Billing Analysis & Environment that “Re-Sets” Savings for Programmable Thermostats in New Homes

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ABSTRACT

Historically, the energy efficiency program evaluation field has seldom found energy savings from programmable thermostat programs. Circumstances, however, are quite different in Québec where more than 90% of homes use electricity as their main heating source and thermostats are installed in each room. Québec utility’s residential Electronic Thermostat - New Construction program (ETNC) provides incentives to electricians to install electronic thermostats and programmable electronic thermostats. The electronic thermostat provides a more accurate temperature control compared to the older bi-metal technology, and tests performed in a climatic chamber demonstrate the savings achieved from the reduction of hot air convection over windows. The program design provided an excellent built-in research designed to analyze savings from programmable thermostats.

Using the program participants database, which covers more than 80% of all single-family new homes within the last year, a regression analysis was conducted to compare participants who only installed electronic thermostats with those who installed at least one programmable thermostat. Energy usage over the heating season for the last three years was obtained from billing records of all participants and used in conjuncture with the regional weather database, to complete an analysis of covariance regression model.

Annual savings for a new single-family home with at least one programmable thermostat was estimated to be of 434 kWh, a reduction of 3.6% of the heating load. An estimate of savings from programmable thermostats placed in new multi-family dwellings was made, based upon the single-family new home estimates and information on thermostats per home type. Hydro-Québec uses these savings estimates to calculate their program impact on the jurisdiction of energy consumption.

INTRODUCTION

Québec's utility, Hydro Québec, initiated the ETNC program in 2003 to promote the installation of electronic thermostats (programmable and non-programmable) in residential new constructions (single-family and multi-family dwellings). The program provided incentives for electronic thermostats at a level that ensured most new homes received electronic thermostats. Then, additional efforts were made to promote programmable thermostats.

Some past evaluations have found high variability amongst sites regarding energy savings from programmable thermostat programs[1]. However, these programs were U.S.-based and circumstances are quite different in Québec. More than 90% of Québec homes use electricity as their main heating source. In addition, most homes will have a thermostat in almost every room (with single-family homes averaging 9.5 thermostats per home). This environment makes Québec quite unique.

The program reaches around 80% of the residential new construction market. Measuring the impacts of the additional component that promoted programmable thermostats was a major issue and an accurate evaluation estimate is not easily accomplished. The best solution considered was a billing analysis even though such analysis is not often undertaken in the new construction market.

METHODOLOGY

Research Design

"Impact evaluation (therefore) involves estimating a change in energy use. Since it is possible to only directly measure consumption, to estimate savings one must observe the energy use characteristics of a program participant over time and from this generally infer what the energy consumption of the participant might have been in the absence of the program." (2004 California Evaluation Framework, TecMarket Works et. al., 97)

A primary driver for energy consumption, for any measure or end-use that either directly or indirectly affects heating or cooling, is weather. This variant can change significantly from time period to time period. Consumption changes due to weather must therefore be controlled or corrected to provide accurate program impact estimates.

Almost all impact evaluations of energy efficiency programs involve regression analysis or engineering methods (such as those presented in the International Measurement and Verification Protocols, IPMVP). Regression analyses of large samples or census of participant's consumption over time can provide reliable gross savings impact estimates. This cross-sectional time-series regression design can easily incorporate and correct weather differences over the analysis period[2] (this form of impact evaluation is commonly referred to as billing analysis.) Almost all energy efficiency program impact analyses using regression — billing analysis — are a form of pre- and post-design (Figure 1).

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[1] Advanced Line-Voltage Thermostats For Electric Resistance Heating, Gregerson, 1997

[2] See Chapter 6 of the *2004 California Evaluation Framework* for a thorough discussion of impact evaluation methodologies used for energy efficiency program evaluation and references to this body of work.

In the figure below, "O_1" represents energy usage before program intervention. The "X" variable represents treatment and O_2 is energy usage post-treatment. The customer's historical patterns of usage are assumed to be what would have occurred in the post-retrofit time period if this customer had not participated in the program.

O_1	X	O_2

Figure 1: One Group Pre-test Post-test Design (Cook and Campbell 1976, 99)

The primary reason billing analysis is seldom used in evaluating new construction programs is because there is no "pre-test" period of consumption (O_1). It is also difficult to have data for a new construction comparison group that could reasonably be expected to have many of the characteristics of the treatment group (It is strictly referred to as a comparison group rather than a control group since the research design is not experimental but quasi-experimental.)

Hydro-Québec's program design for the residential ETNC program does, however, provide an excellent built-in research design. The program reached 80% of the residential new construction market, getting builders to install electronic thermostats. The program also offered incentives for programmable thermostats but a much smaller proportion of the new homes had programmable thermostats installed by the participating electricians.[3] This provides information for residential new construction homes that obtained only electronic thermostats and those that obtained both electronic and programmable thermostats. In its simplest perspective, the difference between those programmable electronic thermostats and those non-programmable is the impact. This is represented as a research design of post-comparison group only (Figure 2). In Figure 2, "X_1" is the treatment of electricians installing electronic thermostats instead of bi-metallic thermostats with program incentives. The billing data for those homes is represented by "O_1". New homes with programmable thermostats are those with incentives (treatment) for both electronic thermostats and programmable thermostats, X_{1+2}. The usage for the programmable thermostats is represented by O_{1+2} in Figure 2.

X_1	O_1
X_{1+2}	O_{1+2}

Figure 2: Comparison Group with Differential Treatments

Historically, the energy efficiency program evaluation field has found high variability on energy savings from programmable thermostat programs. Knowing this, the evaluators needed a research design that could provide reliable savings estimates (if existent) from stable coefficients even if these savings were small. Hydro-Québec's additional efforts for programmable thermostats were based on their estimates of energy savings from reduced heating usage. In order to increase the likelihood of obtaining statistically significant stable coefficients for savings estimates (if existent) the billing analysis was restricted to the

[3] Please note that the program participants for the Hydro Québec ETNC program are electricians, not home buyers.

winter months, reducing noise and other primary drivers of electricity usage. In order to capture winter data variability, increase the billing periods and the overall sample size for analysis billing data for the two groups of participants, billing information was collected over a three-year period. Since the treatment is a permanent feature (programmable thermostats have to be installed in a home/room at construction phase, it can not be added afterward), repeated measurements from each participant is somewhat equivalent to multiple post-treatment measurements (such as shown in the research design, Figure 3). So the greater the number of post-periods, not only more data but more weather response variations that can be captured, the higher the likelihood of obtaining more reliable coefficients of the underlying overall response.

X_1	O_1	X_1	O_1	X_1	O_1
X_{1+2}	O_{1+2}	X_{1+2}	O_{1+2}	X_{1+2}	O_{1+2}

Figure 3: Comparison Group with Differential Treatments and Multiple Post-Treatment Measurements

PROGRAM PARTICIPANTS' BILLING DATA AND ITS PREPARATION

The savings coming from programmable thermostats result from the automatic use of the setback option to reduce heating when the dwelling is expected to be empty. Estimating those savings in residential new construction requires comparing electricity consumption from dwellings with programmable thermostats to those without them. Hydro-Québec, which promotes electronic thermostats installation through incentives, kept each participant's information in their database. The information included is detailed; data ranging from personal, demographic, financial, to technical.

Information was extracted from the program database for all participants who purchased a single-family dwelling. For those each individual 25,703 customers, electricity consumption for the last three years and the corresponding Heating Degree-day (HDD) for each period were assembled, totaling 206,861 observations (billing periods). Only the winter billings were used for the analysis. This ensured a clean measurement of the programmable thermostat impact on heating energy without the inaccuracies or noise from summer usage. For each billing period, the final analysis data set included the following variables:

- Customer number
- Weather zone
- Start and finish date of the billing period
- Electricity consumption over the billing period
- Number of heating degree-days corresponding to the billing period
- Number of electronic thermostats installed (programmable and non-programmable)

Before running this analysis, the data set was cleaned to remove customers with billing data indicating a high probability of errors and remove those considered outliers. These observations could distort the analysis and the coefficients achieved (biasing the resulting savings estimates). However, care was taken to ensure that the removed observations really represented incoherence. In this case, the criteria used to determine outliers or problematic billing data were:

- Billing periods covering more than 80 days.[4]
- Customers having an average daily electric consumption smaller than 15 kWh will be removed since their homes/rooms are most likely not inhabited all year long.
- Customers owning more than 30 electronic thermostats will be removed
- Customers owning more than 10 programmable thermostats will be removed

The last two criteria were chosen after analysis of the average, standard deviation and distribution of these variables. It is common practice in Québec to have one thermostat per room. As such, participants with electronic thermostats had on average 9.5 of them in their dwelling, whereas participants with programmable thermostats had an average of 3.5. After removing the outliers, the data set totaled 178,354 observations, representing 23,851 customers.

ANALYSIS OF COVARIANCE (ANCOVA) MODEL

The analysis of covariance (ANCOVA) model is one way to address the problem of error terms, not being truly random. It does so through measuring the covariance among categorical variables. Often, these types of models are divided into two categories: random effects model (or variance components models) and fixed effects model. Much of the work in this field involves providing the appropriate estimators for differing circumstances or assumptions about the components and relationships of the error terms (Aigner & Hirschberg 1985, Aigner & Lillard 1984, Amemiya & McCurdy 1986, Megdal, Paquette & Greer 1993a, Megdal, Paquette & Greer 1993b).

The ANCOVA method was the specific regression method selected in order to correct for the non-random errors that would be present in billing analysis (a time-series cross-sectional analysis) due to characteristics of specific homes or households. ANCOVA will also reduce noise in the billing analysis allowing program effects to be found if any. The ANCOVA model is also referred to as a "fixed effects" model. This model allows each individual to act at its own control. The only effects of the stable but unmeasured characteristics of each customer are their fixed effects from which this method takes its name. These fixed effects are held constant. The fixed effects nature of the model means the ANCOVA does not need to include unchanging customer characteristics such as square footage, number of floors, equipment in the home, etc. Controlling for fixed effects controls the amount of variance (noise) the model is faced to, since each customer has a different baseload, a different response to weather, and a different pattern of consumption that changes over time. This approach also provides a much closer fit to the data than most models as individual responsiveness is incorporated. At the same time, using individual responsiveness is more meaningful than including lagged usage variables.

[4] Standard practice for billing analysis is to remove very long billing periods that would contribute to greater measurement errors.

The ANCOVA model framework used in the evaluation of Québec ETNC program was as follows:

$$E_{it} = B_1 S_{it} + B_2 W_{it} + C_{it} + e_{it}$$

Where:

E_{it}	=	Average daily electricity consumption for customer "i" in period "t", from the billing data, with the consumption for the billing period, divided by the number of days in the billing period.
S_{it}	=	Dummy variable = 1 if customer "i" in period "t" had installed programmable thermostat; = 0, if no programmable thermostat had been installed.
W_{it}	=	Average of heating degree-days for customer "i" in period "t", as defined by that customer's billing period.
C_{it}	=	Constant representing the dwelling baseload electricity consumption for customer "i" in period "t".
β_1, β_2	=	Estimated coefficients for entire sample.

ANALYSIS AND FINDINGS

Based on the ANCOVA model and the final (cleaned) dataset, the initial analysis was to test the simple specification of whether or not the presence of at least one programmable thermostat in a single-family dwelling had an influence on its electricity consumption compare to dwellings with only electronic non-programmable thermostats. The results are presented in Table 1. The coefficient for all programmable thermostats was negative (savings found) and its t-statistic was well over 2 at 12.97.

Table 1: Initial ANCOVA on Effect of Programmable Thermostats Presence

R-Square:		**0.4226**
Variable	**Coefficient**	**t-Statistic**
Presence of programmable thermostat	**-1.74**	**-12.97**
Average of heating degree-days	3.03	360.90
Baseload	29.98	204.82

This initial analysis of covariance model revealed that there was indeed a relation between the electricity consumption and the presence of programmable thermostats. Customers owning at least one programmable thermostat will consume on a daily basis 1.7 kWh less than a customer with only non-programmable thermostats. When multiplied by the average observed days of consumption each year, savings of 385 kWh were estimated. The average single-family dwelling required approximately 12,500 kWh of electricity for annual heating. The savings obtained from the installation of programmable thermostats translates in a reduction of 3% of the heating load.

An easily overlooked regression problem is misspecification of the model. A critical assumption in regression analysis is that the model is correctly specified, i.e., that it represents the underlying process. In a way, regression assumes that the regression model being tested is the one and only true representation of the process determining the dependent variable. Using regression analysis for causality assumes that the independent variables cause the actions being measured in the dependent variable, not just a correlation. This assumption pertains to the variables, the mathematical form of the interaction, and the treatment of non-random error term effects. These are strong assumptions, and most practitioners realize that a regression model may be missing some variables and data (some of which may be important). It is important, however, not to get complacent about the imperfections, testing and correcting for misspecification (Megdal, Paquette & Greer 1995a, Megdal, Paquette & Greer 1995b).

It is hard to know when a model is misspecified. Specifying the model is generally based upon the relevant theory, experience, the literature on similar work, and testing alternative models. Non-linear effects of weather are the most common non-linear variables used within billing analysis, particularly with commercial customers. Alternative non-linear forms of model specification, however, are far less common.

In testing alternative model specifications and examining coefficient stability, this study final billing analysis is based upon conducting ANCOVA separately for six groups of weather categories. This allows savings estimates for programmable thermostats to vary by weather, as would be expected. This regression specification allows a non-linear interactive effect between temperature and programmable thermostats. This specification allows the program effect, the coefficient on presence of programmable thermostat, to vary with weather; the colder the weather the more savings that could be obtained from temperature setbacks on programmable thermostats.[5] There is not, however, a significant body of literature to indicate customer behavior regarding thermostat usage as weather varies and how behavior might change during extreme weather patterns.

By splitting the billing period into categories based on the heating degree-days, six groups were made to represent different heating stages. Using the ANCOVA model again on those groups proved that the previously observed relation was present in each group, confirming evidence of programmable thermostat impacts. The results for each Heating Degree-days (HDD) group are presented in Table 2 through Table 7 below.

Table 2: ANCOVA for 0-5 HDD Heating Stage: Effect of Programmable Thermostats Presence

R-Square:		**0.035**
Variable	**Coefficient**	**t-Statistic**
Presence of programmable thermostat	**-0.30**	**-1.66**
Average HDD	2.48	32.66
Baseload	31.268	123.07

Table 3: ANCOVA for 5-10 HDD Heating Stage: Effect of Programmable Thermostats Presence

R-Square		**0.050**
Variable	**Coefficient**	**t-Statistic**
Presence of programmable thermostat	**-0.65**	**-3.07**
Average HDD	3.13	42.71
Baseload	28.60	50.68

[5] A simpler specification of heating degree-days and heating degree-days squared was initially tested. This simpler form of non-linearity did not statistically provide significant coefficients with signs in the expected direction for all variables in the model. The final set of models by heating stage followed a logical pattern, coefficients were all in the expected direction and 16 of the 18 variables were statistically significant.

Table 4: ANCOVA for 10-17 HDD Heating Stage: Effect of Programmable Thermostats Presence

R-Square:		0.066
Variable	**Coefficient**	**t-Statistic**
Presence of programmable thermostat	**-2.64**	**-10.56**
Average HDD	3.33	53.72
Baseload	27.95	33.02

Table 5: ANCOVA for 17-22 HDD Heating Stage: Effect of Programmable Thermostats Presence

R-Square:		0.018
Variable	**Coefficient**	**t-Statistic**
Presence of programmable thermostat	**-3.24**	**-9.13**
Average HDD	3.22	23.89
Baseload	31.08	11.65

Table 6: ANCOVA for 22-27 HDD Heating Stage: Effect of Programmable Thermostats Presence

R-Square:		0.006
Variable	**Coefficient**	**t-Statistic**
Presence of programmable thermostat	**-2.71**	**-6.01**
Average HDD	1.90	11.70
Baseload	57.03	14.60

Table 7: ANCOVA for 27-35 HDD Heating Stage: Effect of Programmable Thermostats Presence

R-Square		0.002
Variable	**Coefficient**	**t-Statistic**
Presence of programmable thermostat	**-0.70**	**-0.64**
Average HDD	0.99	3.63
Baseload	76.41	9.52

The savings for each subgroup can be estimated by taking the coefficient estimated for the presence of programmable thermostat and multiplying it by the average observed days of consumption each year. Each subgroup's savings must then be weighted to obtain an estimate of the annual electricity savings average. To obtain the weights for each weather subgroup an analysis of the weather was conducted from the information of the last five years. Table 8 below summarizes the savings estimated for each subgroup and the cumulative savings obtained with the weighting of the subgroup estimates.

Table 8: Savings Estimates by Weather Subgroup and Overall Savings Estimate

Subgroups (HDD)	Subgroup Weight Based on Weather Database	Savings (kWh)	Weighted Savings (kWh)	Cumulative Savings (kWh)
0-5	7.48 %	64	5	5
5-10	16.69 %	136	23	28
10-17	31.34 %	562	176	204
17-22	18.06 %	705	127	331
22-27	14.12 %	597	84	415
27-35	12.31 %	156	19	**434**

The savings attained by subgroups are deemed logical, considering single-family dwelling heating needs. The maximum saving has been reached by the 17-22 HDD subgroup, which is equal to temperatures of approximately -7 to -2°C. However, savings were shown to rise when the temperature got colder until a tipping point, when the savings started to drop. The trade-off between maintaining comfort and how much they would have to spend on their utility bill was assumed to explain this pattern. This regression analysis does not provide conclusive evidence as to the causes of this non-linearity, but two hypotheses for this effect seem quite plausible:

- In extreme cold, the loss of body heat towards the external environment by radiation through the windows is more important, and the temperatures of internal areas of walls connected to the outside are also colder. These can make occupants more sensitive to temperatures and unwilling to use their setback option.
- In extreme cold, room temperature, once lower, will need more time to return to a comfortable temperature. Moreover, the air temperature often reaches the set point temperature for comfort although the surroundings are still colder than required, since time is needed for the heat exchange to happen. This can increase discomfort such that occupants are unwilling to apply the setback option on their programmable thermostat for future extreme cold.

CONCLUSION

Model specification can make significant differences in program savings estimates. Alternative model specifications should be tested as indicated by program theory, past literature, thermal performance, and behavioral theory.

Annual savings for a single-family home with at least one programmable thermostat was estimated to be 434 kWh, a reduction of 3.6% of the heating load. Savings can be accumulated over 15 years, the life expectancy of the thermostat. The savings level per thermostat (average savings divided by the average number of thermostats per new single-family home) was then used to estimate what would be expected to happen within multi-family dwellings (given their average number of programmable thermostats per new multi-family unit). Québec’s utility now uses those numbers to calculate their program impact on the energy consumption jurisdiction.

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