Bells, Whistles, and Common Sense: Billing Analysis of a Residential HVAC Rebate Program

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Billing analysis for impact evaluation has seen several innovations in recent years designed to improve the precision and reduce the bias of impact estimates. These innovations include

- incorporation of engineering models
- use of pooled time-series/cross-sectional data using monthly models
- more careful specification of appropriate comparison groups
- estimation of gross savings models with separate analysis to address free ridership or other net-to-gross factors

This paper presents a billing analysis of a residential HVAC rebate program, combining and refining these innovations. Features of the analysis include the following:

- The pooled time-series/cross-sectional load impact regression model accounts for first-order correlations of errors both across customers and across time, to reduce the potential for inflated estimates of precision.
- A comparison group is included in the pooled regression model for gross savings, to control for exogenous changes.
- Extensive attention is paid to developing appropriate diagnostic and screening methods for the complex pooled model.
- A three-option nested logit approach is applied to estimate free ridership, without requiring information on nonparticipant installation dates.

The emphasis of the analysis is on developing an informative, meaningful model that avoids identifiable biases and makes efficient use of the available information and methods.

INTRODUCTION

Recent years have seen numerous advances in methods for estimating net savings and free ridership. These advances include the use of pooled time series-cross-sectional billing analysis models (e.g., Schiffman 1994 and Megdal et al. 1995); and three-option nested logit models for free rider estimation (Train et. al 1994). The increasing sophistication of net savings estimation methods brings with it increasing challenges for developing meaningful model specifications and interpreting results. This paper describes an evaluation study that utilized and refined all of the above methods. The emphasis is on maintaining a sensible outlook and providing useful, credible information.

Program Description

Southern California Edison's 1994 Residential HVAC Rebate Program provides rebates for replacing existing central air conditioners with new, high-efficiency units, and for installing evaporative coolers in households that have central air conditioning. In 1994, there were 6202 customers who received central air conditioning rebates and 1624 customers who received evaporative cooler rebates. This paper focuses on the analysis of the evaporative cooler participants.

Overview

The impact analysis consisted of the following components

- estimation of a load impact regression model for gross savings

- identification of and adjustment for bias in the load impact regression model

- estimation of the free rider effect using a discrete-choice analysis

- calculation of net/tracking realization rate from the results of these three components.

The Methodology section describes the data sources used in the study, and the modeling and bias adjustment approaches. The application of these methods to develop the final realization rates, and additional investigations to corroborate the findings are presented in the Results section. General methodological lessons from the analysis are offered in the Conclusions.

METHODOLOGY

The data sources used in this study are introduced below. The analytic methods, which are dependent on the details of the available data, are then described. This section concludes with a discussion of the diagnostic procedures used both to screen for data anomalies and to confirm that the complex modeling had been implemented as intended.

Data Sources

The data used in this study were the following.

- **SCE's 1995 Residential Appliance Saturation Survey (RASS).** Data available from this survey included end uses present in the household, recent changes to end-use equipment, and the dates of such changes. By design, the RASS included a sample of 656 1994 evaporative cooler rebate program participants. Thus, the RASS served as the survey database for the impact evaluation.

- **Customer billing records from January 1993 through September 1995.** In addition to consumption data, the billing records identified the weather station for each customer.

- **Weather data.** The weather data were provide by SCE from their 23 weather stations. The data provided included daily average temperatures for each day in the study period, and average degree-days based on the period 1988 through 1995.

- **Tracking data.** The program tracking data identified the type of HVAC equipment installed by each customer, the installation date, and an estimate of annual energy and peak demand savings.

Load Impact Regression Model

The impact estimation approach was a pooled time series/ cross sectional regression model of billing data. That is, each customer at each time period (month) defined a different observation, in a single model. The model included both 1994 program participants and a group of nonparticipants. The nonparticipants included in the evaporative cooler models were customers who reported on the 1995 RASS that they had both central air conditioning and evaporative coolers. Evaporative cooler technology is not suitable for all climates or households. This restriction on the comparison group ensured that participants were compared with other customers for whom the measure would make sense.

For participants, the date of installation of the evaporative cooler was available from the tracking system. For nonparticipants, the installation date was known for central air conditioners, but not for evaporative coolers. The model was structured as if all customers in the comparison group had evaporative coolers in place as of the first time period in the analysis. A correction for possible bias resulting from this assumption was made subsequently, as discussed below.

The impact model fit was

$$y_{it} = \mu_i + \tau_t + \beta^{HT} f_{it}^{HT} + \beta_{NP}^{ACEV} (1 - P_i)^* f_{it}^{AC} \\ + \beta_P^{AC} P_i^* f_{it}^{AC} + \eta_P P_{it}^* f_{it}^{EV} + \varepsilon_{it}.$$

The terms in this model are the following.

- **the dependent usage variable y_{it} for customer i at period t**, in Wh per day

- **a fixed effect μ_i for each customer i**. These terms eliminate the first-order correlation in the pooled model among observations from the same customer at different times.

- **a fixed effect τ_t for each time period t**. These terms eliminate the first-order correlation in the pooled model among observations from the same time period, across different customers. The terms also control for exogenous time trends across the study period.

- **an engineering estimate f_{it}^{HT} of electric heating use for customer i at time period t.**

- **an engineering estimate f_{it}^{AC} of base central air conditioner use for customer i at time period t**, with different coefficients estimated for participants than for non-participants.

- **an engineering estimate f_{it}^{EV} of evaporative cooler use for customer i at time period t**, for participants only.
- **a cross-sectional participation dummy variable P_i,** interacted with the central air conditioning variable
- **a time-dependent participation dummy variable P_{it},** interacted with the evaporative cooler variable. This variable is zero until the time period t that customer i installed the evaporative cooler, and one thereafter.

The fixed effects μ_i and τ_t and the coefficients β^{HT}, β_{NP}^{ACEV}, β_P^{AC}, and η_P are coefficients estimated by the regression. The terms ε_{it} are random errors, assumed to be uncorrelated with each other and with the predictor variables.

The coefficients β^j are adjustment factors to the engineering estimates f^j. The coefficient η_p is the incremental effect of adding an evaporative cooler, as a fraction of the engineering estimate of evaporative cooler use. Thus, this coefficient isolates the impact of interest.

For a given customer and time period, the engineering estimates for central air conditioning and for the evaporative cooler are close. As a result, the model was not expected to be able to distinguish between the terms f^{AC} and f^{EV} for nonparticipants. However, the combined effect of these two terms should be well estimated. For this reason, only the central air term f^{AC} was included for nonparticipants. Its coefficient β^{ACEV} combines the effects β^{AC} and η that are separately estimated for participants. For participants, the term f^{EV} is zero in the summer of 1993, and becomes positive only after the participation date. Thus, the incremental effect η_p of adding the evaporative cooler to the existing central air conditioning system should be well determined for the participants.

Our modeling assumption is that all the nonparticipants included in the model had evaporative coolers in place as of the beginning of the study period. However, some fraction of these customers acquired their units during the study period. If we assumed this fraction to be the same as the fraction of participants who would have installed evaporative coolers on their own, we would interpret the impacts estimated by the model as net savings, with free ridership accounted for. However, equating these two fractions is not justified. Instead, our approach is to treat the savings estimated by the model as gross savings, but to make a separate, explicit correction to this gross savings estimate to account for the effect of nonparticipants adding evaporative coolers.

Model Bias

The gross savings estimated by the evaporative cooler model is biased downward because the nonparticipant group includes some customers who added evaporative coolers during the study period. The savings experienced by these customers is included in the estimated trend terms. As a result, the gross savings estimated for participants is biased downward. The proportion of such customers among the nonparticipants, and the approximate effect on the gross savings estimate, was estimated by analyzing 1990 and 1995 RASS data.

The modeling period ran from early 1993 through the summer of 1995, and excluded the summer of 1994. The effect on the impact estimate of a nonparticipants adding an evaporative cooler depends on the timing of the addition. For those who added the unit after the summer of 1993 and before the summer of 1995, the average contribution would be the full gross savings. For those who added before the summer of 1993 or after the summer of 1995, there would be no effect. For those who added sometime during the summer of 1993 or sometime during the summer of 1995, the contribution, averaged across the range of installation times, would be approximately one half of gross savings.

Thus, the proportional effect of nonparticipant installations is the proportion who installed units between the end of the summer of 1993 and the beginning of the summer of 1995, plus one-half the proportion who installed units during either summer. For simplicity, we estimate this combined proportion as the proportion I_{NP} who installed between the middle of the summer of 1993 and the middle of the summer of 1995.

This proportion is the estimated proportion of gross savings that was incorporated into the trend terms, rather than being reflected in the impact estimate. Thus, once the proportion I_{NP} is determined, the gross impact estimated by the model is multiplied by the factor $1/(1-I_{NP})$ as an adjustment for the bias.

The nonparticipant installation proportion I_{NP} can be estimated only roughly, as follows. The fraction of the total population that had evaporative coolers was obtained from the 1990 and 1995 RASS results. The difference between these two fractions is the fraction who installed units between 1990 and 1995. We multiplied this fraction by 2/5, and divided by the 1995 fraction, to get I_{NP}. That is, out of all customers who had evaporative coolers by the time of the 1995 survey, I_{NP} is the estimated fraction who installed the evaporative coolers during the two-year period from mid 1993 to mid 1995. Because the total number of units installed by the general population is much greater than the number installed through the program, it is reasonable to assume that this installation proportion applies to the program nonparticipants.

Free Rider Adjustment Factor

The inclusion of the nonparticipants in the model ensures that the effects of exogenous changes are accounted for. The bias adjustment accounts for nonparticipants who installed evaporative coolers during the study period. Not accounted for, however, is the extent to which participants would have installed evaporative coolers during 1994 without the program. That is, the billing analysis, with the bias adjustment, captures the gross effect of adding the evaporative cooler, and also incorporates measure installation and persistence, usage, participant snapback and participant spillover, but does not account for free ridership.

To obtain net savings, the adjusted savings coefficient $\eta_p / (1-I_{NP})$ must be multiplied by a ‘‘net-to-gross’’ factor that accounts for free ridership. This factor is one minus the proportion of free riders among the evaporative cooler participants.

To develop the free rider adjustment factor, we followed the three-option nested logit approach of Train, et al. (1994). The analysis involves fitting a 2-stage logistic regression model that distinguishes three possible choices

(1) Participate by installing an evaporative cooler

(2) Install an evaporative cooler without participating, and

(3) Do not install an evaporative cooler, and do not participate.

In other applications of this method, the three choices are all based on actions taken during the program year. That is, we compare customers who choose to participate, install but not participate, or do neither, all within the same time period. For this study, however, we cannot identify which nonparticipants installed evaporative coolers during 1994. We get around this problem by implementing the three-option approach in a way that does not require that information. Specifically, we define installation to mean ‘‘installed by the time of the 1995 RASS’’. Participation means ‘‘participated by installing an evaporative cooler during 1994.’’

Defining the installation time period (‘‘by the 1995 RASS’’) to be different from the participation time period (‘‘during 1994’’) at first may appear illogical. However, the three-option discrete choice method can provide a valid estimate of the free rider proportion even with these inconsistent timing definitions, as explained further below.

The three-option nested logit analysis determines

- the proportion p_I of customers who have implemented the measure (by 1995)
- the proportion p_0 who would have implemented the measure (by 1995) in the absence of the (1994) program
- the proportion p_P who implemented (by 1995) by participating (in 1994).

The net-to-gross ratio due to free ridership is then calculated as

$$F = (p_I - p_0)/p_P.$$

The numerator of the free rider estimate is the difference in installations attributable to the 1994 program. Even though the installations counted in both p_I and p_0 include installations before and after 1994, this difference is still the amount that can be credited to the 1994 program. Thus, the analysis estimates the incremental evaporative cooler installations attributable to the 1994 program, as a fraction of the number of units installed under that program.

The choice model requires inclusion of nonparticipants with and without evaporative coolers. However, for many customers with this equipment, it would not make sense to install it. To limit the domain of this analysis to customers for whom the measure could be appropriate, we restricted our attention to survey respondents who both had central air conditioning and lived in the weather station region from which the largest portion of the evaporative cooler participants came.

Self-Selection

Self-selection bias is a general concern for impact regression models. The basis of the concern is that customers who choose to participate in the program may tend to have changes in consumption that are different from those of customers who choose not to participate, apart from the effects of the program measures themselves. This issue is of particular concern in net impact regression models, where the comparison group implicitly controls for the changes, including natural measure adoption, that would have taken place in the absence of the program. In principle, there is a potential for self-selection bias in a gross impact regression model also. However, we consider this threat to be much less than in the case where the model estimates net savings. Since the evaporative cooler model estimates gross savings, we do not include self-selection correction terms.

Diagnostics

Regression diagnostics are an important component of model development for energy impact analysis using billing data.

Ideally, the results obtained from the model should not be highly sensitive to the inclusion or exclusion of a few observations. If such sensitivity is observed, the results are questionable, even if the estimated standard errors are small for the fit with a particular set of included points.

In cross-sectional impact models, a particularly useful diagnostic is DFBETAs. For a particular model coefficient, this diagnostic indicates how much effect each observation has on the value of that coefficient. Examining the DFBETAs statistics for the coefficient corresponding to the program realization rate indicates the robustness of the estimated realization rate. A large value of this coefficient's DFBETA for an observation indicates that the realization rate is changed considerably depending on whether that observation is included or not. Observations with high DFBETAs tend to be those with high leverage, and with y values that would not lie on the line that would be estimated from all the other points. High leverage means that the observation has extreme values of a critical combination of the predictor variables.

Applying standard diagnostic to the pooled time series/cross-sectional model is computationally difficult, because of the size of the estimation calculation. In addition, given the construction of the regression data set, it is unlikely that individual customer-month observations would be extreme in terms of predictor variables. For the majority of the predictors, the values are the same for each month for a given customer. For those predictors that vary with degree-days, the variation is similar for many customers.

Based on these considerations, our approach to exploring the robustness of the fitted model was to look for cross-sectional indicators of high-leverage customers. Our primary focus was on the variable f^{AC}. The coefficients associated with this variable, by itself and interacted with dummies, provide the estimates of base UEC and incremental effects of replacement, addition, and participation. By its construction, the variable f^{AC} is not strongly correlated with other variables in the pooled model. As a result, we can get a reasonable sense of its influence by looking at values of f^{AC} directly. Because the variation in f^{AC} is systematic across customers, we looked only at the annual estimate—i.e., the 1994 12-month total of the variable—for each customer.

A first concern was that a customer with extremely high predicted annual air conditioning would have high leverage. That is, if this customer's cooling degree-day response was substantially higher or lower than the engineering estimate indicated, all the coefficients related to f^{AC} could be strongly affected by the inclusion or exclusion of this customer. A related concern was that some of the high predicted values of f^{AC} resulted from data errors. The engineering estimate is basically the product of cooling degree-days and floorspace, with small adjustments for house characteristics. If the floorspace was incorrectly reported on the survey, the resulting estimates could be substantially off for a customer, for all months.

To test for erroneous reporting of square footage, we compared reported floorspace with the reported number of rooms in the house. We then applied successively tighter screens to the data set, eliminating customers if their average floorspace per room exceeded successively lower thresholds. The final analysis excluded customers with more than 1,000 square feet per room (four customers).

We did not screen for customers with consistently high consumption. If this consumption was not related to degree-days, or to the presence of other end-uses, the generally high consumption level would be accounted for in the customer's fixed-effect term, and would not affect the other estimates. If the high consumption was related to cooling degree-days, we hoped to capture any anomalies with the floorspace screen. However, we did screen out individual customer-month observations that were unusually high, as discussed further below.

An additional screen on the evaporative cooler model was to restrict the nonparticipants to those who had both evaporative coolers and central air conditioners at the time of the 1995 RASS. These restrictions were implemented to avoid comparing the 1994 participants with customers for whom evaporative coolers would not even have made sense, for either climate or technology reasons.

The date of installation was not reported on the survey, but was taken from the tracking system. Because of concern that the actual installation date might differ from the tracking date by a few months, we eliminated observations during the summer of 1994 (June through September read date) from the analysis. This step effectively meant that the air conditioning terms were estimated from the summers of 1993 and 1995. For nonparticipants, the single air conditioning coefficient is estimated across those two summers. For participants, the central air coefficient is determined by the summer of 1993, while the savings is determined by the comparison of the summer of 1995 to the summer of 1993.

We made a variety of data checks, including the following.

- Verified that all customers coded as evaporative cooler participants reported on the RASS that they had an evaporative cooler.
- Plotted the engineering estimates f^{AC} against f^{EV} to confirm that these estimates were close to one another, as they should be if the engineering algorithms have been properly implemented.

- Plotted f^{AC} and f^{EV} against time for participants and nonparticipants, to confirm that these had the expected patterns.

- Plotted consumption against f^{AC} to identify extreme values.

Based on the last of these checks, we excluded as anomalously extreme all observations with consumption greater than 60 kWh/day. We also limited the analysis to customers who reported both central air conditioning and evaporative coolers on the 1995 RASS; and to those who had not also acquired a new central air conditioner or multiple evaporative coolers during the study period. The final analysis data set included 447 participants and 215 nonparticipants.

RESULTS

The coefficients from fitting the evaporative cooler model after the screening described above are shown in Table 1. The evaporative cooler model provides separate estimates of the following:

- nonparticipant combined central air conditioning and evaporative cooler use

- participant base central air conditioning use

- the incremental effect of evaporative coolers for participants.

The coefficient of -0.127 on the evaporative cooler variable f^{EV} means that the savings associated with installing the evaporative cooler was 12.7 percent of the engineering estimate of usage. That savings is an average of 392 kWh/year for the customers included in the regression sample. This estimate is only 32 percent of the tracking estimate of savings, which averaged 1236 kWh/year for these customers. Similarly low estimates in the early stages of the modeling prompted an investigation both of the data and model, and of other estimates of evaporative cooler savings.

Evidence of Low Cooling Usage Among Evaporative Cooler Households

One factor that may contribute to low savings is low base usage. For the evaporative cooler customers, the air conditioning usage is estimated at 27 percent of the engineering central air conditioning estimate for nonparticipants (coefficient of $(1-P_i) * f_{it}^{AC}$) and at 42 percent of this estimate for participants prior to participating (coefficient of $P_i * f_{it}^{AC}$). The nonparticipants are expected to have cooling loads uniformly lower than what the engineering model of central air conditioning would predict, because they also had evaporative coolers. The estimate of 42 percent for participants prior to participating is also low compared to that observed for central air conditioning in the general population (96 percent). This difference in base usage, relative to the engineering estimates, is one reason the central air and evaporative cooler participants were modeled separately.

This suggestion of low usage is borne out by the behavior reported on the RASS. Thirty-one percent of evaporative cooler participants, and 27 percent of evaporative cooler owners who were not 1994 participants, reported using their air conditioners only rarely. By contrast, only 13 percent of the general population reported rare cooling use.

Support for the Low Savings Estimate Based on Simple and Robust Analyses

As an alternative analysis, we conducted a simple robust comparison. For each customer with evaporative coolers and central air conditioning, we computed the difference between 1995 and 1993 consumption, separately for each month. The difference between the participant and nonparticipant change, totaled over the summer months (June through September) provides an alternate estimate of the savings associated with participation. (Table 2.) The result was an estimated savings of 311 kWh/year comparing the median summer changes, or 477 kWh/year comparing the means. These estimates correspond to gross realization rates of 25 and 39 percent, respectively.

Support for Low Savings Estimate Based on Other Sources

Other studies have reported savings for evaporative coolers on the order of 60 percent. (See, for example, Hoeschele 1994 and references there.) However, these results were found in field tests of equipment installed and used. Hoeschele reported that 3 of the 6 monitored units intended for that study were not used at all during the summer of monitoring. Thus, the extent to which cooling equipment is used appears to be an important factor affecting savings, as suggested above.

The evaluation of Edison's 1990–91 Direct Assistance Program found average savings of 464 kWh per year for installation of evaporative coolers and energy-efficient heat pumps (Barakat and Chamberlin, 1993). This estimate was 27 percent of the original projection, 1755 kWh/year. While these results are for a low-income population, they do indicate that the tracking estimate for the HVAC Rebate program may be a substantial overestimate.

Table 1. *Coefficients of Estimated Evaporative Cooler Model*

Description	Variable	Coefficient	t-value	p-value
Base CAC Est * Non Part Dummy	$(1\text{-}P_i)^* f_{it}^{AC}$	0.270	14.64	0.0001
Base CAC Est * Part Dummy	$P_i * f_{it}^{AC}$	0.420	32.27	0.0001
New Evap Est * Part Dummy	$P_{it} * f_{it}^{EV}$	−0.127	−6.81	0.0001
engineer est of heater consumption	f_{it}^{HT}	113	14.09	0.0001
Customer Fixed Effects*	i		48.7	0.0001
January 1993 Dummy		−5753	−1.38	0.1679
February 1993 Dummy		−7871	−18.73	0.0001
March 1993 Dummy		−8559	−21.36	0.0001
April 1993 Dummy		−9025	−22.14	0.0001
May 1993 Dummy		−8209	−20.52	0.0001
June 1993 Dummy		−6466	−16.4	0.0001
July 1993 Dummy		−1931	−4.58	0.0001
August 1993 Dummy		−1659	−3.96	0.0001
September 1993 Dummy		−1491	−3.59	0.0003
October 1993 Dummy		−5733	−14.5	0.0001
November 1993 Dummy		−8050	−20.33	0.0001
December 1993 Dummy		−7140	−17.97	0.0001
January 1994 Dummy		−6647	−16.77	0.0001
February 1994 Dummy		−7847	−19.62	0.0001
March 1994 Dummy		−8336	−21.49	0.0001
April 1994 Dummy		−8689	−22.33	0.0001
May 1994 Dummy		−8125	−21.27	0.0001
October 1994 Dummy		−6401	−17.53	0.0001
November 1994 Dummy		−8195	−21.42	0.0001
December 1994 Dummy		−6734	−17.31	0.0001
January 1995 Dummy		−6144	−15.89	0.0001
February 1995 Dummy		−8029	−20.78	0.0001
March 1995 Dummy		−8519	−22.52	0.0001
April 1995 Dummy		−8969	−23.26	0.0001
May 1995 Dummy		−8864	−23.73	0.0001
June 1995 Dummy		−7868	−21.82	0.0001
July 1995 Dummy		−5598	−15.14	0.0001
August 1995 Dummy		−2527	−6.42	0.0001
September 1995 Dummy		0	0	0

*F-value shown in place of t-value.

Table 2. *Comparison of Consumption Change from 1993 to 1995 for Evaporative Cooler Participants and Comparison Group (kWh)*

	Medians			Means		
	Participants	Non-participants	Difference	Participants	Non-participants	Difference
June	− 61.1	− 12.9	− 48.2	− 115.2	− 39.7	− 75.4
July	− 240.8	− 43.0	− 197.8	− 287.6	− 63.8	− 223.8
August	− 71.2	72.2	− 143.4	− 21.5	142.2	− 163.7
September	− 20.8	59.0	− 79.7	4.4	90.9	− 86.4
Summer Total	− 293.0	18.0	− 311.0	− 362.8	114.4	− 477.2

Model Bias

Following the methods described above, the gross savings estimate from the regression analysis was adjusted for the estimated proportion I_{NP} of nonparticipants who installed their evaporative coolers during the study period. The analysis of the 1990 and 1995 RASS surveys indicated that 8.8 percent of the nonparticipants in the model installed their evaporative coolers between mid 1993 and mid 1995. Based on this analysis, the gross savings estimate from the regression was increased by a factor of 1.096 (= 1/(1-0.088)). With this adjustment, gross savings is estimated at 14.0 percent of the engineering estimate of base central air conditioning use, or 35 percent of the tracking estimate. Even with this adjustment, then, the gross savings estimate is still low, compared with the tracking estimate.

Calculation of Savings Estimates

The regression equation and bias adjustment presented above provide an estimate of program savings as a fraction of a base estimate of air conditioner use. To translate these fractions into energy savings, they are multiplied by the average annual base energy use for the corresponding regression sample subgroup. The result is annual energy savings per customer, for the sample subgroup. The annual base energy is computed by evaluating the engineering models using long-run normal degree-days. Thus, the energy savings estimate is for long-run normal conditions.

The gross savings estimate is then multiplied by the free rider adjustment factor F. This factor was calculated by the three-option nested logit method described above. The resulting net-to-gross ratio was estimated as 0.54, with a standard error of 0.08. With the free rider adjustment, net savings is estimated as 233 kWh/year per participant.

To relate the net savings estimate for the regression sample to the program tracking information, the sample average net energy savings derived from the regression is divided by the average savings estimate from the tracking system for the same set of customers. This ratio is the realization rate (net savings to tracking estimate). This calculation yielded a realization rate of 18.8 percent for evaporative coolers, with a standard error of 4.1 percentage points.

CONCLUSIONS

The experience from this study underscores several points regarding the use of pooled time series/cross-sectional models for impact estimation. First is that diagnostics for such models are complex, but crucial. The diagnostics we applied included cross-sectional screening for anomalous customers, as well as screens on extreme values of individual observations, guided by a variety of data plots. In general, diagnostic and screening steps should include

- Confirmation that the pooled data set has been properly constructed, with time-dependent variables correctly computed. These checks involve inspection of plots and univariate statistics.

- Identification of high leverage points, and testing of model sensitivity to screens on potentially high leverage points. Dimensions for exploring high leverage points can be determined by consideration of the model structure. Once these dimensions are determined, plots and univariate statistics can be applied.

A second point regarding the use of pooled models is the importance of the time-period fixed-effect dummies (τ_t in our model). These terms were strongly significant in our model (p-values of 0.0001 in Table 1-1), indicating the potential for substantial omitted variable bias if they are left out. Indeed, exclusion of these terms from the fitted model gave a savings estimate 64 percent higher than our final estimate.

A third point is the importance of including a comparison group, even if the pooled model is used to estimate gross rather than net savings. The comparison group is necessary to control for exogenous time trends across the study period. In this study, all 1994 participants were nonparticipants during the first summer (1993) and all were participants as of the last summer (1995). A model fit with only 1994 participants gave a negative savings estimate.

Another valuable refinement of existing methods is the use of the three-option nested logit approach for estimating the free rider rate, even when the implementation date is not available for nonparticipants. This approach has the potential to broaden the applicability of the method, and reduce the cost and complexity of data collection required for the logit modeling.

Finally, we emphasize the importance of investigating the reasonableness and plausibility of results from as many perspectives as possible.

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