Equipoise Consulting, Inc.

Energy Analysis

Project Management

Training

Final Report for

Pacific Gas & Electric's
Stand Alone Attic Ventilation Pilot Study

Submitted by:

Equipoise Consulting Incorporated

in association with

Ridge & Associates

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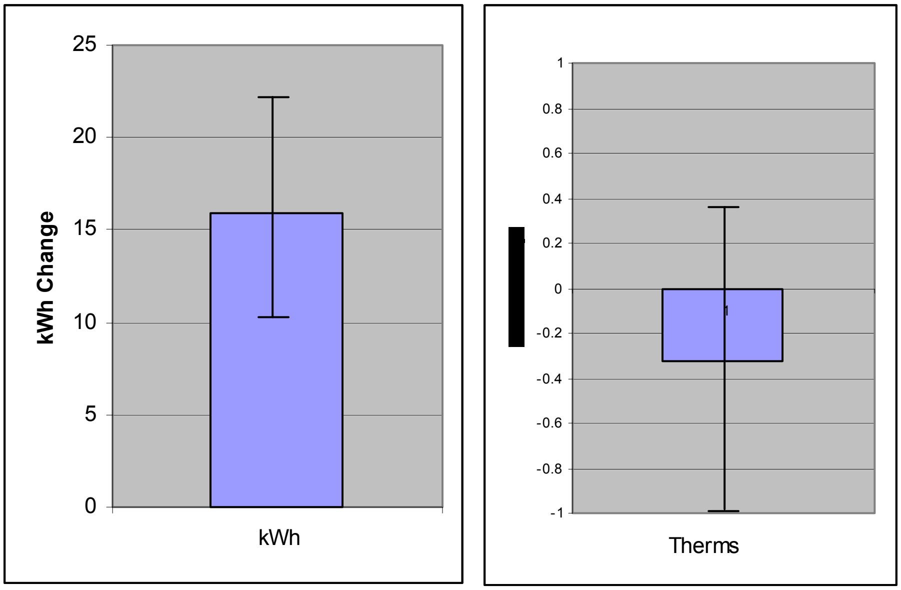
1. EXECUTIVE SUMMARY

On January 20, 1999, the California Public Utilities Commission Energy Division (CPUC Energy Division) issued Resolution E-3586 mandating installation of attic ventilation as a stand-alone measure for 1999 Low Income Energy Efficiency Programs (LIEE). On April 19, 1999 PG&E informed CPUC that installation of attic ventilation would be conducted as a Pilot Program beginning June 1, 1999 and that it would be reported as part of PY2001 planning and application process. Although the timeline has subsequently been extended, this report fulfills that requirement. PG&E files this report pursuant to Decision 01-06-082, Ordering Paragraph 3.

Industry literature suggests that attic ventilation as a stand-alone measure will have a limited impact in the California climate. From the literature, attic ventilation is expected to result in a 2% to 15% effect, depending on climate, with the majority of the estimates being on the lower end of the spectrum. No studies could be located that actually document effects with measured, credible data. However, because single-family residences were most likely to give a clear indication of any effect of stand alone attic ventilation, PG&E decided to limit the pilot program to single family residences.

Two hundred and fifty homes in the Central Valley were recruited as a convenience sample of homes that had had ceiling insulation installed via the LIEE, but had no vent installation. Additionally, only residences with electric and gas service from PG&E (i.e., no utility service from other sources) and relatively stable inhabitants were included in the sample. Multiple regression models were estimated in an effort to detect any energy savings due to the attic vent installation. Exhibit 1.1 shows the results of the regression model.

Exhibit 1.1
Model Results Due to Stand-Alone Attic Vent Installation



As shown here, there is a small but statistically significant <u>increase</u> in energy use that is being attributed to the installation of the attic vents (15.91 kWh per month with a 90% confidence interval of +/-5.83 kWh). This is approximately 3% of the average monthly usage for the sampled households. It should be emphasized that the evaluation team does not believe that the installation of a vent actually caused an increase in kWh. Rather, it is believed that other things that could explain the increase were not measured by the study and are being incorrectly attributed to the attic vent installation. The changes in gas usage (therms) are not significant. It does not appear that the installation of the vent produced any changes in therm usage.

The results of this study did not identify measurable energy savings due to the installation of stand-alone attic ventilation. The hypothesis going into the study was that the group of participants used for this study would have the largest impact, and thus the highest probability of a measurable result, from the installation of vents of any population within the LIEE program. If the studied group were to show an impact that was statistically significant and of practical importance, it was expected that this measure could be added to the portfolio with an expectation of savings, albeit small. Conversely, if a measurable effect could not be found for this group, then there was very little likelihood that the measure would produce savings for the broader LIEE Program. The results of the analysis indicate that this measure would not save energy. Therefore it is recommended that this measure <u>not be included</u> in the LIEE portfolio of measures for the purpose of energy conservation.

2. INTRODUCTION AND REVIEW OF ISSUES

On January 20, 1999, the California Public Utilities Commission Energy Division (CPUC Energy Division) issued Resolution E-3586 mandating installation of attic ventilation as a stand-alone measure for 1999 Low Income Energy Efficiency Programs. On April 19, 1999 PG&E informed CPUC that installation of attic ventilation would be conducted as a Pilot Program beginning June 1, 1999 and that it would be reported as part of PY2001 planning and application process. Although the timeline has subsequently been extended, this report fulfills that requirement. PG&E files this report pursuant to Decision 01-06-082, Ordering Paragraph 3.

Equipoise Consulting Inc. (Equipoise) was contracted in August of 1999 to estimate impact of the stand-alone attic ventilation measures. While Equipoise was responsible for documenting the impacts, the installing the ventilation measures was contracted (Western Insulation Inc.) directly by PG&E.

2.1 Study Issues

From the beginning of the study there were a few issues that were anticipated to be challenges for this study.

Small Measure Impact. Industry literature suggests that attic ventilation as a stand-alone measure will have a limited impact in the California climate. Attic ventilation is expected to result in a 2% to 15% effect, depending on climate, with the majority of the estimates being on the lower end of the spectrum. No studies could be located that actually document effects with measured, credible data.

Twelve Months of Data Collection Necessary. The study is intended to assess overall energy impacts, not just electricity impacts. Thus, it was necessary for the study to span a full 12-month period to properly account for expected heating losses, as well as anticipated air conditioning (AC) gains, resulting from the installation of attic ventilation.

2.2 Research Objectives

The two objectives for this study were:

1. Complete the installation of a pilot set of stand-alone attic ventilation systems in a sample of low-income homes.
2. Assess the energy impacts of the installed attic ventilation systems and report the results.

The team hypothesized that impacts due to a vent installation would be highest in single-family homes that are located in a warm climate. This is because any air conditioning system in a single-family home would respond to the heat through the ceiling from the attic space, whereas in a multi-family residence, only the top floor residences would experience the primary effects of the attic temperature.

The study methodology is presented next.

3. METHODS

This section describes the data sources and overall study approach.

3.1 Data Sources

3.1.1 Existing Data Sources

The primary existing data for the study was the participant information collected at the time that they enrolled in the Energy Partners Program (this program has subsequently been renames Low Income Energy Efficiency Program and will be referred herein as LIEE), customer billing data, and weather data.

LIEE Participation data. Exhibit 3.1 presents the LIEE participation data, by year and housing type, which met the criteria of having no attic ventilation installation while having ceiling insulation installation. It illustrates that 61% of the participants between 1993 and 1998 occupied single-family residences met these criteria. Because single-family residences were the most likely type of housing to a measurable effect of stand alone attic ventilation, PG&E decided to limit the study to single-family residences.

Exhibit 3.1
Distribution of Criteria-meeting Projects by Participant and Project Type

	1993	1994	1995	1996	1997	1998*	Total	%
Single Family	480	3,101	4,619	2,396	2,118	1,938	**14,652**	**61%**
2-4 Plexes	285	1,032	2,489	1,097	599	839	**6,341**	**27%**
Multi-Unit	9	257	1,230	651	356	382	**2,885**	**12%**
Total	**774**	**4,390**	**8,338**	**4,144**	**3,073**	**3,158**	**23,877**	**100%**
%	**3%**	**18%**	**35%**	**17%**	**13%**	**13%**	**100%**	

* No house type in 1998 Database, prorated on other years.

By merging the data in the LIEE database with information from PG&E's Marketing Decision Support System (MDSS) and Customer Information System (CIS), PG&E and Equipoise were able to further limit the sample of participants recruited for the study as follows:

- Only single family residences,
- Only residences that have housed the same occupants for one year or more and, by extension, residences with 12 months of pre-installation billing data (i.e., the meter set date in the CIS was older than one year),
- Residences with electric and gas service from PG&E (i.e., no utility service from other sources),
- Only residences in the "hot" climate zones.

Customer Billing Data. Billing data were obtained from PG&E for the 250 participants in the ventilation pilot program covering the period from 1/1/99 through 8/31/01. For each billing cycle, the prior read date, the current read date, kWh, therms, rate schedule, and bill amount were gathered.

Weather Data. For each of nine weather stations, the Equipoise Team obtained the daily maximum and minimum temperatures. As described below, these data were used to create heating and cooling degree-days for incorporation into the regression model. There were 22 different cities in the final population of 250 participants. The weather stations used and how they were mapped to the city is shown in Exhibit 3.2.

Exhibit 3.2
Weather Station Mapping to City

City	Weather Station	Source
Davis	Davis	Department of Water Resources
Woodland	Davis	Department of Water Resources
Manteca	Manteca	Department of Water Resources
Oakdale	Modesto	Department of Water Resources
Patterson	Modesto	Department of Water Resources
Riverbank	Modesto	Department of Water Resources
Rocklin	Sacramento	National Weather Service
West Sacramento	Sacramento	National Weather Service
Stockton	Stockton	National Weather Service
Auburn	Auburn	Pacific Gas & Electric
Forresthill	Auburn	Pacific Gas & Electric
Lincoln	Marysville	Pacific Gas & Electric
Marysville	Marysville	Pacific Gas & Electric
Wheatland	Marysville	Pacific Gas & Electric
Yuba City	Marysville	Pacific Gas & Electric
Atwater	Merced	Pacific Gas & Electric
Livingston	Merced	Pacific Gas & Electric
Merced	Merced	Pacific Gas & Electric
Dixon	Vacaville	Pacific Gas & Electric
Fairfield	Vacaville	Pacific Gas & Electric
Vacaville	Vacaville	Pacific Gas & Electric
Winters	Vacaville	Pacific Gas & Electric

HVAC Systems. The type of heating and cooling systems were also obtained for each participating household from the PG&E billing data.

3.1.2 Collected Data

The recruitment, measure installation, and data collection took place from December of 1999 through July of 2000.

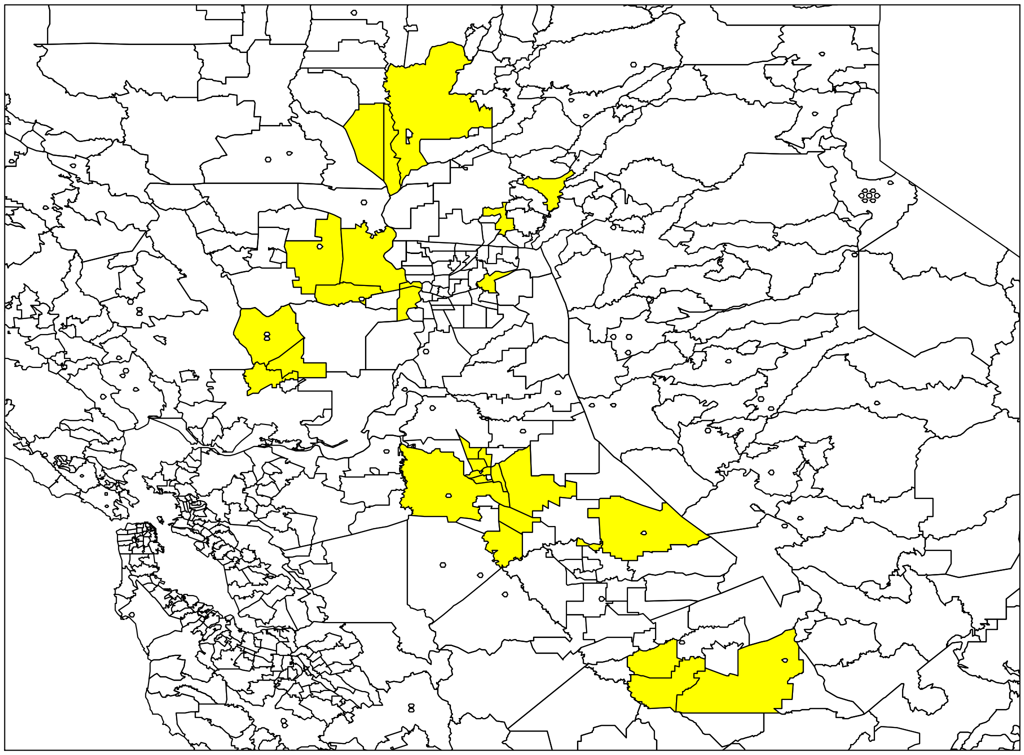
Because the planned analysis was a straightforward billing data regression model, very little additional data were required. The data that was collected during the recruitment process were:

- Name, address, and phone number for current residence
- Confirmation of housing type
- Confirmation that the customer had lived in the residence for the past 12 months
- Confirmation of account numbers from the customer's bills
- Confirmation that the house was only used PG&E utilities and did not have other heating source.

The onsite audit form in Appendix A shows the format used to collect this data. These data basically updated and confirmed the information already available from the PG&E databases. They also confirmed that the correct billing account number was properly associated with each residence to limit inconsistencies in the analysis.

There were 250 residences that had attic ventilation installed as part of this study. Of those, 248 were single-family detached units, 1 was a 2-4 plex, and the last was of an unknown type. The sites, as specified in the research plan, were located in the center portion of the state in hot climate zones (See Exhibit 3.3).

Exhibit 3.3
Location of Installed Sites by Zip Code



3.1.3 Sampling Design

After the data screening criteria mentioned in Section 3.1.1 were applied to the single-family housing cohort, 10,727 participants remained in the overall sample. The contact information for these participants was supplied to the installation contractor, sorted by geographical area. In conjunction with the PG&E project manager and the installation contractor, geographic areas were chosen for customer recruiting, based primarily on convenience to the installation contractor. While all customers in these specific geographic regions were eligible for participation, it was left up to the contractors to solicit customers, a process that was unlikely to have been random.

No attempt was made to distribute participation across PG&E's service territory in proportion to customer population. This is because the primary goal was to see if there was an effect in the potentially high impact areas and, if so, to determine the size of the effect.

3.2 Analysis Approach

The approach selected for this study was straightforward. As shown in Exhibit 3.1, single-family housing represented over 60% of the Energy Partners Program/LIEE participation from the beginning of 1993 through the end of 1998. Since single-family detached housing has the minimum interaction with adjacent residences and the maximum interaction with the attic space, it is the most likely type of residence to produce a measurable effects from stand-alone attic ventilation installation. As a result, PG&E decided to limit the study to this customer type.

The study selected houses from previous LIEE participants who had attic insulation installed, but did not have attic ventilation installed at the same time as the insulation, and who have been in the residences for one year. It was assumed that the homes received at least rudimentary weatherization due to participation in the program. These houses were recruited for participation in the study, at which time they were checked to be sure they did not have working attic ventilation. Working ventilation was defined as roof turbines or working low and high side ventilation systems. Customers with existing but inadequate ventilation were included in the program because these systems are highly ineffective. Practically, it was necessary to include these houses because most are constructed with some type of crude ventilation.

The purpose of the pilot program was to determine the feasibility of including the stand-alone attic ventilation measure as part of the Low Income Energy Efficiency Program. Consequently, the study ventilation installation followed PG&E's Weatherization Installation Standards (WIS) manual to ensure the same installation standards as attic ventilation installed under the Low Income Energy Efficiency Program.

Also, to maximize the probability of observing an effect, the study was fielded primarily in the Central Valley. This is the area in which an attic vent will be most likely to have a significant effect on energy bills because the weather is extremely hot in the summer and cool in the winter.

The study team collected both electric and gas billing data for 12 months pre-installation and 12 months post-installation. The data was analyzed using statistical regression analysis to estimate the size of the impact observed.

3.2.1 Sample and Effect Size Determination

A sample size of 250 has an 80% chance of statistically detecting a reasonably small reduction in energy usage at the 95% level of confidence. Reasonably small is defined as a negative correlation of 0.10 between the installation of ventilation and energy consumption. This means that there is a reasonable possibility of seeing a change in kWh of 5% or greater. However, if reduction in energy usage is even smaller than anticipated, the chances of statistically detecting any impact decreases.

The 95% confidence intervals were calculated for both the kWh and therm impact estimates.

3.2.2 Model Specifications

A variety of models were considered, with model specification depending on the quantity and quality of data available. The basic specification is as follows:

$$E_{i,t} = \alpha + \beta_1 CDD_{i,t} + \beta_2 HDD_{i,t} + \beta_3 Install_{i,t} + \beta_4 Crisis_t + \beta_5 Spring_t + \beta_6 Summer_t + \beta_7 Winter_t + \sum_{k=1}^{K} \beta_k X_{i,k} + \varepsilon_{i,t} \quad (1)$$

where

$E_{i,t}$ =	Recorded energy consumption (kWh or therms) of household i at time t
α =	Intercept
$CDD_{i,t}$ =	Cooling degree-days for household i at time t
$HDD_{i,t}$ =	Heating degree-days for household i at time t
$Install_{i,t}$ =	A dummy variable indicating the installation of the ventilation equipment for household i at time t.
$Crisis_t$ =	The beginning of the energy crisis in California defined as 0 prior to 1/1/2001 and 1 beginning on 1/1/2001
$Spring_t$ =	A dummy variable representing the spring
$Summer_t$ =	A dummy variable representing the summer
$Winter_t$ =	A dummy variable representing the winter
$X_{i,k}$ =	A vector of other explanatory variables, such as type of cooling equipment, type of heating equipment, rate schedule for the i^{th} household
β_1 =	Coefficient that reflects the average change in overall household energy consumption that would result from a one-unit change in CDD
β_2 =	Coefficient that reflects the average change in overall household energy consumption that would result from a one-unit change in HDD
β_3 =	Coefficient that reflects the average change in overall household energy consumption that would result from the installation of the ventilation equipment.
β_4–β_7 =	Coefficient that reflects the average change in overall household energy consumption that result from the crisis or different seasons
β_k =	A vector of k coefficients that reflect the household energy change associated with a one-unit change in the k^{th} explanatory variables
$\varepsilon_{b,t}$ =	Captures the energy consumption not explained by the model

In this model, β_3 associated with the installation dummy variable ($Install_{i,t}$) represents the estimate of the gross kWh or therm impacts.

Another model was also estimated that allowed for household-specific intercepts. Allowing such intercepts captures a host of household-specific characteristics that could not be measured in this study due to data and budget constraints. This model takes the following form:

$$E_{i,t} = \alpha_i + \beta_1 CDD_{i,t} + \beta_2 HDD_{i,t} + \beta_3 Install_{i,t} + \beta_4 Crisis_t + \beta_{56} Spring_t + \beta_6 Summer_t + \beta_7 Winter_t + \varepsilon_{i,t} \quad (2)$$

Another approach was considered but rejected. This approached would have involved focusing on the cooling months in 1999 and 2001. In effect, this would have treated the summer of 2000 as a deadband. However, this approach would have made it impossible to take into account the effect of the energy crisis since the installation variable (0 in the pre period and 1 in the post period) would have been perfectly collinear with the energy crisis variable (0 in the pre period and 1 in the post period).

3.2.3 Data Description

The dependent variable and each of the independent variables are described below.

3.2.3.1 Dependent Variables

The dependent variable in the cross-sectional, time series model described above is the recorded kWh and therm consumption for the participating premises from 1/1/99 through 8/31/01. The kWh and therm data are in the form of billing cycle, not calendar month. A common issue in billing data occurs when one billing cycle is extraordinarily long and the following one is very short. This causes noise in the kWh and therm data as the months are not comparable. This problem was dealt with by standardizing the billing cycle-based data into 30.4-day months. Specifically, the kWh and therm value for each billing cycle was divided by the number of days in the billing cycle and then multiplied by 30.4.

3.2.3.2 Explanatory Variables

The vector of explanatory variables is comprised of several categories. These variables fall into six groups:

Cooling Degree-days (CDD): PG&E billing files were merged with weather station files so that the appropriate weather data could be attached to each customer living in the area covered by the weather station.

To calculate the cooling degree-days for a particular day, the day's average temperature was calculated by adding the day's high and low temperatures and dividing by two. If the number is below a temperature set point of 65, for example, there are no cooling degree-days that day. If the number is greater than 65, 65 is subtracted from it to find the number of heating degree-days. For example, if the day's high is 90 and the day's low is 70, the day's average is 80. Eighty minus 65 is 15 cooling degree-days. Different temperature set points were calculated and used in the models to determine which version of CDD has the greatest explanatory power. Set points of 65, 70, and 74 were used. This variable was also standardized to a 30.4-day month.

Heating Degree-days: PG&E billing files were merged with weather station files so that the appropriate weather data could be attached to each customer living in the area covered by the weather station.

To calculate the heating degree-days for a particular day, the day's average temperature was calculated by adding the day's high and low temperatures and dividing by two. If the number was above a temperature set point of 65, for example, there are no heating degree-days that day. If the number is less than 65, the temperature was subtracted from 65 to find the number of heating degree-days. For example, if the day's high temperature was 60 and the low was 40, the average temperature was 50 degrees. Sixty-five minus 50 is 15 heating degree-days. Different temperature set points were calculated and used in the models to determine which version of HDD has the greatest explanatory power. Set points of 65, 60, and 55 were used. This variable was also standardized to a 30.4-day month.

Install: This is a dummy variable representing the installation of the ventilation equipment for each household. It is set to 0 prior to the installation date and to 1 at the installation date and for every period thereafter. The date of installation varied across the sample of households.

Note that the installation occurred in the middle of a billing cycle. Including this cycle in the analysis could have added noise to the analysis. For example, if the post-installation is defined as beginning in the month of the installation and a given customer installed on the last day in the billing cycle, then, for that customer, any reduction for the first post-installation month would appear to be very low. To eliminate any such bias from the analysis, a deadband was created that eliminated the installation month from the analysis.

Heating Type: The type of heating system used in each household was obtained from the program tracking database. This variable does not change over time was included in the analysis because of its ability to explain base energy consumption.

Cooling Type: The type of cooling system used in each household was obtained from the program tracking database. This variable does not change over time was included in the analysis because of its ability to explain base energy consumption.

Seasonal Dummies: Four dummy variables were constructed, each representing one of the four seasons. Only three of the four seasonal dummies were ever used in the model so as not to violate a key assumption of ordinary least squares regression that there be no perfect linear relationship among the independent variables.

Energy Crisis: It was necessary to create a variable to captures the effect of the energy crisis. While a precise beginning point would be hard to define, the beginning of the energy crisis could reasonably be defined as occurring at the start calendar 2001. The 2000-2001 winter saw a series of power interruptions, thus causing alarm about what might happen in the summer of 2001. Customers in San Diego were aware of problems much earlier than other regions due to price increases that occurred in the San Diego Gas & Electric service territory. However, this knowledge was not widespread, so the beginning of 2001 saw a more intense focus on energy shortages and calls for conservation. This variable was set to 0 prior to January 2001 and 1 afterwards.

3.2.4 Attrition Bias

Beginning with the creation of the participants and non-participants sample frames, attrition has occurred for a variety of reasons. Of the original 250 households, 31 households were dropped because PG&E control numbers could not be identified for these households. Failure to have the control numbers meant that kWh and therm data could not be obtained for these households. However, there is no reason to believe that these households are systematically different from those for which control numbers were available. Two more households were eventually dropped because they turned out to be duplicates or were missing substantial amounts billing data that could not be reliably imputed. This left a total of 217 households in the analysis dataset.

3.2.5 Regression Diagnostics

The robustness of the models was validated by performing a variety of diagnostic checks referred to in the Quality Assurance Guidelines (Ridge et al., 1994). Checks were conducted for heteroskedasticity, outliers, multicollinearity and autocorrelation using methods described by Kennedy (1992), Pindyck & Rubinfield (1981), and Belsey et al. (1980). The diagnostics are briefly discussed next.

3.2.5.1 Heteroskedasticity

Heteroskedasticity refers to the situation where the variances around estimates are different for different levels or values of the predicted independent variable. This problem is common in cross-sectional analyses, but does not result in biased estimates; rather, it results in inefficient estimates. The first step taken to identify this problem was to plot the residuals against the predicted independent variable. This allows visual identification of situations where the differences between predicted values and observed values are larger at some points of the regression line than others. Most commonly, heteroskedasticity takes the form of larger variances for higher values of the independent variable.

The eventual correction for heteroskedasticity is not predictable. The correction depends on the form of the relation between the independent variable and the predicted variable. The researcher tries different corrections for different functional problems and evaluates the results to determine whether the correction is appropriate. Sometimes the problem can be corrected or reduced by adding variables to the model that will explain the additional variance. This study used the Breusch-Pagan test since it allows one to test for more than one independent variable simultaneously. The analysis revealed that heteroskedasticity was not a problem in this study.

3.2.5.2 Outliers and Influential Observations

The ordinary least squares method is very susceptible to the influence of cases that have extreme values. The bulk of the cases may be clustered in a rather tight area, with one case residing far away from the rest on the independent variable. This extreme case would have a very strong impact on the estimate of the regression coefficient, and would result in a biased estimate. Because of this influence on the prediction, such cases often cannot be detected by visual inspection or by observation of errors. This is because the prediction "line" may be close to the outlier *because* of its influence. However, graphical observation can still be used to look for potential influential cases. Another common method is the DFFITS procedure, which calculates a predicted value two ways, once with a potential influential observation and once without it. If there is a large difference between the two, the case is considered influential.

Once detected, these observations were retained in the analysis but assigned a lower weight that non-influential observations. The weight used were developed by Welsch (1980) is as follows:

$$w_i = \frac{1}{|\mathrm{DFFITS}_i|} \quad \text{if } |\mathrm{DFFITS}_i \leq 0.34 \tag{3}$$

or

$$w_i = \frac{0.34}{|\mathrm{DFFITS}_i|} \quad \text{if } |\mathrm{DFFITS}_i > 0.34 \tag{4}$$

A number of outliers were identified and weighted appropriately.

3.2.5.3 Multicollinearity

Multicollinearity refers to the situation where two or more independent variables in a model are highly intercorrelated. This level of intercorrelation causes difficulties in the model. Specifically, multicollinearity results in higher variances for both predicted and explanatory variables. It also creates difficulty in partitioning variance among the competing explanatory variables. First, however, the problem must be detected. There are several ways to approach this task.

The approach used to detect multicollinearity is one recommended by Belsley et al (1980, chapter 3) and involves the analysis of structure. This approach entails the eigenvalues of the correlation matrix of the set of independent variables. The square root of the ratio of the largest to smallest eigenvalue is called the *condition index,* which provides a single statistic for indicating the severity of multicollinearity. A condition index larger than 30, indicates a problem.

Once detected, there is no consensus on what to do about it. Some recommend doing nothing. Others recommend obtaining more data, which, given both time and budget constraints, is unfeasible. Omitting one of the variables implicated is perhaps the most common approach. However, this makes sense only if the true coefficient of the omitted variable is zero. If the true coefficient of that variable is not zero, however, a specification error is created. Yet another approach is to group the collinear variables together to form a composite index capable of representing the group of variables by itself. The condition indices for the set of final models were all far less than 30, indicating no problem with multicollinearity in this analysis.

3.2.5.4 Autocorrelation

In time series models, it is often the case that an important assumption of ordinary least squares (OLS) is violated. Specifically, it is that in repeated sampling from the population, the correlation between any pair of disturbance terms across the conditional disturbances is zero. The violation of this assumption results in less *efficient* (not minimum variance) parameter estimates, although the parameters themselves are unbiased. The practical implications are that interval estimation and hypotheses testing can no longer be trusted. The Durbin-Watson (DW) statistic was used to detect any autocorrelation. In cases where autocorrelation was present, the data was transformed using a simple approach that uses the Durbin-Watson statistic (d-statistic) to compute ρ, the autoregressive coefficient. This is referred to as p-differencing (Maddala, 1992). The estimate of ρ ($\hat{\rho}$) is calculated as:

$$\hat{\rho} \approx 1 - \frac{1}{2}(d) \qquad (5)$$

Next, the data are transformed as follows:

$$Y_{i,t}^{*} = Y_{i,t} - \hat{\rho} Y_{i,t-1} \qquad (6)$$

$$X_{i,t}^{*} = X_{i,t} - \hat{\rho} X_{i,t-1} \qquad (7)$$

To recover the correct intercept when such transformed data are used requires that the intercept be multiplied by $1/(1-\hat{\rho})$.

Not surprisingly, in the time series model used in this analysis, autocorrelation was a serious problem with DW statistics hovering consistently around .30 to .50. The data were transformed using p-differencing, which resulted in DW statistics that hovered around 2.00, indicating substantial reduction of autocorrelation.

3.2.5.5 Weights

Since the participants were a convenience sample of 250 households, the use of analysis weights was mute. That is, to weight when the sample may not be representative makes little sense.

3.2.6 Weather Normalization

There are two basic approaches to producing weather-normalized estimates of gross impacts. The first is to weather normalize the kWh data first and then estimate models using the weather normalized kWh data as the dependent variable. Having taken out the effect of abnormal weather, *typical* weather can of course still play a role in the models.

The other is to estimate models using recorded kWh in which *observed* weather can play a role. Once the model has been estimated, it can be evaluated using the long-term normal weather average. The latter approach was chosen.

This approach was originally chosen for several reasons. First, there was the concern that by weather normalizing first, not only would the effect of abnormal weather be removed, but also perhaps some unknown portion of the pilot program effect. For example, if one first weather-normalized the kWh consumption data before the installation and then weather normalized kWh consumption after the installation, the coefficients on CDD for the pre period might be different than the coefficient for CDD in the post period. Of course, this difference could reflect differences in weather sensitivity. However, it could also at least partially reflect the fact that the new ventilation equipment uses less kWh and is interpreted as lower weather sensitivity. Thus, to weather-normalize may inadvertently remove some portion of the program effect. The solution was to estimate the model(s) using observed consumption and controlling for, among other things, the weather observed during the analysis period.

Once the final model(s) were estimated, it was planned to forecast gross impacts under normal weather conditions. More specifically, the estimated model(s) were to be evaluated (simulated) using long-term average HDD and CDD from PG&E weather stations. Unfortunately, long-term average HDD and CDD from PG&E weather stations were not available.

3.2.7 Generalizability

Since the sample was a convenience sample, described in Section 3.1.3, the gneralizability of the results of this analysis are limited. At best, the results can be generalized to those households in the same weather zones as those households that participated. At worst, the generalizability is unknown since the process contractors used to solicit homes for participation and how the homes selected might differ from those homes not selected are unknown.

However, as has been said previously in this report, the results of these households in these hotter climates represent the maximum opportunity to observe an effect from the installation of attic ventilation as a stand-alone measure.

4. RESULTS AND RECOMMENDATIONS

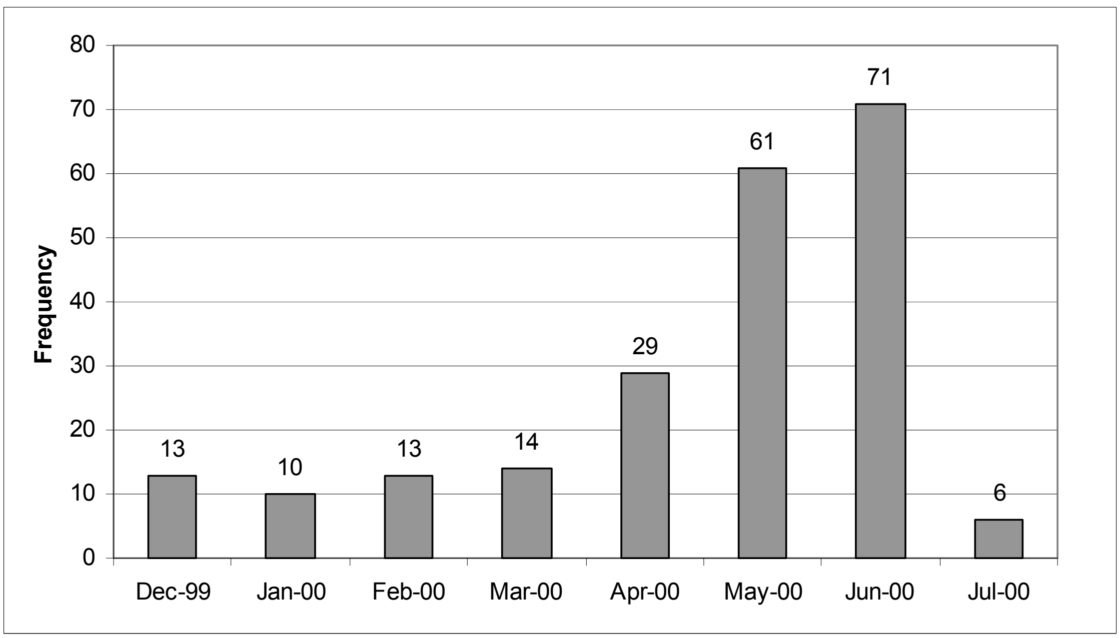
This section first provides some descriptive statistics of the stand-alone attic ventilation pilot program participant group, followed by the model results and recommendations.

4.1.1 Descriptive Statistics

This section presents some of the basic descriptive statistics for the 217 households included in the analysis.

First, the date of the installation varied across households, beginning in December 1999 and ending in July 2000. Exhibit 4.1 presents the installation date distribution by the month of installation.

Exhibit 4.1. Distribution of Installation Dates



The distributions of pre-installation monthly mean kWh and therm use are presented in Exhibit 4.2 and Exhibit 4.3.

Exhibit 4.2. Mean Pre-Installation kWh Use per Month

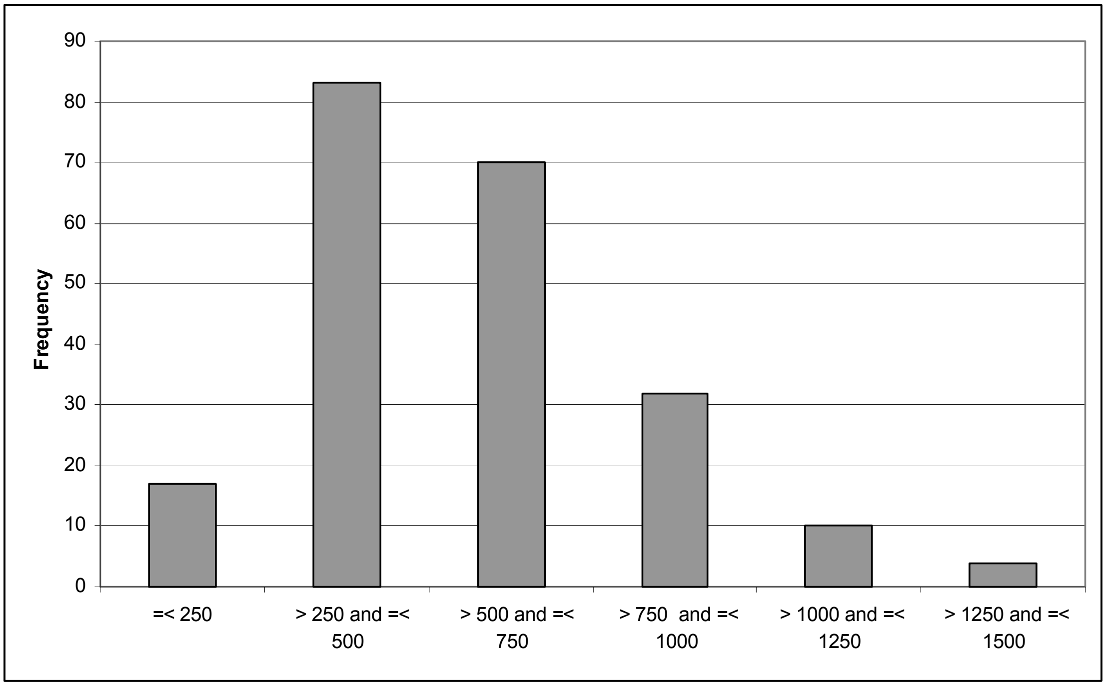
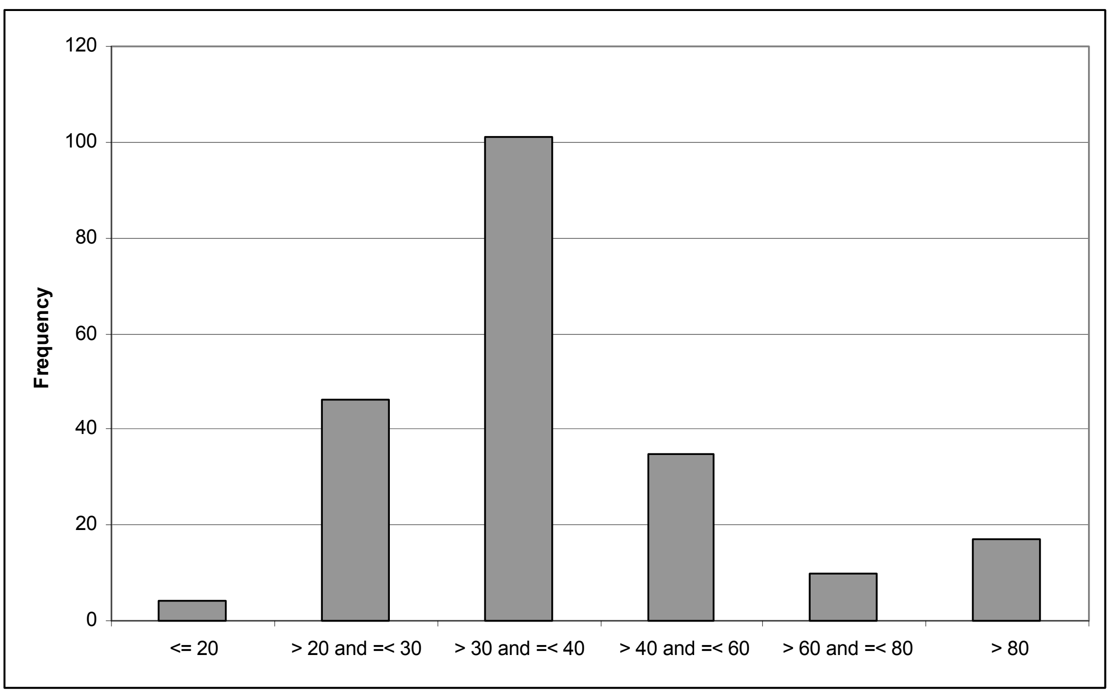


Exhibit 4.3. Mean Pre-Installation Therm Use per Month



The average pre- and post-installation kWh and therm consumption, cooling degree days for an air conditioning set point of 74 degrees F (CDD74) and heating degree days for a heater set point of 60 degrees F (HDD60), as well as the standard deviations and t statistics are presented in Exhibit 4.4.

Exhibit 4.4 Mean Pre- and Post-Installation for kWh, Therms, CDD74, and HDD60 and Standard Deviations and t Statistics

Means & Standard Deviations	Pre-Installation	Post-Installation	t statistic
Mean kWh per Month	552.2	580.2	3.9
Standard Deviation	293.2	323.4	
Mean Therms per Month	52.5	40.2	13.8
Standard Deviation	39.5	34.8	
Mean CDD74 per Month	13.5	34.6	24.5
Standard Deviation	27.7	42.6	
Mean HDD60 per Month	147.5	116.0	8.7
Standard Deviation	146.8	156.1	

The t tests were calculated to determine whether the differences in the pre- and post-installation means are statistically significant for both kWh and therms. The t statistics reported in Exhibit 4.4 indicates that all the differences are statistically significant. Thus, based on the observed kWh and therm data suggest that there is a statistically significant increase in kWh and a statistically significant decrease in therm consumption. This is consistent with the changes in heating degree-days and cooling degree-days that indicate that the post-installation period was hotter in the summer and warmer in the winter than the pre-installation period. Therefore, the estimation of the gross impact attributable to the installation of ventilation must rely on statistical controls or adjustments to arrive at a final impact.

Information regarding the types of cooling and heating systems may also help to explain the observed kWh and therm consumption. Exhibit 4.5 and Exhibit 4.6 present the frequencies for the types of heating and cooling systems in the 217 households included in the study.

Exhibit 4.5. Types of Heating Systems

Heating Type	Frequency	Percent
Central Heating System	128	59.0%
Wall Heater	60	27.6%
Floor Heater	13	6.0%
Space Heater	2	0.9%
No Heating System	1	0.5%
Missing	13	6.0%
Total	217	100.0%

Exhibit 4.6. Types of Cooling Systems

Cooling Type	Frequency	Percent
Central AC	119	54.8%
Wall AC	57	26.3%
Swamp cooler	25	11.5%
None	2	0.9%
Missing	14	6.5%
Total	217	100.0%

Note that the research hypothesis is that there should be a reduction in kWh resulting from the reduced cooling load and perhaps an increase in therms given the heat loss through the vent during the heating season. The maximum expected impact should be in homes with central air conditioners because of the larger size of the AC unit. However, only 55.8 percent of the households have central air conditioners. Nearly 39 percent have wall units or swamp coolers that have a much lower kWh use. The savings, if there are any, are therefore expected to be smaller than expected and therefore more difficult to detect statistically.

Another issue about which very little known is the price sensitivity of these participants. While the beginning of the energy crisis has been defined as January 2001, some low-income households were shielded from price increases due to their participation in the CARE program, which is PG&E's discount program for low-income households and housing facilities. CARE provides a 20 percent discount on monthly energy bills and ensures that its CARE customers are not subject rate increases imposed during 2001. Thirty-three percent of the households in which vents were installed currently participate in the CARE Program. This suggests that those on the CARE Program may be less responsive to the energy crisis when it took the form of increased rates. On the other hand, those not in the CARE Program were not shielded from the price increases, and, as a result, may have been more motivated to reduce their energy use.

Another impact of the energy crisis is that there was an enormous effort to assist low-income households through a variety of other energy conservation and energy efficiency programs, sponsored by utilities as well as the State of California. For example, the State of California, through the Civilian Conservation Corps, distributed, free of charge, millions of compact fluorescent light bulbs in low-income neighborhoods.

All of these issues help to underscore the importance of trying to model the impact of the energy crisis and the difficulty of teasing out the impact of the vent installations, while having only limited information available.

4.1.2 Model Results

This section presents the estimates of kWh and therm impacts that evolved from the statistical models. A wide variety of specifications were attempted. The results presented below provided the most satisfying results in terms of the R^2 and the fact that the signs of the coefficients are in the expected direction. The final kWh and therm models are identical in their specifications. Both employ a customer specific intercept, seasonal dummies[1], and variable for CDD74, HDD60, and the energy crisis. The customer-specific intercept attempts to capture the effects of a variety of household and demographic characteristics for which information was not available. This means that any customer-specific variables that do not change over time (e.g., type of cooling system) is dropped from the models since it will be perfectly collinear with the customer-specific intercept, making the model mathematically impossible to solve.

4.1.2.1 kWh Results

The results of the regression analysis for kWh are presented in Exhibit 4.7. When the value of the probability (p) is equal to or less than 0.05, then it is an indicator that this parameter is statistically significant. Using this criterion, all the parameters are significant except for Winter.

[1] Note that the reference category for the seasonal dummies is the fall. For example, a coefficient of 15.00 for the Summer variable means that the kWH consumption in the summer is 15 kWh higher in the summer than in the fall.

Exhibit 4.7. kWh Impact Regression Results

	Parameter Estimate	p > |t|
CDD74	1.78	< 0.0001
HDD60	0.21	< 0.0001
Spring	23.99	< 0.0001
Summer	53.22	< 0.0001
Winter	8.91	0.0641
Installation	15.91	< 0.0001
Energy Crisis	-32.75	< 0.0001
R^2=.309		

Using this model, the Crisis variable accounts for a 32.75 kWh per month reduction while an increase of 15.91 kWh per month (90% confidence interval of +/-5.83 kWh) is associated with the installation of the vent. It should be emphasized that the evaluation team does not believe that the installation of a vent actually caused an increase in kWh. Rather, it is believed that other things that could explain the increase were not measured by the study and are being attributed to the attic vent installation.

Even when the Crisis variable is removed from the model, the coefficient for Installation changes to –2.19, which is the expected sign, but it is not even close to being significant (p=0.4711). Note also that the positive relation between HDD60 and kWh is likely due to the fact that some of the households have electric heat and that there is an increased use of lighting in the evening during the winter.

Based on this analysis, it does not appear that the installation of the vent produced any kWh savings.

4.1.2.2 Therm Results

The results of the therm analysis are presented next in Exhibit 4.8. Again, when the value of the probability (p) is equal to or less than 0.05, then it is an indicator that this parameter is statistically significant. With this criterion, all the parameters are significant except for the installation parameter.

The Energy Crisis variable accounts for a 1.40 therm reduction per billing cycle and an unexpected decrease of 0.32 therms per billing cycle (90% confidence interval of +/-0.67 therms) is associated with the installation of the vent. However, the decrease in therm usage is not statistically significant. Note that when the Energy Crisis variable is removed from the model, the coefficient for Installation changes to –1.09, which, again, is not the expected sign (direction of change), but is significant (p=0.0005). In this case, it is believed that the effect of the energy crisis is being incorrectly attributed to the installation of the vent. Based on this analysis, it does not appear that the installation of the vent produced any therm savings or increases.

Exhibit 4.8. Therm Impact Regression Results

Variable	Parameter Estimate	p > |t|
CDD74	-0.59	< 0.0001
HDD60	0.14	< 0.0001
Spring	-0.88	0.1001
Summer	-0.45	< 0.3908
Winter	3.92	< 0.0001
Installation	-0.32	0.4370
Energy Crisis	-1.40	0.0029
R^2=.678		

The original Research Plan for this study stated that the effect would be evaluated with the effects for both kWh and Therms combined into British Thermal Units (Btu). However, given the results presented above for the individual energy sources, no advantage was seen for performing those estimations.

4.1.3 Conclusions

Based on the sample size chosen, this study should have been able to detect energy savings, if there were any, due to the installation of the stand-alone attic vents in the range of 3% to 6% of the base energy use. Those savings were not observed. While there were several important confounding variables (e.g., energy crisis, the impact of other conservation efforts sponsored by the State of California and utilities, the lack of data on household-specific characteristics that might have changed over time), the population studied was the sub-group of the low-income population with the highest expected effect from the installation of stand-alone attic ventilation. Therefore, it is the conclusions of this study that the expected savings for those in the sample appear to be smaller than 3% of the base energy consumption and would be expected to be even smaller for the larger population of all low-income households.

4.1.4 Recommendations

Based on the results of this study, it is recommended that the stand-alone attic ventilation measure should not be included in the LIEE portfolio of measures for the purpose of energy conservation.

A DATA COLLECTION INSTRUMENT

Draft Form for
Ventilation Pilot Program Data Collection Instrument

Name:______________________________________

Address:____________________________________

____

*City:____________________ Zip:_________

Phone Number:______________________________

*House type:

______ Single Family Detached

______ 2-4 Plex (customer must be on top floor) {If we decide to do both house types}

*Has this customer lived at this address for at least 1 year? _____Yes ______No

If no, do not perform installation.

*Current PG&E Electric Account Number: __________________________

*Is this the account number on the customer's bill? _____ Yes ______No

If not, what is the account number on the customer's bill? __________________________

*Current PG&E Gas Account Number:____________________________________

*Is this the account number on the customer's bill? _____ Yes ______No

If not, what is the account number on the customer's bill? __________________________

_______*This site does not have a PG&E gas bill because it is an all electric house. (Continue with installation)

_______This site does not have a PG&E gas bill because it uses something other than electric or gas to heat the house. (Do not perform insulation)

*Date of Ventilation Installation: ________________

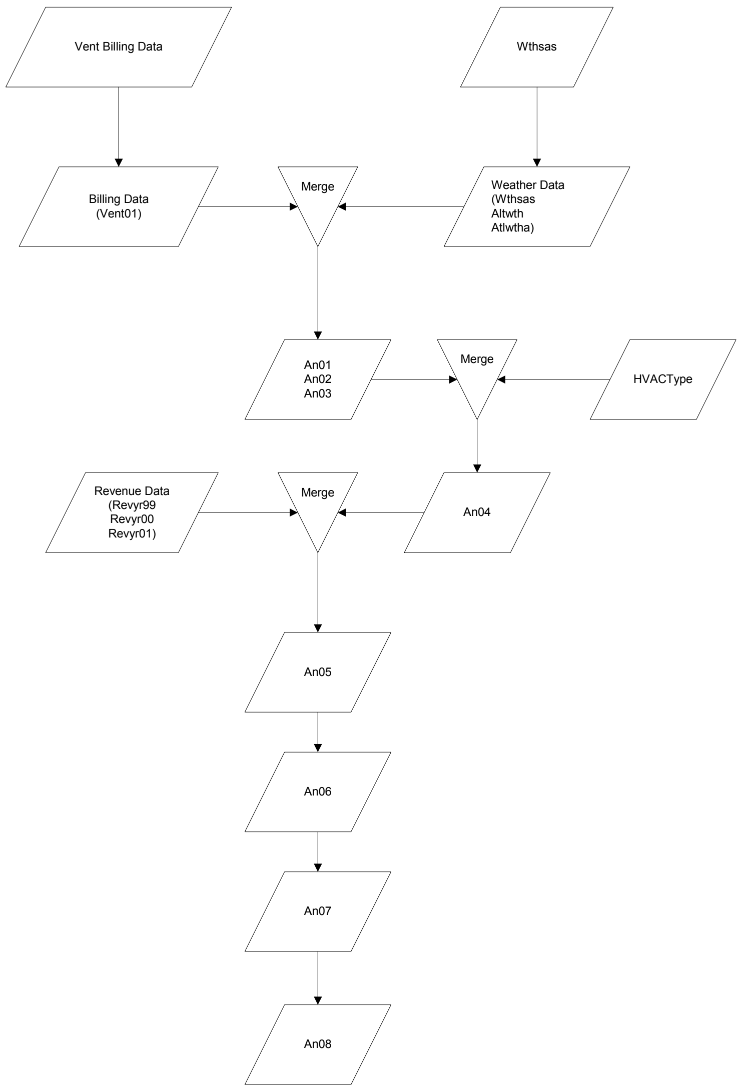
*Must have this data for the analysis

B DATA DOCUMENTATION

This Appendix first presents a flowchart that illustrates the construction of the analysis databases used in estimating gross kWh and therm impacts of the PG&E Ventilation Program.

The flowchart in Figure B-1 illustrates the construction of the analysis databases.

Figure B-1. Data Flow



Next, Table B-1 describes:

1. each input file and its number of observations and variables,
2. the SAS code that uses each input file, and
3. each output file and its number of observations and variables.

This is followed by a data dictionary of the terms used throughout the analysis.

Exhibit B-1. Input and Output Files and Related SAS Code Used in Estimating Ventilation Impacts

INPUT FILE	INPUT FILE OBS.	INPUT FILE VARS	SAS CODE	OUTPUT FILE	OUTPUT FILE OBS.	OUTPUT FILE VARS	FUNCTION
HVACTYPE.XLS	250	5	N/A DBMS COPY	HVACTYPE.sas7bdat	250	5	Creates customer and HVAC type file.
WTHSAS.XLS	974	48	N/A DBMS COPY	WTHSAS.sas7bdat	974	48	Creates CDD65 and HDD65
VENT BILING DATA.XLS	250	131	N/A DBMS COPY	VENT01.sas7bdat	250	157	Creates billing file
VENT01.SAS7BDAT WTHSAS.SAS7BDAT	250 974	157 48	RUN01.SAS	AN01.SAS7BDAT	9000	14	Merges weather file (CDD65/HDD65 with billing file.
WTHSAS.SAS7BDAT	974	48	RUN02.SAS	ALTWTH.SAS7BDAT	9	2,923	Creates CDD70 and HDD60
WTHSAS.SAS7BDAT	974	48	RUN03.SAS	ALTWTHA. SAS7BDAT	9	2,923	Creates CDD74 and HDD55
AN01.SAS7BDAT ALTWTH.SAS7BDAT	9000 9	14 2,923	RUN04.SAS	AN02.SAS7BDAT	7,812	16	Merges AN01.SAS7BDAT & ALTWTH.SAS7BDAT
AN02.SAS7BDAT ALTWTHA.SAS7BDAT	7,812 9	16 2,923	RUN05.SAS	AN03.SAS7BDAT	7,812	18	Merges AN01.SAS7BDAT & ALTWTH.SAS7BDAT
AN03.SAS7BDAT	7,812	18	RUN06.SAS	AN04.SAS7BDAT	7,812	28	Merges AN02.SAS7BDAT with HVAC type file
AN04.SAS7BDAT	7,812	28	RUN07.SAS	AN05.SAS7BDAT	7,811	32	Merges revenue data
AN05.SAS7BDAT	7,811	32	RUN08.SAS	AN06.SAS7BDAT	7,051	140	Creates additional variables and labels.
AN06.SAS7BDAT	7,051	140	RUN09.SAS	AN07.SAS7BDAT	7,019	154	Creates CARE Program variables and size variables
AN07.SAS7BDAT	7,019	154	RUN10.SAS	AN08.SAS7BDAT	7,019	164	Conducts analyses

All data are contained in one self-extracting zip file: PGE Ventilation Project.EXE

Data Dictionary

Variable Name	Variable Description
INSTALLDT	Date ventilation installed
CRISIS	Defines the pre and post energy crisis in California (coded 0 before 1/1/2001 and 1 thereafter)
CDD65	Billing cycle cooling degree-days for closest weather station for each sample household: Base 65°F
CDD70	Billing cycle cooling degree-days for closest weather station for each sample household: Base 70°F
CDD74	Billing cycle cooling degree-days for closest weather station for each sample household: Base 74°F
HDD50	Billing cycle heating degree-days for closest weather station for each sample household: Base 50°F
HDD55	Billing cycle heating degree-days for closest weather station for each sample premise: Base 55°F
HDD60	Billing cycle heating degree-days for closest weather station for each sample premise: Base 60°F
LCDD65	The lag of billing cycle cooling degree-days for closest weather station for each sample household: Base 65°F
LCDD70	The lag of billing cycle cooling degree-days for closest weather station for each sample household: Base 70°F
LCDD74	The lag of billing cycle cooling degree-days for closest weather station for each sample household: Base 74°F
LHDD50	The lag of billing cycle heating degree-days for closest weather station for each sample household: Base 50°F
LHDD55	The lag of billing cycle heating degree-days for closest weather station for each sample premise: Base 55°F
LHDD60	The lag of billing cycle heating degree-days for closest weather station for each sample premise: Base 60°F
KWH	Billing cycle recorded kWh consumption
THERM	Billing cycle recorded therm consumption
PART	Code 0 prior to installation date and 1 on the installation date and for all the billing cycles thereafter.
WINDOW	Coded 1 if cooling system is window, 0 otherwise.
CENTRAL	Coded 1 if cooling system is central unit, 0 otherwise.
WALL	Coded 1 if cooling system is wall or floor unit, 0 otherwise.
SWAMP	Coded 1 if cooling system is swamp cooler, 0 otherwise.
SPRING	Coded 1 if billing cycle is in the period 3/21 to 6/21, 0 otherwise
SUMMER	Coded 1 if billing cycle is in the period 6/21 to 9/21, 0 otherwise
FALL	Coded 1 if billing cycle is in the period 9/21 to 12/21, 0 otherwise

Variable Name	Variable Description
WINTER	Coded 1 if billing cycle is in the period 12/21 to 3/21, 0 otherwise
DEAD	Identifies the deadband month (1=deadband, 0 otherwise)
HCENTRAL	Coded 1 if central heating, 0 otherwise
HFLOR	Coded 1 if floor heater, 0 otherwise
HSPAC	Coded 1 if space heater, 0 otherwise
HWAL	Coded 1 if wall heater, 0 otherwise
PARTC65	Interaction of installation and CDD65
PARTC70	Interaction of installation and CDD70
PARTC74	Interaction of installation and CDD74
PARTH55	Interaction of installation and HDD55
PARTH60	Interaction of installation and HDD60
PARTH65	Interaction of installation and HDD65
EREV	Monthly PG&E electricity bill
GREV	Monthly PG&E gas bill
ESMALL	Coded 1 for small electricity use, 0 otherwise
EMEDIUM	Coded 1 for small electricity use, 0 otherwise
ELARGE	Coded 1 for small electricity use, 0 otherwise
GSMALL	Coded 1 for small therm use, 0 otherwise
GMEDIUM	Coded 1 for small therm use, 0 otherwise
GLARGE	Coded 1 for small therm use, 0 otherwise

C RESULTS FROM ALTERNATIVE REGRESSION MODELS

Dependent Variable: kWh

Root Mean Square Error	1586.40615
Dependent Mean	155.39446
Coefficient of Variation	1020.88979
R-Square	0.2819
Adjusted R-Square	0.2808

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	Squared Semi-partial Corr Type II	Squared Partial Corr Type II
Intercept	183.17	5.02	36.49	<.0001	.	.
CDD74	1.39	0.04	32.25	<.0001	0.11004	0.13287
HDD60	0.14	0.02	8.29	<.0001	0.00726	0.01001
Winter	12.96	4.30	3.02	0.0026	0.00096216	0.00134
Spring	12.09	4.68	2.58	0.0098	0.00070684	0.00098332
Summer	47.88	4.66	10.28	<.0001	0.01118	0.01533
Central AC	32.22	3.10	10.4	<.0001	0.01145	0.0157
CARE	-3.24	3.04	-1.07	0.2856	0.00012065	0.00016797
Small	-151.66	5.22	-29.04	<.0001	0.08922	0.11051
Medium	-74.70	4.63	-16.14	<.0001	0.02756	0.03696
Energy Crisis	-14.04	3.20	-4.38	<.0001	0.00203	0.00282

Dependent Variable: kWh

Root Mean Square Error	1588.5
Dependent Mean	155.4
Coefficient of Variation	1022.3
R-Square	0.280
Adjusted R-Square	0.279

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	Squared Semi-partial Corr Type II	Squared Partial Corr Type II
Intercept	180.61	5.234	34.50	<.0001	.	.
CDD74	1.37	0.043	31.70	<.0001	0.10662	0.12897
HDD60	0.15	0.017	8.78	<.0001	0.00818	0.01123
Winter	8.93	4.199	2.13	0.0335	0.00047989	0.00066602
Spring	8.80	4.622	1.90	0.057	0.00038461	0.00053386
Summer	44.23	4.601	9.61	<.0001	0.0098	0.01343
Central AC	32.24	3.101	10.40	<.0001	0.01147	0.01568
CARE	-3.19	3.041	-1.05	0.294	0.00011683	0.00016222
Small	-151.67	5.230	-29.00	<.0001	0.08921	0.11024
Medium	-74.52	4.635	-16.08	<.0001	0.02743	0.03669
Installation	2.81	2.770	1.01	0.3102	0.00010928	0.00015175

Dependent Variable: kWh

Root Mean Square Error	1583.7
Dependent Mean	155.4
Coeff Var	1019.2
R-Square	0.284
Adjusted R-Square	0.283

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	Squared Semi-partial Corr Type II	Squared Partial Corr Type II
Intercept	174.76	5.30	33.0	.	.	
CDD74	1.37	0.04	31.8	<.0001	0.10673	0.12979
HDD60	0.13	0.02	7.9	<.0001	0.00665	0.00921
Winter	19.00	4.46	4.3	<.0001	0.00191	0.00266
Spring	17.25	4.79	3.6	0.0003	0.00137	0.00191
Summer	49.90	4.67	10.7	<.0001	0.01205	0.01656
Central AC	32.31	3.09	10.5	<.0001	0.01152	0.01584
CARE Program	-3.53	3.03	-1.2	0.2443	0.00014299	0.00019978
Small Customer	-152.22	5.21	-29.2	<.0001	0.08984	0.11155
Medium Customer	-74.73	4.62	-16.2	<.0001	0.02758	0.03711
Energy Crisis	-26.92	4.13	-6.5	<.0001	0.00447	0.00621
Installation	17.55	3.57	4.9	<.0001	0.00255	0.00355

Dependent Variable: kWh [1]

R-Square	Coefficient of Variation	Root Mean Square Error	kWh Mean
0.331105	1000.956	1555.43	155.3945

Variable	Parameter Estimate	Standard Error	t Value	Pr>|t|
CDD74	1.40	0.04	33.1	<.0001
Spring	11.33	4.59	2.5	0.0136
Summer	47.14	4.57	10.3	<.0001
Winter	13.22	4.22	3.1	0.0017
HDD60	0.14	0.02	8.2	<.0001
Energy Crisis	-14.19	3.14	-4.5	<.0001

[1] Customer-specific intercepts used.

Dependent Variable: kWh [1]

R-Square	Coefficient of Variation	Root Mean Square Error	kWh Mean
0.329241	1002.35	1557.596	155.3945

Variable	Parameter Estimate	Standard Error	t Value	Pr>|t|
CDD74	1.38	0.04	32.52	<.0001
Spring	8.12	4.54	1.79	0.0736
Summer	43.38	4.51	9.61	<.0001
Winter	9.28	4.12	2.25	0.0243
HDD60	0.14	0.02	8.71	<.0001
Installation	3.93	2.74	1.44	0.151

[1] Customer-specific intercepts used.

Dependent Variable: Therms[1]

R-Square	Coefficient of Variation	Root Mean Square Error	kWh Mean
0.678343	682.9	88.40776	12.94593

Variable	Parameter Estimate	Standard Error	t Value	Pr>|t|
cdd74L	-0.059	0.005	-10.88	<.0001
spring	-0.787	0.524	-1.50	0.1332
summer	-0.413	0.524	-0.79	0.4299
winter	4.036	0.485	8.33	<.0001
Hdd60L	0.140	0.002	72.76	<.0001
crisis_A	-1.630	0.360	-4.52	<.0001

[1] Customer-specific intercepts used.

Dependent Variable: Therms[1]

R-Square	Coefficient of Variation	Root Mean Square Error	kWh Mean
0.677932	683.3365	88.46427	12.94593

Variable	Parameter Estimate	Standard Error	t Value	Pr>|t|
CDD74	-0.06	0.01	-10.76	<.0001
Spring	-1.37	0.51	-2.67	0.0077
Summer	-0.75	0.52	-1.45	0.146
Winter	3.40	0.47	7.16	<.0001
HDD60	0.14	0.00	73.28	<.0001
Installation	-1.09	0.31	-3.49	0.0005

[1] Customer-specific intercepts used.

Dependent Variable: Therms

Root Mean Square Error	88.22
Dependent Mean	12.95
Coefficient of Variation	681.46
R-Square	0.67
Adjusted R-Square	0.67

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	Squared Semi-partial Corr Type II	Squared Partial Corr Type II
Intercept	14.236	0.755	18.86	<.0001	.	.
CDD74	-0.059	0.005	-11	<.0001	0.00598	0.01777
HDD60	0.140	0.002	72.95	<.0001	0.26310	0.44317
Winter	4.057	0.483	8.39	<.0001	0.00348	0.01042
Spring	-0.777	0.522	-1.49	0.1365	0.00011	0.00033
Summer	-0.395	0.522	-0.76	0.4493	0.00003	0.00009
Central Heat	0.114	0.320	0.35	0.7228	0.00001	0.00002
Smal Customer	-9.691	0.672	-14.42	<.0001	0.01027	0.03014
Medium Customer	-5.845	0.666	-8.78	<.0001	0.00381	0.01139
CARE Program	0.860	0.338	2.54	0.0111	0.00032	0.00096
Energy Crisis	-1.644	0.359	-4.57	<.0001	0.00103	0.00312

Dependent Variable: Therms

Root Mean Square Error	88.27
Dependent Mean	12.95
Coefficient of Variation	681.81
R-Square	0.67
Adjusted R-Square	0.67

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	Squared Semi-partial Corr Type II	Squared Partial Corr Type II
Intercept	14.773	0.773	19.11	<.0001	.	.
CDD74	-0.059	0.005	-10.84	<.0001	0.00582	0.01727
HDD60	0.141	0.002	73.49	<.0001	0.26730	0.44682
Winter	3.402	0.473	7.2	<.0001	0.00256	0.00769
Spring	-1.372	0.513	-2.68	0.0075	0.00035	0.00107
Summer	-0.732	0.515	-1.42	0.1551	0.00010	0.00030
Central Heat	0.112	0.321	0.35	0.7258	0.00001	0.00002
Smal Customer	-9.710	0.673	-14.44	<.0001	0.01031	0.03022
Medium Customer	-5.836	0.666	-8.76	<.0001	0.00380	0.01134
CARE Program	0.874	0.339	2.58	0.0099	0.00033	0.00099
Installation	-1.160	0.311	-3.73	0.0002	0.00069	0.00208

D REFERENCES

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