Quantifying Savings from Comparative Usage Programs: Are the Differences Reconcilable?

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ABSTRACT

Various utilities are considering fielding "comparative usage programs" through which a utility uses energy reports to provide information to its residential customers on their energy use as compared to usage of similar customers. However, utilities considering whether to start a comparative usage program for their customers need information for answering some basic questions. How much savings can be achieved? How can savings be measured and verified? How will customers react to receiving the reports? This paper addresses these issues by comparing and contrasting methods and results from several different studies of data from the first large-scale implementation of a comparative usage program. It is intended to contribute to providing information for drawing on in considering implementation of a comparative usage program.

Introduction and Overview

Various utilities have been or are considering fielding "comparative usage programs" through which a utility provides information to its residential customers on how their energy use compares to usage of similar residences. In California, legislation (SB 488) was passed that requires electric and gas utilities in the state to adopt pilot programs to use either billing statements or separate mailings to disclose information to their residential customers that shows how the energy used by the particular customer compares to energy use of similar customers in the area.

Although savings estimates for comparative usage programs have been reported, how best to quantify the savings from such programs is still an open topic for research. Because large numbers of customers are targeted in a comparative usage program, there can be significant differences in estimates of aggregate savings depending on where savings lie within this range. Uncertainty measuring savings from a comparative usage program brings into question estimates of aggregate savings from the program.

This paper addresses the issue of quantifying savings for comparative usage programs by comparing and contrasting the methods and results from several different studies of data from the Home Electricity Reports Program, a pilot comparative usage program fielded by the Sacramento Municipal Utility District (SMUD). Because SMUD's program was the first large-scale implementation of a comparative usage program, there have been several studies of its impacts, including ADM (2009), Summit Blue (2009), Ayres Raseman and Shih (2009), Costa and Khan (2010), and Navigant Consulting (2011)[1]. All of these studies analyzed customer billing data to estimate kWh savings impacts. Because these studies all addressed a program of a particular utility, there are no differences across utilities that need to be controlled for in comparing methods of analysis and results.

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[1] The ADM study was an evaluation of the program commissioned by SMUD. The studies by Summit Blue and Navigant were commissioned by OPOWER. The studies by Ayres Raseman and Shih and by Costa and Khan were academic-based studies using data supplied by SMUD and augmented by independent data collection.

Selection of Customers for Program

The Home Electricity Report Program was a pilot program set up by SMUD and its implementation contractor (then named Positive Energy, now renamed OPOWER). The program had both treatment and control groups to allow scientifically valid impact evaluation to be carried out. Households for the program were selected from among census tracts in SMUD's service territory that were geo-codable and that had a high density of single-family homes with addresses that could be verified with the county assessor's office. For the Census tracts that met these conditions, additional criteria were applied to identify customers that would be eligible for inclusion in the study as either a test or control site. These criteria included

- Customer had to have a current, active account with SMUD.
- Customer's residence had to be on one of the primary meter read cycles for that census tract.
- Residence had to be a single family house, not an apartment building.
- Square footage of the house had to be between 250 and 99,998.
- First bill date for customer had to be at least 12 months prior to the start of the pilot program.

Approximately 84,000 residential customers were selected by applying these criteria.

Groups of contiguous census blocks (containing 50-200 houses) were randomly assigned either to a treatment group (that would receive the reports) or to a control group. The process was to first randomly assign a census "block batch" of five contiguous census blocks to the treatment group and then randomly assign a contiguous census "block batch" to the control group. This process continued until approximately 35,000 customers had been assigned to the treatment group and 35,000 customers had been assigned to the control group. The remaining census blocks and 14,000 customers were then also assigned to the control group.

Households in the treatment group were assigned to two groups, one to receive reports monthly and the other quarterly. The assignment was based on average daily kWh usage in the year prior the program. Approximately 25,000 households with higher energy usage (above 21.86 kWh per day) were assigned to receive reports monthly. About 10,000 households with lower energy usage were assigned to receive reports quarterly.

Mailing of reports to customers in the program began in April 2008 with reports being mailed to customers in the monthly group; mailings to customers in the quarterly group began May 2008.

Comparability of Treatment and Control Groups

The block batch method that was used to assign households to the treatment or control groups made the program a quasi-experiment rather than a truly randomized experiment. That is, the method of assigning households to groups was not strictly random. An important question therefore was whether there were any initial pre-treatment between-group differences that made the treatment and control groups substantively different.

Table 1 shows differences in some characteristics between the groups prior to the program. Because of the large sample sizes, the differences are statistically significant. However, the differences are small in magnitude and therefore have little substantive ramifications. In their study, Ayres Raseman and Shih (2009) also examined pre-treatment differences in energy use between the treatment and control groups after controlling for house characteristics, household demographics, and weather conditions. It was their conclusion that there was no systematic difference in energy usage between the groups after controlling for these factors.

Table 1. Differences in Characteristics between Treatment and Control Groups
Prior to Home Electricity Report Program

Household Characteristic	Treatment Group Mean	Control Group Mean	T-C Difference
Age in Years	36.7	38.0	-1.37
Square Feet	1,724	1,737	-13.5
% Electric Accounts	26.05	24.53	1.5
kWh per Day	30.65	31.02	-0.37

Comparison of Estimates for First-Year kWh Savings

The studies by ADM, by Ayres Raseman and Shih and by Summit Blue all used regression analyses of customer billing data to determine kWh savings attributable to the program. The estimates for kWh savings (both absolute and percentage-wise) from these three studies are reported in Table 2.

Table 2. Results from Regression Analyses of Savings Impacts from First Year of Program

Study	Annual Average kWh Savings per Household	Savings Percentage
ADM (2009)	211 kWh	1.90%
Summit Blue (2009)	241 kWh	2.13%
Ayres Raseman & Shih (2009)	233 kWh	2.10%

Another method of estimating the kWh savings effects from the Home Electricity Report Program is to use a difference-in-differences approach. This approach (as well as the regression-based approach) was used in the Summit Blue (2009) and Navigant (2011) studies. In the Summit Blue study, a difference-in-differences analysis conducted for program year 1 provided an estimate of average annual savings of 257 kWh (a savings of 2.2 percent).

For SMUD, the utility whose program is discussed here, weather conditions are important in determining the energy use of its residential customers. However, the difference-in-differences approach does not explicitly incorporate adjustments for changes in weather. The implicit assumption for the difference-in-differences analysis is that a change in energy use in response to a change in weather conditions would be the same for the control group and the treatment group in the absence of the program. (In the econometric literature (e.g., see Cameron and Trivedi 2005), this is termed the "common trends" assumption.) If this assumption holds, then the change in energy usage of the control group in response to a change in weather conditions can be applied to predict what the (counterfactual) energy use of the treatment group would have been under the changed weather conditions in the absence of the program. This allows the difference between actual post-treatment energy use of the treatment group and the counterfactual predicted energy use to be calculated as the savings attributable to the program.

On the other hand, if there are substantial differences between the treatment and control groups in how their energy use responds to changes in weather conditions, applying the difference in differences analysis becomes more problematic. The change in energy use for the control group is no longer a good predictor for the counterfactual energy use of the treatment group.

Comparison of Approaches for Regression Analysis

Regression analysis is more robust than difference-in-differences analysis as an approach to examining the impacts of the program. A regression approach allows for specific control in quantifying the effects of weather in that weather variables can be explicitly entered as explanatory variables in the regression equation. Other variables can also be added to quantify the effects of different customer characteristics on their responses to receiving Home Electricity Reports.

The results reported in Table 2 were all developed by applying a variant of panel data regression analysis to billing data for the customers in the treatment and control groups of the Home Electricity Report Program. The billing data spanned 24 months from April 2007 to March 2009, thus covering 12 months prior to the program (April 2007 through March 2008) and 12 months during the first year of the program (April 2008 through March 2009).

The ADM and Summit Blue studies used a similar "fixed-effects" specification for the panel model in their studies.[2] The purpose of this specification is to control for those determinants of a household's electricity use that are constant over time. The basic idea underlying this specification is that each household acts as its own control, both for household characteristics that are easily measured (like house size and age) and for characteristics more difficult to measure (like interest in conservation, etc.) Time-varying variables are handled by measuring and putting them as covariates in a "fixed effects" regression model.

Conceptually, a "fixed effects" regression analysis involves applying a least squares dummy variable (LSDV) covariance estimate procedure. In this approach, as described in Allison (2006), a binary dummy variable is created for each household in the sample, with the variable assigned a value of 1 for each observation that is associated with the household and a value of 0 for each observation that is not. The full set of these dummy variables is included in the regression analysis. In effect, the equation estimated contains a unique constant term for each household that captures the effects of all the determinants of that household's electricity use that are constant over time. This approach automatically controls for differences among households that influence the average level of consumption across households. The specification of customer-specific effects allows the regression model to capture much of the baseline differences across households while obtaining reliable estimates of the treatment effect.

In practice, the large number of households in the billing database for the Home Electricity Report Program precluded an analysis where an explicit dummy variable could be created for each household. The computational requirement in estimating coefficients for all the dummy variables would have been burdensome for the large sample. Accordingly, the estimation in the ADM and Summit Blue studies was accomplished using a mean deviation method that is described in Allison (2006). ADM implemented this procedure using PROC GLM in SAS, with household id being used as a variable in an ABSORB statement. Summit Blue implemented the procedure by constructing the mean-deviation variables and running an ordinary regression on the constructed variables.[3]

Analysis of Effects of Reports on Weather-Related Savings

Weather conditions are important in affecting electricity usage of SMUD residential customers, particularly in affecting their use of air conditioning during the summer. The panel data regression

[2] In the study by Ayres Raseman and Shih, an approach was used whereby multiple variables were entered as control variables in the regression.

[3] The procedure for the mean deviation approach is as follows. For each customer, means over time are first computed for each time-varying variable (both response and predictor variables). The customer-specific means are then subtracted from the observed values of each variable for that customer. The resulting variables are then used in the regression analysis.

models in the ADM and Summit Blue studies were specified to enable measuring the impact that receiving a Home Electricity Report would have on the coefficients measuring responsiveness to changes in weather conditions (both heating and cooling).[4] However, the studies differed in how weather conditions were measured.

In the Summit Blue study, heating and cooling degree days were used as the variables measuring weather conditions. However, in the ADM study, heating and cooling degree-hours were used rather than degree-days.[5] ADM used degree-hours because they better represent the effects of weather conditions on energy use, particularly for cooling. Cooling a house is more sensitive to hourly rather than daily temperatures. Cooling degree hours calculated using hourly temperatures therefore provide a better measurement of the actual cooling load as compared to cooling degree days calculated on the basis of average daily temperature. ADM calculated values of the degree-hour variables for each customer that matched the periods of time covered in the billing records for that customer.

Decomposing the total savings estimated in the ADM and Summit Blue studies between weather-related and non-weather-related influences showed that weather-related savings accounted for about three-fourths of average annual savings per customer estimated in the ADM study and for about half of savings in the Summit Blue study. However, when the models from the two studies are used to determine how savings for the first year of the program were distributed by season, the results are fairly similar.

For each model, the general equation for determining savings is as follows:

$$AAES = \alpha_0 + \alpha_1 HWV + \alpha_2 CWV$$

where AAES is annual average electricity savings, HWV and CVW are weather-related variables (HWV for heating, CWV for cooling), and α_0, α_1, and α_2 are coefficients determined through the regression analysis. HWV and CWV were measured as degree hours for the ADM study and as degree days for the Summit Blue study. For each model, weather data appropriate for that model for the year April 2008 through March 2009 were used to estimate savings. Savings were determined for different seasons of the year according to the values of the heating and cooling variables occurring in those seasons. Table 3 shows the results of this exercise for the two models.

Table 3 shows that the two regression models give fairly comparable estimates for savings when weather data over the same year are used to derive the estimates. The average annual savings reported for the ADM model in Table 3 differs from the value given in Table 1 because of a difference in the year for which the weather data are taken. Weather data for April 2007 through March 2008 (pre-treatment year) were used to derive the estimate in Table 1, while weather data for April 2008 through March 2009 (program year 1) were used to derive the estimate in Table 3. Degree hours for both cooling and heating were higher for program year 1 than for the pre-treatment year, increasing energy use and thereby also savings.

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[4] In the Ayres Raseman and Shih study, weather variables (heating and cooling degree days) were entered into the regression analysis as control variables. The regression model for the Ayres Raseman and Shih study was not specified so that the impact of the Home Electricity Reports on weather responsiveness could be estimated.

[5] Huang et al. (1987) compared degree-hours computed from hourly temperature data with degree-hours computed by the common practice of multiplying the degree-days by 24 h in a day. For 45 locations across the United States, annual degree-hours computed from hourly data were always higher than the number computed from daily data. The greatest differences were found in mild, arid climates with large diurnal temperature swings. Sacramento's climate is mild with noticeable diurnal temperature swings.

Table 3. Comparison of Seasonal Distribution of Annual Savings as Estimated with Results from ADM and Summit Blue Regression Models

Season*	ADM Model	Summit Blue Model
Summer	85.7	86.9
Winter	77.5	89.1
Shoulder	62.8	62.2
Average annual savings	226.0	238.2

*Summer season includes June, July, August, September. Winter season includes December, January, February, March. Shoulder months are April, May, October, November.

Analyses of Impacts for Subgroups

The various studies reported findings on the effects of the Home Electricity Reports on subgroups of customers within the treatment group.

The ADM study found the following effects of the Home Electricity Reports when the regression analysis was applied to particular subgroups of treatment households.

- Households with swimming pools had average annual savings of 363 kWh, a savings of 2.4 percent.
- Households in houses built between 1993 and 2001 had annual savings of 294 kWh (2.4 percent), while those in houses built before 1978 had annual savings of 196 kWh (1.9 percent).
- Households residing in smaller sized houses (defined as 1,600 square feet or less) had annual savings of 195 kWh (2.0 percent). Households in larger houses (defined as greater than 1,600 square feet) had annual savings of 183 kWh (1.4 percent).

The Ayres Raseman and Shih study showed that customers with high electricity usage and receiving monthly reports saved 2.35 percent, while those customers with lower electricity usage and receiving quarterly reports saved 1.7 percent. However, these estimates do not provide direct evidence on the particular effects of monthly reports *versus* quarterly reports because those effects are confounded with the level of electricity usage. That is, monthly reports went only to higher users and quarterly reports only to lower users.

In their study of data from the SMUD program, Costa and Kahn showed that a single savings value estimated over the entire population of information recipients obscures significant differences in the responsiveness of different types of households to the conservation message the information provides. In particular, their study provided estimates showing that registered Democrats who give to environmental organizations and live near other liberals reduced their electricity usage by 3 percent. For liberals who started out as heavier-than-average users, the reduction was almost 6 percent. Republicans who lived in conservative neighborhoods and had no record of giving to environmental organizations increased energy usage by 1 percent.

The results of subgroup analyses from these various studies show that estimates of a program average savings value depend on the distribution of households across subgroups within the treatment population. An average savings determined from a program for one utility therefore may not apply to a program for another utility that has a different distribution of households across subgroups.

Survey Findings on Effectiveness of Home Electricity Reports

To complement the quantitative analysis of the savings induced by the Home Electricity Reports, interviews were conducted with 78 SMUD households that had received the reports and that had been seen in the quantitative analysis to have been substantial energy savers during the first year of the pilot program. Almost all of the households surveyed (96 percent) remembered receiving the Home Electricity Reports. However, only a little more than half (55 percent) said they had made energy saving changes in response to the information contained in the Home Electricity Reports.

The majority of energy saving changes (57 percent) was behavioral in nature. The most common kinds of behavioral changes cited by these high energy savers included the following:

- Turning off lights in unoccupied rooms;
- Setting thermostats to save energy;
- Using alternatives to electrical power (e.g., washing dishes by hand) or not using electrical power when there were alternatives (e.g., sleeping without air conditioning, turning off the AC when away from home);
- Reducing air conditioning costs by using fans;
- Keeping out the sun's heat; and
- Unplugging stereos and other devices when not in use.

High energy savers who said they didn't achieve their savings by following any of the tips in the Home Electricity Reports were primarily households that had already implemented energy saving changes and said the reports did not provide them with any new ideas. Other customers either have a misperception or lack information about residential energy conservation. For example, renters might believe that saving energy requires significant financial investment which they are reluctant to make because they do not own the property. These are customers who could be targeted with more specific educational or behavioral information on energy saving tips.

Analysis of the survey data suggested that a higher proportion of households receiving Home Electricity Reports became involved in a SMUD rebate and / or financing program than did households in the control group. While this could have come about as a way to support the implementation of energy efficiency changes that may have been prompted by the information contained in the Home Electricity Reports, further research is required to verify the process by which this may have taken place.

Subjects for Further Research

There are several subjects for which further research on this comparative usage program will be useful. These subjects pertain to (1) persistence of savings and (2) effects of program on subgroups (market segments).

The estimates for kWh savings provided in the studies reviewed are based on the first year of the program. However, because the Home Electricity Report Program has now been in operation for several years, data are available for further research to develop a better understanding of how long the savings achieved with the reports persist. Initial estimates of savings persistence are provided in Navigant (2011), but SMUD itself is sponsoring further evaluation to examine the issue of persistence. Researchable issues include the following:

- Given that much of the first-year savings appeared to result from behavioral changes, does this behavior persist?
- As the program extends out over years, is there evidence that customers are responding not only through behavior but also through purchases of appliances that are more energy efficient?
- What can be determined about customer responsiveness to changes in weather conditions when electricity use is analyzed for a longer period of time for which there is greater variation in weather conditions? (For example, Navigant (2011) notes that the summer of 2010 was about 25 percent cooler than the summer of 2009.)

Besides further quantitative examination of savings resulting from the program, there is also opportunity for further qualitative research using survey data. The survey conducted by ADM (2009) was relatively small in scale, and a larger survey with a broader scope could provide data with which to examine more fully the processes and actions taken by customers who received Home Electricity Reports that resulted in them achieving savings. This would include using the results of market segmentation work that SMUD has undertaken to determine what different types of customers do with the information they get from the Home Electricity Reports and how their actions are reflected in savings.

There are also researchable issues about what interactions there are between Home Electricity Reports and other of SMUD's energy conservation programs (e.g., rebate and financing programs). Similarly, survey data could be used to examine what non-participants do to save energy on their own and in cooperation with SMUD rebate and financial assistance opportunities.

Conclusions

This paper compared and contrasted the methods and results from several different studies of one of the first comparative usage programs fielded by a utility. All of the studies reviewed determined savings through analysis of billing data.

Because of the importance of weather in determining electricity usage of the customers in the program, regression analysis allows a more robust approach to quantifying the savings achieved with the program. By contrast, a difference-in-differences approach does not allow for this control. Results from several regression analyses of the program showed savings for the first year of the program that were in the range of 1.9 to 2.13 percent.

The quantitative analysis of savings was complemented by a qualitative analysis of survey data collected from a sample of program participants. Almost all of the households surveyed remembered receiving the Home Electricity Reports. However, only a little more than half said they had made energy saving changes in response to the information contained in the Home Electricity Reports. The majority of energy saving changes was behavioral in nature.

Subjects for which further research on this comparative usage program will be useful pertain to (1) persistence of savings as the program progresses and (2) effects of program on different subgroups of customers (i.e., different market segments).

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