THE IMPORTANCE OF USING ANALYSIS OF COVARIANCE, DIAGNOSTICS, AND CORRECTIONS WITHIN BILLING ANALYSIS FOR LARGE C&I CUSTOMERS

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Introduction

Boston Edison Company's (BECo) Large Commercial/Industrial Retrofit Program provides DSM services to approximately 3,000 customers with a peak demand over 150 kilowatts (kW). The program operates on two fronts; one for institutional customers and one for non-institutional customers. The incentive levels and incentive pay-outs (length of time over which the incentive is paid out to the customer) differ according to the customer types. The institutional customers include buildings owned by governments or hospitals that may face particular financing barriers for making energy efficiency investments. The non-institutional customers include all other large customers, such as manufacturers, and office buildings.

This program had the highest expected energy savings from Boston Edison's demand-side management (DSM) programs. The importance of the program and evaluation difficulties previously experienced due to the unique characteristics of many of the largest savers created the need for a more comprehensive impact evaluation. It also drove the decision to use new analytical techniques for the billing analysis in this evaluation.

The design for this comprehensive impact evaluation included a two-pronged billing analysis approach combined with a strong engineering analysis. The two-pronged billing approach was also designed to include a high level of disaggregation and attention to detail. Individualized time-series econometric regression was used for some of the largest energy and demand savers. Econometric regression analysis was performed by sector for the other participants using an Analysis of Covariance (ANCOVA) procedure. These methods were complemented by a significant level of examination for potential bias problems and correction for these problems when they were found. This paper will explain these methods and their importance in our findings.

Advantages of the Analysis of Covariance (ANCOVA) Methodology

Understanding How ANCOVA Fits With Other DSM Billing Analysis Techniques

In order to understand how ANCOVA fits with other DSM billing analysis techniques, we divide the typology of methods used into two types: model specification and parameter estimation. These are the four general types of econometric billing analysis specifications versus the regression type used to estimate the models' parameters. We are providing these two typologies so that the differences between and within them can be better understood. This will allow different combinations between the two typologies to also become clearer.

The general approach for measuring energy savings in program evaluation, is some form of pre and post billing analysis. There is, however, some confusion with the terms used for the different types of billing analysis models. There are four general model types of econometric billing analysis used for energy impact program evaluations. These are:

1. Regression Adjusted Billing Analysis;
2. Conditional Demand Analysis (CDA);
3. Change Models; and
4. Statistically Adjusted Engineering (SAE) Models.

There is a variety of billing analysis techniques that use econometric regression. A pre-post comparison of utility bills would be all that is really necessary if no other changes occurred over the time period. But this is never the case. At a minimum, the weather is never exactly the same, and one of the greatest predictors of energy consumption is weather. Weather adjustments can occur within a normal regression analysis framework by including weather variables, such as heating degree days. Another common technique used is PRISM, developed by Dr. Margaret Fels of Princeton University (Fels, 1986). PRISM performs the billing regression weather adjustment on an individual customer basis, so that the baseline temperature point of increased heating (or cooling) usage can be set differently for each customer.

The term conditional demand analysis (CDA) model was coined by Dr. Michael Parti, to describe a regression in which observed energy consumption is estimated as a function based upon binary (dummy) variables, for the presence or absence of major end uses (Parti and Parti, 1980). The resulting coefficients represent the marginal contribution, to overall energy use associated with each end use. This type of regression model is very useful in predicting energy use, and explaining energy use to customers.

Over time, Dr. Parti, and others have used this terminology to represent a wide range of hybrid models that incorporate program data, change data and engineering data. This, along with the fact that all multiple regressions are inherently conditional models, has led to some confusion in the terms used in this field.

In the traditional interpretation of terminology, a “Change Model” was different from a CDA Model. The CDA model is designed to explain energy uses, while a Change Model is designed to explain changes in energy usage. That means there is a difference in the dependent variable being explained by the model.

Statistically-Adjusted Engineering (SAE) models are models that incorporate the engineering estimate of savings, in the regression analysis. The SAE models were first developed by Dr. Kenneth Train (Train et al., 1985) as a technique to include engineering in the estimation of hourly end-use energy loads. The term has evolved to include any energy regression model that includes engineering estimates (of savings or usage, normally made prior to installation and referred to as engineering priors). As used in DSM evaluation, the regression coefficient for the SAE variable measures the percentage of the savings estimate, on average, actually being obtained. If the billing data reveals that the actual savings are greater than the prior estimates than the SAE regression coefficient will be greater than one. Analogously, the SAE regression coefficient will be less than one when the billing analysis finds actual savings to be less on average than the prior estimates.

The second typology we reference is that of regression type (the technique used to estimate the model's parameters). In general, there are three methods of estimation: moments, least squares, and maximum likelihood (Kmenta, 1971, p. 171-174). Under certain sets of assumptions, the estimators found by these three methods are the same and are consistent. However, there are many economic models in which estimators derived by least squares are inconsistent. The discovery of these circumstances and models, where least squares provides inconsistent estimators, has led to techniques that are used with maximum likelihood estimation to provide consistent estimators. In fact, the majority of the field of econometrics is devoted to this type of analyses.

Almost all of the non-PRISM econometric billing analysis has been conducted with least squares estimation methods. Least squares estimation methods include ordinary least squares (OLS) and generalized least squares. Usually, these two techniques produce similar results. Generalized least squares, as its name implies, is a more generalized statistical equation form that uses maximum likelihood estimation. There are differences, however, that lead to the decision of which technique is more appropriate for different circumstances.

OLS, is the most commonly used of these techniques, and the easiest to use in most statistical software packages. It is important that our estimator of the model's coefficients is unbiased (centered around the correct answer), and consistent (that we would approach the exact population coefficient as our sample size gets larger). According to the Gauss-Markov theorem, the best (minimum variance producing) linear unbiased estimator can be achieved with ordinary least squares, as long as four assumptions are met. If, however, any of these assumptions is incorrect, generalized least squares should be used. If, OLS is inappropriately used in cases where one of these assumptions is violated, it will produce an estimator with greater variance, than generalized least squares would have produced (e.g., not as accurate). There are also common techniques that can be used along with generalized least squares to correct for cases that violate the OLS assumptions. This is because the only assumed error structure in the generalized method is that the variance-covariance matrix of the error terms be multiplicative scalar and positive definite (Pinkdyck and Rubinfeld, 1981, pp. 165).

There are a few demand-side management (DSM) evaluations (the majority of energy program evaluations), which have used other econometric techniques rather than ordinary least squares. One of these is the Analysis of Covariance (ANCOVA) model

Background on the Analysis of Covariance Methodology and Its Use in DSM Evaluations

An Analysis of Covariance (ANCOVA) model measure covariance among categorical variables. The ANCOVA model is often used as a method to address a problem with the error term (i.e., the error term is not truly random). This field of interest decomposes the error term and examines its pieces with varying assumptions. Often these types of models are divided into random-effects models (or variance components models) and fixed effects models. Much of the work in this field involves providing the appropriate estimators for differing circumstances or assumptions in the components and relationships of the error terms. (See the following articles for more detailed discussions of this work and its applications: Aigner and Hirschberg, 1985; Aigner and Lillard, 1984; Amemiya and MaCurdy, 1986; Balestra and Nerlove, 1966; Cornwell and Rupert, 1988; England et al., 1988; Hausman, 1978; Hausman and Taylor, 1981; Jasso, 1985; Lillard and Acton, 1981; Maddala, 1971; Megdal et al., 1993; Megdal et al., 1995; Mundlak, 1978; Ozog et al., 1995; Schutte and Violette, 1994; Sumi et al., 1993; and Wallace and Hussain, 1969.)

The ANCOVA model has been used in several fields as a “fixed-effects” model. This involves an ANCOVA model for a time-series cross-sectional sample that provides the cross-sectional differences to be held constant. This type of model allows each individual to act as its own control. The unique effect 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 initial econometric proposal for this type of model primarily comes from the 1981 work by Hausman and Taylor that demonstrated how instrumental variables could be used to obtain the time-invariant parameters.

In a cross-sectional time-series' analysis the standard regression error component is divided into that which is specific to the cross-sectional entities (i.e., individuals, or customers) and that which is truly random error. The customer-specific error term is replaced by a customer-specific regression specification. This customer-specific specification allows all the customer-specific component to be removed from the error, reducing the customer-specific error term to zero.

The Analysis of Covariance (ANCOVA) technique creates an estimate of the fixed-effect for each individual. This is the effect that does not vary over time for an individual and differentiates that individual from others, apart from the other causal explanatory variables in the regression. This allows a greater decomposition of effects within a cross-section time-series analysis. For this reason, the ANCOVA or fixed-effects model has been used in demography (Jasso, 1985) to explain differences in the effects of cohort, marriage cohort, and marriage length on coital frequency, where the fixed-effects captured the great variation that occurs across couples. This work’s publication in the American Sociological Review led to the techniques use in labor sociology/economics to explain occupational sex segregation’s impact on wages; England, Farkas, and Barton, 1988. The technique has also been used in energy to predict customer’s responses to time-of-use pricing (Aigner and Hirschberg, 1985; and Aigner and Lillard, 1984).

ANCOVA’s capturing of the individual-specific effects, in cross-section time-series models, also radically reduces the noise in most of these models. This comes from the fact that much of what can not be explained within cross-section time-series models involving human behavior are the unmeasured components that make us each individuals. These features are our “fixed-effects”. ANCOVA’s control of these fixed-effects provides a much tighter fitting model, reducing the model’s noise. It is this feature that makes this technique so valuable for DSM billing analysis.

This capability of ANCOVA was recognized by Dr. Lori Megdal while she was simultaneously leading DSM evaluation efforts at the City of Austin and pursuing her Ph.D. studies under the guidance of Dr. George Farkas, and Dr. Paula England, two of the authors of the England, Farkas, and Barton publication mentioned above. The primary goal of the DSM billing analysis was to obtain an accurate, clean, estimate of the program's impact. The fixed-effects model would provide usage explanation, such as a CDA model, but could significantly reduce model "noise" by removing customer-specific differences. The ANCOVA technique removes all fixed-effects of the customer. This means that an ANCOVA model can account for all the energy usage differences between customers, every characteristic of their dwelling and household patterns, not just those measured in an audit or survey. It does not explain the differences between customers. Yet, ANCOVA can provide the cleanest DSM savings estimate by removing all customer differences from the modeling.

The City of Austin's use of ANCOVA for DSM billing analysis was first published in 1992, in their evaluation of the City's Direct Weatherization Program. This work was then included in a paper describing several techniques developed by the City of Austin for residential DSM evaluation, published in the Proceedings of the 1993 Energy Evaluation Conference: Megdal, Haynes, and Rammaha, 1993.

Almost simultaneously, Sumi, Oblander, and Schneider independently discovered the advantages of using ANCOVA for DSM billing analysis, as also reported in the 1993 Proceedings of the Energy Evaluation Conference.

The ANCOVA model is well-suited for DSM evaluation using billing analysis. The technique greatly controls the amount of variance, or noise the model is faced with, by being able to reflect the fact that each customer has a different baseload, a different response to weather, and a different pattern of consumption changes over time. This approach also provides for a much closer fit to the data than most models, and yet, does not rely on a direct inclusion of prior consumption to predict post consumption.

Given these advantages for DSM evaluation, the use of ANCOVA has been spreading rapidly. After Dr. Megdal joined Cambridge Systematics, she introduced the technique for use in a commercial program evaluation, being conducted by Cambridge Systematics, for Puget Sound Power and Light. This work became part of Hopkins, Weisbrod, and Megdal, 1994. This technique has now become the standard technique at Cambridge Systematics, used in all of Cambridge Systematics' econometric billing analysis since that time. The use of ANCOVA has also been used by other consultants and utilities: HBRS (Sumi, et. al., 1993), RCG/Hagler, Baily (Ozog et al., 1995), Xenergy (Schutte and Violette, 1994), and San Diego Gas and Electric Company (Schiffman, 1994). (The Sumi et al., 1993 work is actually a random-effects model. Hausman, 1978 pp. 1263, proves that the fixed-effects estimator and the random effects estimator should be approximately the same, if the conditional mean of the fixed-effect error term within the general error term is not correlated with the independent variables in the model.)

There are several ways in which an ANCOVA or "fixed-effects" model can be performed. The customer effects can be captures by dummy variables for each customer (with the standard one fewer dummy variables than number of categories). It can also be accomplished by a first-differences model, where customer-specific measurements are measured as differences from the mean. These methods, however, do not produce complete ANCOVA estimators. As such, there is some documentation that in some circumstances they made not be efficient estimators. The easiest application method also provides actual ANCOVA estimators. This is the current availability of using the general linear model (GLM) with an added identification specification for the customer, a procedure commercially available in SAS©.

We have made the distinction of two typologies; DSM billing analysis model type, and regression model type. We have placed ANCOVA as a regression model type. This was done so that it was easier to understand that ANCOVA is not an alternative to CDA models, change models, or SAE models. Rather, it is an alternative to the ordinary least squares regression model with a common cross-sectional time-series' error term. This means that ANCOVA can be used in conjunction with DSM billing analysis model types. The ANCOVA model used in Megdal, et. al., 1993 was a regression adjusted billing analysis. The ANCOVA being reported in this paper were performed using an SAE model type.

Our Findings from the Evaluation of BECo's Large C&I Retrofit Program

Analysis of Covariance (ANCOVA) Results

The ANCOVA modeling was performed by sector (with the largest expected savers removed for individual analysis). The ANCOVA model framework used in the evaluation of BECo's Large C&I Retrofit Program was as follows:

$$E_{it} = B_1S_{itj} + B_2W_{it} + B_3G_{it} + B_4C_{it} + B_{5i} + ... + B_{ni} + e_{it}$$

where:

E_{it} = Average daily energy consumption for customer "i" in month "t", from the billing data, with the consumption for the billing cycle, divided by the number of days in the billing cycle.

S_{itj} = Dummy variable = 1 if customer "i" in month "t" had installed measure "j"; = 0, if the conservation measure had not yet been installed. For a SAE model, the measure savings estimates would be included in place of the "1" for the months after installation.

W_{it} = Average weather for customer "i" in month "t", as defined by that customer's billing cycle.

G_{it} = Growth/contraction over time for customer "i" in month "t", as displayed by employment for that customer.

C_{it} = Characteristics within a sector in month "t" for customer "i".

$B_{5i}...B_{ni}$ = For ANCOVA, customer "i", included as own control for fixed-effects. The coefficient adjusts for the customer's base usage as differentiated from the usage for the sector based upon the other variables in the model. Interacted with weather, the coefficient adjusts for the customer's weather sensitive usage, as differentiated from the usage for the group as a whole, based upon the other variables in the model.

$B_1 \ldots B_n$ = Estimate coefficients.

e_{it} = Statistical error term, for unexplained variance in observed average daily energy consumption, for customer "i" in month "t".

The coefficient of "S" provided either the average daily consumption savings from the measures installation, or the percentage of the engineering estimate obtained; depending on whether a dummy variable is used, or whether all sample participants have program engineering estimates available for all measures installed. If the engineering estimates were fully available for a sector, these were used, making the model an SAE model type. If not available, this ANCOVA model was a regression adjusted billing analysis.

Modeling was performed for three sectors. These were: manufacturing, office, and schools. In order to simplify this presentation, and keep the paper of reasonable length, all modeling results are not presented. Nevertheless, the office results presented in this paper are representative of all our results. (The results for the manufacturing sector can be found in Megdal et al., 1995.)

The initial (prior to modeling corrections) office sector energy model was a SAE ANCOVA model for 15 1992 office-sector participants. As shown in Table 1, this model achieves an R-square of 0.98 with a t-statistic for the engineering savings estimate of 5.40. This model provides a realization rate for lighting measures of 90 percent. The customer-specific identification variables were significant for all customers. The weather variables were also statistically significant.

The customer identification coefficients represent the customer's baseline consumption for each customer. The id variables allow the model to capture much of the heterogeneity that is found in this customer class. This coefficient represents a separate intercept for each customer. The id coefficients are not a pure measure of a customer's base load. It is the customer's fixed-effect that provides the best fitting sector consumption model.

Regression Diagnostics and Corrections

Regression diagnostics were performed on all the models for this evaluation, regardless of how "good" the initial modeling results appeared. Regression diagnostics are not often performed in DSM evaluations. These diagnostics should become standard practice in DSM evaluations, especially given our finding of problems discovered in apparently "good" models with high R-squares. Our regression diagnostics included: the probability that the residuals were normally distributed; skewness measurement; kurtosis measurement; a Pearson's correlation coefficient between the residual and the lagged residual; and an examination of residual plots against the predicted values, the savings estimate, average heating degree days, average cooling degree days, and time.

Table 1 ANCOVA Results for the Office Sector's Energy Usage

R-Square		0.98
Number of Participants		15
Time Period		1/1989 - 10/1993
Number of Observations		540
Variable	Coefficient	t-Statistic
Lighting savings estimate	-0.90	5.40
Average CDD	176.41	7.56
Average HDD	13.98	2.34
ANCOVA Variables		
ID variables		
ID 1	1,340	5.44
ID 18	2,168	9.07
ID 24	4,225	16.53
ID 25	1,023	4.29
ID 38	3,124	12.12
ID 39	1,899	7.67
ID 42	2,939	12.32
ID 46	40,222	136.41
ID 47	2,851	12.07
ID 48	7,562	31.49
ID 54	6,003	24.81
ID 55	4,995	20.79
ID 58	6,237	26.17
ID 60	3,738	12.37
ID 62	2,255	9.33

Our regression diagnostics found problems in the office, manufacturing, and school sector models. As an example, the initial office sector energy model (presented in Table 1) had significant problems with heteroscedacity. This was solved by creating two models, one for one large customer who had had much of its retrofitted space vacant in the post-period and another model for the remainder of the sector. The initial model had a probability of normally distributed residuals of 71 percent, a skewness measure of 2.43, and a residual plot showing one customer with consistently higher consumption and savings. The correction of two models allowed the sector model to raise the probability of normally distributed residuals to 90 percent, and the skewness measure fell from over two to -0.8. The final office sector model is presented in Table 2. The results from the modeling of the individual customer pulled from the office sector is given in Table 3.

Table 2 Final Office Sector Energy Model

R-Square		0.93
Number of Participants		14
Time Period		1/1989 - 10/1993
Number of Observations		504

Variable	Coefficient	t-Statistic
Lighting savings estimate	-0.45	4.63

ANCOVA Variables

ID Variables

All ID variables achieved statistical significance with t-statistics ranging from 5.82 through 32.32. The coefficients ranged from 1,569 through 8,073.

ID Interacted with Average HDD

One-fifth of the interactions with HDD were statistically significant.

ID Interacted with Average CDD

Almost 80% of the interactions with CDD were statistically significant with coefficients ranging from 14 through 192.

Table 3 Energy Model for Customer 904468

R-Square		0.47
Number of Participants		1
Time Period		1/1989 - 10/1993
Number of Observations		36

Variable	Coefficient	t-Statistic
Intercept	37,518.59	21.71
Lighting savings estimate	-1.48	1.84
Cooling Degree Days	1,073.69	4.28
Heating Degree Days	102.55	1.61

All of the ANCOVA models achieved high R-squares and t-statistics for the savings estimate. Nevertheless, we also discovered that these “good” models needed to also have regression corrections made. These corrections found significant differences in the realization rates achieved for the savings estimates, proving the importance of this type of examination.

Conclusions

We have seen how useful analysis of covariance (ANCOVA) can be in DSM evaluations using billing analysis. This regression type can be an invaluable tool to obtain tight fitting models, even with large DSM participants, the hardest category for performing billing analysis. In fact, ANCOVA is most important to the performance of billing analysis for large C&I customers. ANCOVA controls for differences between customers. This can control for the great amount of heterogeneity found in this customer class. This may allow for regression-based DSM evaluation where models may not have previously been able to be fitted. It will also greatly reduce the potential of model biasing problems created by heteroscedasticity.

ANCOVA, however, does not automatically solve all potential modeling problems. Our regression diagnostics provided evidence that further corrections for heteroscedasticity and autocorrelation still had to be made in the DSM billing analysis of large C&I customers. Model corrections were made for these problems and significantly different findings were obtained. These corrected models are the proper specification for these customers' billing analyses.

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Published in the *Proceedings of the 1995 Energy Program Evaluation Conference*,
Pages 433 – 439.