# Finding Hidden Energy Savings: Operational, Maintenance and Behavioral Savings for Large Commercial Customers

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## Abstract

This paper summarizes an impact evaluation of BC Hydro's e.Points Bonus initiative for large commercial customers. e.Points Bonus rewards customers participating in BC Hydro's Power Smart Partner program for improvements in aggregate energy efficiency measured over customer sub-accounts and sites. The program assumes energy savings primarily arise from behavioral, operational, and maintenance savings. This evaluation explores: (1) customer participation using an econometric choice model; (2) gross and net energy savings associated with energy efficient behavioral, operational, and maintenance activities; and (3) how to distinguish program savings from savings previously claimed by other programs. Gross savings were calculated using 60 months of consumption data for participants and non-participants in a pre-post comparison design with a comparison group.

Key findings: (1) Freerider rates are 66% based on survey responses. (2) Significant influences on participation include frequency of contact with the Account Manager, number of employees, sector, and the incidence of previous energy efficiency projects with BC Hydro. (3) 73% of the gross aggregated energy savings associated with other BC Hydro Power Smart programs are realised in the customer billing data. The generalized realization rate confirms previous evaluation findings for the Power Smart Partner incentive program. (4) Gross and net energy savings for the reward initiative are 13.6 GWh and 4.6 GWh respectively (or 35% and 12% of reported savings). The results were used to recalibrate program reported energy savings.

## Introduction

BC Hydro's e.Points Bonus initiative for commercial customers launched in 2002 as a component of the Power Smart Partner (PSP) program.[1] e.Points Bonus is available to BC Hydro's largest commercial, institutional, and government customers who are participating in the Power Smart Partner program. Selection into the e.Points Bonus initiative is a two-phase process in which participants must first be Power Smart Partners (sign the Power Smart Partner agreement) and then sign up for e.Points Bonus. Key Account Managers (KAMs) market the program. At the end of 2005, 49% (or 151 out of 311) commercial Power Smart Partners were signed up for the initiative representing approximately 3500 facilities and 7500 accounts (for the purpose of this evaluation, the commercial group includes customers in the government and institutional sectors).

Participating customers who reduce their overall average energy intensity (EI) by at least 5% are awarded e.Points dollars, which they can use to fund additional energy efficiency projects through other Power Smart programs. Consequently, energy savings associated with e.Points Bonus are of two types: (1) savings associated with retrofit projects funded by e.Points reward dollars, and (2) savings associated with efficiency activities implemented to meet the 5% program target. The program assumes that the second type of savings primarily arise from behavioral, operational, and maintenance activities (BOM

[1] Power Smart Partners is BC Hydro's major Power Smart initiative within the business sector. This program is designed to identify and capture long-term energy savings opportunities among BC Hydro's largest commercial and industrial customers. Customers with revenues to BC Hydro greater than $50,000 per year are eligible for the Power Smart Partner program.

savings), although customers can rely on a variety of means to achieve their 5% reduction target including installing energy efficient technologies.[2,3]

Customer energy intensity is measured as the total kWh consumption of all eligible accounts divided by a customer specific base metric (e.g. tonnes produced, building square footage). Each year the change in energy intensity is measured relative to the customer's baseline year.[4] Customers who have not reduced their EI by 5% do not receive any reward and their baseline is unchanged. These customers remain eligible to earn e.Points again in the following year. Customers who have reduced their EI by 5% (or more) are awarded e.Points dollars and their baseline is adjusted to reflect their lower intensity.[5] In an effort to limit financial risk, the e.Points dollar reward is capped at 5%, so that customers who reduce their EI by more than 5% only receive e.Points worth 5% of their baseline energy. Customers have a full year from the date of award to spend their e.Points dollars on any BC Hydro approved project at any of the customer's BC Hydro supplied facilities.

## Evaluation Purpose and Overview

The purpose of this study is to determine the gross and net energy savings associated with the energy efficiency activities implemented to meet the e.Points Bonus 5% energy intensity reduction target. The evaluation covers program impacts for the 151 e.Points Bonus participants signed up for the initiative as of December 2005. The key issues addressed by the evaluation include: (1) customer participation using an econometric choice model; (2) gross and net energy savings associated with behavioral, operational, and maintenance related energy efficiency activities; and (3) separating program savings from savings previously claimed by other programs.

## Evaluation Objectives and Approach

The primary objectives for the evaluation of e.Points Bonus initiative are to (1) assess customer characteristics, customer experiences with the initiative, and energy conservation activities, (2) determine freerider rates based on self-reported survey results, (3) develop a statistical model for customer participation in the initiative, and (4) determine the gross and net energy savings associated with the 5% energy intensity reduction target. The evaluation methods include a telephone survey of participants and non-participants, a participation choice model, and a gross savings regression model. Each of these methods is described in the next sections.

### Telephone Survey

A telephone survey of program participants and non-participants was conducted in November 2005 to determine customer characteristics, program experiences, conservation activities under the e.Points initiative, and self-reported freerider rates. The survey data was also used in the development of the participation choice model. Although a census sample was attempted, surveys were completed

[2] Behavioral, operational and maintenance (BOM) savings are associated with customer activities such as turning off computers and lights (behavioral), re-commissioning existing control systems (operational), and cleaning heat exchangers (maintenance). Hard-wired savings are associated with capital energy efficiency related upgrades.

[3] Energy savings from other Power Smart funded projects may count towards the 5% reduction target.

[4] The customer nominates a baseline year starting at the beginning of a month and ending a year later. The customer must also provide the metric data (e.g. square footage, production units) for its facilities during the baseline period. The customer's baseline energy (the total energy for all of its accounts) is measured and its baseline energy intensity is calculated by dividing the baseline annual energy consumption by the baseline metric data.

[5] e.Points award = Baseline year consumption (kWh) * 5% * $/kWh

with 64 of 151 participants and 51 of 160 non-participants. For the purpose of the evaluation, e.Points Bonus participants are defined as those eligible customers who have signed up for e.Points Bonus. Non-participants are defined as eligible customers who have not signed up for the program.[6]

**Participation Choice Model**

Choice modelling is a quantitative statistical method for analysing decisions or choices made by individuals between distinct alternatives. The determinants of choice behavior are estimated by fitting a statistical model to real or experimental data describing the choices made by individuals and important variables thought to influence the decision process. Choice models can provide information that is useful for designing and marketing energy efficiency programs by examining factors that are important in a customer's voluntary decision to participate in programs and to implement energy efficiency measures. In addition, statistical methods have been developed that use participation and implementation models to estimate freerider rates for energy efficiency programs and control for self-selection in consumption models designed to estimate net energy savings (Kandel 1999a, 1999b; Tiedemann et al. 2004; Train 1994; Train & Paquette 1995; Train et al. 1994).[7]

For the e.Points Bonus initiative, a choice model of the customer decision to participate was developed using information derived from the participant and non-participant surveys and customer data extracted from the program database.[8] This model was used to examine the influence of various customer and program factors on the decision to participate in the program.

The decision to participate in an initiative can be modelled by fitting a logit or probit model to the following discrete choice (yes/no) equation.[9]

(1) $$Participate = f(\beta x) + \varepsilon;$$

Where Participate is a dummy variable indicating whether or not the customer participated in the initiative, x is list of variables thought to influence the customer's decision to participate, $\beta$ is the regression coefficient for each participation variable, and $\varepsilon$ is an error term associated with the unobserved factors that influence the participation decision.

If a logit model is used as the functional form, the model reduces to a simple closed form equation in which the probability (P) that a customer will participate in the initiative is calculated as a function of the variables found to predict participation (Equation 2).[10] Equation 2 may be rearranged to solve for the probability of participation (P), as shown in Equation 3.

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[6] To be eligible for e.Points, customers must first be a Power Smart Partner. Power Smart Partners sign an agreement indicating their commitment to energy efficiency at the corporate level. Large commercial customers who have not signed the Power Smart Partner agreement are excluded from the analysis, since they are not eligible for the program.

[7] Traditionally econometric approaches that combined discrete choice models and regression analysis for estimating net energy savings only included a participation decision model. These methods are called Discrete-Continuous billing methods. However, approaches of this type have been criticized for failing to correctly identify net energy savings (Paquette 1996).

[8] Attempts were also made to calibrate a model that described the implementation decision as a function of participating. This type of model can be used to statistically estimate the freerider rate since the coefficient on participation indicates how participating in the program influences the customer's decision to implement energy efficiency measures (see Train 1994). Unfortunately, no specifications were found that could adequately model the relationship between the participation and implementation (all suffered from low log-likelihood ratio tests and insignificant coefficients on the predictor variables).

[9] Logit and probit describes the type of functional form assumed for the error term. The probit model assumes a familiar normal distribution function and the logit model assumes a Type I Extreme Value function. These functions are quite similar, but the logit model has slightly fatter tails on the distribution. When estimating a choice model, these functions are used in their cumulative form (the familiar S-shaped curve), which is a good representation of choice behavior since these non-linear distributions are bounded by 0 and 1.

[10] In mathematics, an equation or system of equations is said to have a closed-form solution if, and only if, at least one solution can be expressed analytically in terms of a bounded number of certain "well-known" functions. Other equations or systems of equations cannot be solved exactly; instead the solution must be approximated using numerical estimation techniques.

(2) $$Logit(P) = \log\left(P \big/ (1-P)\right) = \beta x + \varepsilon$$

(3) $$P = e^{\beta x} \big/ (1 + e^{\beta x})$$

The model described in Equation 3 can be used to calculate the probability (P) of participation for each customer, given the values of the predictor variables (x-values) for a given customer and the regression coefficients (β-values) from the logistic regression model (2).

## Gross and Net Energy Savings

Gross savings are calculated using billing analysis and a pre-post comparison design with a comparison group. In this quasi-experimental design, the changes in consumption between participants and non-participants are compared both before and after the program period. This model assumes that the non-participant group can control for changes in natural conservation in the participant group, but does not adequately control for self-selection bias, which occurs when customers who are pre-disposed to save energy are more likely to be found in the participant group than the non-participant group.[11] Self-selection bias was addressed by further adjusting the savings estimate derived from the regression analysis with a freerider rate calculated from the self-reported survey results.

Sixty months of participant and non-participant consumption data are included in the billing analysis as well as data from the customer surveys, program history records, and general account information. Since the program measures customer progress towards achieving the 5% energy intensity reduction target by looking aggregately across all eligible sub-sites and accounts, the analysis is completed at the customer level by aggregating account level data. The aggregated consumption data was analyzed using a Univariate General Linear Model in SPSS with customer specific constants set as fixed effects and all other variables set as covariates (this method is also referred to as ANCOVA or Analysis of Covariance). The customer specific constants capture the influence of unique (and often unmeasurable) customer characteristics on consumption, and allow each customer to act as its own control, while also compensating for the lack of comprehensive data on square footage.[12] Other variables in the regression include weather data, savings data for other concurrent programs, time trend values, and the date the customer joined the e.Points program. The method produces estimates of gross energy savings for the reward program and aggregate realization rates for the savings associated with other programs.

The following specification is used for the regression model:

(1) $$ADC_{it} = \alpha_i + CUST_i + \beta_1 JOINED_{it} + \beta_2 TIME_t + \beta_3 SAVINGS_{it} + \beta_4 HDD_{it} + \beta_5 CDD_{it} + \varepsilon_{it};$$

Where for each customer i and calendar month t, $ADC_{it}$, the dependent variable, is the average daily consumption for participants and non-participants for each month t during the pre- and post-

[11] If customers who are pre-disposed to save energy or were planning energy efficiency improvements are more likely to participate in the program, the non-participant group is not a good model for what participants would have done in the absence of the program; it is not an unbiased comparison group.

[12] The customer specific constants include the unmeasured customer characteristics (such as facility size, business type) that do not change over time but determine a base consumption level. For this evaluation, there were large differences among customers with respect to factors known to influence electricity consumption (such as square footage) and a lack of comprehensive data on these variables at the site or even customer level. Given these limitations, a "fixed effects" approach is a reasonable approach to capture the characteristics that affect electricity use.

participation periods. $\alpha_i$ is a general intercept for the regression model. $CUST_i$ is a unique customer specific constant for each participant and non-participant. $JOINED_{it}$ is a dummy variable (0 or 1) indicating whether or not customer i joined the initiative during month t. $TIME_t$ is a variable indicating the number of months elapsed since the start of the model period. $SAVINGS_{it}$ is the estimate of cumulative total gross Power Smart program savings claimed for customer i in month t and controls for the impact of other energy conservation projects on customer consumption.[13] $HDD_{it}$ and $CDD_{it}$ are the weighted average daily heating degree and cooling degree-days based on the facility locations of all the customer sub-accounts. $\varepsilon_{it}$ is the error term. $\beta_1$ through $\beta_5$ represent the regression coefficients estimated for each predictor variable and indicate the contribution of each variable to customer consumption. Additional detail on the development of the key model variables is provided in Table 1.

The general terms, the regression equation states that average daily electricity consumption for a given customer is a function of a constant or base consumption, participation in the e.Points Bonus initiative, natural change over time, savings from other Power Smart projects, and weather variables. Since this specification includes both participant and non-participant consumption data over the same time period, the model controls for non-program related factors that influence electricity consumption such as economic factors (e.g. electricity prices, phases of growth and recession). Other than the customer specific constants, the variables in the model were measured over all customers. As a result, the regression coefficients (*βs)* reflect the average customer response to unit changes in the underlying variable. Of particular interest is the coefficient on JOINED, which represents the average change in daily consumption associated with participation in e.Points Bonus and is an estimate of the savings for the e.Points initiative. The coefficient on SAVINGS provides a gross realization rate on the savings associated with other Power Smart projects.

**Table 1.** Development of Key Model Variables

| **Variable** | **Derivation** |
|---|---|
| **Average Daily Consumption, ADC** | **Calculated as the customer's monthly consumption divided by the number of days in the month. For each customer, monthly consumption data were aggregated from a billing extract of account level information that included 60 months of consumption data from January 2001 to December 2005.** |
| **Customer Specific Constant, CUST** | **A total of 282 separate constants were created for the 148 participants and 134 non-participants in the final model. Each variable was dummy coded (0, 1) to signify when the data referred to a specific customer.** |
| **Date customer joined e.Points, JOINED** | **This variable was by default equal to '0' for non-participants during all program periods and was equal to '1' for participants after the company joined the initiative.** |
| **TIME** | **This variable ranged from 1 to 60 corresponding to each month in the 60 months (5 years) of consumption data.** |
| **Cumulative Power Smart Savings from other Programs, SAVINGS** | **The estimate of cumulative total gross Power Smart program savings claimed for customer i in month t was based on program tracking records. The estimates represent measured and verified** |

[13] Customer savings towards the 5% intensity reduction target may include savings associated with other Power Smart projects and programs. In order to derive an uncontaminated estimate of e.Points program savings, it is essential to remove the savings already attributed to other Power Smart programs through the "SAVINGS" variable.

| | |
|---|---|
| | **values except for programs that do not have M&V. The savings data were summarized by account number and project implementation date, converted to units of average daily gross savings, and then aggregated to the customer level.** |

### Gross Savings Regression Model - Data Sources and Development

Data on the predictor variables were obtained from three main sources: BC Hydro's e.Points tracking database (program dates, energy intensity data), BC Hydro Customer Information System (customer and account information, consumption histories), and meteorological data from four regional weather stations in British Columbia (HDD and CDD).

A data extract containing five years of customer account information (monthly consumption, sector, region, building type, etc.) was obtained for the participant and non-participant customer accounts. The data were cleaned to remove 4347 anomalous cases. The primary reasons for removing cases include incomplete consumption histories during the time period of interest (Jan 2001 to Dec 2005), large changes in consumption during the analysis period, and outliers identified using a statistical test.[14] The characteristics of the final sample of participant and non-participant accounts used in the analysis are shown in Table 2.

**Table 2.** Characteristics of the Participant and Non-participant Accounts Used in the Analysis

| | Participant | Non-Participant |
|---|---|---|
| **Number of Accounts** | **5417** | **3346** |
| **Number of Customers** | **148** | **134** |
| **Average Annual Consumption (kWh)** | **398,719** | **434,743** |

## Research Findings

### Participation Model

A choice model of program participation was developed using program data and information from the participant and non-participant surveys. The model was calculated using the sub-sample of participants and non-participants who had completed the survey, since many of the potential explanatory variables were only available for this sub-population (e.g. contact with the Key Account Manager). The variables included in the model were those thought to influence the customer's decision to participate. This decision was based on prior knowledge and analysis, and a literature review (Habart and Associates 2003; Train 1994).[15]

The results of the participation model analysis are shown in Table 4. The estimated model coefficients can be used to assess the overall magnitude and direction of the influence of the explanatory variable on the decision to participate in the initiative, while the p-values indicate if the coefficients are significantly different from zero. With the exception of the model constant, all the coefficients have the expected signs and are significant at the 10% level. Two variables with p-values less than 0.05, namely 'Government Sector' and 'Previously Completed a Power Smart Project,' are highly significant. The

[14] Grubb's test for identifying outliers in a data set.

[15] Other variables investigated but excluded from the final model include the importance of energy efficiency in decision making (too little variation in responses), total consumption per account (not significant), and number of facilities (not significant).

R-square values can be interpreted as a type of 'pseudo' R-squared, which measure the goodness of fit of logistic regression models (in comparison with the familiar R-squared values that are used to indicate goodness of fit for ordinary regression analysis). The overall model has a reasonably good fit considering the very limited sample size of 98 customers.[16]

**Table 3.** Choice Model of the Decision to Participate in e.Points Bonus

| **Explanatory Variable** | **Estimated Coefficients (β)** | **Standard Error** | **Significance (p-value)** |
|---|---|---|---|
| **Commercial Sector (yes/no)** | **-1.151** | **0.642** | **0.073** |
| **Government Sector (yes/no)** | **-2.155** | **0.672** | **0.001** |
| **Previously Completed a Power Smart project (yes/no)** | **1.518** | **0.545** | **0.005** |
| **Contact with Key Account Manager (# per year)** | **.0530** | **0.032** | **0.099** |
| **Number of Employees (1000s)** | **0.026** | **0.015** | **0.086** |
| **Constant** | **-0.114** | **0.690** | **0.869** |
| **Overall Model Statistics:** | | | |
| **- 2 log likelihood (model with no explanatory variables): 101.24**<br>**Model Chi-square (with all explanatory variable included): 31.995** | | | |
| **Cox and Snell R square: 0.279**<br>**Nagelkerke R square: 0.375** | | | |
| **Number of Observations: 98** | | | |

The model coefficients suggest that, in general, customers who have completed a Power Smart project in the past, have more contact with their KAM, and have more employees are significantly more likely to participate in the e.Points Bonus initiative (these coefficients are all positive and significant).[17] In addition, the results suggest that both Government and Commercial customers are significantly less likely than Institutional customers to participate in the e.Points initiative (these coefficients are negative and significant). Note that sector variables are dummy coded with the Institutional sector forming the basis for comparison. Consequently, the Institutional sector does not appear as a separate variable in the model. The coefficient associated with the model constant implies that, all other things being equal, customers are more likely to not participate in the initiative, but this effect is insignificant.[18]

[16] The "R-squared" value calculated for logistic models does not have the same interpretation as that used in standard regression. While the R-squared values associated with linear regression models indicate the percentage of variation in the dependent variable that is explained by the estimated model, pseudo R-squared values are generally based on a comparison of the log-likelihood function with all the model parameters included and the value of the function taken at zero parameters. Furthermore, models estimated with different samples or different sets of alternatives (e.g. with different L(0) values) cannot be compared using their pseudo R-squared values (Train 2003). The same expectations for R-squared values cannot be used to judge the validity of choice models. For example, it has been suggested that values of MacPherson's R-square (another pseudo R-square measure) between 0.20 and 0.40 are indicative of extremely good model fit (Louviere et al. 2000, pg. 54).

[17] The correct interpretation of the Beta coefficients in a logistic model is the change in the logit of the outcome variable associated with a one-unit change in the predictor variable (Field 2000). Due to the non-linearities in the underlying model and differences in the scales used to define the variables, the model coefficients cannot be directly compared in an attempt to assess which variables are more important in the participation decision. The easiest way to see the relative effect is to use the model coefficients in the logistic model (Equation 3) to calculate the probability of participation for combinations of variable levels.

[18] This result is not surprising given the approximate 50/50 split in Power Smart Partners between participants and non-participants (there are slightly more non-participants than participants overall).

## Gross Energy Savings

The results of the regression model of gross savings are described in Table 4. The model shows a strong statistical fit (model $R^2$ of 0.986) and all coefficients have the right (expected) sign. For example, the coefficient on HDD is positive indicating that consumption increases as the number of monthly heating days increases. With the exception of the coefficient on JOINED, all regression coefficients are statistically significant at the 0.001 or higher level.

**Table 4.** Estimated Parameters of the e.Points Bonus Gross Savings Regression Model.

| **Dependent variable = Average Daily Consumption of customer "i" in month "t"** | | | | | |
|---|---|---|---|---|---|
| **Explanatory Variable** | **Estimated Model Coeff. (Betas)** | **T-values** | **p-values** | **95% CI – Lower bound** | **95% CI – Upper bound** |
| **General Model Intercept** | **8878873** | **25.5** | **<0.001** | **8197529** | **9560217** |
| **Customer Specific Constant* (CUST)** | **-31,482.1*** | **-17.9*** | **<0.001** | **-** | **-** |
| **Joined e.Points initiative (JOINED)** | **-244.7** | **-0.90** | **0.371** | **-780.3** | **290.9** |
| **Time (TIME)** | **22.0** | **4.0** | **<0.001** | **11.1** | **32.8** |
| **Power Smart Project Savings (SAVINGS)** | **-0.73** | **-12.7** | **<0.001** | **-.84** | **-0.61** |
| **Average Heating Degree Days (HDD)** | **9.7** | **18.1** | **<0.001** | **8.7** | **10.7** |
| **Average Cooling Degree Days (CDD)** | **38.4** | **5.4** | **<0.001** | **24.5** | **52.2** |

*The customer specific constant displayed is an average of the values across all customers in the model.

As shown by the positive coefficient on TIME, on average, participant and non-participant average daily consumption increased by about 22 kWh each month in the time period analysed. Furthermore, as expected, customer consumption is also, on average, positively correlated with increasing HDD and CDD.[19] The regression coefficient on the Power Smart Savings variable (-.73) is in effect a generalized realization rate on the M&V'd (measured and verified) gross savings for all Power Smart projects completed by the customers included in this analysis. Consequently, the model suggests that on average 73% of the gross Power Smart project savings are realised in the consumption data. This result supports and confirms a previous evaluation of the Power Smart Partners Incentive program that was completed in 2005 (Quantec 2005).[20] Using a similar approach, the evaluation of the PSP program found savings realization rates of 74% for lighting projects and 93% for other projects.

The regression coefficient on JOINED indicates that the average daily gross savings associated with joining the e.Points Bonus initiative (but net of naturally occurring conservation) is 244.7 kWh/day. The regression coefficient in units of average daily consumption translates into energy savings of 13.6 GWh/year when multiplied over the 152 program participants. However, there is a lot of uncertainly around the estimate as highlighted by the wide confidence intervals and the insignificant t-value. In fact, the confidence interval around the savings estimate is 43.3 GWh/year to -16.1 GWh/year.

[19] There seems to be stronger association between consumption and cooling degree-days than consumption and heating degree-days. A similar result was also found in the Power Smart Partner Impact evaluation (Quantec 2005).

[20] e.Points Bonus participants are all Power Smart Partners and many have also participated in the Power Smart Partners Incentive program, which provides financial incentives for energy studies and technical retrofits, and energy manager funding.

**Freerider Rates and Net Energy Savings**

Estimates of freerider rates were derived from the participant survey for three categories of energy efficiency activities. Participants were asked to rate the importance of participating in the e.Points Bonus initiative on their organization's decision to implement the energy efficiency improvement on a scale from one to five where 1 is 'not at all important' and 5 is 'very important'. For installed technologies, a customer was identified as a freerider if an answer of '1', '2', or '3' was given on the 5-point scale and/or if the installation was funded by another program. For BOM improvements, a customer was identified as a freerider if an answer of '1', '2', or '3' was given on the 5-point scale. The freerider rate was calculated as the ratio of identified freerider customers in the sample to the total sample count. Table 5 summarizes the results of the freerider analysis. The results indicate very high freerider rates, which suggest that the initiative had limited success in encouraging participants to make energy efficiency improvements beyond what they would have made if the initiative had not existed.

**Table 5.** Freerider Rates Estimated from Self-reported Survey Results.

| **Activity Type** | **Freerider rate** |
|---|---|
| **Installations of Energy Efficient Technologies** | **69%** |
| **Energy Efficient Operational and Maintenance Changes** | **64%** |
| **Energy Efficient Behavioral Changes** | **58%** |
| **Overall** | **66%** |

Since the consumption model did not account for selection bias, it is necessary to further correct the estimate of energy savings for the effect of freeriders. Multiplying the overall weighted average freerider rate based on the self-reported survey results (66%) by the point estimate of energy savings derived from the consumption model (13.6 GWh/year), results in a net savings estimate of 4.6 GWh/year for the e.Points Bonus Commercial initiative.

**Summary of Research Findings and Comparison with Program Expectations**

Table 5 summarizes the evaluated results and compares them with planning estimates as documented in the business case and reported program estimates when available.

**Table 5.** Summary of Research Findings and Comparison with Planned and Reported Results

| | **Planned** | **Reported** | **Evaluated** |
|---|---|---|---|
| **Free Rider Rate** | **-** | **12%** | **66%** |
| **Gross Energy Savings (GWh/year)** | **241** | **-** | **13.6 (±29.7)** |
| **Net Energy Savings (GWh/year)** [21] | **-** | **39.0** | **4.6** |

[21] The e.Points Bonus reported savings were calculated as 1.1% of the monthly-normalised consumption of participating accounts, which was a value derived from a previous evaluation of the original e.Points initiative (Sulyma 2003). However, the original e.Points program had important differences from the e.Points program. In particular, the original initiative only included each customer's top ten accounts, while the e.Points Bonus initiative includes all eligible customer accounts. Since the original initiative was based on select accounts which may not have been representative of the activity associated with all customer accounts, using the original evaluated results to estimate the reported savings for e.Points Bonus may have resulted in inflated savings estimates. Furthermore, the 1.1% value included both BOM and another type of savings called Consultative Savings (defined in the discussion section), so it is not surprising that the evaluated savings estimate (which excludes Consultative Savings) is less than the reported value (which includes an estimate of Consultative Savings).

## Discussion and Lessons Learned

### Program Specific Findings and Discussion

The evaluated net energy savings associated with the e.Points commercial initiative of 4.6 GWh/year is 12% of reported savings (or 34.4 GWh/year less). Due to the large standard error associated with the estimate of gross savings, the confidence interval around the estimate is wide and includes zero and even negative energy savings. This result suggests that the impact is inconsistent across all customers and is not very different from the changes seen in the non-participant group. The small and uncertain estimate of net savings derived from the billing analysis is supported by the results of the participant and non-participant surveys, which generally found insignificant differences between participants and non-participants with respect to implementing various energy efficient actions and behaviors and also revealed large expected freerider rates on all types of conservation actions.

Although the savings associated with the e.Points Bonus program were significantly smaller than expected, readers should not conclude that this suggests that behaviorally based energy efficiency programs are ineffective. It is likely that other factors including program design, process/operational problems, and competition from other programs had a negative impact on the ability of the e.Points Bonus initiative to generate energy savings as discussed in the following sections.

**Program Design Limitations.** The program design provided incentives for customers who were able to save at least 5%, but the incentives did not increase if the customer achieved greater savings. Capping e.Points incentives at 5% of baseline was a program feature intended to limit financial risk. Unfortunately this feature was probably detrimental to the program because it was likely perceived by customers as a disincentive to conserve energy, since customers who wanted to save more (and get more incentives) would not benefit. Furthermore, customers who were already undertaking energy efficiency activities and upgrades would be encouraged to participate, since they could receive incentives for minimal effort. Due to these design limitations, it might be expected that participants and non-participants would exhibit similar energy savings and freeriders would be high. These expectations are confirmed by the results of this impact evaluation (Vine 2006).

**Process/Operational Limitations.** The initiative operates by providing e.Points dollars to reward customers for achieving their 5% energy intensity reduction targets; however, as part of the PSP agreement, all PSPs agree to try to reduce their consumption by 5%. As a result, e.Points dollars are the key mechanism through which the initiative can be expected to achieve additional energy savings. Theoretically these dollars could provide an added incentive to push the e.Points participants to achieve greater energy efficiency improvements over their non-participant counterparts. Unfortunately, there is evidence that e.Points dollars might not be an effective incentive for participants (PA Consulting 2006). In particular, e.Points dollars have not been redeemed as expected. If customers are having a difficult time spending the rewards they earn under the initiative, there is little incentive to try to save additional energy in order to earn more points.

**Competition from other Programs.** A final limitation for the e.Points initiative is that the savings associated with a variety of energy efficient activities pursued by e.Points customers could be claimed elsewhere as 'Consultative Savings'. At BC Hydro, Consultative Savings may be claimed when a customer implements a project that saves energy without the help of BC Hydro incentives and it can be documented that BC Hydro had a substantial influence on the customer's decision to implement the project.[22] If an activity associated with e.Points has already been claimed as a Consultative Savings project, the overall effect will be to reduce the net savings for the initiative, since the Consultative Savings are included in the Power Smart project savings variable. The decision to report a project as Consultative Savings is strongly influenced by BC Hydro's incentive structure for Key Account Managers (KAMs), which rewards GWh targets. By claiming a project as Consultative Savings, the KAM can ensure the savings will be documented and associated with his/her portfolio, whereas savings associated with the e.Points Bonus 5% Energy Intensity target are not associated with KAM portfolios. A review of the Consultative Savings project records revealed a number of BOM type projects that customers could have pursued to meet their energy intensity reduction target for e.Points such as adjusting pump controls and optimizing compressed air systems.

**Conclusions**

Quantifying energy savings from behavior-based programs is challenging. Unlike retrofit programs, which generally have well-defined savings associated with the installation of a specific technology at a specific time, behavioral activities can be difficult to identify (or even define), are often ongoing or dispersed in time, and may not have clearly defined savings. Despite these challenges, energy savings from behavior-based programs can be quantified with analysis techniques designed to tease out program effects from the background noise associated with natural change, weather impacts, customer variation in load, the effects of other programs, and other confounding factors.

The approach presented in this paper quantifies behavioral energy savings associated with participating in the e.Points program using a customer specific analysis of consumption which controls for weather, natural change over time, and savings from other energy efficiency programs. The use of customer specific constants controls for a significant amount of the variation in base consumption levels between customers in the analysis, leaving the other parameters in the model to account for changes over time. In this way, the model combines the advantages of individualized and aggregate modelling methods. A number of model expansions or improvements could be considering for other contexts. One improvement could be to expand the model to include additional individual specific variables and interactions. For example, customer-specific time trend variables could be included to allow even an even closer fit of the model to the actual consumption data for each customer. Additional improvements might include using survey data (or other data sources) to provide more precision around the implementation timing of energy efficient behavioral activities and more detail about the types of changes (e.g. operational, maintenance, educational initiatives).

The low realization rates on the reported energy savings for the e.Points program highlight the challenges associated with designing and operating an effective behavior-based energy efficiency program. In particular, effective incentive structures must be in place to reward desired behaviors. In addition, program developers must be careful to ensure that behavioral programs have clearly defined logic, which defines how the program elements are expected to result in the desired customer actions. Logic models are one tool that could help program developers think carefully about the causal relationships affected by their program structure. Finally, program developers must be careful to position behavior based programs when they are provided as a part of a suite of program offerings, so that other programs do not have a negative impact on ability of the program to capture energy savings.

[22] A good example of a situation in which Consultative Savings are claimed is when the customer identifies an energy saving opportunity through a BC Hydro funded energy study but does not receive funding for the project because it has a payback of less than one year (this is a criterion for incentive funding under the Power Smart Partner Incentive program).

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