1995 In-Home Audit Program Evaluation

Study ID No. 528 (A)

Submitted to:

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February 12, 1997

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Executive Summary

1.1 Overview

This report presents the results of an evaluation of the impacts of Southern California Edison Company's In-Home Audit (IHA) Program. The evaluation was conducted by Regional Economic Research, Inc. (RER) under contract to Southern California Edison (SCE or Edison). In addition, Katherine Randazzo of KVQ Research Consulting prepared a discussion on the existence of market barriers to the implementation and use of energy efficient appliances. The evaluation effort was managed by Shahana Samiullah of the SCE Marketing Department. The project focused on both gross and net energy and demand impacts, and explored a series of questions relating to the kinds of activities that generate these impacts.

1.2 Background

The In-Home Audit Program, which is a component of Edison's overall Energy Management Services Program, offers a variety of energy conservation recommendations and information about high efficiency appliances to interested SCE residential customers at no cost. The In-Home Audit program offers both on-site and telephone options. The on-site version entails a walk-through audit and site-specific conservation recommendations are provided. The telephone audit is essentially identical to the on-site audit. Program recommendations relate to behavioral changes, or *practices*, or to changes requiring some financial outlay, or *measures*. However, no direct recommendations relating to equipment/appliance replacements are made. Instead, information on the availability of high-efficiency equipment options is provided to each participant.

1.3 Project Objectives

The evaluation had three primary objectives:

- To estimate the program's first-year net energy and coincident demand impacts, by end use,

- To estimate the first-year gross energy and coincident demand impacts by end use, and
- To estimate program level results (all end uses combined).

Secondary objectives were:

- To assess the distribution of direct program impacts across measures and practices,
- To evaluate the indirect impact of program participation on the purchase of high-efficiency appliances, and
- To assess reduction of market barriers as a result of the Program.

1.4 Data

The impact evaluation of the In-Home Audit Program required the development of an extensive integrated database. The key elements of the database included:

- In-Home Audit Program data, which included general information on participants' features as well as indications of the specific measures and practices recommended to individual households,
- Participant survey data on a variety of factors including implementation of Audit Program recommendations, appliance stocks, housing features, demographic characteristics, and recent changes at the site,
- Nonparticipant survey data encompassing appliance stocks, housing features, demographic characteristics, and recent changes at the site,
- SCE Master File billing data covering participant energy usage before and after the audit, as well as usage by a sample of nonparticipants, and
- Weather data covering the period of time for which the billing analysis was conducted.

1.5 Methodology

Estimation of Net Energy Impacts. As explained in Section 4, this analysis considered several approaches in the course of the project, including direct participation impact modeling, traditional conditional demand analysis, simplified (change form) conditional demand, and realization rate analysis. Program impacts were ultimately estimated using a hybrid approach that can be considered an extension of *direct participation modeling.* Direct participation modeling entails the use of regression analysis to infer the impact of program participation on the level of or change in energy usage. A program variable (typically a binary pre-post participation variable) is included in the model to reflect program impacts, and other variables are included to control for other determinants of changes in consumption, such as variations in weather, changes in household size, appliance acquisitions or replacements, and structural changes. For reasons explained below, this approach was modified through the incorporation of information on adoptions by end use and category (measures and practices). It was also refined to incorporate weights reflecting rough engineering estimates of impacts of specific actions.

Estimation of End-Use Savings and Measure/Practice Savings. In most applications of direct participation modeling, a binary variable is used to represent the post-audit period for participants and the coefficient of this variable is interpreted as the impact of participation. This reliance on a single binary indicator of participation had to be modified somewhat in order to accommodate the achievement of two project objectives: the estimation of impacts by end use and the assessment of the relative impacts of measure and practices. In the refined model, information on end-use actions reportedly taken as a result of the audit was interacted with the participation variable. This resulted in several impact terms, each representing an end use and, in one version of the model, either measures or practices. The estimated coefficients of these terms reflected the specific impacts of participation by end use and by measure/practice category.

Correction for Self-Selection Bias. Because direct participation modeling essentially entails a statistical comparison of energy use of nonparticipants and participants (after the program), it is particularly susceptible to self-selection bias. Self-selection bias arises from the fact that participants self-select themselves into the program, and may differ systematically from nonparticipants in their disposition toward conservation activities. In order to mitigate this bias, we used an approach termed the *Double Mills Ratio Approach*. With this approach, an inverse Mills Ratio is included as a free-standing term as well as an interaction term with the participation variable. Again, the standard Double Mills Ratio Approach had to be modified somewhat to accommodate other refinements in the direct participation model. This modification entailed the interaction of the Mills Ratio with a composite variable representing an initial estimate of program impacts.

Estimation of Gross Energy Impacts. In general, direct participation models are estimated with data on both participants and nonparticipants, and are best suited for the estimation of net program impacts. However, it can be shown that, under general conditions, gross impacts can be inferred from the estimated model if nonparticipants are excluded from the estimation sample. In this application, the coefficient(s) on the participation term will essentially reflect gross changes in participant consumption attributable to participation. These estimated impacts can be considered gross in the sense that they do not account for conservation activities of nonparticipants. This approach was used to generate estimates of gross program impacts by end use.

Estimation of Demand Impacts. Demand impacts were estimated using a set of end-use peak ratios. These were computed as ratios of the end use's contribution to SCE's peak to the annual energy associated with this end use. Peak ratios were developed from the results of Edison's 1991 end-use metering project. They were then multiplied by estimated annual end-use energy savings to compute estimated coincident demand impacts.

1.6 Summary of Project Results

Table 1-1 summarizes the estimated savings per participant. As shown, the impact of the In-Home Audit is decomposed into savings by end use. Savings associated with weather-sensitive end uses are weather-normalized. The following conclusions can be made on the basis of these results:

- For the overall program, average per-participant net impacts are 343 kWh per year under normal weather conditions.
- Net impacts of the in-home delivery approach are approximately 432 kWh annually under actual post-audit weather conditions. The net impacts of the phone version of the audit are 154 kWh.
- Net impacts are dominated by refrigeration actions. Over 74% of all savings come from this end use.
- Gross impacts are somewhat higher than net impacts across all end uses. The implied net-to-gross ratio for total energy impacts is 72%. This is a plausible value for this kind of program.
- While it is not indicated in Table 1-1, practices account for all of the savings of the program. Refrigerator practices include disconnecting second refrigerators, checking condenser coils, keeping the unit full, and lowering the thermostat setting. These practices appear to dominate the results of the program.
- The data show that customers are usually not experiencing an information barrier. Therefore, the audits do not, strictly speaking, have an information barrier to overcome. However, there is some support for the idea that, while vaguely aware of the energy benefits of the recommended actions, customers do not always act on this knowledge until it is specifically suggested by an Edison expert.

Table 1-1: Estimated Net and Gross Impacts per Home, Normal Weather

End Use	Net Impacts (kWh)	Gross Impacts (kWh)
Air Conditioning	20.7	25.4
Space Heating	12.5	18.7
Water Heating	16.4	17.9
Refrigeration	254.2	365.4
Other	38.8	50.7
Total Estimated Impacts	342.6	478.1
In-Home versus Phone Audits		
In-Home Audit	432.7	
Phone Audit	154.4	

Table 1-2 presents a summary of total program energy and demand savings. As indicated in Table 1-2, total annual weather-normalized energy savings from the 1995 program are over 3.4 million kWh, assuming there were 10,000 Program participants during that year. The associated coincident peak demand savings amount to 740 kW. Approximately half of these demand savings come from refrigeration actions, while most of the rest are attributable to air conditioning actions.

Table 1-2: Total Program Energy and Demand Savings, Normal Weather

End Use	Total Net Program Savings (kWh)	Peak Load Factor	Estimated Demand Savings (kW)
Air Conditioning	207,000	0.001370	283.6
Space Heating	125,000	0.000000	0.0
Water Heating	164,000	0.000077	12.6
Refrigeration	2,542,000	0.000146	371.1
Other	388,000	0.000187	72.6
Total Estimated Savings	3,426,000	-	739.9

2

Introduction

2.1 Overview

This report presents the results of an evaluation of the impacts of Southern California Edison Company's In-Home Audit (IHA) Program. The project focused on both gross and net energy and demand impacts, and explored a series of questions relating to the kinds of activities that generate these impacts. This section presents a brief background for the program, specifies project objectives, discusses methodologies used in the evaluation, and previews the remainder of the report.

2.2 Background

The In-Home Audit Program, which is a component of Edison's overall Energy Management Services Program, offers a variety of energy conservation recommendations and information about high-efficiency appliances to interested SCE residential customers at no cost. The In-Home Audit Program offers both on-site and telephone options. The on-site version entails a walk-through audit and site-specific conservation recommendations are provided. The telephone audit is essentially identical to the on-site audit. Program recommendations relate to behavioral changes, or *practices*, or to changes requiring some financial outlay, or *measures*. However, no direct recommendations relating to equipment/appliance replacements are made. Instead, information on the availability of high-efficiency equipment options is provided to each participant.

2.3 Project Objectives

The evaluation had three primary objectives:

- The first objective was to estimate the program's net first-year energy and coincident demand impacts, by end use. These impacts are designed to reflect the savings attributable to the program, net of any free-rider effects.
- The second objective was to estimate the gross first-year energy and coincident impacts. These gross impacts reflect the savings enjoyed by participants,

including those that would have been forthcoming even in the absence of the program.

- The third objective of this analysis was to estimate program level results by end use and,further, by measures and practices.

The project also had three secondary objectives relating to the assessment of program impacts:

- The first was to assess the distribution of direct program impacts across measures and practices. This portion of the analysis provided insights with respect to the paths via which savings are generated, and could be useful in evaluating participant costs.
- The second was to evaluate the indirect impact of program participation on the purchase of high-efficiency appliances. While auditors do not make explicit recommendations with respect to replacing appliances with high-efficiency units, they do mention to participants that such models are available.
- The third as to assess reduction of market barriers due as a result of the Program.

2.4 Data

The impact evaluation of the In-Home Audit Program required the development of an extensive integrated database. The key elements of the database included:

- In-Home Audit Program data, which included general information on participants' features as well as indications of the specific measures and practices recommended to individual households,
- Participant survey data on a variety of factors including implementation of Audit Program recommendations, appliance stocks, housing features, demographic characteristics, and recent changes at the site,
- Nonparticipant survey data encompassing appliance stocks, housing features, demographic characteristics, and recent changes at the site,
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- Weather data covering the period of time for which the billing analysis was conducted.

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Estimation of Net Energy Impacts. As explained in Section 4, this analysis considered several approaches over the course of the project, including direct participation impact modeling, traditional conditional demand analysis, simplified (change-form) conditional demand, and realization rate analysis. Program impacts were ultimately estimated using a hybrid approach that can be considered an extension of *direct participation modeling*. Direct participation modeling entails the use of regression analysis to infer the impact of program participation on the level of or change in energy usage. A program variable (typically a binary pre-post participation variable) is included in the model to reflect program impacts, and other variables are included to control for other determinants of changes in consumption, like variations in weather, changes in household size, appliance acquisitions or replacements, and structural changes. For reasons explained below, this approach was modified through the incorporation of information on adoptions by end use and category (measures and practices). It was also refined to incorporate weights reflecting rough engineering estimates of impacts of specific actions.

Estimation of End-Use Savings and Measure/Practice Savings. In most applications of direct participation modeling, a binary variable represents the post-audit period for participants and its coefficient is interpreted as the impact of participation. This reliance on a single binary indicator of participation had to be modified somewhat in order to accommodate the achievement of two project objectives: the estimation of impacts by end use and the assessment of relative impacts of measure and practices. In the refined model, information on end-use actions reportedly taken as a result of the audit was interacted with the participation variable. This resulted in several terms, each representing an end use and, in one version of the model, either measures or practices. The estimated coefficients of these terms reflected the specific impacts of participation by end use and by measure/practice category.

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Estimation of Demand Impacts. Demand impacts were estimated using a set of end-use peak ratios. These were computed as ratios of the end use's contribution to SCE's peak to the annual energy associated with this end use. Peak ratios were developed from the results of Edison's 1991 end-use metering project. They were then multiplied by estimated annual end-use energy savings to compute estimated coincident demand impacts.

2.6 Report Organization

The remainder of this report is organized as follows:

- Section 3 describes the development of the integrated database,
- Section 4 presents the methodology for estimation of Program impacts,
- Section 5 presents the results of the analysis,
- Appendix A describes the sample design,
- Appendix B includes the final survey questionnaires,
- Appendix C contains the pre- and post-survey letters,
- Appendix D includes the In-Home Audit Survey instrument,
- Appendix E details the classification of Program recommendations used in the analysis,
- Appendix F presents the engineering priors used to weight individual actions,
- Appendix G presents describes the procedure for replacing nonresponse values, and
- Appendix H details the derivation of net and gross Program impacts.

3

Integrated Database Development

3.1 Introduction

This chapter discusses the development of the integrated database for analysis of the 1995 In-Home Audit (IHA) Program. The first subsection outlines the basic components of the database and subsections 3.2 through 3.5 describe each component of the database in detail. Subsection 3.6 reviews data preparation methods, including the replacement of missing values and the identification of anomalous consumption data. The final integrated database is described in subsection 3.7. Finally, a summary of household demographic, economic, and electricity end-use characteristics is presented in subsection 3.8.

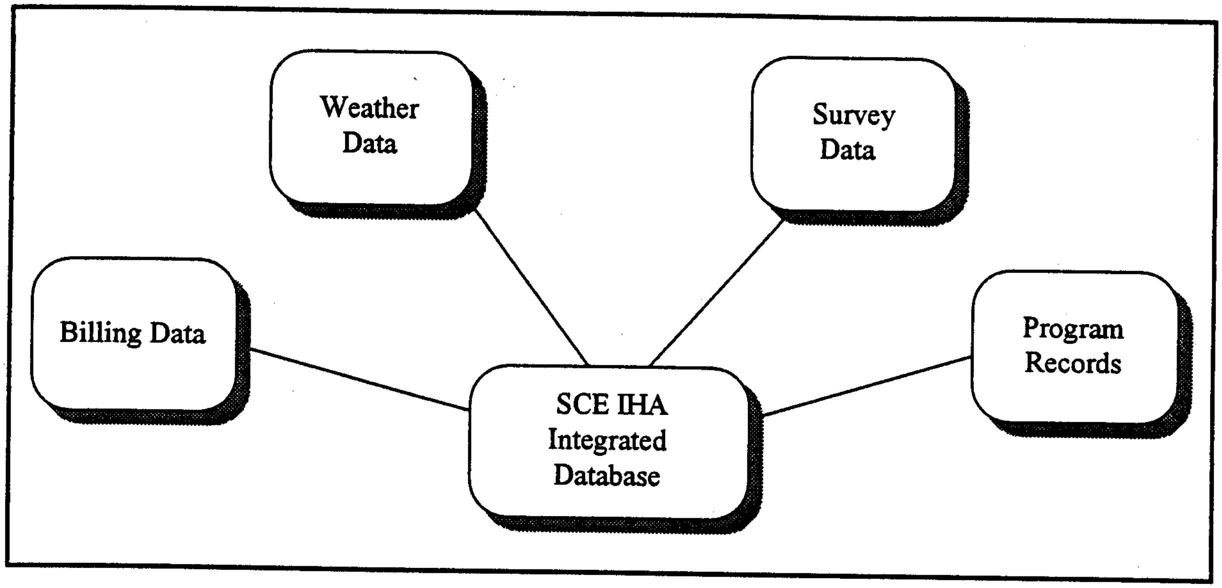
3.2 Integrated Database Components

The impact evaluation of the SCE In-Home Audit Program requires the development of an integrated database. Figure 3-1 provides an overview of the information needed to construct the database. The key components include:

- Participant and Nonparticipant Survey Data,
- 1995 In-Home Audit Program Participant Data,
- Consumption Data, And
- Actual and Normal Weather Data.

Each of these elements is discussed in detail in the following sections.

Figure 3-1: Overview of Database



Participant and Nonparticipant Survey Data

The evaluation of the 1995 In-Home Audit Program was supported by the collection of telephone survey data for both participants and nonparticipants. The objective of the nonparticipant telephone survey was to collect information on household characteristics and timing of appliance purchases and replacements. The objective of the participant telephone survey was to obtain data reflecting post-audit behavior and responses to program recommendations, as well as the timing of appliance purchases and replacements. This section describes the design, implementation, and results of these surveys. In particular, this subsection presents the following:

- Development of participant and nonparticipant sample frames,
- Sample design and selection,
- Survey design,
- Survey implementation,
- Survey response rates, and
- Survey results.

Development of Sample Frames

As a starting point for the development of sampling frames, SCE provided information on all 1995 program participants and a preliminary sample of 50,000 nonparticipants. Table 3-1 summarizes the development of the participant frame. This process developed a frame of participants with sufficient pre-audit and post-audit consumption data to be used in the sample design and billing analysis. The specific screening process is described below.

- ***Step 1.*** Develop unique customer identifiers (PREMNO9) from the customer account numbers for all 10,000 participants. This list was matched against a master list of all SCE customers from 1994 to present and resulted in 9,347 participants with valid PREMNO9s.
- ***Step 2.*** Match valid identifiers from Step 1 against the current (July, 1996) master billing file. This indicated that there are 7,857 participants with current accounts. This screen ensures adequate post-audit consumption data.
- ***Step 3.*** Match current customers from Step 2 with 1994 customer billing records. A total of 6,805 customers were found to have at least some record of consumption during 1994. Total kWh usage and number of billing days were used to construct estimates of annual pre-audit consumption to support the sample design.
- ***Step 4.*** Implement a final screening of consumption data. This entails dropping customers with normalized annual kWh less than 600 kWh or more than 70,000 kWh from the frame. All master metered accounts (USECODE = 11, 12, 13, 14, 15 or 16) and customers with unknown or non-residential use codes (USECODE = 09 or USECODE = 05, respectively) were also eliminated. This screen left 6,638 customers in the final participant frame.

Table 3-1: Summary of Participant Sampling Frame

	Dropped from Sample	Total Remaining
All Participants		10,000
No valid PREMNO9	653	9,347
Not Current Customer (July 1996)	1,490	7,857
No Consumption in 1994	1,052	6,805
Consumption data screens	167	6,638

Table 3-2 summarizes the development of the nonparticipant sampling frame. The following steps were taken to develop the final nonparticipant frame:

- ***Step 1.*** Match the current customer billing file against records of all SCE customers who have participated in SCE sponsored programs since 1982. Customers who were found to have participated any program were deleted from the database. A sample of 50,000 customers was selected from the remaining customers.

- ***Step 2.*** Match this sample of nonparticipants with 1994 SCE customers. This resulted in a sample of 33,335 nonparticipants with 1994 billing data.
- ***Step 3.*** Drop customers with normalized annual kWh less than 600 kWh or more than 70,000 kWh from the frame. All master metered accounts (USECODE = 11, 12, 13, 14, 15 or 16), customers with unknown use codes (USECODE = 09), and customers with non-dwelling use codes (USECODE = 05) were also eliminated. This final screen left 32,956 qualified customers from which the initial sample of nonparticipants was drawn.

Table 3-2: Summary of Nonparticipant Sampling Frame

	Dropped from Sample	Total Remaining
Nonparticipants		50,000
No Consumption in 1994	16,665	33,335
Consumption data screens	379	32,956

Sample Design

The initial samples of participants and nonparticipants were stratified by residence type, pre-audit consumption level, and weather zone. The sample of participants was further stratified by audit type. The specific stratification criteria are described below.

- ***Residence Type.*** To ensure adequate representation of both multi-family and single family dwellings in the participant sample, the initial sample was stratified by the following two residence types:
  - single family (USECODE = 01, 02 and 04), and
  - multi-family (USECODE = 03).

  Proportional stratification across dwelling types resulted in just under 20% of the initial participant sample being drawn from the multi-family dwelling type.[1]
- ***Phone Versus In-Home Audit.*** The In-Home Audit Program included both telephone audits (20%) and in-home audits (80%). In order to provide for the ability to compare the effectiveness of these two program designs, the initial sample was stratified by audit type, as follows:
  - participants who received the on-site audit (AUDTTYPE = I), and
  - participants who received the telephone audit (AUDTTYPE = O).

[1] Neyman allocation could have also been used to determine initial sample sizes by dwelling type. However, this would have resulted in too small a sample of multi-family dwellings to permit sufficient precision in estimating the impacts of some multi-family measures.

Proportional stratification across audit types resulted in roughly 20% of the initial participant sample being phone participants.

- ***Pre-Audit Consumption.*** Pre-audit (1994 annualized) consumption was stratified into high, medium, and low for single and multi-family residence types. The Delanius-Hodges method determined the following optimal break points for the consumption strata:
  - single family low (less than 7,925 kWh),
  - single family medium (greater than 7,925 kWh and less than 11,736 kWh),
  - single family high (greater than 11,736 kWh),
  - multi-family low (less than 5,321 kWh),
  - multi-family medium (greater than 5,321 kWh and less than 7,584 kWh), and
  - multi-family high (greater than 7,584 kWh).

  Neyman allocation distributed the initial participant sample across consumption strata within residence types. Neyman allocation essentially minimizes the total variance of electricity consumption with respect to the distribution of sites across weather zones, based on the variability of total electricity usage within and across these strata. While our objective is not to estimate total usage per se, this optimization should be expected to improve the precision with which program savings can be estimated.

- ***CEC Weather Zone.*** Because of the importance of space heating and cooling in the In-Home Audit Program, coupled with the significant variation in weather conditions across SCE's service area, the initial participant sample was further stratified by CEC weather zone. For economy in defining strata, however, the eight CEC weather zones in the service area were collapsed into the following five weather zones:
  - Coastal and LA Basin (06 and 08),
  - Valley and Inland Empire (09 and 10),
  - Joaquin and High Desert (13 and 14),
  - Low Desert (15), and
  - Mountain (16).

  Neyman allocation distributed the initial sample of participants across weather zones. Again, this approach maximizes the precision of the total usage estimates with respect to the weather zone distribution, and should improve the efficiency of the program savings estimates.

Table 3-3 summarizes the targeted sample design for participants. The targeted participant sample consists of 300 households. Appendix A presents the population distribution of participants, as well as the sample distributions that would have resulted from alternative sample designs, including proportional sampling across weather zones, consumption levels, dwelling types, and program elements, "pure" Neyman allocation across all strata, and the final sample design used in this evaluation.

Table 3-4 presents the complete targeted sample design for nonparticipants. The targeted nonparticipant sample consists of 300 homes. The stratification design essentially mirrors that of the participant scheme, except for the omission of the phone and in-home strata. The nonparticipant strata targets are identical to the participant targets after collapsing the phone and in-home strata.

The participant and nonparticipant samples were selected according to the sample design described above. Initial samples were drawn randomly within strata and were twice as large as the target values, reflecting our assumption that the response rates within strata would be greater than 50%.

Survey Design

The telephone surveys elicited information about the 1995 In-Home Audit Program participants' responses to and perceptions of the audit recommendations, in addition to information regarding changes at participant and nonparticipant households. The three types of data obtained from the survey are described below.

- ***Implementation Records.*** A series of questions pertained to the implementation of various conservation measures and practices covered by the program elements in question. These questions specifically addressed the timing of implementation, a factor paramount to the statistical analysis. This data was collected from participants only.
- ***Perceptions of Audit Recommendations.*** The participant interviews helped to ascertain participants' recollections and perceptions of audit recommendations and to assess free ridership. This data was collected from participants only.
- ***Recent Changes at the Site.*** Both participants and nonparticipants were queried with respect to recent changes at the site, including remodeling, appliance acquisitions and removals, and changes in household size. This information was used in the statistical analysis.

Copies of the participant and nonparticipant questionnaires are presented in Appendix B.

Table 3-3: Completed Sample Design - Participants

Residence Type	kWh Stratum	Audit Type	Weather Zone					
			Coastal and LA Basin	Valley and Inland Empire	Joaquin/ High Desert	Low Desert	Mountain	All Zones
Single Family	Low	In-Home	27	15	3	2	1	48
	Low	Phone	9	4	2	1	0	16
	Medium	In-Home	14	10	2	1	0	27
	Medium	Phone	3	2	1	0	0	6
	High	In-Home	38	58	10	8	1	115
	High	Phone	6	8	10	5	1	30
Multi-Family	Low	In-Home	11	4	1	1	0	17
	Low	Phone	4	1	0	0	0	5
	Medium	In-Home	6	1	0	0	0	7
	Medium	Phone	1	0	0	0	0	1
	High	In-Home	20	1	0	1	0	22
	High	Phone	3	3	0	0	0	6
All Homes	Low	In-Home	38	19	4	3	1	65
	Low	Phone	13	5	2	1	0	21
	Medium	In-Home	20	11	2	1	0	34
	Medium	Phone	4	2	1	0	0	7
	High	In-Home	58	59	10	9	1	137
	High	Phone	9	11	10	5	1	36
Single Family			97	97	28	17	3	242
Multi-Family			45	10	1	2	0	58
	Low		51	24	6	4	1	86
	Medium		24	13	3	1	0	41
	High		67	70	20	14	2	173
		In-Home	116	89	16	13	2	236
		Phone	26	18	13	6	1	64

Table 3-4: Completed Sample Design - Nonparticpants

Residence Type	kWh Stratum	Weather Zone					
		Coastal and LA Basin	Valley and Inland Empire	Joaquin/ High Desert	Low Desert	Mountain	All Zones
Single Family	Low	36	19	5	3	1	64
	Medium	17	12	3	1	0	33
	High	44	66	20	13	2	145
Multi-Family	Low	15	5	1	1	0	22
	Medium	7	1	0	0	0	8
	High	23	4	0	1	0	28
All Homes	Low	51	24	6	4	1	86
	Medium	24	13	3	1	0	41
	High	67	70	20	14	2	173
Single Family		97	97	28	17	3	242
Multi-Family		45	10	1	2	0	58
	Low	51	24	6	4	1	86
	Medium	24	13	3	1	0	41
	High	67	70	20	14	2	173

Survey Implementation

Personnel from Taylor Research conducted and implemented the telephone survey in the following manner:

- A pre-test of the survey was conducted with 20 participants and 20 nonparticipants. The primary objectives of the survey pretest were to identify any inconsistencies in the format and protocol of the survey, and to determine the instrument's ability to collect information in an unambiguous and straightforward way. RER staff met with Taylor Research staff to discuss problems encountered by Taylor during the pre-test. In addition, SCE staff were present at the Taylor Research facility during a portion of the pre-test. No significant changes were made to the survey instruments as a result of pre-testing. Some minor changes on the format of certain questions were agreed upon by SCE, RER, and Taylor staff.
- Initial samples of 600 participants and 600 nonparticipants were provided to the fieldwork team. An additional sample of 600 participants and two samples of 300 nonparticipants each were provided as interviewers exhausted the original samples. The final sample consisted of 1,200 participants and 1,200 nonparticipants.
- To minimize sample error and non-response bias, Taylor attempted each household up to three times and applied standard sample rotations. If a call resulted in no contact with a respondent (e.g., no answer, busy, answering machine, etc.), the case was returned to the sample pool for a callback at a different day and time. This ensured that each case had a reasonable chance of contact when someone was available to respond.
- Taylor monitored responses by strata. Once a particular strata target was met, no further effort was made to contact remaining customers in that strata.

Two steps minimized the intrusiveness of the data collection effort:

- A letter was mailed to all households targeted for the telephone surveys. The letter explained the purposes of the survey to encourage cooperation. A copy of the pre-survey letter is provided in Appendix C.
- Post-survey thank you letters were mailed to all survey respondents. A copy of the letter is provided in Appendix C.

Completed Sample Structure and Survey Response Rates

Table 3-5 and Table 3-6 present an overview of the response rates for the participant and nonparticipant survey, respectively. Each table includes the number of completed interviews for each strata, in addition to the strata target and the number of contacts needed to complete the interviews. As shown in Table 3-5, 849 contacts were required to interview 301 participants, with a response rate of 35.5%. A total of 833 contacts were necessary to interview 300 nonparticipants, yielding a response rate of 36%. The overall response rate for the entire sample is 35.7%.

Table 3-5: Completed Sample Structure and Response Rates - Participants

kWh Stratum	Audit Type	Weather Zone: Coastal and LA Basin			Valley and Inland Empire			Joaquin/ High Desert			Low Desert			Mountain			All Zones			
		Target	# Complete	# Contacts	Target	# Complete	# Contacts	Target	# Complete	# Contacts	Target	# Complete	# Contacts	Target	# Complete	# Contacts	Target	# Complete	# Contacts	Response Rate
Single Family																				
Low	In-Home	27	28	69	15	17	38	3	3	6	2	2	4	1	1	3	48	51	120	42.5%
Low	Phone	9	11	22	4	4	7	2	2	7	1	1	3	0	0	0	16	18	39	46.2%
Med.	In-Home	14	15	49	10	7	20	2	2	6	1	1	2	0	0	0	27	25	77	32.5%
Med.	Phone	3	2	7	2	4	7	1	1	3	0	0	0	0	0	0	6	7	17	41.2%
High	In-Home	38	40	110	58	58	164	10	10	29	8	8	16	1	1	2	115	117	321	36.4%
High	Phone	6	5	21	8	8	30	10	10	24	5	5	20	1	1	2	30	29	97	29.9%
Multi-Family																				
Low	In-Home	11	12	43	4	4	8	1	0	2	1	0	2	0	0	2	17	16	57	28.1%
Low	Phone	4	4	10	1	1	3	0	0	0	0	0	0	0	0	0	5	5	13	38.5%
Med.	In-Home	6	7	18	1	0	4	0	0	0	0	0	0	0	0	0	7	7	22	31.8%
Med.	Phone	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	100.0%
High	In-Home	20	19	60	1	1	3	0	0	0	1	1	2	0	0	0	22	21	65	32.3%
High	Phone	3	2	12	3	2	8	0	0	0	0	0	0	0	0	0	6	4	20	20.0%
All Homes																				
Low	In-Home	38	40	112	19	21	46	4	3	8	3	2	6	1	1	5	65	67	177	37.9%
Low	Phone	13	15	32	5	5	10	2	2	7	1	1	3	0	0	0	21	23	52	44.2%
Med.	In-Home	20	22	67	11	7	24	2	2	6	1	1	2	0	0	0	34	32	99	32.3%
Med.	Phone	4	3	8	2	4	7	1	1	3	0	0	0	0	0	0	7	8	18	44.4%
High	In-Home	58	59	170	59	59	167	10	10	29	9	9	18	1	1	2	137	138	386	35.8%
High	Phone	9	7	33	11	10	38	10	10	24	5	5	20	1	1	2	36	33	117	28.2%
Single Family		97	101	278	97	98	266	28	28	75	17	17	45	3	3	7	242	247	671	36.8%
Multi-Family		45	45	144	10	8	26	1	0	2	2	1	4	0	0	2	58	54	178	30.3%
Low		51	55	144	24	26	56	6	5	15	4	3	9	1	1	5	86	90	229	39.3%
Med.		24	25	75	13	11	31	3	3	9	1	1	2	0	0	0	41	40	117	34.2%
High		67	66	203	70	69	205	20	20	53	14	14	38	2	2	4	173	171	503	34.0%
	In-Home	116	121	349	89	87	237	16	15	43	13	12	26	2	2	7	236	237	662	35.8%
	Phone	26	25	73	18	19	55	13	13	34	6	6	23	1	1	2	64	64	187	34.2%
TOTAL PARTICIPANTS		142	146	422	107	106	292	29	28	77	19	18	49	3	3	9	300	301	849	35.5%

Table 3-6: Completed Sample Structure and Response Rates - Nonparticipants

		Weather Zone																		
Residence Type	kWh Stratum	Coastal and LA Basin			Valley and Inland Empire			Joaquin/ High Desert			Low Desert			Mountain			All Zones			
		Target	# Complete	# Contacts	Target	# Complete	# Contacts	Target	# Complete	# Contacts	Target	# Complete	# Contacts	Target	# Complete	# Contacts	Target	# Complete	# Contacts	Response Rate
Single Family																				
	Low	36	38	120	19	18	59	5	6	12	3	3	8	1	1	4	64	66	203	32.5%
	Med.	17	17	38	12	14	40	3	3	6	1	1	1	0	0	0	33	35	85	41.2%
	High	44	43	128	66	66	174	20	18	52	13	14	29	2	2	5	145	143	388	36.9%
Multi-Family																				
	Low	15	14	48	5	5	17	1	1	2	1	1	2	0	0	0	22	21	69	30.4%
	Med.	7	7	21	1	1	3	0	0	0	0	0	0	0	0	0	8	8	24	33.3%
	High	23	23	45	4	4	15	0	0	0	1	0	4	0	0	0	28	27	64	42.2%
All Homes																				
	Low	51	52	168	24	23	76	6	7	14	4	4	10	1	1	4	86	87	272	32.0%
	Med.	24	24	59	13	15	43	3	3	6	1	1	1	0	0	0	41	43	109	39.4%
	High	67	66	173	70	70	189	20	18	52	14	14	33	2	2	5	173	170	452	37.6%
Single Family		97	98	286	97	98	273	28	27	70	17	18	38	3	3	9	242	244	676	36.1%
Multi-Family		45	44	114	10	10	35	1	1	2	2	1	6	0	0	0	58	56	157	35.7%
TOTAL NONPARTICIPANTS		142	142	400	107	108	308	29	28	72	19	19	44	3	3	9	300	300	833	36.0%

Survey Dispositions

The survey protocol required that a maximum of three contact attempts be made to each sample customer. Taylor Research tracked the disposition of each active sampled customer and logged the result of each call. Table 3-7 and Table 3-8 summarize the disposition of calls for the participant and nonparticipant samples, respectively.

Table 3-7: Disposition of Calls - Participants

Disposition	1st Call	2nd Call	3rd Call
Complete	175	81	45
Scheduled Callback	12	9	1
Left Message	3	0	0
Busy	22	11	10
Answering Machine	186	128	88
No Answer	98	53	38
Call Back Later	137	75	32
Over Quota	5	16	4
Not Qualified	3	1	0
Wrong Number	28	13	4
Initial Refusal	60	38	9
Mid-Terminate	15	4	5
Business/Fax	28	5	7
Disconnected Number	53	6	6
Language Barrier	16	4	1
Deceased	8	1	0

Table 3-8: Disposition of Calls - Nonparticipants

Disposition	1st Call	2nd Call	3rd Call
Complete	174	84	42
Scheduled Callback	2	0	0
Left Message	0	0	0
Busy	23	4	1
Answering Machine	167	121	111
No Answer	173	110	46
Call Back Later	77	41	25
Over Quota	1	0	1
Not Qualified	4	1	0
Wrong Number	35	15	5
Initial Refusal	85	40	14
Mid-Terminate	4	6	0
Business/Fax	38	4	2
Disconnected Number	47	1	2
Language Barrier	10	6	1
Deceased	1	0	0

Survey Results

The following section summarizes some of the key findings from the telephone survey. This includes information pertaining to changes in household appliance stocks and participant satisfaction and perceptions of program savings.

The telephone survey collected information regarding the changes in appliance stocks for both participants and nonparticipants. Table 3-9 presents the number of households who have purchased major electrical appliances since the time of the audit for participants and since January 1, 1995 for nonparticipants.

Table 3-9: Appliance Purchases

End Use	All # Acquiring Appliance (%)	Participants[2] # Acquiring Appliance (%)	Nonparticipants[3] # Acquiring Appliance (%)
Central Air Conditioner[4]	7 *(1.2)*	7 *(2.3)*	N/A
Room/Wall Air Conditioner	7 *(1.2)*	2 *(0.7)*	5 *(1.7)*
Evaporative Cooler	12 *(2.0)*	6 *(2.0)*	6 *(2.0)*
Free-Standing Food Freezer	12 *(2.0)*	2 *(0.7)*	10 *(3.3)*
Color TV	37 *(6.2)*	2 *(0.7)*	35 *(11.7)*
Electric Clothes Dryer	4 *(0.6)*	2 *(0.7)*	2 *(0.7)*
Automatic Clothes Washer	6 *(0.9)*	0 *(0)*	6 *(2.0)*
Personal Computer	64 *(10.6)*	17 *(5.6)*	47 *(15.7)*
Heated Water Bed	0 *(0)*	0 *(0)*	0 *(0)*
Electric Spa/Jacuzzi	4 *(0.6)*	0 *(0)*	4 *(1.3)*
Swimming Pool	3 *(0.5)*	2 *(0.7)*	1 *(0.3)*

In addition to providing specific recommendations for decreasing energy consumption, the 1995 In-Home Audit Program provided consumers with information about energy-efficient appliances. Table 3-10 presents the number of participants that recalled the auditor explaining the availability of energy-efficient appliances, and the appliances that the auditor specifically mentioned. Of the 185 participants that recalled explanations of energy-efficient appliances, a majority recalled explanations about energy-efficient refrigerators, approximately 50% remembered explanations about freezers and clothes washers and dryers, while only a small portion (23.8%) recalled a mentioning of evaporative coolers. It is important to note here that purchases or replacements with high-efficiency appliances were

[2] Purchased since audit month.

[3] Purchased since January 1, 1995.

[4] Data available for participants only.

not directly recommended to Program participants. However, information regarding high-efficiency appliances was provided to each household during the audit.

Table 3-10: Recalls Auditor Explaining Availability of Energy-Efficient Appliances (Q.80)

Recalls Auditor...	Frequency	Percentage
Explaining availability of energy-efficient appliances	185	61.5
Refrigerator	152	82.2
Freezer	93	50.3
Electric Water Heater	73	39.5
Evaporative Cooler	44	23.8
Room/Wall Air Conditioner	50	27.0
Central Air Conditioner	76	41.1
Clothes Dryer	88	47.6
Clothes Washer	88	47.6
Dishwasher	80	43.2

Table 3-11 presents the number of households who have replaced major electrical appliances, as well as the number of households that replaced appliances with high-efficiency units. According to these results, there is no general tendency for participants to be more likely than nonparticipants to opt for high-efficiency appliances. This result should probably be viewed skeptically. In particular, there may be considerable bias in the estimates of the proportions of customers who purchased high-efficiency units for both participants and nonparticipants. It is unclear that the respondents even knew what models were high-efficiency options, at least for some appliances. Moreover, there may have been a tendency to respond with the socially acceptable answer to this question. As will be discussed in Section 5, there is some reason to believe that participants do choose higher efficiency levels than nonparticipants when replacing refrigerators.

Table 3-11: Appliance Replacements

	All		Participants[5]		Nonparticipants[6]	
End Use	# Replacing Appliance (%)	# Replaced w/High Efficiency Units (%[7])	# Replacing Appliance (%[8])	# Replaced w/High Efficiency Units (%[10])	# Replacing Appliance (%[9])	# Replaced w/High Efficiency Units (%[10])
Central Air Conditioner	19 *(3.2)*	18 *(94.7)*	7 *(2.3)*	7 *(100)*	12 *(4.0)*	11 *(91.7)*
Room/Wall Air Conditioner	3 *(0.5)*	1 *(33.3)*	1 *(0.3)*	0 *(0)*	2 *(0.7)*	1 *(50.0)*
Evaporative Cooler	4 *(0.7)*	1 *(25.0)*	1 *(0.3)*	0 *(0)*	3 *(1.0)*	1 *(33.3)*
Refrigerator	68 *(11.3)*	60 *(88.2)*	39 *(13.0)*	36 *(92.3)*	29 *(9.7)*	24 *(82.8)*
Electric Water Heater	6 *(1.0)*	6 *(100.0)*	4 *(1.3)*	4 *(100)*	2 *(0.7)*	2 *(100.0)*
Range or Oven	24 *(4.0)*	15 *(62.0)*	8 *(2.7)*	8 *(100)*	16 *(5.3)*	7 *(43.8)*
Free-Standing Food Freezer	7 *(1.2)*	7 *(100.0)*	3 *(1.0)*	3 *(100)*	4 *(1.3)*	4 *(100.0)*
Electric Dryer	16 *(2.7)*	9 *(56.3)*	9 *(3.0)*	6 *(66.7)*	7 *(2.3)*	3 *(42.9)*
Automatic Clothes Washer	28 *(4.7)*	16 *(67.9)*	16 *(5.3)*	11 *(68.8)*	12 *(4.0)*	8 *(66.7)*

Participant Satisfaction and Perception of Realized Savings from the Program

The participant telephone survey elicited data on customer satisfaction with their In-Home Audit and their perceptions of energy savings due to participation in the program. Table 3-12 reveals that over 84% of participants were somewhat or very satisfied with the program. Table 3-13 indicates that over 50% of participants believed they had some savings on their monthly bill due to the audit. Further, just over 30% estimated their savings to be in excess of 10% of their monthly bill.

[5] Replaced since audit month.

[6] Replaced since January 1, 1995.

[7] Percentage of replacements made with high-efficiency units.

Table 3-12: Satisfaction with Thoroughness of Audit (Q.82)

Opinion	Frequency	Percentage
Very satisfied	178	59.1
Somewhat satisfied	76	25.2
Somewhat dissatisfied	18	6.0
Very dissatisfied	9	3.0
No opinion	20	6.6

Table 3-13: Perceptions of Savings on Monthly Bill Due to Audit (Q.81)

Savings	Frequency	Percentage
More than 20%	35	11.6
10 to 20%	59	19.6
Under 10%	74	24.6
Nothing	86	28.6
Don't know	47	15.6

1995 In-Home Audit Program Participant Data

To supplement the telephone survey data, SCE staff provided RER with participant files from the 1995 In-Home Audit Program database. In particular, variables utilized from the program data include those that reflect household characteristics such as ownership status, square footage of home, residence type, and appliance stocks and electricity end uses. The In-Home Audit Program data was merged with other database components by household-unique work order numbers.

Consumption Data

SCE provided consumption data for all sampled participants and nonparticipants for the period spanning January 1993 through September 1996. These historical consumption data are used in the billing analysis and satisfy the CPUC protocols, which require the use of at least nine months of post-audit consumption. There were less than nine months of post-audit consumption for approximately 0.3% of the sample (eight accounts). However, because a monthly realization rate model is used to estimate gross impacts CPUC protocols are satisfied.

Consumption data were merged with other database components by household-unique premise numbers.

Actual and Normal Weather Data

Weather conditions can be expected to affect usage levels of appliance stocks for space conditioning end uses. SCE staff provided RER with historical daily minimum and maximum temperatures spanning January 1988 through September 1996 for each of the 23 distinct weather zones covering the SCE service territory represented in the evaluation sample. The weather data was sufficient to cover the same period as the billing data (January 1993 through September 1996). These data were then used to compute actual and normal HDD and CDD for use in billing analysis and weather-normalizing weather-sensitive savings. The normal weather data are computed as the averages of heating and cooling degree days over the eight-year period which the SCE weather database spans.[8]

Figure 3-2 presents the actual cooling and heating degree days averaged over all SCE weather stations represented in the evaluation sample during 1993, 1994, and 1995. To depict the variation of weather conditions across the SCE service territory, Figure 3-3 and Figure 3-4 present the normal annual cooling and heating degree for each weather station, respectively. As shown by these graphs, the SCE weather zones represented in the sample depict a fairly wide range of weather conditions.

Weather data was merged with other database components by SCE weather station account numbers and read dates.

[8] Heating and cooling degree days are computed as follows:

CDD base 70 = max{0, (Daily Average Temperature - 70) }.

HDD base 60 = max{0, (60 - Daily Average Temperature) }.

Daily Average Temperature = (Daily Max. Temperature + Daily Min. Temperature)/2.

Figure 3-2: Average Cooling and Heating Degree Days

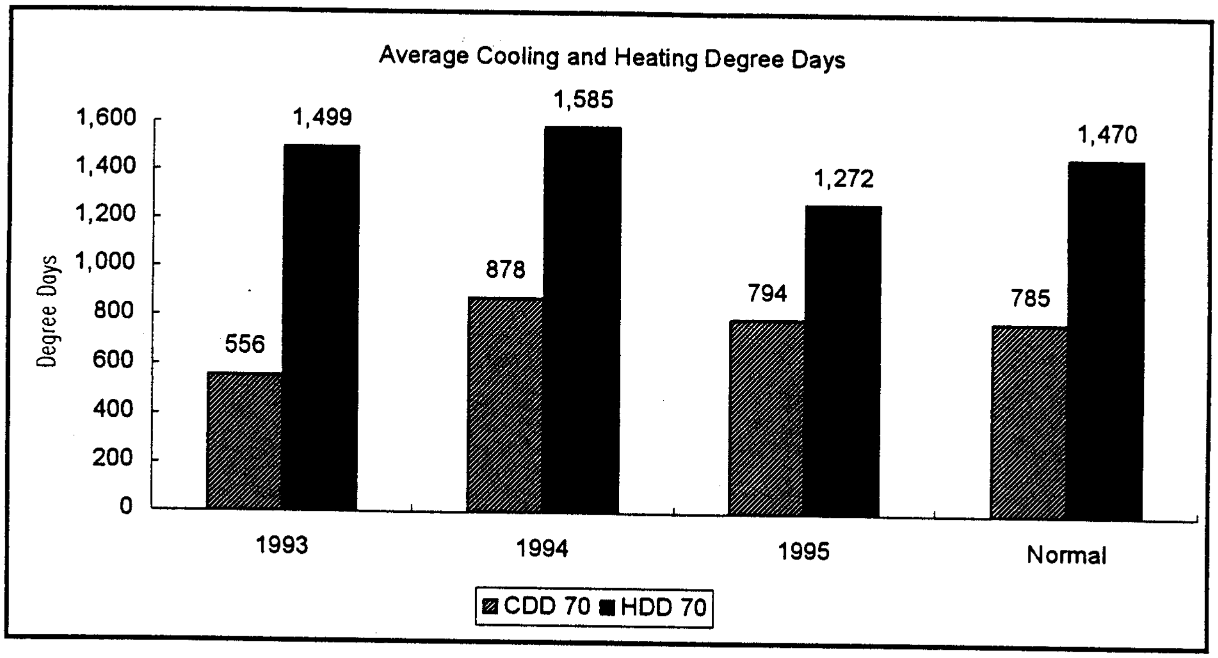


Figure 3-3: Normal Weather Cooling Degree Days

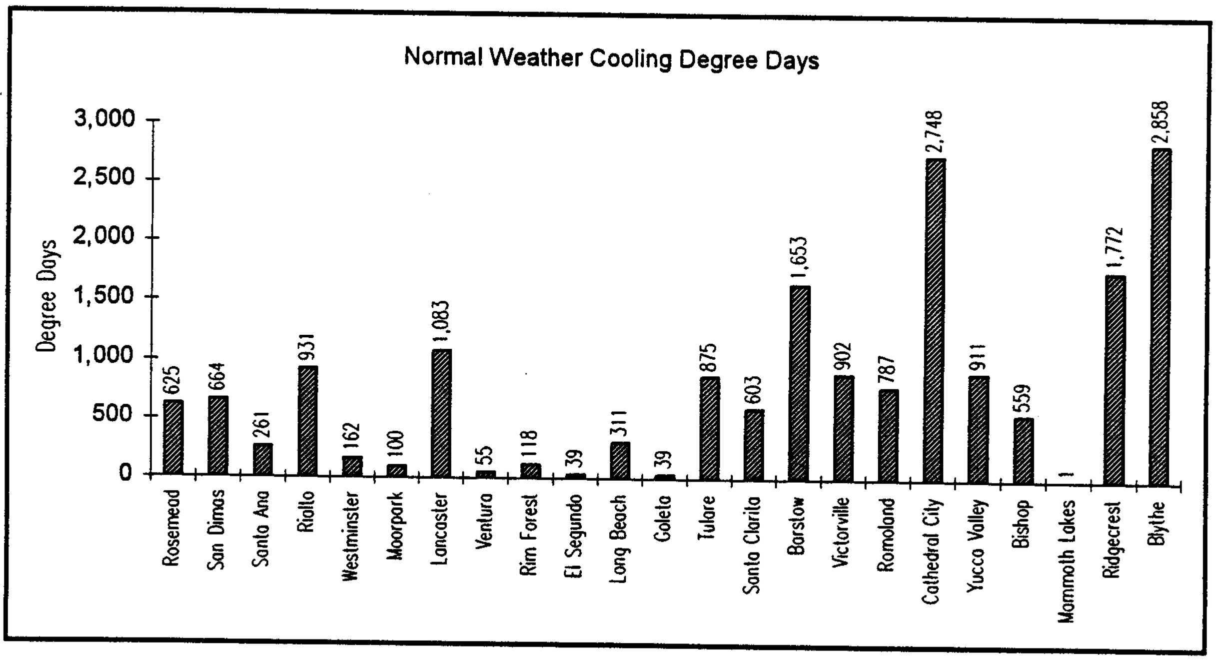
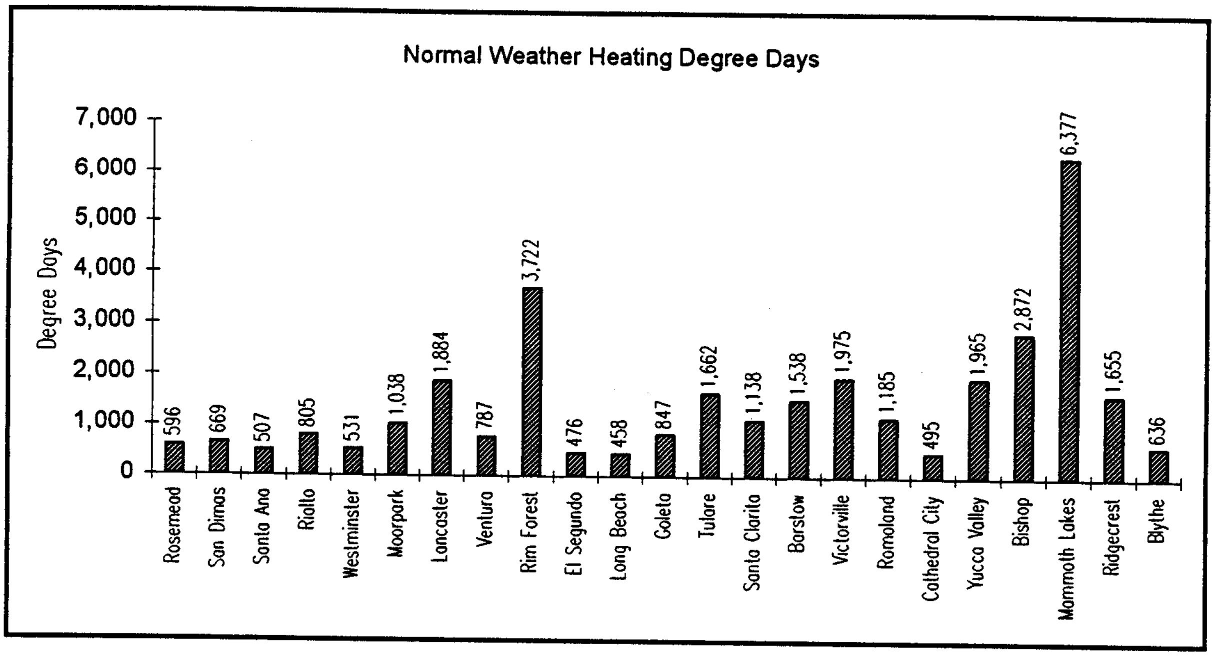


Figure 3-4: Normal Weather Heating Degree Days



3.3 Data Preparation

The data are generally viewed as providing an accurate picture of respondents' electricity usage patterns, appliance ownership, and demographic and household characteristics. Nevertheless, a number of cross-checks were performed to identify errors in reported data and to fill missing values. The following subsections describe in detail the methods utilized to identify anomalous data.

Inspection of Consumption Data

The consumption data in the IHA database is derived directly from customer billing files. These billing records, while reasonably accurate, contain some anomalies that can be troublesome in the analysis. The billing records of the sample were inspected closely for the following problems:

- Erroneous billing days and/or read dates,
- Abnormal monthly consumption,
- Missing or zero electricity usage (the latter may indicate an inactive account), and
- Special billing flags (estimated bills, correction billing, etc.).

At the discretion of RER staff, the consumption of suspect observations were set to missing or accounts were completely excluded from the analysis. More specifically, a total of 11 customer accounts, in addition to approximately 265 observations from the remaining sample, were excluded from the analysis due to the billing anomalies described above.

Inspection of End-Use Survey Responses

End-use variables are inspected carefully to identify anomalous responses. Misreporting is a chronic problem in survey-based analysis and careful inspection of responses is one of the most important aspects of data preparation. In most cases, comparing electricity consumption patterns and end-use responses helped to identify erroneous responses. For example, a customer may report not having central air conditioning, but an investigation of their consumption patterns may indicate clearly that central air conditioning is present. In cases where evidence of misreporting is clear, end-use designations in the database are overridden. End-use responses for a total of 10 accounts, all of which pertained to the presence or absence of either room or central air conditioning, were overridden after inspection of consumption patterns.

Replacement of Item Non-Response

As with virtually any residential survey database, the IHA database contains a substantial number of missing values. Simply allowing these missing values to disqualify an observation from the regression data set will reduce the sample size and can create non-response bias in the estimation of model parameters. In order to preserve as many observations as possible (and maintain the highest level of statistical power when drawing inferences from the data), missing values were filled with predicted values and corrected for a self-selection misreporting bias where necessary. Responses to survey questions can be predicted by a subset of variables in the database which are used to form the fitted values which replace missing values. In this analysis, missing values for income, household size, and square footage were filled using the two-step procedure described in Appendix G. As shown in Table 3-14, approximately 196 missing values in the IHA database were replaced using this technique.

Table 3-14: Replacement of Missing Values

Variable	# Plugged Missing Values
Income	177
Square Footage	18
Household Size	1

3.4 Final Database Structure

The final IHA database consists of four primary elements:

- Participant and Nonparticipant Survey Data,
- 1995 IHA Participant Program Data,
- Consumption Data, and
- Weather Data.

This time-series cross-sectional database contains unique (constant) household characteristics that have been "fanned out" with monthly consumption and weather data, thereby creating monthly observations for each household.

With the integrated database in place, the following data transformations were conducted to ensure consistency across customer accounts with different read dates.

- Historical consumption data and weather data were normalized to a 30.4-day billing period with the use of billing days and read dates.
- With the use billing days and meter read dates, weather data was converted to billing cycle degree-day measures. In order to make these values consistent with the usage levels contained in billing records, degree days were also normalized to a 30.4-day billing period.

The final integrated database, containing survey and program data in addition to monthly consumption and weather data, consists of 24,556 observations for the sample of 601 households.

3.5 Summary of Household Characteristics

Completion of the impact analysis requires information on household characteristics. Table 3-15 and Table 3-16 compare household characteristics by participant status, including economic and demographic characteristics, appliance saturations, and end use shares. The telephone survey provided this data for the nonparticipant sample. For participants, however, information on house square footage and appliance ownership was collected from the program participant files.

Table 3-15: Summary of Household Characteristics[9]

	Participants	Nonparticipants
Income	48,240	39,862
Number of Occupants	2.9	2.8
Square Footage	1,786	1,640
Residence Type:		
Single Family	82.1%	80.8%
Multi-Family	17.9%	19.2%

Table 3-16: Summary of Electricity End Uses[10]

	Participants	Nonparticipants
Have Central Air Conditioner	55.2%	36.7%
Have Room/Wall Air Conditioner	5.5%	16.6%
Have Evaporative Cooling	3.0%	20.2%
Electric Water Heating	15.8%	8.1%
Primary Space Heating	16.4%	11.3%
Supplemental Space Heating	3.1%	17.7%
Free-Standing Freezer	23.8%	29.5%
Electric Clothes Dryer	25.2%	30.5%
Electric Range[11]	39.0%	N/A

[9] Statistics represent weighted means of household characteristics.
[10] Statistics represent weighted means of household characteristics.
[11] Data available for participants only.

4

Methodology

4.1 Methodology Overview

This section discusses the methodology used for the analysis of the impacts of the 1995 In-Home Audit Program. Because of the multiple objectives underlying this project, a number of distinct approaches were utilized. More specifically, the evaluation made use of four distinct model specifications:

- The Traditional Direct Participation Approach,
- The End-Use Action Approach,
- The End-Use Measure/Practice Approach, and
- The Composite "Impact" Approach.

Each of these modeling approaches has advantages and disadvantages, all of which are discussed in the following subsections. Despite their differences, all models are derived from the direct participation methodology.

4.2 Traditional Direct Participation Approach

The first approach to the evaluation of the 1995 In-Home Audit Program can be termed the *traditional direct participation approach*. This approach is best suited for the estimation of net impacts, but can also be used to estimate gross realized impacts. In this approach, the evaluation of *net* program impacts involves the estimation of the net impact of participation on the observed change in consumption over a specified period of time. This technique, which is applied to a sample of both participants and nonparticipants, yields a comprehensive estimate of net program savings (which essentially embodies realization rates and net-to-gross factors).

Description of the Traditional Direct Participation Model

The general form of the traditional direct participation impact model can be specified as:

(1) $$\Delta kWh_{it} = \sum_{k=1}^{K} f_k\left(\Delta PART_{it}, SC_i, EDC_i, WC_{it}, MR_i, \varepsilon_{it}\right) S_{ikt}$$

where ΔkWh_{it} is the 12-month change in the household's level of consumption, f_k can be considered a UEC function, and S_{ikt} is a binary variable indicating the presence of the *kth* electric end use. The household's UECs depend upon a variety of factors. $\Delta PART_{it}$ is a binary variable reflecting participation in the program, SC_i consists of site characteristics (e.g., square footage or residence type), EDC_i reflects the economic and demographic characteristics of the household, WC_{it} is an indicator of weather conditions, MR_i is a Mills Ratio term to correct for self-selection bias, and ε_{it} is a random error term. Note that the participation variable is defined to be equal to 0 for participants for the period prior to program participation, equal to 1 for 12 periods after the audit date, and equal to 0 again for all remaining periods.

It is convenient for many purposes to estimate this model in change form as:

$$(2)\quad \Delta kWh_{it} = \Delta \sum_{k=1}^{K} f_k\left(PART_i, SC_i, EDC_i, WC_{it}, \varepsilon_{it}\right) S_{ik}$$

where the operator Δ indicates a 12-month change in the variable in question. Expanding this change in the products of UECs and saturations, we have the first-order approximation:

$$(3)\quad \Delta kWh_{it} = \sum_{k=1}^{K} \begin{bmatrix} \Delta f_k\left(PART_i, SC_i, WC_i, EDC_{it}, \varepsilon_{it}\right) S_{ik} \\ + f_k\left(PART_i, SC_i, WC_i, EDC_{it}, \varepsilon_{it}\right) \Delta S_{ikt} \end{bmatrix}$$

The above expression simply states that changes in electricity consumption result from changes in both end-use saturations and level of appliance usage.

Of course, expression (3) is cast in very general terms. The operational form of this model was designed to cover all major end uses. Its specific design was based on both theoretical and practical considerations. (The latter considerations, of course, consist of having tried a large number of other variables in the model, only to have them prove insignificant.[1]) The specific model is presented below. Throughout the remainder of this report, the first 22 terms of expression (4) are referred to as X_{it} and are present in all estimated models. The twenty third term, or the participation term, is replaced with multiple terms representing program participation in subsequent models.

[1] The following changes to a much more comprehensive model were made in the course of model development:

- All terms interacted with $\Delta SQFT$ were omitted, and $\Delta SQFT$ was included as a stand-alone variable.
- All terms pertaining to electric range/ovens, color televisions, clothes washers, personal computers, waterbeds, and spas were omitted from regressions due to their insignificance.
- For room air conditioning, evaporative cooling, space heating, and supplemental space heating, the only terms included are products of saturations, square footage and the relevant change in weather conditions. For water heating, only the product of the saturation and the change in number in household was retained.

$$(4)\ \Delta kWh_{it} = \beta_0 + \beta_1\Delta SQFT_{it} + \beta_2\Delta ISREF_{it} + \beta_3\Delta DSREF_{it} + \beta_4\Delta SRAC_{it}$$

$$+ \beta_5\Delta SEDRY_{it} + \beta_6\Delta SSPA_{it} + \beta_7\Delta SPOOL_{it}\Delta CDD_{it} + \beta_8\Delta SEVC_{it}CDD_{it}$$

$$+ \beta_9 SCAC_i\Delta CDD_{it}SQFT_i + \beta_{10}SCAC_i\Delta RCAC + \beta_{11}SRAC_i\Delta CDD_{it}SQFT_i$$

$$+ \beta_{12}SEVC_i\Delta CDD_{it}SQFT_iEVAPONLY_i + \beta_{13}SEVC\Delta REPEVC_{it} + \beta_{14}SESH_i\Delta HDD_{it}SQFT_i$$

$$+ \beta_{15}SSUPPESH_i\Delta HDD_{it}SQFT_i + \beta_{16}SEWH_i\Delta NHH_{it} + \beta_{17}SCAC_i\Delta CDD_{it}SQFT_i\Delta PART_{it}$$

$$+ \beta_{18}ACACT_{it}\Delta CDD_{it}SQFT_i\Delta PART_{it} + \beta_{19}ESHACT_i\Delta HDD_{it}SQFT_i\Delta PART_{it}$$

$$+ \beta_{20}SCAC_iCDD_{it}SQFT_i + \beta_{21}\Delta RREF_{it}SREF_iPART_i + \beta_{22}\Delta RREF_{it}SREF_iNPART_i$$

$$+ \beta_{23}\Delta PART_{it} + \varepsilon_{it}$$

where:

$SCAC_i$	=	have central AC (0,1)
$SRAC_i$	=	have window/wall AC (0,1)
$SEVC_i$	=	have evaporative cooling (0,1)
$SESH_i$	=	have primary electric heating (0,1)
$SEWH_i$	=	have electric water heating (0,1)
$SSUPPESH_i$	=	have supplemental electric heat (0,1)
$SREF_i$	=	have at least one refrigerator (0,1)
$SEDRY_i$	=	have electric clothes dryer (0,1)
$SSPA_i$	=	have spa/jacuzzi (0,1)
$SPOOL_i$	=	have heated pool (0,1)
$ISREF_{it}$	=	number of refrigerators increased
$DSREF_{it}$	=	number of refrigerators decreased
$RCAC_{it}$	=	replaced central AC (0,1)
$RRAC_{it}$	=	replaced room AC (0,1)
$REVC_{it}$	=	replaced evaporative cooler AC (0,1)
$RREF_{it}$	=	replaced refrigerator (0,1)
$SQFT_{it}$	=	square footage of home
CDD_{it}	=	cooling degree days
HDD_{it}	=	heating degree days
NHH_{it}	=	household size

$ACACT_i$	=	a binary variable indicating that at least one air conditioning action was implemented (0,1)
$ESHACT_i$	=	a binary variable indicating that at least one space heating action was implemented (0,1)
$EVAPONLY_i$	=	only air conditioning in household is evaporative cooling (0,1)
$PART_i$	=	program participant (0,1)
$NPART_i$	=	program nonparticipant (0,1)

Note that all weather-sensitive end uses are interacted with square footage and either heating or cooling degree days, and that water heating terms are interacted with household size.

Estimating Net Program Savings

In the absence of self-selection bias as well as other differences between participants and nonparticipants, estimation of program impacts in the context of direct participation modeling is straightforward. First, rewrite the above model in simplified form as:

(5) $\Delta kWh_{it} = \beta_0 + \beta_1 \Delta X_{it} + \beta_2 \Delta PART_{it} + \varepsilon_{it}$

where X is a vector of all variables other than the participation variable. *Net program savings* (the change in kWh due to participation in the program) can represented as:

(6) $\text{Net Impact of Participation} = \dfrac{\partial \Delta kWh_{it}}{\partial \Delta PART_{it}} = \beta_2$

Three specific issues need to be addressed, however, in estimating net impacts.

- First, self-selection bias may be significant, so some means of mitigation will have to be implemented.
- Second, the impact of the audit may be spread over time as measures are purchased and practices are implemented.
- Third, some means of treating outliers must be implemented.

These problems are discussed below.

Self-Selection Bias. In general, we can expect self-selection bias to be a potential problem for voluntary programs like the In-Home Audit Program. For this kind of model, mitigating this bias generally involves the incorporation of an inverse Mills Ratio (call this MR_i) into the direct participation model. The Mills Ratio is derived from a participation equation of the form:

(7) $PART_i = g(SC_i, EDC_i, STRUC_i, WC_i, \mu_i)$

where, as before, SC_i consists of site characteristics, EDC_i reflects the economic and demographic characteristics of the household, and WC_i is an indicator of weather conditions. The variable μ_i is a random error term. Note that all explanatory variables in expression (7) are constant for each household. The Mills Ratio is a function of the predicted value of participation as derived from the estimated form of expression (7) and differs across participants and nonparticipants. The application of the inverse Mills Ratio is a subject of some controversy in evaluation literature. However, a recent paper by Goldberg and Train (1996) suggest that the ratio should be entered twice in the energy change equation: once as a free-standing term and once interactively with the participation term. The logic of this specification is that the Mills Ratio affects the change in usage as well as the impact of the participation variable in the energy change equation. With this specification, the net impact of participation on the change in energy consumption is a function of the Mills Ratio (MR_i):

$$(8) \quad \text{Net Impact of Participation} = \frac{\partial kWh_{it}}{\partial \Delta PART_{it}} = h(MR_i)$$

The direct participation specification incorporating the Double Mills Ratio Approach yields:

$$(9) \quad \Delta kWh_{it} = \beta_0 + \beta_1 \Delta X_{it} + \beta_2 \Delta PART_{it} + \beta_3 MR_i \Delta PART_{it} + \beta_4 MR_i + \varepsilon_{it}$$

and

$$(10) \quad \text{Net Impact of Partipation} = \frac{\partial \Delta kWh}{\partial \Delta PART_{it}} = \beta_2 + \beta_3 (\overline{MR_i \Delta PART_{it}}).$$

As shown in expression (10), program impacts are equal to the estimated coefficient of the participation term plus the conditional mean of the product of the Mills Ratio and the participation term multiplied by its coefficient. In order to take advantage of this approach to mitigating self-selection bias, then, two terms— $MR_i \Delta PART_{it}$ and MR_i —were introduced into the direct participation model.

Implementing a Deadband. As it stands, the traditional direct participation model does not capture the dynamics of audit impacts. Participant implementations are typically distributed over time. Some practices are implemented soon after the audit, but others (especially those requiring an initial investment) are implemented only after some time has elapsed. Using a single participation variable to reflect these impacts can lead to an understatement of the savings from the program. This problem will be addressed to some extent by defining a three-month "deadband" immediately after each participant's audit. This practice essentially excludes those months over which the impact of the audit may not be complete. Given the use of a deadband, $\Delta PART_{it}$ is defined to be equal to 0 prior to audit, equal to 1 after the audit for twelve months, then equal to 0 again for the remainder of the sample period.

Outliers. Often, regression results can be unduly influenced by outliers, or observations with extreme residuals. In this project, we did not attempt to screen out such observations per se, but we did review large residuals in order to identify data anomalies. The following kinds of anomalies qualified an observation for deletion from the regression:

- When billing codes indicated that observations were either estimated bills or subsequent makeup bills, and when these consumption reads were abnormal, they were set equal to missing.
- When consumption values indicated long periods of vacancy for a home, these values were set equal to missing.
- In a very few cases where reads simply seemed erroneous, they were also set equal to missing.

These deletions tended to improve the standard error of the regression and increase t values, but had virtually no influence on the estimated coefficients or on savings. At one point, a model was rerun with all deletions reinserted into the estimation database, and the level of estimated savings was virtually unchanged.

Direct Participation Model Results

Table 4-1 presents the estimation results of the traditional direct participation modeling approach. As shown, two versions of the model were estimated: one without any correction for self selection, and one using the Double Mills Ratio Approach. In the former model, the participation term is significant and suggests an impact of 55 kWh per month per participant. When the Mills Ratio terms are added, both participation terms remain significant and the estimated savings actually increase to 60 kWh per month. Clearly, these values appear considerably higher than expected for a program of this sort. There are several possible explanations for this result. One is that self selection is not fully resolved. This will be discussed further in the next section. Another is that the model may not fully account for weather conditions. The summer of 1993 was very mild, while the summer of 1994 was much more normal. The 12-month change in consumption in 1994, then, was very large in the summer months. While we included a number of terms in the model to account for weather changes, the average residuals in the summer of 1994 were generally positive. This probably means one of two things: either cooling requirements are not roughly proportional to cooling degree days over the range of weather experienced, or other excluded weather conditions (e.g., humidity) are responsible for some of the movement in air conditioning loads. In either event, this version of the direct participation model does not perform particularly well here. Some of the limitations of this approach are discussed in the next subsection. In the next major section, means of resolving these issues are developed.

Table 4-1: Traditional Direct Participation Model

Variable	Estimated Coefficients and t-values	
	Excluding Mills Ratio Terms	Including Mills Ratio Terms
INTERCEPT	10.2 *(4.79)*	6.4 *(2.50)*
ΔSQFT	0.032 *(0.34)*	0.02 *(0.21)*
ΔSREF (increase)	89.2 *(2.94)*	92.9 *(3.06)*
ΔSREF (decrease)	72.7 *(3.05)*	68.3 *(2.87)*
ΔSRAC	-83.4 *(-1.12)*	-71.0 *(-0.95)*
ΔSEDRY	80.1 *(1.39)*	72.5 *(1.26)*
ΔSSPA	107.5 *(1.86)*	112.1 *(1.94)*
ΔCDD70 * ΔSPOOL	0.7 *(1.29)*	0.7 *(1.30)*
ΔSEVC * CDD70	-0.8 *(-6.08)*	-0.7 *(-5.98)*
SCAC * ΔCDD70 * SQFT	0.001 *(41.06)*	0.001 *(40.99)*
SCAC * ΔRCAC	-63.7 *(-2.19)*	-59.2 *(-2.04)*
SRAC * ΔCDD70 * SQFT	0.0001 *(6.53)*	0.0007 *(6.54)*
SEVC * ΔCDD70 * SQFT * EVAPONLY	0.0003 *(4.18)*	0.0003 *(4.16)*
SEVC * ΔREVC	144.4 *(2.14)*	141.8 *(2.11)*
SESH * ΔHDD60 * SQFT	0.001 *(17.59)*	0.0007 *(17.43)*
SSUPPESH * ΔHDD60 * SQFT	0.0002 *(3.45)*	0.0001 *(3.40)*
SEWH * ΔNHH	70.5 *(3.49)*	69.6 *(3.45)*
ΔRREF * SREF * PART	-55.1 *(-2.26)*	-54.1 *(-2.22)*
ΔRREF * SREF * (1-PART)	-55.8 *(-2.45)*	-51.0 *(-2.23)*
SCAC * ΔCDD70 * SQFT * ΔPART	-0.0008 *(-6.77)*	-0.0007 *(-6.74)*
ACACT * ΔCDD70 * SQFT * ΔPART	0.0007 *(5.62)*	0.0007 *(5.68)*
ESHACT * ΔHDD60 * SQFT * ΔPART	0.0002 *(3.93)*	0.0002 *(3.81)*
SCAC * CDD70 * SQFT	0.00001 *(0.81)*	0.00001 *(0.98)*
ΔPART	-55.1 *(-6.14)*	-281.7 *(-3.51)*
MILLS RATIO	-	-2.9 *(-2.68)*
ΔPART * MILLS RATIO	-	-32.8 *(-2.67)*
Model R-Squared	0.18	0.18

Limitations of the Traditional Direct Participation Modeling Approach

The direct participation modeling approach is generally a useful and reasonably simple approach to estimating program impacts, especially for a program inducing a wide range of DSM activities. However, it does have some interrelated drawbacks that are addressed in subsequent approaches.

- First, the approach does not make use of information on customer direct responses to participation in the audit. In essence, it assumes that impacts are invariant across households. Because of this, the direct participation model is (arguably) particularly susceptible to self-selection bias. The rationale for this claim is that the change in consumption due to participation is probably more strongly driven by the factors that influence participation than factors influencing specific actions taken after the audit. As indicated above, a self-selection correction technique can be used to mitigate this bias. However, there is some question as to whether or not this or any other approach truly resolves the problem. In sum, approaches that include more information on participants' post-audit actions may be less susceptible to the self selection.
- Second, the traditional model does not easily permit the decomposition of impacts by end use. It will be recalled that this decomposition was one of the objectives of the study, primarily because it accommodates the derivation of demand impacts.
- Third, the traditional direct participation model does not directly permit the separation of the impacts of measures and practices. Again, this separation was a project objective aimed at obtaining insights with respect to the transmission mechanism for impacts and the assessment of participant costs.
- Fourth, the inclusion of pre-audit participant observations in a change-form model like the one used above can introduce biases in the baseline for net savings. The true baseline for net savings is the change in consumption that participants would have experienced in the post-audit period in the absence of the program. But expression (10) derives net savings as the derivative with respect to a binary variable that takes on the value 1 for participants in the post-audit impact period and 0 for both nonparticipants *and* participants in any periods other than the impact period. Thus, participant changes in consumption outside the impact periods are part of the baseline for net savings. Even though the model is designed to control for differences between participants and nonparticipants and mitigating self-selection bias, it does not control for unexplained differences between participants in the pre- and post-audit periods. For instance, if the model performs poorly in explaining the high air conditioning levels in the summer of 1994 (which it does), then this will yield an artificially high baseline for estimated savings. Moreover, it can be argued that participants can be expected to implement relatively little conservation in the months after the impact period to the extent that opportunities for further conservation are limited, and this will yield relatively high changes in consumption. Again, using these changes in

consumption will bias upward the base for estimating net savings. In order to mitigate this problem, we excluded all observations on participant changes in consumption outside of the impact period.[2]

The following two sections outline approaches for resolving these problems.

4.3 Action and Measure/Practice Approaches

In order to accommodate the estimation of savings by end use and to resolve some of the other problems described above, we developed several means of incorporating information on actual implementations of recommended actions. Our attempts to use individual binary variables for individual actions proved fruitless because of the large number of conservation actions covered by the audit (approximately 70). Attempts to use binary variables representing end uses for which any actions were taken provided some insights, but suffered from some of the same drawbacks as the traditional direct participation model. For instance, they assumed that the savings for participants taking one or more refrigeration actions would be the same. Ultimately, it was decided to develop a set of engineering estimates of savings to use as relative weights for individual actions.

These engineering estimates were not based directly on extensive primary analysis, since this type of analysis was not included in the work scope. Instead, they were drawn from prior studies done by RER, preliminary results of model versions using binary variables for specific actions, and judgment. The judgmental approach was necessary for those actions that are too loosely defined to support rigorous engineering analysis. For instance, we were hard-pressed to conduct (or even find) a study on the savings associated with covering pots while cooking, or with lowering thermostat settings when away from home for prolonged periods of time. Prior to estimation, the estimates based on other studies were adjusted for local actual weather conditions faced by individual households. Savings associated with heating and air conditioning were also scaled to reflect the square footage of the home. Finally, water heating savings were adjusted for differences in household size. These estimates are presented in Appendix F.

[2] Keep in mind that this does *not* mean that we exclude pre-audit consumption for participants, since it is embedded in the change in usage in the impact period.

As will be seen below, the resultant engineering estimates need not be comparable across end uses, since we allow separate adjustment coefficients for each end use. Instead, they are probably best considered estimates of *relative weights* for various actions within end uses. While we do not defend their accuracy in absolute terms, they should be clearly superior to using simple counts of actions or binary variables representing that one or more actions within an end use. The availability of these relative weights allowed us to aggregate individual actions in useful ways. Two types of aggregation were implemented:

- First, savings associated with actions reported to have been taken by participants were aggregated by end use. The use of these models is referred to as the *end-use action* approach.
- Savings were aggregated by end use and type of action. Two types of actions were defined: measures, which entailed the purchase of conservation goods or services; and practices, which entailed changes in behavior. The use of these variables is termed the measures and practices approach. Both approaches are described below.

End-Use Action Approach

The basic model specification is identical to the models presented above with expressions (4) and (5), with the exception of the participation variable. In the end-use action approach, the simple binary participation variable was interacted with a set of end-use action terms. The savings term for each household and end use *k* (S_ACT_{ik}) equals the sum of engineering savings for all actions implemented in the end-use category by the household in question. For example, the savings for air conditioning actions by household *i* is equal to the sum of calculated savings of all implemented air conditioning actions. The general derivation of the action variables is represented by:

$$(11) \quad S\_ACT_{ikt} = \sum_j EEST_{jkt} SACT_{ijk}$$

Where $EEST_k$ denotes estimated savings of end use *k* and *SACT* is a binary variable indicating implementation of conservation action *j*.

The general model specification of the end-use action model is:

$$(12)\ \Delta kWh_{it} = \beta_0 + \beta_1 \Delta X_{it} + \beta_2 (SAC\_ACT_{it} \Delta PART_{it})$$

$$+ \beta_3 (SSH\_ACT_{it} \Delta PART_{it})$$

$$+ \beta_4 (SWH\_ACT_i \Delta PART_{it})$$

$$+ \beta_5 (SREF\_ACT_i \Delta PART_{it})$$

$$+ \beta_6 (SOTH\_ACT_i \Delta PART_{it}) + \varepsilon_{it}$$

where *SAC_ACT, SSH_ACT, SWH_ACT, SREF_ACT,* and *SOTH_ACT* are savings terms for air conditioning, space heating, water heating, refrigeration, and other end uses, and where the generic term ΔX_{it} denotes the first 22 terms in expression (4). Note that the Mills Ratio terms are not included in this model. The reason is a practical one: the Mills Ratio should technically be interacted with all of the participation terms, but this causes overwhelming multicollinearity. We recognize that the omission of the Mills Ratio terms will leave self-selection bias unresolved, but we will return to this problem and mitigate it in a later analysis. For now, we are primarily interested in the *relative* impacts across end uses, and there is no reason that these relative impacts are affected by self-selection bias.

The first numerical column of Table 4-2 presents the estimation results of the end-use action model. The model was estimated omitting participant changes in consumption outside the impact period. First-order autocorrelation was diagnosed and corrected with generalized least squares. As shown, the coefficients of all of the action terms take on the appropriate sign. However, only refrigerator actions are significant. This results from the high collinearity across action terms, given the tendency for some participants to take actions in more than one end use, and for some others to report taking no actions at all. These coefficients will be used later in what we refer to as the composite approach.

Table 4-2: End-Use Action and Measures/Practices Models

Variable	Estimated Coefficients and t-values	
	Action Approach	Measure/Practice Approach
INTERCEPT	5.6 *(2.27)*	5.9 *(2.35)*
ΔSQFT	0.05 *(0.50)*	0.04 *(0.43)*
ΔSREF (increase)	108.3 *(3.00)*	100.7 *(2.79)*
ΔSREF (decrease)	34.8 *(1.38)*	28.4 *(1.13)*
ΔSRAC	-92.2 *(-1.23)*	-111.0 *(-1.48)*
ΔSEDRY	82.1 *(1.45)*	75.8 *(1.35)*
ΔSSPA	110.0 *(1.93)*	111.4 *(1.96)*
ΔCDD70 * ΔSPOOL	0.7 *(1.33)*	0.8 *(1.35)*
ΔSEVC * CDD70	-0.8 *(-6.06)*	-0.8 *(-6.06)*
SCAC * ΔCDD70 * SQFT	0.001 *(36.76)*	0.001 *(36.83)*
SCAC * ΔRCAC	-54.2 *(-1.83)*	-44.8 *(-1.52)*
SRAC * ΔCDD70 * SQFT	0.0007 *(5.99)*	0.0007 *(5.99)*
SEVC * ΔCDD70 * SQFT * EVAPONLY	0.0004 *(4.41)*	0.0004 *(4.42)*
SEVC * ΔREVC	147.4 *(2.23)*	147.4 *(2.23)*
SESH * ΔHDD60 * SQFT	0.0006 *(15.80)*	0.0006 *(15.73)*
SSUPPESH * ΔHDD60 * SQFT	0.0001 *(3.20)*	0.0002 *(3.31)*
SEWH * ΔNHH	69.7 *(3.49)*	63.0 *(3.15)*
ΔRREF * SREF * PART	-71.1 *(-2.61)*	-68.3 *(-2.47)*
ΔRREF * SREF * (1-PART)	-50.6 *(-2.25)*	-51.0 *(-2.27)*
SCAC * ΔCDD70 * SQFT * ΔPART	-0.0009 *(-7.06)*	-0.0009 *(-6.76)*

Table 4-2 (cont'd.): End-Use Action and Measures/Practices Models

Variable	Estimated Coefficients and t-values	
	Action Approach	Measure/Practice Approach
ACACT * ΔCDD70 * SQFT * ΔPART	0.0008 *(5.83)*	0.0008 *(5.79)*
ESHACT * ΔHDD60 * SQFT * ΔPART	0.0002 *(4.06)*	0.0002 *(3.84)*
SCAC * CDD70 * SQFT	0.00001 *(0.43)*	0.00001 *(0.40)*
SAC_ACT* ΔPART	-0.1 *(-1.53)*	-
SSH_ACT * ΔPART	-0.1 *(-0.97)*	-
SWH_ACT * ΔPART	-0.4 *(-0.99)*	-
SREF_ACT * ΔPART	-1.3 *(-4.53)*	-
SOTH_ACT * ΔPART	-0.2 *(-0.77)*	-
SAC_MEAS* ΔPART	-	0.2 *(1.12)*
SAC_PRAC* ΔPART	-	-0.5 *(-2.55)*
SSH_MEAS* ΔPART	-	-0.006 *(-0.09)*
SSH_PRAC* ΔPART	-	-2.5 *(-1.77)*
SWH_MEAS* ΔPART	-	0.4 *(0.50)*
SWH_PRAC* ΔPART	-	-1.5 *(-1.54)*
SREF_MEAS* ΔPART	-	-0.3 *(-0.10)*
SREFRAC* ΔPART	-	-1.0 *(-3.40)*
SOTH_MEAS* ΔPART	-	1.8 *(4.51)*
SOTH_OPRAC* ΔPART	-	-1.2 *(-4.30)*
Model R-Squared	0.20	0.20

End-Use Measure/Practice Approach

The Measure/Practice Approach is designed to disaggregate savings by both end uses and measures and practices. It is similar to the end-use action approach, except that the end-use actions savings terms expanded to distinguish between measures and practices. The measures/practices model is given by:

$$(13)\quad \Delta kWh_{it} = \beta_0 + \beta_1 \Delta X_{it} + \beta_2 (SAC\_MEAS_{it} \Delta PART_{it})$$

$$+ \beta_3 (SAC\_PRAC_i \Delta PART_{it})$$

$$+ \beta_4 (SSH\_MEAS_i \Delta PART_{it})$$

$$+ \beta_5 (SSH\_PRAC_{it} \Delta PART_{it})$$

$$+ \beta_6 (SWH\_MEAS_{it} \Delta PART_{it})$$

$$+ \beta_7 (SWH\_PRAC_{it} \Delta PART_{it})$$

$$+ \beta_8 (SREF\_MEAS_i \Delta PART_{it})$$

$$+ \beta_9 (SREF\_PRAC_i \Delta PART_{it})$$

$$+ \beta_{10} (SOTH\_MEAS_i \Delta PART_{it})$$

$$+ \beta_{11} (SOTH\_PRAC_i \Delta PART_{it}) + \varepsilon_{it}$$

where the suffix _MEAS indicates savings from implemented measures and the suffix _PRAC reflects savings from implemented practices. Again, all other terms in the model are represented by ΔX_{it}. As was the case for the action model, we cannot readily include the appropriate interactive Mills Ratio terms in this model, because it would cause dramatic collinearity. Again, however, we can gain some insights about the relative impacts of measures and practices if we assume that the self-selection bias is roughly proportional across measures and practices.

The second numerical column of Table 4-2 presents the estimation results for this model. These results are mixed, but do show some general tendencies. In particular, it appears that practices are responsible for the lion's share of savings. Practices related to air conditioning, space heating, refrigeration, and other end uses are negative and significant at the 10% level, while none of the measures terms are negative and significant.

Composite End-Use Approach Estimation

As noted above, the end-use action and measure/practice approaches offer the advantage of decomposing impacts; however, they also make the mitigation of self-selection bias extremely difficult. Thus, the estimated savings coefficients in Table 4-2 are biased. The composite end-use approach is designed to retain the ability to decompose savings by end use, but to enable resolution of self-selection bias.

With this approach, the coefficients of the action variables are used as weights on the end-use action variables, and the weighted action savings are summed. The resultant sum (call this $IMPACT_{it}$) can be expressed as:

$$(14)\quad IMPACT_{it} = \sum_{k} \hat{\beta}_k S\_ACT_{ikt}$$

The revised model can be specified to include the impact term (interacted with the participation variable) as well as the appropriate Mills Ratio terms:

$$(15)\quad \Delta kWh_{it} = \beta_0 + \beta_1 \Delta X_{it} + \beta_2 IMPACT_{it} \Delta PART_{it}$$

$$+ \beta_3 MR_i IMPACT_{it} \Delta PART_{it} + \beta_4 MR_i + \varepsilon_{it}$$

If the *relative* values of the coefficients of the individual action variables are unbiased, then this specification mitigates self-selection bias.

The first column of Table 4-3 presents the estimation results for the composite approach model. Again, we focus on the program impact terms. Note that the impact term is defined to be negative, so its expected coefficient is positive. As shown, the free-standing impact term is significant, as is the Mills Ratio. However, the Mills interaction term is not significant. While we will leave the discussion of impacts for Section 5, we note that the overall net impacts fall appreciably relative to those yielded by the action model, which did not have self-selection correction terms.

Table 4-3: Composite Approach Model Estimates

Variable	Coefficients and t-values		
	Combined	In-Home	Phone
INTERCEPT	6.0 *(2.31)*	5.7 *(2.18)*	5.4 *(2.10)*
ΔSQFT	0.03 *(0.35)*	0.04 *(0.47)*	-0.05 *(-0.32)*
ΔSREF (increase)	116.0 *(3.20)*	115.8 *(3.16)*	-39.3 *(-0.75)*
ΔSREF (decrease)	37.5 *(1.50)*	28.6 *(1.11)*	-6.2 *(-0.15)*
ΔSRAC	-85.2 *(-1.14)*	-86.4 *(-1.14)*	-202.5 *(-2.52)*
ΔSEDRY	76.3 *(1.35)*	79.1 *(1.37)*	182.4 *(2.42)*
ΔSSPA	107.6 *(1.89)*	99.6 *(1.71)*	141.5 *(2.34)*
ΔCDD70 * ΔSPOOL	0.7 *(1.32)*	0.7 *(1.25)*	0.7 *(1.20)*
ΔSEVC * CDD70	-0.8 *(-6.04)*	-0.9 *(-6.15)*	-0.6 *(-4.85)*
SCAC * ΔCDD70 * SQFT	0.001 *(36.84)*	0.001 *(36.63)*	0.001 *(36.90)*
SCAC * ΔRCAC	-53.9 *(-1.82)*	-54.4 *(-1.81)*	-51.4 *(-1.45)*
SRAC * ΔCDD70 * SQFT	0.0007 *(5.99)*	0.0007 *(5.93)*	0.0007 *(5.46)*
SEVC * ΔCDD70 * SQFT * EVAPONLY	0.0004 *(4.39)*	0.0004 *(4.60)*	0.0004 *(4.49)*
SEVC * ΔREVC	142.1 *(2.14)*	157.2 *(2.31)*	182.8 *(2.41)*
SESH * ΔHDD60 * SQFT	0.0006 *(15.80)*	0.0006 *(14.53)*	0.0006 *(13.78)*
SSUPPESH * ΔHDD60 * SQFT	0.0001 *(3.20)*	0.0002 *(3.34)*	0.0002 *(3.65)*
SEWH * ΔNHH	68.1 *(3.41)*	67.5 *(3.33)*	94.3 *(3.41)*
ΔRREF * SREF * PART	-64.0 *(-2.32)*	-78.9 *(-2.44)*	-1.2 *(-0.02)*
ΔRREF * SREF * (1-PART)	-51.5 *(-2.29)*	-52.0 *(-2.27)*	-42.8 *(-1.83)*

Table 4-3 (cont'd.): Composite Approach - Estimation Results (Net)

Variable	Coefficients and t-values		
	Combined	In-Home	Phone
SCAC * ΔCDD70 * SQFT * ΔPART	-0.0009 *(-6.98)*	-0.0009 *(-6.90)*	-0.0009 *(-2.72)*
ACACT * ΔCDD70 * SQFT * ΔPART	0.008 *(5.94)*	0.001 *(6.30)*	0.0005 *(2.07)*
ESHACT * ΔHDD60 * SQFT * ΔPART	0.0002 *(3.95)*	0.0002 *(2.78)*	0.0003 *(3.62)*
SCAC * CDD70 * SQFT	0.00001 *(0.42)*	0.00001 *(0.66)*	0.00001 *(0.56)*
IMPACT	3.9 *(2.97)*	3.4 *(2.78)*	11.8 *(2.13)*
MILLS RATIO	0.5 *(2.26)*	0.4 *(2.01)*	1.7 *(1.84)*
IMPACT * MILLS RATIO	1.8 *(0.92)*	2.2 *(1.04)*	-0.4 *(-0.14)*
Model R-Squared	0.20	0.20	0.21

The second and third numerical columns of Table 4-3 present the estimated composite models for two versions of the audit program: the in-home audit and the phone audit. We caution the reader not to focus on the free-standing participation coefficient when inspecting these results. While the coefficient of this variable is larger for the phone audit than for the in-home audit, the interaction term is far smaller. As will be discussed in the next section, the resultant net savings for the phone audit is considerably smaller than the savings associated with the in-home audit.

A Digression on Confidence Intervals. When the Double Mills Ratio Approach is used, developing a confidence interval for per-participant savings becomes fairly complex. This follows from the fact that savings depend upon two coefficients (as well as the conditional mean of the Mills Ratio. However, we can estimate at least an approximate standard error for the impact and construct a corresponding confidence interval confidence interval with the following approach:

- First, the model is estimated and the coefficients of the program terms are retrieved. From equation (9), these coefficients can be used to define a composite variable. Calling this $COMP_{it}$, we have:

$$COMP_{it} = \hat{\beta}_2 IMPACT_{it} \Delta PART_{it} + \hat{\beta}_3 MR_i IMPACT_{it} \Delta PART_{it}$$

- Second, the equation is re-estimated with $COMP_{it}$ as an explanatory variable replacing the two participation terms. By construction, the coefficient on $COMP_{it}$ will be equal to 1.0, and the standard error on this coefficient will be the relative standard error of the impact. It is a relative standard error in the sense that it is the standard error of the normalized coefficient. This standard error can then be used to develop confidence intervals.

The Fruits of Subtlety. There is one other interesting finding from the composite impact model. Note that there are two refrigerator replacement terms, one for participants and one for nonparticipants. As shown in Table 4-3, the coefficients on both *ΔRREF*SREF*PART* and *ΔRREF*SREF*NPART* terms are negative, which reflects the savings associated with replacing an old unit with a new one. However, the participant coefficient is -64.0, while the nonparticipant coefficient is -51.5. This suggests that participants reduce usage by approximately 150 kWh more than nonparticipants when replacing refrigerators.[3] If both sets of households start with the same usage on the old units, this may indicate that participants tend to buy more efficient refrigerators when making these replacements. While we should not make a strong conclusion in this respect, it appears that the subtle mention of the availability of high-efficiency refrigerators by auditors may influence participant behavior.

4.4 Estimating Gross Impacts

The Protocols require estimates of gross as well as net program impacts. While it may not be an ideal framework for this purpose, the direct participation model can also be used to estimate gross impacts. This application entails the estimation of the direct participation model with one of the following approaches:

- First, the model could be estimated with a sample of participants only. With this approach, the participation variable essentially captures the gross difference in (the change in) energy usage between the pre- and post-program periods, controlling for other factors. Since no nonparticipants are included in the estimation sample, the coefficient of the participation variable no longer nets out reductions in energy usage associated with nonparticipant conservation activity. Note that the binary variable for participants outside the impact period would be dropped from the model, insofar as it would be perfectly collinear with the program impact binary ($\Delta PART_{it}$). Note also that the Mills Ratio is no longer needed in this version of the model, since self selection is no longer an issue. It is often argued that other variables should be incorporated to control for other factors when estimating this model without nonparticipants. However, the model already controls for all

[3] The difference of 150 kWh is derived by subtracting the annual savings of a nonparticipant (-51.5*12) from the annual savings of a participant (-64.0*12).

known changes affecting participants' consumption. Other factors (say, changes in income or employment) are not known, or they would have been included in the basic form of the model.

- Alternatively, the model could be estimated with a binary variable representing nonparticipants. This is logically equivalent to the first approach, although it may yield slightly different results for any given dataset.

We chose the first approach and applied it to the actions model. The results are presented in Table 4-4. As indicated, the relative gross impacts of end-use actions are remarkably similar to the net impacts. In the next section, we will present these impacts and discuss the implied net-to-gross ratios.

Table 4-4: Composite Approach, Gross Savings

Variable	Coefficients and t-values
INTERCEPT	7.9 *(0.95)*
ΔSQFT	0.1 *(1.00)*
ΔSREF (increase)	156.1 *(2.24)*
ΔSREF (decrease)	54.3 *(2.28)*
ΔSRAC	103.1 *(0.39)*
ΔSEDRY	-63.6 *(-0.94)*
ΔSSPA	-
ΔCDD * ΔSPOOL	0.6 *(0.42)*
ΔSEVC * CDD70	-1.1 *(-4.71)*
SCAC * ΔCDD70 * SQFT	-0.00004 *(-0.05)*
SCAC * ΔRCAC	-87.2 *(-1.93)*
SRAC * ΔCDD70 * SQFT	0.001 *(2.83)*
SEVC * ΔCDD70 * SQFT * EVAPONLY	-0.00008 *(-0.25)*
SEVC * ΔREVC	128.5 *(0.91)*
SESH * ΔHDD60 * SQFT	0.001 *(11.48)*
SSUPPESH * ΔHDD60 * SQFT	-0.0005 *(-3.20)*
SEWH * ΔNHH	43.1 *(1.69)*
ΔRREF * SREF * PART	-78.1 *(-3.58)*
ΔRREF * SREF * (1-PART)	-
SCAC * ΔCDD70 * SQFT * ΔPART	0.0004 *(0.55)*
ACACT * ΔCDD70 * SQFT * ΔPART	0.0008 *(5.33)*
ESHACT * ΔHDD60 * SQFT * ΔPART	0.0001 *(2.19)*
SCAC * CDD70 * SQFT	-0.00001 *(-0.31)*
IMPACT	0.97 *(5.86)*
Model R-Squared	0.20

5

Results

5.1 Overview of Results

This section presents the estimated Program impacts and demand savings of the 1995 In-Home Audit Program. Subsection 5.2 addresses actual and weather-normalized energy savings; all savings are annualized. Subsection 5.3 presents an overview of total 1995 program energy and demand savings. Subsection 5.4 discusses the presence of market barriers to implementation of site-specific conservation recommendations and energy efficient appliances.

5.2 Net and Gross Energy Savings

Energy savings are estimated directly from the models presented in Section 4. In the case of overall net savings and savings by end use, these estimates are based on the composite impact approach (Table 4-4). Recall that this model permits mitigation of self-selection bias. Estimates of gross savings are derived from the model presented in Table 4-4. Insights related to measures and practices are based on the measure/practice model (Table 4-2), even though it was not purged of self selection. As a result, we focus on relative, rather than absolute savings. Finally, estimates of net savings from the two components of the Program (in-home and phone) are based on the corresponding models presented in Table 4-4. Appendix H presents the derivation of Program savings in more detail.

Net and gross energy impacts under actual weather conditions are presented in Table 5-1. The following conclusions can be made on the basis of these results:

- For the overall program, average per-participant impacts are 344 kWh per year under the weather conditions observed in the impact period.
- Net impacts of the in-home delivery approach are approximately 450 kWh annually under actual post-audit weather conditions. The net impacts of the phone version of the audit are 133 kWh.
- Net impacts are dominated by refrigeration actions. Over 73% of all savings come from this end use.

- Gross impacts are somewhat higher than net impacts across all end uses. The implied net-to-gross ratio for total energy impacts is 72%. This is a plausible value for this kind of program. Appendix H details the derivation of program impacts.
- While it is not indicated in Table 5-1, practices account for all of the savings of the program. Refrigerator practices include disconnecting second refrigerators, checking condenser coils, keeping the unit full, and lowering the thermostat setting. These practices appear to dominate the results of the program.

Table 5-1: Estimated Net and Gross Impacts per Home, Actual Weather

End Use	Net Impacts	Gross Impacts
Air Conditioning	25.9	31.8
Space Heating	8.9	13.4
Water Heating	16.4	17.9
Refrigeration	254.2	365.4
Other	38.8	50.7
Total Estimated Impacts	344.2	479.2
In-Home versus Phone Audits		
In-Home Audit	450.2	
Phone Audit	133.2	

Table 5-2 presents weather-normalized energy impacts. Overall, these are very similar to the impacts under actual weather. However, air conditioning impacts are somewhat lower and space heating effects are higher after normalization. More specifically, air conditioning impacts decrease by a factor of 0.8 and space heating impacts increase by a factor of 1.4.

Table 5-2: Estimated Net and Gross Impacts per Home, Normal Weather

End Use	Net Impacts	Gross Impacts
Air Conditioning	20.7	25.4
Space Heating	12.5	18.7
Water Heating	16.4	17.9
Refrigeration	254.2	365.4
Other	38.8	50.7
Total Estimated Impacts	342.6	478.1
In-Home versus Phone Audits		
In-Home Audit	432.7	
Phone Audit	154.4	

As indicated in Section 4, it is possible to construct a confidence interval for net energy savings, even with the Double Mills Ratio Approach. The overall standard error for weather-normalized per-participant savings is 64.23, and the 90% confidence interval for this savings estimate is 236.9 to 448.3. While this interval is larger than we would like, it is unsurprising for this type of program.

5.3 Total Program Energy and Demand Impacts

Table 5-3 presents a summary of total 1995 program energy and demand savings. Energy savings were computed as annualized values for all 1995 participants. These first-year savings amount to roughly 3.4 million kWh, with a 90% confidence interval of 2.37 million to 4.48 million kWh per year.

Demand impacts were estimated using a set of end-use peak ratios. These were computed as ratios of the end use's contribution to SCE's peak to the annual energy associated with this end use. Peak ratios were developed from the results of Edison's 1991 end-use metering project.[1] They were then multiplied by estimated annual end-use energy savings to determine estimated coincident demand impacts. Peak load factors and the associated demand impacts are presented in Table 5-3.

As indicated in Table 5-3 and Table 5-4, the total net and gross annual weather-normalized energy savings from the 1995 program are over 3.4 million kWh and 4.7 million kWh, respectively. The associated coincident peak demand savings amount to 740 kW. Approximately half of these demand savings come from refrigeration actions, while most of the rest are attributable to air conditioning actions. A 90% confidence interval for total program demand savings would be 511.7 to 968.1.

[1] Southern California Edison Company, *Residential Appliance End-Use Survey - 1990 Results*, Energy Efficiency and Market Services Division, October 1991.

Table 5-3: Total Net Program Energy and Demand Savings, Normal Weather

End Use	Total Net Program Savings (kWh)	Peak Load Factor	Estimated Demand Savings (kW)
Air Conditioning	207,000	0.001370	283.6
Space Heating	125,000	0.000000	0.0
Water Heating	164,000	0.000077	12.6
Refrigeration	2,542,000	0.000146	371.1
Other	388,000	0.000187	72.6
Total Estimated Savings	3,426,000	-	739.9

Table 5-4: Total Gross Program Energy and Demand Savings, Normal Weather

End Use	Total Gross Program Savings (kWh)	Peak Load Factor	Estimated Demand Savings (kW)
Air Conditioning	254,000	0.001370	347.9
Space Heating	187,000	0.000000	0.0
Water Heating	179,000	0.000077	12.5
Refrigeration	3,654,000	0.000146	533.5
Other	507,000	0.000187	94.8
Total Estimated Savings	4,781,000	-	988.7

5.4 Overcoming the Information Market Barrier

This section addresses the issue of whether or not the recommendations provided by this program served the purpose of overcoming the market barrier of lack of information. In other words, had these participants failed to take the recommended action prior to the energy audit because they lacked the information about the possible savings that could be realized by employing it?

Toward addressing this question, two measures of the existence of an information market barrier were taken for each energy-efficiency item. The first measure was a question asking the respondents if, prior to the audit, they were aware that the item could save energy, if employed. The second measure of the information barrier was a question asking the respondents if, prior to the audit, they realized the importance of the action. Both questions were asked in connection with all 77 action items covered by the program. Also asked was whether the respondents recalled the recommendation being made. This question was important because it would be difficult to attribute any energy-efficiency action taken to the audit recommendation when a recommendation was not remembered.

At a very basic level, one could say that the indicator of overcoming the information barrier is the proportion taking the action who both remembered the action recommendation and were *not* aware of its benefits prior to the audit. This proportion for each measure can be seen in Table 5-5. However, it is difficult to interpret these numbers without a point of comparison. The logical point of comparison is with that group of participants who were aware of the benefits of the action (and remembered a recommendation). This point of comparison is also shown in Table 5-5. However, a more fundamental issue is precipitated by inspection of the table and is discussed in the next paragraph.

Awareness Levels

Perhaps the most important observation about the proportions in Table 5-5 is the small number of respondents found in the lack of awareness category. That is, most of the respondents in this sample were already aware of the potential energy savings associated with these 77 energy-efficiency items. For these already-aware respondents, no information barrier apparently existed. One can get the general impression of these levels of awareness from Table 5-5. However, a more complete picture of awareness in the entire participant sample can be had from Table 1-10. This table (among other things) shows the percent of the participant sample who were aware that each action could save energy. The complement to this percentage is the percent who had been experiencing an information barrier. Overall, it is clear that there is a high level of awareness for most of these actions. This is an important point for program planners. There is a limit to how important an information program can be in terms of informing customers of the benefit of these specific actions. However, it is also true that, for some actions, awareness is *not* high. Table 5-6 displays each item for which there was at least 50% of the sample who were *not* aware. These are the items where information programs can have the maximum impact. There are 13 of them and the list is topped by the recommendation to install a timer on the water heater, turning off the extra refrigerator when not in use, and keeping lamp fixtures clean.

Overcoming the Information Barrier

The central point of this section, however, is addressed by the comparisons made within Table 5-5. It can be argued that if the audit recommendations overcame an information market barrier, then those who did not know about the action prior to the audit would have a higher rate of taking the action than those who already knew about the potential savings of the action. This would be true because those who already knew of the benefits would, presumably, have already taken the action to the extent that they were interested in saving energy. Those who were *not* aware of the benefits would, upon hearing of the benefits, follow the recommendation, if the information barrier was indeed the issue.

This question can be assessed for both of the market barrier questions: the awareness question and the importance question. Focusing first on the awareness question, we would, according to the hypothesis, expect the percent who followed the recommendation to be higher among those who were *not* aware of the savings potential before the audit than the percent among those who *were* aware. A cursory look at the first two data columns of Table 5-5 shows the hypothesis not to be supported. In only 12 of the 77 actions is the percent taking the action higher among the previously unaware than among the aware. Further, in all of those comparisons, the number of cases on which the unaware percentages is based is extremely small, implying substantial instability. When inspecting only those items where there were at least 10 cases where the participant indicated no awareness (an arbitrary number), there are no comparisons that support the hypothesis. There are 17 comparisons that meet this criterion. If the inspection cut-off point is set at 15 cases, the results are the same, but based on 12 comparisons. There are two comparisons, among all 77, where the *unaware* participants had very slightly higher action rates than the aware. In all of the other comparisons, the results are noticeably against the hypothesis.

The same type of comparison is not feasible for the other measure of the information barrier, not knowing the importance of the action. There were too few participants who did not know the importance. This is because the importance question was only asked of those who indicated awareness. The small numbers probably reflect the fact that, if one is aware of the benefits of an action, one is also aware of its importance to saving energy. Nevertheless, the result is that meaningful comparisons cannot be made between those who knew of the importance of the actions and those who did not prior to the audit.

A reasonable interpretation of the comparison between those aware and those not aware is that the audit recommendations served as a reminder to do what the customer already knew would be beneficial. One does not always do what is known to be beneficial, and a concrete suggestion from an expert may have been what was needed to stimulate action. It is also true that, in spite of "being aware" that an action would save energy, that knowledge may have been vague before hearing the specifics from an Edison representative. Understanding what was at stake in each action could well have taken the customer's "awareness" to another level, i.e., a level that precipitated action.

While the above is a reasonable interpretation of the data presented, it is also possible that participants were reporting what they had already done for achieving energy efficiency even before the audit. The questions were framed specifically to ask about actions taken as a result of the recommendation; however, it is possible that respondents reported prior actions as well. This would be consistent with the fact that those who were "aware" acted more frequently than those who were not "aware." To test this idea, the group who did *not* remember the recommendations having been made was brought into the analysis. If there was an information effect, a higher rate of installation would be expected among those who received and remembered recommendations compared to those who did not. To the extent that people were simply reporting actions they had taken at any time, before or after the audit, the action rates should be similar. Table 5-7 displays the action information for the group that did not remember recommendations. In this table, for the interested reader, the figures are once again broken out by the awareness variable, although this break-out is not critical to the present question.

The point of this analysis is made by the comparison of remembering versus non-remembering participants. The comparison can be made by looking at Table 5-5 and Table 5-6. However, for convenience, Table 5-8 is presented. This table shows the total action rate for those who did and did not remember receiving a recommendation. The patterns are clear. In virtually all of the action types, the recommendation-remembering group has a very substantially higher action rate than the non-remembering group. This argues, though not conclusively, for an information or reminder effect of the recommendations. Of course the comparison also argues for a certain level of over-reporting of audit-related actions: some percentage of respondents who said they did not remember a recommendation nevertheless reported following it. Presumably, this reflects some reporting of having taken the action irrespective of the recommendation, possibly predating the recommendation. Still, many more customers who remember the recommendation report following it than those who do not remember receiving it. This difference argues for the impact of receiving information from Edison.

Summary

The data show that customers are usually not experiencing an information barrier. Therefore, the audits do not, strictly speaking, have an information barrier to overcome. However, there is some support for the idea that, while vaguely aware of the energy benefits of the recommended actions, customers do not always act on this knowledge until it is specifically suggested by an Edison expert.

Also of interest is the fact that there are some 13 energy efficiency measures in the list of 77 covered for which at least 50% of the participant group was not aware of the potential savings that could accrue as a result of taking the action.

Table 5-5: Percent of Participants Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits and by Knowledge of Importance of the Actions

End Use	Aware of Measure	Not Aware of Measure	Knew of Importance	Didn't Know of Importance	Total Actions
Air Conditioning					
Set Air Conditioning Thermostat to 78 Degrees	86.1 (72)	87.5 (16)	87.0 (69)	66.7 (8)	86%
Add Reflective Coating or Solar Screening to Windows	51.2 (43)	41.3 (29)	54.1 (37)	33.3 (6)	47%
Install Attic Vents	73.3 (30)	25.0 (12)	73.3 (30)	0	60%
Turn Off Air Conditioner When Away for Extended Periods of Time	95.0 (20)	100.0 (1)	95.0 (20)	0	95%
Reduce the Use of Appliances that Generate Heat During Hot Weather	94.1 (17)	100.0 (6)	94.1 (17)	0	96%
Clean or Replace Dirty Air Filters	81.3 (64)	86.7 (15)	85.0 (60)	25.0 (4)	82%
Use Outside Air for Cooling	78.6 (14)	66.7 (3)	76.9 (13)	100.0 (1)	77%
Shade Windows from Direct Sunlight	80.4 (51)	100.0 (4)	80.4 (51)	0	82%
Space Heating					
Set Heater Thermostat to 68 During the Day and 58 at Night	100.0 (11)	66.7 (3)	100.0 (11)	0	93%
Install Automatic Setback Thermostat on Heating System	50.0 (2)	33.3 (3)	50.0 (2)	0	40%
Turn Heat Off or Down When Away for Extended Periods of Time	100.0 (1)	100.0 (1)	100.0 (1)	0	100%
Close Windows When the Heat is On	100.0 (1)	0	100.0 (1)	0	100%
Limit Use of Portable Electric Heaters	88.9 (9)	0	100.0 (1)	0	89%
Clean or Replace Dirty Heating System Filters	100.0 (9)	50.0 (2)	100.0 (8)	100.0 (1)	91%
Install R-19 Ceiling Insulation	50.0 (16)	0.0 (8)	50.0 (16)	0	33%
Install R-11 Wall Insulation	40.0 (20)	33.3 (9)	42.1 (19)	0.0 (1)	38%
Install Floor Insulation	60.0 (10)	25.0 (4)	60.0 (10)	0	50%

Table 5-5 (continued): Percent of Participants Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits and by Knowledge of Importance of the Actions

End Use	Aware of Measure	Not Aware of Measure	Knew of Importance	Didn't Know of Importance	Total Actions
Install Duct Insulation	77.8 (9)	100.0 (2)	77.8 (9)	0	82%
Weatherize Door and/or Windows	68.3 (60)	60.0 (5)	68.3 (60)	0	68%
Install Storm Doors or Windows	60.0 (20)	0.0 (5)	50.0 (20)	40.0 (5)	48%
Keep Windows Closed in the Winter	100.0 (2)	0	100.0 (2)	0	100%
Use Window Treatments	84.0 (50)	43.8 (16)	83.0 (47)	100.0 (3)	74%
Close Fireplace Dampers	87.5 (40)	60.0 (10)	87.2 (39)	100.0 (1)	82%
Water Heating					
Wrap Water Heater	66.7 (12)	100.0 (2)	66.7 (12)	0	71%
Turn Down Water Heater Temperature to 120 Degrees	95.5 (22)	50.0 (8)	95.5 (22)	0	83%
Insulate Hot Water Pipes	66.7 (24)	50.0 (6)	66.7 (24)	0	63%
Install Low Flow Showerheads and/or Faucet Aerators	87.5 (16)	100.0 (1)	87.5 (16)	0	88%
Install a Water Heater Timer	62.5 (8)	33.3 (6)	62.5 (8)	0	50%
Repair Leaky Faucets and Pipes	87.5 (8)	100.0 (1)	87.5 (8)	0	89%
Repair Leaky Tanks, Pipes, and Faucets	0	0	0	0	0%
Turn Down Water Heater Temp. When Away for Extended Periods	95.3 (21)	75.0 (4)	94.7 (19)	100.0 (2)	92%
Pool/Spa					
Operate Pool Equip. During Cool Time of Day	81.3 (32)	75.0 (12)	83.9 (31)	0.0 (1)	80%
Minimize Operation of Pool Pumps and Sweeps	90.9 (33)	33.3 (3)	90.6 (32)	100.0 (1)	86%
Keep Pool Filters and Strainers Clean	100.0 (8)	0	100.0 (8)	0	100%
Cover Pool When Not in Use	59.3 (27)	30.8 (13)	61.5 (26)	0.00 (1)	50%

Table 5-5 (continued): Percent of Participants Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits and by Knowledge of Importance of the Actions

End Use	Aware of Measure	Not Aware of Measure	Knew of Importance	Didn't Know of Importance	Total Actions
Home Appliances					
Limit Use of Self-Cleaning Oven Features	88.3 (17)	100.0 (3)	88.3 (17)	0	90%
Preheat Oven Only When Necessary	95.7 (23)	100.0 (3)	95.7 (23)	0	96%
Cover Pots and Pans When Cooking	100.0 (13)	100.0 (2)	100.0 (12)	100.0 (1)	100%
Use Microwave or Toaster Oven for Small Meals	100.0 (20)	100.0 (2)	100.0 (20)	0	100%
Cook by Time and Temperature	100.0 (10)	100.0 (1)	100.0 (10)	0	100%
Turn Off Extra Refrigerator When Not in Use	50.0 (68)	57.1 (7)	51.6 (64)	25.0 (4)	51%
Keep Refrigerator Temperature at 37-40 Degrees	93.1 (87)	85.1 (47)	92.9 (84)	100.0 (3)	90%
Check Refrigerator Door Seals	91.1 (90)	69.2 (26)	91.0 (89)	100.0 (1)	86%
Check Refrigerator Condenser Coils	89.0 (91)`	72.9 (59)	89.4 (85)	83.3 (6)	83%
Keep Refrigerator as Full as Possible	87.5 (40)	50.0 (38)	86.8 (38)	100.0 (2)	69%
Turn Off Extra Freezer When Not In Use	69.7 (33)	100.0 (1)	71.9 (32)	0.0 (1)	71%
Keep Freezer Temperature at 0-10 Degrees	95.3 (21)	71.4 (14)	95.3 (21)	0	86%
Check Freezer Door Seals	80.0 (25)	50.0 (8)	80.0 (20)	0	73%
Check Freezer Condenser Coils	81.8 (33)	77.8 (9)	81.3 (32)	100.0 (1)	81%
Keep Freezer as Full as Possible	92.9 (14)	100.0 (6)	92.9 (14)	0	95%
Dry Full Loads of Laundry	100.0 (6)	66.7 (3)	100.0 (6)	0	89%
Dry Consecutive Loads of Laundry	88.9 (9)	75.0 (4)	88.9 (9)	0	85%
Operate Clothes Dryer During Cool Times of Day/Evening	100.0 (13)	100.0 (3)	100.0 (12)	100.0 (1)	100%

Table 5-5 (continued): Percent of Participants Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits and by Knowledge of Importance of the Actions

End Use	Aware of Measure	Not Aware of Measure	Knew of Importance	Didn't Know of Importance	Total Actions
Clean Lint Filter on Dryer Regularly	100.0 (6)	100.0 (1)	100.0 (6)	0	100%
Direct Dryer Vent Exhaust Air to the Outside	100.0 (3)	100.0 (3)	100.0 (3)	0	100%
Turn Off Dishwasher During Drying Cycle	77.3 (66)	52.6 (19)	78.5 (65)	0.0 (1)	72%
Operate Dishwasher During Cool Times of Day/Evening	100.0 (13)	100.0 (2)	100.0 (12)	100.0 (1)	100%
Wash Full Loads of Dishes	92.9 (14)	100.0 (1)	92.9 (14)	0	93%
Wash Full Loads of Clothes	94.1 (17)	50.0 (2)	94.1 (17)	0	89%
Use Warm/Cool Water to Wash Clothes	94.9 (39)	71.4 (7)	94.7 (38)	100.0 (1)	91%
Operate Clothes Washer During Cool Times of Day Evening	95.0 (40)	85.7 (7)	95.0 (40)	0	94%
Make Waterbed with a Comforter	100.0 (2)	100.0 (2)	100.0 (2)	0	100%
Turn Down Waterbed Temperature	100.0 (2)	100.0 (2)	100.0 (2)	0	100%
Operate Well Pumps During Cool Times of Day/Evening	0	0	0	0	0%
Turn Off Beverage Coolers When Not in Use	0	0	0	0	0%
Locate Beverage Coolers in Air Conditioned Space	0	0	0	0	0%
Operate Miscellaneous Appliances During Cool Times of Day/Evening	0	0	0	0	0%
Lighting					
Replace Incandescent Bulbs with Compact Fluorescent	65.3 (121)	44.4 (45)	67.5 (114)	28.6 (7)	60%
Install Timers or Photocells on Security Lights	80.0 (30)	52.9 (17)	80.0 (30)	0	70%
Turn Off Unnecessary Lights	98.2 (55)	0	98.2 (55)	0	98%
Keep Lamp Fixtures Clean	100.0 (23)	89.5 (19)	100.0 (22)	100.0 (1)	95%

Table 5-5 (continued): Percent of Participants Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits and by Knowledge of Importance of the Actions

End Use	Aware of Measure	Not Aware of Measure	Knew of Importance	Didn't Know of Importance	Total Actions
Use Energy Efficient Lighting Where Possible	0	0	0	0	0%
Turn Off Decorative Lighting	94.6 (37)	25.0 (4)	94.4 (36)	100.0 (1)	88%
Office Equipment					
Turn Off Office Equipment When Not In Use for Extended Periods	0	0	0	0	0%
Buy Bubble/Ink Jet Printer Instead of Laser Printer	0	0	0	0	0%
Purchase Power Saver Options on Office Equip. When Possible	0	0	0	0	0%
Install Motion Sensors/Photocells on Air Conditioned Space	0	0	0	0	0%

Table 5-6: Energy-Efficiency Actions Where Participant Lack of Awareness Exceeds 50%

Action Item		% Not Aware
1	Installing a water heater timer	72.5%
2	Turning off the extra refrigerator when not in use	67.5%
3	Keeping lamp fixtures clean	63.0%
4	Installing floor insulation	60.9%
5	Keeping the freezer temperature between 0-10 deg	60.0%
6	Making a waterbed with a comforter	60.0%
7	Installing R-11 wall insulation	58.4%
8	Directing dryer vent exhaust air to the outside	55.6%
9	Installing R-19 ceiling insulation	55.4%
10	Installing timers or photocells on security lights	55.3%
11	Installing attic vents	53.5%
12	Installing duct insulation	52.9%
13	Turning down waterbed temperature	50.0%

Table 5-7: Percent of Participants Not Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits

End Use	Awareness of Measure	Not Aware of Measure	Total Actions
Air Conditioning			
Set Air Conditioning Thermostat to 78 Degrees	55.6 (18)	10.0 (20)	32%
Add Reflective Coating or Solar Screening to Windows	6.3 (32)	8.7 (23)	7%
Install Attic Vents	23.5 (17)	4.8 (42)	10%
Turn Off Air Conditioner When Away for Extended Periods of Time	66.7 (6)	0.0 (1)	57%
Reduce the Use of Appliances that Generate Heat During Hot Weather	50.0 (2)	0	50%
Clean or Replace Dirty Air Filters	50.0 (20)	10.0 (10)	37%
Use Outside Air for Cooling	66.7 (3)	0.0 (1)	50%
Shade Windows from Direct Sunlight	45.0 (20)	0.0 (5)	36%
Space Heating			
Set Heater Thermostat to 68 During the Day and 58 at Night	57.2 (7)	0.0 (11)	22%
Install Automatic Setback Thermostat on Heating System	25.0 (4)	7.2 (14)	11%
Turn Heat Off or Down When Away for Extended Periods of Time	33.3 (3)	0	33%
Close Windows When the Heat is On	100.0 (1)	0	100%
Limit Use of Portable Electric Heaters	12.5 (8)	0.0 (3)	9%
Clean or Replace Dirty Heating System Filters	37.5 (8)	0.0 (4)	25%
Install R-19 Ceiling Insulation	40.0 (5)	0.0 (18)	9%
Install R-11 Wall Insulation	33.3 (12)	0.0 (36)	8%
Install Floor Insulation	12.5 (8)	0.0 (24)	3%
Install Duct Insulation	28.6 (7)	0.0 (1)	25%

Table 5-7 (continued): Percent of Participants Not Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits

End Use	Awareness of Measure	Not Aware of Measure	Total Actions
Weatherize Door and/or Windows	38.2 (34)	0.0 (7)	32%
Install Storm Doors or Windows	0.0 (9)	0.0 (14)	0%
Keep Windows Closed in the Winter	33.3 (3)	0	33%
Use Window Treatments	26.9 (26)	9.5 (21)	19%
Close Fireplace Dampers	45.5 (11)	11.1 (9)	30%
Water Heating			
Wrap Water Heater	25.0 (4)	0.0 (1)	20%
Turn Down Water Heater Temperature to 120 Degrees	42.9 (7)	14.3 (7)	29%
Insulate Hot Water Pipes	22.2 (9)	18.2 (11)	20%
Install Low Flow Showerheads and/or Faucet Aerators	33.3 (6)	16.7 (6)	25%
Install a Water Heater Timer	33.3 (3)	0.0 (23)	4%
Repair Leaky Faucets and Pipes	66.7 (3)	0	67%
Repair Leaky Tanks, Pipes, and Faucets	0	0	0%
Turn Down Water Heater Temp. When Away for Extended Periods	16.7 (6)	10.0 (10)	13%
Pool/Spa			
Operate Pool Equip. During Cool Time of Day	42.9 (7)	22.2 (18)	28%
Minimize Operation of Pool Pumps and Sweeps	66.7 (6)	0.0 (2)	50%
Keep Pool Filters and Strainers Clean	66.7 (3)	0.0 (1)	50%
Cover Pool When Not in Use	8.3 (12)	14.3 (7)	11%

Table 5-7 (continued): Percent of Participants Not Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits

End Use	Awareness of Measure	Not Aware of Measure	Total Actions
Home Appliances			
Limit Use of Self-Cleaning Oven Features	62.5 (8)	5.6 (18)	23%
Preheat Oven Only When Necessary	56.3 (16)	16.7 (6)	24%
Cover Pots and Pans When Cooking	42.9 (7)	20.0 (5)	33%
Use Microwave or Toaster Oven for Small Meals	66.7 (9)	16.7 (6)	47%
Cook by Time and Temperature	55.6 (9)	0.0 (8)	29%
Turn Off Extra Refrigerator When Not in Use	33.3 (12)	0.0 (9)	19%
Keep Refrigerator Temperature at 37-40 Degrees	43.8 (16)	10.3 (39)	20%
Check Refrigerator Door Seals	53.1 (32)	10.5 (19)	37%
Check Refrigerator Condenser Coils	38.7 (31)	6.0 (50)	19%
Keep Refrigerator as Full as Possible	70.6 (17)	14.3 (14)	45%
Turn Off Extra Freezer When Not In Use	14.3 (7)	0.0 (6)	8%
Keep Freezer Temperature at 0-10 Degrees	60.0 (5)	4.0 (25)	13%
Check Freezer Door Seals	33.3 (9)	0.0 (3)	25%
Check Freezer Condenser Coils	20.0 (10)	0.0 (13)	9%
Keep Freezer as Full as Possible	75.0 (4)	12.5 (8)	33%
Dry Full Loads of Laundry	0.0 (2)	0	0%
Dry Consecutive Loads of Laundry	33.3 (3)	0.0 (6)	11%
Operate Clothes Dryer During Cool Times of Day/Evening	0.0 (1)	0.0 (2)	0%

Table 5-7 (continued): Percent of Participants Not Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits

End Use	Awareness of Measure	Not Aware of Measure	Total Actions
Clean Lint Filter on Dryer Regularly	0.0 (2)	0	0%
Direct Dryer Vent Exhaust Air to the Outside	0.0 (1)	0.0 (2)	0%
Turn Off Dishwasher During Drying Cycle	38.1 (21)	3.7 (27)	19%
Operate Dishwasher During Cool Times of Day/Evening	66.7 (3)	0.0 (8)	18%
Wash Full Loads of Dishes	0.0 (1)	0.0 (1)	0%
Wash Full Loads of Clothes	100.0 (5)	0.0 (3)	63%
Use Warm/Cool Water to Wash Clothes	50.0 (6)	33.3 (3)	44%
Operate Clothes Washer During Cool Times of Day Evening	55.6 (9)	14.3 (14)	30%
Make Waterbed with a Comforter	0	0.0 (1)	0%
Turn Down Waterbed Temperature	50.0 (2)	0.0 (2)	25%
Operate Well Pumps During Cool Times of Day/Evening	0	0	0%
Turn Off Beverage Coolers When Not in Use	0	0	0%
Locate Beverage Coolers in Air Conditioned Space	0	0	0%
Operate Miscellaneous Appliances During Cool Times of Day/Evening	0	0	0%
Lighting			
Replace Incandescent Bulbs with Compact Fluorescent	16.3 (43)	4.7 (43)	11%
Install Timers or Photocells on Security Lights	31.3 (16)	5.0 (40)	13%
Turn Off Unnecessary Lights	53.9 (13)	0.0 (1)	50%
Keep Lamp Fixtures Clean	63.6 (11)	7.7 (39)	20%

Table 5-7 (continued): Percent of Participants Not Remembering Recommendations Who Took Actions by Awareness of Energy Savings Benefits

End Use	Awareness of Measure	Not Aware of Measure	Total Actions
Use Energy Efficient Lighting Where Possible	0	0	0%
Turn Off Decorative Lighting	37.5 (24)	0.0 (12)	25%
Office Equipment			
Turn Off Office Equipment When Not In Use for Extended Periods	0	0	0%
Buy Bubble/Ink Jet Printer Instead of Laser Printer	0	0	0%
Purchase Power Saver Options on Office Equip. When Possible	0	0	0%
Install Motion Sensors/Photocells on Air Conditioned Space	0	0	0%

Table 5-8: Percent of Participants Taking Actions by Whether They Remembered the Recommendations

End Use	Remember Recommendation	Doesn't Remember Recommendation
Air Conditioning		
Set Air Conditioning Thermostat to 78 Degrees	86%	32%
Add Reflective Coating or Solar Screening to Windows	47%	7%
Install Attic Vents	60%	10%
Turn Off Air Conditioner When Away for Extended Periods of Time	95%	57%
Reduce the Use of Appliances that Generate Heat During Hot Weather	96%	50%
Clean or Replace Dirty Air Filters	82%	37%
Use Outside Air for Cooling	77%	50%
Shade Windows from Direct Sunlight	82%	36%
Space Heating		
Set Heater Thermostat to 68 During the Day and 58 at Night	93%	22%
Install Automatic Setback Thermostat on Heating System	40%	11%
Turn Heat Off or Down When Away for Extended Periods of Time	100%	33%
Close Windows When the Heat is On	100%	100%
Limit Use of Portable Electric Heaters	89%	9%
Clean or Replace Dirty Heating System Filters	91%	25%
Install R-19 Ceiling Insulation	33%	9%
Install R-11 Wall Insulation	38%	8%
Install Floor Insulation	50%	3%
Install Duct Insulation	82%	25%
Weatherize Door and/or Windows	68%	32%
Install Storm Doors or Windows	48%	0%
Keep Windows Closed in the Winter	100%	33%
Use Window Treatments	74%	19%
Close Fireplace Dampers	82%	30%
Water Heating		
Wrap Water Heater	71%	20%
Turn Down Water Heater Temperature to 120 Degrees	83%	29%
Insulate Hot Water Pipes	63%	20%
Install Low Flow Showerheads and/or Faucet Aerators	88%	25%
Install a Water Heater Timer	50%	4%
Repair Leaky Faucets and Pipes	89%	67%
Repair Leaky Tanks, Pipes, and Faucets	0%	0%
Turn Down Water Heater Temp. When Away for Extended Periods	92%	13%
Pool/Spa		
Operate Pool Equip. During Cool Time of Day	80%	28%
Minimize Operation of Pool Pumps and Sweeps	86%	50%
Keep Pool Filters and Strainers Clean	100%	50%
Cover Pool When Not in Use	50%	11%

Table 5-8 (continued): Percent of Participants Taking Actions by Whether They Remembered the Recommendations

End Use	Remember Recommendation	Doesn't Remember Recommendation
Home Appliances		
Limit Use of Self-Cleaning Oven Features	90%	23%
Preheat Oven Only When Necessary	96%	24%
Cover Pots and Pans When Cooking	100%	33%
Use Microwave or Toaster Oven for Small Meals	100%	47%
Cook by Time and Temperature	100%	29%
Turn Off Extra Refrigerator When Not in Use	51%	19%
Keep Refrigerator Temperature at 37-40 Degrees	90%	20%
Check Refrigerator Door Seals	86%	37%
Check Refrigerator Condenser Coils	83%	19%
Keep Refrigerator as Full as Possible	69%	45%
Turn Off Extra Freezer When Not In Use	71%	8%
Keep Freezer Temperature at 0-10 Degrees	86%	13%
Check Freezer Door Seals	73%	25%
Check Freezer Condenser Coils	81%	9%
Keep Freezer as Full as Possible	95%	33%
Dry Full Loads of Laundry	89%	0%
Dry Consecutive Loads of Laundry	85%	11%
Operate Clothes Dryer During Cool Times of Day/Evening	100%	0%
Clean Lint Filter on Dryer Regularly	100%	0%
Direct Dryer Vent Exhaust Air to the Outside	100%	0%
Turn Off Dishwasher During Drying Cycle	72%	19%
Operate Dishwasher During Cool Times of Day/Evening	100%	18%
Wash Full Loads of Dishes	93%	0%
Wash Full Loads of Clothes	89%	63%
Use Warm/Cool Water to Wash Clothes	91%	44%
Operate Clothes Washer During Cool Times of Day Evening	94%	30%
Make Waterbed with a Comforter	100%	0%
Turn Down Waterbed Temperature	100%	25%
Operate Well Pumps During Cool Times of Day/Evening	0%	0%
Turn Off Beverage Coolers When Not in Use	0%	0%
Locate Beverage Coolers in Air Conditioned Space	0%	0%
Operate Miscellaneous Appliances During Cool Times of Day/Evening	0%	0%

Table 5-8 (continued): Percent of Participants Taking Actions by Whether They Remembered the Recommendations

End Use	Remember Recommendation	Doesn't Remember Recommendation
Lighting		
Replace Incandescent Bulbs with Compact Fluorescent	60%	11%
Install Timers or Photocells on Security Lights	70%	13%
Turn Off Unnecessary Lights	98%	50%
Office Equipment		
Keep Lamp Fixtures Clean	95%	20%
Use Energy Efficient Lighting Where Possible	0%	0%
Turn Off Decorative Lighting	88%	25%
Turn Off Office Equipment When Not In Use for Extended Periods	0%	0%
Buy Bubble/Ink Jet Printer Instead of Laser Printer	0%	0%
Purchase Power Saver Options on Office Equip. When Possible	0%	0%
Install Motion Sensors/Photocells on Air Conditioned Space	0%	0%

Appendix J

Protocol Tables 6 and 7

Table 6: 1995 In-Home Audit Program Energy Impacts

	Point Estimate	Item 5: 90% confid interval	Item 5: 80% confid interval	Reference
Item 1: Average Participant Group and Average Comparison Group Usage				
A. Not applicable[1]				
B. Not applicable[1]				
Item 2: Average Net and Gross End Use Load Impacts For the Impact Year				
A. Load Impacts				
SCE Total Program Gross Impact (MWh) [2]	na	na	na	SCE
SCE Total Program Net Impact (MWh) [2]	3,143	na	na	SCE
Estimated Total Program Gross Impacts (MWh) [3]	4,781	3,477-6,085	3,765-5,797	Gross Load Impact Model
Estimated Total Program Net Load Impacts (MWh)	3,426	2,370-4,480	2,602-4,249	Net Load Impact Model
B. Load Impacts Per Designated Unit				
SCE Gross Impact per Home (kWh)[2]	na	na	na	SCE
SCE Net Impact per Home (kWh) [2]	314.3	na	na	SCE
Estimated Gross Load Impacts per Home (kWh) [3]	478.1	347.7-608.5	376.5-579.7	Gross Load Impact Model
Estimated Net Load Impacts per Home (kWh)	342.6	237.0-448.0	260.2-424.9	Net Load Impact Model
C. Percent Change in Usage of the Participant Group and Comparison Group				
Not applicable.				

[1] This study does not provide UEC estimates.
[2] SCE Estimates are taken from SCE's first-year earnings claim.
[3] Gross evaluation estimates are annualized and weather-normalized.

Table 6: 1995 In-Home Audit Program Energy Impacts (continued)

	Point Estimate	Item 5: 90% confid interval	80% confid interval	Reference
D. Net and Gross Impact Realization Rates[4,5]				
Gross Impact Realization Rate, Total Program Savings	na	na	na	Gross Impact / Filed Gross Savings
Gross Impact Realization Rate, Savings per Household	na	na	na	Gross Impact / Filed Gross Savings
Net Impact Realization Rate, Total Program Savings	1.090	0.754-1.426	0.828-1.352	Net Impact / Filed Net Savings
Net Impact Realization Rate, Savings per Household	1.090	0.754-1.426	0.828-1.352	Net Impact / Filed Net Savings
Item 3: Net-to-Gross Ratios[6]				
A. Net-to-Gross Ratios based on Program Load Impacts	0.716	na	na	Net Impact/ Gross Impact
B. Net-to-Gross Ratios based on Average Load Impacts per Home	0.716	na	na	Net Impact/ Gross Impact
Item 4: Designated Unit Intermediate Data				
Not applicable.				
Item 6: Measure Count Data				
Not applicable.				

4 No gross savings realization rate could not be determined, insofar as SCE did not file a gross savings estimate in its first-year earnings claim.

5 Net savings realization rates are defined as the ratios of evaluation estimates of net savings to the net savings estimate filed with SCE's first-year earnings claim.

6 Net-to-Gross ratios presented here are defined as evaluation estimates of net savings divided by evaluation savings of net savings.

Table 6: 1995 In-Home Audit Program Demand Impacts

	Point Estimate	Item 5: 90% confid interval	Item 5: 80% confid interval	Reference
Item 1: Average Participant Group and Average Comparison Group Usage				
A. Not applicable[7]				
B. Not applicable[7]				
Item 2: Average Net and Gross End Use Load Impacts For the Impact Year				
A. Load Impacts				
SCE Total Program Gross Impact (kW)	na	na	na	SCE
SCE Total Program Net Impact (kW)	409.0	na	na	SCE
Estimated Total Program Gross Impacts (kW)	1,033.0	751-1,315	813-1,253	Gross Load Impact Model
Estimated Total Program Net Load Impacts (kW)	740	512-968	562-897	Net Load Impact Model
B. Load Impacts Per Designated Unit				
SCE Gross Impact per Home (W)	na	na	na	SCE
SCE Net Impact per Home (W)	40.9	na	na	SCE
Estimated Gross Load Impacts per Home (W)	103.3	75.1-131.5	81.3-125.3	Gross Load Impact Model
Estimated Net Load Impacts per Home (W)	74.0	51.2-96.8	56.2-89.7	Net Load Impact Model
C. Percent Change in Usage of the Participant Group and Comparison Group				
Not applicable.				
D. Net and Gross Impact Realization Rates[8]				
Gross Impact Realization Rates				
Study Gross Impact Realization Rate, Total Program Savings	na	na	na	Gross Impact/ Filed Gross Savings
Study Gross Impact Realization Rate, Savings per Household	na	na	na	Gross Impact/ Filed Gross Savings

[7] This study does not provide UEC estimates.

[8] A gross savings realization rate could not be determined, insofar as SCE did not file a gross savings estimate in its first-year earnings claim.

Table 6: 1995 In-Home Audit Program Demand Impacts (continued)

	Point Estimate	Item 5: 90% confid interval	Item 5: 80% confid interval	Reference
Net Impact Realization Rates				
Net Impact Realization Rate, Total Program Savings[9]	1.81	1.474 - 2.146	1.474 - 2.146	Net Impact / Filed Net Savings
Net Impact Realization Rate, Savings per Household[11]	1.81	1.474 - 2.146	1.474 - 2.146	Net Impact / Filed Net Savings
Item 3: Net-to-Gross Ratios[10]				
A. Net-to-Gross Ratios based on Program Load Impacts	0.716	na	na	Net Impact/ Gross Impact
B. Net-to-Gross Ratios based on Average Load Impacts per Home	0.716	na	na	Net Impact/ Gross Impact
Item 4: Designated Unit Intermediate Data				
Not applicable.				
Item 6: Measure Count Data				
Not applicable.				

Item 7: 1995 IHA Market Segmentation Data

CEC Climate Zone	Participant Group	Comparison Group
06 Coastal/08 LA Basin	55.5%	47.4%
09 Valley/10 Inland Empire	30.0%	36.0%
13 Joaquin/14 High Desert	9.0%	9.3%
15 Low Desert	4.3%	6.3%
16 Mountain	1.2%	1.0%
All Zones	100.0%	100.0%

[9] Each net realization rate is the ratio of the evaluation estimate of net savings to the net savings estimate filed by SCE in its first earnings claim.

[10] Net-to-Gross ratios presented here are defined as evaluation estimates of net savings divided by evaluation savings of gross savings.

Table 7: 1995 In-Home Audit Program Data Quality and Processing

7.A Overview Information

1. 1995 In-Home Audit Program Evaluation, study ID number 528 (A).
2. The program year is 1995. See Section 1.2 for program description.
3. The end uses/measures covered in the study include those covered by the Program recommendations. The Program offered approximately 77 possible recommendations, all of which were classified into five primary categories: air conditioning, space heating, water heating, refrigeration, and all other end uses. Appendix E details the classification of Program recommendations by end use.
4. This analysis utilizes a composite "impact" approach to estimate Program impacts. Inclusion of a composite "impact" term, which is the sum of action terms weighted by their respective coefficients, enables Program savings to be estimated by end use and allows for mitigation of self-selection bias. See Section 4 for a detailed discussion of the methods and model specification used in the analysis.
5. Program participants are defined as any SCE customer that participated in the In-Home Audit Program during 1995; there were approximately 10,000 participants in the Program. Nonparticipants are defined as any SCE residential customer that did not participate in the 1995 In-Home Audit Program.
6. The analysis utilized 24,556 monthly observations for the 601 households in the sample.

7.B Database Management

1. The key components include participant and nonparticipant survey data, 1995 In-Home Audit Program participant data, consumption data, and actual and normal weather data. See Section 3.2 for a description and diagram of the relationship between these data elements.
2. SCE provided all billing, weather and Program data, and interview data was collected as part of this analysis. Sources for each data element are identified in Section 3.2.
3. The program database consisted of 10,000 participants; 3,362 customers were dropped from the sample frame due to the reasons detailed in Table 3-1. The final sample consisted of 301 participants. The comparison group (nonparticipants) frame consisted of a sample of 50,000 nonparticipants; 17,044 customers were dropped from the frame due to the reasons detailed in Table 3-2. The final sample consisted of 300 nonparticipants. A total of 11 customer accounts, in addition to approximately 265 individual monthly observations, were excluded from the analysis due to billing anomalies, as discussed in Section 3.3, pages 3-20 and 3-21.

Table 7: 1995 In-Home Audit Program Data Quality and Processing (continued)

4. Interview data and customer billing records were matched by unique SCE premise identification numbers. Program data was matched by unique work order numbers, and weather data was merged to the database by SCE weather station account numbers and read dates.

5. Not applicable.

7.C Sampling

1. Sampling of Program participants and non-participants were stratified proportionally by residence type, audit type, pre-audit consumption levels, and CEC weather zone. The initial sampling frame of participants was based upon valid customer account identification numbers, status of the account (active since July 1996), consumption prior to the audit year (1994), and overall level of consumption. The initial sample frame of non-participants was based upon consumption in 1994 and overall consumption levels. See Section 3.2, pages 3-2 through 3-6, for a detailed description of sampling procedures and protocols. Appendix A details the sample design and the final sample structures for participants and non-participants are presented in Tables 3-5 and 3-6, respectively.

2. Survey instruments are provided in Appendix A.

   The response rate for participants was 35.5%, while the response rate for nonparticipants was 36%. Response rates are summarized in Tables 3-5 and 3-6, and reasons for refusals are detailed in Table 3-7 and 3-8.

   To preserve as many observations as possible (and maintain the highest level of statistical power when drawing inferences from the data), missing values were filled with predicted values and corrected for a self-selection misreporting bias where necessary. Responses to survey questions can be predicted by a subset of variables in the database, which are used to form the fitted values which replace missing values. In this analysis, missing values for income, household size, and square footage were filled using the Heckman two step procedure described in Appendix G. As shown in Table 3-4, approximately 196 missing values in the IHA database were replaced using this technique. Refer to Section 3.3, page 3-21 and Appendix G for treatment of item non-response bias.

   This analysis incorporates an inverse Mills Ratio to mitigate self-selection bias. The Mills Ratio is a function of the predicted value of participation as derived from the estimated form of a participation equation and differs across participants and nonparticipants. The Mills Ratio essentially affects the change in usage as well as the impact of the participation variable in the energy change equation. Pages 4-4 and 4-5 of section 4.2 discuss the mitigation of self-selection bias in more detail.

Table 7: 1995 In-Home Audit Program Data Quality and Processing (continued)

3. Tables 3-9 and 3-11 summarize the appliance purchases and replacements for both participants and non-participants, respectively. In general, less than 10% of the complete sample purchased each appliance, with a similar result for appliance replacements. However, a majority of participants that replaced appliances replaced with high-efficiency units. Tables 3-15 and 3-16 summarize the sample's household characteristics and electricity end uses.

7.D Data Screening and Analysis

1. Missing values were filled using the Heckman two-stage procedure which predicted values derived from a regression model, with a self-selection correction term for non-response bias. This correction procedure is detailed in Appendix G.

   In this project, we did not attempt to screen out such observations per se, but we did review large residuals in order to identify data anomalies. The following kinds of anomalies qualified an observation for deletion from the regression: (1) estimated bills or subsequent makeup bills, and when these consumption reads were abnormal, they were set equal to missing, (2) consumption values indicated long periods of vacancy for a home, these values were set equal to missing, and (3) in cases where reads simply seemed erroneous, they were also set equal to missing. Refer to Section 4.2, page 4-6 for a discussion of the treatment of influential data points and outliers.

   Weather adjustments were accomplished by including actual weather conditions in the load impact models, then simulating impacts under normal weather conditions.

2. Not applicable.

3. A number of cross-checks were performed to identify errors in reported data and to fill missing values. This process included inspection of consumption data for anomalous data, inspection of end-use responses for misreporting. Item non-response was mitigated using the Heckman two-step procedure, with which missing values are filled with predicted values. See Section 3.3 and Appendix G for discussions on the methods used to screen data for inclusion into the final analysis database.

4. See Tables 4-1 through 4-4 for regression statistics for all final models.

Table 7: 1995 In-Home Audit Program Data Quality and Processing (continued)

5. Section 4 reviews the rationale, advantages, and disadvantages of each model specification in the analysis . Each model accounts for factors that affect changes in consumption independent of program effects, such as changes in weather conditions, site characteristics (i.e, square footage, residence type, household size), and end-use saturations.

   The basic model specifies the twelve month change in consumption as a function of UECs and electricity end uses. Exogenous factors such as changes at the site and weather variation are accounted for in the model. Section 4.2 presents a detailed discussion of the basic model specification and the use of a double Mills Ratio method used to mitigate self selection bias.

   Factors and measures that were omitted from the analysis are summarized in Footnote 1 of Section 4. Essentially this entailed omitting terms relating to electric ranges/ovens, color televisions, washers and dryers, personal computers, waterbeds, and spas from the regression.

   In the most general sense, net savings are equal to the product of the conditional mean of the savings term and its respective coefficient. With respect to the composite impact approach, net savings by end use are computed as the sum of two products: the estimated end-use coefficients, the estimated IMPACT coefficient, and the conditional mean of the impact term, and the product of the estimated end-use coefficient, the estimated *MR**IMPACT* coefficient, and the conditional mean of the Mills Ratio interaction term. The derivation of net impacts is briefly discussed in Section 4.2 and detailed in Appendix H.

6. This analysis did not address the issue of measurement error.

7. Autocorrelation, which is the correlation of the error term over time for individual sites, is typical in analyses of energy usage over time. This problem was mitigated with generalized least squares, a standard remedy. All models presented in the study correct for the presence of autocorrelation.

8. This analysis did not specifically address the issue of heteroskedasticity. This is seldom a problem in this type of analysis of changes in household-level usage.

9. The issue of collinearity was addressed in this analysis through careful specification of interaction terms and through omission of some variables found to be highly collinear with others. Moreover, individual savings terms were aggregated with prior weights in some specifications in order to mitigate collinearity across program variables.

10. The following kinds of influential data points qualified an observation for deletion from the regression: (1) estimated bills or subsequent makeup bills, and when these consumption reads were abnormal, they were set equal to missing, (2) consumption values indicated long periods of vacancy for a home, these values were set equal to missing, and (3) in cases where reads simply seemed erroneous, they were also set equal to missing. Refer to Section 4.2, page 4-6 for a discussion of the treatment of influential data points and outliers.

Table 7: 1995 In-Home Audit Program Data Quality and Processing (continued)

11. Missing values were filled with predicted values derived from a regression model, with a self-selection correction term for non-response bias. This correction procedure is detailed in Appendix G.
12. Standard errors on estimated parameters are a standard output of statistical analysis packages. Tables 4-1 through 4-1 present the t-statistics for each estimated parameter in the analysis. See page 5-3, Section 5.2 for a discussion on the use of standard errors and confidence intervals for savings estimates.
7.E Data Interpretation And Application
1. Net Program impacts are calculated to be 342.6 kWh per year per household. These savings are weather normalized. Estimated net and gross Program impacts are presented in Tables 5-1 and 5-2, page 5-2.
2. Refer to Section 4.2 for a discussion of the process and rational for choices with respect to final model specification.