standard errors with clustering of errors by customer.

For the MBC approach the estimated savings for each month of EPY5 and each customer is derived using Model 3 in the appendix. Standard errors are calculated analytically using the approach suggested by Abadie and Imbens.

Table 3-1. C3-CUB Program Gross (and Net) Program Savings, EPY5

Type of Statistic	Method VIA	RPPM	MBC
	(standard errors in italics)		
Number of Participants used in analysis	8,137	6,973	6,973
Average Percent Savings	3.81%	3.86%	3.57%
	0.59%	*0.42%*	*0.21%*
Average kWh savings per customer per day	0.985	1.037	0.956
	0.152	*0.112*	*0.056*
Average kWh savings per customer, EPY5	360	379	349
Gross Verified MWh Savings†	*2,916*	*3,070*	*2,835*
	449	*332*	*166*

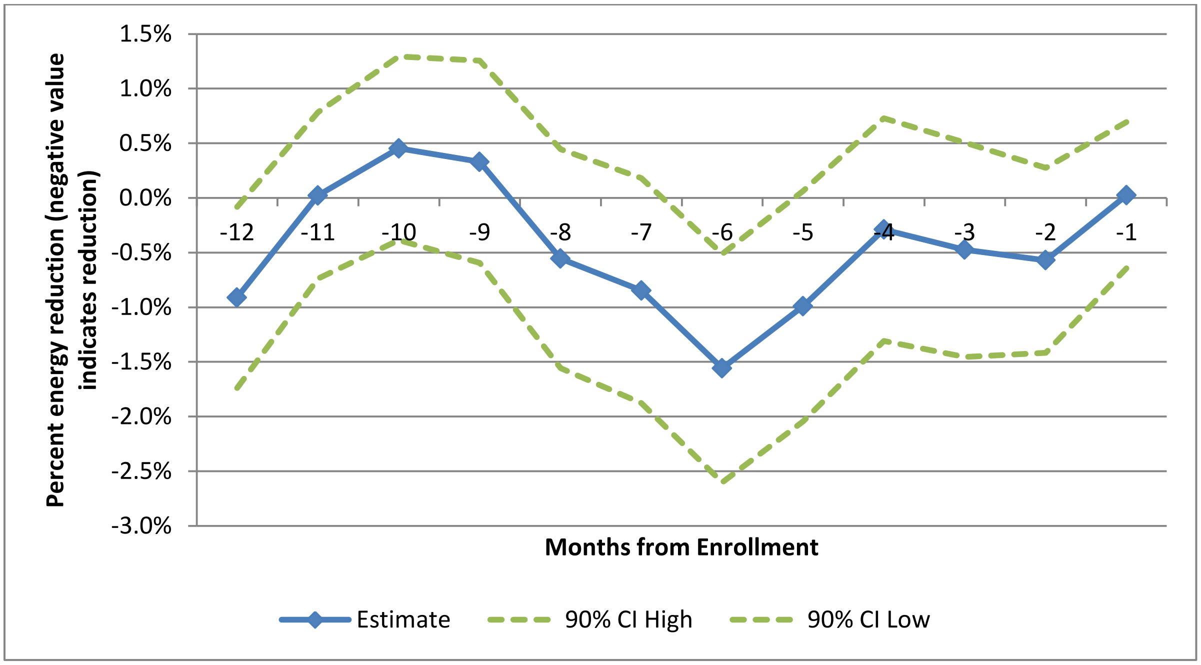
Source: ComEd billing data, C3 implementation data, and Navigant analysis.
†Total savings are pro-rated for participants that close their accounts during EPY5.

3.3 Estimated monthly savings in the VIA approach

Figure 3-1 graphs the average program savings on a percentage basis in the months before program enrollment. In eight months the program effect is negative, in two months the effect is positive, and in two months it is virtually zero. In only one month (the month T-6, indicating 6 months before enrollment) is the program effect statistically different than zero at a 90% confidence level. At this confidence level, chance alone would cause an average of one month out of ten to be statistically significant. We conclude that results are reasonably consistent with the assumption that there is no significant program effect before the start of the program, and thus no significant evidence for selection bias.

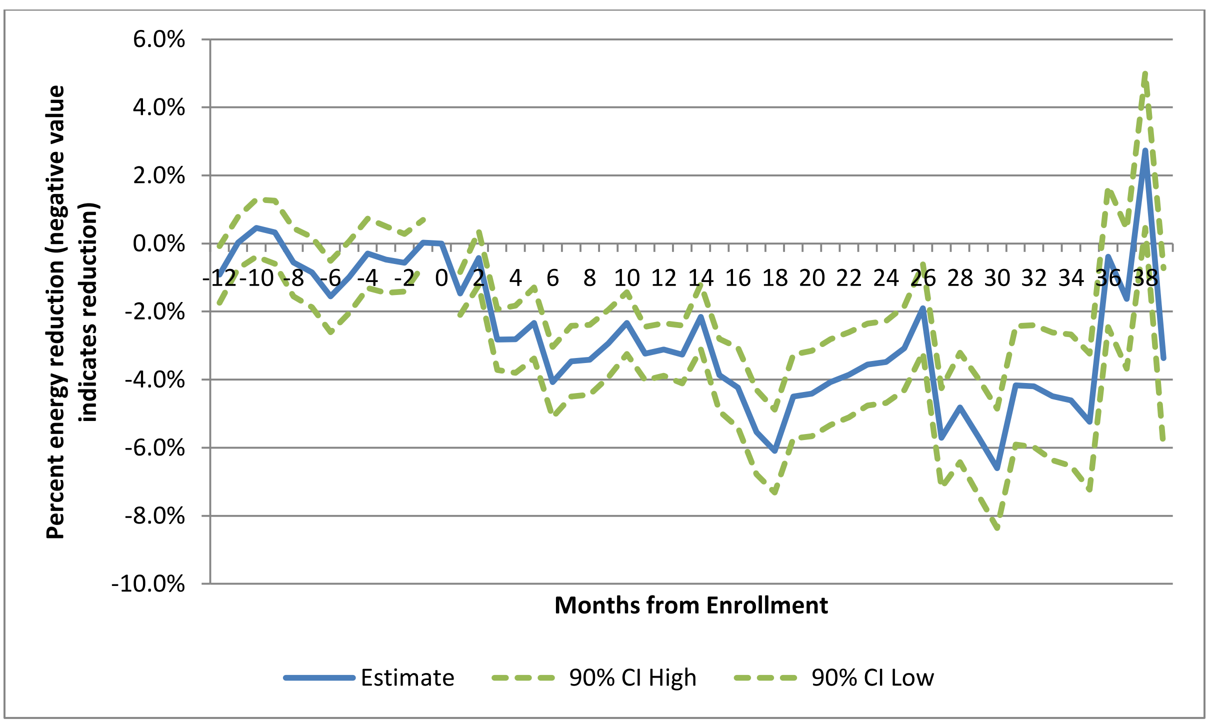
Figure 3-2 extends the graph of average monthly savings to include the post-enrollment months. There is a substantial drop in energy use after the program begins, and this drop appears to deepen as customers enter the second year of the program. There is some evidence that the effect of the program weakens after three years, but this must be interpreted with caution, for two reasons. First, the increase is an amplification of a 12-month cycle of reduced energy savings that suggests the model assumption that differences among customers are not correlated with the timing of enrollment is somewhat questionable. Second, the amplification is likely associated with the fact that relatively few customers (1,613) have been in the program for more than three years.

Figure 3-1. Estimated average percent reduction in energy use due to the C3-CUB program in the 12 months before program enrollment (negative values indicate energy savings)



Source: Navigant analysis

Figure 3-2. Estimated average percent reduction in energy use due to the C3-CUB program (negative values indicate energy savings)

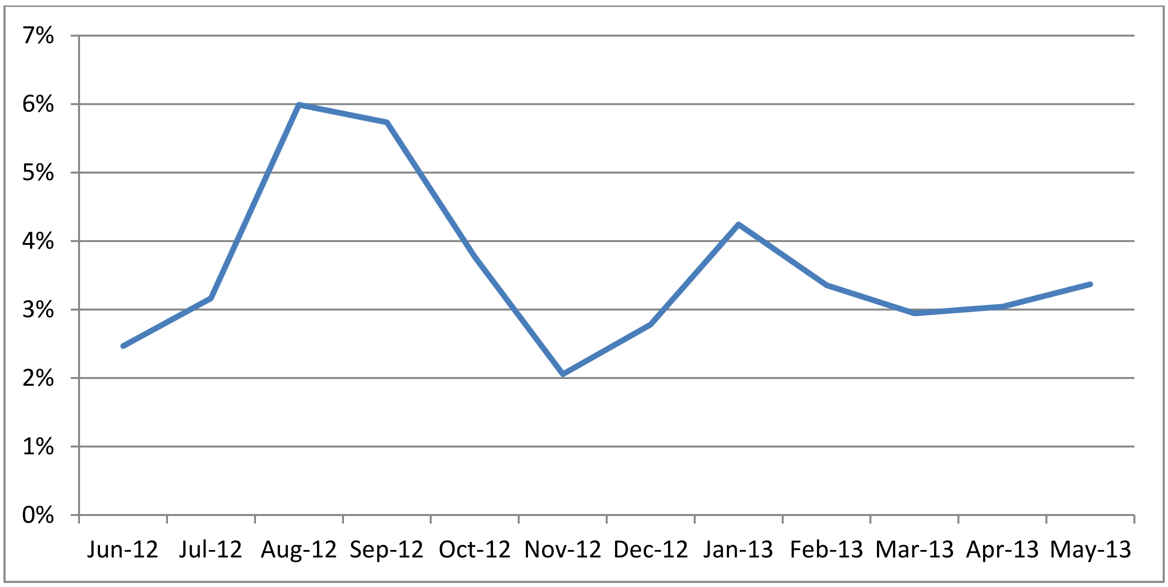


Source: Navigant analysis

3.4 Estimated EPY5 monthly savings in the MBC approach

The RPPM approach enlisted for this evaluation does not estimate monthly savings after program enrollment. It is possible, on the other hand, to calculate average EPY5 monthly savings using the MBC approach, and results are presented in Figure 3-3. On a percentage basis, estimated savings are highest in August 2012, and higher in September 2012 than July 2012, and peak again in January 2013. It deserves emphasis that the month is the bill month, with August bills averaging as many days in July (the latter half of July) as days in August (the first half of August), and September bills averaging as many days in August as days in September.

Figure 3-3. Average percent monthly energy savings, EPY5, MBC model



Source: Navigant analysis

4. Net Savings after removing Joint Savings

Program savings 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 very small proportion of the total savings: 2.4 MWh, which is 0.08% of net savings. Subtracting these savings from net savings generates a final net savings estimate of 2,914 MWh.

Table 4-1 presents a summary of the EPY5 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 6-4 in the appendix presents the details of the calculation of the double-counted savings for each for the five ComEd energy efficiency programs considered in the analysis.

The estimate of double-counted savings is surely an *overestimate* because it presumes participation in the other EE programs occurs at the very start of EPY5. Under the more reasonable assumption that participation occurs at a uniform rate throughout the year, the estimate of double-counted savings would be approximately 1.2 MWh, half the estimated value of 2.4 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 4-1. EPY5 Uplift of Savings in Other EE programs

	FFRR	CSR	SFHES	MF	CW
Participation uplift in other EE programs (# participants)	*-19*	*19*	*41*	*-3*	*-12*
Savings Uplift in other EE programs (MWh)	*-20*	*15*	*18*	*-1*	*-1*

Source: Navigant analysis

5. Conclusions and Recommendations

This section summarizes the key impact findings and recommendations. Overall, the program continues to generate savings at the level expected.

Finding 1. Energy savings appear to average 3.81% in EPY5, are statistically significant, and more generally appear to persist to the third year of program enrollment. But program enrollment is below targeted levels.

Recommendation. Continue the program in its current form. There is a possibility that savings diminish after 3 years; this will warrant investigation in the PY6 evaluation since declining savings may lead to a decision to discontinue the program.

Recommendation. Given the relatively high savings per participant compared to other behavioral programs, and the presumably low cost of running the program, attempts to increase enrollment should be considered, though only if such attempts also address the recommendation below.

Finding 2. Based on results from the matching analysis, there remains a concern about selection bias. This has implications for whether program savings are gross savings or net savings.

Recommendation. In the future the program should take proactive steps to investigate the issue of selection bias. For instance, a brief questionnaire to discern selection bias could be developed and administered to new enrollees upon enrollment. Navigant can assist in the development of the questionnaire.

6. Appendix

6.1 Detailed impact methodology

Navigant used three methods to estimate impacts: the variation in adoption (VIA) approach, matching with bias correction (MBC), and regression with pre-program matching (RPPM). Each is presented below.

6.1.1 VIA approach

The method takes advantage of the differential timing of program enrollment by customers to identify program savings. It essentially takes the perspective that the best comparison group for customers enrolled at time *t* is those that enroll later in the program period.

The method uses a fairly simple, but flexible, linear fixed effects regression model of energy consumption by households. The base model casts monthly electricity consumption as a function of a household-specific fixed effect, month/year fixed effects, and the time-distance from activation (both pre-activation and post-activation). This is a two-way fixed effects model that accounts for all time-invariant customer characteristics, and all month/year factors affecting all customers (such as weather and the inflation rate). Formally we have,

Model 1

$$ADU_{kt} = \alpha_k + \beta_t + \sum_{j=-\bar{m}}^{\bar{m}} \gamma_j D_{kt}^j + \varepsilon_{kt}$$

where,

ADU_{kt}	=	Average daily energy use by household *k* in month *t*;
α_i	=	Household-specific constant (fixed effect);
β_t	=	Month/year specific constant (fixed effect);
D_{kt}^j	=	A 0/1 indicator variable, taking a value of 1 if month *t* is the j^{th} month before/after household *k* activates the web portal. Month $\bar{m} = 0$ is the month before enrollment.
γ_j	=	Coefficient on the indicator variable D_{kt}^j;
ε_{kt}	=	Model error term.

The underlying assumption of the VIA approach is that, after controlling for customer fixed effects, customers *j* periods from enrollment are the same on average as customers *j*+*s* periods from enrollment, where *s* can be negative or positive. So, for instance, customers that are 4 months from enrolling in January 2011 are the same on average as customers who enrolled 6 months prior to January 2011. An important feature of the model is that it reveals, via the values of γ_j for *j*<0, whether customers are more likely to start reducing their energy consumption as they approach enrollment, after controlling for monthly fixed effects (an indication of selection bias). If they are not reducing their energy use, and customers are the same on average regardless of enrollment date (again, after controlling for customer fixed effects), then γ_j =0 for all j<0.

6.1.2 Overview of the Matching Methods

In program evaluation, 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 2.1.3. Both the RRPM and MBC approaches 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 for both the RRPM and the MBC approaches, 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.

6.1.2.1 The RPPM approach

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.

As described in section 2.1.3, we matched participant and comparison customers on energy use during the pre-treatment period, and then estimated the following model for all post-program observations:

Model 2

$$ADU_{kt} = \alpha_{0t} + \alpha_1 PREkWh_{kt} + \alpha_2 Treatment_k + \varepsilon_{kt}$$

where:

ADU_{kt}	=	Average daily energy use by household *k* in month *t*;
α_{0t}	=	Month/year specific constant (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. We include a monthly fixed effect to account for unobserved time-related factors, such as weather, that affect all customers.

6.1.2.2 *The MBC approach*

The second matching method follows the approach summarized in Imbens and Wooldridge (see footnote 6) and applied in Abadie and Imbens (see footnote 4). In this model, the effect of the program in month *t* is the difference between the energy use of participant *k* and its estimated counterfactual (baseline) consumption. The estimated counterfactual consumption is the average consumption of its matched household amended to reflect differences between participants and their matches in the covariates ***X*** affecting energy use. Formally we have,

Model 3

$$Savings_{kt} = ADU_{kt} - ADU_{kt}^{C}$$
$$ADU_{kt}^{C} = ADU_{kt}^{M} + \hat{\alpha}\left(\mathbf{X}_{kt} - \mathbf{X}_{kt}^{M}\right)$$

where:

ADU_{kt} = the average daily electricity use by household *k* during month t;

ADU_{kt}^{C} = the estimated counterfactual energy use by household *k* during month *t*;

ADU_{kt}^{M} = the energy use by household *k*'s match during month *t*;

$\mathbf{X}_{kt}$ = the values for household *k* in month *t* of the independent variables **X** affecting energy use;

$\mathbf{X}_{kt}^{M}$ = the values of **X** in month *t* for household *k's* match.

$\hat{\alpha}$ = the factors used to adjust household *k*'s energy use to reflect differences between household *k* and its match in the value of **X.**

The values of the adjustment factors $\hat{\alpha}$ used in Model 2 are derived from a regression model applied to the post-program period, estimated using *only* the matched comparison households. In the current analysis the regression model used for adjustment purposes is identical to Model 2 except that the variable *Treatment* is dropped, as the model is applied only to the matched comparison households. Formally,

$$ADU_{kt} = \alpha_{0t} + \alpha_1 PREkWh_{kt} + \varepsilon_{kt} \quad ,$$

To apply this regression equation to Model 3, we define **X=** $PREkWh$, and $\hat{\alpha} = \hat{\alpha}_1$. We estimate this regression separately for each month of the program year, generating twelve values of $\hat{\alpha}_1$.

6.1.3 Detailed impact results: parameter estimates

6.1.3.3 Parameter estimates for VIA approach

The variables of interest for the VIA approach are the indicators of months before/after program enrollment. Coefficient estimates for these variables are presented in Table 6-1. Variable names D+k correspond to indicator variable D^k in Model 1; so, for instance, D-1 corresponds to variable D^{-1} in Model 1, the month just before program enrollment. The baseline month is the month just before enrollment, D=0. The results in Table 6-1 indicate that in the months before enrollment in the program the program effect is not statistically different than zero at a 90% confidence level, but is generally statistically different than zero after enrollment in the program.[11]

Table 6-1. Parameter Estimates for VIA Model (Model 1)

Variable	Coefficient	Standard Error	t-statistic
D-12	-0.2410	0.1669	-1.44
D-11	0.0163	0.1572	0.10
D-10	0.0968	0.1826	0.53
D-9	0.0277	0.1984	0.14
D-8	-0.1893	0.2054	-0.92
D-7	-0.2377	0.2059	-1.15
D-6	-0.3797	0.2127	-1.79
D-5	-0.1899	0.2227	-0.85
D-4	-0.1089	0.2139	-0.51
D-3	-0.2211	0.1964	-1.13
D-2	-0.2051	0.1720	-1.19
D-1	-0.0523	0.1357	-0.39
D=0			

[11] A t-statistic greater in absolute value than 1.65 indicates statistical significance at the 90% confidence level. There is one month in the pre-program period – month D-6 –for which the t-statistic is -1.79, but in an examination of 12 coefficients we can expect that one month will be statistically significant at the 90% confidence level due purely to chance.

Variable	Coefficient	Standard Error	t-statistic
D+1	-0.4754	0.1349	-3.52
D+2	-0.2225	0.1790	-1.24
D+3	-0.8763	0.1906	-4.6
D+4	-0.7840	0.1971	-3.98
D+5	-0.5742	0.2020	-2.84
D+6	-1.0191	0.2058	-4.95
D+7	-0.9571	0.2141	-4.47
D+8	-0.9409	0.2100	-4.48
D+9	-0.8379	0.1952	-4.29
D+10	-0.6704	0.1748	-3.83
D+11	-0.9061	0.1569	-5.78
D+12	-0.9161	0.1564	-5.86
D+13	-0.9826	0.1929	-5.09
D+14	-0.7601	0.2246	-3.39
D+15	-1.1585	0.2375	-4.88
D+16	-1.1557	0.2445	-4.73
D+17	-1.4466	0.2452	-5.9
D+18	-1.5574	0.2459	-6.33
D+19	-1.2469	0.2545	-4.9
D+20	-1.2451	0.2587	-4.81
D+21	-1.1060	0.2556	-4.33
D+22	-1.1189	0.2469	-4.53
D+23	-1.0077	0.2390	-4.22
D+24	-0.9011	0.2529	-3.56
D+25	-1.0205	0.2816	-3.62
D+26	-0.7320	0.3117	-2.35
D+27	-1.8117	0.3359	-5.39
D+28	-1.3970	0.3481	-4.01
D+29	-1.6337	0.3444	-4.74
D+30	-1.8821	0.3576	-5.26
D+31	-1.2487	0.3556	-3.51
D+32	-1.2085	0.3795	-3.18
D+33	-1.2330	0.3946	-3.12
D+34	-1.2775	0.3910	-3.27
D+35	-1.5569	0.3880	-4.01
D+36	-0.3177	0.4079	-0.78
D+37	-0.6530	0.4560	-1.43
D+38	0.5965	0.5597	1.07
D+39	-1.2413	0.6309	-1.97

Source: Navigant analysis

6.1.3.4 *Parameter estimates for RPPM approach*

Parameter estimates for the two variables of interest in Model 2, and $PREkWh_{kt}$ and $Treatment_k$, are presented in Table 6-2.

Table 6-2. Parameter Estimates for RPPM Model (Model 2)

Parameter	Coefficient	Standard Error	t statistic
PREkWh	0.76842	0.00806	95.28
Treatment	-1.03656	0.11739	-8.83

Source: Navigant analysis

6.1.3.5 *Parameter estimates for MBC Bias Correction Regression*

The parameter of interest for the bias correction of the MBC model is the coefficient on $PREkWh_{kt}$. Because we ran the bias correction separately for each month of the program year, we generated twelve coefficients. These are presented in Table 6.3 below. The values range from a low of 0.736 for May 2013 to 0.957 for December 2012.

Table 6-3. Coefficients on PREkWh variable, Bias Correction Regression for MBC Method

Month	Coefficent	Standard Error	t statistic
June 2012	0.7503	0.0061	124.07
July 2012	0.7585	0.0077	98.08
August 2012	0.7770	0.0106	73.52
September 2012	0.8349	0.0104	80.59
October 2012	0.7365	0.0074	98.95
November 2012	0.9043	0.0086	105.37
December 2012	0.9570	0.0063	153.01
January 2013	0.7527	0.0059	126.85
February 2013	0.7733	0.0061	127.61
March 2013	0.8578	0.0074	116.22
April 2013	0.9182	0.0095	96.2
May 2013	0.8531	0.0102	83.64

Source: Navigant analysis

6.1.4 Savings due to participation uplift in other EE programs

Table 6-4 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.

Table 6-4. Estimates of Double Counted Savings in EPY5

	Program				
	FFRR	**CSR**	**SFHES**	**MF**	**CW**
Average program savings (annual kWh per participant)	1,041	769	451	234	54
# C3-CUB Treatment Customers	7,940	7,940	7,940	7,940	7,940
Program participation, EPY5	166	35	52	37	59
Change in participation from pre-program Year	39	-	-	-	-
# Comparison Customers	7,940	7,940	7,940	7,940	7,940
Program participation, EPY5	124	16	11	48	75
Change in participation from pre-program	50	-	-	-	-
DID/(POD) statistic	-0.23%	0.23%	0.50%	-0.04%	-0.15%
Participation uplift	-11	19	41	-11	-16
Statistically Significant at the 90% Confidence Level?	Yes	Yes	Yes	No	No
Savings attributable to other programs (kWh)	**-11,451**	**14,611**	**18,491**	**-2574**	**-864**

Source: Navigant analysis.