# Alectra (Powerstream) and Collus Powerstream Social Benchmarking Program Evaluation PY2016

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**Prepared for:**

The Independent Electricity System Operator

120 Adelaide Street West

Toronto, ON M5H 1T1

CADMUS

**Prepared by:**
Jason Christensen
Cheryl Winch
Cynthia Kan, PhD
Jane Colby

CADMUS

# Table of Contents

**Acronyms and Abbreviations ... ii**

**Executive Summary ... 1**

Program Description ... 1

Methodology ... 2

Key Observations and Conclusions ... 2

**Impact Evaluation ... 4**

Methodology ... 4

Billing Analysis ... 4

Estimate Program Savings ... 5

Impact Findings ... 8

Gross Verified Energy Savings ... 8

Gross Verified First-Year Energy and Summer Peak Demand Savings ... 10

Program Wave Net Verified Savings ... 11

**Cost Effectiveness ... 13**

Methodology ... 13

Total Resource Cost Test ... 13

Program Administrator Cost Test ... 14

Levelized Unit Electricity Costs ... 14

Inputs and Assumptions ... 14

Findings ... 15

**Appendix A. Billing Analysis ... 16**

Model Specification ... 17

Demand Savings Analysis ... 19

# Acronyms and Abbreviations

| Acronym | Definition |
|---|---|
| AMI | Advanced Metering Infrastructure |
| CDD | Cooling degree day |
| D-in-D | Differences-in-differences |
| EUL | Effective Useful Life |
| HDD | Heating degree day |
| IESO | Independent Electricity System Operator |
| LDC | Local distribution company |
| LUEC | Levelized unit electricity cost |
| NTG | Net to gross |
| PAC | Program administrator cost |
| PY | Program year |
| RCT | Randomized control trial |
| SEE Action | State and Local Energy Efficiency Action Network |
| TRC | Total resource cost |
| UMP | Uniform Methods Project |

# Executive Summary

The Cadmus team evaluated the Social Benchmarking Program, which was offered by two local distribution companies (LDCs) in program year (PY) 2016: Alectra PowerStream and Collus PowerStream. Collus PowerStream's program is also run by Alectra PowerStream but is funded separately by Collus PowerStream, has separate goals and targets, and is referenced as Collus Powerstream throughout the report. Additionally, Horizon Utilities is now part of Alectra Utilities (along with Alectra PowerStream) but Horizon's Social Benchmarking program launched as a pilot in 2014 and is evaluated separately for 2016. Upon reviewing the 2017 evaluation results for Alectra PowerStream and Collus PowerStream, the IESO determined a portion of participation began in 2016 and was not previously evaluated. This report provides impact findings for the first six months (PY2016) of these programs.

With the evaluation, Cadmus sought to address the following research objectives:

- Examine performance against participation and energy savings targets
- Evaluate gross energy and summer and winter peak demand savings
- Determine the pilot's cost-effectiveness and greenhouse gas impacts

## *Program Description*

In all forms, behavioural intervention programs are designed to change the behaviour of utility customers, leading to changes in energy consumption. Alectra (PowerStream) and Collus PowerStream implemented a uniquely designed program, using components based in behavioural science to reduce residential electrical demand, energy consumption and to encourage participation in other utility energy efficiency programs. The Social Benchmarking Program used a randomized control trial (RCT), enabling measurement control and relying on statistical power to determine whether a treatment proved effective.

The Alectra (PowerStream) and Collus PowerStream program deployed home energy reports (HERs), which were emailed to a large proportion of customers randomly selected to receive behavioural treatment. The reports stimulated customer interest and worked to change behaviours by putting customers' energy use into context with usage comparisons to other similar homes and by providing personalized actionable recommendations to reduce customers' energy usage.

The program launched in three separate waves, with treatment and control groups drawn randomly from distinct populations of customers. Alectra (PowerStream) launched the first wave in June 2016, Alectra (Collus PowerStream) launched the second wave in August 2016 and the final Alectra (PowerStream) wave launched in November of 2016. Participant counts for each wave are shown in Table 1.

# Methodology

The Cadmus team verified energy and demand savings for the PY2016 Alectra Social Benchmarking Program, consistent with the *Protocols for Evaluating Behavioral Programs.*[1] The team used a difference-in-differences (D-in-D) regression of monthly bills to determine gross verified energy savings, a program uplift analysis to account for savings already claimed by other LDC programs and ultimately produce net verified savings and a D-in-D regression of interval data to determine peak demand savings (winter and summer)[2].

# Key Observations and Conclusions

The program treated customers in 207,767 homes in PY2016. Table 1 shows the number of treated homes by LDC and wave.

**Table 1. PY2016 Participant Counts**

| LDC | Wave | Participants (# of Treated Homes) | Control Group (# of Homes in 2017) |
|---|---|---|---|
| Alectra PowerStream | PowerStream Jun 2016 | 183,267 | 29,500 |
| | PowerStream Nov 2016 | 16,000 | 12,999 |
| Collus PowerStream | Aug 2016 | 8,500 | 1,847 |
| **Total** | | **207,767** | **44,346** |

As shown in Table 2, the Alectra Social Benchmarking Program achieved 9,024 MWh net verified energy savings in 2016 and a summer peak demand reduction of 3.6 MW.

1 Ontario Power Authority's *Protocols for Evaluating Behavioral Programs*: http://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=2ahUKEwi3rPSrs-3dAhWIyIMKHfSeD5gQFjAAegQIChAC&url=http%3A%2F%2Fwww.ieso.ca%2F-%2Fmedia%2Ffiles%2Fieso%2Fdocument-library%2Fconservation%2Fldc-toolkit%2Femv-protocols-and-requirements-10312014.pdf%3Fla%3Den&usg=AOvVaw2AAPTQvJRCAIxeAf_DhLWZ

2 RCT experimental design means the D-in-D model estimates savings net of naturally occurring conservation via the control group. However, for reporting purposes net verified savings refer to savings net of program uplift savings. These terms are defined in more detail in the Estimate Program Savings section.

**Table 2. Net Verified First-Year Energy and Demand Savings**

| Wave | PY2016 | |
|---|---|---|
| | MWh | MW |
| Collus PowerStream Aug 2016 | 361 | - |
| Alectra PowerStream Jun 2016 | 8,663 | 3.6 |
| Alectra PowerStream Nov 2016 | * | * |
| **Total** | **9,024** | **3.6** |
| * The wave did not operate long enough to show significant savings | | |

The PY2016 Social Benchmarking Program was not cost-effective from a Total Resource Cost (TRC) perspective for each LDC, with a test result of 0.12 for Collus PowerStream and 0.19 for Alectra PowerStream, as well as from a Program Administrator Cost (PAC) perspective for each LDC, with a test result of 0.10 for Collus PowerStream and 0.16 for Alectra PowerStream. This is due to initial program start-up costs and a shorter time in which to achieve savings.

***Observation 1. Verified savings across waves were within the typical range observed for HER programs with savings of 1% to 2% of average daily consumption.*** The Collus PowerStream wave achieved savings of 1.6% average daily consumption and the June 2016 Alectra PowerStream wave achieved savings of 1.1% of average daily consumption. The November 2016 wave did not show significant savings due to launching late in the year with only 19 treatment days per home, on average.

***Observation 2. Savings estimates were limited by available data****.* The anonymized account IDs were not consistent between LDCs, program implementers and the data provided to the IESO and Cadmus. Cadmus was not able to map the anonymized account IDs between billing data, interval data and other program tracking data for local programs or pilot programs in which HER treatment or control homes could participate. Therefore, any additional savings that overlapped with other programs could not be accounted for, potentially leading to double-counting of savings and affecting the cost-effectiveness calculations.

- **Recommendation 2a.** Improve coordination between LDCs, the IESO, evaluators and implementers to facilitate mapping of anonymized account IDs between data sources when needed.

# Impact Evaluation

The Cadmus team used a combination of statistical methods and engineering adjustments to determine net verified energy and peak demand savings (winter and summer) for each of PowerStream's social benchmarking local program waves in 2016.

## *Methodology*

The Cadmus team estimated energy and summer peak demand savings from the Social Benchmarking program by conducting several activities:

- Performed regression analysis using D-in-D of monthly billing data to estimate gross energy savings[3]
- Performed regression analysis using D-in-D with hourly interval data for demand savings
- Applied secondary sources to estimate program uplift savings from the Instant Discount and Coupons programs and subtracted the uplift from gross energy and summer peak demand savings to determine adjusted gross savings

Equation 1 summarizes the net savings calculation.

**Equation 1. Net Savings Calculation**

$$\begin{aligned} Net\ Savings &= [(preperiod\ consumption)_{treatment} \\ &- (postperiod\ consumption)_{treatment}] \\ &- [(preperiod\ consumption)_{control} - (postperiod\ consumption)_{control}] \\ &- Program\ uplift\ savings \end{aligned}$$

The following sections present an overview of the approach, billing analysis steps, model specification and estimated program savings that the Cadmus team used to derive energy and demand savings.

### Billing Analysis

To estimate savings, the Cadmus team used a D-in-D regression of consumption data with residential customer fixed effects, as recommended by the U.S. Department of Energy's Uniform Methods Project (UMP) behaviour-based program impact evaluation protocols[4]. D-in-D accounts for the effects of

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3 D-in-D measures the first difference as the change from the pre- to the post-period for the treatment and control groups and measures the second difference as the change in pre- to post-period usage between the treatment and control groups.

4 Steward, James, A. Todd, and C. Kurnik. *The Uniform Methods Project: Methods for Determining Energy Efficiency Savings for Specific Measures.* "Chapter 17: Residential Behavior Protocol." January 2015. Available online: https://www.energy.gov/sites/prod/files/2015/02/f19/UMPChapter17-residential-behavior.pdf

naturally occurring efficiency and other non-program impacts on energy use during the evaluation period (changes that are unrelated to the program but may impact energy usage such as changes in occupancy in a home, changes in usage due to economic constraints, home remodels, new appliances, etc.).

### Consumption Data

Cadmus obtained monthly energy consumption for the period spanning one year prior to the treatment's start for all 2016 treatment group and control group customers. Table 3 lists pre-treatment periods for each wave and the average number of treatment days observed.

**Table 3. Monthly Pre-Treatment Billing Periods by Cohort Wave**

| LDC | Wave | Pre-Treatment Period | Treatment Period | Average # Treatment Days per Home |
|---|---|---|---|---|
| Collus PowerStream | Aug 2016 | December 2015–July 2016 | August 2016–December 2016 | 148 |
| Alectra Utilities Corporation | PowerStream Jun 2016 | June 2015–May 2016 | June 2016–December 2016 | 202 |
| | PowerStream Nov 2016 | January 2015–November 2016 | December 2016 | 19 |

Note: Hourly interval advanced metering infrastructure (AMI) meter data were used for all treatment and control group customers for each wave.

In addition to consumption data, the Cadmus team requested customer program tracking data showing waves, assignments to treatment or control groups, dates of first reports and accounts' inactive dates (if applicable).

Finally, Cadmus collected daily weather data (associated with customer postal codes) for Alectra Utilities' and Collus Powerstream's service territories.

The steps the Cadmus team followed to prepare and analyse the data are presented in detail in Appendix A. Billing Analysis.

## Estimate Program Savings

Due to the RCT experimental design, the control group accounts for naturally occurring conservation and non-program related changes in consumption. Therefore, net savings are typically equal to gross savings with an RCT design. However, for reporting purposes gross and net savings (energy and demand) will be defined as follows:

- **Gross verified savings** are equal to the estimated average daily savings per customer (the regression model estimates) multiplied by the average number of treatment days per home.
- **Program uplift savings** are savings generated through upstream programs
- **Net verified savings are equal to gross verified savings less program uplift savings**

The Cadmus team used regression estimates of average daily savings per customer to estimate PY2016 annual savings per customer, for the Social Benchmarking program overall for each LDC wave. To annualize program savings, the team multiplied the regression estimates of average daily savings per customer by the average number of PY2016 treatment days per home, as provided by Equation 2:

**Equation 2. Net Verified Energy Savings During PY2016**

$$PY2016\ Verified\ Energy\ Savings = -\beta_j * \left(\sum_{i=1}^{N} Treatment\ Days_i\right)$$

Where:

$\beta_j$ = Average daily savings per customer for calendar year 'j' from the estimation of regression using Equation 1.

$Treatment\ Days_i$ = Number of days during calendar year 'j' that the customer account remained active after the first report date.

## *Uplift for Downstream Rebate Programs*

The HERs sent to treatment group customers promote energy-efficient lighting as one opportunity to save energy. As a result, a large number of customers are likely to purchase LEDs in retail stores through the Coupons program. The HERs may also encourage customers to participate in other local or pilot efficiency programs (such as the HVAC Program, marketed as Save on Energy's Heating and Cooling Incentive). However, participant tracking data was unavailable to match HVAC program participants with treatment or control homes in the Social Benchmarking program. Therefore, the team was not able to account for overlapping savings from the Heating and Cooling Program. Only a small proportion of IESO customers participate in the Heating and Cooling program.

In PY2016, the IESO also offered LED discounts in retail stores throughout the province through the Coupons programs. Because the Coupons programs do not track customer identifying data, the Cadmus team applied secondary research to estimate treatment group lighting purchases so that savings are not double-counted. The team followed the methodology established in the Alectra (Horizon) and HONI Social Benchmarking pilot evaluation, calculating the program uplift savings as depicted in Equation 3.[5]

**Equation 3. Program Uplift Savings**

$$\begin{aligned} &\text{Additional kWh savings attributable to Coupons or Instant Discount programs} \\ &\qquad = \text{additional bulb per treatment customer} \times \text{per} - \text{bulb net kWh savings} \\ &\qquad \times \text{number of treatment customers} \end{aligned}$$

[5] Nexant. *Social Benchmarking Pilot Evaluation*. November 7, 2016.

The Cadmus team applied two assumptions:

- **Additional bulb per treatment customer.** Consistent with the PY2016 Social Benchmarking evaluations of other Social Benchmarking programs in Ontario, the Cadmus team assumed that treatment group customers purchased 0.95 more LEDs per home than control group customers in PY2016. This approach is based on the same 2012 evaluation cited in the Social Benchmarking pilot evaluation for Pacific Gas & Electric[6] revealing that each HER recipient purchased approximately one (0.95) more CFL than control group participants.
- **Per-bulb kilowatt-hour savings**. The Cadmus team derived the per-bulb kilowatt-hour savings from the PY2017 Coupons and Instant Discount programs evaluation, calculated as total energy savings for each program divided by the total quantity of bulbs sold through both programs, resulting in 25.83 kWh per bulb. This represented the mix of general service and specialty bulbs purchased across Ontario.[7]

The team calculated program uplift peak summer demand savings using PY2017 evaluated per-bulb net kilowatt savings from the Coupons and Instant Discount programs. For treatment homes, the team subtracted the overlapping savings of 0.0017 kW from estimated annual per-home demand savings.

### *Demand Savings Analysis*

The Cadmus team estimated peak demand savings using AMI interval data for all customers in the treatment and control groups.

The team conducted a D-in-D regression analysis very similar to that described for the energy savings analysis, comparing the peak demand of treatment customers to the peak demand of control group customers.

The Cadmus team used the IESO's Evaluation Measurement & Verification Protocols V.2.0 definition of summer peak (weekdays from 1 p.m. to 7 p.m. in June, July and August) and winter peak (weekdays between 6 p.m. and 8 p.m. in December, January and February).[8] Similar to the energy savings approach, the Cadmus team estimated gross demand savings using a D-in-D methodology, calculating estimated impacts as the difference in average loads between treatment and control customers during peak hours minus the two groups' average differences during the peak period for the year prior to

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[6] TRC. Lighting Savings Overlap in 2014 IOU Residential Behavioral Programs. TRC (June 30, 2015). Revised TRC memo, Proposed Changes to Draft ULP HER Lighting Savings Overlap for 2014, (October 22, 2015). Available online: http://www.calmac.org/publications/Final_HER_2014_Upstream_Lighting_Savings_OverlapES.pdf

[7] Cadmus applied the PY2017 Coupons and Instant Discount savings to both the PY2016 and PY2017 Social Benchmarking savings to maintain consistency in evaluation assumptions.

[8] The Independent Electricity System Operator. *Conservation First (2015–2020) EM&V Protocols and Requirements*. Available online: http://www.ieso.ca/sector-participants/conservation-delivery-and-tools/evaluation-measurement-and-verification

program launch. The team subtracted the program uplift savings described above to estimate net verified savings. Because of the RCT group design, verified net demand savings are equal to adjusted gross demand savings.

Table 4 details the pre-treatment and treatment peak periods by wave and peak season.

**Table 4. Hourly Peak Periods by LDC, Wave and Season**

| LDC | Wave | Pre-Treatment | | Treatment | |
|---|---|---|---|---|---|
| | | Summer | Winter | Summer | Winter |
| Collus PowerStream | Aug 2016 | June–July 2016 | December 2015–February 2016 | August 2016 | December 2016 |
| Alectra Utilities | PowerStream Jun 2016 | June–August 2015 | December 2015–February 2016 | June–August 2016 | December 2016 |
| | PowerStream Nov 2016 | June–August 2015 | December 2015–February 2016 | NA | December 2016 |

Due to the short treatment periods observed, demand savings were not significant for the Alectra (Collus PowerStream) wave or the November 2016 wave.

Summer interval data for the June 2016 wave was unavailable for most accounts, thus the summer demand savings for the June 2016 wave could not be modeled. The hourly AMI data Cadmus received for this wave was missing a significant number of customers in the summer months in 2016, with only 128 out of 183,267 treatment accounts observed between June and August 2016. This was an insufficient sample to analyse and extrapolate to the remaining treatment sample. Instead Cadmus applied adjusted savings from the PY2017 evaluation of Alectra's Social Benchmarking program. Detailed results are provided in the Gross Verified First-Year Energy and Summer Peak Demand Savings section.[9]

# *Impact Findings*

This section outlines the gross and net verified savings results, based on the definitions outlined in the methodology section. First the daily energy savings are described and then annualized to obtain first-year gross verified impacts.

## Gross Verified Energy Savings

Total savings for each wave are the product of average daily kilowatt-hour savings per home, the number of homes and the average number of treatment days per home for each wave.

[9] Typically, future program year results are not available when a prior program year is evaluated. However, since Cadmus evaluated 2016 and 2017 simultaneously the 2017 results for summer demand estimates were the most representative secondary data source for the June 2016 PowerStream wave.

This subsection presents the model estimates of average daily kWh savings by LDC and wave. The results tables for each LDC present the model parameter estimate, the treatment effect representing the difference in daily kWh between treatment and control homes. Additionally, the tables show the confidence intervals and p-values.

The lower and upper confidence limits reported express the range of values that is believed to contain the true population estimate calculated at 95% confidence. The p-value describes the probability that there is evidence to support or reject the null hypothesis – the hypothesis that there is no significant difference between treatment and control groups. Specifically, the p-value represents the probability of observing an effect at least as extreme as the estimated parameter if the null hypothesis was true.

Using the values in Table 5 as an example, if there were no treatment effect (no difference in daily kWh consumption between the treatment and control homes after treatment) the p-value of 0.0007 means the probability of observing a difference of 0.36 daily kWh or more is 0.07%.

**Table 5. PowerStream Customer Consumption Regression Results by Wave**

| | Model | Lower Confidence Limit | Upper Confidence Limit | P-value |
|---|---|---|---|---|
| **Collus PowerStream Aug 2016** | | | | |
| Average daily savings per customer–2016 | -0.3582 | -0.5645 | -0.1519 | 0.0007 |
| Customer Fixed Effects | Yes | -- | -- | -- |
| Weather Variables | Yes | -- | -- | -- |
| Month-Year Fixed Effects | Yes | -- | -- | -- |
| **PowerStream Jun 2016** | | | | |
| Average daily savings per customer–2016 | -0.3048 | -0.3559 | -0.2537 | <.0001 |
| Customer Fixed Effects | Yes | -- | -- | -- |
| Weather Variables | Yes | -- | -- | -- |
| Month-Year Fixed Effects | Yes | -- | -- | -- |
| **PowerStream Nov 2016** | | | | |
| Average daily savings per customer–2016 | -0.0747 | -0.1746 | 0.0253 | 0.1431 |
| Customer Fixed Effects | Yes | -- | -- | -- |
| Weather Variables | Yes | -- | -- | -- |
| Month-Year Fixed Effects | Yes | -- | -- | -- |

The Alectra (Collus PowerStream) wave and the Alectra (PowerStream) wave launched in June 2016 showed daily kWh savings substantially higher than the latter Alectra (PowerStream) wave (launched in November 2016). The difference resulted from lower average daily consumption observed in the homes. Nominal kWh savings potential was lower in homes with lower average daily consumption.

Additionally, the November Alectra (PowerStream) wave estimates are not statistically significant at the 95% confidence level due to the small number of homes included in this wave and only one full month of treatment in 2016. Therefore, there are no verified savings in 2016 for this wave.

Table 6 shows relative savings by wave.

**Table 6. PowerStream Customer Relative Savings by Wave**

| Wave | Control Energy Consumption (daily kWh) | Relative Energy Savings | Confidence Bound at 95% |
|---|---|---|---|
| Collus PowerStream Aug 2016 | 23.0 | 1.6% | ± 0.9% |
| PowerStream Jun 2016 | 28.4 | 1.1% | ± 0.18% |
| PowerStream Nov 2016 | 13.7 | 0.5% | ± 0.73% |

HER programs typically generate savings of 1% to 2% of average daily savings.[10] Both the Alectra (Collus PowerStream) and the June 2016 Alectra (PowerStream) wave showed typical savings of 2% of average daily consumption. The November 2016 Alectra (PowerStream)wave showed savings of only 0.6%, but, again, the savings estimates were not statistically significant after only one month of treatment. The November wave may show significant savings in future years as treatment continues and savings ramp up over time.[11]

## Gross Verified First-Year Energy and Summer Peak Demand Savings

Cadmus did not estimate summer peak demand savings for Collus PowerStream or the November Alectra PowerStream waves. The Collus PowerStream wave launched in August of 2016, resulting in only one month of treatment in the summer peak period, which was not sufficient to identify savings. The Alectra PowerStream wave launched in November and did not treat any customers over the summer of 2016. Similarly, each of the three waves had only one observed treatment month during the winter peak period, December 2016.

Alectra PowerStream's June wave did treat customers over the summer. However, the hourly interval data was unavailable for all but 128 accounts over the summer of 2016. The lack of hourly data precluded a D in D regression model similar to the energy savings analysis.

Cadmus instead applied the evaluated summer demand savings from the PY2017 evaluation of the June 2016 Alectra (PowerStream) wave. However, because HER program savings tend to ramp up over time, 2017 summer demand savings are likely greater than 2016 savings. To account for this, Cadmus scaled the PY2017 summer demand savings using the ratio of PY2016 daily kWh savings to PY2017 daily kWh savings. Equation 4 shows the equation for PY2016 summer demand savings (with input values shown in parentheses):

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[10] Allcott, Hunt, and Todd Rogers. 2014. "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation." American Economic Review, 104(10): 3003-37. DOI: 10.1257/aer.104.10.3003

[11] The likelihood of finding statistically significant savings increases as the effect size increases even when the size of the treatment and control groups remains fixed.

**Equation 4. June 2016 Wave Average Summer Peak Hour Savings**

$$\text{PY2016 Summer Peak Hour Savings } (0.021) = \text{PY2017 Summer Peak Hour Savings } (0.037) \times \frac{\text{daily kWh savings PY2016 } (0.30)}{\text{daily kWh savings PY2017 } (0.53)}$$

Total savings for each wave are the product of average daily kWh savings per home, the number of homes and the average number of treatment days per home for each wave. Table 7 shows the total MWh energy savings and MW demand savings by LDC  wave along with the inputs.

**Table 7. Total Gross Verified Savings by LDC and Wave**

| Wave | Treatment Group (# of homes) | Average Treatment Days | Daily Energy Savings (kWh) | Annual Energy Savings (kWh) per Home | Total Verified Gross Energy Savings (MWh) | Total Verified Gross Demand Savings (MW) |
|---|---|---|---|---|---|---|
| Collus PowerStream Aug 2016 | 8,500 | 148 | 0.36 | 53 | 449 | NA |
| PowerStream Jun 2016 | 183,267 | 202 | 0.30 | 62 | 11,280 | 3.92 |
| PowerStream Nov 2016 | 16,000 | 19 | NA | NA | NA | NA |

## Program Wave Net Verified Savings

As described in the *Methodology* section, each program wave was designed as an RCT; therefore, net verified savings are equal to gross verified savings. The Cadmus team estimated net verified savings by subtracting program uplift associated with the Instant Discount and Coupons lighting programs from the model estimated gross savings.

The program uplift savings estimate represents the average annual program uplift savings per home. The Cadmus team assumed that the program uplift savings per home did not vary between waves. However, since the average number of treatment days per account varied by wave, the team adjusted the annual program uplift savings to account for the proportion of the year the program operated. For example, it would not be appropriate to assume a full year of lighting savings for the June 2016 wave since the program launched in June 2016. The average number of treatment days was 202 per home. Therefore, 55% of program uplift savings were subtracted for the June wave.[12]

Table 8 presents total energy savings for each program wave, net of overlapping savings.  Table 9 presents demand savings.

[12] 202/365.25 = 55%

Table 8. Total Energy Savings by LDC and Wave Net of Overlapping Upstream Savings

| Wave | Total Verified Gross Savings (MWh) | Overlapping Lighting Savings | Net Verified Savings (MWh) |
|---|---|---|---|
| Collus PowerStream Aug 2016 | 449 | 89 | 361 |
| Alectra PowerStream Jun 2016 | 11,280 | 2,617 | 8,663 |
| Alectra PowerStream Nov 2016 | NA | NA | NA |

Table 9. Total Demand Savings by LDC and Wave Net of Overlapping Upstream Savings

| Wave | Total Verified Gross Savings (MW) | Overlapping Lighting Savings | Net Verified Savings (MWh) |
|---|---|---|---|
| Collus PowerStream Aug 2016 | NA | NA | NA |
| Alectra PowerStream Jun 2016 | 3.92 | 0.31 | 3.61 |
| Alectra PowerStream Nov 2016 | NA | NA | NA |

# Cost Effectiveness

This section provides the cost-effectiveness methodology and findings for the Social Benchmarking program.

## Methodology

The Cadmus team reviewed the initial program planning cost-effectiveness inputs prepared by the local distribution companies, then used the IESO's Conservation and Demand Management Cost Effectiveness Tool to calculate the TRC test, PAC test and levelized unit energy costs. These tests assess several critical performance metrics: benefits, costs, net benefits and benefit/cost ratios. Programs are cost-effective when the benefits exceed the costs, meaning the program must have a benefit/cost ratio greater than 1.0.

Table 10 shows the various components included in each test and whether they are treated as a benefit or cost.

**Table 10. Cost-Effectiveness Test Components**

| Component | TRC | PAC | LUEC |
|---|---|---|---|
| Avoided Energy Costs | Benefit | Benefit | - |
| Non-Energy Benefits | Benefit | - | - |
| Secondary Fuel Savings (Natural Gas) | Benefit | - | - |
| Incremental Participant Costs | Cost | - | - |
| Administration Costs | Cost | Cost | Cost |
| Incentive Payments | - | Cost | Cost |
| Participant Bill Savings | - | - | - |
| Discounted Lifetime Energy Savings | - | - | Benefit |

The remainder of this section presents the three cost-effectiveness tests in detail, as well as CDM Cost Effectiveness Tool inputs.

### Total Resource Cost Test

The TRC measures the overall impacts of program benefits and costs. The test compares the total resource benefits to the total resource costs to society to determine if the benefits received by the populace outweigh the total costs incurred by the customers, the LDC and the IESO. In addition, the TRC includes a non-energy benefit adder of 15%. The TRC uses the following benefit/cost ratio equation shown in Equation 5:

**Equation 5. Total Resource Cost Test**

$$TRC\frac{B}{C} = \frac{PV\ [(Value\ of\ Gross\ Saved\ Energy + Value\ of\ Gross\ Non\ Energy\ Benefits) * NTG]}{PV\ [Program\ Adminstrative\ Costs\ + (Incremental\ Participant\ Cost\ * NTG)]}$$

Where:

B = Benefits

C = Costs

PV = Present value (discount rate (real) + societal discount rate (real) = 4.00%)

Value of Gross Saved Energy = Gross savings multiplied by utility avoided energy and capacity costs

Incremental Participant Cost = Additional costs incurred by participants to install the energy-efficient technology over baseline or standard equipment typically installed in the absence of efficient technology

NTG = Net-to-gross

## Program Administrator Cost Test

The PAC examines program benefits and costs solely from the administrator's perspective using the following benefit/cost ratio equation:

**Equation 6. Program Administrator Cost Test**

$$PAC\frac{B}{C} = \frac{PV\ [Value\ of\ Gross\ Saved\ Energy * NTGR]}{PV\ [Adminstrative\ Costs\ +\ Incentive\ Payments]}$$

## Levelized Unit Electricity Costs

The levelized unit electricity cost (LUEC) is a measure of the overall competitiveness of different electricity sources, which allows for comparing demand-side management programs, programs over different time frames or supply-side options. The LUEC represents the annualized costs (discounted costs and lifetime savings) per lifetime kilowatt-hours from the PAC test perspective (administrative, delivery and incentive costs) using the following equation (costs divided by kilowatt-hours):

**Equation 7. Levelized Unit Electricity Costs**

$$LUEC = \frac{PV\ [Adminstrative\ Costs\ +\ Incentive\ Payments]}{PV\ [Gross\ Lifetime\ kWh * NTGR]}$$

# *Inputs and Assumptions*

For the cost-effectiveness analysis, the Cadmus team relied on these evaluation impact results:

- Net verified energy savings
- Net verified summer peak demand savings
- Program participation summary
- Treatment effective useful life (deemed at one year by the IESO)

The team combined the evaluation data with the following program financial data provided in the CDM Cost Effectiveness Tool:

- Administrative costs (LDC)
- IESO and LDC variable program costs

The team used the "PSP-Consumer-Residential--Miscellaneous" load profile in the LDC-provided CDM Cost Effectiveness Tool from the IESO's library of load shapes.

## *Findings*

As shown in Table 11, the PY2016 Social Benchmarking Program is not cost-effective for each LDC from a TRC perspective or from a PAC perspective.

**Table 11. TRC and PAC Ratios by LDC**

| LDC | TRC | | | PAC | | |
|---|---|---|---|---|---|---|
| | Ratio | Benefits ($) | Costs ($) | Ratio | Benefits ($) | Costs ($) |
| Collus | 0.12 | $14,976 | $124,919 | 0.10 | $13,022 | $124,919 |
| Alectra | 0.19 | $397,015 | $2,114,369 | 0.16 | $345,231 | $2,114,369 |

Table 12 shows each LDC's LUEC.

**Table 12. LUEC Ratio Results for Energy Savings by LDC**

| LDC | Ratio ($/kWh) | Costs ($) | Benefits |
|---|---|---|---|
| Collus | 0.34 | $124,919 | $364,435 |
| Alectra | 0.24 | $2,114,369 | $8,752,778 |

The PY2016 program was not cost-effective due to the EUL being set at one year and the fact that savings for HER programs typically ramp up over time. In PY2016, each program was also not in market for the full year, resulting in each LDC not being able to realize savings for a full program year. In PY2017 these program waves are evaluated again for savings persistence and a separate cost effectiveness tool is calculated to account for persisting savings.

# Appendix A. Billing Analysis

The following subsections present the steps Cadmus followed to prepare and analyze the data for the energy savings analysis.

## *Customer Monthly Billing Data Preparation*

After collecting the monthly consumption data, the Cadmus team prepared the data for regression analysis by:

- Calculating heating degree days (HDDs) and cooling degree days (CDDs) for each customer billing cycle using daily mean temperature data and a base temperature of 18°C.
- Expressing consumption, HDDs and CDDs as daily averages for the month.

During data preparation, the Cadmus team encountered a challenge with billing data where the duration of observations in the billing data was inconsistent over time. Specifically, billing data was delivered in bimonthly (60 day) observation periods in 2015 and 2016.

Monthly energy consumption tends to vary between months, even after controlling for weather-related variation.[13] Because of this variation, the contribution of each month to the overall consumption observed in the bi-monthly billing periods is not equal, that is – overall consumption within a billing period differs with one additional day from a higher than average month rather than a lower than average month. It is therefore necessary to account for the contribution of each month represented in each bi-monthly period.

With regular monthly billing periods Cadmus would create dummy variables for each calendar month that capture the change in consumption between months. However, because the bi-monthly bills spanned multiple months, the Cadmus team included the proportions for each calendar month represented in the billing periods in place of binary, dummy variables.

For example, if consumption tends to increase in January, overall consumption should be greater in a billing period where January accounts for 50% of the days in the billing period than in a period where January accounts for 15% of the days. The proportional variables allow the model to capture this variation.

Additionally, the team weighted each observation in the regression by its duration, accounting for differing information amounts contained in each bill (for example, a 60-day bill would be weighted twice

[13] There are a number of potential unobserved factors that could account for this variation over time, such as changing in lighting schedules in response to daylight hours, as well as school, work, or vacation schedules that could follow seasonal patterns. Month fixed effects control for these unobserved variations and separate seasonal variation from the treatment effect.

as heavily as a 30-day bill). To prepare the final analysis data, Cadmus merged customer program data with billing data for treatment and control group customers.

To prepare the final analysis dataset, the Cadmus team merged customer program participation data (such as treatment versus control group assignment, treatment start date and inactive date when applicable) with billing data.

## Model Specification

The Cadmus team followed the UMP to develop a D-in-D panel regression of customer monthly energy consumption, which estimated average PY2016 daily savings per customer.

The model accounted for customer fixed effects,[14] month-by-year fixed effects and HDDs and CDDs to control for differences in baseload energy use between customers, changes in energy use over time and changes in demand over time for space heating and space cooling.

Ultimately, the Cadmus team modelled each wave separately (as each program was designed with a separate experimental design), selecting a consistent specification that applied across all waves. The Cadmus team estimated average daily consumption ($ADC_{it}$) of electricity of customer 'i' in month 't' using Equation 8.

**Equation 8. Average Daily Consumption**

$$ADC_{it} = \alpha_i + \beta_1 PART_{it} * POST2016_{it} + \gamma_1 * HDD_{it} + \gamma_2 * CDD_{it} + \gamma_3 * SQHDD_{it} + \gamma_4 * SQCDD_{it} + \tau_t + \varepsilon_{it}$$

Where:

| | | |
|---|---|---|
| $ADC_{it}$ | = | Average daily electricity consumption for customer 'i' in period 't.' |
| $\alpha_i$ | = | Average energy consumption for customer 'i' not sensitive to time or weather. The model controlled for baseload energy use by including customer fixed effects. |
| $PART_{it}$ | = | An indicator variable for assignment of customers to treatment groups (= 1 if the customer was in the treatment group; = 0 otherwise). |

[14] Customer fixed effects are the non-time varying customer-specific mean usage that help the model distinguish between *within* customer variation and *between* customer variation. Customer A may have higher average monthly usage than customer B but we do not have enough information to explain the difference explicitly in the model. It could be customer A has a larger home or a greater number of occupants than customer B. Our data did not include measurements of homes size or occupancy and therefore we cannot explicitly account for home size or occupancy, Customer fixed effects account for the fact that, across time periods, customer A has higher consumption than customer B. Including fixed effects estimators isolates the remaining time varying effects within a variable to be estimated – changes in usage related to weather (which varies over time) and program treatment (varies between the pre and post periods) and improves the precision of the estimates.

$POST2016_{it}$ = Indicator variable determining whether the month was a calendar year 2016 post-treatment month for customer 'i.' This variable equaled one if the month was in 2016 and if the first report was received in that or a subsequent month. This variable equaled zero for all other months.

$HDD_{it}$ = Average Daily HDDs for customer 'i' in period 't.'

$CDD_{it}$ = Average daily CDDs for customer 'i' in period 't.'

$SQHDD_{it}$ = Average Daily HDDs squared for customer 'i' in period 't.'

$SQCDD_{it}$ = Average daily CDDs squared for customer 'i' in period 't.'

$\tau_t$ = Average energy consumption in month 't' reflecting unobservable factors specific to the month. The model controlled for these effects by including month-by-year fixed effects.[15]

$\varepsilon_{it}$ = Error term for customer 'i' in month 't.'[16]

$\beta_1$ = Coefficient indicating the average effect of receiving a HER on daily electricity consumption in calendar year 2016. Average daily kWh savings per treated customer equaled -1* $\beta_1$.

The Cadmus team estimated the model coefficients using maximum likelihood estimation[17] and reported confidence intervals and p-values calculated using Huber-White standard errors that account for the correlation of each home's energy use over time.[18] This estimation produced an estimate of average daily savings per treated customer for 2016.

15 The regression did not include POST as a standalone variable in the regression because very little variation occurred between treatment group homes for the month of the first report delivery. If little variation occurs, the model can be estimated with POST or month-by-year fixed effects, but not with both.

16 Any statistical model cannot account for all variation in consumption. The error term is the variation that is not explained by the other terms included in the model

17 Maximum likelihood estimation is a method for determining values for the parameters of a model that maximise the likelihood that the process described by the model produced the data actually observed.

18 Bertrand, Marianne, E. Duflo, and S. Mullainathan. "How Much Should We Trust Difference-in-Differences Estimates?" *Quarterly Journal of Economics* (119:1, p. 249–275). 2004.

The team tested several versions of Equation 8 to check the savings estimates' robustness to changes in model specifications. Such specifications tested the effects of including (or excluding) customer fixed effects and POST[19] rather than month-by-year fixed effects.

## Demand Savings Analysis

The Cadmus team modelled average peak hour consumption ($AHC_{it}$) of electricity of customer 'i' in hour 't' for the remaining peak period waves using Equation 9.

**Equation 9. Demand Savings**

$$AHC_{it} = \alpha_i + \beta_1 PART_{it} * POST2016_{it} + \gamma_1 * HDH_{it} + \gamma_2 * CDH_{it} + \gamma_3 * SQHDH_{it} + \gamma_4 * SQCDH_{it} + \tau_t + \varepsilon_{it}$$

Where:

$AHC_{it}$ = Average hourly electricity consumption for customer 'i' in period 't.'

$\alpha_i$ = Average energy consumption for customer 'i' not sensitive to time or weather. The model controls for baseload energy use by including customer fixed effects.

$\beta_1$ = Coefficient indicating the average effect of receiving a HER on hourly electricity consumption in PY2016. The average hourly kilowatt savings per treated customer are equal to -1 * $\beta_1$.

$PART_{it}$ = An indicator variable for assignment of customers to a treatment group (= 1 if the customer was in the treatment group; = 0 otherwise).

$POST2016_{it}$ = An indicator variable for whether the hour was a PY2016 post-treatment peak hour for customer 'i' (= 1 if the hour was a peak hour in PY2016; = 0 for all other hours).

$HDH_{it}$ = Average heating degree hour for customer 'i' in period 't.'

$CDH_{it}$ = Average cooling degree hour for customer 'i' in period 't.'

$SQHDH_{it}$ = Average heating degree hour squared for customer 'i' in period 't.'

$SQCDH_{it}$ = Average cooling degree hour squared for customer 'i' in period 't.'

$\tau_t$ = Average energy consumption in hour 't' reflecting unobservable factors specific to the month. The model controlled for these effects by including hour-by-month-by-year fixed effects.[20]

[19] POST refers to post-treatment. The regression did not include POST (as an indicator for the treatment period) as a stand-alone variable in the regression, as very little variation occurred between treatment group homes for the month of the first report delivery. If little variation occurs, the model can be estimated with POST or month-by-year fixed effects—but not with both.

$\varepsilon_{it}$ = Error term for customer 'i' in year-month-hour 't.'

The Cadmus team estimated the model using maximum likelihood and reported confidence intervals and p-values using Huber-White clustered standard errors, adjusting for the correlation of each home's energy use over time. This produced an estimate of average daily savings per treated customer for PY2016.

As with the daily energy savings model described previously (Equation 8) the team estimated several versions of Equation 9 to check the savings estimates' robustness to changes in model specifications. Such specifications tested the effects of including (or excluding) customer fixed effects and POST rather than month-by-year fixed effects.

[20] POST was not included as a stand-alone variable in the regression since very little variation occurred between treatment group homes in the month of the first report delivery. With such little variation, the model could be estimated with POST or month-by-year fixed effects, but not with both.