AN EVALUATION OF SOUTHERN CALIFORNIA GAS COMPANY'S 1995 COMMERCIAL NEW CONSTRUCTION PROGRAM

Volume I

Submitted to

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January 1998

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EXECUTIVE SUMMARY

This report provides original estimates of the impacts of Southern California Gas Company's Commercial New Construction program on natural gas consumption for efficiency measures paid during the program year 1995. The impacts of cooking-related measures (which account for 99% of the original estimated energy savings) are explored in detail.

Prior to this evaluation, SoCal Gas Company estimated that 1995 program activities had resulted in an annual energy conservation level of 2,296,781 therms per year. This *ex ante* level of savings had originally been estimated on an equipment-level basis for each participant.

The gross savings analysis conducted through this study adopted an approach to calculating gross savings which was similar to SoCal Gas Company's. The computer program developed by SoCal Gas Company to estimate gross savings was largely adopted in this project. However, some changes were made to prevent the overstatement of possible efficiency impacts of equipment with multiple efficiency features. 150 site visits were conducted on the premises of program participants to collect information on equipment efficiency, operating hours, equipment load factors, equipment usage patterns, and other data necessary to accurately re-estimate equipment-level savings. Estimates of the likely energy savings associated with various equipment types and equipment features were developed based on a review of engineering studies, information from manufacturers, and other sources. Baseline features for equipment within each category of cooking equipment were re-defined, based on the results of a telephone survey of program participants and non-participants.

This gross savings analysis conducted here resulted in an overall gross realization rate of 0.58; i.e., the results of the gross savings analysis reported here are 58% of the *ex* *ante* savings estimated by the utility. For all types of cooking equipment, the data collection efforts undertaken through this study revealed higher operating hours than originally assumed by SoCal Gas Company. Further, some of the load factors developed in this study were higher than those originally assumed by SoCal Gas Company. However, other factors led to a net reduction in the gross savings estimates developed here. Based on an analysis of data collected through the telephone survey, many of the measures for which incentives were provided through the program were found to be statistically indistinguishable from "standard" features, and thus should have been considered features of "baseline" equipment. Further, the energy savings associated with certain specific equipment (particularly equipment with multiple efficiency features) appeared to be overstated in the *ex ante* estimates.

The net savings analysis reported here estimates the level of energy savings which would have been achieved in the absence of the 1995 Commercial New Construction program. For the three types of equipment (fryers, griddles, and ranges) for which sufficient data were obtained through a telephone survey of program participants and nonparticipants, a four option qualitative choice model was estimated. This analysis revealed a net-to-gross ratio of 0.33 for these types of equipment; i.e., 67% of the program participants would have implemented the associated efficiency measures even in the absence of the program. For other defined types of equipment, the "self-report" results from the telephone survey were used to discern free ridership. The net-to-gross ratios for these types of equipment ranged from 0.0 to 0.02. The net-to-gross ratio for miscellaneous types of equipment was set at the weighted average for all equipment types, 0.158.

Table ES.1 summarizes the results of this study. The estimate of the net impact of the program reported here (214,837 therms), is over 90% lower than the *ex ante* gross savings estimate originally prepared by SoCal Gas Company.

Table ES.1
Summary of Results for Cooking-Related Measures

Equipment Type	*Ex Ante* Savings Estimate (Therms)	Gross Saving Estimate from this Evaluation (Therms)	Net-to-Gross Ratio Estimate from this Evaluation	Net Savings Based on this Evaluation (Therms)
Braising Pan	17,247	1,714	0.00	0
Broiler	132,665	203,576	0.02	4,072
Cabinet Steamer	121,037	49,495	0.00	0
Fryer	573,805	187,011	0.33	61,714
Griddle	204,631	225,050	0.33	74,267
Hot Food Table	20,620	0	0.00	0
Other	62,508	31,848	0.158	5,032
Oven	708,716	436,342	0.02	8,727
Range	399,064	184,924	0.33	61,025
Steam Kettle	56,486	10,020	0.00	0
Total	2,296,781	1,329,980	N/A	214,837

Chapter 1
INTRODUCTION AND OVERVIEW

This evaluation of Southern California Gas Company's (SoCal Gas Company's) 1995 Commercial New Construction Program was undertaken to determine the program's gross and net impacts on natural gas consumption.[1] The project team was composed of three independent consulting firms – Planergy, Pacific Consulting Services, and Equipoise Consulting. This evaluation was conducted in accordance with the requirements established by the California DSM Advisory Committee (CADMAC).

Overview of Program

The Commercial New Construction Program was established as a result of an agreement with the California Public Utilities Commission (CPUC) during SoCal Gas Company's 1990 general rate case to provide financial incentives and technical assistance to commercial establishments served by SoCal Gas Company to encourage the installation of high efficiency natural gas-consuming equipment. The program was terminated following the completion of program year 1995 activities as a part of SoCal Gas Company's strategy to shift away from ratepayer-subsidized incentive programs and toward participant-funded programs.

During the program year 1995, three types of equipment were eligible for financial incentives from SoCal Gas Company: high efficiency boilers, cooking equipment with a higher efficiency or productivity rate than called for by standard practices, and high efficiency double-effect absorption chillers. However, the vast majority of the equipment purchased through the program was cooking equipment by

[1] In this report, "gross impacts" refer to the impacts of the program before free ridership is taken into account, i.e. before considering the number of customers likely to have undertaken the efficiency measure even in the absence of the program. "Net impacts" refer to the remaining impacts of the program after accounting for free ridership.

restaurants. Table 1.1 reports program activity, *ex ante* energy savings estimates, and incentive costs for the program year 1995.

Table 1.1
Program Activity, Costs, and *Ex Ante* Energy Savings Estimate for FY 1995

Measure	Actual Number of contracts	Actual Number of Measures	Reported Gross Annual Energy Savings (therms)	Actual Incentive Costs ($)
Boilers	37	48	47,396	34,542
Cooking	1,491	1,653	2,296,781	903,219
Gas A/C — Double Effect	1	1	(25,384)	20,000
TOTAL	1,529	1,702	2,318,793	957,761

Prior to this evaluation, SoCal Gas Company had estimated 2,318,793 therms of savings as a result of program year 1995 activities, based on estimates prepared by the sales engineers responsible for administering the program. SoCal Gas Company reported expenditures on this program of $1.708 million for 1995.[2]

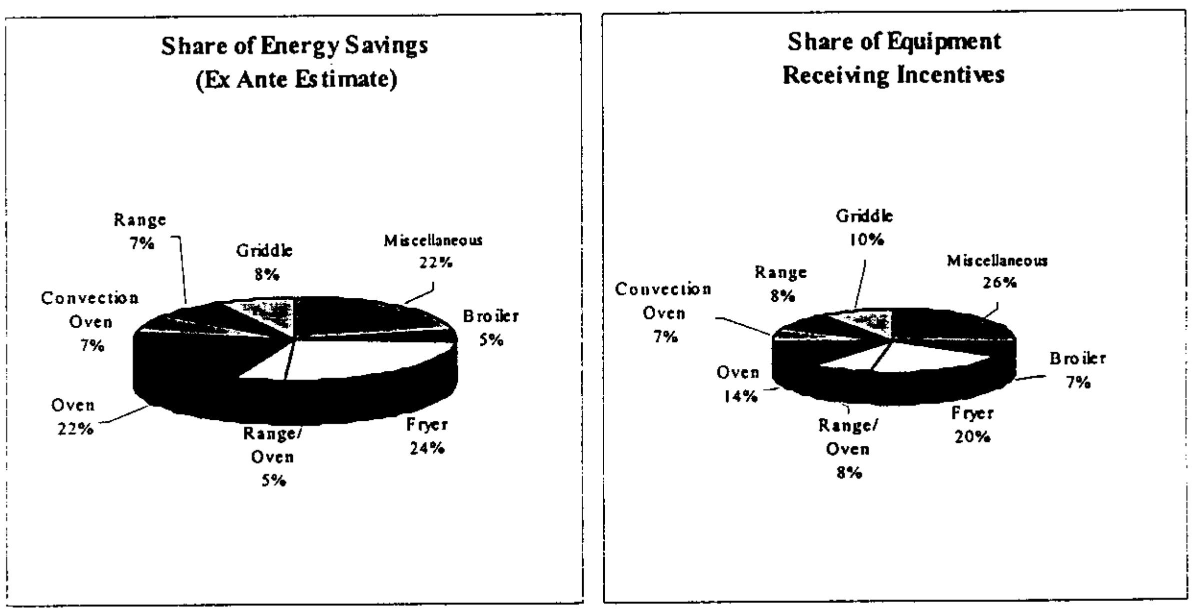
To market the program, a SoCal Gas Company account executive or customer service representative visited the new establishment to discuss the program with the client and explain the features or measures for which the financial incentives are available. A "cooking calculator" program (*CookCalc*) was used to develop SoCal Gas Company's estimate of the energy savings associated with various cooking equipment and the incentives which might be paid by SoCal Gas Company if the customer purchased such equipment. The *CookCalc* takes into account factors such as likely operational hours, rated Btu input for the equipment, equipment cost, and equipment features (efficiency measures). An application for a rebate was created once a customer had agreed to

[2] SoCal Gas Company, April 1996, p. II-24.

purchase qualifying equipment. Once the equipment was purchased, SoCal Gas Company obtained a copy of the invoice. A check was mailed or handed to the customer after the application was completed, the equipment was installed, and its installation was verified on site.

As noted in Figure 1.1, fryers and ovens accounted for nearly one-half of the *ex ante* estimated energy savings and 36% of the equipment for which financial incentives were awarded.

Figure 1.1
Cooking Equipment for Which Incentives Were Awarded in FY 1995



Consistency with CADMAC Requirements

To permit a more accurate evaluation of the effects of this program, the project team requested a waiver from some of the measurement and evaluation protocols established by the California DSM Advisory Committee (CADMAC). The waiver requested four exceptions:

- Permit use of a simplified engineering model for the estimation of gross savings.
- Permit the gross impacts to be determined based on 150 on-site visits, using no *direct* comparison group.
- Establish the baseline using self-report data.
- Use a discrete choice analysis to estimate the net impacts of the program.

The Protocols require that either a load impact regression model or a calibrated engineering approach supplemented with a building energy use simulation model be used to estimate the gross impacts associated with this type of program. Since this is a new construction program (and data for gas usage prior to installation of the efficiency measures are unavailable), estimation of a load impact regression model using time-series data would be impractical. A cross-sectional regression approach would also prove difficult, due to the heterogeneous nature of the eligible customer base. Whole building modeling would require the collection of large amounts of data with no relevance to cooking end uses. Similarly, end-use metering of gas consumption would prove prohibitively expensive, intrusive for the customer, and impractical on a large scale. Consequently, the project team concluded that simplified engineering analysis would be the most practical and accurate means of estimating the gross impacts of this program.

The protocols require site-visits to a comparison group, when on-site visits are used to collect data for the participant group. The project team felt that the results from a telephone survey of participants and non-participants would provide sufficient information to define appropriate baselines. Self-report data collected through the on-site visits to participating facilities and the telephone survey of both participating and non-participating facilities were used to develop the baselines.

Because of the diversity of eligible customers, the range of measures, and restriction that participants be new or remodeled facilities, a comparison of bills between participants and non-participants would not provide an accurate measure of free ridership or net program effects. Consequently, the project team requested permission to pursue discrete choice modeling to determine the net effects of the program. Discrete choice modeling explores the decision-making process and options available to eligible customers, and estimates the impacts that would have likely occurred in the absence of the program.

The waiver request was approved by CADMAC in May of 1997.

Key Features of Evaluation Approach

Because cooking equipment accounted for the nearly 99% of the program's *ex ante* energy savings, this evaluation focused exclusively on the cooking-related energy impacts of this program.

No analysis was performed for boiler measures or for AC-double effect measures installed under the program. Therefore, the *ex ante* estimate of savings for these two measures were used as the *ex post* gross savings estimate.

Commercial cooking equipment (hereafter just called cooking equipment) is used within a myriad of commercial businesses of varying business hours. These businesses have high employee and management turnover and have a relatively high rate of business closure.

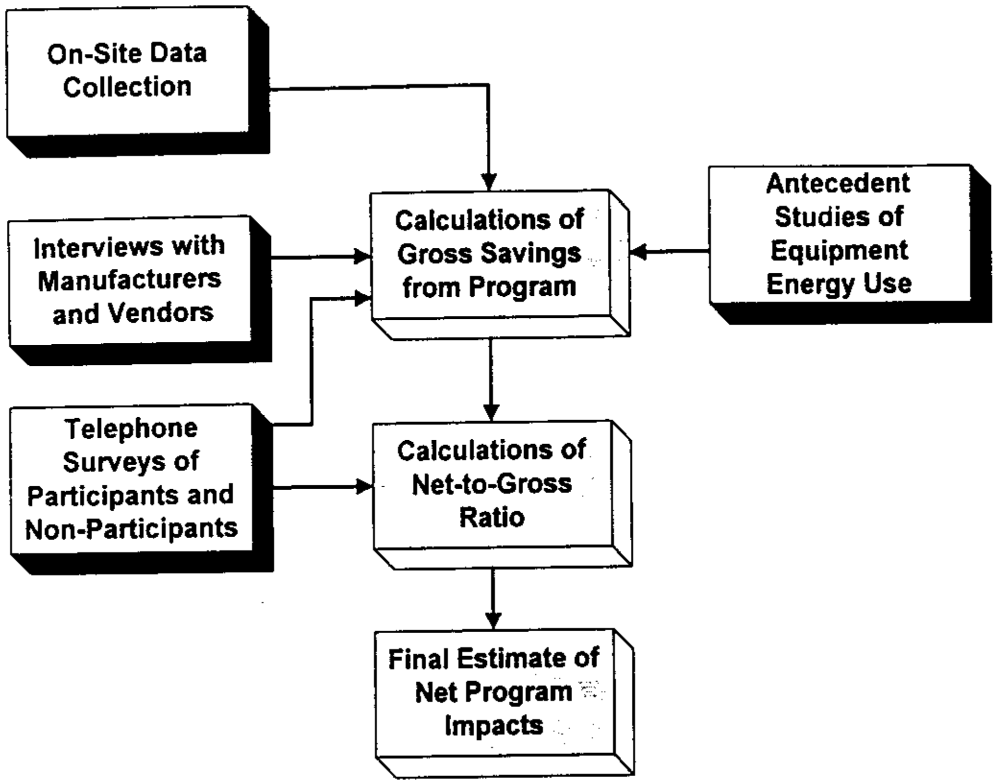
The nature of this program posed some unique challenges for this evaluation study. There is no generally-accepted energy efficiency testing and rating procedures for gas cooking equipment, as there are for many types of electric appliances. Cooking equipment lags other types of equipment (such as air conditioning) for standardization of testing and labeling. Baseline efficiency standards are non-existent. Consequently, the energy efficiency savings associated with many features available on gas cooking equipment are not well known or readily quantifiable. Further, CADMAC's Protocols for evaluating demand-side management (DSM) programs — developed largely with electric utility programs in mind — could not be readily applied to an evaluation focusing on gas cooking equipment. Therefore, waivers were requested from some of the Protocol requirements.

Key features of the approach adopted in this study include the following:

- On-site visits were conducted at 150 participant facilities to acquire an updated equipment inventory, equipment usage data, and other information necessary for this evaluation.
- A telephone survey was conducted to acquire equipment and attitudinal information from 85 participants in the program and 115 eligible establishments that elected to not participate in the program to discern differences in the equipment chosen and factors affecting such decisions.
- Estimates of the gross savings associated with various cooking equipment features were developed through a review of previous studies of equipment performance.
- Net-to-gross ratios (measuring free ridership) were developed through two approaches: an interpretation of the information collected through the telephone survey (a "self report" approach), and through statistical modeling. (For those equipment types for which sufficient data were available to support statistical modeling).

An overview of the approach adopted in this evaluation is depicted in Figure 1.2. Through this approach, we believe that we have produced one of the most comprehensive impact evaluations ever undertaken on a natural gas utility DSM program.

Figure 1.2
Overview of Project Approach



Overview of Report

This report provides a complete presentation of all techniques, assumptions, and findings from this study.

The following chapter reviews all data collection procedures. The sampling plan and data collection procedures for the on-site visits are reviewed. Telephone surveying activities are discussed. Findings from these data collection activities are summarized.

Chapter 3 describes the analysis performed to estimate the gross impacts associated with the New Construction program. Calculation procedures and data sources are described in detail. Gross impact estimates are reported.

Chapter 4 presents estimates of the net impacts of the program based on a combination of both "self-report" and modeling based approaches.

A companion Volume II provides a complete set of workpapers, including database contents, survey instruments, formulas used to estimate gross and net savings, and sources of assumptions regarding equipment-level energy savings. Tables 6 and 7 required by the CADMAC Protocols are provided.

Chapter 2
DATA COLLECTION

Overview

Two major data collection activities were completed in order to provide an accurate assessment of the impacts of the New Construction Program: on-site visits and a telephone survey. On-site visits were conducted at 150 facilities which participated in the program in 1995. The on-site visits were used to confirm whether the equipment acquired with the assistance of the program was indeed present at the facility. Through the on-site visits, the information required for the gross savings analysis was also collected.

A telephone survey of 85 program participants and 115 establishments that were eligible to participate in the program yet elected not to provide much of the information necessary for the net savings analysis. The telephone survey results also were used to distinguish "standard" equipment features from those energy efficiency features that were not routinely present on the cooking equipment sold in the SoCal Gas service territory during the study period. In addition, a supplemental telephone survey of equipment venders was conducted to determine the extent to which the market for used cooking equipment might affect the determination of baseline equipment efficiencies and features. Seven equipment vendors were interviewed. We attempted to contact twenty-nine.

This chapter describes the data collection activities completed through this project. Sampling techniques are described. Data collection procedures are reviewed. Key results are summarized.

On-site Visits

150 on-site visits were conducted at the sites of participants in the Commercial New Construction Program to confirm that the incented equipment was indeed installed,

and to provide information regarding the actual use of the equipment. The engineering algorithm adopted in this study to estimate gross savings requires four types of information: (1) the rated energy input for the equipment, (2) average load factor, (3) hours of operation of a piece of equipment, and (4) the change in energy requirements associated with the efficiency features of the equipment installed through the program. Generally, such information may best be obtained from a person at the facility, such as a manager or a chef.

This section reviews the sample design and approach to the on-site data collection. In addition, some key results are presented.

Design of Sample for On-Site Visits

The design of the participant sample was developed to meet multiple objectives:

1. Provide for a minimum of 150 site visits, as specified in Table 5 of the Protocols.
2. Sample with ±10% precision at 90% confidence, based on premise-level therm consumption, as specified in Table 5 of the Protocols.
3. Focus on cooking end-use projects.
4. Minimize the potential for multiple contact attempts per project contact person.
5. Group substantially similar projects for more precise extrapolation of analysis results from the sample to the population of program participants.

A subset of the participants reported in SoCal Gas Company's program tracking system forms the sample for the on-site data collections activities. The program tracking system (Blitzer) file documents 1,653 measures from cooking projects for which incentives were issued under the 1995 Commercial New Construction Program.

Accomplishment of the first two objectives entailed matching program measures to customer billing data. As a preparatory step, the project team compared customer identification information from the Blitzer extract with the same information from a file of customer billing data for SoCal Gas Company's commercial customers. Based on a comparison of customer name and site address, we were able to fill in a number of missing premise identification numbers in the Blitzer extract and resolved apparent inconsistencies for a number of other cases.

It was sometimes difficult to determine the appropriate contact for a project. A number of project contact persons were listed in the program file as being responsible for projects at multiple premises. Closer review revealed that multiple premises associated with any given contact person were generally very similar in nature. Thus, for example, a single contact person would be listed for a number of projects implemented by a fast food chicken franchise at restaurants throughout the SoCal Gas Company service territory.

Based on this finding, we determined that the multiple sampling objectives could be best balanced by sampling primarily at the project contact level. Sampling occurred in two steps. First, we drew a stratified random sample of 150 project contact persons, based on average premise-level therm consumption summed over all premises associated with each project contact. For each sampled project contact, we then selected the single premise with the greatest average monthly therm consumption. In this way, we ensured that similar premises were grouped together (objective 4), and that each contact person would be selected into the sample no more than once (objective 5). The resulting sample contained 150 premises, as required by objective 1. Objective 2 was accomplished by calculating the sampling precision for the selected sample as if it had been drawn using a premise-level sampling strategy. Objective 3 was satisfied by the definition of the Blitzer extract used as our starting point for the sampling process. The entire sampling process is described in step-by-step detail below.

Make corrections to premise identification numbers. We first compared customer identification information from the Blitzer extract with the same information from a file of customer billing data for SoCal Gas Company's commercial customers. Based on a comparison of customer name and site address, we were able to fill in ten missing premise identification numbers in the Blitzer extract and resolved apparent inconsistencies for seven other cases. To protect the confidentiality of customer information, these revised premise identification numbers are not listed here.

After implementation of these changes, the modified file still contained 36 measures lacking a premise identification number. These measures corresponded to twelve unique site addresses. The remaining 1,617 measures corresponded to 501 unique premise identification numbers.

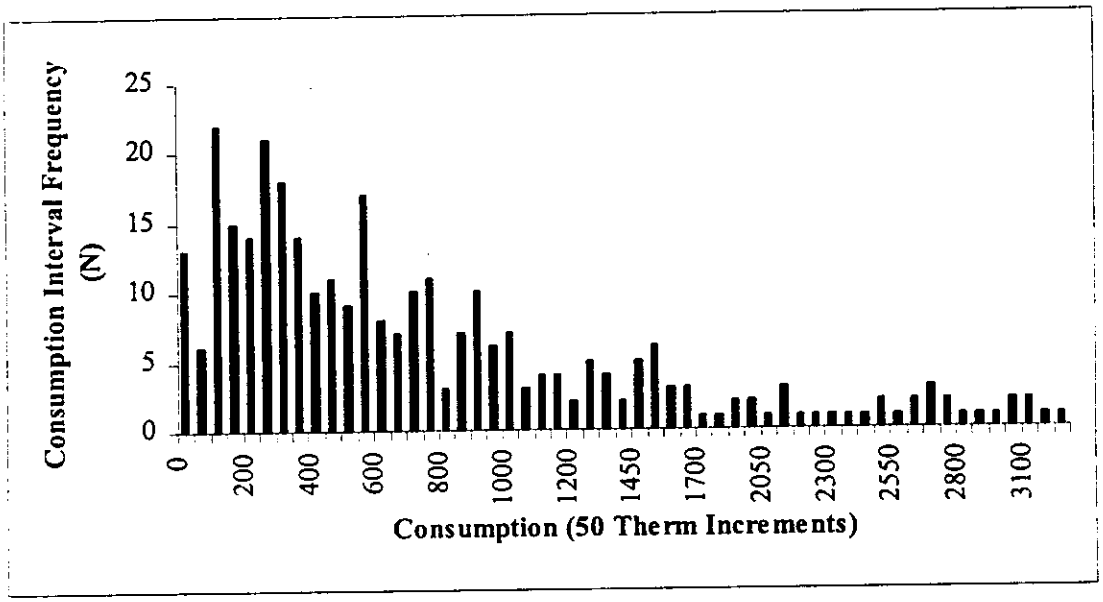
Link program data to customer billing data and aggregate to project contact level. Premise identification numbers from the Blitzer extract were linked to monthly therm consumption data spanning the period January, 1994–December, 1996 for 186,700 commercial customers in the SoCal Gas Company service territory. Of the 513 sites in the file (501 premises + 12 street addresses), we were able to link program data to billing data for 460 premises, leaving 53 premise/sites with no matching billing history. For premises with available billing data, we calculated average monthly therm consumption. For each contact in the program file, we then calculated total consumption as the average consumption summed over all premises associated with the contact. This exercise produced a sample frame of 372 contacts, including 333 with therm consumption data.

Draw random sample of contacts with missing consumption data. A total of 39 contacts had missing therm consumption, representing 10.5% of the sample frame. To minimize sampling bias, we defined contacts with missing consumption as a separate stratum and allocated 10.5% of the sample quota to it. Out of a total sample quota of 150, this stratum was thus allocated 16 contacts. These contacts were selected at random.

Census 20 contacts with largest total consumption. Because the contact-level distribution of therm consumption was skewed, a census of the 20 contacts with largest consumption was found to greatly reduce the consumption variability for the remaining 313 contacts for whom consumption data were available.

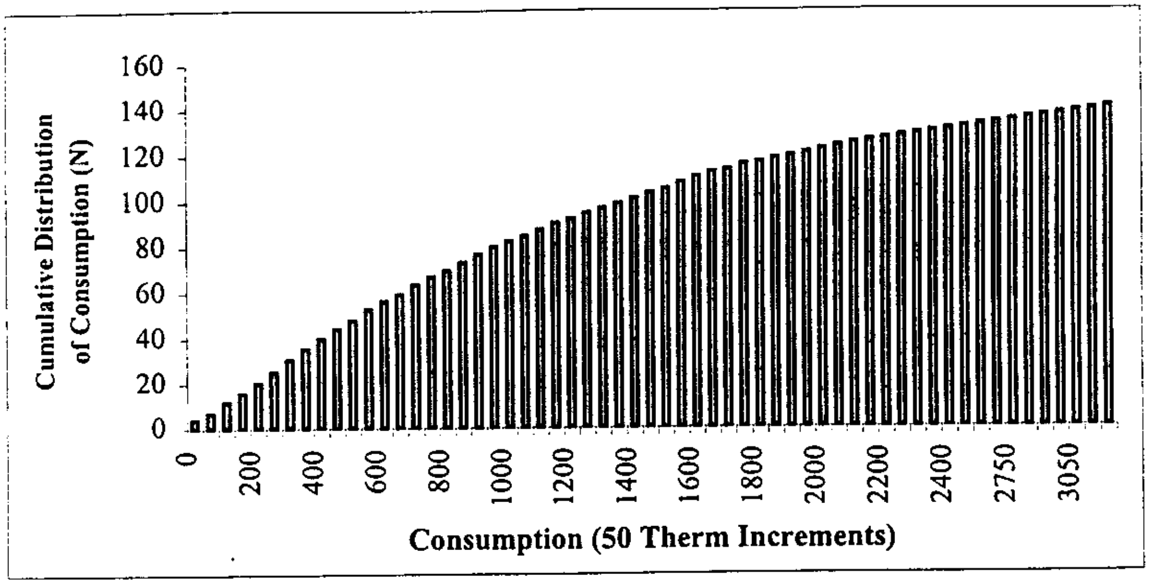
Determine optimum stratum breakpoints for the remaining population of contacts. We segmented the remaining contacts into three strata. Stratum breakpoints were determined using Dalenius and Hodges' method for minimum variance stratification. This procedure defines the boundaries that produce the greatest reduction in sampling error for the specified number of strata. Applying this method, we first recoded the contact-level therm consumption as a discrete variable with a constant bin width of 50 therms. The frequency distribution of the recoded consumption is presented in Figure 2.1, below.

Figure 2.1
Frequency Distribution of Contact-Level Consumption



After determining the frequency distribution of therm consumption, we then determined the cumulative square root of frequencies as a function of consumption, as shown in Figure 2.2.

Figure 2.2
Cumulative Square Root of Frequency Distribution



Finally, we determined stratum breakpoints by dividing the cumulative square root of frequency range into three equal parts and identified the corresponding consumption interval for each part. Including the census of 20 contacts with greatest consumption as stratum 4, the consumption intervals thus determined were:

Stratum 1:	0 therms	-	499 therms
Stratum 2:	500 therms	-	1,299 therms
Stratum 3:	1,300 therms	-	3,249 therms
Stratum 4:	greater than 3,250 therms		

Given these stratum definitions, we next calculated statistics for the distribution of therm consumption for the population of 333 contacts for whom consumption data were available. These statistics are given in Table 2.1.

Table 2.1
Population Statistics by Stratum

	Total	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Pop.					
N	333	144	112	57	20
Mean (μ)	1,294	249	817	2,101	9,192
STD (σ)	3,049	132	220	595	9,148
Total Consumption	430,848	35,806	91,455	119,736	183,850
% Total	100%	8%	21%	28%	43%

Allocate the 114 sample units to the three strata using the Neyman sampling method. The Neyman method determines the ideal number of sampled units from each stratum, N_g (where g=1 to 3), by allocating the total sample number, n, in proportion to the stratum population, N_g, and the associated variance, σ_g^2. It can be shown that this strategy is an efficient allocation method when the stratum variances are known and some are different from others.

Applying this method, using the statistics presented in Table 2.1, we determined the following distribution of 114 sampled contacts (excluding 20 already allocated to stratum 4 and 16 contacts lacking consumption allocated to stratum 5):

Stratum 1:	28
Stratum 2:	36
Stratum 3:	50

Randomly select the specified number of contacts from each population stratum. We randomly selected contacts from each population stratum according to the allocation plan described above. Population and sample statistics are given in Table 2.2. Figures in bold type are statistics for the population of accounts; figures in normal type are statistics for sampled accounts. The overall mean and standard deviation are much higher for the sample than for the population because stratum 4 is more heavily represented in the sample.

Table 2.2
Population and Sample Statistics

	Total	Stratum 1	Stratum 2	Stratum 3	Stratum 4
POPULATION					
N	333	144	112	57	20
Mean (μ)	1,294	249	817	2,101	9,192
STD (σ)	3,049	132	220	595	9,148
Total	430,848	35,806	91,455	119,736	183,850
% Total	100%	8%	21%	28%	43%
SAMPLE					
N	134	28	36	50	20
Mean (x)	2,429	261	798	2,112	9,192
STD (s)	4,553	107	197	608	9,148
Total	325,465	7,311	28,720	105,584	183,850
% Total	100%	2%	9%	33%	57%

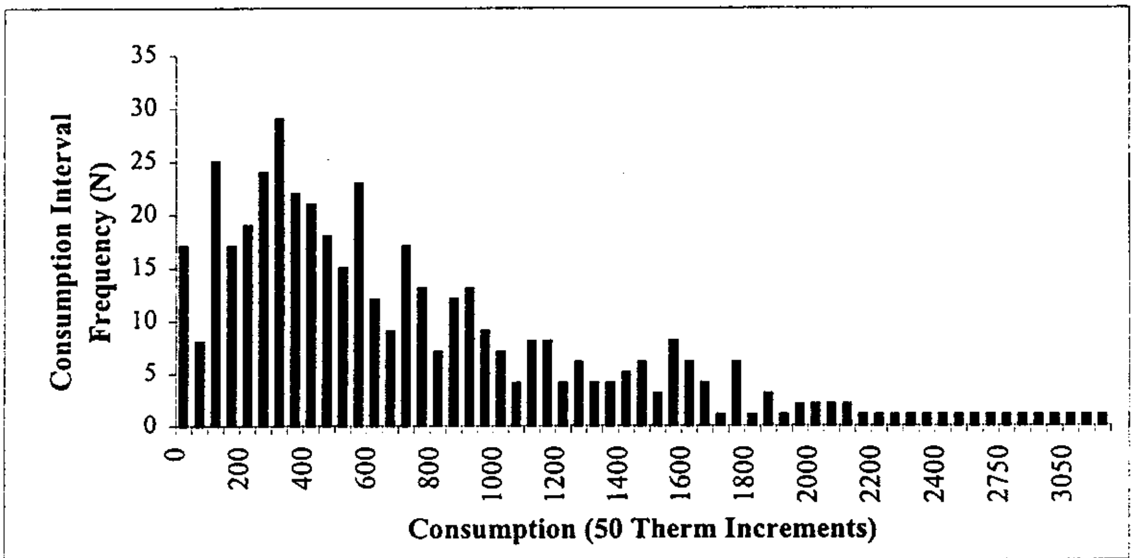
Select one premise per sampled contact. For each sampled project contact, we selected the single premise with the greatest average monthly therm consumption, with two exceptions. For two sampled contacts, a premise other than the premise with greatest average monthly consumption had previously been selected to pretest the on-site survey instrument. By giving these two premises priority, we ensured that all five pretest sites would be incorporated in the final on-site sample.

The 114 sampled premises in strata 1 through 3 came from a pool of 441 premises in the program population with nonmissing premise-level consumption, after excluding the 20 premises from stratum 4 that had sampled with certainty. After completing the sample selection, we estimated the degree to which the sampled premises represented this population, based on premise-level average therm consumption. To calculate the sampling precision, we proceeded as described below.

Determine optimum stratum breakpoints for the population of premises. As in the initial sampling procedure, we segmented the 441 premises into three strata. Stratum breakpoints were again determined using Dalenius and Hodges' method for minimum variance stratification. Applying this method, we first recoded the premise-level therm consumption as a discrete variable with a constant bin width of 50 therms. The frequency distribution of the recoded consumption is presented in Figure 2.3, below.

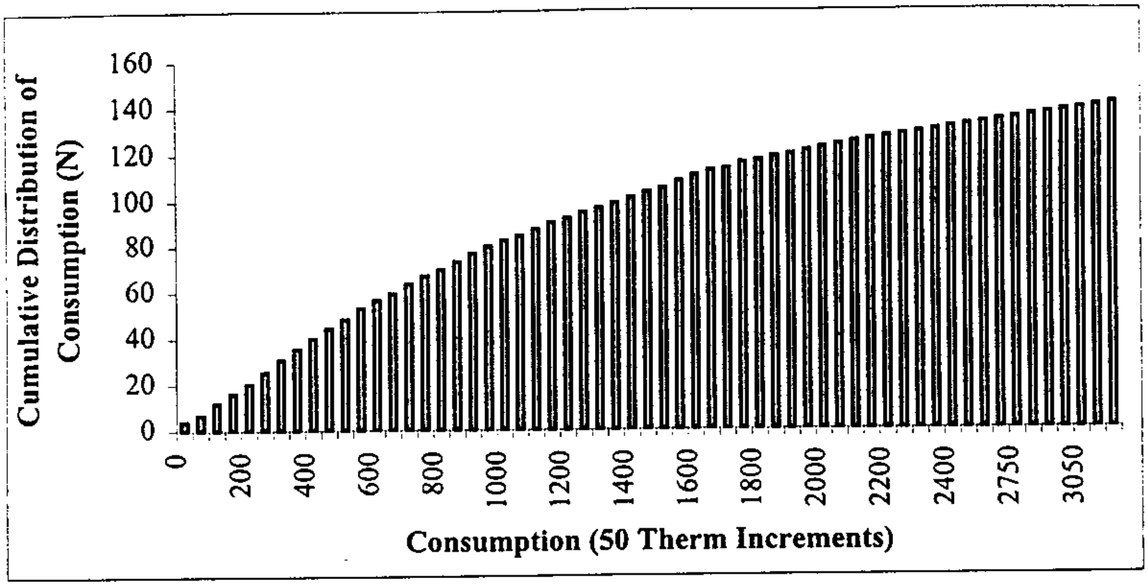
Figure 2.3

Frequency Distribution of Premise-Level Consumption



After determining the frequency distribution of therm consumption, we then determined the cumulative square root of frequencies as a function of consumption, as shown in Figure 2.4.

Figure 2.4
Cumulative Square Root of Frequency Distribution



Finally, we determined stratum breakpoints by dividing the cumulative square root of frequency range into three equal parts and identifying the corresponding consumption interval for each part. The consumption intervals thus determined were:

Stratum 1:	0 therms -	499 therms
Stratum 2:	500 therms -	1,249 therms
Stratum 3:	1,250 therms -	3,249 therms

Given these stratum definitions, we next calculated statistics for the distribution of average premise-level therm consumption for the population of 441 premises. These statistics are given in Table 2.3.

Table 2.3
Population Statistics by Stratum

	Total	Stratum 1	Stratum 2	Stratum 3
SAMPLE				
N	441	200	159	82
Mean (μ)	747	266	800	1,814
STD (σ)	622	135	208	491
Total Consumption	329,256	53,271	127,227	148,758
% Total	100%	16%	39%	46%

Calculate distribution statistics for sampled premises. Applying the premise-based stratum definitions given above, the 114 premises in the sample were each assigned to a stratum. We then calculated distribution statistics for premise-level therm consumption for the full sample and by stratum. These statistics are shown in Table 2.4, below.

Table 2.4
Sample Statistics by Stratum

	Total	Stratum 1	Stratum 2	Stratum 3
POPULATION				
N	114	28	49	37
Mean ($\underline{x}$)	1,045	256	806	1,957
STD (s)	756	105	190	566
Total Consumption	119,076	7,161	39,499	72,416
% Total	100%	16%	39%	46%

Calculate sample variance. The sample variance was calculated using the following equation for the weighted variance of a sample representing a population divided into g strata (in this case 3):

$$s^2 = \sum_{g=1}^{4} \frac{N_g^{\ 2}}{N^2} \frac{(N_g - n_g)\sigma_g^{\ 2}}{(N_g - 1)n_g}$$

This equation is just the sum of the stratum-level sample variances $(\sigma_g{}^2/N_g)$ weighted by the population proportions $(N_g/N)^2$, and applying the finite population correction factor $((N_g - n_g)/(N_g - 1))$. Using this method, we calculated the sample variance for the selected sample as 321.19. It can be shown that the sample meets the given precision criterion as long as the actual sample variance is less than the critical sample variance, as calculated below.

Calculate critical sample variance. The critical value for σ^2 is determined by imposing the sample design precision criterion of ±10% precision with 90% confidence. Mathematically, ±10% precision can be expressed as:

$$|\underline{x}| < \mu \pm 0.1 \mu$$

where $\underline{x}$ is the weighted sample mean and μ is the population mean.

We know $\underline{x}$ is an unbiased estimator of μ with a variance σ^2. Hence we can write:

$$|\underline{x}| < \mu \pm t\sigma$$

where the t-statistic, t, has a value of 1.66 for a two-tailed t-test with 90% confidence. Solving for σ^2 gives

$$\sigma^2 = \frac{(0.1 \mu)^2}{t^2}$$

Using this equation, we calculated a critical value for the variance equal to 2,022.83. The actual value of the sample variance is well below this critical value, indicating that the selected sample satisfies the established precision criterion.

Data Collection Methods

An ACCESS database was created first and a one-page data collection sheet was then put together to be used in the field during the on-site visits. The data collection sheet consisted of questions recording customer information, building specific information, hours of operation, equipment, and equipment use information. Once the data was collected, the information was input either into EXCEL or directly into ACCESS.

Results from the first 60 on-site visits were input into EXCEL and then imported into ACCESS. At that point there were modifications made to the EXCEL spreadsheet based on what was found in the field. These changes were then made to the ACCESS database and information collected from the remaining 90 visits were input directly into ACCESS. The resulting database is presented in Volume II of this report.

Data was collected for all gas cooking equipment found at the facility, regardless of whether incentives were provided by SoCal Gas Company to encourage the purchase of that equipment.

In the database, there is a field in On-Site Customer ("audit_quality") which was used to indicate the quality of the audit. The following format was used: 2=complete with all good data, 1=complete with some missing data, 0=incomplete, do not use this site. Most of the audits were a "1" with most of the missing data being in the equipment baseline questions. It was rare that we found an on-site person that knew what equipment would have been purchased had the program had not been available.

In some cases, information pertaining to the rated energy requirements of a piece of equipment could not be easily determined during the on-site visit. Often the nameplate data was on the back of equipment which could not be moved, and it could not be seen using a small mirror. In such cases, the value contained in SoCal Gas Company's program tracking database was used.

The load factor of a piece of cooking equipment was defined as the equipment's average energy use to its maximum rated energy requirement. When first turned on, many pieces of equipment use close to the full input rate for a certain period of time to bring the equipment up to the desired temperature. When there is little call for cooking, the piece sits idle and may use somewhere from fifteen to twenty percent of the full input rate. When the kitchen is busy and the equipment is cooking, the input rate can rise anywhere from fifty to ninety percent of the full input rate. The idle and cooking rate are equipment specific. The average load factor is a function of how the equipment performs during warm-up, idle, and cooking periods and when those periods occur.

The average load factor was determined from multiple sources, including information gathered during the on-site audit. The on-site visit collected the 'busy' times of the kitchen by daytype to determine when the cooking equipment was in a 'cooking' (busy) versus an 'idle' (nonbusy) mode. Equipment-specific questions sought to determine the load factor during the cooking and idle periods.

The hours of operation for various equipment for various daytypes were based on the hours of operation of the kitchen by daytype. Such data were obtained through interviews with on-site personnel.

Characterization of Establishments

As noted earlier, all gas cooking equipment identified at a site was surveyed, regardless of whether it was purchased with the assistance of the program. The most frequently represented equipment types were: fryers (25% of all equipment), ranges (18%), griddles (16%), and broilers (16%). Together, these four types of equipment accounted for 75% of all equipment identified at the establishment visited.

Figure 2.5
Distribution of Equipment Types

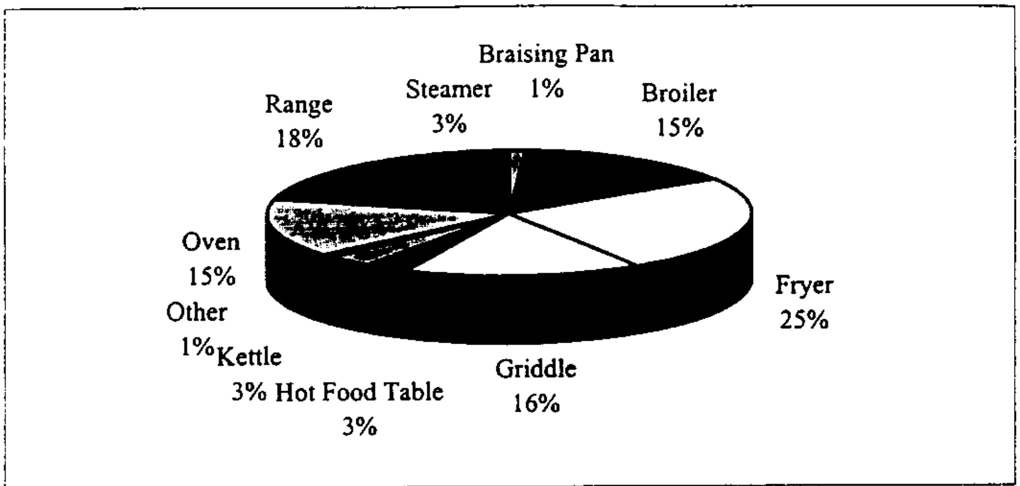
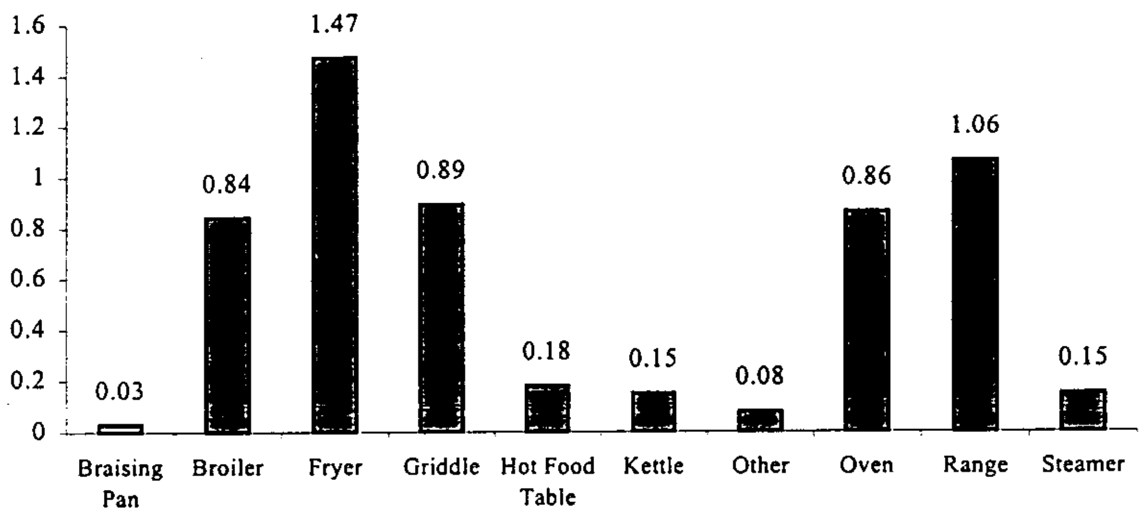
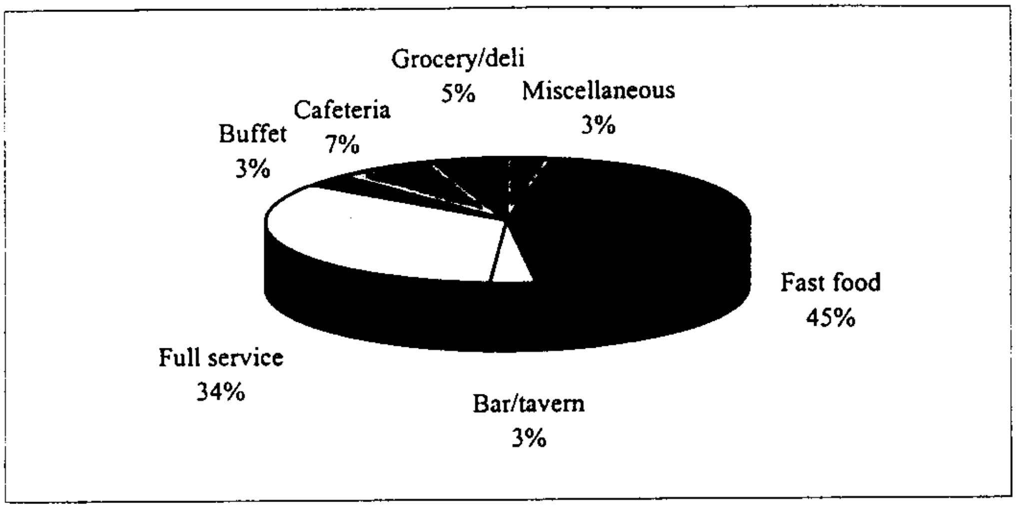


Figure 2.6
Average Number of Pieces of Equipment



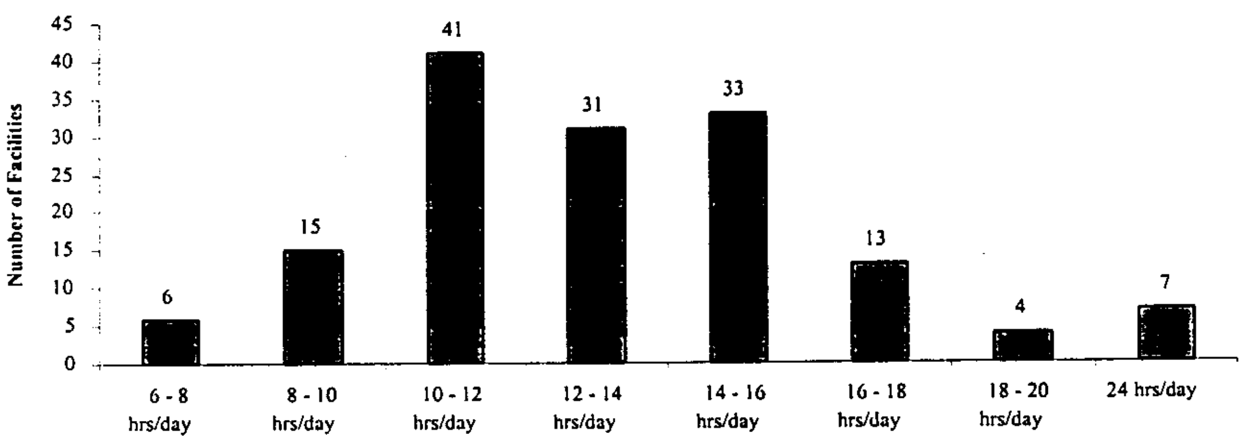
The vast majority (79%) of the 150 establishments surveyed were restaurants; with fast food restaurants the most common type, at 45%, while full service restaurants represented 34%. These figures are noted in Figure 2.7.

Figure 2.7
Business Types



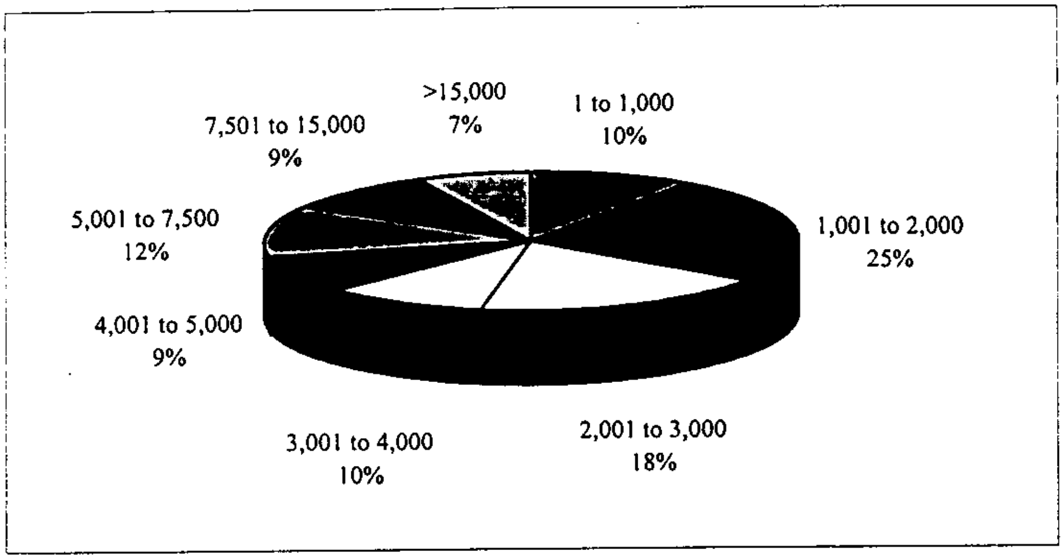
A small proportion of the establishments surveyed had extended average operating hours (16% open for an average of more than 18 hours per day). The majority (70%) were open from 10 to 16 hours per day. Average operating hours were 13.9 hours per day.

Figure 2.8
Average Operating Hours by Establishment



The majority of establishments were small: 53% were under 3,000 square feet. Figure 2.9 provides the distribution of participant facilities by size.

Figure 2.9
Facility Size Square Feet



Telephone Survey of Participants and Non-participants

Two considerations drove the decision to rely on telephone survey data for the statistical analysis of net impacts:

- The proposed analysis method required comparable information for both participants and non-participants
- The proposed analysis method required information about the factors that decision-makers considered when deciding whether to adopt energy efficiency measures or participate in the program

The first consideration effectively dictated that supplemental data collection would be required. The program tracking system recorded only information about program participants; it was not a viable source of information about non-participants. The second consideration favored a telephone survey approach to data collection. Since decision-makers involved in new construction projects are generally not the people involved in operating the facility on a day-to-day basis after construction, an on-site visit would not be a productive method of gathering information from decision-makers. Furthermore, the type of information to be elicited from decision-makers could easily be communicated over the phone and did not entail detailed on-site measurement and observation.

Sample Design

The waiver filed with CADMAC as part of this project specified that net impacts would be assessed by conducting a discrete choice analysis using data from 350 participant and 350 comparison group customer telephone responses. Given the small participant and non-participant populations (discussed below), we attempted to survey all eligible participants and non-participants to meet the specified survey targets. Applying this census approach, it was not necessary to develop a sample design.

The participant sample frame was constructed from a subset of measures from the program database. Program measures were included in the subset if they (1) were cooking measures for which a rebate was provided in 1995, (2) they showed *ex ante* therm savings estimates greater than zero, and (3) incentives were recorded as having been paid. This subset corresponded to 1,653 cooking measures installed at 514 premises by 372 decision-makers (assumed to be the project contacts recorded in the database). SoCal Gas Company staff manually reviewed the list of decision-makers and projects and identified four customers whose projects had been canceled or who had gone out of business. In addition, projects assigned to six decision-makers at a single fast food chain were reassigned to a single decision-maker. As a result of these changes, the final sample frame consisted of 362 decision-makers.

Development of the non-participant sample frame was done with the objective of producing a list of eligible non-participant decision-makers. Eligibility in this case was defined as being a decision-maker that was responsible for a commercial new construction project in 1995 that involved the installation of gas cooking equipment. Preliminary eligibility was determined using information from SoCal Gas Company's customer billing files. Final determination of eligibility was then made via a set of screening questions that were included in the phone survey instrument.

Construction of the non-participant sample frame began with a database of SoCal Gas Company commercial customers representing 187,600 premises. To identify likely new construction projects, this list was first restricted to those premises with meter set dates in 1994 or later, resulting in 4,577 premises. To identify likely projects with gas cooking equipment, the list was then restricted to premises with an SIC value that matched one of the 24 SICs represented in the participant database. This restriction reduced the list of premises to 2,119. Qualifying SIC values are listed in Volume II.

Customers with missing customer names were next excluded, bringing the number of premises to 2,103. At this stage the premise list was compared to the list of premises from the 1995 program database and any matches were excluded. This step produced a list of 1,884 non-participant premises that were considered likely to have been eligible to participate in the 1995 program. This list constituted the calling list for the non-participant survey.

The list of 362 participant contacts was called multiple times (more than 6 times, in some cases), producing the call disposition indicated in Table 2.5:

Table 2.5
Disposition of Calls to Program Participants

Completed surveys	86
Not qualified 1: contact no longer reachable	12
Not qualified 2: no recollection of program participation	24
Not qualified 3: contact not involved in participation decision	19
Terminated interview	7
No contact	214
Total	362

The "no contact" category includes disconnected and wrong numbers, residential customers, contacts who could not communicate in English, and no answers. Almost 7% of the sample frame reported having no recollection of having participated in the program. This is a surprisingly high percentage, which we were never able to explain.

As a consequence of the small number of contacts in the participant sample frame, the contact list was exhausted without satisfying the survey quota of 350 participants.

The list of 1,884 non-participant contacts was called multiple times (more than 6 times, in some cases), producing the call disposition indicated in Table 2.6

Table 2.6
Disposition of Calls to Non-Participants

Completed surveys	117
Not qualified 4: no new construction/remodel project	347
Not qualified 5: contact no longer reachable	168
Not qualified 6: no cooking equipment installed	96
Terminated interview	20
No contact	1,085
No phone number	51
Total	1,884

Again, the "no contact" category includes disconnected and wrong numbers, residential customers, contacts who could not communicate in English, and no answers. It is worth noting that, of the 1,884 premises that passed the preliminary eligibility screens, less than 21% met the eligibility criteria as determined from the survey screening questions. This percentage is derived by comparing the number of demonstrated eligible premises ("Completed surveys") with the total number of premises with conclusively determined eligibility ("Completed surveys" plus "Not qualified 4" plus "Not qualified 6"). In particular, meter set date was generally a poor indicator of new construction projects, as indicated by the high fraction of "Not qualified 4" (62% of the pool of premises with conclusively determined eligibility). As a consequence of the high incidence of ineligibility among the targeted non-participant sample frame, the contact list was exhausted without satisfying the survey quota of 350 non-participants.

Description of the Survey Instrument and the Type of Data Collected

Survey Instrument Description

Phone survey development began with the participant instrument. The participant instrument was organized as follows:

- The initial series of questions included screens to determine whether the interviewer was speaking with the right person, and whether the time of the call was convenient.
- The next section, questions 1 through 6, addressed the cooking equipment selection and purchase process, including who was responsible for various decisions and their source of information about cooking equipment.
- Questions 7 through 11 addressed participation in the program, including when participants heard about the program and the information source.
- Questions 12 and 13 addressed factors that affected customers' decisions to participate in the program and to purchase the equipment they selected.
- Questions 14 through 71 identified the equipment they purchased, specific equipment features, and whether they would have purchased anything different in the absence of the program.
- The final survey questions collected general customer and facility characteristics.

The non-participant instrument was essentially the same as the participant instrument, with the following modifications.

- Question 6 was modified to test non-participants' awareness of the program.
- Questions 12 through 16 were inserted to determine whether non-participants had interacted with the program in some significant way, short of getting a rebate for installing qualifying equipment.
- The wording on participant question 12 (non-participant question 17) was broadened to address factors that would affect customers' decisions to "participate in an incentive program offered by SoCal Gas Company for construction projects involving gas cooking equipment."
- Finally, questions about what customers would have purchased in the absence of the program were omitted from the battery of questions about specific equipment they had purchased and the equipment features (non-participant questions 19 through 45).

The participant and non-participant survey instruments are included in their entirety in Volume II.

Data Screening

One participant was excluded from the net impact analysis who replied "Don't know" to all phone survey questions. A non-participant was excluded who reported having received cooking equipment as a donation. Another non-participant was excluded after it was determined that he should have been interviewed using the participant survey instrument. Thus, as a properly classified participant, he had missing data for several critical questions. As a result of this screening, the final analysis dataset contained 85 participants and 115 non-participants, for a total of 200 customers.

Summary of Findings

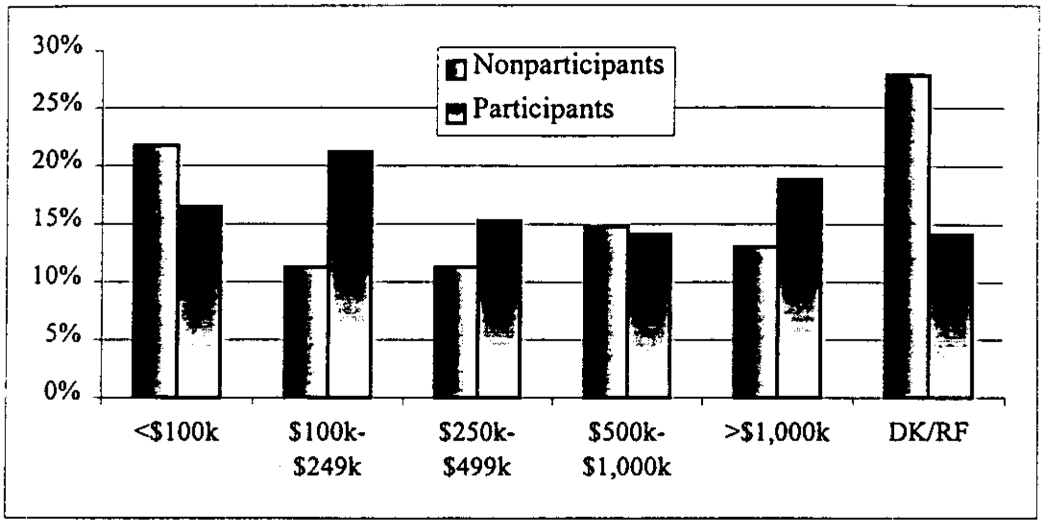
As a preliminary step in the analysis, the raw survey results were reviewed to check for inconsistencies and to gain a general understanding of the types of customers in the sample. Particular attention was paid to comparisons of participants and non-participants. Selected tabulations are provided below. More complete tabulations of responses are provided in Volume II.

Table 2.7
Comparison of Participant and Non-participant Facility Types

	Participants		Non-participants		Total	
Facility Type	**Number**	**Percent**	**Number**	**Percent**	**Number**	**Percent**
Other	18	21%	54	47%	72	36%
Full service restaurant	28	33%	21	18%	49	25%
Self-serve cafeteria	4	5%	3	3%	7	4%
Take-out food	32	38%	35	30%	67	34%
Other food service	3	4%	2	2%	5	3%
Total	85	100%	115	100%	200	100%

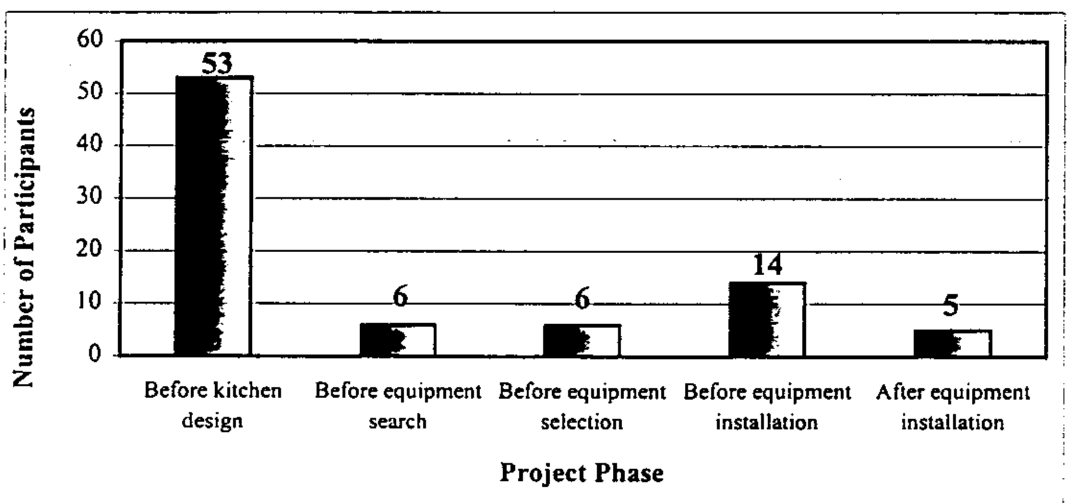
Food service facilities make up 79% of the participant group but only 53% of the non-participant group.

Figure 2.10
Comparison of Participant and Non-participant
Food and Beverage Sales



Compared to participants, non-participants were more likely to provide no information about 1996 annual food and beverage sales or to have sales less than $100,000.

Figure 2.11
Phase at Which Participants Learned of Program



Fourteen participants did not learn about the program until after equipment selection and another five participants did not learn about the program until after equipment installation.

Table 2.8
Role of Person Responsible for Kitchen Design Decisions

	Participants		Non-participants		Total	
Design Decision	**Number**	**Percent**	**Number**	**Percent**	**Number**	**Percent**
Owner	53	62%	61	53%	114	57%
Architect	13	15%	30	26%	43	22%
Contractor	8	9%	13	11%	21	11%
Other	7	8%	6	5%	13	7%
Tenant	3	4%	1	1%	4	2%
Property Mgt. Co.	1	1%	0	0%	1	1%
Unknown	0	0%	2	2%	2	1%
Developer	0	0%	2	2%	2	1%
Total	85	100%	115	100%	200	100%

Owners are slightly more likely to be responsible for kitchen design decisions among participants; architects are slightly more likely to have that responsibility among non-participants.

Table 2.9
Role of Person Responsible for Kitchen Equipment Selection Decisions

	Participants		Non-participants		Total	
Selection Decision	**Number**	**Percent**	**Number**	**Percent**	**Number**	**Percent**
Architect	6	7%	6	5%	12	6%
Consultant	1	1%	1	1%	2	1%
Contractor	2	2%	7	6%	9	5%
Developer	1	1%	2	2%	3	2%
Facility Engineer	0	0%	4	3%	4	2%
Facility Manager	0	0%	1	1%	1	1%
Food Service Director	3	4%	6	5%	9	5%
Other	7	8%	13	11%	20	10%
Owner	59	69%	69	60%	128	64%

Property Mgt. Co.	2	2%	0	0%	2	1%
Supervisor/Manager	1	1%	2	2%	3	2%
Tenant	3	4%	2	2%	5	3%
Unknown	0	0%	2	2%	2	1%
Total	85	100%	115	100%	200	100%

As with kitchen design decisions, owners are more likely to be responsible for kitchen equipment selection decisions among participants.

SoCal Gas Company outreach to customers proved to be the most successful tool for disseminating information about the program, accounting for 46% of the information sources cited. Word of mouth among contractors, developers, architects, and vendors accounted for another 32% of the information sources, as noted in Table 2.10.

Table 2.10
Tabulation of Participants' Information Source About the Program

Information Source	N	Pct
Approached by Gas Co.	39	46%
Saw Gas Co. brochure	10	12%
Heard - Other Contractor	5	6%
Heard - Other Developer	6	7%
Heard - Other Architect	6	7%
Heard - Other Vendors	6	7%
Heard - Other Colleagues	4	5%
Previous participation	3	4%
I approached Gas Co.	2	2%
Other	4	4%
Total	85	100%

Question 12 reads: "Please indicate the importance of the following factors in your decision to participate in the program." Respondents were asked to rank seven factors as extremely important, very important, somewhat important, or not important. In the following tables, customer responses have been aggregated and ranked (1=most important, 7=least important). Reported results include non-participant responses to this question.

Table 2.11
Comparison of Participant and Non-participant Responses to Question 12

Participation Decision Factors	Importance Ranking	
	Participants *(N=85)*	Non-participants *(N=115)*
Lower energy bills	1	1
Ease of application process	2	4
Compatibility between facility needs and qualifying equip.	3	2
Quality of previous involvement w/Gas Co.	4	5
The Gas Co. Rebate amount	5	6
Low purchase cost of equip. available under program	6	3
Design assistance from the Gas Co. Rep.	7	7

The biggest difference in rank is for "Low purchase cost of equip. available under program." Non-participants ranked this factor third in order of priority, while participants ranked it sixth out of seven.

Question 13 reads: "Please indicate the importance of the following factors in the selection of cooking equipment you installed." Respondents were asked to rank 16 factors as extremely important, very important, somewhat important, or not important. In the following tables, customer responses have been aggregated and ranked (1=most important, 16=least important). Responses are summarized on Table 2.12.

Table 2.12
Comparison of Implementer and Non-implementer Responses to Question 13

Implementation Decision Factors	Importance Ranking	
	Implementers (N=171)	Non-implementers (N=29)
Quality of food production	1	3
Production capacity of equipment	2	5
Low anticipated repair needs/costs	3	5
Lower Energy Bill	4	7
Ease of use and maintenance	5	1
Warranty for equipment	6	11
Desire to support energy conservation	7	7
Purchase cost of equipment	8	3
Availability of equipment	9	8
Lower environmental compliance costs	10	10
Ease of installation	11	9
Availability of incentive or rebate	12	13
Company policy	13	12
Recommendation of contractor/architect	14	14
Effect on the value of property	15	15
Design assistance from Gas Co. Rep.	16	16

Implementers and non-implementers of energy efficiency measures gave notably different rankings to three factors: "Ease of use and maintenance," "Warranty for equipment," and "Purchase cost of equipment." Implementers gave higher priority to "Warranty for equipment," while non-implementers gave higher priority to "Ease of use and maintenance" and "Purchase cost of equipment."

Additional Data Collection: Survey of Equipment Vendors

In the course of collecting on-site and telephone survey data for this project, we learned that there existed a viable market for used equipment in SoCal Gas Company service territory, generally due to the rapid turnover among restaurants. This finding led us to research the possibility that the used equipment market, if sufficiently large, might skew the analysis results unless adequately accounted for.

To explore this issue, we surveyed vendors in SoCal Gas Company service territory to determine the relative amount of new and used equipment they had sold in the past two years. Vendors were asked to provide proportional splits for each of nine equipment types: braising pans, broilers, cabinet steamers, fryers, griddles, hot food tables, ovens, ranges, and steam kettles. The disposition of those calls is provided in Table 2.13, below. Table 2.14 summarizes the interview results by cooking equipment type, listing the number of vendors who handled used equipment and the minimum, median, and maximum percentages that used equipment comprised of the vendors' total sales volumes.

Table 2.13
Phone Interview Disposition

	Manufacturer's Reps	Wholesalers	Total
Number called	13	16	29
Vendors selling new equipment only	—	—	17
Vendors unreachable by phone	—	—	5
Vendors selling new and used equipment	4	3	7

Table 2.14
Phone Interview Results

Equipment Type	# vendors of used equipment	Minimum % used equipment sold	Median % used equipment sold	Maximum % used equipment sold
Braising Pan	2	0	0	0
Broilers	6	0	18	50
Cabinet Steamer	2	0	0	0
Fryer	7	0	11	50
Griddle	6	0	22	37
Hot Food Table	0	—	—	—
Oven	7	0	33	100
Range	5	15	29	33
Steam Kettle	3	0	0	100

NOTE: One vendor sold a far greater percentage and absolute number of used fryers and ovens than all other vendors. This vendor's total fryer sales were 4,000 total units, of which 50% were used units. The same vendor also sold 400 ovens in the last two years, all of them used.

In addition to questions of relative sales volumes, vendors were queried about their perceptions of changes in the market for used cooking equipment in recent years.

- Five of seven vendors said the amount of used equipment sold has changed.
- Four of seven vendors surveyed said the amount of used equipment sold since 1994 has decreased.
- Of these four vendors, three attributed the decrease in used sales to an improving economic climate in Southern California, resulting in fewer restaurants going out of business.

Our conclusions based on these interviews are primarily qualitative rather than quantitative. We were unable to calculate total market share for used equipment because we lacked total sales volume data for some survey respondents and for all vendors who reported selling only new equipment. However, based on the small fraction of vendors who sell used equipment and the generally small proportion of used equipment those vendors reported selling, we feel confident in concluding that the used cooking equipment market is not so large as to threaten the validity of this analysis. Nevertheless, a viable resale market does appear to exist and probably warrants consideration during the design of future market transformation programs targeted to gas cooking equipment or evaluations of those programs.

Chapter 3
ESTIMATION OF GROSS IMPACTS

This chapter presents estimates of the "gross" impacts of SoCal Gas Company's 1995 Commercial New Construction program. The following chapter adjusts these estimates for free-ridership to provide an estimate of the program's "net" impacts.

Approach to the Estimation of Gross Savings

The results from the 150 on-site visits and telephone interviews with 85 participants and 115 non-participants provided the data necessary to estimate the "gross" impacts of the program. Antecedent engineering analyses were relied upon extensively to discern the likely impacts of various equipment efficiency factors upon energy use. The sources relied upon included the following:

1. Electric Power Research Institute Research Report 3544-01. *Foodservice Equipment Applications Handbook.* Prepared by Architectural Energy Corporation. December 1995.

2. National Technical Information Services, Report DOE/CE/23821—T1. *Characterization of Commercial Building Appliances.* Prepared by Arthur K. Little, Incorporated. August, 1993.

3. Natural Resources Canada, Consumers Gas Company, Ltd., and Ontario Ministry of Environment and Energy. *Technology Review of Commercial Food Service Equipment, Volumes I & II.* Prepared by the Canadian Gas Research Institute and Fisher Consultants. May, 1996.

4. PG&E Food Service Technology Center, Report 008.1-89.2. *Development and Application of a Uniform Testing Procedure for Griddles.* March 1989.

5. PG&E Food Service Technology Center, Report 008.1-90.8. *Cooking Appliance Performance Report.* May 1990.

6. PG&E Food Service Technology Center, Report 008.1-90.30. *PG&E Production Test Kitchen Appliance Performance Report: "Cleveland" Electric Pressureless Steamer.* June 1991.

7. PG&E Food Service Technology Center, Report 008.1-91.4. *Frymaster® Model H-14 Electric Fryer Performance Report.* September 1991.

8. PG&E Food Service Technology Center, Report 008.1-90.22. *Development and Application of a Uniform Testing Procedure for Open, Deep-fat Fryers.* October 1991.

9. PG&E Food Service Technology Center, Report 008.1-91.11. *Appliance Performance in Production: Blodgett Model DGF-50 Gas Half-Size Convection Oven.* December 1992.

10. PG&E Food Service Technology Center, Report 008.1-94.12. *Development and Application of a Uniform Testing Procedure for a Convection Oven.* October 1994.

11. PG&E Food Service Technology Center, Report 5011.94.6. *Montague Model V136-5 Heavy Duty 30,000 Btu/h Open Top Gas Range: Application of ASTM Standard Test Method F 1521-94.* October 1995.

12. PG&E Food Service Technology Center, Report 5016.95.23. *Delicatessen Appliance Performance Testing.* October 1995.

13. PG&E Food Service Technology Center, Report 5011.95.27. *Custom Electronics Energy Saver Gas Control System for Commercial Broilers.* October 1995.

14. Southern California Gas Company. *25th Edition Foodservice Gas Equipment Catalog.* Copyright 1996.

Most *ex ante* cooking estimates used (to some extent) the proprietary software from SoCal Gas Company called *CookCalc* to determine estimated therm savings. The algorithm used within this software is the following:

$$\text{Therm Impact} = \text{Therms Used} * \Sigma\% \text{ Savings from Measures} \qquad (3.1)$$

The variable "Therms Used" is calculated as follows:

$$\text{Therms Used} = \text{Hours of Operation} * \text{Load Factor} * \text{kBtu/hr Input} * \text{Conversion} \qquad (3.2)$$

The hours of operation variable refers to the business hours of operation. The load factor is the hourly average percent of total rated input for that equipment type. The load factor used in the software was developed by SoCal Gas Company based on engineering judgement and was capped at 0.50. The kBtu/hr input is input based on the equipment type. The conversion variable changes kBtu to therms (1therm=100 kBtu).

The *CookCalc* software has specific efficiency measure and equipment type selection available as choices. If more than one efficiency measure is chosen from the available list, the percentage is added to the current total percentage and then applied to the therms used variable. Equipment is binned into nine types with a catch-all "miscellaneous" bin as the tenth bin. Each equipment type has only certain efficiency measures, which can be applied. These values are shown in Table 3.1.

Table 3.1
Ex Ante Savings Measure by Equipment

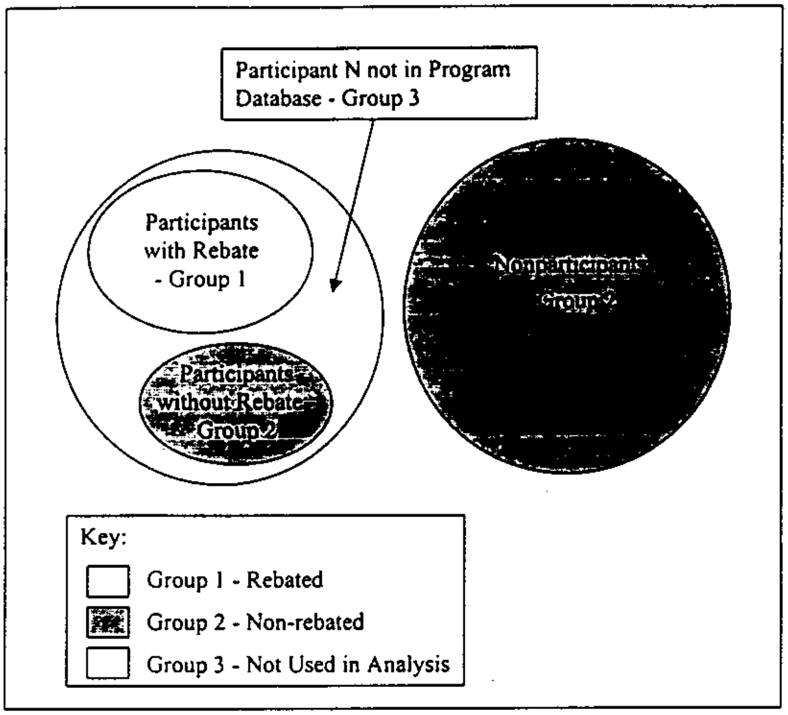
Measure	Braising Pan	Broiler / Cheesemelter	Cabinet Steamer	Fryer	Griddle	Hot Food Table	Misc.	Oven	Range	Steam Kettle
Automatic Basket Lifts				5%						
Automatic On/Off		20%					20%			
Automatic Tilt Control	5%						5%			
Chrome Griddle Surface					30%					
Cold Zone				5%						
Combination Oven								50%		
Convection Oven							40%	40%		
Convection Oven (Base)					40%				40%	
Conveyor		20%		5%			5%	5%		
Cover or Hood	5%	5%				5%	5%			
Double Sided Contact, All Gas					60%					
Double Sided Heat Source, All Gas		20%					20%			
Double Sided Noncontact, All Gas					40%					
Easy Access Deliming Port or Indicator			5%							
Fan Control							5%	5%		
Filter System				5%			5%			
Independent Timer							5%	5%		
Individual Compartment Controls						20%				
Infrared Burner		30%			30%		30%			
Infrared or Power Burner				30%				30%		
Insulation					5%		5%		5%	10%
Manual Controls			5%		5%		5%			
Manual Thermostat	10%						10%			
Power Burner							20%			20%
Proofer				5%			5%			
Self-Contained Water Supply										20%
Solid Fuel Capability							20%	20%		
Solid State Controls	15%		15%	10%	15%		10%	10%		10%
Stand By Mode			10%				10%			
Steam Forced Convection			20%							
Substitute Braising Pan	30%									
Substitute Pressure or Pressureless Steamer			40%							
Substitution of Steamer										30%
Thermostat		10%				10%				
Top Power Burner									30%	
Variable Speed		5%					5%			

The project team concluded that the algorithms contained in *CookCalc* and used by SoCal Gas Company to determine *ex ante* savings were basically sound. The decision was made to implement the *ex ante* algorithm with updated variables based on data collected during the evaluation. The on-site audit data was used to determine average kitchen hours of operation by equipment type and, when the data were robust, average load factors. The telephone survey data was used to determine the baseline efficiency measures by equipment type.

The 'baseline' for the evaluation was defined as "the equipment efficiency measures being purchased by non-participants and participants who did not receive a rebate for that equipment type." This definition of baseline did not necessarily match the baseline adopted by SoCal Gas Company to estimate *ex ante* savings. SoCal Gas Company had defined a 'base' piece of equipment as the least efficient equipment readily available. For example, in the development of SoCal Gas Company's *ex ante* estimates, the base fryer was assumed to have an atmospheric burner, no electrical connection, and a manual thermostat. All *ex ante* efficiency measure savings estimates were based on the difference between this base fryer and a fryer with a particular efficiency measure. It is not appropriate to subscribe savings to a measure if it was purchased by everyone inside or outside of the program. Therefore, the evaluation determined the baseline equipment features.

To determine the baseline, the telephone surveys were constructed to map directly to the *ex ante* equipment types and measures shown in Table 3.1. The customer was asked to provide information regarding the number of pieces of equipment purchased and the efficiency measures for that equipment type. Information pertaining to all equipment was gathered, regardless of whether SoCal Gas Company had provided a rebate for its purchase. Information collected through the telephone surveys was then compared to the program database and divided into three distinct groups. The first group (Group 1) represented the number of pieces of equipment incented under the program. The second group (Group 2) represented the number of pieces of equipment for which a rebate was not received under the program (Non-Rebated). This group included all the non-participants and those participants who were not provided a rebate for that particular equipment type. The number of pieces of incented equipment reported over the phone by the customer did not always match the program database. The third group (Group 3) represented the number of pieces of equipment greater than the number in the program database (For example, if the customer stated he had three fryers, but only one was rebated by the program, then one unit was put into Group 1 and the other two units were put into Group 3.) The responses for each efficiency measure by equipment type were tallied, put into a percentage using the number of pieces of equipment, and compared between Groups 1 and 2 (shown below in Figure 3.1).

Figure 3.1
Baseline Data from Telephone Surveys



If there was a positive difference between Groups 1 and 2 at the 90% confidence level, it was assumed that the efficiency measure was above baseline (i.e., induced by the program). The 90% confidence level was determined as follows:

$$\frac{p_r - p_n}{\sqrt{S_r^2 + S_n^2}} > 1.282 \qquad (3.3)$$

Where:

$S_r = \sqrt{\frac{(N-n)*p*(1-p)}{(N-1)*n}}$ (standard deviation of rebated equipment)

$S_n = \sqrt{\frac{p*(1-p)}{n}}$ (standard deviation of non-rebated equipment)

N = Number of pieces of equipment type rebated under the program

n =	Subset of number of pieces of equipment type from telephone survey (rebated or non-rebated)
k =	Number of pieces of equipment in telephone survey with a given energy efficient measure
p =	k/n
p_r =	proportion of rebated equipment with a given measure
p_n =	proportion of non-rebated equipment with a given measure

The telephone survey data provided a smaller set of efficiency measures which were determined to be above baseline. Each of the remaining efficiency measures were researched within the technical references to determine if the per measure *ex ante* percent savings estimated were feasible. If no information could be found which supported or denied the per-measure *ex ante* estimate, then the *ex ante* savings estimate was adopted in this evaluation.

After determining the efficiency savings percentages, which would be applied for each measure, the therm savings algorithm was analyzed. The formula has four variables: annual hours of operation, load factor, kBtu/hr input, and the conversion factor. The hours of operation data collected during the on-site visits were specific to the kitchen, rather than the establishment's business hours, since kitchens often open prior to the business in order to cook items for the day. Although average kitchen hours of operation based on business type would have yielded results, those results could not readily be applied to all participants because the program database variable for facility description was only 21% populated. Therefore, the hours of operation were averaged and applied based on equipment type. The on-site audit sites were randomly selected. As such, the use of average hours of operation by equipment type, while representative of those sites and equipment types audited, was deemed acceptable for the evaluation.

Load factor data collected from the on-site audits was robust enough for analysis of four different equipment types: broiler, hot food table, oven, and range. The auditor collected information regarding each piece of equipment for busy and non-busy cooking periods. For example, a range may have had six total burners. According to the head chef, five of those burners were on during busy periods and four were on during non-busy periods. (Periods of busy times were also collected on-site to determine an average load factor for an hour, weighted by busy and non-busy time periods.) Therefore, the busy load factor was 5/6 (83%) and the non-busy load factor was 4/6 (67%).

Some additional assumptions were required to complete the analysis. For broilers and ranges, it was assumed that the burner was on 100% if on at all. Although it is realized that this is not how the burners may have been used (e.g., a burner may be on at 50% capacity), the level of detail available for collection curtailed such analysis. Ovens had the maximum temperature collected from the oven dial. The chef was then asked the average temperature of the oven during busy and non-busy times to determine a load factor for the oven. Six hot food tables with usable load factor data were audited. Three of these showed a 'low', 'medium', or 'high' level for the burner. A load factor was assumed for each setting (0.33, 0.67, and 1.0, respectively). If no level was shown for the hot food table, a 'high' level was assumed.

The kBtu/hr input value was used directly from the Program database to determine the gross therm savings.

Results: Gross Savings Estimate

The data points used in the gross savings estimates are shown in Table 3.2.

Table 3.2
Data Points Used in Gross Savings

Equipment Type	Piece of Equipment			
	Population	On-Site Audited	Telephone Survey	
			Rebated	Non-Rebated
Braising Pan	23	5	3	35
Broiler	209	126	22	74
Cabinet Steamer	83	22	3	48
Fryer	456	221	62	144
Griddle	256	134	37	83
Hot Food Table	65	27	13	21
Other	75	46	-	-
Oven	489	127	54	223
Range	365	161	46	110
Steam Kettle	61	22	5	19
Total	**2082**	**891**	**245**	**757**

Using the information from the telephone surveys, the differences between the implementation percentages of rebated and non-rebated group efficiency measures by equipment type are shown in Table 3.3 (rebated percent implemented minus non-rebated percent implemented). The efficiency measures which are in gray are those measures which were significantly different at the 90% confidence level, and set as above the baseline.

Table 3.3
Differences between Rebated and Non-rebated Implementation Percentages

Measure	Braising Pan	Broiler	Cabinet Steamer	Fryer	Griddle	Hot Food Table	Oven	Range	Steam Kettle
Automatic Basket Lifts				-23%					
Automatic On/Off		-17%							
Automatic Tilt Control	-30%								
Chrome Griddle Surface					18%				
Cold Zone				-8%					
Combination Oven									
Convection Oven									
Convection Oven (Base)					-32%			17%	
Conveyor		23%		-6%			-4%		
Cover or Hood	11%	10%				-19%			
Double Sided Contact, All Gas					1%				
Double Sided Heat Source, All Gas		13%							
Double Sided Noncontact, All Gas					-5%				
Easy Access Deliming Port or Indicator			27%						
Fan Control							24%		
Filter System				-3%					
Independent Timer							20%		
Individual Compartment Controls						-16%			
Infrared Burner		13%			12%				
Infrared or Power Burner				3%			3%		
Insulation					-11%			-11%	23%
Manual Controls			12%		-3%				
Manual Thermostat	-47%								
Power Burner									-9%
Proofer				1%					
Self-Contained Water Supply									30%
Solid Fuel Capability							-14%		
Solid State Controls	12%		39%	19%	30%		7%		36%
Stand By Mode			41%						
Steam Forced Convection			59%						
Substitute Braising Pan	-13%								
Substitute Pressure or Pressureless Steamer									-42%
Substitution of Steamer			16%						
Thermostat		28%				8%			
Top Power Burner								9%	
Variable Speed		32%							

(Items shaded in gray are statistically different at the 90% confidence level)

As Table 3.3 indicates, many efficiency measures were part of the baseline. Even though there was a positive difference between the rebated and non-rebated percentages, such as solid state controls for braising pans (12%), it does not mean that the two groups are significantly different. It was only those measures which were different as determined by Equation 3.3 that were stated to be above the baseline equipment measures.

There were two measures for ovens which fell outside of this analysis and do not show up in Equation 3.2. The convection and combination ovens were treated as separate pieces of equipment, not as an efficiency measures. Other data from the telephone survey were examined in hopes of determining if there was a difference between what the customer purchased and what they said they would have purchased. However, a comparison of what the customer said they would have purchased without the program for these two types of ovens proved inconclusive. These two measures were kept within the ovens as above baseline efficiency measures.

Each one of the above baseline efficiency measures were researched to determine if the *ex ante* percent of savings (shown in Equation 3.1) was acceptable based on current information. The results are shown in Table 3.4.

Table 3.4
Comparison *Ex Ante* and *Ex Post* Efficiency Measure Savings for "Above-Baseline" Efficiency Measures

Equipment Type	Measure	*Ex Ante* % of Savings	*Ex Post* % of Savings
Braising Pan	Cover or Hood	5%	5%
Broiler	Conveyor	20%	30%
	Cover or Hood	5%	5%
	Double Sided Heat Source	20%	5%
	Infrared Burner	30%	15%
	Thermostat	10%	10%
	Variable Speed	5%	5%
	Maximum Possible Savings	*90%*	*54%*
Cabinet Steamer	Easy Access Deliming Port or Indicator	5%	5%
	Manual Controls	5%	0%
	Solid State Controls	15%	10%
	Standby Mode	10%	10%
	Steam Forced Convection	20%	20%
	Maximum Possible Savings	*55%*	*38%*
Fryer	Solid State Controls	10%	10%
Griddle	Chrome Surface	30%	15%
	Infrared Burner	30%	15%
	Solid State Controls	15%	10%
	Maximum Possible Savings	*75%*	*35%*
Oven	Combination Oven	50%	0%
	Convection Oven	40%	20%
	Fan control	5%	5%
	Independent Timer	5%	5%
	Maximum Possible Savings	*100%*	*28%*
Range	Convection Oven (Base)	40%	20%
Steam Kettle	Insulation	10%	10%
	Self-Contained Water Supply	20%	0%
	Solid State Controls	10%	10%
	Maximum Possible Savings	*40%*	*19%*

In Table 3.5, the maximum possible savings row refers to the *ex ante* and *ex post* maximum savings for the measures indicated. As shown, the savings are summed for the *ex ante* estimates and multiplied for the *ex post* savings (i.e., $[1-((1-N_1)*(1-N_2)*(1-N_3)\ldots)]$. The program database did not indicate which individual efficiency measure had been implemented for each piece of equipment. A single value represented all measures for which the equipment was rebated. Therefore, the *ex post* maximum possible savings value was set as a cap to the efficiency savings when applied to each piece of equipment. For example, two griddles may have efficiency savings percentages within the program database of 50% and 15%, respectively. The first griddle would be limited by the *ex post* savings to 35%, while the second griddle would have the *ex ante* value of 15% applied during the determination of therm savings. Table 3.5 compares the average efficiency savings attributed to each equipment type for the *ex ante* and *ex post* values. The average *ex ante* values are taken directly from the program database and represent all potential efficiency savings applied, not just the above baseline measures shown in Table 3.5.

Table 3.5
Average Efficiency Savings by Equipment Type

Equipment Type	***Ex Ante* Efficiency Savings**	***Ex Post* Efficiency Savings**	
	Average	**Average**	**Maximum**
Braising Pan	43%	5%	5%
Broiler	37%	33%	54%
Cabinet Steamer	48%	37%	38%
Fryer	35%	10%	10%
Griddle	36%	28%	35%
Hot Food Table	31%	0%	0%
Other	43%	23%	25%*
Oven	57%	28%	28%
Range	46%	17%	20%
Steam Kettle	40%	19%	19%

*Set to weighted mean of all other equipment types

Based solely on a comparison of efficiency savings, the expectation is that the therm savings would decrease. However, the efficiency savings are only part of the algorithm. The results from the determination of therms used is discussed next.

The evaluation used the following algorithm:

$$\text{Therms Used} = \text{Hours of Operation} * \text{Load Factor} * \text{\# of Pieces of Equipment} * \text{kBtu/hr Input} * \text{Conversion Factor} \tag{3.4}$$

This equation has two variables which were affected by the evaluation – hours of operation and load factor. The annual hours of operation data used in developing the *ex* *ante* estimate were based on facility hours. It was unclear whether these were considered to be the hours the business was open to the public, or when the doors were locked and unlocked for employees. Regardless, as stated previously, the on-site visits collected the annual hours of operation of the kitchen. This was to assure that, when multiplied by the average hourly load factor, the average use of the equipment was captured. Table 3.6 shows the average annual operating hours for the *ex ante* and *ex post* estimates. As indicated, all pieces of equipment were used slightly more than originally estimated (9% higher overall), with braising pans showing the greatest difference (37%) and "Other" equipment only slightly above the *ex ante* estimate (1%).

Table 3.6
Average Annual Operating Hours

Equipment Type	*Ex Ante* Operating Hours	*Ex Post* Operating Hours	Difference	Percent of *Ex Ante*
Braising Pan	3867	5294	1426	137%
Broiler	4776	5250	474	110%
Cabinet Steamer	4310	4989	679	116%
Fryer	5081	5369	288	106%
Griddle	5341	5497	156	103%
Hot Food Table	4841	5192	351	107%
Other	5601	5666	65	101%
Oven	4687	4947	260	106%
Range	4602	4769	167	104%
Steam Kettle	4760	5354	594	112%
Average	**4787**	**5233**	**446**	**109%**

The load factor (sometimes called duty cycle) is defined as the average rate of energy consumption divided by the rated input. As discussed earlier, data collected through the on-site visit supported analysis of an average load factor for four pieces of equipment. Table 3.7 shows development load factor estimates adopted in this analysis and identifies their source.

Table 3.7
Load Factors

Equipment Type	Source of Data	Number of Equipment in Calculation	Busy Load Factor	Nonbusy Load Factor	Hourly Load Factor	Ex Post Average Load Factor	Ex Ante Average Load Factor	Percent of Ex Ante
Braising Pan	PG&E Report 008.1-90.8, p. 9-10	NA	0.62	0	-	0.24	0.46	52%
Broiler	On-Site Audit	77	0.89	0.67	-	0.74	0.48	153%
Cabinet Steamer	Technology Review of Commercial Food Service Equipment, Volume II, p. 8-9	NA	-	-	0.15	0.15	0.39	38%
Fryer	PG&E Report 008.1-90.22 p. 3-6	NA	0.85	0.44	-	0.56	0.46	123%
Griddle	PG&E Report 008.1-89.2 p. 1-5	NA	0.84	0.46	-	0.57	0.44	129%
Hot Food Table	On-Site Audit	6	-	-	0.41	0.41	0.47	87%
Other*	NA	NA	NA	NA	NA	0.48	0.43	112%
Oven	On-Site Audit	96	0.71	0.35	-	0.46	0.42	108%
Ranges	On-Site Audit	82	0.76	0.19	-	0.36	0.47	78%
Steam Kettles	PG&E Report 008.1-90.8, p. 9-10	NA	-	-	0.13	0.13	0.42	31%

*Calculated as the sum product of the calculated hourly load factors and the population percentages of equipment number
**([Busy Load Factor] * [Busy Hours] + [Nonbusy Load Factor] * [Nonbusy Hours]) / Total Hours

No antecedent load factor estimates for hot food tables could be found within the technical information reviewed. Therefore, the evaluation relied on the small amount of load factor information gathered during the on-site audits.

In the development of the *ex ante* estimates, SoCal Gas Company had capped all load factors at 0.50. A comparison of the load factor assumptions used on the *ex ante* analysis and the *ex post* load factor shows that the *ex post* load factor was higher for half of the equipment types.

To further validate the load factor estimates developed through this evaluation, Table 3.8 presents estimates prepared by the Canadian Gas Research Institute and Fisher Consultants for Natural Resources Canada. This reference pulled information from private resources as well as much of the work performed by the PG&E Test Kitchen. As such, it was a good source of comparison for agreement of the evaluation load factors with other work within the commercial cooking field.

Table 3.8
Typical Duty Cycles

Appliance	Duty Cycle, %
Fryer	
deep fat	20
pressure/kettle	30-33
flat bottom	14-20
Griddle	25-30
Broiler	70-80
Range	20-40
Oven	
Standard	25-40
Deck	20-30
Conveyor	50
Rotisserie	60-65
Steamer	13-20
Steam Kettle	40
Tilting Skillet	45-50

Source: Natural Resources Canada, Consumer Gas Company, Ltd., and Ontario Ministry of Environment and Energy. *Technology Review of Commercial Food Service Equipment, Volumes I & II.* Prepared by the Canadian Gas Research Institute and Fisher Consultants. May, 1996.

The *ex post* load factors agree with the values in Table 3.8 for broilers, ranges, ovens, and steamers. The *ex post* value is higher than "typical" for fryers and griddles and lower than "typical" for steam kettles and braising pans (tilting skillets). However, since the load factors for fryers, griddles, steam kettles, and braising pans came directly from test results, they were kept for use within the evaluation.

Data from the evaluation effort were applied by equipment type. Therms used was determined using the number of pieces and rated input from each piece of equipment in the program database. The annual hours of operation and load factor were static across equipment types. The load factor was capped at the values shown in Table 3.7, but allowed to go lower if the program database had a lower number. The results are shown in Table 3.9.

Table 3.9
***Ex Post* Estimate of Gross Savings**

	Ex Ante		*Ex Post*		
Equipment Type	**Savings Estimate**	**Percent of Total**	**Savings Estimate**	**Percent of Total**	**Percent of *Ex Ante* Estimate**
Braising Pan	17,247	1%	1,714	0%	10%
Broiler	132,665	6%	203,576	15%	153%
Cabinet Steamer	121,037	5%	49,495	4%	41%
Fryer	573,805	25%	187,011	14%	33%
Griddle	204,631	9%	225,050	17%	110%
Hot Food Table	20,620	1%	0	0	0
Other	62,508	3%	31,848	2%	51%
Oven	708,716	31%	436,342	33%	62%
Range	399,064	17%	184,924	14%	46%
Steam Kettle	56,486	2%	10,020	1%	18%
Total	**2,296,781**	**100%**	**1,329,980**	**100%**	**58%**

The realization rate for the gross saving estimate, as shown above, is 0.58. Ovens continued to have the largest percent of *ex post* savings, with griddles and broilers following. The differences between the *ex ante* and *ex post* estimates can be traced to load factors and efficiency savings measures. Since all equipment types had increased annual hours of operation, the interaction of the efficiency measures above baseline with the load factors determined the equipment-specific realization rates.

Chapter 4
ESTIMATION OF NET SAVINGS

Approach to Estimating Net Savings

In this chapter, net-to-gross ratios are developed to adjust the gross program impacts developed in the previous chapter for free rider effects.

Importance of Quantifying Net Impacts

A key component of most electric utility program evaluations is the attribution of observed impacts to the program. This component, commonly referred to as net impact evaluation, seeks to determine the portion of observed program impacts that were, in fact, caused by the program, in the sense that they would not have occurred in the absence of the program intervention. In California, net impact estimation has received particular attention because the incentives ratepayers pay to the shareholders to fund DSM programs is linked to the demonstrable effect of the programs. Ratepayers need assurances that observed impacts were indeed caused by the program.

By definition, all net impact evaluation methods must address the issue of estimating what would have happened in the absence of the program. Addressing this issue presents a methodological challenge since events that would have occurred in the absence of the program are unobservable. A standard strategy for addressing this issue is to compare program participants' measure installation decisions with those of a comparable group of non-participants. This strategy, based on theories of quasi-experimental design, is consistent with Protocol requirements.

It would be tempting to make a simple comparison of participants' and non-participants' implementation decisions, interpreting the non-participant implementation rate as the implementation rate one would have observed among participants in the absence of the program. But this approach is only valid if customers' participation decisions are not influenced by their propensity to implement energy efficiency measures. In fact, as long as program participation is voluntary, evaluators have every reason to believe that those customers who choose to participate are the very ones most inclined to implement energy efficiency measures. As a result, the influence or causation is bi-directional; the implementation decision influences the participation decision and the participation decision influences the implementation decision. In econometric terms, the two variables, participation and implementation, are said to be endogenous. The practical effect of this endogeneity is that the non-participant group will be systematically different from the participant group. Any comparison between the two groups will produce biased results unless the endogeneity is explicitly controlled for.

Statistical Modeling Approach

The approach we originally planned to pursue consisted of applying a qualitative choice model to estimate the probability of a customer's making one of three choices regarding an eligible measure:

1. Implement the measure within the program.
2. Implement the measure outside the program.
3. Do not implement the measure.

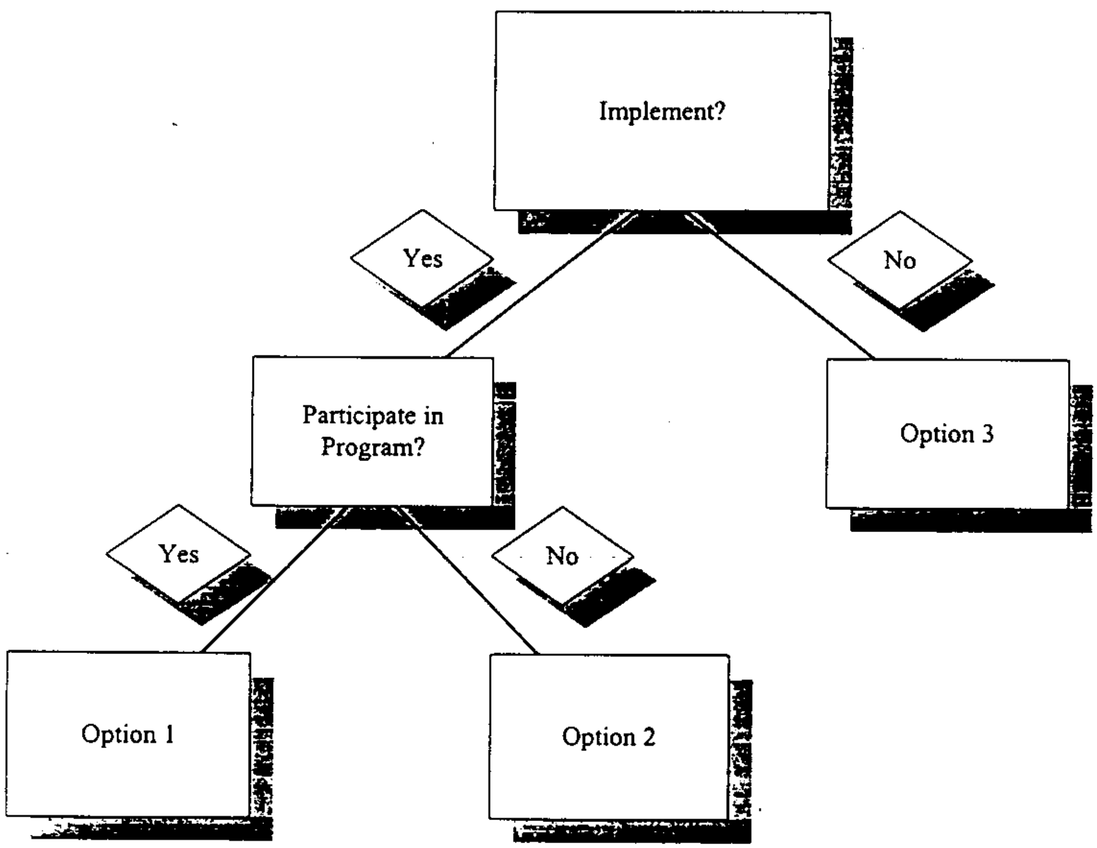
This three-option model is appropriate for a rebate program for which participation is contingent on implementation. In other words, choosing to participate in the program and not implement a measure is not a valid option. For the three choices enumerated above, program participants are customers who choose option 1, while non-participants choose either option 2 or 3. To determine net savings, a qualitative choice model is estimated that describes customers' choices among these options, using data on the actual choices that customers made during the program period.

With qualitative choice analysis (QCA), the two similar options—in this case options 1 and 2—are nested together. Thus, the model structure consists of two parts:

- a "bottom" model of whether customers participate in the program given that customers implement one or more of the measures promoted by the program
- a "top" model of customers' choices of whether to implement a measure, incorporating their probable participation in the set of explanatory factors

Figure 4.1 illustrates such a system.

Figure 4.1
Three-Option Qualitative Choice Analysis Model Structure



Once the three-option model is estimated, it is used to simulate the behavior of customers with the first option removed (that is, to "forecast" what customers would have done if they had not had the option of implementing the measure with an incentive). This simulation indicates the extent to which customers would have implemented the measures without the program; the energy savings under this simulation are the estimate of naturally occurring savings. The net savings of the program are then calculated as the difference between (1) the savings that occurred with the program (i.e., when all three options are available), and (2) the naturally occurring savings.

Distribution of Implementers and Participants Using Program Baseline

For estimation of this model to be feasible, customer decisions must be well distributed across the three decision options shown in Figure 4.1. To check the distribution, we classified all program participants and non-participants as either implementers or non-implementers, based on the equipment features they reported adopting in their responses to the telephone survey. The list of candidate features for each equipment type reflects the features used in SoCal Gas Company's *CookCalc* software to calculate *ex ante* gross savings estimates, shown in Table 4.1.

Table 4.1
Efficiency Measures Considered Above Program Baseline

Braising Pan	Automatic Tilt Control
	Compartment Cover
	Manual Thermostat
	Solid State Controls
	Substitute Braising Pan
Broiler/Cheese Melter	Automatic on/off
	Conveyor
	Double Sided Heat Source (all gas)
	Hood or Cover
	Infrared Burner
	Thermostat
	Variable Speed conveyer belt
Cabinet Steamer	Easy Access Deliming Port or Indicator
	Manual Controls
	Solid State Controls
	Standby Mode
	Steam Forced Convection
Fryer	Automatic Basket Lifts
	Cold Zone

	Conveyor
	Filter System
	Infrared of Power Burner
	Proofer
	Solid State Controls
Griddle	Chrome Griddle Surface
	Convection Oven (Base)
	Double Sided Contact
	Double Sided Non-Contact
	Infrared Burner
	Insulation
	Manual Controls
	Solid State Controls
Hot Food Table	Hoods or Lids
	Individual Compartment Controls
	Thermostat
Oven	Conveyor
	Fan Control
	Independent Timer
	Infrared Burner or Power Burner
	Solid Fuel Compatibility
	Solid State Controls
Range	Convection Oven (Base)
	Insulation
	Top Power Burner
Steam Kettle	Insulation
	Power Burner
	Self-Contained Water Supply
	Solid State Controls
	Substitution of Steamers

If a customer reported adopting any one feature for any eligible cooking equipment type, then the customer was classified as an implementer. By definition, all participants are implementers, and, not too surprisingly, the vast majority of non-participants were also classified as implementers. The distributions of implementers and nonimplementers are shown in Table 4.2.

Table 4.2
Tabulation of Participation and Implementation
Using Program Definition of Baseline

	Non-implementers		Implementers		Total	
	Number	**Percent**	**Number**	**Percent**	**Number**	**Percent**
Non-participants	8	4.0	107	53.5	115	57.5
Participants	0	0.0	85	42.5	85	42.5
Total	8	4.0	192	96.0	200	100.0

From this table, it is evident that only eight customers chose option 3, "do not implement a measure." This represents only 7% of the non-participant sample and only 4% of the total sample. This distribution does not permit the estimation of a statistical model that explains the implementation decision as a function of independent factors. In particular, it is not possible to demonstrate, using this modeling approach, that program participation played any significant role in customers' implementation decisions.

Distribution of Implementers and Participants Using Revised Baseline

Building on the baseline analysis conducted as part of the gross analysis, we developed an alternate definition of implementation that excluded those measures the gross analysis identified as baseline measures or measures with zero gross savings. By revising the net analysis to focus only on those measures that make a positive contribution to gross savings, this approach, in effect, recognizes that measures with zero gross savings cannot make a contribution to net savings.

This alternate definition thus relied on a reduced universe of measures to identify implementation of energy-efficient or productivity-enhancing equipment features. The list of remaining measures is shown in Table 4.3 and the revised tabulation of customer implementation and participation is shown in Table 4.4.

Table 4.3
Efficiency Measures With Nonzero Gross Savings

Braising Pan	Compartment Cover
Broiler/Cheese Melter	Conveyor
	Double Sided Heat Source (all gas)
	Hood or Cover
	Infrared Burner
	Thermostat
	Variable Speed conveyer belt
Cabinet Steamer	Easy Access Deliming Port or Indicator
	Solid State Controls
	Standby Mode
	Steam Forced Convection
Fryer	Solid State Controls
Griddle	Chrome Griddle Surface
	Infrared Burner
	Solid State Controls
Oven	Fan Control
	Independent Timer
Range	Convection Oven (Base)
Steam Kettle	Insulation
	Solid State Controls

Table 4.4
Tabulation of Participation and Implementation Using Evaluation Definition of Baseline

	Non-implementers		Implementers		Total	
	Number	**Percent**	**Number**	**Percent**	**Number**	**Percent**
Non-participants	22	11.0	93	46.5	115	57.5
Participants	5	2.5	80	40.0	85	42.5
Total	27	13.5	173	86.5	200	100.0

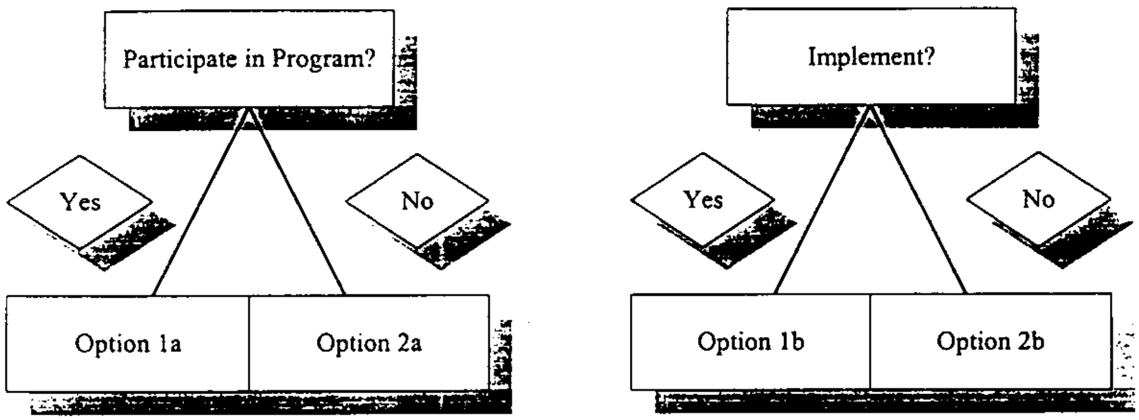
By reducing the universe of qualifying measures, fewer customers are assigned to the implementation category. Nonimplementers now make up 13.5% of the overall total and 11% of the non-participant group. Even more significantly, given the stricter baseline definition, it is now possible for program participants to lack any qualifying measures, making them nonimplementers. Nonimplementers now make up 2.5% of the participant group.

Revised Modeling Approach

Using this revised baseline definition (referred to hereafter as the evaluation baseline), the modeling approach described above cannot be applied. The above approach is valid only if customers are presented with two inter-related decisions with a combined total of only three possible choices. It assumes that participation without implementation is not a valid choice. Applying the evaluation baseline, this last condition no longer holds.

To accommodate the evaluation baseline, we modified the econometric modeling method to relax the assumption that participants, by definition, implemented measures. This approach is represented graphically in Figure 4.2. It illustrates the notion that all customers could have participated in the program regardless of their implementation decision, and all customers could have implemented a measure regardless of their participation. However, the implementation and participation decisions are inter-related.

Figure 4.2
Four-Option Discrete Choice Analysis Model Structure



To apply this model, one first estimates a participation model, where the probability of participation, P, is described by a logit function with the following form:

$$P = \frac{e^{\beta Z_i}}{1 + e^{\beta Z_i}} \tag{4.1}$$

In this equation, Z is a vector of characteristics of the customer that relate to the participation decision. β is a vector of parameters indicating how the characteristics Z relate to participation. This model can be estimated by standard logit routines (e. g., the Logistic procedure in SAS). The probability that a customer is a non-participant is, necessarily, 1-P.

It is expected that the decision to participate in the program is related to the customer's predisposition to implement a measure. If the direction of influence or causation were in one direction only, from participation to implementation, then one could reflect the relationship by estimating a model of measure implementation, described by a logit function with the following form:

$$I = \frac{e^{\alpha D_i + \delta X_i}}{1 + e^{\alpha D_i + \delta X_i}} \tag{4.2}$$

In this equation, X is a list of characteristics of the customer that affect this decision and D is a dummy variable that identifies whether the customer participated in the program. The impact of the program is captured by α, the coefficient of this participation dummy. This coefficient reflects the extent to which the program increased the customer's probability of implementing the measure.

But estimation of this model is complicated by the fact that the critical explanatory variable, the participation dummy D, depends on the customer's predisposition to implement the measure. One strategy for addressing this problem is to replace the participation dummy with the probability of participating, estimated in Step 1; that is:

$$I = \frac{e^{\alpha P_i + \delta X_i}}{1 + e^{\alpha P_i + \delta X_i}} \tag{4.3}$$

As in the three-option approach, the revised approach consists of estimating a participation model and then constructing a variable that proxies participation for inclusion in the implementation model. Unlike the three-option approach, estimation of the participation model in this case is not restricted to the subset of customers that implemented a measure.

There are three steps to calculating the NTG ratio for the four-option model approach. The first is to calculate the probability of contributing to gross savings. The probability of contributing to gross savings is the product of the probability of participation and the probability of implementing a measure, that is:

Probability of contributing to gross savings = P * I,

where P and I are defined as shown above.

Next, the probability of contributing to net savings is calculated as the probability of implementing a measure with the program, minus the probability of implementing a measure in the absence of the program.

Probability of contributing to net savings = I - A

$$\text{where } A = \frac{e^{\delta X_i}}{1 + e^{\delta X_i}} \qquad (4.4)$$

A comparison of the equations for A and I reveals that A is equal to I with the probability of participation, P, set equal to zero. In effect, it represents the forecasted probability of implementation when participation in the program is not an option.

The third step is to form the NTG ratio as the ratio of Probability of contributing to net savings to the Probability of contributing to gross savings, or

$$NTG = (I - A)/(P * I). \qquad (4.5)$$

Customer-specific values for P, I, A, and NTG are first calculated and then the average of NTG is calculated over all customers in the sample, applying sample weights.

Results

Introduction

Summary of Equipment Type Restriction

Because of the low nonimplementation rate for the program as a whole, modeling in the manner which was originally intended became impossible. However, we were able to produce defensible QCA estimates for a restricted group of installers of any of three equipment types: fryers, griddles, and ranges. For the five other equipment types, NTG ratios were calculated using self-report data from the telephone survey.

Summary Model Selection Process and Criteria

Because the results of the participation model feed directly into the implementation model, our first order of business was to build a good participation model. We started with a list of factors from our available data judged likely to influence the participation decision. We chose our final participation model based on several criteria. First, we confirmed that the sign and significance of each parameter was what we expected *a priori*. Next, we looked for high concordance rates. We then examined the change in log likelihood for the participation model, comparing these levels with other participation models' levels having comparable degrees of freedom. (Concordance and change in log likelihood and their interpretations are discussed in greater detail in Volume II.) After selecting the best participation model, we worked on the implementation model. Again, we confirmed parameter signs against expectations, and we examined the change in log likelihood and concordance rates, looking for high values of each.

NTG Results

The final models yielded a point estimate for the NTG ratio of 0.33. The 90 percent confidence interval for the NTG ratio is (0.177, 0.514).

For those equipment types not included in modeling, self-report NTG ratios were calculated. Table 4.5 summarizes the NTG ratios for all eight equipment types.

Table 4.5
Tabulation of NTG Ratios

Variable	Calculation method	Mean NTG	Std. Dev.
Braising Pan	Self-report	0.00	0.00
Broiler	Self-report	0.02	0.08
Cabinet Steamer	Self-report	0.00	0.00
Fryer	QCA	0.33	0.10
Griddle	QCA	0.33	0.10
Oven	Self-report	0.02	0.07
Range	QCA	0.33	0.10
Steam Kettle	Self-report	0.00	0.00

Rationale for Restricting List of Equipment Types

Only those measures above baseline are considered to be energy-efficient. Under the evaluation baseline several measures were no longer considered to be above baseline. Hot food tables had only baseline measures and so were eliminated from consideration entirely. Even after applying the evaluation baseline instead of the program baseline, only 13.5% of the total sample of 200 customers were nonimplementers. Because the implementer/nonimplementer split was very uneven, we anticipated problems would arise in modeling if we continued to use the entire list of equipment types. With such a large proportion of the sample being implementers, too little variation existed in the implementation model's dependent variable, thus providing little opportunity to accurately model the implementation decision. Indeed, preliminary modeling attempts run on the entire sample and all equipment types confirmed our suspicions, and we were not able to produce stable models with dependable results.

Rather than turning to self-report methods for each equipment type individually, we sought to find a combination of equipment types that would lend itself to successful modeling with robust results. The following is a table showing implementation for each equipment type for the subset of customers who said they had installed that particular equipment type on the telephone survey. Equipment types are organized in descending order of nonimplementation rates.

Table 4.6
Tabulation of Implementation

	Feature Nonimplementers		Feature Implementers		Total Number Installers by Equipment	
Equipment	**Number**	**Percent**	**Number**	**Percent**	**Number**	**Percent**
Ranges	71	69.6	31	30.4	102	100.0
Fryers	52	45.6	62	54.4	114	100.0
Griddles	26	31.0	58	69.0	84	100.0
Ovens	39	28.7	97	71.3	136	100.0
Cabinet Steamers	8	25.8	23	74.2	31	100.0
Braising Pans	4	16.6	20	83.4	24	100.0
Steam Kettles	2	12.5	14	87.5	16	100.0
Broilers	2	4.0	47	96.0	49	100.0

Several equipment types were immediately discarded from the pool of modeling candidates to be grouped together due to implementer/nonimplementer splits that were too disparate. For example, only 4.0% of broiler installers were nonimplementers. Braising pans, cabinet steamers, and steam kettles also had uneven implementation splits, and so were not included in the model. Another common feature among braising pans, broilers, steamers, and kettles was that these equipment types had small numbers of installers. This left fryers, griddles, ovens, and ranges as possibilities. Because ovens represent the largest installation group with 136 installers, we initially included this equipment type in our subgroup of equipment types. However, including ovens caused the implementation rate within the grouping of four remaining equipment types to become asymmetric, as Table 4.7 shows.

Table 4.7
Joint Implementation of Fryer, Griddle, Oven, or Range Measures

	Nonimplementers		Implementers		Total	
	Number	Percent	Number	Percent	Number	Percent
Nonparticipants	26	13.4	85	43.8	111	57.2
Participants	10	5.2	73	37.6	83	42.8
Total	36	18.6	158	81.4	194	100.0

For this reason, we restricted the equipment list to three types of equipment: fryers, griddles and ranges. Individually, all three types have high installation rates and relatively even splits for implementation versus nonimplementation. When the installers of the three equipment types were grouped together, the implementation split was still even with respect to the entire subset of fryer, griddle, or range installers, and had the desirable feature of being evenly split within participation status as well. Such a grouping offered a much better prospect for modeling which would yield robust results. With this new definition of implementation, any customer who installed a fryer, griddle, or range with at least one energy-efficient measure was an implementer. Table 4.8 shows the implementer/nonimplementer splits for the fryer, griddle and range equipment grouping used in modeling.

Table 4.8
Joint Implementation of Fryer, Griddle, or Range Measures

	Nonimplementers		Implementers		Total	
	Number	Percent	Number	Percent	Number	Percent
Nonparticipants	35	21.5	60	36.8	95	58.3
Participants	18	11.0	50	30.7	68	41.7
Total	90	32.5	110	67.5	163	100.0

Participation Model

Universe of Explanatory Factors and Coding Strategy

The first step in modeling was to determine which customer characteristics and attitudes could be expected to play key roles in a customer's decision to participate in the program. The universe of candidate explanatory factors is shown in Table 4.9.

Table 4.9
Universe of Candidate Explanatory Factors

Participation Model Explanatory Factor	Participant Survey Question #*
Role of primary decision-maker regarding kitchen design	2
Role of primary decision-maker regarding cooking equipment selection	4
The most influential information source in cooking equipment purchase decision	5
When customer learned about program relative to project stages	8-11
Importance of rebate amount	12a
Importance of lower energy bill	12b
Importance of design assistance from SCG	12c
Importance of low purchase cost of equipment available under program	12d
Importance of compatibility between facility needs and qualifying equipment	12e
Importance of quality of previous involvement with SCG	12f
Importance of ease of application process	12g
Type of business	72
Who pays gas bill	73
Annual food and beverage sales	74
Hours of operation	77
History of late bill payments†	n/a
Previous participation in SCG DSM programs†	n/a

*Non-participant survey is numbered differently, but same questions are asked about all factors, above
†From utility's customer databases

Logit functions require explanatory variables that are either continuous or dichotomous. In order for the information from a variable that was originally categorical to be used, its categories must be re-coded to become dichotomous variables, each representing the presence or absence of a customer characteristic. Re-coding also accomplishes improved variation for characteristics and reduced effects of correlation by methods such as grouping categories together.

"Role of primary decision-maker regarding kitchen design" was turned into indicator variables to represent who was the design decision-maker. For example, "Owner designed kitchen" is a flag for whether or not the owner was involved in the kitchen design, and appears in the final participation model. By including only one indicator for the kitchen design, we have eliminated problems of correlation among other kitchen design decision flags. "Role of primary decision-maker regarding cooking equipment selection" was made into several flags. "Outside information sources" is a flag for whether information most influential in the customer's purchase decision came from outside sources as opposed to past experience or another source not named in survey question 5. This is another example of grouping variables to gain a more representative variable while limiting the number of variables included in modeling. It covers the explanatory factor "The most influential information source in cooking equipment purchase decision." "When customer learned about program relative to project stages" was coded as flags for whether the customer became aware of the program before kitchen design, before gathering information about equipment, before equipment selection, before equipment installation, or after equipment installation.

The next seven factors, "Importance of rebate amount" through "Importance of ease of application process," were initially coded as seven dichotomous variables, "Rebate amount extremely important" through "Ease of application process extremely important." These indicators were equal to one when the customer said the factor was extremely important, and zero otherwise. However, because there was too little variability in these indicators, the less extreme and more representative "Rebate amount very important" through "Ease of application process very important" were used instead indicate whether certain factors were very important in the customer's decision to participate in the program. Here, if the customer responded that the factor was either extremely or very important, the flag had a value of 1, otherwise it had a zero value.

"Type of business" is represented by two indicator variables in the final model, "Business type: Full Service Restaurant" and "Business type: Takeout Restaurant" which have the "Eating Places" four digit SIC code 5812. "Who pays gas bill" shows up in the model as "Owner pays gas bill," which tells whether or not the owner was responsible for paying the gas bill at the remodeled facility, and reflects the importance of the owner paying the bill to the participation decision relative to all other gas bill payers, such as building operators. We constructed four "Annual Food and Beverage Sales" category flags: "Sales: Less than $249,000, " which was built from two sales categories $0-$100,000 and $100,000-$249,000, "Sales: Up to $499,000," "Sales: Up to $1 million," and "Sales: More than $1 million." "Hours of operation" was already a continuous variable, and so needed no re-coding. Finally, "History of late bill payments" was re-coded to show the presence or absence of credit history problems, and "Participant in 1994 Audit" was chosen as appropriate indicator for "Previous participation in SCG DSM programs." This variable was included in the final model because we expected those customers who had participated in previous DSM programs to be more likely to participate again in other programs.

Elimination of Explanatory Factors

Some of the explanatory factors that we thought would be key to the participation decision were not included in the final model. "When customer learned about program relative to project stages" was removed from the participation model's list of candidates because of possible endogeneity. Putting an awareness variable into the participation model, one assumes that the only direction of causation is from awareness to participation. However, the flow from participation to awareness is also a possibility. If a customer is interested in the benefits being offered through the program, then he may be pre-inclined to participate, and pay more attention to the program information. Similarly, a customer who is not interested in the program benefits might be inclined to ignore any program information. Predisposition to participate would thus stimulate awareness of the program.

Flags were created for each of four sales groupings for "Annual sales food and beverage sales:" $0-$249,000, $249,000-$499,000, $499,000-$1,000,000, and more than $1,000,000. In the participation model, the sales range that proved to be the most suitable indicator and was used in modeling was the flag "Sales: Less than $249,000." As a result, none of the other annual sales categories were included in the model.

"History of late bill payments" was originally included in the universe of variables because we anticipated that customers who pay bills late are more likely to have cash flow problems, and so might participate to obtain the rebate. However, this characteristic turned out not to be valuable in explaining the participation decision because it was extremely insignificant in the participation model. "Hours of operation" was eliminated due to the number of missing values. All other characteristics on the original list of candidates remained in the model.

Model Selection and Results

The participation model's evolution began with the full universe of variables. Then the endogenous awareness variable was removed. Next, the information source variables were collapsed into the single indicator variable "Outside information sources are most influential in purchase decision." The seven variables measuring whether factors were extremely important to the participation decision were then replaced with variables measuring whether the factors were very important because they were better at capturing more realistic indications of the importance of the factors. The next step was limiting the sales category to just one. Finally, insignificant variables were removed from the model.

The participation model results are given in Table 4.10, below. These results include the maximum likelihood estimate of the parameter; the estimated standard error of the parameter estimate, computed as the square root of the corresponding diagonal element of the estimated covariance matrix; the Wald Chi-square statistic, computed as the square of the parameter estimate divided by its variance estimate; and the probability of falsely rejecting the null hypothesis that the parameter estimate is not significantly different from zero. Overall goodness-of-fit statistics are shown in the form of the unrestricted and restricted log-likelihood scores. These scores are discussed in greater detail in Volume II.

Table 4.10
Participation Model Results

Variable	Parameter Estimate	Standard Error	Wald Chi-Square	Pr >Chi-Square
Intercept	-2.92	0.40	53.01	0.0001
Owner designed kitchen	0.80	0.26	9.64	0.0019
Outside information sources are most influential in purchase decision	1.15	0.26	19.57	0.0001
Rebate amount very important	0.05	0.29	0.03	0.8747
Lower energy bills very important	0.41	0.43	0.94	0.3334
Design assistance from SCG very important	-0.27	0.29	0.91	0.3407
Low purchase cost of equipment under program very important	-1.38	0.34	16.16	0.0001
Compatibility between facility needs and qualifying equipment very important	0.01	0.36	0.0003	0.9856
Quality of previous involvement with SCG very important	1.11	0.33	11.52	0.0007
Ease of application process very important	-0.16	0.30	0.30	0.5882
Owner pays gas bill	0.85	0.28	8.99	0.0027
Business type: Full service restaurant	2.63	0.38	47.81	0.0001
Business type: Takeout restaurant	2.04	0.34	37.03	0.0001
Annual sales: Less than $249,000	-0.85	0.28	9.26	0.0023
Participant in 1994 Audit	0.62	0.33	3.45	0.0634
Number of observations	163			
Percent concordance	74.6%			
LLU	-248.043			
LLR	-360.482			
-2(LLR-LLU)	224.878			

Model results show that "Owner designed kitchen," "Outside information sources are most influential in purchase decision," "Low purchase cost of equipment under program very important," "Quality of previous involvement with SCG very important," "Owner pays gas bill," "Business type: Full service restaurant," "Business type: Takeout restaurant," "Annual sales: Less than $249,000," and "Participant in 1994 Audit " are all significant predictors of the participation decision. Of these, only "Low purchase cost of equipment under program very important" and " Annual sales: Less than $249,000" are negative predictors. Many of the factors derived from survey question 12, namely the "importance of rebate amount," "lower energy bills," "design assistance from SCG," "compatibility between facility needs and qualifying equipment," and "ease of application process" appear to have had little impact the customer participation decision process.

The signs of the parameter estimates are as we expected. For example, the parameter estimate for "Owner designed kitchen" is positive, indicating that when the owner was involved with the kitchen design, participation was more likely. This is plausible because the owner would experience greater benefits from program participation than contractors and architects and would have more discretion to pursue innovative kitchen designs.

If a customer's most influential purchase information source was a persuasive one, such as a gas company representative or brochure, vendor representative or literature, or word of mouth from a business colleague, then that customer was more likely to participate in a program, compared to a customer whose most influential source was past experience, which may not have included experience with energy-efficient cooking equipment purchases. The positive estimate sign for "Outside information sources are most influential in purchase decision," therefore, is plausible.

"Low purchase cost of equipment under program very important" has a negative coefficient, consistent with our expectations. Since energy-efficient equipment available under the program included more features and would thus be more expensive than other cooking equipment, then customers for whom low cost was very important to the participation decision would be less likely to participate in the program.

Past experience with a company is a very powerful force for predicting whether a customer will be a repeat customer. With this possibility in mind, those customers who felt "Quality of previous involvement with SCG" was very important, and whose involvement had been a positive experience, would be more likely to participate in an SCG program. Therefore a positive coefficient for "Quality of previous involvement with SCG very important" is not unreasonable.

As expected, "Owner pays gas bill" also has a positive parameter estimate, meaning that when the owner paid the gas bill, participation was more likely than when someone else paid the gas bill. Owners would desire lower energy bills if they pay the gas bill. Owners who do not pay the bill would have less incentive to participate.

Both business types in the model have positive parameter estimates. This indicates that full service and takeout restaurants were more likely to participate in the program than bars, taverns, other food service establishments, and non-restaurant businesses. This makes sense if restaurants generally install a greater number of pieces of cooking equipment than non-restaurants, use this equipment more often, and are more inclined to install energy-efficient equipment and participate in the program.

The negative coefficient for "Annual sales: Less than $249,000" is also plausible because smaller customers often have less money available and less access to financing than larger ones. Since, even with the rebate, energy-efficient equipment is ordinarily more expensive than standard equipment, small customers are less likely to participate. Furthermore, small customers are least likely to be courted by program sponsor service reps who make special efforts to offer services to their large customers.

Based on our past experience, we also expected those who had participated in previous programs to want to participate again, and so the positive coefficient for "Participant in 1994 Audit" makes sense. Customers who had participated in the 1994 program were more likely to have participated in the 1995 program.

The final participation model resulted in a concordance rate of 74.6%. This statistic means that 74.6% of the time, the predicted probability of participation for participants is higher than the predicted probability of participation for nonparticipants. A few alternative specifications produced slightly higher concordance rates, but these models were less good in other important aspects, such as signs of coefficients or low numbers of observations included in the modeling.

The change in log likelihood (-2(LLR-LLU)) value of 224.878 for 14 degrees of freedom was larger than values for other implementation models with comparable degrees of freedom. The change in log likelihood has a chi-square distribution, and its high value leads us to conclude that our chosen model is more powerful at explaining the participation decision than alternative models.

Implementation Model

Universe of Explanatory Factors and Strategy for Coding Variables

Table 4.11 below shows those factors that were expected to be key to the customer implementation decision.

Table 4.11
Universe of Candidate Explanatory Factors

Implementation Model Explanatory Factor	Participant Survey Question #
Role of primary decision-maker regarding kitchen design	2
Role of primary decision-maker regarding cooking equipment selection	4
The most influential information source in cooking equipment purchase decision	5
Importance of lower energy bill	13a
Importance of availability of manufacturer/vendor rebate	13b
Importance of design assistance from SCG	13c
Importance of equipment purchase cost	13d
Importance of ease of installation	13e
Importance of ease of use and maintenance	13f
Importance of low anticipated repair needs/cost	13g
Importance of equipment warranty	13h
Importance of production capacity	13i
Importance of quality of food production	13j
Importance of lower environmental compliance costs	13k
Importance of availability of equipment	13l
Importance of recommendation of contractor/architect	13m
Importance of effect on property value	13n
Importance of company policy	13o
Importance of desire to support energy conservation	13p
Type of business	72
Who pays gas bill	73
Annual food and beverage sales	74
Number of staff on peak hour shift	75
Design capacity of the restaurant	76
Hours of operation	77

As with the participation model, categorical variables had to be re-coded as dichotomous variables for use in the implementation model. Again, characteristics and categories were combined so that they were more representative indicators for explaining the implementation decision.

"Role of primary decision-maker regarding kitchen design" and "Role of primary decision-maker regarding cooking equipment selection" were combined into one variable, "Owner involved in neither kitchen design nor equipment selection." The purpose of consolidating these two decision-making questions was two-fold. First, several of the kitchen-design flags were correlated with one another as well as with the flags for equipment selection. Combining the variables into a single indicator variable reduces the effects of correlation on the modeling process. Second, by concentrating on owners in the new indicator variable, we have captured the largest group of decision-makers, and therefore have maximized the variability, while minimizing the number of variables used to represent kitchen design and equipment selection decision-making in the model. "The most influential information source in cooking equipment purchase decision" was re-coded as in the participation model.

The next 16 characteristics, "Importance of lower energy bill" through "Importance of desire to support energy conservation" were each originally made into flags to reflect whether these factors were extremely important to the customer's decision to implement energy-efficient measures or not. As with the flags in the participation model derived from survey question 12, these flags derived from question 13 were improved as explanatory factors when a either an "extremely important" or "very important" response indicated the factor in question was very important to the client's decision.

"Business type," "Who pays gas bill," and "Annual food and beverage sales" and "Hours of operation" are coded as they are in the participation model. "Number of staff on peak hour shift" and "Design capacity of the restaurant" are continuous variables, and so can be used as they are.

Elimination of Explanatory Factors

"Source of information for selecting cooking equipment," while important to the participation model, was not used in the implementation model because it was highly insignificant. Similarly, only "Business type: Takeout," was included because "Business type: Full service restaurant" was insignificant. Because of their many missing values, "Number of staff on peak hour shift," "Design capacity of the restaurant," and "Hours of operation" were all discarded as variable choices for modeling. Instead, "Annual food and beverage sales," which is also representative of business size, was included. As with the participation model, only one sales category was included in the implementation model due to correlation among the sales categories. In order to minimize correlation with the participation variable, we chose the sales category, "Sales: More than $1 million," which was the sales category at the other extreme of the sales spectrum from the category in the participation model, and a good explanatory variable to characterize the implementation decision. This variable reflects how likely businesses of this size were to implement energy-efficient measures relative to all other business sizes. The remainder of the characteristics, listed above, are taken into account in the implementation model.

Model Selection and Results

We began the implementation modeling process using the full universe of implementation explanatory factors. Then highly insignificant variables were removed from the model. Following this, we restricted the annual sales categories to the most influential on the implementation decision. The final step was to group the kitchen design and equipment selection decisions together into a single variable, namely "Owner involved in neither kitchen design nor equipment selection."

As with the participation model, we selected the final implementation model based on several factors. We looked at how reasonable the signs of the parameters were, whether all vital characteristics were significant in the model, the value of the change in log likelihood, and the rate of concordance.

Considering all of these success measures, the following model was the best choice overall. Model results are given in Table 4.12, below. These results include the maximum likelihood estimate of the parameter; the estimated standard error of the parameter estimate, computed as the square root of the corresponding diagonal element of the estimated covariance matrix; the Wald Chi-square statistic, computed as the square of the parameter estimate divided by its variance estimate; and the probability of falsely rejecting the null hypothesis that the parameter estimate is not significantly different from zero. Overall goodness-of-fit statistics are shown in the form of the unrestricted and restricted log-likelihood scores. These scores are discussed in greater detail in Volume II.

Table 4.12
Final Estimation Results

Variable	Parameter Estimate	Standard Error	Wald Chi-Square	Pr >Chi-Square
Intercept	-0.86	0.51	2.87	0.0903
Owner involved in neither kitchen design nor equipment selection	0.85	0.29	8.63	0.0033
Lower energy bill very important to selection decision	0.54	0.42	1.61	0.2038
Availability of rebate very important to selection decision	-1.04	0.35	9.00	0.0027
Design assistance from SCG rep very important to selection decision	0.36	0.35	1.08	0.2995
Purchase cost of equipment very important to selection decision	-1.63	0.51	10.14	0.0014
Ease of installation very important to selection decision	-0.08	0.40	0.04	0.8464
Ease of use and maintenance very important to selection decision	-0.50	0.56	0.82	0.3666
Low anticipated repair needs/costs very important to selection decision	0.22	0.61	0.14	0.713
Warranty for equipment very important to selection decision	0.67	0.44	2.30	0.1293
Production capacity of equipment very important to selection decision	0.17	0.47	0.13	0.7178
Quality of food production very important to selection decision	0.85	0.54	2.48	0.1154

Lower environmental compliance costs very important to selection decision	0.86	0.42	4.13	0.0421
Availability of equipment very important to selection decision	0.55	0.36	2.24	0.1341
Recommendation of contractor or architect very important to selection decision	-0.76	0.34	4.84	0.0277
Effect on value of property very important to selection decision	0.01	0.37	0.0013	0.9708
Company policy very important to selection decision	-0.47	0.33	1.97	0.1606
Desire to support energy conservation very important to selection decision	-0.07	0.41	0.03	0.8676
Business type: Takeout restaurant	1.18	0.31	14.86	0.0001
Owner pays gas bill	0.40	0.32	1.55	0.2129
Annual sales: More than $1 million	2.02	0.56	12.95	0.0003
Probability of participation	1.92	0.48	15.71	0.0001
Number of observations	163			
Percent concordance	73.2%			
LLU	-211.047			
LLR	-267.059			
-2(LLR-LLU)	112.024			

The positive sign and significance of the parameter for "Owner involved in neither kitchen design nor equipment selection," indicates that when the group of decision-makers other than owners was involved in either the kitchen design or equipment selection or both, implementation was positively impacted. Conversely, when the owner was involved, the implementation rate was affected negatively. Considered in isolation, the sign appears implausible. However, the positive role of the owner in the implementation decision is already largely accounted for via the probability of participation variable, which is a function of owner involvement in the design process. "Owner involved in neither kitchen design nor equipment selection" merely explains the residual variation in implementation after controlling for the probability of participation.

Only four of the sixteen factors customers were asked to rate as very important or not in their equipment selection decision are significant in the implementation model. These are "Availability of rebate," "Purchase cost of equipment," "Lower environmental compliance costs," and "Recommendation of contractor or architect." Of these, all except "Lower environmental compliance costs" has a negative impact on the implementation rate. The negative sign of "Availability of rebate" suggests that if availability was very important to the customer, implementation was less likely. The negative coefficient on "Purchase cost of equipment" is intuitive, assuming the efficient equipment was more expensive and caused those who were concerned with cost not to implement efficiency measures. The negative estimate for "Recommendation of contractor or architect" is also plausible, since contractors and architects may have been more concerned with cost containment than energy-efficiency, and so have recommended equipment based on cost only. When a customer considered "Lower environmental compliance costs" to be a very important factor in equipment selection, then implementation was more likely. This makes sense because customers are generally in favor of reducing any of their costs and especially these environmental compliance costs.

"Business type: Takeout restaurant" has a positive and significant coefficient, indicating that relative to the group of all business types other than takeout restaurants, takeout restaurants were more likely to implement energy efficient measures. This is intuitive because more takeout restaurants operate 24 hours a day, and so could easily recoup the investment in energy-efficient measures, and in the long run reap energy savings.

"Annual sales: More than $1 million" also has a positive and significant parameter, leading us to conclude that the group with more than $1 million in annual sales was more likely to implement efficient measures than the group with annual sales figures other than more than one million dollars. The parameter sign is reasonable in that those businesses with high sales volumes can afford to look over the long run, are less constrained by the up-front cost outlay.

The concordance rate is 73.2. This means that 73.2% of the time, the predicted probability of implementation is higher for implementers than for nonimplementers. In alternative specifications where we saw slightly higher concordance rates, the models had flaws which rendered them to be inferior model choices to the final implementation model.

Likewise, the change in log likelihood (-2(LLR-LLU)) value of 112.024 for 21 degrees of freedom was larger than values for other implementation models with comparable degrees of freedom. The high value of the change in log likelihood leads us to conclude that our chosen model has is more powerful at explaining the implementation decision than alternative models.

NTG Ratio and Confidence Interval

We obtained a point estimate for the NTG ratio of 0.33. In addition, a 90% confidence interval for the NTG ratio was calculated to be (0.177, 0.514).

Self-Reported NTG Ratios for Remaining Equipment Types

In order to examine the effect of the program on installation of energy-efficient measures for the remaining five equipment types not included in modeling, we calculated NTG ratios on each type using self-report data from the telephone survey. In the survey, the customer was asked what energy-efficient measures he actually implemented for each equipment type. The customer was then asked which measures he would have installed in the absence of the program. The customer's free-ridership rate was calculated to be the ratio of his savings in the absence of the program to the savings with the program. By definition, the NTG ratio for the customer is 1-(free-ridership rate). Table 4.13 below contains the self-report NTG ratio results for the remaining equipment types. The mean for each is calculated over the subset of customers who were installers of that equipment type. It is interesting to note that the NTG ratios are zero or close to zero, indicating that for these five equipment types, the program had little impact on inducing customers to implement energy-efficient measures. This result is consistent with the finding that virtually all customers who installed these types of equipment could be considered implementers regardless of their participation status.

Table 4.13
Self Report NTG Results: Evaluation Baseline

Variable	N	Mean	Std. Dev.	Min.	Max.
Braising Pan NTG	2	0.00	0.00	0.00	0.00
Broiler NTG	17	0.02	0.08	0.00	0.33
Cabinet Steamer NTG	2	0.00	0.00	0.00	0.00
Oven NTG	33	0.02	0.07	0.00	0.33
Steam Kettle NTG	4	0.00	0.00	0.00	0.00

Chapter 5
SUMMARY AND CONCLUSIONS

This report provides original estimates of the impacts of SoCal Gas Company's Commercial New Construction program on natural gas consumption for efficiency measures paid during the program year 1995. The impacts of cooking-related measures are explored in detail.

The estimates developed through this study for the program's impact on energy conservation are considerably lower than the *ex ante* estimates prepared by the utility. The divergence in estimates may be traced to the following factors:

- Many of the cooking equipment features that SoCal Gas originally deemed to be "efficiency features" of cooking equipment were found to be "standard features," and thus part of the baseline used in determining energy savings in this study.
- The energy savings associated with certain specific equipment (particularly equipment with multiple efficiency features) were found to be overstated in the *ex ante* estimates.
- The net-to-gross ratios estimated in this study were considerably lower than those assumed by SoCal Gas Company. For fryers, griddles, and ranges, use of a four option qualitative choice model resulted in a net-to-gross ratio of 0.33. For other defined types of equipment, the net-to-gross ratio ranged from 0.0 to 0.02. The overall weighted average net-to-gross ratio was 0.158.

The estimate of the net impact of the program's cooking-related measures reported here (214,837 therms) is over 90% lower than the *ex ante* gross savings estimate originally prepared by SoCal Gas Company. Much lower program impacts were estimated despite the finding that SoCal Gas Company had underestimated equipment usage and a number of load factors in its *ex ante* energy savings estimates.