Self-Reports and Market Transformation: A Compelling New Approach

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Abstract

Energy efficiency programs that are in place for multiple years move the entire market towards energy efficiency by making energy efficient equipment more desirable and available, even to those not participating. While market transformation effects should be credited to the program responsible for them, quantifying them in terms of energy savings is a challenging task. Pacific Gas and Electric Company (PG&E), together with Quantum Consulting (QC), recently completed a market transformation effects study of one of the largest energy efficiency incentives programs in the country, the Commercial Energy Efficiency Incentives (CEEI) Program. This paper explores the challenges, advantages and pitfalls of the methods we used to estimate the market transformation effects in terms of energy savings of the 1994 CEEI Program from 1994 to 1997.

Quantum Consulting implemented a self-report analysis, verified by a multi-year billing regression analysis to verify the self-report results. Survey data gathered in the PG&E service territory over a four-year period were analyzed and compared with out-of-state control groups to determine market transformation effects. PG&E service territory data regarding equipment adoptions were used to estimate total market effects. Similar data gathered in various out-of-state territories served as a market baseline, or estimate of natural conservation. Data regarding program awareness, influence, and the persistence of measures were used to quantify the dynamics of spillover, free-ridership, and persistence over the four-year window. These results were combined with estimates of the gross impact of measures to derive the final market transformation effects results.

Viable methods for measuring market transformation are of growing concern, and this paper will be of interest to utilities across the nation. Our approach is particularly compelling because of its ability to derive results in terms kWh savings. Also, incorporating the behaviors of spillover, free-ridership and persistence over time allows us greater precision in evaluating longer-term program effects.

1. Overview Of The Approach

The overall goal of PG&E's multi-year billing analysis study on their 1994 Commercial Lighting Program (the Study) is to estimate total net load impact over a four year period. This goal can be achieved by estimating gross load impact, the effects of persistence on gross load impact, free-ridership, spillover effects, and Market Effects over time. Net load impact estimation can then be decomposed into the following six intermediate objectives.

(1) Gross load impacts are estimated for the 1994 PG&E commercial lighting rebate population, using results from the 1994 evaluation.

(2) Gross load impacts are adjusted by the persistence of installed lighting measures.

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(3) Free Rider contribution are subtracted from gross load impacts.

(4) Participant spillover contributions are added to the gross load impacts.

(5) A second adjustment is made to the gross load impact due to natural conservation practices.

(6) Finally, nonparticipant market transformation effects are accounted for in gross load impact.

These six objectives are calculated and verified using a variety of analysis techniques which are discussed in the following sub-sections

1.1 An Integrated Approach

One of the keys to obtaining the greatest accuracy from any evaluation is an appropriate use of available data sources. The primary existing data sources utilized for the Study include:

- Participant and nonparticipant survey samples from the 1994 Commercial Lighting Evaluation;
- Nonparticipant and canvass survey samples collected as part of the 1995 and 1996 Commercial Lighting Evaluations;
- Program applications (paper files) and the participant tracking system (Marketing Decision Support System [MDSS]) database from 1994 through 1997;
- PG&E billing and weather data from 1993 through 1997; and,
- 1997 Statewide Market Effects Studies.

In addition to the existing primary data available, the 1994 participants and 1994 and 1995 nonparticipants are resurveyed to gather additional information.

1.2 Analysis Elements

This sub-section describes the six objectives used to estimate both the gross and net load impacts for the Multi-Year Study in further detail. The analysis approach illustrated in Exhibit 1 consists of five primary analysis segments: the engineering analysis, the gross billing analyses, the net billing analyses, the self-report analysis, and the market transformation effects analysis. These five segments are used to estimate and verify the six intermediate objectives introduced above. This integrated approach reduces a complicated problem into manageable components, while incorporating the comparative advantages of each method.

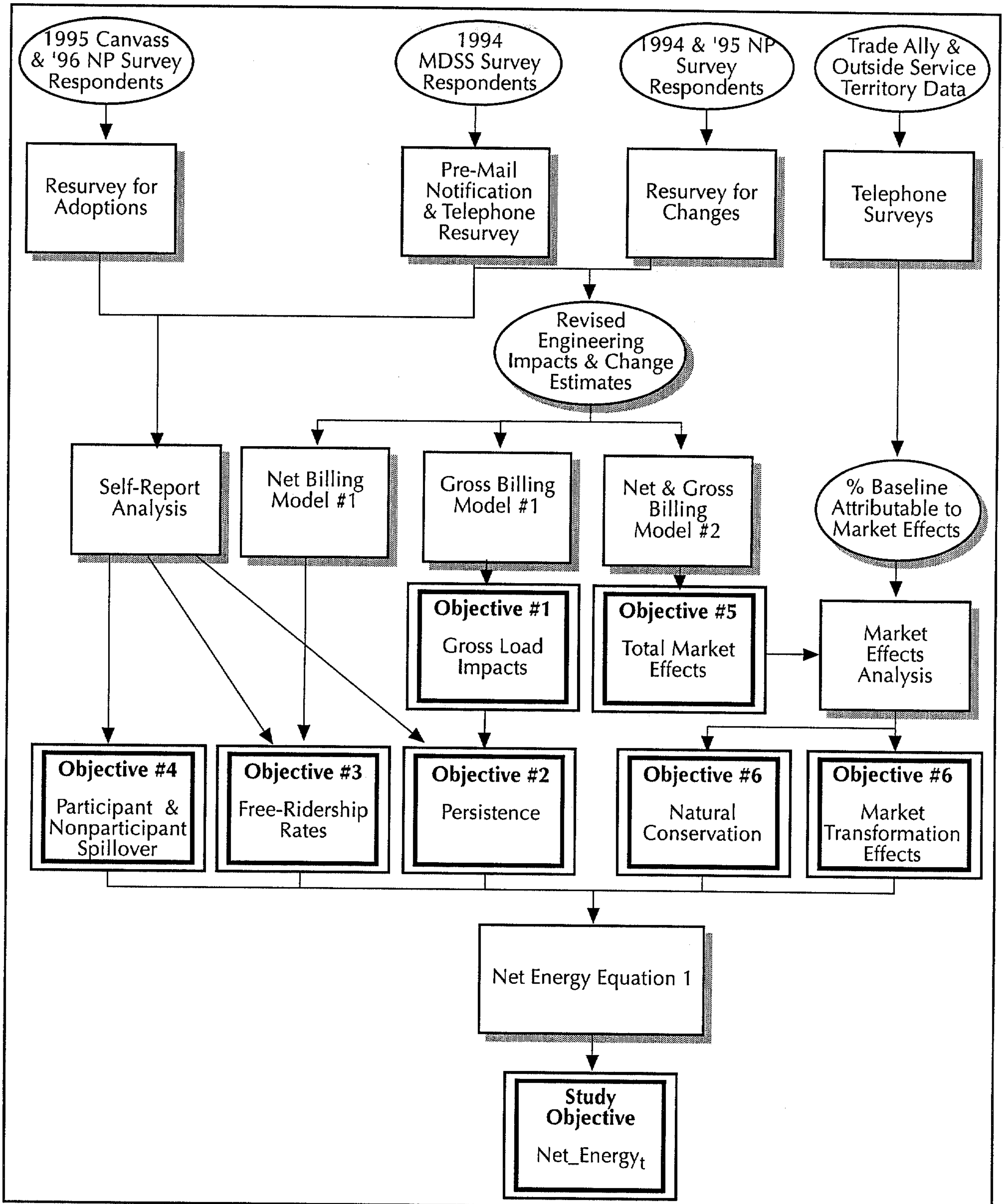

Figure 1. Overall Analysis Approach

Objective 1: Estimate Gross Load Impact

Gross engineering estimates of load impact are derived from the results of the 1994 Commercial Lighting Evaluation, which are based on the results of the gross billing analysis, discussed in *Section 3*.

Objective 2: Adjust for Persistence

Persistence rates are estimated through a self-report analysis of survey data, and verified using the gross billing analysis (gross model #1). Existing data from the 1994 and 1995 Commercial Lighting Evaluation, in addition to data collected from the re-surveying of participants, are used to support the analysis. The details surrounding the persistence estimates from the engineering analysis and the gross billing analysis are discussed in *Section 2* and *Section 3*, respectively.

Objective 3: Subtract Free-ridership

Estimates of free-ridership are expected to increase over time, because participants are more likely to have installed measures in the absence of the Program (that is, one component of free-ridership is *accelerated* adoption; as time progresses from the base installation year, acceleration rates drop off). Free-ridership is estimated using two analysis techniques: a self-report analysis (from data already gathered as part of the 1994 Evaluation) and a net billing analysis (Net Model #1). The approach for these two methods are described in the self-report and net billing sections (*Section 4* and *Section 3*, respectively).

Objective 4: Add Participant Spillover

Participant spillover estimates are re-calculated using existing data from the 1994 participant survey, and additional data gathered from the re-survey effort. Lighting Program participants are re-surveyed to determine if additional high efficiency technology adoptions have been made since they were last surveyed, and whether these adoptions were influenced by their participation in the Lighting Program. Data are collected for the new efficient technologies installed outside of the rebate programs, with adoption rates leveraged to the 1994 participant population. The approach for estimating participant spillover is described in the self-report analysis (*Section 2.4*).

Objective 5: Estimate Total Market Effects

Total Market Effects estimates are due, in part, to load impacts influenced by the Lighting Program. Total Market Effects can be described as consisting of two components: the Market Transformation Effects (i.e. those Effects that the Program has influenced), as well as natural occurring conservation among the nonparticipant comparison group had there been no Program. Total Market Effects are estimated using the gross and net billing analysis (Models #2). Existing data from the 1994 and 1995 Commercial Lighting Evaluation, as well as data from the re-survey efforts are used to support the analyses. The two approaches are described in the billing regression analysis section (*Section 3*).

Objective 6: Differentiate Between Natural Conservation and Market Transformation Effects

To determine the market penetration of the Program, Total Market Effects are disaggregated into two components: Market Transformation Effects and natural conservation practices. Natural conservation is estimated by using baseline energy consumption measurements obtained from a service territory without Energy Efficient Programs. Efforts to identify Market Transformation Effects are supplemented by spillover rates of nonparticipants estimated in the self-report analysis. This requires data from all available surveys and the re-survey efforts, as well as the PG&E Market Transformation Evaluation results from previous studies. The approach for estimating nonparticipant spillover is described in *Section.4*. The approach for estimating Total Market Effects is described in *Section 3*. And finally, the approach for disaggregating the Total Market Effects is described in *Section 6*.

Our approach is based on a decomposition of net load impact, such that net load impact can be specified as a combination of the six objectives. Estimates of net load impact can be calculated using the following model, referenced as Equation #1 throughout our discussion:

EQUATION #1

$$NetImpact_t = GrossImpact * Parts * Persist_t * [(1 - FR_t) + P\_Spill_t] * (1 - NC_t) + GrossImpact * Nonparts * Persist_t * MTE_t$$

Where,

$NetImpact_t =$	Total net load impact in year t ;
$GrossImpact =$	Mean ex-post gross lighting load impact for the 1994 participants;
$Parts =$	Number of 1994 participants;
$Nonparts =$	Number of 1994 nonparticipants;
$Persist_t =$	Rate of persistence in year t ;
$FR_t =$	Free-ridership rate in year t ;
$P\_Spill_t =$	Participant rate of spillover in year t ;
$NC_t =$	Decrease in baseline energy usage, expressed as a percentage of gross load impact, in year t, attributable to naturally occurring lighting conservation; and,
$MTE_t =$	Decrease in baseline energy usage, expressed as a percentage of gross load impact, in year t, attributable to the program's market transformation effects.

The first component of Equation 1 is the load impact contribution made by 1994 Lighting Program participants. The persistence factor, ($Persist_t$), adjusts the load impacts for decreases in measure retention over time. In addition, the participant gross load impact must be adjusted by free-ridership (FR_t) and spillover (P_Spill_t). Because of naturally occurring conservation, the baseline used to measure load impacts will become more efficient in years following the analysis base year. Therefore, load impact must be adjusted downward to compensate for natural conservation (NC_t) over time.

The second component of Equation 1 is the load impact contributed by nonparticipants. The nonparticipant net load impact is due to the Market Transformation Effects of the Program influencing customers to install measures (spillover), plus an additional supply side effect caused by changes in stocking practices by trade allies and vendors. In our equation, this is represented by the MTE_t term, which is expressed as a percentage of the gross Program impacts, and is expected to increase over time.

Because the Market Transformation Effects are expressed as a *rate* of the gross Program impacts (both with and without the Program), this value will also be *reduced* over time due to persistence effects and movement in the market's baseline efficiency. It is still anticipated, however, that the overall Market Effect will increase over time.

The following sections discuss in detail the analysis methods for estimating the six intermediate objectives. Each section identifies the terms in Equation 1 that are estimated as a result of the analysis.

2. Engineering Analysis

The primary objectives of the engineering analysis will be to develop estimates of persistence based on self-reported survey data. The telephone survey data collected asks respondents to estimate how many of the originally installed measures are still in operation; or if replaced, whether the replacement technology was also high efficiency. Based on customer responses, the engineering estimate is adjusted for each customer, for each analysis period. A separate estimate of gross load impact (for analysis period t) can then be calculated based on the modified number of units. Any customer reported changes in the operating schedule is not included in these load impact estimates. The persistence rate for each customer in the analysis sample can then be calculated as the ratio of the adjusted gross load impact to base period gross load impact.

The persistence estimates developed in the engineering analysis are not applied directly in Equation 1. Instead, these estimates are used to verify the results of the gross billing analysis Model #1.

3. Gross and Net Billing Analyses

The methods used for the gross and net billing analyses are presented in this section.

3.1 Gross Billing Regression Analysis

The objectives of the gross billing analysis are to: (1) estimate the ex-post gross load impacts, (2) estimate the effects of persistence over time, and (3) estimate the total effects of market movement (both naturally occurring and market transformation) over time. There are two gross billing data regression models developed, one to meet the first two objectives, and a second model to meet the third objective. The only difference between the two models is that the first directly captured the effects of the lighting changes made outside of the Program, and the second incorporates the effects of the lighting changes made outside of the Program into the baseline estimate of usage.

The gross billing analyses is conducted on three different sets of post-installation periods: 1995, 1996, and 1997. The same set of engineering estimates is used in all three models. The engineering estimates for customer reported number of units do not change. By doing so, the SAE Coefficients[1] from the gross billing model over time should decrease corresponding to the persistence of the measures installed. The difference in the SAE Coefficients will provide a statistically derived estimate of persistence.

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[1] The SAE Coefficient is the resulting regression parameter estimate from the SAE billing analysis associated with the engineering estimate, indicating the percentage of the engineering estimate realized in the billing analysis.

3.1.1 Gross Billing Regression Model #1.

In the gross billing regression analysis, two separate multivariate regression models are integrated to provide unbiased and robust model estimates of gross load impacts and persistence. The key feature of the approach is that it employs a simultaneous equation approach to account for both the year-to-year and cross-sectional variation in a manner that consistently and efficiently isolates Program impacts.

A baseline model is initially estimated using only the comparison (nonparticipant) group sample. This model estimates a relationship that is then used to forecast the post-installation-year energy consumption for participants as a function of pre-installation year usage. In this way, baseline energy usage is forecasted for participants by assuming that their usage changes, on average, in the same way that usage changed for the comparison group. The baseline model explains post-installation energy usage as a function of pre-installation energy usage, weather changes, and customer self-report of factors that could affect energy usage (such as changes at their facility). In order to isolate the Program impact from the energy usage changes, only the comparison group is used to fit this model. The baseline model has the following functional form:

$$kWh_{post,i} = \sum_j (\alpha_j + \beta_j kWh_{pre,i}) + \gamma(\Delta CDD_i) * kWh_{pre,i} + \phi(\Delta HDD_i) * Elec_i * kWh_{pre,i}$$
$$+ \sum_k \eta_k Chg_{i,k} + \varepsilon$$

Where,

$kWh_{post,i}$ and $kWh_{pre,i}$ are customer i's annualized energy usage for the post- and pre-installation periods, respectively. The Study used one pre-installation period of 1993 and three post-installation periods of 1995-1997;

ΔCDD_i and ΔHDD_i are the annual change of cooling degree days and heating degree days (base 65°F) between the post-installation year and pre-installation year for the ith customer;

$Elec_i$ is an indicator variable (0/1) for the ith customer, which equals 1 if the customer has electric heating;

$Chg_{i,k}$ are the customer self-reported change variables from the survey data, including adding, replacing, or removing equipment associated with major end uses, and changes in number of employees and square footage;

α_j is the indicator variable (0/1) for the jth business type, which equals 1 if the customer is in that business type and 0 otherwise;

β, γ, ϕ, and η are the estimated slopes on their respective independent variables. Separate slopes on pre-usage are estimated by business type; and,

ε is the random error term of the model.

For each customer in the analysis dataset, a post-installation predicted usage value is calculated using the parameters of the baseline models estimated for the pre- to post-analysis period. They both take the same functional form with different segment-level intercept series (α_j) and slopes (β, γ, and ϕ).

$$\hat{kWh}_{post,i} = F_{pre}(kWh_{pre}, \Delta CDD, \Delta HDD)$$
$$= \sum_j (\alpha_j + \beta_j kWh_{pre,i}) + \gamma(\Delta CDD_i) * kWh_{pre,i} + \phi(\Delta HDD_i) * Elec_i * kWh_{pre,i}$$

Using the predicted post-installation usage values estimated in the baseline model, a simultaneous equation model is specified to estimate the SAE coefficients on load impact. The SAE simultaneous system is described as follows:

$$\Delta Usage_i = kWh_{post,i} - \hat{kWh}_{post,i}$$
$$= kWh_{post,i} - F_{pre}(kWh_{pre}, \Delta CDD, \Delta HDD)$$
$$= \sum_m \beta'_m Eng_{i,m} + \sum_k \eta'_k Chg_{i,k} + \mu_i$$

Where, $Eng_{i,m}$ is the engineering estimate for measure m, customer i.

The difference between predicted and actual usage in the post-installation period is used as the dependent variable in the SAE model. Based upon the estimated participation month and the pro-rated engineering estimates, change variables are used to explain the deviation in actual usage from the predicted usage. As discussed above, the predicted usage is estimated using only the comparison group to forecast the post-installation period usage as a function of pre period usage and change of cooling and heating degree days from pre to post. This usage prediction presents what would have happened in the absence of the Program and any changes made at the facility outside of the Program.

Gross Load Impact Estimates. The coefficients of the engineering impact, termed the SAE coefficients, is then be applied to the unadjusted engineering estimates of load impact for each customer in the analysis sample. This product yields ex-post gross load impacts. Taking a mean of the ex-post gross load impact for all participants in the telephone sample provides us with the ***GrossImpact*** term in Equation #1. The ex-post gross load impacts is also used to estimate annual persistence rates.

Annual Persistence Estimates. The above models are run with three different post-installation periods: 1995, 1996, and 1997. For each technology group, there are three resulting SAE Coefficients, corresponding to each model run. Adjusted load impacts for persistence is estimated using each set of SAE Coefficients. Recall that differences in the gross billing model over time (i.e. the different post-installation periods) can be attributed to the persistence of the installed measures. This can be specified as:

$$Persist_t = \frac{ExPostLoad_t}{ExPostLoad_{95}}$$
$$= \frac{\sum_m \beta'_{t,m} Eng_m}{\sum_m \beta'_{95,m} Eng_m}$$

Where the terms $\beta'_{t,m}$ are the coefficients from the second stage SAE model for each technology group m, for the three post-installation period analysis time frames (1995, 1996, and 1997).

The ***Persist****$_t$* term in Equation #1 is determined by the ratio of the ex-post load impacts in year t to the first year ex-post load impacts, as illustrated in the equation above. This value is validated by the engineering result described in *Section 2.*

3.1.2 Gross Billing Regression Model #2.

The second gross billing model specification is identical to the first model with one exception. All lighting changes made outside of the rebate program are not included in the $Chg_{i,k}$ variable in both the Baseline and SAE model stages. One effect of this is that, in the Baseline model, the parameter estimates on the building-specific intercepts and pre-usage will capture any effects of reduced baseline energy usage due to the installation of efficient lighting.

In other words, the baseline model's parameter estimates of building type is reduced, because they are capturing the effects of any installation of efficient lighting (assuming that the parameter coefficient is negative). With this specification, the estimated post usage (using the lower parameter estimates) can now be interpreted as what participant post usage would have been in the absence of the Program if lighting measures had been installed in a manner identical to the nonparticipants.

Reducing the estimate of (baseline) post-installation period usage results in a smaller difference between actual and estimated post usage. This in turn results in smaller realized load impacts, thereby reducing the SAE Coefficients of load impact. This is due to the fact that the baseline now incorporates the efficient lighting installations made by the nonparticipant sample.

Therefore, the difference between the SAE Coefficients obtained in the second stage of the second model, and those obtained in the second stage of Model #1, can be attributed to the total effects of market movement (both naturally occurring and market transformation) with regards to lighting changes. That is, Gross Billing Model #2 is capturing the effects of what rebate participants would have done in the absence of the Lighting Program. This is the Total Market Effects.

It is not possible to differentiate between Program Effects and naturally occurring conservation in the gross billing models. The results of the market effects analysis (*Section 6*) enables us to disaggregate the two. The Total Market Effects can be described as:

$$
\begin{aligned}
TME_t &= MTE_t + NC_t \\
&= 1 - \left(\frac{GrossSavings_2}{GrossSavings_1} \right) \\
&= 1 - \left(\frac{\sum_m \beta''_{t,m} * Eng_m}{\sum_n \beta'_{t,m} * Eng_m} \right)
\end{aligned}
$$

Where,

TME_t = is the **rate** of Total Market Effects at time t;

$GrossSavings_{1,2}$ = are the adjusted estimates of gross engineering load impacts, adjusted for persistence, for Gross Billing Models #1 and #2, respectively;

$\beta''_{t,m}$ = is the SAE coefficient for technology group m, post- period t, from Model #2; and,

$\beta'_{t,m}$ = is the SAE coefficient for technology group m, post- period t, from Model #1.

The value of one minus the ratio of the adjusted gross load impact (from Model #2) to the gross load impact from the first model is an estimate of the rate (in terms of kWh) of total effects of market movement for the given post-installation period. The measured rate of Total Market Effects for each post-installation period, is the MTE_t plus the NC_t terms in Equation #1.

3.2 Net Billing Regression Analysis

The objective of the net billing analysis is to: (1) estimate free-ridership, and (2) derive another estimate of the total effects of market movement. There are two net billing data regression models developed, one to estimate free-ridership (Model #1), and a second to estimate the Total Market Effects (Model #2). These two models are identical to the gross billing models with three exceptions:

- An Inverse Mills Ratio is included.
- A second Inverse Mills Ratio is interacted with the engineering estimate of load impact.
- Both nonparticipants and participants are included in the second stage SAE model.

The only difference between the two net models is that the first directly captures the effects of the lighting changes made outside of the Program, and the second incorporates the effects of the lighting changes made outside of the Program into the baseline estimate of usage.

Inverse Mills Ratio Estimation

To calculate the Inverse Mills Ratio, the first step is to estimate a probit model of Program participation. The probit model includes all factors thought to influence the decision to make an equipment purchase:

$$PARTICIPATE = \alpha + \beta'X + \beta'Y + \beta'Z + \varepsilon$$

where $PARTICIPATE$ is an indicator variable with a value of one for Program participants and a value of zero for nonparticipants. The X term includes firmographic variables such as business type and electricity usage, Y includes variables reflecting equipment characteristics such as cost and electricity impact, and Z reflects Program variables such as rebate amount and Program awareness. Information on these variables for both participants and nonparticipants is obtained from the participant tracking system as well as from the participant and nonparticipants surveys. Supplementary surveys are conducted on all of these customers to obtain additional information to be included in the estimate of the Inverse Mills Ratio. For more details on the Mills Ratio, please refer to Heckman (1976, 1979[2]) and (Goldberg and Train, 1996[3]).

Net Billing Regression Model #1.

The model specification for the net billing analysis is similar to that of the gross billing analysis with the exception that the load impacts are captured through the Inverse Mills Ratio terms.

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[2] Heckman, J. 'The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models.", Annals of Economic and Social Measurement, Vol. 5, pp. 475-492, 1976.

Heckman, J. "Sample Selection Bias as a Specification Error." Econometrica, Vol. 47, pp. 153-161, 1979.

[3] Goldberg, Miriam and Kenneth Train. 'Net Savings Estimation: An analysis of Regression and Discrete Choice Approaches', prepared for the CADMAC Subcommittee on Base Efficiency by Xenergy, Inc. Madison, WI, March 1996.

As with the gross billing model, the group of nonparticipants are used to estimate what participant energy usage would have been in absence of the Program using 1993 as the pre-period. The same first stage baseline model specification that is used in the Gross Billing Model #1 is applicable.

To estimate net load impact in the second stage SAE model, the coefficients of load impact are interacted with the Inverse Mills Ratios. Inverse Mills Ratios are also modeled as independent variables in the following specification:

$$\begin{aligned}\Delta Usage_i &= kWh_{post,i} - k\hat{W}h_{post,i} \\ &= kWh_{post,i} - F_{pre}\left(kWh_{pre}, \Delta CDD, \Delta HDD\right) \\ &= \hat{\delta}\, M_i + \sum\nolimits_m \hat{\beta}_m M_i E\hat{n}g_{i,m} + \sum\nolimits_k \hat{\eta}_k Chg_{i,k} + \mu_i\end{aligned}$$

Where,

M_i = is the Inverse Mills Ratio for customer i; and,

The net billing model provides load impacts for program measures in a single year, taking into account free-ridership among Lighting Program participants. In this model, both participants and nonparticipants have a value for the first Inverse Mills Ratio term (M_i). The second Inverse Mills Ratio term ($M_i E\hat{n}g_{i,m}$) is interacted with the engineering estimate - because nonparticipants have no engineering estimate of load impact, this value is zero for nonparticipants. The resulting SAE coefficients on these second Inverse Mills Ratio terms ($\hat{\beta}_m$) reflect the net load impact for participants that can be attributed to free-ridership.

The net-to-gross adjustment (or 1-FR), is simply the ratio of the SAE coefficients from the second Inverse Mills Ratio terms, with their corresponding parameter estimates from the gross billing Model #1, interacted with the mean Inverse Mills Ratio for the mth technology group.

$$\left(1 - FR_m\right) = \frac{\hat{\beta}_m}{\beta'_m} * \overline{Mills_m}$$

Where,

$(1 - FR_m)$ = is the net ratio of load impact for technology group m;

$\hat{\beta}_m$ = is the SAE coefficient from Net Billing Model #1 for technology group m;

β'_m = is the SAE coefficient from Gross Billing Model #1 for technology group m; and,

$\overline{Mills_m}$ = is the mean Inverse Mills Ratio for all participants installing a measure m.

Controlling for Persistence. Since the lighting changes made outside of the Program are accounted for in the change variables, the estimate of baseline energy should not vary over time. Any variance in the SAE coefficients should therefore be due to the persistence of the measures. If the engineering estimates are adjusted for persistence prior to estimating the net model, the SAE coefficients should remain stable over time. Therefore, the engineering estimates that serve as inputs to the net billing model are adjusted for persistence.

When persistence is controlled for in the model, the model can be estimated using various post-installation periods. This will result in three (1995-1997). Depending on the stability of the model, either the 1995 estimate or the average of the three estimates are used to calculate the ***FR*** term in Equation #1.

Net Billing Regression Model #2.

The second net billing model that is employed is identical to the first model with one exception: all lighting changes made outside of the Program will not be included in the $Chg_{i,k}$ variable in both the Baseline and SAE model stages. As in the gross billing model, the baseline usage now incorporates the effects of lighting market movement, and the SAE coefficient estimates are expected to decrease.

The SAE coefficients from the second net billing model reflect the effects of free-ridership, in addition to the effects of market movement. As with the gross model, it is not possible to differentiate between the effects of natural conservation and market transformation, but the results of the market transformation effects analysis will be used to disaggregate the two.

As with the gross billing model, we can directly estimate the rate of total effects of market movement, which is the $\boldsymbol{MTE_t}$ plus the $\boldsymbol{NC_t}$ terms in Equation #1. This can be done by applying the SAE coefficients from both net billing models and estimating a net load impact (Model #1) and adjusted net load impact (Model #2). One minus the ratio of this adjusted net load impact to the net load impact from the first model gives an estimate of the rate of total effects on market movement. This can be done over time to come up with separate estimates of Total Market Effects as those derived in the gross billing model. The Total Market Effects are either verified using the gross billing analysis results, or augmented, depending on the results of the self-report analysis.

4. Self-Report Analysis

Although the net billing analysis provides us with an estimate of Total Market Effects, this result should be substantiated using more traditional analysis techniques. To address these issues, a self-report method for free-ridership and spillover is employed for this study. While Total Market Effects (less naturally occurring conservation) derived from the gross and net billing Models #2 should be a viable estimate of Total Market Effects, participant and nonparticipant spillover actions can be used as an accurate measurement of the lower bound of these effects. A separate estimate of free-ridership is also derived from the telephone survey data to supplement the values derived from the gross billing Model #1.

Participant spillover derived here will be represented as a percentage of the gross savings and will enter Equation #1 in the form of the $\mathbf{P\_Spill_t}$ term. We don't expect to use the self-reported rates of free-ridership or nonparticipant spillover directly in Equation #1. Instead, we expect to validate the free-ridership rates developed in the net billing analysis described below. In addition, we use the spillover estimates to validate the rates of market transformation effects (spillover is a lower bound for market transformation effects) and to disaggregate the market transformation effects into spillover and supply side effects, such as stocking practices.

5. Market Transformation Effects Analysis

The objective of the market transformation effects analysis is to estimate the percentage of the Total Market Effects that are attributable to the 1994 Commercial Lighting Program. In virtually all of our evaluations that include market transformation assessments, a strong emphasis is placed on the observed actions of customers to determine the extent to which market transformation has taken place, using an appropriate, accurate market baseline. Moreover, we have found that to isolate market transformation attributable to the Program from natural conservation, such a baseline must include a control group that enables us to simulate the market that would have existed in the absence of the DSM programs -- something that is simply not available in a billing analysis. Using this approach, we compare the lighting replacement actions of customers outside PG&E's Lighting Program (but within PG&E's service territory) to those of customers in an area unaffected by any similar program. Our reasoning is that such a control group is essential if there is to be any hope of quantifying or otherwise isolating market transformation effects from market changes that would have taken place even without the Program.

This approach relies on a systematic comparison of the actions of nonparticipants to estimate the extent of market transformation. In addition, we believe that customer attitudes and perceptions of market barriers provide an important indication of the permanence of Market Effects as well as of the mechanism by which the observed degree of market transformation has been affected.

Based on the thousands of in-service territory nonparticipant and canvass surveys conducted, we estimate the nonparticipant rate of lighting adoptions. We estimate separate rates for high and standard efficiency adoptions. In addition, for high efficiency adoptions, we use self report values for the type and number of fixtures installed to estimate the impact per adoption. Based on the adoption rate and the per adoption impact, we also estimate the impact per nonparticipant.

Using survey data collected for SCE's and PG&E's market transformation studies, we conduct a similar analysis on customers outside of PG&E's service territory, in areas where there is no commercial lighting programs in place. For these customers, we estimate the adoption rates of standard and high efficiency lighting, the impact per adoption, and the impact per nonparticipant.

To dissagregate the effects of total market movement into market transformation and naturally occurring conservation, we compare the in- and out-of-service territory estimates of impact per nonparticipant. The rate of naturally occurring conservation as a percentage of total market movement is estimated as the ratio between the in-service territory nonparticipant impact and out-of-service territory nonparticipant impact. This allows us to directly estimate the $\boldsymbol{MTE_t}$ and $\boldsymbol{NC_t}$ terms in Equation #1.

6. Integrated Analysis

The integrated analysis consists of combining the results of the engineering analysis, the statistical billing analysis, the self-report analysis, and the market effects analysis. The outputs of these analyses are the six intermediate objectives that ultimately result in an estimate of net load impact for the 1994 Lighting Program for the years 1994-1997.

Recall that estimates of net load impact can be measured using the following equation:

$$\begin{aligned} NetImpact_t &= GrossImpact * Parts * Persist_t * \left[(1 - FR_t) + P\_Spill_t\right] * (1 - NC_t) \\ &+ GrossImpact * Nonparts * Persist_t * MTE_t \end{aligned}$$

Each term in the above equation can be explained using the six objectives as our framework. Objectives 1-5 estimate participant load impacts attributable to the Program, and Objective 6 estimates nonparticipant load impacts attributable to the Program.

Conclusions And Recommendations

Through the process of completing this study, certain methodological issues were brought to our attention. These discoveries and their ramifications should be noted for use in future, similar studies. Methodological recommendations are presented for each study objective.

Objective 1
Estimate Gross load impacts for the 1994 PG&E commercial lighting rebate population.
Recommendation: Billing analysis, in combination with engineering analysis, is the most effective method for calculating gross load impacts over time. This study sustains the capability of a billing analysis to measure gross load impacts, whether for first year impacts or impacts over time.

Objective 2
Adjust for the Persistence of installed lighting measures.
Recommendation: For a study with four years of data, persistence rates of installed lighting measures are identified more precisely with a self-report analysis than with a billing analysis. The rate of equipment attrition is too small over a four-year period to detect with billing analysis. In addition, failed equipment is often not replaced, or replaced with equally efficient equipment. As a result, the equipment failure is associated with either no change in energy consumption or a decline in consumption. It is important that self-reported data be verified, because its accuracy is a principal concern. The billing analysis is a useful tool in determining persistence because it can validate the self-report analysis results. Moreover, we recommend conducting on-site audits to verify self-reported data whenever possible.

Objective 3
Determine rates of free-ridership over time.
Recommendation: We found both self-report and billing analysis to be reliable, effective techniques for estimating free-ridership. However, billing analysis requires a very large sample size in order to get valid results. For example, our sample was too small to yield statistically significant results for most technologies; only fluorescents had a statistically valid result. In addition, the multiple regression analysis steps and required sample censoring introduce potential estimation error and bias. Finally, self-report techniques are able to capture the dynamic effects of accelerated adoption, while the billing analysis produces a static result.

Objective 4
Identify participant spillover adoptions and load impact.
Recommendation: Self-report data is used to determine whether participants were influenced by the program to make non-rebated high efficiency lighting adoptions. Billing analysis provides an estimate of the load impact derived from all of the non-rebated lighting adoptions. This estimate is an upper bound for participant spillover, and can be used to validate the self-report analysis results.

Objective 5
Estimate nonparticipant market transformation load impacts.
Recommendation: Market transformation is estimated by combining estimates of total nonparticipant load impact and nonparticipant natural conservation. In this study, total nonparticipant load impact was captured using self-report adoption rates, combined with ex-post load impacts estimated with billing analysis. This method was both efficient and effective, and we recommend that it continue to be utilized in future studies.

The best method for estimating natural conservation is less clear. Two methods are presented in this study: one using out-of-state samples from territories where there are no programs similar to the Lighting Program, and the second using data gathered in the PG&E service territory.

Using out-of-state samples requires the assumption that the out-of-state territory is representative of the behavior that would have occurred in California in the absence of the program. Every territory is unique, and so results are dependent upon which territory is selected. Nonetheless, we believe this is the best estimation approach. Using California data requires the assumption that lighting adoptions by individuals *unaware* of being influenced by the lighting program are due to natural conservation. This approach underestimates market transformation because it ignores hidden market effects. This approach could be improved with surveys of other market "actors" such as distributors, to determine other ways the program has altered the market from the supply side. Nonetheless, this result is useful in providing a lower bound estimate of market transformation.

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