512

FINAL REPORT
1994 RESIDENTIAL HVAC REBATE PROGRAM IMPACT EVALUATION

CEC Study ID #512

Prepared for

Southern California Edison Company

Prepared by

XENERGY Inc.
Madison, Wisconsin

February 28, 1996

ma:wsce13:reports:final:title

1 INTRODUCTION

1.1 OVERVIEW

This report presents the results of an impact evaluation of Southern California Edison's (SCE's) 1994 Efficient HVAC Equipment Rebate Program. The evaluation provides net impacts for calendar year 1994 participants. The impacts are based on analysis of participant and nonparticipant billing records, together with survey information from SCE's 1995 Residential Appliance Saturation Survey (RASS), and weather data.

1.2 EVALUATION OBJECTIVES

The purpose of the evaluation is to determine net energy impacts (kWh/year) by equipment type. The evaluation method also provides estimates of annual unit energy consumption (UEC's) for air conditioning. However, this result is not a primary evaluation goal.

1.3 PROGRAM DESCRIPTION

The HVAC rebate program provided rebates for efficient central air conditioners, heat pumps, and evaporative coolers. The program was designed to provide rebates for efficient new equipment purchased to replace existing equipment, or, in the case of evaporative coolers, to complement existing central air conditioning systems. In a few cases, however, participants reported that rebates had been obtained for equipment installed as new or additional capacity, rather than for replacement units.

1.4 SUMMARY OF FINDINGS

The participation levels and estimated impacts are summarized in Table 1-1, by program component. The "central air" category includes heat pumps. The tracking system used for later participants separated out heat pumps, but the system used for the first few months of the program did not. Based on the proportions in the later system, about 13 percent of the central air/heat pump participants purchased heat pumps.

Table 1-1
Summary of Impact Estimates

Program Component	Number of Participants	Realization Rate (Net/ Tracking)	Savings Estimates: Tracking Unit (kWh/year)	Tracking Program Total (GWh/year)	Net Unit (kWh/year)	Net Program Total (GWh/year)
Central Air	6202	1.23	474	2.94	583	3.62
Evaporative Coolers	1624	0.19	1509	2.45	284	0.46
Total Program	7826	0.76	689	5.39	521	4.08

The table shows that a total of 7,826 customers participated in the program during 1994. About 80 percent of the rebates were for central air conditioners. Net impacts for central air/heat pumps were close to those projected by the tracking system, with a realization rate of 1.23. For evaporative coolers, however, net impacts were smaller than the projections, resulting in an overall realization rate for the program of 0.76. The relative standard error of the overall savings was 15 percent.

1.5 Organization of the Report

The impact estimation methods and results are presented in the next Section. Appendix A contains a copy of the RASS survey instrument. Details of alternative impact models explored are in Appendix B. Appendix C presents technical details of the self-selection correction method, and Appendix D provides the engineering models used in the regression analysis. The sample desing for the 1995 RASS is described in Appendix E. A data flow chart and attrition analysis are given in Appendix F.

2 NET IMPACTS

2.1 OVERVIEW OF ANALYTIC APPROACH

The impact analysis uses customer billing data combined with survey data. The monthly billing data for participant and nonparticipant customers are fit by a pooled time series/cross-sectional model. Coefficients of this model provide estimates of the effects of program participation.

The basic structure of the impact model is a monthly conditional demand model. For each customer for each billing period, the predictor variables are engineering estimates of the individual end uses present for that customer. For heating and cooling, these estimates are based on the customer's house characteristics and local weather.

The structure of the model isolates the incremental effects of replacing an existing air conditioning unit with a newer one; of adding new air conditioning capacity; and of participating in the program given that equipment is being replaced or added. Also included in the model are fixed effects for each customer and each time period, and self-selection correction terms.

The next subsection describes the data sources used in the analysis. The construction of the analytic data set is then described. We then describe the impact estimation models, and present the results of the analysis.

2.2 DATA SOURCES

2.2.1 Tracking Data

Two different tracking data sets were used for the 1994 program year. The first was used for participants from the beginning of the year through early May. The second was used for participants after that date. For this study, the information taken from the tracking system was the following:

- account ID
- participation type (central air/heat pump or evaporative cooler)
- participation date

- program estimate of savings (kWh/year).

2.2.2 Billing Data

Billing data for the participant and nonparticipant samples covered the period from January 1993 through September 1995. Information provided by the billing system for each customer included the following:

- account ID
- meter reading dates and consumption amounts (kWh) for each billing record within the study period
- actual/estimated flags for each billing record
- weather station ID.

2.2.3 Weather Data

Weather data were provided by SCE. For each of their 23 weather stations, daily average temperatures (°F) were given from 1990 through December 1995. SCE also provided long-run normal heating and cooling degree-days, as the average over the years 1988 through 1995, for each day of the year. Weather data were linked to billing records by the account ID, which includes a weather station code. Data from January 1993 through September 1995 were used in fitting the load impact regression models. The long-run normal data were used to compute savings from the model results.

2.2.4 1995 Residential Appliance Saturation Survey

SCE's 1995 Residential Appliance Saturation Survey (RASS) was fielded by XENERGY under a separate contract from July through November of 1995. Questions on the survey included

- electric end uses present in the household
- presence of central air conditioning, heat pump, and evaporative cooler
- addition or replacement of central air/heat pump, and date of this change
- house and equipment features affecting air conditioning consumption.

A copy of the survey instrument is given in Appendix A.

The RASS sample was designed to include a large number of HVAC rebate program participants. Surveys were completed for 1,652 participants and 8,888 nonparticipants, as summarized in Table 2-1. The customers with completed surveys were all targeted for inclusion in the billing analysis. Billing records were found and used for almost all of these customers.

Table 2-1
Respondents to 1995 RASS by 1994 Program Participation

	All	With Good Billing Data
Total completed surveys	10540	10537
1994 CAC participants	996	996
1994 EC participants	656	656
Nonparticipants	8888	8885

A data flow chart and attrition tables are given in Appendix F. These displays will be better understood after a review of the analytic approach and final model fits.

2.3 Analytic Data Set Construction

2.3.1 Variables used in the impact estimation model

The impact estimation model is a pooled time series/cross-sectional regression model. There is one observation for each customer for each billing period.

The dependent variable y_{it} in the regression is the consumption per day for customer *i* during billing period *t*. This value is computed by dividing the consumption reported on the billing file by the number of days in the billing period. Any billing record flagged as an estimated read is combined with the next record for that customer, to create a longer period bounded by actual reads.

The first set of predictor variables in the model are engineering estimates of each end use for the customer and time interval, on a per-day basis. These engineering estimates are based on the survey information indicating whether the end use is present, and in some cases using additional information on the equipment or household to characterize usage.

For heating, the engineering estimate depends on the heating degree-days for the time interval, as well as on the size of the home and on factors related to physical characteristics of the dwelling, reported on the survey. A similar engineering estimate is used for cooling. The engineering formulas are specified in Appendix D.

A customer's cooling estimate can change from month to month not only because the weather (cooling degree-days) is different, but also because the customer added or replaced cooling capacity. The 1995 RASS collected data on the types and dates of such changes.

The evaporative coolers are modeled separately from the central air conditioners. Modeling the two types of units jointly appeared to degrade the quality of the estimates for both.

Variables in the Central Air Conditioning Model

To isolate the program effects, the cooling estimate for customers who added or replaced equipment enters the central air conditioning model in several terms. For all customers the base usage that would occur if the customer retained the original equipment throughout the study period is included in the model. This base usage is also included interacted with dummy variables

- for replacing cooling equipment
- for adding additional capacity
- for replacing cooling equipment and participating in the program
- for adding capacity and participating in the program.

The replacement and addition dummies are all zero in the first time period, and change to one at the time the customer replaced or added the equipment. For consistency between participants and nonparticipants, these dates are based on the RASS data. Participation dates are available for participants from the tracking system, but corresponding information is not available for nonparticipants.

The coefficient of the base usage alone is an adjustment factor to the engineering estimate of use, for the equipment present at the beginning of 1994. This factor multiplied by the average base use engineering estimate gives an estimate of the average air conditioning UEC at that time.

The coefficient of the usage-replacement variable is the proportional change in usage associated with replacing equipment. The coefficient of the usage-replacement-participation variable is the proportional change in usage associated with participating in the program, for those who replaced equipment. That is, given that customers are replacing equipment, their usage would be expected to change by the amount indicated by the replacement coefficient. The replacement-participation coefficient indicates the savings for participants relative to this level.

Also included among the predictor variables is a dummy variable for each time period (January 1993 through August 1995). Each observation is assigned the dummy corresponding to the month and year of the meter reading date. These time period fixed effects account for exogenous changes that are not controlled for by the degree-day terms. Similarly, a dummy variable is included for each customer. Fitting these two sets of fixed effects eliminates two important potential source of intercorrelation among the model residuals.

The original model specification also includes correction terms for self-selection. These terms are variants of the standard Dubin-McFadden terms based on discrete choice models. Self-selection correction is more complicated in the pooled time series/cross sectional model than in a cross-sectional model. In principle, a choice is made in each month whether to replace or add equipment and if so whether to participate. However, a customer cannot choose to replace and participate in one month, then choose to be a nonreplacer or nonparticipant in a subsequent month.

To address this potentially complex issue, we model the choices cross-sectionally only. The estimated correction terms from the cross-sectional model are then interacted with the time-dependent replacement, addition, and participation terms.

As it turns out, the model including the self-selectin correction is unstable. These terms are therefore not included in the final model fitted. The specific form of the correction terms, and the reason for their exclusion from the final model are given below, in Section 2.4.5.

Variables in the Evaporative Cooler Model

For the evaporative coolers, a different model form was required. This difference related both to the way evaporative coolers are used and to the way information was collected on them.

Evaporative coolers are effective during hot, dry weather. In climates that are typically hot and dry, this equipment can be used as an alternative to conventional central air conditioners. A household that already has a conventional unit may choose to add an evaporative cooler, and use one or the other depending on weather conditions. Thus, an evaporative cooler can be present by itself, or in conjunction with a conventional unit. SCE's program provided rebates for evaporative coolers acquired by homes with existing central air conditioning. These evaporative coolers may have completely replaced the old system, or, more likely, may have been used in conjunction with it.

The 1995 RASS survey asked customers if they had a central air conditioner, and also asked if they had an evaporative cooler. Many customers indicated that they had both. However, some of these customers may have only an evaporative cooler, which they think of as a central air conditioning unit.

The RASS did not ask when the evaporative cooler was installed. Installation dates can be determined for participants from the tracking system, but are unavailable for nonparticipants. Thus, it is not possible to identify nonparticipants who installed evaporative coolers during 1994, analogously to identifying replacers and adders for central air conditioners.

To address these data limitations, the following changes were made to the model structure.

- The model was restricted to nonparticipants and participants who reported that they had both evaporative coolers and central air conditioning on the 1995 RASS.
- Nonparticipants were assumed to have evaporative coolers as of the beginning of the evaluation study period (January 1993).
- Participants were assumed to have central air conditioners as of the beginning of the study period, and to add evaporative coolers at the participation date indicated in the tracking system.

The cooling variables included in the evaporative cooling model are then

- the base use central air conditioning engineering estimate, for nonparticipants
- the base use central air conditioning engineering estimate, for participants
- the evaporative cooling engineering estimate for participants.

For participants, it is possible to distinguish the effects of the central air conditioner and the evaporative cooler, because we have earlier observations where only the former is present, and later observations where both are present. For nonparticipants, the two effects cannot be distinguished, because, as far as we know, both are present for all the observations. For this reason, we estimate a different coefficient of central air conditioning for nonparticipants than for participants. For nonparticipants, the coefficient reflects the combined effects of central air conditioning with the evaporative cooler. For participants, the coefficient reflects central air conditioning alone. A separate term captures the effect of adding the evaporative cooler, for participants.

The assumption that the nonparticipants with evaporative coolers had this equipment as of the beginning of 1993 is of course not correct for all customers. Some fraction of these customers actually installed evaporative coolers over the course of the evaluation study period. The resulting savings for these customers is reflected in the regression model as part of the "exogenous trend." That is, the estimated trend shows increased savings, and the estimated program-related savings are correspondingly decreased. The magnitude of this bias is roughly estimated by examining the rate of adoption of evaporative coolers in the general population. This issue is explored in more detail in the discussion of the regression results.

2.3.2 Summary of Variables

The analysis variables included in the central air and evaporative cooler models are summarized in Table 2-2.

Table 2-2
Summary of Analysis Variables

Variable	Name	Type	Definition
y_{it}	Consumption	Dependent Variable, numeric	the consumption for customer *i* during time period *t* (Wh/day)
f_{it}^{j}	End-Use Estimate *j*	Numeric	the consumption estimates for end use *j* for customer *i* during period *t*
f_{it}	End-Use Estimates	Numeric Vector	vector whose elements are f_{it}^{j}
f_{it}^{AC}	Base AC Estimate	Numeric	the central AC consumption estimate (for customer *i*, period *t*) based on the system installed at the beginning of the study
f_{it}^{NAC}	New AC Estimate	Numeric	the central AC consumption estimate (for customer *i*, period *t*) based on the new system installed, for those customers who installed new AC
f_{it}^{EV}	Evaporative Cooler Estimate	Numeric	the evaporative cooler consumption estimate (for customer *I*, period *t*) for evaporative cooler participants
R_{it}	Replacer	Dummy	1 if customer *i* replaced CAC by period *t*, 0 otherwise
N_{it}	New AC	Dummy	1 if customer *i* got a new CAC by period *t*, 0 otherwise
P_{it}	Participant (time-dependent)	Dummy	1 if customer *i* participated in the program by period *t*, 0 otherwise
P_{i}	Participant (cross-sectional)	Dummy	1 if customer *i* participated in the program, 0 otherwise
CR_{ik}	Replacer Correction Term	Numeric	Probability that customer would choose replacement option k
CN_{ik}	New AC Correction Term	Numeric	Probability that customer would choose new addition option k
μ_i	Customer	Dummy	1 for customer *i*, 0 otherwise
τ_t	Time Period	Dummy	1 for time period *t*, 0 otherwise.

2.3.3 Installation Date

In the pooled models used for both the central air and evaporative cooler components of the program, effects of replacing or adding equipment are estimated by the installation variables that become positive at the date of installation. Errors in the installation dates could therefore introduce errors into the estimates.

For the central air model, the installation date used was the date reported on the RASS. For the majority of participants, this date was within one or two months of the date reported in the tracking system (Table 2-3). For over fifteen percent of participants, however, the customer-reported installation date was several years before the program year (Table 2-4). These customers either did not install the rebated equipment in their homes, or did not recall replacing the unit. The central air model relied on the installation date reported on the RASS, even for participants who reported an installation date prior to the beginning of 1993. These participants are treated as having already installed the efficient equipment as of the first time period included in the regression model.

A similar comparison of survey reports with tracking system records could not be made for evaporative coolers. The installation date of this equipment was not collected on the RASS. For evaporative coolers, the tracking date was used for all participants.

Table 2-3
Comparison of Tracking System and RASS Reported Installation Dates, for Central Air Participants
Number of Customers

RASS Reported Date (Quarter)	Tracking System Dates (Quarter)				All 1994 CAC Participants
	Quarter 1 1994	Quarter 2 1994	Quarter 3 1994	Quarter 4 1994	
<Quarter 1 1993	12	41	84	3	140
Quarter 1 1993	2	0	3	0	5
Quarter 2 1993	2	10	7	0	19
Quarter 3 1993	2	2	9	0	13
Quarter 4 1993	3	2	1	1	7
Quarter 1 1994	45	12	0	1	58
Quarter 2 1994	10	122	43	0	175
Quarter 3 1994	2	40	292	5	339
Quarter 4 1994	4	4	18	25	51
Quarter 1 1995	1	2	3	5	11
Quarter 2 1995	0	1	7	0	8
Quarter 3 1995	0	4	4	3	11
Total	83	240	471	43	837

Table 2-4
The Difference Between Tracking System Central Air Conditioning Participants Installation Date and RASS Report(Tracking Date - Survey Date in Days, Based on 837 Differences)

Percentiles								
Min	5%	10%	25%	50%	75%	90%	95%	Max
-453	-111	-48	-11	7	66	2701	5340	10730

2.4 IMPACT ESTIMATION MODELS

2.4.1 Central Air Conditioning Model

The original impact estimation model specified for central air conditioners was as follows:

$$
\begin{aligned}
y_{it} = {} & \mu_i + \tau_t + \beta^T f_{it} + \beta_{AC} f_{it}^{AC} \\
& + \gamma_R R_{it} * f_{it}^{AC} + \eta_R P_{it} * R_{it} * f_{it}^{AC} \\
& + \gamma_N N_{it} * f_{it}^{NAC} + \eta_N P_{it} * N_{it} * f_{it}^{NAC} \\
& + \sum_{k=1}^{3} \kappa_{Rk} CR_{ik} * R_{it} * f_{it}^{AC} + \sum_{k=1}^{3} \kappa_{PRk} CR_{ik} * P_{it} * R_{it} * f_{it}^{AC} \\
& + \sum_{k=1}^{3} \kappa_{Nk} CN_{ik} * N_{it} * f_{it}^{AC} + \sum_{k=1}^{3} \kappa_{PNk} CN_{ik} * P_{it} * N_{it} * f_{it}^{AC} + \varepsilon_{it}
\end{aligned}
$$

The basic variable definitions are as given in Table 2-2 above. The superscript 'T' denotes vector transpose. As noted above, and explained further below, the terms involving the correction factors CR and CN were dropped from the final model.

The terms *CR* and *CN* are self-selection correction terms for replacement, participation, and new addition choices. Replacement is an option only for customers who had a central air conditioner as of the beginning of 1994. Installing a new unit was an option only for customers who did not. Separate self-selection models were therefore fit for customers in these two groups. For customers who already had an air conditioner, there were three options:

1. Do not replace and do not participate.
2. Replace and do not participate.
3. Replace and participate.

The term CR_{ik} is the correction term associated with choice *k* for customer *i*. Appendix C provides the theoretical derivation of this form of the self-selection correction. Analogous choices and correction terms CN_{ik} apply for customers who begin with no central air conditioning.

The parameters estimated by the regression include the customer-specific level μ_i, the time-specific level τ_t the adjustment factors (β 's) to the engineering estimates of end-use consumption, and the coefficients of the change terms. The coefficients of the self-selection correction terms are not of interest in themselves; these terms are included to reduce the potential bias associated with relying on self-selected samples.

The coefficients of greatest interest are those of the installation variables, and in particular the participation variables. For example, the effect of replacing an air conditioner, as a fraction of the engineering estimate of base AC use, is given by γ_R The incremental effect of participating for those who are replacing, again as a fraction of the base AC estimate, is given by η_R. These coefficients provide the net impacts. Likewise, the coefficients γ_N and η_N give the effects of adding a new unit, and the net effect of participation for those who added new units, as fractions of the engineering estimates for the new units.

The interpretation of the coefficients η_R and η_N as net savings follows from their construction, and from the other terms included in the model. First, because the general replacement and new-addition terms are included in the model, the participant terms capture the incremental change associated with participation, over and above the basic changes associated with replacing or purchasing new equipment. The general replacement and new-addition terms captures the average efficiency of units purchased outside the program. That is, the extent to which customers would have purchased high-efficiency equipment anyway-- i.e., the free rider effect-- is accounted for in these terms. There remains the possibility that customers who would tend to participate in the program would also tend to purchase equipment of higher (or lower) efficiency, or would change their equipment's capacity or usage by more or less, if the program didn't exist than would nonparticipants who acquired air conditioners during the study period. This possibility is accounted for by the self-selection correction terms.

The model structure is designed to exclude from the savings coefficients identifiable changes in consumption unrelated to the program. Changes resulting from acquisition of other equipment are accounted for, to the extent possible, by changes in the terms f_{it}^j over times t. Changes associated with general trends that affect the residential population as a whole, but are not related to the program, are captured in the time-period dummies τ_t. Estimating the model across both participants and nonparticipants strengthens the estimates of these coefficients, as well as of the coefficients of the engineering estimates f_{it}^j.

Other factors that need to be accounted for in determining net savings are captured in the "net savings" coefficients. These factors include the actual usage of the new air conditioning unit, noninstallation or failure of the unit, physical interactions with other electric equipment, and behavioral snapback or participant spillover. These effects are all captured in the impact coefficients because they are all included in the observed consumption that is the dependent regression variable. Thus, the impact coefficients give the combined effects of corrections to the gross savings estimate, measure installation and persistence, equipment usage, snapback, participant spillover, and free ridership. However, none of these effects is isolated. Not included in the net savings estimated by these coefficients are free drivers, or nonparticipant spillover effects.

2.4.2 Evaporative Coolers

The model fit for evaporative coolers was the following.

$$\begin{aligned} y_{it} &= \mu_i + \tau_t + \beta^T f_{it} \\ &+(\beta+\eta)_{NP}(1-P_i) * f_{it}^{AC} \\ &+\beta_P P_i * f_{it}^{AC} \\ &+\eta_P P_{it} * \ f_{it}^{EV} + \varepsilon_{it}. \end{aligned}$$

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 combines the effects β 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.

The inclusion of the nonparticipants in the model ensures that the effects of exogenous changes are accounted for. Not accounted for, however, is the extent to which evaporative coolers would have been installed during 1994 without the program in homes that had central air conditioning but not evaporation coolers. That is, the billing analysis captures the gross effect of adding the evaporative cooler, and also incorporates measure installation and persistence, usage, participant snapback and spillover, but does not account for free ridership. For this reason, the savings coefficient η_p in this model by itself does not give net savings.

To obtain net savings, the savings coefficient 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. The analysis to determine this free rider adjustment factor is described below.

2.4.3 Free Rider Adjustment Factor

To develop the free rider adjustment factor, we follow the three-option nested logit approach of Train, et al. (1994). This method hinges on estimating certain probabilities relating to customers' actions both with and without the program. In particular, the nested logit model estimates for each customer i:

- $\pi_i^{(prog)}$, the probability of implementing in the presence of the program,
- $\pi_i^{(noprog)}$, the probability of implementing without the program, and
- π_{ip}, the probability of implementing by participating in the program.

Let S_i be the gross savings that would be expected if customer i implemented the measure (installed an evaporative cooler). Then the total savings expected to occur in the presence of the program is

$$T = \sum_i \pi_i^{(prog)} S_i .$$

These total savings include not only the savings that the program generates but also the natural savings that would have occurred even if the program had not existed. In an expression that is completely analogous to the above, the natural savings are

$$N = \sum_i \pi_i^{(noprog)} S_i .$$

Now the difference between T and N is the net savings that we can correctly attribute to the program. We express this net savings as a fraction of the expected gross savings

$$G = \sum_i \pi_{ip} S_i$$

that occur as the direct result of participants' behavior. Thus the adjustment factor to account for free ridership could be calculated as

$$F = \frac{T - N}{G}.$$

We make the simplifying assumption that all the S_i are equal to one another (or at least are independent of the probabilities $\pi_i^{(j)}$) to get the formula used to calculate F from the estimated probabilities π :

$$F = \frac{\sum_i \pi_i^{(prog)} - \sum_i \pi_i^{(noprog)}}{\sum_i \pi_{ip}}.$$

The analysis involves fitting a 2-stage logistic regression model as follows. Consider the 3 different possible choices a customer could make

- choice 1, participate by installing an evaporative cooler,
- choice 2, install an evaporative cooler without participating, and
- choice 3, do not install a 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. This problem is finessed by defining installation to mean "installed by the time of the 1995 RASS". Participation means "participated by installing an evaporative cooler during 1994." Thus, the difference T-N is the incremental savings associated with evaporative cooler installations attributable to the 1994 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

- had central air conditioning and
- lived in weather station 181 (Palm Springs, in CEC weather zone 15) — the region from which nearly half of the evaporative cooler participants came.

These respondents constitute the *overall population* of the analysis.

The first step of the nested logit method is restricted to the *1st level subpopulation* consisting of those members of the overall population who made choices 1 or 2—the installers. The analysis fits a binary logistic regression model to these customers that establishes a relationship between the participation decision and certain explanatory variables. The 1st level subpopulation is not a random sample of the set of all SCE customers, but includes an over-sample of program participants. This disproportionate representation is adjusted for by adjusting the constant or intercept term until the proportion of respondents that the model predicts as being participants nearly matches the actual proportion for the true subpopulation.

Denote the vector of explanatory variables for the *i*th customer as $x_i^{(1)}$ and denote the corresponding vector of parameters—which is constant over individuals—as γ.

The second step involves returning to the larger overall population—central air conditioner users in weather station 181—and calculating for each individual a transformed version of the propensity to participate based on the parameters estimated in the first step. The exact form of this value is

$$I_i = \log(1 + \exp(\gamma^T x_i^{(1)})).$$

Then the analysis fits a binary logistic regression model to these customers that establishes a relationship between the installation decision—choice 1 or 2 vs. choice 3—and certain explanatory variables, including I_i. We also modify the intercept term as before to reflect the true proportion of installers in the actual population.

Denote the vector of explanatory variables—excluding I_i—as $x_i^{(2)}$, and denote the corresponding vector of parameters as β. Let λ be the estimated coefficient for I_i.

Define the inverse logit function

$$\theta(x) = \frac{\exp(x)}{1 + \exp(x)}.$$

Now based on the above two models we can calculate

$$\pi_i^{(prog)} = \theta(\beta^T x_i^{(2)} + \lambda I_i)$$

and

$$\pi_i^{(noprog)} = \theta(\beta^T x_i^{(2)}).$$

Also, if we let $\pi_{ip|r}$ be the probability that customer *i* participates given that they implement then we can also calculate

$$\pi_{ip|r} = \theta(\gamma^T x_i^{(1)})$$

and get

$$\pi_{ip} = \pi_{ip|r} \pi_i^{(prog)}.$$

The calculation of the free ridership factor F follows as described above.

To assess the precision of the estimate, we followed the resampling method outlined by Train et al. Essentially this involves calculating the free rider adjustment factor F many times using the fitted models and constant β and γ. With each iteration *k* we select a new $\lambda^{(k)}$ from the normal distribution whose mean is the original λ from the 2nd-stage fit and whose variance is the estimated variance of that parameter. Then we take this empirically-derived distribution of F estimates and use the sample standard deviation or quantiles to define confidence intervals. In this study, we used 500 resampling iterations to determine the precision of the estimated free rider adjustment.

2.4.4 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 coefficients of the f^{AC} variables for different screens are summarized in Appendix B. For the central air conditioner model, we found little change in the results for floorspace-per-room cut-offs of 1,000 and 600. The results did change substantially when a ceiling of 300 square feet per room was used. However, at this point a substantial fraction of the customers were excluded from the regression, as discussed further below. The results presented are for a ceiling of 1,000 square feet per room.

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.

2.4.5 Regression Results

Central Air Conditioning: Load Impact Regression Model for Net Savings

Statistics of the variables and observations included in the final central air conditioning model described above are presented in Table 2-5. Coefficients of the estimated model are presented in Table 2-6. The final fit excluded customers with greater than 1,000 square feet per room based on the RASS responses, and individual observations greater than 60 kWh/day.

Table 2-6 shows that all the air conditioning effects estimated by the model are well determined. The base UEC for air conditioning is estimated at 96 percent of the engineering estimate, or 1349 kWh per year. However, some of the seasonality of consumption is captured not in the cooling coefficient, but in the time trend terms. While these terms are necessary to provide unbiased savings estimates, a more accurate estimate of cooling loads might be obtained by excluding them.

The effect of replacement is an increase in air conditioning usage, by about 25 percent of the base level. This result is somewhat surprising. Replacing an existing unit with a newer one, even at current standard efficiency, should mean an improvement in efficiency. The increase in consumption associated with replacement suggests that either capacity or usage tends to be increased after replacement, offsetting the efficiency gain. On the other hand, the effect of participation, given that a customer is replacing equipment, is a savings of 25 percent of base use.

For installation of new, additional equipment, the increase in use is 94 percent of the base level. This increase is greater than for replacement, as would be expected. However, the effect of participation is an even greater increase, by another 63 percent. That is, among participants who were installing new air conditioners for the first time, the average increase in consumption associated with the addition was substantially greater than for nonparticipants who added new air conditioners. Savings for participant adders are negative.

The overall program effect for central air conditioning is the weighted average of the replacement and adder effects. Because only a small fraction of participants identified themselves as adders, this overall effect is similar to that for replacers alone. The overall effects for CAC participants are computed below, in Section 2.4.6.

Table 2-5
Variables Included in the Central Air Conditioner Load Impact Regression Model

Description	Variable	Number of Customers with non-zero values: Participant	Number of Customers with non-zero values: Non-participants	Number of Observations: Participants	Number of Observations: Non-participants	Average Over All Observations: Participants	Average Over All Observations: Non-participants
consumption (from billing file) (Wh/day)	USAGE	929	6323	27765	153393	26544	17030
engineer est of cac consumption (Wh/day)	F_CAC	747	3527	22500	83946	2863	1218
Base CAC Est * Rep Dummy (Wh/day)	F_CAC_R	592	62	17988	1639	1364	18
Base CAC Est * Rep Dummy * Part Dummy (Wh/day)	F_CAC_RA	592	0	17988	0	1364	0
engineer est of new cac consumption (Wh/day)	F_NCAC	35	153	989	2826	26	32
New CAC Est * Part Dummy (Wh/day)	F_NCAC_A	35	0	989	0	26	0
engineer est of heater consumption (kWh/day)	F_HEAT	269	1817	7798	42622	3.01	2.85
engineer est of refrigerator consumption	F_REF	923	6241	27586	151507	13.99	12.89
engineer est of freezer consumption	F_FRZ	926	6250	27680	151763	6.19	5.48
engineer est of TV consumption	F_TV	862	5817	25775	141322	1.08	0.96
clothes washer dummy	FD_WASH	860	4799	25831	121939	0.93	0.79
clothes dryer dummy	FD_DRY	376	1518	11260	37174	0.4	0.24
stove dummy	FD_STV	510	1656	15173	40446	0.54	0.26
oven dummy	FD_OVN	563	2054	16748	50611	0.59	0.33
number of microwave ovens	FN_MIC	878	5593	26220	137247	0.97	0.91
number of dishwashers	FN_DIS	801	4174	23933	102094	0.86	0.67
number of stereos	FN_STE	641	4311	19083	104829	0.82	0.82
number of vcrs	FN_VCR	808	5266	24165	128913	1.2	1.13
number of humidifiers	FN_HUM	66	446	1933	10996	0.07	0.07
number of dehumidifiers	FN_DHM	7	80	213	1884	0.01	0.02
number of air filters	FN_AIR	115	533	3445	13181	0.12	0.1
number of heated water beds	FN_BED	50	398	1453	9469	0.06	0.08
number of well pumps	FN_WEL	15	120	439	2916	0.02	0.02
number of water heaters	FN_HW	163	641	4666	14498	0.18	0.1
spa dummy	FD_SPA	81	250	2480	6623	0.08	0.04
pool timer dummy	FD_POOL	218	479	6594	13304	0.23	0.08

Table 2-5 (con't)

Description	Variable	Number of Customers with non-zero values		Number of Observations		Average Over All Observations	
		Participant	Non-participants	Participants	Non-participants	Participants	Non-participants
January 1993 Dummy	.	6	37	6	37	0.000	0.000
February 1993 Dummy	.	717	3174	717	3174	0.021	0.026
March 1993 Dummy	.	856	3954	856	3954	0.026	0.031
April 1993 Dummy	.	859	3797	859	3797	0.025	0.031
May 1993 Dummy	.	747	3602	747	3602	0.023	0.027
June 1993 Dummy	.	864	4004	864	4004	0.026	0.031
July 1993 Dummy	.	817	3871	817	3871	0.025	0.029
August 1993 Dummy	.	825	3981	825	3981	0.026	0.030
September 1993 Dummy	.	853	4054	853	4054	0.026	0.031
October 1993 Dummy	.	804	4081	804	4081	0.027	0.029
November 1993 Dummy	.	799	3978	799	3978	0.026	0.029
December 1993 Dummy	.	873	4184	873	4184	0.027	0.031
January 1994 Dummy	.	889	4513	889	4513	0.029	0.032
February 1994 Dummy	.	777	4061	777	4061	0.026	0.028
March 1994 Dummy	.	961	4899	961	4899	0.032	0.035
April 1994 Dummy	.	849	4502	849	4502	0.029	0.031
May 1994 Dummy	.	898	4661	898	4661	0.030	0.032
June 1994 Dummy	.	979	5079	979	5079	0.033	0.035
July 1994 Dummy	.	819	4572	819	4572	0.030	0.029
August 1994 Dummy	.	978	5348	978	5348	0.035	0.035
September 1994 Dummy	.	921	5123	921	5123	0.033	0.033
October 1994 Dummy	.	885	5050	885	5050	0.033	0.032
November 1994 Dummy	.	860	5083	860	5083	0.033	0.031
December 1994 Dummy	.	895	5323	895	5323	0.035	0.032
January 1995 Dummy	.	916	5490	916	5490	0.036	0.033
February 1995 Dummy	.	854	5361	854	5361	0.035	0.031
March 1995 Dummy	.	1025	6281	1025	6281	0.041	0.037
April 1995 Dummy	.	872	5546	872	5546	0.036	0.031
May 1995 Dummy	.	946	6101	946	6101	0.040	0.034
June 1995 Dummy	.	950	6294	950	6294	0.041	0.034
July 1995 Dummy	.	825	5684	825	5684	0.037	0.030
August 1995 Dummy	.	907	6389	907	6389	0.042	0.033
September 1995 Dummy	.	739	5318	739	5318	0.035	0.027

Table 2-6
Coefficients of Estimated Central Air Conditioner Load Impact Regression Model

Description	Variable	Coefficient	t-value	p-value
engineer est of cac consumption (Wh/d)	F_CAC	0.958	206.09	0.0001
Base CAC Est * Rep Dummy (Wh/d)	F_CAC_R	0.251	6.73	0.0001
Base CAC Est * Rep Dummy * Part Dummy (Wh/d)	F_CAC_RA	-0.249	-6.57	0.0001
engineer est of new cac consumption (Wh/d)	F_NCAC	0.945	29.25	0.0001
New CAC Est * Part Dummy (Wh/d)	F_NCAC_A	0.634	6.37	0.0001
engineer est of heater consumption (kWh/d)	F_HEAT	101	36.79	0.0001
engineer est of refrigerator consumption (kWh/d)	F_REF	-355	-17.56	0.0001
engineer est of freezer consumption (kWh/d)	F_FRZ	-105	-1.94	0.0524
engineer est of TV consumption (kWh/d)	F_TV	-616	-4.28	0.0001
clothes washer dummy	FD_WASH	0 .	.	
clothes dryer dummy	FD_DRY	1214	3.06	0.0022
stove dummy	FD_STV	-3540	-6.99	0.0001
oven dummy	FD_OVN	2892	5.61	0.0001
number of microwave ovens	FN_MIC	439	2.1	0.0361
number of dishwashers	FN_DIS	373	0.86	0.3901
number of stereos	FN_STE	765	4.92	0.0001
number of vcrs	FN_VCR	787	5.48	0.0001
number of humidifiers	FN_HUM	1123	3.1	0.0019
number of dehumidifiers	FN_DHM	1464	1.55	0.1205
number of air filters	FN_AIR	1143	3.64	0.0003
number of heated water beds	FN_BED	3576	4.02	0.0001
number of well pumps	FN_WEL	-12016	-3.81	0.0001
number of water heaters	FN_HW	-1425	-1.97	0.0489
spa dummy	FD_SPA	4575	10.82	0.0001
pool timer dummy	FD_POOL	9362	22.57	0.0001
Customer Fixed Effects	PREMISE		95.15*	0.0001
January 1993 Dummy		1672	1.68	0.0920
February 1993 Dummy		-1000	-7.69	0.0001
March 1993 Dummy		-1263	-9.93	0.0001
April 1993 Dummy		-2347	-18.24	0.0001
May 1993 Dummy		-2166	-16.46	0.0001
June 1993 Dummy		-697	-4.87	0.0001
July 1993 Dummy		1923	13.24	0.0001
August 1993 Dummy		2020	13.96	0.0001
September 1993 Dummy		1703	13.22	0.0001
October 1993 Dummy		-505	-3.94	0.0001
November 1993 Dummy		-1719	-13.44	0.0001
December 1993 Dummy		-808	-6.73	0.0001
January 1994 Dummy		-81	-0.69	0.4925
February 1994 Dummy		-791	-6.52	0.0001
March 1994 Dummy		-1274	-10.56	0.0001
April 1994 Dummy		-2048	-16.58	0.0001
May 1994 Dummy		-2218	-18.12	0.0001
June 1994 Dummy		-463	-3.39	0.0007
July 1994 Dummy		2575	18.17	0.0001
August 1994 Dummy		3443	24.78	0.0001
September 1994 Dummy		2386	19.42	0.0001
October 1994 Dummy		-597	-4.91	0.0001
November 1994 Dummy		-1218	-10.14	0.0001
December 1994 Dummy		0	0	0.0000
January 1995 Dummy		730	6.51	0.0001
February 1995 Dummy		-951	-8.4	0.0001
March 1995 Dummy		-1208	-10.54	0.0001
April 1995 Dummy		-1745	-14.79	0.0001
May 1995 Dummy		-1984	-17.13	0.0001
June 1995 Dummy		-1036	-7.87	0.0001
July 1995 Dummy		1373	10.09	0.0001
August 1995 Dummy		4002	29.39	0.0001
September 1995 Dummy		5746	46.8	0.0001

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

Interpretation of the Coefficients

The cooling variables are all in the same units as the dependent usage variable, Wh/day. The coefficients of the cooling variables all represent fractions of the base use engineering estimate. The other engineering estimates are entered in the model in kWh/day. If these engineering estimates were perfect, the expected coefficient would be 1,000, since the dependent variable is in Wh/day.

For heating, the estimated coefficient is around 100, indicating that the heating load is around 10 percent of the engineering estimate. This result is not unreasonable, because the engineering estimate used for heating is based on whole-house main heating, while many of the customers with this end use had only supplemental electric heat. On the other hand, the coefficients for refrigerators, freezers, and televisions are all negative, which is clearly not reasonable. Since virtually every house has this equipment, in virtually every time period, it is difficult to isolate its effect in a regression model.

The other end uses are entered not as explicit engineering estimates of energy use, but as dummy variables for the presence of the end use, or as counts of the number of units present. The coefficients of these variables therefore represent estimates of the unit energy use, in Wh/day. Many of these coefficients, including those for microwaves, dishwashers, and dehumidifiers, are in line with estimates from other studies. However, the coefficients for stoves, water heaters, and well pumps are all negative. The effects of these appliances are evidently absorbed in the customer and time dummies, or else confounded with other equipment.

Developing a meaningful set of conditional demand estimates of unit energy consumption was not a goal of this study. We therefore did not attempt to reduce the model specification to a set of variables that could be well determined and meaningful. Our primary concern was to control for as much exogenous change as possible, to estimate the cooling terms of interest. The inclusion of the time and customer dummies makes some of the other end-use terms difficult to identify, but is important for estimation of the terms of interest. With a more extensive model specification effort, it may be possible to develop a model that satisfies the evaluation objectives and also provides valid UEC estimates for at least a limited set of end uses. For the model developed here, however, we caution against over-interpretation of the coefficients as UEC's.

Reliability of the Savings Estimates

As discussed above, the CAC model was fit with different data screens, and also with self-selected correction terms included. Results of different fits are summarized in Appendix B.

The replacement and addition impact coefficients η_R and η_N were stable at 25 percent and -63 percent as different cut-offs for floorspace-per-room were used, none, 1,000 or 600. With a cut-off of 300 square feet per room, the replacement savings estimate η_R fell to 17 percent. However, this screen eliminated 37 percent of the observations, necessarily including large consumers, and was deemed too severe a screen.

With consumption points above 60 kWh/day or above 45 kWh eliminated, the replacement savings coefficient was higher, around 30 to 35 percent, but again stable over different cut-offs. With a cut-off of 30 kWh/day, the replacement savings coefficient again fell to below 20 percent, for a range of floorspace cut-offs. However, this consumption cut-off eliminates many of the high summer consumption points, and would be expected to result in a downward bias of the savings coefficient. Thus, this screen was also deemed too severe.

The central air model was also fit without the end-use variables f^j_{it} except for the heating and cooling terms. For most customers, who did not change their appliance ownership, these terms had the same value for all observations in the regression. The effects of these appliances were therefore lumped in with the customer-specific intercepts μ_i, and did not affect the heating and cooling coefficients. Almost no change was seen in the coefficients of interest when the other end use terms were dropped from the model.

Much less stability was seen when the correction terms for the replacement choices were included in the model. (The form of the correction terms and the fitted logistic model used to estimate them are presented in Appendix C.) The estimated net relative savings ranged from 70 percent to negative 20 percent across fits with different cut-offs. The t-statistics of the net savings was less than one in most cases.

The model without the correction terms indicates that customers who replaced air conditioners outside the program increased air conditioning usage by about 25 percent, while those who replaced by participating in the program did not have this increase. Though the savings coefficient varied with different cut-offs, it was always close in magnitude to the coefficient of replacement. In effect, then, the savings estimated for the participants is based less on a decline among this group than on the absence of the increase seen among nonparticipant replacers.

What we cannot be sure of is whether those replacers who chose to participate would have increased their consumption by more or less, in the absence of the program, than those replacers who chose not to participate. This difference in change associated with the choice to participate is what the correction terms are intended to account for. The instability and low t-statistics for the savings estimates when the correction terms are included means that we can't tell, or correct for, how the participant and nonparticipant replacers would have been different in the absence of the program. We therefore rely on the model without correction terms for the final estimate of savings, with the recognition of its limitation.

The results of the fits for different screening criteria, with and without the correction terms, are summarized in Appendix B. The results reported in Table 2-6 as our best estimate are from the fit excluding customers with greater than 1,000 square feet per room, but no screen on extreme usage. This estimate is at the low end of those from the screens that were not considered too severe.

Evaporative Coolers: Load Impact Regression Model for Gross Savings

Statistics of the variables and observations included in the final evaporative cooling model described above are presented in Table 2-7. Coefficients of the estimated model are presented in Table 2-8.

Table 2-7
Variables Included in the Evaporative Cooler Impact Estimation Model

Description	Variable	Number of Customers with non-zero values: Participants	Number of Customers with non-zero values: Non-participants	Number of Observations: Participants	Number of Observations: Non -participants	Average Over All Observations: Participants	Average Over All Observations: Non-participants
consumption (from billing file) (Wh/d)	USAGE	447	224	10483	4799	22471	18298
Base CAC Est * Non Part Dummy (Wh/d)	F_CAC_N	0	215	0	4565	2653	0
Base CAC Est * Part Dummy (Wh/d)	F_CAC_P	447	0	10483	0	0	4945
New Evap Est * Part Dummy (Wh/d)	F_NEP	447	0	10483	0	0	2222
engineer est of heater consumption (KWh/d)	F_HEAT	84	71	1880	1498	2.29	4.33
January 1993 Dummy	.	2	0	2	0	0.000	0.000
February 1993 Dummy	.	298	116	298	116	0.028	0.024
March 1993 Dummy	.	350	158	350	158	0.033	0.033
April 1993 Dummy	.	312	143	312	143	0.030	0.030
May 1993 Dummy	.	333	145	333	145	0.032	0.030
June 1993 Dummy	.	343	161	343	161	0.033	0.034
July 1993 Dummy	.	272	146	272	146	0.026	0.030
August 1993 Dummy	.	306	153	306	153	0.029	0.032
September 1993 Dummy	.	294	150	294	150	0.028	0.031
October 1993 Dummy	.	335	164	335	164	0.032	0.034
November 1993 Dummy	.	364	155	364	155	0.035	0.032
December 1993 Dummy	.	377	158	377	158	0.036	0.033
January 1994 Dummy	.	384	166	384	166	0.037	0.035
February 1994 Dummy	.	367	155	367	155	0.035	0.032
March 1994 Dummy	.	424	176	424	176	0.040	0.037
April 1994 Dummy	.	390	172	390	172	0.037	0.036
May 1994 Dummy	.	416	175	416	175	0.040	0.036
October 1994 Dummy	.	416	181	416	181	0.040	0.038
November 1994 Dummy	.	428	181	428	181	0.041	0.038
December 1994 Dummy	.	426	186	426	186	0.041	0.039
January 1995 Dummy	.	436	196	436	196	0.042	0.041
February 1995 Dummy	.	423	191	423	191	0.040	0.040
March 1995 Dummy	.	461	215	461	215	0.044	0.045
April 1995 Dummy	.	412	188	412	188	0.039	0.039
May 1995 Dummy	.	463	212	463	212	0.044	0.044
June 1995 Dummy	.	443	221	443	221	0.042	0.046
July 1995 Dummy	.	364	188	364	188	0.035	0.039
August 1995 Dummy	.	350	184	350	184	0.033	0.038
September 1995 Dummy	.	294	163	294	163	0.028	0.034

Table 2-8
Coefficients of Estimated Evaporative Cooler Model

Description	Variable	Coefficient	t-value	p-value
Base CAC Est * Non Part Dummy	F_CAC_N	0.270	14.64	0.0001
Base CAC Est * Part Dummy	F_CAC_P	0.420	32.27	0.0001
New Evap Est * Part Dummy	F_NEP	-0.127	-6.81	0.0001
engineer est of heater consumption	F_HEAT	113	14.09	0.0001
Customer Fixed Effects	PREMISE		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

The evaporative cooler model has a different structure from the central air conditioning model, as discussed above. It is not possible to identify from the surveys nonparticipants who added evaporative coolers during 1994. As a result, the model provides separate estimates of

- nonparticipant combined central air conditioning and evaporative cooler use
- participant base central air conditioning use
- the incremental effect of evaporative coolers for participants.

The estimates of end uses other than heating and cooling were excluded from the evaporative cooler model. As discussed further below, we were concerned about the reasonableness of the model results, and wanted to exclude the possibility of erroneous effects caused by the inclusion of one of these variables. In the central air conditioning model, inclusion or exclusion of the nonHVAC end use variables had almost no effect on the coefficients of interest, as discussed above.

For the evaporative cooler customers, the air conditioning usage is estimated at 27 percent of the engineering central air estimate, and at 42 percent of this estimate for participants prior to participating. 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 indicates that their usage of air conditioning is 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 CAC and evaporative cooler participants were modeled seperately.

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.

The coefficient of -.13 on the F_NEP variable means that the savings associated with installing the evaporative cooler was 13 percent of the engineering estimate of usage, an average of 375 kWh/year for the customers included in the regression sample. This estimate is only 30 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.

Diagnostics and Screening

The initial 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 summer of 1995 in relation to that.

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_CAC against F_NEP to confirm that these estimates were close to one another, as they should be if the engineering algorithms have been properly implemented.
- Plotted F_CAC and F_EVAP against time for participants and nonparticipants, to confirm that these had the expected patterns.
- Plotted consumption against F_CAC to identify extreme values.

Based on the last of these checks, we excluded observations with consumption greater than 60 kWh/day. The results listed in Table 2-8 are from this fit.

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 2-9.) 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.

Table 2-9
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

In this comparison of changes, the nonparticipant group controls both for differences in weather between 1993 and 1995, and for other exogenous changes. The adjustment is rough. For one thing, there is no control in this analysis for differences in the characteristics of participant and nonparticipant homes, as is included in the regression model. There is also no control for differences in the distribution of these two groups across climate zone; the regression model accounts for these differences via the degree-day variables that go into the engineering estimates of cooling. Finally, there is no weather normalization included in the median comparison. For all these reasons, we regard this analysis as indicative of the magnitude of savings, and qualitatively supporting the findings of the regression analysis, but not as providing the preferred estimate.

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 Huang and Wu 1992) 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.

Magnitude of Model Bias

As discussed above, 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, can be estimated as follows.

Edison's 1990 RASS showed 9.09 percent of customers had evaporative coolers. The 1995 RASS found the proportion was 11.66 percent. That is, over a five-year period the saturation increased by 2.57 percentage points. Roughly, then, over the two-year period from 1993 to 1995 we would expect an increase of 2/5 of this total, or 1.08 percentage points. That is, of the evaporative coolers in place by the time of the 1995 RASS, 8.8 percent (i.e., 1.08/11.66) were installed during the study period.

Thus, if the gross savings resulting from evaporative cooler installation is the same for nonparticipants as for participants, the participant gross savings estimated by the regression model is understated by about 8.8 percent of the true value. An adjusted estimate of gross savings is obtained by increasing the model estimate by a factor of 1/(1 - 0.088) = 1.10. With this adjustment, the gross avings, as a fraction of the engineering estimate, is 0.127 x 1.10 = 0.140.

Evaporative Coolers: Free Rider Adjustment for Net Savings

As discussed above, the evaporative cooler model gives gross savings (combined with snapback, retention and participant spillover). The savings determined by this model must be further adjusted for free ridership to obtain net savings. The two-stage estimation procedure for the free rider adjustment is described above.

Table 2-10 describes the explanatory variables and results of the first stage fit. This is the fit that estimates the probability a customer would participate in the 1994 program, given that the customer had an evaporative cooler in place by 1995.

All variables from the RASS that were thought likely to have an effect on the decision to participate, given that the measure was implemented, were included in the model. A notable exception was income. The income question was not answered by 13 percent of the customers included in the model. Including this question in the model specification would therefore have reduced the number of observations for the fit by this amount. In addition, the fit that did include income failed to converge.

Other variables that turned out to have low t-statistics were left in the model. The effect of retaining variables with low statistical significance is to increase the variance of other estimates. However, these "extraneous" variables will only marginally affect the variance of the predicted propensity to participate, which is the parameter of interest from this stage of the logit analysis. Moreover, excluding a variable that does belong in the model can bias the estimated propensities. On balance, it was considered better to err on the side of somewhat greater variance and lower bias by keeping most of the variables from the initial specification.

Among customers who had evaporative coolers in place as of 1995, one of the main factors affecting the decision to participate in the 1994 rebate program was the composition of the household by age. This composition is captured by the set of OCC variables, whose t-statistics are in the range of 1.5 to 2. Other factors that appeared to be important were the number of days electric appliances were in use during the week in the summer, the number of weekdays the air conditioning was used, and the number of hot meals cooked per day. These variables all relate, at least in part, to whether the home is occupied during the day on weekdays. (This question is not asked explicitly on the RASS, to avoid possible security concerns on the part of respondents.)

A few variables have moderate t-values, between one and two, but are probably not meaningful. These are dummy variables that have the same value for all but a few customers. Included in this set of variables are indicators for military, Asian, renter, and English-speaking households.

The only other variable with a t-statistic greater than one was floorspace (SQFT). Average floorspace was almost the same for participants as for nonparticipants.

Table 2-10
1st Stage Participation Model, Modeling Participation among Implementors

Description	Variable	Means: Participants	Means: Non-participants	Coeff	t-value	p-value
Constant	INTERCPT	1.000	1.000	0.69	2.03	0.04
at home year round?	ALL_YEAR	0.904	0.868	0.36	0.54	0.59
cool thermo kept constant?	COOL_CON	0.364	0.358	0.23	0.49	0.63
English spoken?	ENGLISH	0.979	0.925	-1.98	-1.23	0.22
farmer?	FARMER	0.004	0.075	-0.82	-0.38	0.71
heat thermo kept constant?	HEAT_CON	0.286	0.396	-0.35	-0.75	0.45
higher education?	HI_ED	0.400	0.358	-0.35	-0.76	0.45
q32: hot meals per day	MEAL_D	1.046	0.929	0.52	1.19	0.23
military?	MILITARY	0.004	0.057	-3.09	-1.17	0.24
mobile home?	MOBILEH	0.182	0.189	0.01	0.01	0.99
occupant < 5yr?	NEW_OCC	0.561	0.472	0.22	0.52	0.60
q74: no. occupants	OCC	2.284	2.442	-3.00	-2.07	0.04
q75: no. of occ st 60 <= age	OCC100	0.779	0.755	2.13	1.59	0.11
q75: no. of occ st age <= 12yrs old	OCC12	0.257	0.302	2.76	1.90	0.06
q75: no. of occ st 12 <= age <= 17	OCC17	0.082	0.170	2.21	1.46	0.14
q75: no. of occ st 18 <= age <= 24	OCC24	0.096	0.038	3.23	2.05	0.04
q75: no. of occ st 25 <= age <= 44	OCC44	0.507	0.491	2.46	1.76	0.08
q75: no. of occ st 45 <= age <= 59	OCC59	0.518	0.528	2.11	1.56	0.12
professional?	PROFESS	0.450	0.358	0.46	0.83	0.41
Asian?	R_ASIAN	0.014	0.038	-2.63	-1.69	0.09
Black?	R_BLACK	0.000	0.000	0.00	0.00	0.00
Hispanic?	R_HISP	0.046	0.132	-0.75	-0.68	0.50
White?	R_WHITE	0.861	0.736	0.42	0.49	0.63
renter?	RENTER	0.046	0.094	-2.18	-2.57	0.01
retired?	RETIRED	0.421	0.453	-0.05	-0.07	0.94
sales worker?	SALES	0.121	0.170	-0.26	-0.40	0.69
service worker?	SERVICE	0.036	0.113	0.35	0.35	0.73
single home?	SINGLEH	0.764	0.736	0.50	0.64	0.52
skilled worker?	SKILLED	0.114	0.189	-0.25	-0.39	0.69
q09: floor space, sqft	SQFT	1748	1767	-0.00046	-1.19	0.24
student?	STUDENT	0.011	0.057	-1.16	-0.52	0.60
q27: no. summer weekdays use ac	SUMD_AC	3.201	3.175	-0.21	-1.16	0.24
q12: no. summer weekdays use elec	SUMMERD	2.867	2.453	0.32	2.04	0.04

Table 2-11 summarizes the second stage model, which estimates the probability of implementing as a function of factors including the instrument for participation. The resulting free rider adjustment and its precision are summarized in Table 2-12.

Table 2-11
2nd-Stage Implementation Model
Modeling Implementation among
Participants and Non-Participants

Description	Variable	Implementor Mean	Non-Implementor Mean	Coeff	t-value	p-value
Constant	INTERCPT	1.000	1.000	-2.79	-5.38	0.0001
inclusive (participation) term	BIGI	0.207	0.134	1.04	1.61	0.1084
mobile home?	MOBILEH	0.183	0.043	3.51	7.69	0.0001
occupant < 5yr?	NEW_OCC	0.547	0.468	0.31	1.40	0.1618
q75: no. of occ st 60 <= age	OCC100	0.775	0.966	-0.30	-2.32	0.0204
single home?	SINGLEH	0.760	0.464	2.43	8.32	0.0001

Table 2-12
Free Rider Adjustment Factor Estimate,
Standard Error, and Percentiles Based on
Pseudo-Sample of Size 500

Estimate	0.5383			
Standard Error	0.0849			
	Confidence Intervals			
Confidence Level	99%	95%	90%	80%
Percentile Range	(0.5-99.5%)	(2.5-97.5%)	(5-95%)	(10-90%)
Lower Bound	0.3556	0.4042	0.4186	0.4351
Upper Bound	0.7622	0.7151	0.6926	0.6563

2.4.6 Calculation of Savings Estimates from Load Impact Regression Models

The regression equations presented above provide estimates of program savings as fractions of base air conditioner use. To translate these coefficients 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. For the evaporative cooler model, which provides gross savings, the estimate is multiplied by the free rider adjustment factor F. The central air model provides net savings, so that this adjustment is not required.

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).

The realization rate calculations are presented in Table 2-13. For central air conditioners and heat pumps, the realization rate was 1.23, while for evaporative coolers it was only 0.19.

Table 2-13
Realization Rate Calculations from the Regression Results

Variable	Effect Estimated	Regression Sample Size n	Sample Average Engineering Estimate of Variable* x (kWh/year)	Effect as Fraction of Engineer-ing Estimate p	Effect per customer u = p*x (kWh/year)	Free-Rider Adjust-ment** f	Unit Net Savings s = -f*u	Sample Average Tracking Estimate of Savings t (kWh/year)	Realization Rate relative to tracking r = s/t
CAC MODEL									
Base CAC use, all customers	Base CAC UEC	4555	1408.27	0.9582	1349.40				
Base CAC use, replacers only	Replacement increment	663	1815.41	0.2512	456.03				
Base CAC use, replacer participants only	Net savings for replacement participants	615	1953.18	-0.2493	-486.93	1.00	486.93	356.16	1.37
New CAC use, adders	Added capacity increment	192	1193.63	0.9446	1127.50				
New CAC use, adder participants only	Net savings for adder participants	37	850.40	0.6337	538.90	1.00	-538.90	217.19	-2.48
	Overall CAC participant savings	652					428.71	348.27	1.23
EVAP. COOLER MODEL									
Evap. Cooler use, participants only	Evap. cooler participant savings	451	3089	-0.1396	-431	0.54	233	1236	0.19

*For each customer in the sample, the engineering estimate is computed for full-year usage, with calendar year 1994 weather.
**For the central air impacts, the free rider effects are included in the estimated effect p.

Applying the realization rates to the total tracking estimate of savings gives the estimate of total program savings. The results are given in Table 2-14.

Table 2-14
Net Energy Impacts

Program Component	Number of Participants	Realization Rate (Net/ Tracking)	Savings Estimates: Tracking Unit (kWh/year)	Tracking Program Total (GWh/year)	Net Unit (kWh/year)	Net Program Total (GWh/year)	Realization Rate Standard Error: Absolute	Relative
Central Air	6202	1.23	474	2.94	583	3.62	0.204	16.6%
Evaporative Coolers	1624	0.19	1509	2.45	284	0.46	0.041	21.9%
Total Program	7826	0.76	689	5.39	521	4.08	0.113	14.9%

Evaporative coolers account for only 21 percent of participants, but 51 percent of the total tracking estimate savings. The average tracking estimate of savings was over three times as high for evaporative coolers as for central air conditioners and heat pumps. Thus, the low realization rate for evaporative coolers substantially affects the overall program realization rate. Across both types of units, the program realization rate was 76 percent.

Demand Savings

Demand Savings were estimated by applying the net-to-tracking realization rate from the energy analysis to the tracking system estimates of demand savings. For central air conditioners, 2.4 percent of the tracking system entries were zero. These were assumed to be missing values. The average tracking demand savings were computed excluding zero values for central air conditioning. For evaporative coolers, 65 percent of the tracking estimates of demand savings were zero. For this technology, depending on the specifics of the configuration, there is often no savings on extreme hot days. For this reason, the zero entries were treated as valid savings estimates. The average tracking estimate of demand savings was computed including zero values for evaporative coolers. The results are summarized in Table 2-15.

Table 2-15
Net Demand Impacts

Number of Participants	Realization Rate (Net/ Tracking)	Savings Estimates: Tracking Unit (kW)	Tracking Program Total (MW)	Net Unit (kW)	Net Program Total (MW)	Realization Rate Standard Error: Absolute	Relative
6202	1.23	0.37	2.32	0.46	2.86	0.204	16.6%
1624	0.19	0.29	0.47	0.05	0.09	0.041	21.9%
7826	1.05	0.36	2.80	0.38	2.95	0.170	16.1%

The realization rate for the program as a whole is the weighted average of the realization rates for the central air and evaporative cooler components. The weights are the total tracking estimates of savings. Because these relative weights are different for energy than for demand, the program-level realization rates are different, even though the same realization rate is assumed for energy and demand within each component.

The relative precision of the total program net savings estimate is 15 percent for energy, and 16 percent for demand. Because unit and total savings are equal to the realization rate multiplied by known constants, the same relative precision applies to all three quantities. The confidence intervals for the realization rate, unit savings, and total net savings are shown in Table 2-16.

The precision calculations take into account the variance due to both the regression and the ratio adjustment used to expand from the sample to the population. For evaporative coolers, the variance of the free rider adjustment factor is also included, but variances associated with the bias adjustment is not. Without this adjustment, the realization rate would be approximately two percentage points lower for this component.

Table 2-16
Precision of Net Impact Estimates

	Parameter		Estimate	Standard Error	Confidence Intervals 90 percent	80 percent
Energy	Realization Rate		0.76	0.11	0.57 - 0.94	0.61 - 0.90
	Unit Net Savings	(kWh/year)	521	78	393 - 649	422 - 621
	Program Net Savings	(GWh/year)	4.08	0.61	3.08 - 5.08	3.30 - 4.86
Demand	Realization Rate		1.05	0.17	0.78 - 1.33	0.84 - 1.27
	Unit Net Savings	(kW)	0.38	0.06	0.28 - 0.48	0.30 - 0.45
	Program Net Savings	(MW)	2.95	0.48	2.17 - 3.73	2.34 - 3.56

References

Barakat and Chamberlin 1993. *Impact Evaluation of Southern California Edison's Customer Assistance Programs 1990-91.*

Hoeschele, M. 1994. "Residential Indirect/Direct Evaporative Cooler Performance in Sacramento." *Proceedings from the ACEEE 1994 Summer Study on Energy Efficiency in Buildings, Volume 9*, pp 9.175-9.185. American Council for an Energy-Efficient Economy, Washington DC.

Huang, J. and H. Wu 1992. "Measurements and Computer Modeling of the Energy Usage and Water Consumption of Direct and Two-Stage Evaporative Coolers." *Proceedings from the ACEEE 1992 Summer Study on Energy Efficiency in Buildings, Volume 2*, pp 2.89-2.109. American Council for an Energy-Efficient Economy, Washington DC.

Train, K., S. Buller, B. Mast, K. Parikh, E. Paquette, 1994. "Estimation of Net Savings for Rebate Programs: A Three-Option Nested Logit Approach." *Proceedings from the ACEEE 1994 Summer Study on Energy Efficiency in Buildings, Volume 7*, pp 7.239-7.247. American Council for an Energy-Efficient Economy, Washington DC.

SOUTHERN CALIFORNIA EDISON
M&E PROTOCOLS TABLE 6 - RESULTS USED TO SUPPORT PY94 SECOND EARNINGS CLAIM FOR RESIDENTIAL HVAC REBATE PROGRAM
FIRST YEAR LOAD IMPACT EVALUATION, FEBRUARY 1996, STUDY ID NO. 512

Designated Unit of Measurement: LOAD IMPACTS PER PARTICIPANT
ENDUSE: AIR CONDITIONING

				5. A. 90% CONFIDENCE LEVEL				5. B. 80% CONFIDENCE LEVEL			
				LOWER BOUN	UPPER BOUND	LOWER BOUN	UPPER BOUND	LOWER BOUN	UPPER BOUND	LOWER BOUN	UPPER BOUND
1. Average Participant Group and Average Comparison Group		PART GRP	COMP GRP	PART GRP	PART GRP	COMP GRP	COMP GRP	PART GRP	PART GRP	COMP GRP	COMP GRP
A. Pre-install usage:	Pre-install kW										
	Pre-install kWh										
	Base kW										
	Base kWh										
	Base kW/ designated unit of measurement										
	Base kWh/ designated unit of measurement										
B. Impact year usage	Impact Yr kW										
	Impact Yr kWh										
	Impact Yr kW/designated unit										
	Impact Yr kWh/designated unit										
2. Average Net and Gross End Use Load Impacts		AVG GROS	AVG NET	AVG GROSS	AVG GROSS	AVG NET	AVG NET	AVG GROSS	AVG GROSS	AVG NET	AVG NET
	A. i. Load Impacts - kW	N/A	2,950	N/A	N/A	2,169	3,732	N/A	N/A	2,341	3,560
	A. ii. Load Impacts - kWh	N/A	4,080,017	N/A	N/A	3,078,369	5,081,665	N/A	N/A	3,299,645	4,860,389
	B. i. Load Impacts/designated unit - kW	N/A	0.38	N/A	N/A	0.28	0.48	N/A	N/A	0.30	0.45
	B. ii. Load Impacts/designated unit - kWh	N/A	521	N/A	N/A	393	649	N/A	N/A	422	621
	C. i. a. % change in usage - Part Grp - kW										
	C. i. b. % change in usage - Part Grp - kWh										
	C. ii. a. % change in usage - Comp Grp - kW										
	C. ii. b. % change in usage - Comp Grp - kWh										
D. Realization Rate:	D.A. i. Load Impacts - kW, realization rate	N/A	1.05	N/A	N/A	0.78	1.33	N/A	N/A	0.84	1.27
	D.A. ii. Load Impacts - kWh, realization rate	N/A	0.76	N/A	N/A	0.57	0.94	N/A	N/A	0.61	0.90
	D.B. i. Load Impacts/designated unit - kW, real rate	N/A	1.05	N/A	N/A	0.78	1.33	N/A	N/A	0.84	1.27
	D.B. ii. Load Impacts/designated unit - kWh, real rate	N/A	0.76	N/A	N/A	0.57	0.94	N/A	N/A	0.61	0.90
3. Net-to-Gross Ratios		RATIO		RATIO	RATIO			RATIO	RATIO		
	A. i. Average Load Impacts - kW	N/A		N/A	N/A			N/A	N/A		
	A. ii. Average Load Impacts - kWh	N/A		N/A	N/A			N/A	N/A		
	B. i. Avg Load Impacts/designated unit of measurement - kW	N/A		N/A	N/A			N/A	N/A		
	B. ii. Avg Load Impacts/designated unit of measurement - kWh	N/A		N/A	N/A			N/A	N/A		
	C. i. Avg Load Impacts based on % chg in usage in Impact year relative to Base usage in Impact year - kW										
	C. ii. Avg Load Impacts based on % chg in usage in Impact year relative to Base usage in Impact year -										
4. Designated Unit Intermediate Data		PART GRP	COMP GRP	PART GRP	PART GRP	COMP GRP	COMP GRP	PART GRP	PART GRP	COMP GRP	COMP GRP
	A. Pre-install average value	N/A		N/A	N/A			N/A	N/A		
	B. Post-install average value	N/A		N/A	N/A			N/A	N/A		
6. Measure Count Data		NUMBER									
	A. Number of measures installed by participants in Part Group										
	B. Number of measures installed by all program participants in the 12 months of the program year										
	C. Number of measures installed by Comp Group	N/A									
7. Market Segment Data											
	Number of Participants	7826	N/A								

Table 7

A. Overview Information

1. Study Title and Study ID: 1994 Residential HVAC Rebate Program Impact Evaluation, CEC Study ID #512.

2. Program, Program Year, and Description: 1994 Residential Energy Management Incentive Program. This program provided rebates to residential customers who replaced central air conditioners and heat pumps, and who installed evaporative coolers.

3. End Uses Covered: Electric central air conditioners, heat pumps, and evaporative coolers.

4. Methods Used: The analysis used a combination of engineering estimates and a statistical cross-sectional time series model as described in detail in Section 2.4.

5. Participants and Nonparticipants: All subjects were respondents to the 1994 SCE Residential Appliance Saturation Survey. Appendix E describes the survey design. Participants were those individuals who received rebates for CAC, heat pump, or evaporative cooler equipment.

6. Analysis of Sample Size: Tables 2-1, 2-5, and 2-7 detail the number of customers and observations involved in the various stages of the analysis. See also Appendix F.

B. Database Management

1. Flow Chart Illustrating Relationships between Data Elements: See Figure F-1.

2. Identify the Specific Data Sources for each Element: See Section 2.2.

3. Describe Data Attrition: See Appendix F.

4. Describe Procedures Used to Match Records from Different Data Elements: Customer **PREMISE** number was the key for the billing, survey, and program tracking data. Customer **LSACCT** number linked each customer to a weather region.

5. Summary of Data Collected but not Used: Not Applicable.

C. Sampling

1. Sampling Procedures and Protocols: See Appendix E.

2. Survey Information: See Appendix A for the survey instrument, and Table 2-1 for the number of completes.

3. Statistical Descriptions: These are given in Tables 2-5 and 2-7.

D. Data Screening and Analysis

1. Procedures Used for Treatment of Outliers, Missing Data Points, and Weather Adjustment: Weather adjustment was implicit in the models themselves, and missing data were eliminated. The analysis description beginning on page 2-18 details outlier screening.

2. Controlling for the Effects of Background Variables: The models included nonparticipant comparison groups and time period dummies.

3. Procedures Used to Screen Data: These are described in Appendix F and in the discussion of the individual models themselves in Section 2.4.5.

4. Regression Statistics: These are given in Tables 2-6, 2-8, 2-10, and 2-11.

5. Specification: This is detailed in Section 2.4.

6. Error in Measuring Variables: Statistical models as used here explicitly allow—and account for—random error.

7. Autocorrelation: The regression models included customer-specific dummy variables as described in Section 2.4.

8. Heteroskedasticity: The regression models included customer- and time-specific dummy variables as described in Section 2.4.

9. Collinearity: The model specification addressed issues surrounding problems of collinearity as discussed on pages 2-10 and 2-12.

10. Influential Data Points: See the discussion beginning on page 2-

11. Missing Data: Ample data remained after eliminating observations containing missing data.

12. Precision: Pages 2-16 and 2-37 detail the calculation of standard errors.

E. Data Interpretation and Application

The methods used addressed the problems of exogenous changes, weather-related influences, and free-ridership. Section 2.4 provides a detailed discussion.