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Home Performance with ENERGY STAR: Utility Bill Analysis on Homes Participating in Austin Energy's Program

Technical Report
NREL/TP-640-41903
July 2007

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Executive Summary

Home Performance with ENERGY STAR (HPwES) is a jointly managed program of the U.S. Department of Energy (DOE) and the U.S. Environmental Protection Agency (EPA). This program focuses on improving energy efficiency in existing homes via a whole-house approach to assessing and improving a home's energy performance, and helping to protect the environment.

As a local sponsor for HPwES, Austin Energy's HPwES program offers a complete home energy assessment and a list of recommendations for efficiency improvements, along with cost estimates. The owner can choose to implement only one or the complete set of energy conservation measures. Austin Energy facilitates the process by providing economic incentives to the homeowner through its HPwES Loan program and its HPwES Rebate program. In 2005, the total number of participants in both programs was approximately 1,400. Both programs are only available for improvements made by a participating HPwES contractor.

The study

To determine the benefits of this program, the National Renewable Energy Laboratory (NREL) collaborated with the Pacific Northwest National Laboratory (PNNL) to conduct a statistical analysis using energy consumption data of HPwES homes provided by Austin Energy. This report provides preliminary estimates of average savings per home from the HPwES Loan Program for the period 1998 through 2006. The estimates are based on electricity billing records provided by Austin Energy for more than 7,000 households, and relate only to electricity used for cooling.

Analysts conducted a regression analysis using billing histories and patterns related to energy use, seasonal temperatures, kilowatt hours used, cooling reference temperatures, and other factors.

Analysis results

The results from this preliminary analysis suggest that the HPwES program sponsored by Austin Energy had a very significant impact on reducing average cooling electricity for participating households. Overall, average savings were in the range of 25%-35%, and appear to be robust under various criteria for the number of households included in the analysis.

This study provided a statistically rigorous approach to incorporating the variability of expected savings across the households in the sample together with the uncertainty inherent in the regression models used to estimate those savings. While the impact of the regression errors was found to be relatively small in these particular samples, this approach may be useful in future studies using individual household billing data.

This preliminary analysis provides robust estimates of average savings, but offers no insight into how savings may vary by type of conservation measure or whether savings vary by the amount of cooling electricity used prior to undertaking the measure. Households that use electricity for heating might also be separately analyzed. In potential future work, several methodological improvements could also be explored.

This report outlines the background of the program, the methodology used in the study and the implementation of the analytical approach, the results of the preliminary analysis, and conclusions with possible next steps.

1.0 Background

Austin Energy's Home Performance with ENERGY STAR (HPwES) program, previously known as the Loan and Whole House program, is a residential energy improvement program for existing homes that focuses on the whole house and involves a complete home energy assessment and a set of recommendations with cost estimates. The owner can choose to implement only one or the complete set of energy conservation measures (ECM). Austin Energy facilitates the process by providing economic incentives to the homeowner through its HPwES Loan program and its HPwES Rebate program. In 2005, the total number of participants in both programs was approximately 1,400 with average participation since 1998 ranging from 1,000-1,200 households. Both programs are only available for improvements made by participating HPwES contractors.[1]

Purpose of this study

This report is intended to provide preliminary estimates of average savings per home via the HPwES program for the period 1998 through 2006. To determine the benefits of this program, the National Renewable Energy Laboratory (NREL) collaborated with the Pacific Northwest National Laboratory (PNNL) to conduct a statistical analysis using energy consumption data of HPwES homes provided by Austin Energy.

The estimates are based on electricity billing records provided by Austin Energy for more than 7,000 households. The preliminary values of savings relate only to the estimated amount of electricity used for cooling.

HPwES Loan Program

The HPwES Loan program offers low-interest loans that are unsecured and which do not require a lien on the property. There are different types of loans for the customer to choose from, and these loans can be applied to the costs of the ECMs.

To be eligible for these loans, participants must be Austin Energy electric customers with a single-family home, condominium, townhome, duplex, or rental property.[2] The average loan in this program for a new air-conditioning (A/C) system and typical air-sealing and insulation improvements is about $5,000.

HPwES Rebate Program

The HPwES Rebate program offers a rebate up to 20% of the cost of the ECMs (up to $1,400). Participating contractors provide recommendations and cost estimates for home energy

[1] Also, most participating contractors provide a home energy analysis which takes approximately 30 minutes, free of charge. The participating company arranges for Austin Energy to review its energy analysis and bid estimates, and gets approval on the proposed work. After the work is completed, the Participating Company arranges for a final inspection by Austin Energy. Once Austin Energy inspects the completed work, the homeowner signs the final inspection report and pays for services (or faxes the report to the financing institution in case of a loan).
[2] http://www.austinenergy.com

improvements, including expected rebates. To be eligible for this program, a customer must qualify for $75 in minimum rebates.[3]

Energy Conservation Measures

The ECMs covered under the loan and rebate programs are as follows:

- Installation of a new energy-efficient air conditioner or heat pump (12 SEER[4,5]/10.5 EER or greater)
- Duct repair and air sealing
- Additional attic insulation
- Installation of solar screens, window film or Low-E glass
- Caulking and weather stripping
- Installation of attic radiant barrier/reflective material
- Installation of solar shading or awnings

For additional information on Austin Energy's HPwES loan and rebate program, visit their Web site and follow the energy efficiency link.[6]

2.0 Methodology

This section lays out the general analytical approach that involves estimation of a simple model for each household, using a variable degree-day framework. Various filters were applied to the model results to ensure that only households whose electricity consumption was consistent with the degree-day specification were included in the (pre- and post-measure) comparison statistics.

2.1 General Approach

Total energy used in households is the sum of energy for various end uses. For electricity, the principal uses include space cooling, refrigeration, lighting, cooking, clothes washing and drying, and other miscellaneous uses. The vast majority of homes in the Austin Energy service area use natural gas for space and water heating. In Austin's warm climate, air conditioning in many households appears to be the single largest end use of electricity. For these households, a very simple model for residential electricity use can be formulated as[7]:

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[3] http://www.austinenergy.com
[4] Seasonal Energy Efficiency Ratio
[5] At the time of data collection for this analysis the standard was a minimum of 10 SEER for AC, so the program required installation of 12 SEER or greater. The minimum standard has been increased to 13 SEER, so the program now requires installation of 14 SEER or greater.
[6] http://www.austinenergy.com
[7] This method of computing the average daily temperature is the conventional method used for subsequent computation of degree days. See, for example, the discussion on the following website: http://www.weather2000.com/dd_glossary.html

$$E = a + bCDD(T_{rc}) + e \qquad (1)$$

where E = Energy consumption
a,b = regression-model coefficients (discussed below)
CDD = Cooling Degree Days
T_{rc} = reference temperature for cooling
e = error term

Cooling degree days (CDD) are calculated in the conventional manner. For each day in the observation period (i.e., billing period), the average daily temperature is first computed as the average between the minimum and maximum temperatures over the 24 hours of that day. The number of degree days for a specific day is the difference between the temperature chosen as the reference and the observed mean temperature. For cooling, if the mean temperature is lower than the reference temperature, the CDD is zero. The CDD for each day are summed across the number of days in the observation period to form the variable in Equation (1).

As applied in a statistically based analytical framework, the reference temperature (T_{rc}) is defined as the temperature that maximizes the explanatory power of the model above (i.e., minimizes sum of squared residuals). Physically, T_{rc} approximates the outdoor temperature above which the air conditioning system must operate to maintain a constant indoor air temperature (Hirst et al. 1987).

In this approach, the measure of degree days varies by household, derived from the pattern of actual consumption rather than being based on some fixed temperature (e.g., 65 degrees F., as the most commonly published values). As discussed below, a variety of factors will make the reference temperature different for each household.

Most energy analysts will recognize that this approach is similar to that used by the PRISM (Princeton Scorekeeping Method) algorithm, which first gained popularity in the mid-1980s (Fels 1986). Over reasonably short time intervals, energy consumption is regressed against degree days—either for heating, or cooling, or both. A key feature of the PRISM software is its ability to determine the most appropriate reference temperature(s) and provide some level of statistical confidence for that parameter.[8]

In Equation (1) as focused on cooling, the *b* coefficient indicates the magnitude of the response of air-conditioning electricity use to changes in outside temperature. It incorporates both the thermal integrity of the structure (overall U-factor, solar gains through windows, and infiltration) as well as the efficiency of the cooling equipment (as well as distribution losses through the duct system).

[8] A disclaimer is appropriate at this point regarding PRISM. While motivated by the PRISM approach and many of the published studies using the PRISM software, the work discussed in this report does *not* use that software. The sheer number of observations and the short time frame under which this work was performed precluded the use of the PRISM software. All computations for this study were performed with special routines written in the GAUSS matrix programming language.

Energy consumption for non-space conditioning (often termed base-level consumption) is represented by coefficient *a* in Equation (1). If monthly data is used in (1), then *a* would represent average *monthly* non-space conditioning energy use. For homes using natural gas for space and water heating, this base-level electricity use would primarily result from lights, refrigerators, electronic equipment (including televisions), and other appliances.

Although the majority of households in the Austin sample appear to use natural gas as their primary heating fuel, very high electricity consumption was observed during the winter months in a number of cases—indicating electricity as the major heating fuel. In these cases, the most appropriate model specification includes *heating* degree days as a separate variable. To explicitly account for different lengths of billing periods, the number of days (Days) was also included as a variable in the model. These extensions result in the extended specification shown in Equation (2):

$$E = aDays + bCDD(T_{rc}) + cHDD(T_{rh}) + e \tag{2}$$

where E = Electricity consumption for billing period

a = regression coefficient representing daily energy consumption for non-space conditioning

Days = number of days in a billing cycle

b = regression coefficient measuring the response to cooling degree days

CDD = Cooling Degree Days

T_{rc} = reference temperature for cooling

c = regression coefficient measuring response to heating degree days

HDD = Heating Degree Days

T_{rh} = reference temperature for heating

e = error term

As implemented in this study, the specification in Equation (2) was estimated for *all* households. Even in households where electricity did not appear to be the primary heating fuel, some increase in electricity use was typically observed during the winter—likely stemming from increased fan use for the central heating system or auxiliary electric space heaters (augmented to some degree by increased seasonal use of electricity for lighting and water heating). If there is no significant increase in winter electricity consumption, the estimated coefficient, *c*, in Equation (2) will simply be very small and statistically insignificant.

To show how the reference temperature depends on several key factors, we need to consider more carefully the formal physical foundation for the variable degree-day or PRISM approach. On a steady-state basis in a cooling situation, the heat required to be removed by the A/C system to maintain a constant temperature in a typical residential structure can be represented as:

$$q = uA(T_{out} - T_{in}) + I \qquad (T_{in} < T_{out}) \tag{3}$$

where q = heat removal required to maintain constant indoor temperature (Btu/hr), and

u = overall heat transmission coefficient of envelope

component (Btu/hr-ft^2-°F)
A = Area of envelope components (ft^2)
T_{in} = Indoor temperature (°F)
T_{out} = Outdoor temperature (°F)
I = Internal heat gains from people, appliances, and solar gain(Btu/hr)(B)

The reference temperature, T_{rc}, is the outside temperature at which the air-conditioning system is not required. At this temperature, $T_{rc} = T_{out}$, and $q = 0$. With these conditions, we can rearrange Equation (3) to solve for T_{rc}:

$$T_{rc} = T_{in} - \frac{I}{uA} \tag{4}$$

Equation (3) provides the fundamental explanation of the reference temperature; that is, it is primarily influenced by the indoor temperature but modified by the level of internal gains and the integrity of the building envelope (*u*). As all of these variables on the right-hand side of Equation (3) are expected to vary across households, an approach that permits the most appropriate reference temperature to be estimated directly from the data is desirable.

For the households in this analysis, the principal energy conservation measure was the purchase of a high-efficiency heat pump or air conditioner. As a first approximation, the use of more efficient air-conditioning equipment is not expected to affect the reference temperature.[9]

To summarize, the variable degree-day approach in this analysis differs in several respects from a classical PRISM study: First, in a PRISM analysis, all the model parameters are separately estimated in the pre-ECM and post-ECM periods. In this study, Equation (2) was estimated over the entire period, and the resulting estimate of the reference temperature was subsequently held to be the same for the two sub-period regressions. Holding the reference temperature to be the same in each sub-period is reasonable as the principal conservation measure was the replacement with an ENERGY STAR air conditioner. Assuming that the household maintained similar thermostat settings before and after the measure, the use of the same reference temperature is appropriate. In practical terms, the use of a single reference temperature considerably simplifies the estimation procedure and does not lead to implausible differences in the reference temperatures that may be caused by abnormal consumption in one or more billing periods. In this study, with many thousands of customers, it was not possible to perform a visual inspection of each set of billing data.

Second, because most households in the study do not use electricity as their primary heating fuel, the analysis is focused on cooling use. However, for practical reasons, no attempt was made to distinguish those households that appeared to use electricity for heating from those that did not. Thus, heating and cooling degree-days were included as explanatory variables for all households. As compared to the PRISM's (HC5) electricity model for heating and cooling—where *separate*

[9] In an extended analysis, one might look for evidence of a "take-back" effect, reflecting a household's decision to set the thermostat lower after the installation of a more efficient air conditioner. Such an analysis was not considered for this brief study.

reference temperatures are estimated for heating and cooling—the approach here was to assume that reference temperature for heating was a constant difference from the reference temperature for cooling for all households. This dramatically simplifies the estimation process and precludes unreasonable estimates of the heating reference temperature. Trial values of a constant 5- and 8-degree temperature difference were tested.[10] Eight degrees as the constant temperature difference yielded better overall goodness-of-fit statistics.

2.2. Implementation

The implementation of the analytical approach included the following steps:

1. *Implement billing data adjustments*. The data provided by Austin Energy included billing histories for 7,536 households, with more than 870,000 individual bills. The format for each bill was as follows: Ending date, kWh used, Beginning date, No. of Days, Premise Number. A description of the steps taken to make the data consistent for use in the regression is reported in **Appendix A.**

2. *Link Data Sets.* For the selected customer, the beginning and ending dates for each bill were linked to a corresponding vector of daily average temperatures. The measure installation date was then used to select an analysis period for each customer. For this analysis, the 30 bills before and after the presumed measure installation date were selected out of the complete sample, to give a total data set of 60 bills for each of the 7,536 households. As billing periods generally run about a month, the use of 30 bills in both the pre- and post-ECM analysis is meant to capture two summer seasons of electricity use for each sub-period. (Any customer with fewer than 10 bills for either period was dropped from the analysis. See **Table 3.1** for a breakdown of initial billing data selection criteria.)

3. *Estimate the cooling reference temperature.* A preliminary nonlinear regression with the entire set of bills (typical from 1997 through 2006) was performed using the specification in Equation (2). Using the estimated cooling reference temperature as an initial starting value, a second regression was performed using only the 60-bill final analysis period. In both regressions, the heating reference temperature was fixed to be 8 degrees lower than the cooling reference temperature, as explained in Section 2.1.

4. *Estimate coefficients for each sub-period*. Given the reference temperatures for cooling and heating, the corresponding cooling and heating degree-days are computed for each billing observation for the pre- and post-ECM time period. Using the degree-day variables along with the number of days in each period (Days), the parameters in Equation (2) are estimated for each period using a conventional ordinary least squares calculation.

[10] The choice of the 8-degree was motivated, in part, by the results reported by Stram and Fels (1985). Using PRISM to analyze a sample of 50 electrically heated households in New Jersey, they reported that the median reference temperature for cooling was 5 degrees C higher than that for heating.

5. *Calculate Normalized Consumption and Standard Errors.* The final step is to use the parameter estimates from Step 3 to develop measures of consumption based on average weather conditions. In this analysis, "long-term" average temperatures for each day of the year were based on mean temperatures over the 1998-2006 timeframe. Two normalized measures were constructed: annual total consumption and annual cooling consumption. Annual total consumption simply involves using the full parameter set along with the long-term average degree days. The normalized cooling consumption (NCC) was calculated as the product of the *b* coefficients and the nine-year average cooling degree days.[11] The normalized measures provide a consistent basis from which to measure (and aggregate) the absolute savings across households for which energy efficiency measures were installed in different years. Actual savings in any specific year would, of course, differ depending on whether temperatures were lower or higher than normal.[12]

2.3 Data "Cleaning"

In any empirical study involving individual billing histories, a number of factors can lead to unreasonable behavior of reported consumption over time. Some of these factors include: 1) disruption of service caused by change of owners, 2) low consumption caused by unoccupied periods from vacations or other absence, and 3) very high consumption from faulty equipment or special household projects that use large amounts of electricity for a short period.

Examples of some these anomalous consumption time series are shown in **Section 3.0**. For this preliminary study, no effort was made to "clean" this data or remove individual billing histories prior to the statistical analysis. This decision was prompted by the limited time and resources for this analysis and the large number of households included in the data set. However, as described in the next section, a number of filters were applied to the regression results to remove cases where unreasonable behavior of the time series of electricity consumption was suspected. With the very large number of households in the sample, this approach was not expected to introduce any significant bias into the results.

3.0 Results

The results from this preliminary analysis suggest that the HPwES conservation program conducted by Austin Energy had a very significant impact on reducing average cooling electricity for participating households. Overall, average savings were in the range of 25-35%, and appear to be robust under various criteria for the number of households to be included in the analysis.

Sample Selection

Average levels of participation in Austin Energy's HPwES program ranged from 1,000 to 1,200 households per year. The initial data set provided by Austin Energy contained billing records for

[11] The corresponding standard error for NCC was simply the standard error of *b* times the number of degree days.
[12] Much of the discussion in the results section below focus on *percentage* savings in cooling—thus abstracting from the year-to-year variation in weather conditions.

7,536 households during the period of 1998 through 2006. Forty-two households were not part of the HPwES program and were dropped from the data set. Thus, 7,494 households were considered as the starting point for the statistical analysis.

A number of criteria were applied to initially delete cases where unreasonable or inconsistent behavior was suspected in the underlying billing series. We also deleted households where the number of observations, either prior or subsequent to the installation of the ECM, was judged insufficient to yield a valid estimate of savings. Households with any billing period covering more than 60 days were deleted as well. [13]

Table 3.1 provides a breakdown of how many households were deleted prior to the computation of summary results.

Table 3.1. Initial Selection Criteria for Deleting Customer Billing Histories

Criterion	Description	No. of Cases
1	Fewer than 24 bills total adjacent to measure installation date	8
2	Fewer than 10 bills either before or after measure installation date	16
3	More than 60 days in a billing period	259
4	Estimated cooling reference temperature less than 60 degrees F.	262
5	Estimated cooling reference temperature more than 80 degrees F.	274
	Total cases (households) in data set	7,494
	Total cases deleted	827
	Cases for subsequent analysis	6,667

Because this study is concerned with developing statistically valid estimates of the impact of the Austin Energy program on cooling electricity use, we focused on those households for which the estimates of cooling consumption are satisfactorily estimated. A minimal statistical criterion in our judgment is that estimates of cooling consumption are significantly different from zero in both the pre-ECM and post-ECM at a 95% level of confidence. Operationally, this criterion translates into considering those households where the predicted normalized cooling consumption (NCC) is two times its standard error [or equivalently a relative standard error (RSE) of 50%].[14]

[13] We did not investigate potential reasons for billing periods to be longer than 60 days. In some cases, we speculate that access to the meter may not have been available during the normal meter-reading schedule. Table 3.1 also shows that cases with abnormally low or high estimates of the cooling reference temperature were deleted. We think it unlikely that these cases reflect actual occupant behavior but probably result from data anomalies that yield very low or high estimated reference temperatures.

[14] Because the NCC is basely solely on estimated coefficient for cooling in the regression, this criterion is equivalent to the t-statistics being greater than 2.0.

This criterion is fairly liberal in a study that seeks to estimate *differences* in cooling consumption after the installation of an ECM.[15] Typically, many ECMs are expected to yield savings in the range of 10% to 40%. Thus, it is useful to also examine those households where the statistical precision of predicted cooling is greater. Two other values for statistical precision were also considered—using RSEs of 20% and 10%.[16]

In addition to the reliability criteria, we also wanted to minimize the effect of outliers on the statistics involving the sample mean and variance. Thus, one additional filter was applied that deleted cases that were more than 3 standard deviations from the mean percentage savings. This filter was applied after the deletion of cases under the RSE criteria.

The effect of applying these reliability and outlier criteria to the 6,667 observations shown at the bottom of Table 3.1 is summarized in **Table 3.2**. The different data sets are labeled A, B, C.[17]

Table 3.2. Sample Sizes Using Statistical Precision of Predicted NCC

Sample Set	Criteria (RSE)	Number of Households
After initial filters	None	6,667
A	+/- 50%	6,096
B	+/- 20%	4,082
C	+/- 10%	1,234

To illustrate some of the types of statistical fits that fall into these sample sets, plots of predicted and actual consumption are shown for a few households in **Appendix B**. One of the selected households (in **Figure B.4**) displays electricity used for heating as well as cooling. Examples of several households that did not meet even the criteria for Sample A are also shown in Appendix B.

The subsequent discussion of results will focus only on Sample A. As indicated in Table 3.2, Sample A contains more than 6,000 households, in which the estimated coefficients on CDD were significantly different from zero at the 95% level of confidence. Several appendices are included to discuss the empirical results in more detail than what is presented below. Appendix C describes the method used to derive confidence intervals for the aggregate statistics. Appendix D compares the detailed results for the three samples of households defined in Table 3.2. All three samples produced similar estimates of the average level of energy savings.

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[15] By "liberal," we mean that this criterion only tests whether we can say with some confidence that the household used electricity for cooling. The more rigorous question is whether we can detect a statistically significant difference in cooling before and after the conservation measure.

[16] The choice of an RSE of 0.10 was one of the reliability criteria used in a 1985 study of individual house retrofits in Minnesota (Hewitt et al. 1985). In that study, there was a requirement that the Coefficient of Variation (equivalent to the RSE, but expressed as a fraction) for the Normalized Annual Consumption be greater than 0.1 in both the pre- and post-ECM periods. To support that choice of criterion, Hewitt et al. make reference to an earlier study that apparently performed some empirical experimentation with the PRISM specification.

[17] For Sample A, the reliability criteria (RSE < 50% for NCC) was not met by 485 households. Dropping cases at the tails of the subsequent distribution lowered the final sample size by 86 households, yielding the total of 6,096 as shown in the table.

In addition to the measures of savings that stem from the regression analysis, the variable-degree day approach also provides estimates of the reference temperatures that best explain the household billing data. This study indicates an average reference temperature for cooling of approximately 70 degrees F, with nearly symmetric variation around that value. The results related to the estimated reference temperatures are discussed in **Appendix E.**

Histogram of Percent Changes (Savings)

Using the largest sample (A), **Figure 3.1** shows the distribution of percentage changes in predicted electricity use between the pre- and post-ECM periods. The results yield a very smooth bell-shaped curve centered around a 30% reduction in electricity use after the ECM measure with a slight positive skewness. The median percentage difference (savings) for this sample is -31.9%. Reflecting the skewness of the distribution, the mean percentage difference is somewhat lower with a value of -28.4%.

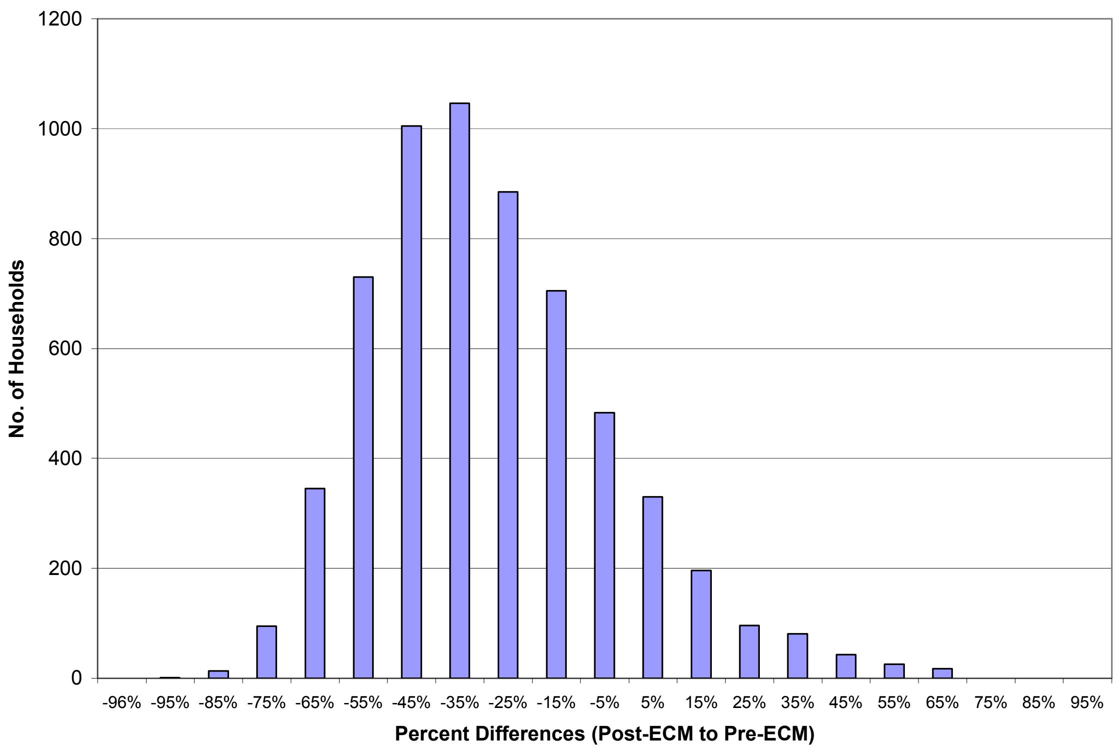

Figure 3.1. Histogram of Percentage Consumption Differences for Sample A

Summary Results – Medians

Measures of central tendency using individual household data can be reported as mean values or median values. Median values are useful in that they are relatively insensitive to outliers. Mean values are useful in that classical measures of the statistical reliability of the central tendency and the variability of the data are readily available. Fels (1986), in her introductory article discussing the PRISM approach, suggests using both measures.

Summary measures using median values of the individual-household regression results are shown in **Table 3.3**. The first column in the table defines the various metrics for the analysis. Recall that the normalized cooling consumption (NCC) is based on the estimated regression coefficient for cooling, multiplied by the nine-year annual average cooling degree days. As described in Section 2, the cooling degree days are computed separately for each household based on the estimated reference temperature for that household.

Table 3.3. Measures of Cooling Consumption and Savings – Median Values[18]

Sample A: Number of Households = 6096

	Median Value	Median S.E. of Value
NCC_pre (kWh/yr)	5,192.4	543.5
NCC_post (kWh/yr)	3,429.8	443.2
ΔNCC (kWh/yr)	-1,515.0	773.7
% = ΔNCC/NCC_pre	-31.9%	12.0%

The median reduction in annual electricity consumption for cooling is 1,515 kWh. On a percentage basis, the median reduction is 31.9%.

The second column in the table provides a measure of the statistical reliability of the estimated values for the pre- and post-ECM period as well as the change in electricity use. The median standard error of the change in consumption (ΔNCC) is about one-half of the absolute change. Thus, for an individual household at the mid-point of the distribution, one can say there is about a 95% probability that there is a positive level of savings.

The standard errors presented in Table 3.3 relate only to the error inherent in the statistical models at the individual household level. The table does not address the variability of predicted savings across household for the selected samples (as illustrated in Figure 3.1 for Sample A).

Summary Results – Means

Table 3.4 presents summary statistics based on means and standard deviations of the various consumption measures. Column (2) reports that the mean percentage reduction for Sample A is 28.4%.

[18] The medians for the absolute and percentage changes in the NCC in the third and fourth lines of the table are calculated on the basis of the individual sample results. Thus, for example, the median difference in the NCC (ΔNCC) is not equal to the difference in the medians of the pre- and post-retrofit NCCs.

Table 3.4. Measures of Cooling Consumption and Savings Based on Mean Values[19]

Sample A - Number of Households = 6,096	Mean	Std. Dev. (Sample)	Std. Error (Mean)
NCC_pre (kWh/yr)	5,627.5	2,659.2	35.7
NCC_post (kWh/yr)	3,883.9	2,160.6	29.0
ΔNCC (kWh/yr)	-1,743.6	1,796.0	26.9
% = ΔNCC/NCC_pre	-28.4%	25.0%	0.4%

The third column in the table provides an indication of the variability of each of the metrics across the full sample. There is obviously considerable variation in the estimated cooling consumption across the households in the sample, as indicated by the standard deviations (2,659 kWh/yr in the years just prior to implementing the conservation measure, and 2,161 kWh after the measure). The standard deviation of the percentage change in consumption in the sample household is 25%. Assuming an approximately normal distribution, the standard error of 25% for the percentage change would suggest that about two-thirds of the households had changes in the range of -53% to -3%. That range is roughly what can be observed in Figure 3.1.

Standard Error of the Mean Values

The final column in Table 3.4 shows the standard error associated with the mean value of savings. As discussed in Appendix C, this standard error reflects an adjustment to include both the sampling variation of predicted savings as well as the regression error inherent in the coefficients used to predict the cooling consumption.[20]

Because this study has a very large number of households (N), the standard errors of the mean values are very small. Looking at the percentage change in energy use in the last row of the table, the standard error is 0.4%. This value indicates that a 95% confidence interval would be about plus or minus 0.8% of the mean change (-28.4%). As a practical interpretation of the confidence interval, we can say that we are 95% confident that the true average level of savings lies between 27.6% and 29.2%.

[19] The mean of the percentage changes in the NCC (% ΔNCC/NCC_pre) in the last line of the table is calculated on the basis of the individual sample results. Thus, it is not equal to the mean change in the NCC (ΔNCC) divided by the mean pre-retrofit NCC. We are simply taking an unweighted average of the percentage changes in NCC across the sample households.

[20] This adjustment to include the regression model error increases the standard error of the mean percentage change (-28.4%) by about 20% over the value it would have taken without the adjustment. See discussion of Table C.1 in Appendix C.

4.0 Conclusions

The individual household billing data—encompassing more than 7,000 households—provided by Austin Energy provides a rich data set to estimate the impacts of its HPwES program. The length of the billing histories is sufficient to develop PRISM-type models of electricity use based on several years of monthly bills before and after the installation of the conservation measures.

Individual household savings were estimated from a restricted version of a PRISM-type regression model where the reference temperature to define cooling (or heating degree days) was estimated along with other parameters. Because the statistical quality of the regression models varies across individual households, three separate samples were used to measure the aggregate results. The samples were distinguished on the basis of the statistical significance of the estimated (normalized) cooling consumption. A normalized measure of cooling consumption was based on average temperatures observed over the most recent nine-year period ending in 2006.

This study provided a statistically rigorous approach to incorporating the variability of expected savings across the households in the sample together with the uncertainty inherent in the regression models used to estimate those savings. While the impact of the regression errors was found to be relatively small in these particular samples, this approach may be useful in future studies using individual household billing data.

The median percentage savings for the largest sample of 6,000 households in the analysis was 32%, while the mean savings was 28%. Because the number of households in the sample is very large, the standard error associated with the *mean* percentage savings are very small, less than 1%. A conservative statement of the average savings is that is falls in the range of 25% to 30% with a high level of certainty.

This preliminary analysis provides robust estimates of average program savings, but offers no insight into how savings may vary by type of conservation measure or whether savings vary by the amount of cooling electricity used prior to undertaking the measure. Follow-up researchers may want to analyze the impacts of specific ECMs. Households that use electricity for heating might also be separately analyzed.

In potential future work several methodological improvements could also be explored. As mentioned in Section 2, there was no formal attempt to clean the data set of outliers and other abnormal patterns of billing data prior to the statistical analysis. The restriction of a constant reference temperature might also be relaxed. This approach may provide evidence as to whether any “take-back” efforts are present, whereby thermostat settings are lowered during the summer months after the measures are undertaken (reflected in lower reference temperatures in the post-ECM period).

A more extended analysis may also justify the investment in and use of the PRISM software package, which may provide more diagnostic measures with respect to the reference temperature. PRISM also appears to contain some built-in capability to detect outliers and other anomalous data points.

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Appendix A – Billing Data Adjustments

The data provided by Austin Energy included billing histories for 7,536 households, with more than 870,000 individual bills. The format for each bill was as follows:

Ending date, kWh used, Beginning date, No. of Days, Premise Number

In a few cases, consumption values were negative, followed by a record with a positive value for consumption with the same dates. These cases were assumed to represent instances where a correction was made to the original meter reading (possibly substituting an actual value for a prior estimated value). The records with the negative readings were manually removed from the data set.

For roughly one-quarter of the households, several other types of inconsistencies were detected in the dates for the billing histories. The simplest inconsistency was the omission of the ending date for the billing record. A second type of inconsistency also involved a zero in the field for the ending date, but accompanied by duplicate starting dates for the adjacent bills.

An example of the first type of inconsistency is shown in the bills shown below. In this case, the ending date for the second bill is presumed to be 7/28/2004, consistent with the starting date for the third bill (7/28/2004 represented as an eight-digit number: year_month_day, or 20040728)

20040623, 1343, 20040524, 30, 1561700
0, 2192, 20040623, 35, 1561700
20040823, 1530, 20040728, 26, 1561700

An example of the second type of inconsistency is shown by the following bills for premise number 2829400. The ending date for the first bill (3/17/2001) is consistent with the starting date for the second bill. However, there is no ending date for either the second or third bills and these bills have duplicate starting dates.

20050317, 1729, 20050215, 30, 2829400
0, 1445, 20050317, 28, 2829400
0, 1932, 20050317, 36, 2829400
20050617, 2081, 20050520, 28, 2829400

An ending date for the second bill of 4/14/2005 can be derived from the number of days in the billing period (28). The missing ending date for the third bill can be filled as 5/20/2005, again consistent with the number of days and the starting date of the fourth bill. The adjusted series of bills, with the changed values in italics, then becomes

20050317, 1729, 20050215, 30, 2829400
20050414, **1445, 20050317, 28, 2829400**
20050520, **1932,** *20050414*, **36, 2829400**
20050617, 2081, 20050520, 28, 2829400

An automated procedure was developed to adjust the starting and ending dates with these problems to produce a consistent series of bills. In some cases, there remain some inconsistencies in the starting and ending dates between adjacent bills. For these cases, we used the number of days in the billing period to take precedence over the starting date in the subsequent bill. In some cases, duplicate bill records with the same starting and ending dates were generated. In these cases, only the last billing record was retained in the final data set.

Appendix B – Regression Results for Selected Households

This appendix presents the regressions for a very small set of households, primarily by means of plots comparing actual and predicted consumption for billing periods. With more than 6,000 households from which to choose, no claim is made that this particular sample is in any way representative. However, the cases were selected to give some illustration of the range of billing consumption patterns observed in the data set.

Table B.1 provides some of the regression model results for six households, with the focus on the t-statistics for the estimated coefficient. As described at beginning of Section 3, the t-statistics on these coefficients were, in essence, the selection criteria for assignment to samples A, B, or C. The six households are ordered from best fit to worst fit.

Table B.1. Selected Regression Results

House-hold No.	Sample	Cooling Coef. (pre-ECM)	t-Stat	Cooling Coef. (post-ECM)	t-Stat	Reference Temp.
1	A	3.14	24.4	1.55	14.2	73.7
2	B	1.99	6.45	1.26	14.1	71.6
3	C	4.70	11.3	2.74	3.1	75.7
4	B	3.83	15.4	2.26	6.0	71.6
5	none	1.85	1.70	1.87	7.35	68.7
6	none	-0.07	-0.2	0.54	5.3	62.8

Figures B.1 through B.6 plot the actual vs. predicted consumption values for the billing periods used in the regression model. The households selected all use 60 bills in the regression. The first 30 correspond to the pre-ECM period and the last 30 correspond to the post-ECM period.

The statistical fit for Household No. 1 is obviously very good, with high statistically significant coefficients on cooling for both pre- and post-ECM periods. The fits for Households No. 2 and No. 3 are not quite as good. For Household No. 3, the t-statistic on the cooling coefficient for the post ECM period is less than 5, putting it into the largest sample for the analysis (A).

Household No. 4 obviously indicates electricity used for heating. In a casual perusal of the data set, a few other households appeared to have relatively high winter consumption, reflecting at least some use of electricity for heating. The example here shows that the specification in Equation (2) provides a very good fit to the data, even without completely independent estimates of the reference temperatures for cooling and heating.

The bills for Households No. 5 and No. 6 display sufficient anomalies as to preclude their use in the overall results. For Household No. 5, the very high bill at the end of pre-ECM period leads to a low t-statistic for the estimated cooling coefficient (1.7 in Table B.1). Clearly, for Household No. 6, the pattern of consumption in the months prior to ECM is such that no meaningful model can be estimated.

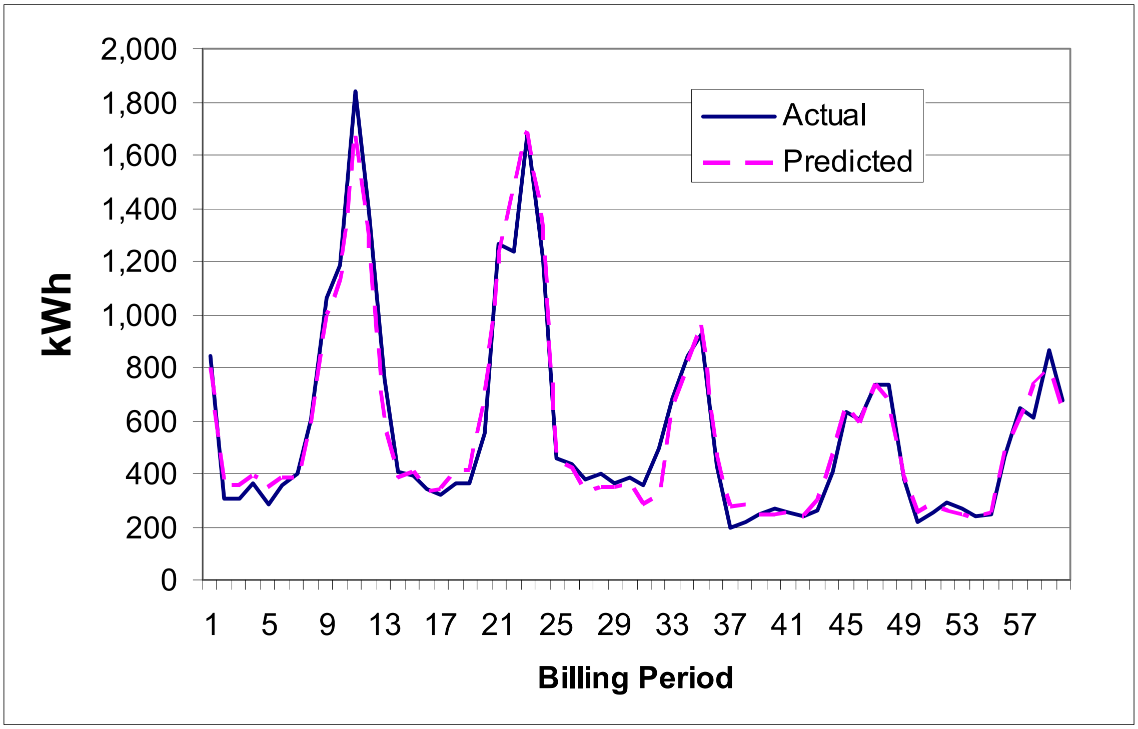

Figure B.1. Predicted vs. Actual Consumption for Household No. 1 (Sample A)

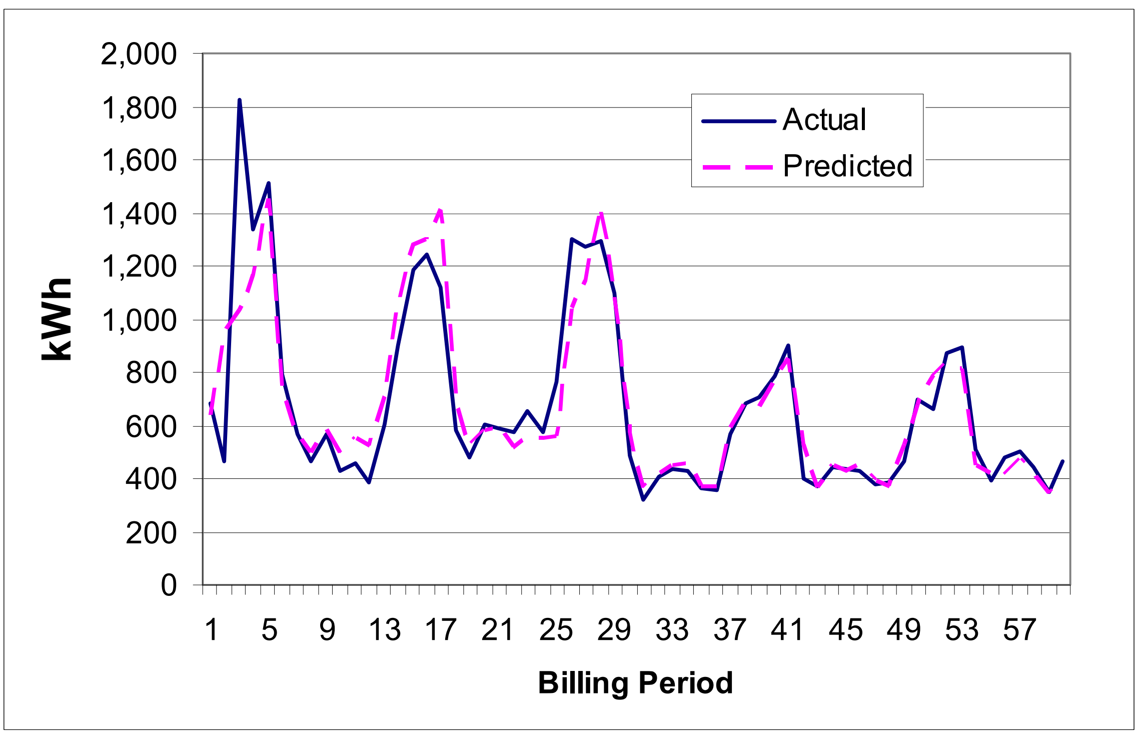

Figure B.2. Predicted vs. Actual Consumption for Household No. 2 (Sample B)

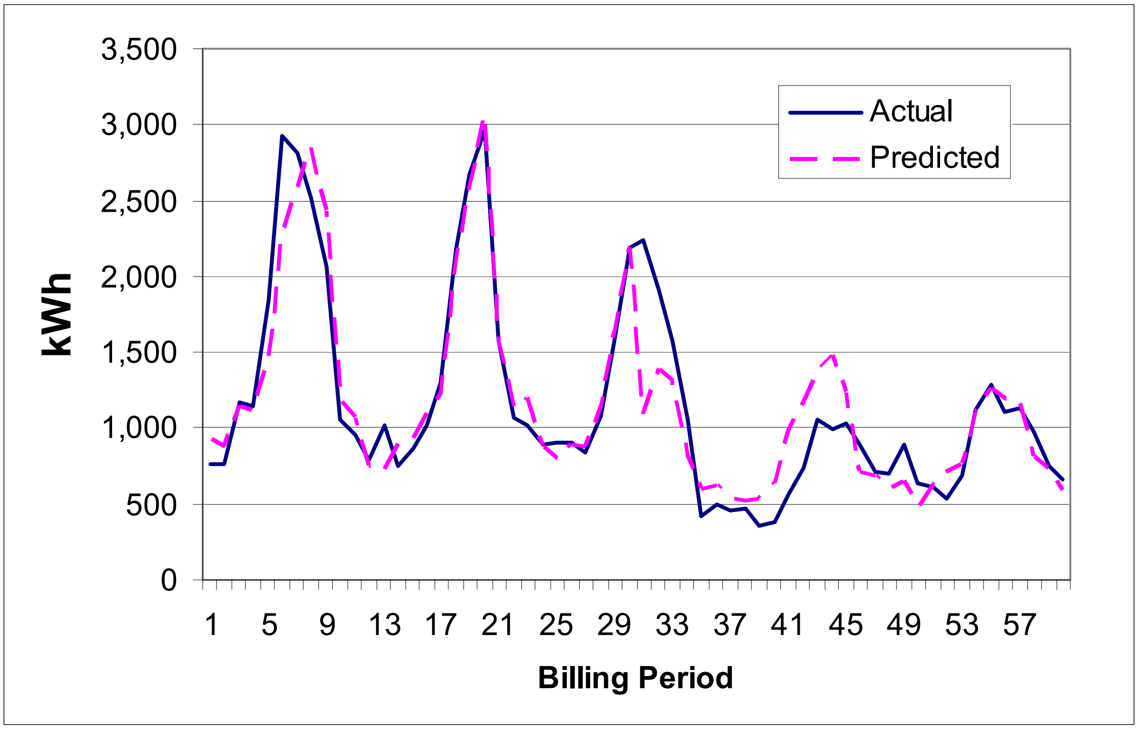

Figure B.3. Predicted vs. Actual Consumption for Household No. 3 (Sample C)

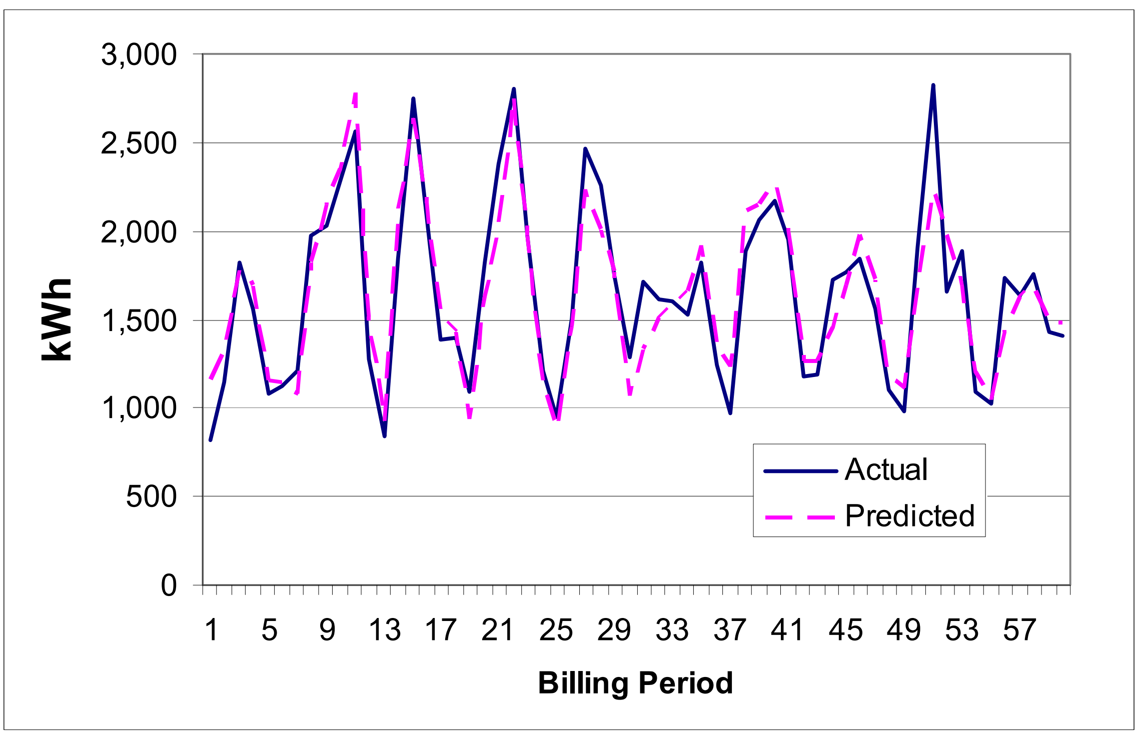

Figure B.4. Predicted vs. Actual Consumption for Household No. 4 (Heating and Cooling)

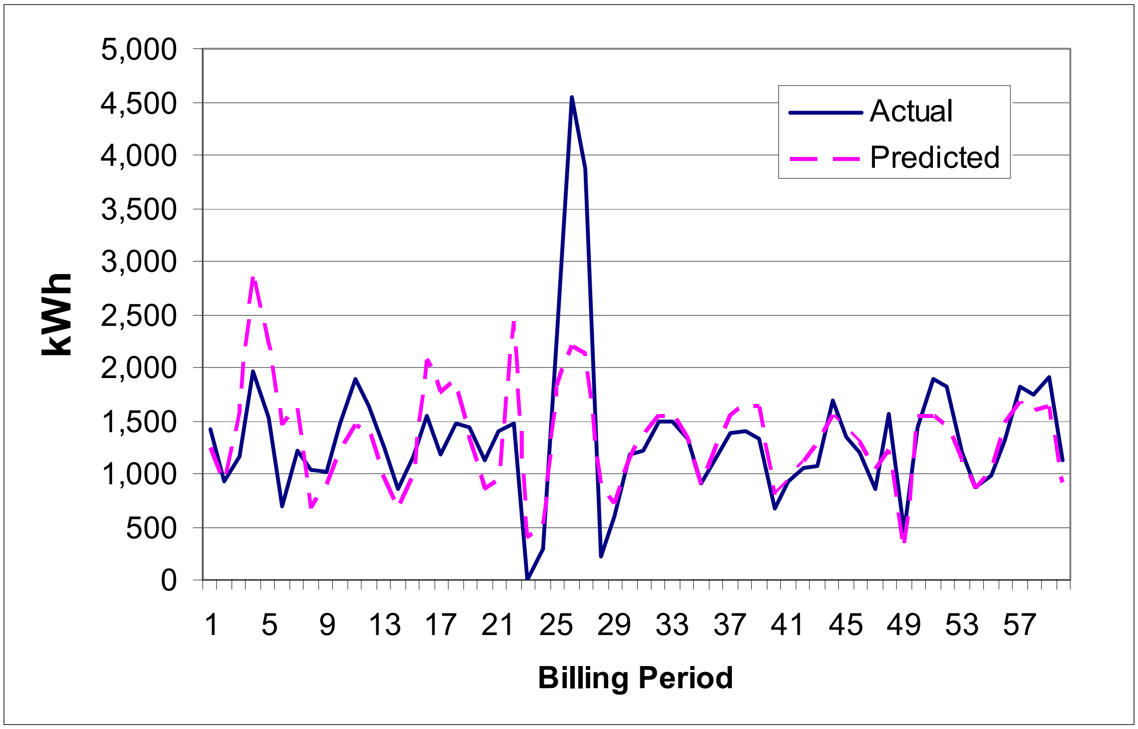

Figure B.5. Predicted vs. Actual Consumption for Household No. 5 (High Single Bill)

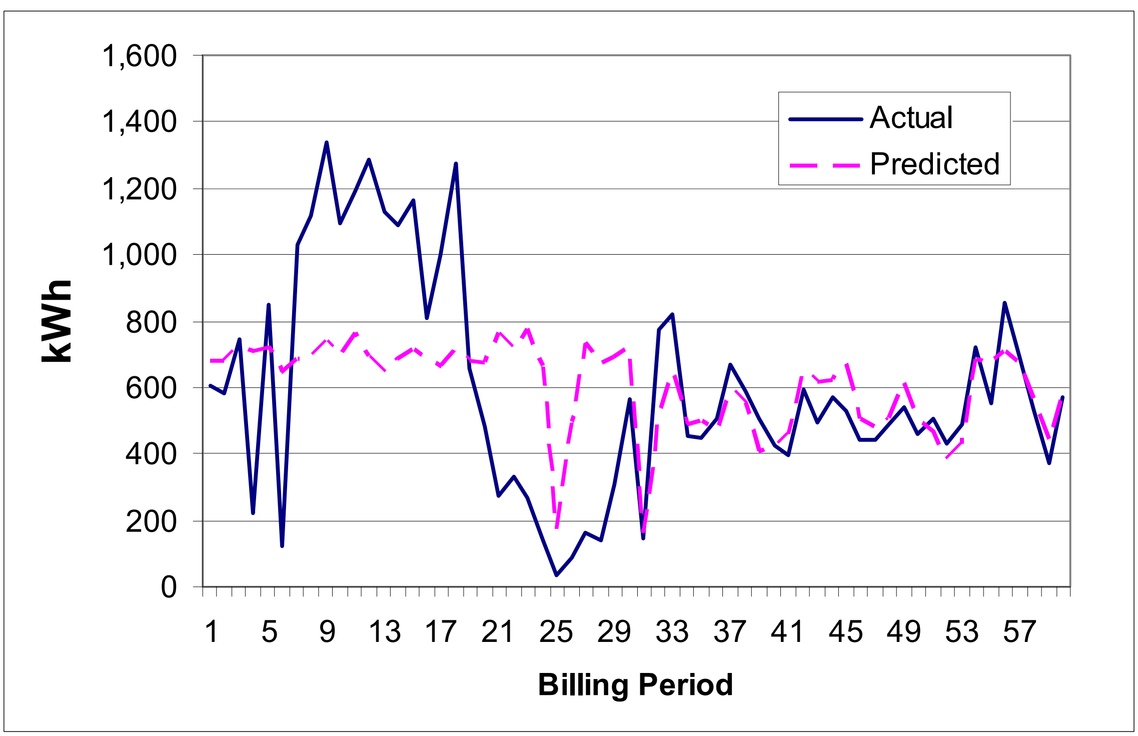

Figure B.6. Predicted vs. Actual Consumption for Household No. 6 (Erratic Behavior)

Appendix C – Standard Errors Associated with the Mean Values of Consumption and Savings Estimates

This appendix discusses how to develop appropriate measures of standard errors for use in statistical tests, in view of the fact that total variability includes both measurement errors from the household-specific regression models as well as the variation of expected effects from the ECMs across households.[21]

To motivate the discussion, an expanded version of the summary results table (Table 3.4 in the main report) is shown below as **Table C.1.** As reproduced from Table 3.4, Column (2) reports that the mean percentage reduction for Sample A was 28.4%. Column (3) provides an indication of the average precision of the predicted values across the sample. For the 6,096 households in the sample, the mean or average standard error from the regression models was 14.8% (indicating that, on average, the estimated percentage reduction in consumption was about 2 times its standard error.)

Table C.1. Measures of Cooling Consumption and Savings Based on Mean Values

(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Regression Model Error	*Regression Model Error*	*Sample Variability*	*Total Variability*	
Sample A - Number of Households = 6,096	Mean Value	Mean Std. Error	Root Mean Squared Error	Std. Dev. (Error) of Sample	Adjusted Std. Error	Std. Error (Mean)
NCC_pre (kWh/yr)	5,627.5	673.6	834.4	2,659.2	2,787.0	35.7
NCC_post (kWh/yr)	3,883.9	553.5	688.6	2,160.6	2,267.7	29.0
ΔNCC (kWh/yr)	-1,743.6	910.2	1,081.8	1,796.0	2,096.6	26.9
% = ΔNCC/NCC_pre	-28.4%	14.8%	17.8%	25.0%	30.7%	0.4%

However, the error associated with the regression models is only one component of the variability of the predicted measures. As shown in Figure 3.1 for the percentage change metric, there is considerable variability across households in the predicted values, without taking into account the regression model error. The discussion below relates to how we blend these two sources of variability to develop appropriate measures of error that should be associated with the mean values in Column (2) in Table C.1. These error measures would then allow us to construct confidence intervals for the means at specified levels of significance.

The values in columns (4) through (6) in Table C.1 are used to develop an estimate of the total variance associated with each of the metrics (the pre- and post-consumption quantities as well as their changes). To consider the total variation, we must consider both the *precision* of the predictions yielded by the regression models for the individual households as well as the variation of the predictions *across* the households in the sample. Formally, to begin to construct

[21] To our knowledge, the approach that is presented in the following pages has not been used in prior studies involving PRISM-type studies applied to large samples of billing records. The approach blends both sources of variability using, in essence, an analysis of variance framework.

a measure of total variation, we must consider that a prediction of a selected metric (either pre- or post-ECM consumption or the absolute or percentage change, represented generically by Y) for a household can be represented as

$$YP_i = \widehat{Y}_i + u_i \qquad \text{(C.1)}$$

where

YP_i = predicted value of Y for household *i*

$\widehat{Y}_i$ = expected value of Y

u_i = stochastic error term for household *i*

Typically, the prediction for Y for household *i* (YP_i) is taken to be the expected value of Y ($\widehat{Y}_i$), under the assumption that the expected value of *u* is zero. For a sample of N households, the mean is thus calculated as mean of the individual values of $\widehat{Y}_i$. In this analysis, these values are shown in Column (2) of Table C.1.

The derivation of variability for the entire sample must account for both terms on the right-hand side of Equation (C.1). In essence, the total variance across the sample is the sum of the variances:

$$\text{Total variance} = \text{Var}(\widehat{Y}_i) + \text{Var}(u) \qquad \text{(C.2)}$$

The variation of the expected values of Y can be calculated in a conventional manner as a variance or standard deviation. In the application here, the standard deviations for each metric for each sample of households are shown in Column (5) of Table C.1.

The stochastic error term in Equation (C.1) results from the imprecision of the individual regression models, as reflected in the standard error of the regression coefficient on cooling degree days (subsequently translated to the error in the NCC or change in NCC). Using the formula for the variance for the mean (where the variance for each household is equal to the square of the standard error), we have

$$\text{Variance of } u \text{ (sample)} = \text{ [se}(u_1)^2 + \text{se}(u_2)^2 + \ldots.. + \text{se}(u_n)^2 \text{] / n)} \qquad \text{(C.3)}$$

In Equation (C.3), se(u_i) is the estimated standard error associated with a particular metric for household *i* (e.g., the standard error ΔNCC).

The sample standard error resulting from the regression model error is calculated as the square root of the right side of Equation (C.3) and is shown in Column (4) of Table C.1 (designated as root mean squared error to distinguish from the other standard errors in the table). Because this statistic includes squared standard errors, it is slightly higher than the arithmetic mean of the standard errors shown in Column (3).

Column (6) shows the adjusted standard errors for the various metrics that combine both effects—regression model error and variation across households.[22] These adjusted standard errors are derived in a conventional manner from the values in Columns (4) and (5) by using the formula for variance shown in Equation (C.2).[23]

Numerical Example of Variance Adjustment

A small numerical example may also help to make this procedure more transparent. **Table C.2** shows a sample of 10 households with the expected value of savings (or any other metric, denoted as "Yhat") in Column (2). Column (3) shows the standard error associated with the expected savings. The bottom-left side of the table shows the sum, mean, variance, and standard deviation associated with the expected savings. The variance around the mean of the expected savings is 20.44 and the standard deviation of 4.52.

Table C.2. Numerical Illustration of Adjusted Variance Procedure

(1) House #	(2) Yhat	(3) SE	(4) Var = SE^2
1	9	2	4
2	12	3	9
3	4	1	1
4	18	3	9
5	7	2	4
6	11	4	16
7	4	2	4
8	13	1	1
9	7	3	9
10	5	2	4
Sum:	90	Sum:	61.0
Mean:	9	Mean Variance:	6.10
Variance:	20.44	SD (SE)	2.47
SD (SE)	4.52		
Sum of Variances		26.54	= (20.44 + 6.10)
Adjusted SE.		5.15	= SQRT(26.54)

The far-right column shows the variance of the measurement error (or, in the context of this study, regression model error) for each household, calculated as the square of the standard error.

[22] An alternative approach to deriving this entire construction would involve terms more familiar in studies using analysis of variance. In the analysis of variance, the variance of the total group can be decomposed into the mean of the variances of the subgroups plus the variance of the means of the subgroups. In the context here, the subgroups can be considered the individual households. The variances of the subgroups are, thus, represented by the regression model variances. The means of the subgroups are the expected or predicted values for each household resulting from the regression model.

[23] Thus, we first square each of the values for the sample standard deviations in Columns (4) and (5), compute their sum (total variance), and then take the square root of the resulting value. The statistics shown in columns (4) through (6) in Table 4.4 are shown in terms of standard errors, rather than variances, to be more consistent with the standard errors shown elsewhere

The sum of squared standard errors is 61.0 [corresponding to Equation (5) above] implying a mean variance of 6.10.

The sum of the two variances is 26.54 as shown at bottom of the table. Taking the square root generates the adjusted standard error of 5.15. In this simple example, the mean standard deviation associated with the measurement error of the individual houses of 2.47 is little more than 50% of the variance of "Yhat" across the houses in the sample (2.47/4.52). This particular ratio implies that taking account of the measurement error yields adjusted standard error for the overall sample that is about 14% higher than considering just the expected values (i.e., 5.15/4.52 = 1.14).

The above example is intended to provide an illustration of the general approach. The simple addition of variances in Equation (C.2) is most appropriate for large samples (as in this study) or for where the true variances are known. In small samples, we need to account for the fact that variances are, in fact, only estimates and that we need to take account of the degrees of freedom in the procedure. As mentioned in the footnote above, the procedure can also be cast in terms of a two-way analysis of variance in which the variation is expressed in terms of sums of squares. The relation between sums of square and the estimated variances depends on the degrees of freedom and the underlying sample size.

Applying this perspective back to Table C.1, we see that for the metric involving the percentage change in electricity use, this adjustment procedure leads to an overall standard error that is about 20% larger than the conventional measure (30.7% divided by 25.0%). This result suggests that about a 20% increase in the total variability in predicted values is caused by including the influence of the errors in the regression model.

As a final note, the example in Table C.2 is intended to provide an illustration of the general approach.

Standard Error of the Mean Values

The final column in Table C.1 shows the standard error (se) for the sample mean using the conventional formula:

$$\text{se}\,[(\text{Mean}(Y)] = \text{se}\,(Y) / \text{sqrt}\,(N) \qquad \text{(C.4)}$$

Because this study has a very large number of households (N), the standard errors of the mean values are very small. For the percentage changes in savings, the standard error is less than one-half percent.

This approach provides a statistically rigorous approach to incorporating the variability of expected savings across the households in the sample together with the uncertainty inherent in the regression models used to estimate those savings. While the impact of the regression errors was found to be relatively modest in this particular sample, this approach may be useful in future studies using individual household billing data.

Appendix D – Detailed Results for Samples A, B, and C

Appendix D compares the results across all three samples selected by the criteria shown in Table 3.2.

Summary Results – Medians

Measures of central tendency using individual household data can be reported as mean values or median values. Median values are useful in that they are relatively insensitive to outliers. Mean values are useful in that classical measures of the statistical reliability of the central tendency and the variability of the data are readily available. Fels (1986), in her introductory article discussing the PRISM approach, suggests using both measures.

Summary measures using median values of the individual-household regression results are shown in **Table D.1.** The first column in the table defines the various metrics for the analysis. Recall that the normalized cooling consumption (NCC) is based on the estimated regression coefficient for cooling multiplied by the nine-year annual average cooling degree days. As described in Section 2, the cooling degree days are computed separately for each household based on the estimated reference temperature for that household.

The top panel in the table shows that median percentage reduction in electricity use for the largest sample (A) to be 31.9%. The median predicted change in annual cooling electricity is a little more than 1,500 kWh.

The second column in the table provides a measure of the statistical reliability of the estimated values for the pre- and post-ECM period as well as the change in electricity use. The median standard error of the change in consumption (ΔNCC) is about one-half of the absolute change. Thus, for an individual household at the mid-point of the distribution, one can say there is about a 95% probability that there is a positive level of savings.

Looking at the panels associated with Samples B and C, one sees that the statistical reliability of the estimated median change increases (as expected from how the samples are selected in Table 3.2). For Sample C, the median standard error of the change in cooling consumption is only about one-third of the median change.

In summary, however, the key finding of Table D.1 is that the median percentage savings across the various samples is relatively constant at around 30%, although slightly smaller in Sample C with the most stringent selection criteria.

The standard errors presented in Table D.1 relate only to the error inherent in the statistical models at the individual household level. The table does not address the variability of predicted savings across household for the selected samples (as illustrated in Figure 3.1 for Sample A).

Table D.1. Measures of Cooling Consumption and Savings – Median Values[24]

Sample A: Number of Households = 6,096

	Median Value	Median S.E. of Value
NCC_pre (kWh/yr)	5,192.4	543.5
NCC_post (kWh/yr)	3,429.8	443.2
ΔNCC (kWh/yr)	-1,515.0	773.7
% = ΔNCC/NCC_pre	-31.9%	12.0%

Sample B: Number of Households = 4,082

	Median Value	Median S.E. of Value
NCC_pre (kWh/yr)	5,449.2	466.5
NCC_post (kWh/yr)	3,655.1	373.1
ΔNCC (kWh/yr)	-1,540.9	646.3
% = ΔNCC/NCC_pre	-31.0%	9.7%

Sample C: Number of Households = 1,234

	Median Value	Median S.E. of Value
NCC_pre (kWh/yr)	5,457.8	335.2
NCC_post (kWh/yr)	3,752.8	264.6
ΔNCC (kWh/yr)	-1,411.1	443.7
% = ΔNCC/NCC_pre	-28.6%	6.9%

Summary Results – Means

Table D.2 presents summary statistics based on means and standard deviations of the various consumption measures. Column (2) reports that the mean percentage reduction for Sample A was 28.4%. Similar to the behavior of the median estimates, the average percentage reduction is slightly smaller for Sample C at 26.7%.

[24] The medians for the absolute and percentage changes in the NCC in the third and fourth lines of each panel of the table are calculated on the basis of the individual sample results. Thus, for example, the median difference in the NCC (ΔNCC) is not equal to the difference in the medians of the pre- and post-retrofit NCCs.

Table D.2. Measures of Cooling Consumption and Savings Based on Mean Values[25]

(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Regression Model Error	*Regression Model Error*	*Sample Variability*	*Total Variability*	
Sample A - Number of Households = 6,096	Mean Value	Mean Std. Error	Root Mean Squared Error	Std. Dev. (Error) of Sample	Adjusted Std. Error	Std. Error (Mean)
NCC_pre (kWh/yr)	5,627.5	673.6	834.4	2,659.2	2,787.0	35.7
NCC_post (kWh/yr)	3,883.9	553.5	688.6	2,160.6	2,267.7	29.0
ΔNCC (kWh/yr)	-1,743.6	910.2	1,081.8	1,796.0	2,096.6	26.9
% = ΔNCC/NCC_pre	-28.4%	14.8%	17.8%	25.0%	30.7%	0.4%
Sample B - Number of Households = 4,082	Mean Value	Mean Std. Error	Root Mean Squared Error	Std. Dev. (Error) of Sample	Adjusted Std. Error	Std. Error (Mean)
NCC_pre (kWh/yr)	5,865.9	556.4	664.8	2,655.5	2,737.4	42.8
NCC_post (kWh/yr)	4,112.8	443.3	528.5	2,216.6	2,278.7	35.7
ΔNCC (kWh/yr)	-1,753.1	733.3	849.3	1,700.4	1,900.7	29.7
% = ΔNCC/NCC_pre	-28.3%	10.7%	11.8%	22.0%	25.0%	0.4%
Sample C - Number of Households = 1,234	Mean Value	Mean Std. Error	Root Mean Squared Error	Std. Dev. (Error) of Sample	Adjusted Std. Error	Std. Error (Mean)
NCC_pre (kWh/yr)	5,864.9	376.3	426.4	2,482.0	2,518.4	71.7
NCC_post (kWh/yr)	4,217.3	299.4	340.4	2,094.6	2,122.0	60.4
ΔNCC (kWh/yr)	-1,647.7	489.2	545.6	1,572.5	1,664.4	47.4
% = ΔNCC/NCC_pre	-26.7%	7.1%	7.5%	20.0%	21.4%	0.6%

An extended discussion of Column (4) through (6) is presented in Appendix C. Column (4), in essence, represents variability across the sample contributed by the errors inherent in the regression models. Note that this metric declines from 17.8% in Sample A to 7.5% in Sample C. This decline is consistent with the more stringent criteria placed on the quality of the regression models in samples B and C as compared to sample A.

Column (5) shows the standard deviation of the various metrics. The standard deviations for the absolute and percentage savings decline slightly going from Sample A to Samples B and C. The lower threshold for the precision of the regression coefficients in Sample A likely results in more cases where the changes are particularly small or large relative to the mean.

As described in Appendix C, the values in Column (6) reflect both the regression error and the variation across the sample in the particular metric. As compared to the standard deviation of the metrics in Column (5), these adjusted standard errors (or, alternatively, standard deviations) are

[25] The mean of the percentage changes in the NCC (% ΔNCC/NCC_pre) in the last line of each panel of the table is calculated on the basis of the individual sample results. Thus, it is not equal to the mean change in the NCC (ΔNCC) divided by the mean pre-retrofit NCC. We are simply taking an unweighted average of the percentage changes in NCC across the sample households.

the most different for Sample A. The adjusted standard error (deviation) is 30.7% compared to the unadjusted value. By contrast, for Sample C, the more rigorous reliability criteria used to select the included households make the contribution of regression error very small relative to the variation across households (thus, the adjusted standard error is different by only 1.4 percentage points [21.4% - 20.0%]).

Standard Error of the Mean Values

The final column in Table C.1 shows the standard error (se) for the sample mean using the conventional formula:

$$\text{se}\,[(\text{Mean}(Y)] = \text{se}\,(Y) / \text{sqrt}\,(N) \qquad \text{(C.4)}$$

Here, the standard errors of Y are taken from column (6), after combining both the regression error and the sampling variation. Because this study has a very large number of households (N), the standard errors of the mean values are very small. For the percentage changes in savings, the standard errors are all less than 1%. Note that the standard error for the mean percentage change is higher in sample C (0.6%) than in either Sample A (0.4%) or Sample B (0.4%). Although the relative standard error (e.g., standard error/mean = 21.4%/26.7% from Columns (2) and (6) for sample C) is higher in Sample C than in Sample A or B, the smaller number of households in this sample results in a lower level of statistical significance for the mean change.

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Appendix E – Estimates of Cooling Reference Temperatures

The most widely published measures of degree days by the U.S. National Oceanic and Atmospheric Administration (NOAA) are based on a reference temperature of 65 degrees F. It may be of interest to compare the results of this study with that convention.

Figure E.1 is a histogram of the cooling reference temperature, based on Sample A with some 6,000 households. The distribution is symmetric, with a median value of 70.0 and a mean of 70.2.[26] Approximately 75 % of the reference temperatures fall between 65 and 75 degrees.

Assuming that the 8-degree difference between the cooling reference temperatures and the heating reference temperatures is roughly correct, we infer that the average heating reference temperature would be about 62 degrees. This value is reasonably close to the reference temperature for heating, using aggregate residential natural gas consumption data for Texas (Belzer and Cort 2004). In that study, the "best" reference temperature was 60.7 degrees, based again on a statistical fit to the 1997-2002 state data.

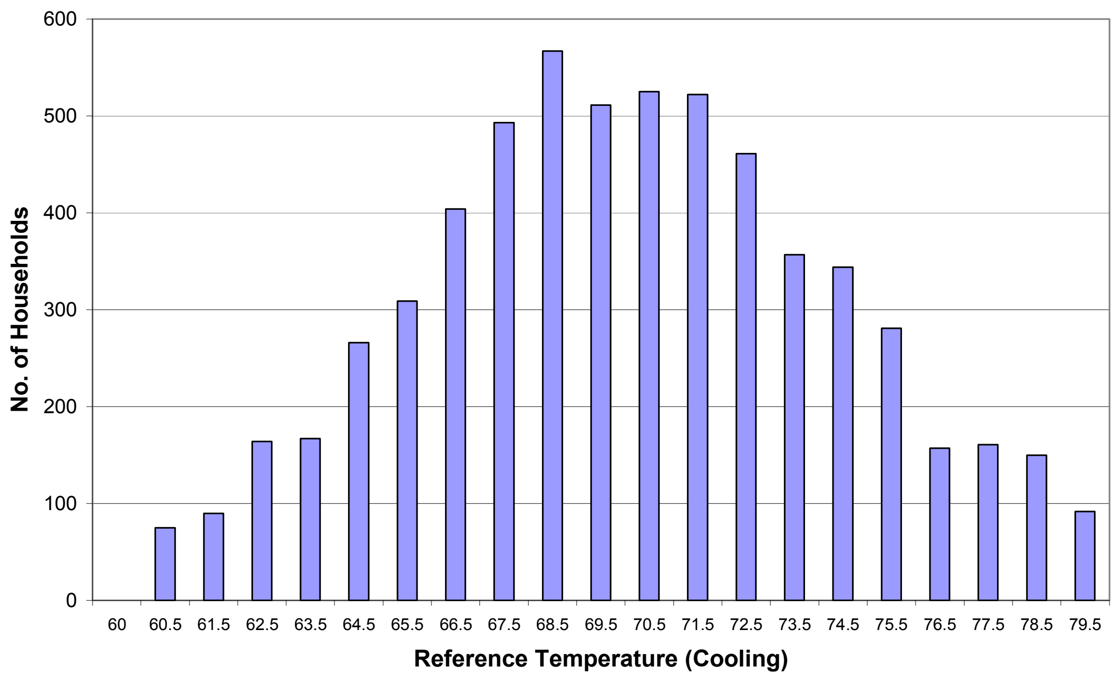

Figure E.1. Histogram of Estimated Cooling Reference Temperature for Sample A

[26] Recall that households in which the estimated reference temperature was lower than 60 degrees or higher than 80 degrees were eliminated from further analysis. As shown in Table 4.1, nearly the same number of households was eliminated via the lower limit as compared to the upper limit. Qualitatively, this suggests that their inclusion would not have significantly influenced the symmetry of the distribution shown in Figure E.1.

Several extensions of this study could provide further insight as to how best to employ the variable degree-day method in analyzing aggregate or household level energy consumption. One extension would explore issues related to aggregation. Thus, a comparison is made between the mean values of the reference temperatures estimated from household data from the reference temperatures estimated from an aggregation of those data. (Various methods of aligning the household bills by time periods would need to be addressed if starting from the data set used in this study).

Many aggregate models use nonlinear functions (or squared terms) of degree days to capture temperature impacts on total consumption use. The household data suggests that this observed nonlinearity may result primarily from different fractions of houses (or buildings in general) that may be cooling (or heating) at a given outside temperature. Thus, a better understanding of the distribution of reference temperatures across households may lead to improvements in how aggregate models are specified.

A second extension might involve an investigation of various methods of defining degree days. In this study, the conventional method of defining degree days was employed—using daily temperatures defined by the mean of the lowest and highest (one-hour) temperatures over the day. As hourly temperature data are readily available, an obvious alternative procedure might define the daily temperature as the average temperatures for all 24 hours in the day. Other explorations might involve the use of degree hours rather than degree days in models applied to billing data (or reported aggregate monthly consumption).

Clearly, more sophisticated methods of accounting for weather impacts in explaining short-term energy consumptions have been used in prior studies. The purpose of these explorations is to recognize the current simplicity of the degree-day method in normalizing reported consumption data for the effects of weather, while at same time suggesting some improvements that could be readily implemented.

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14. ABSTRACT *(Maximum 200 Words)*
Home Performance with ENERGY STAR (HPwES) is a jointly managed program of the U.S. Department of Energy (DOE) and the U.S. Environmental Protection Agency (EPA). This program focuses on improving energy efficiency in existing homes via a whole-house approach to assessing and improving a home’s energy performance, and helping to protect the environment. As one of HPwES’s local sponsors, Austin Energy’s HPwES program offers a complete home energy analysis and a list of recommendations for efficiency improvements, along with cost estimates. To determine the benefits of this program, the National Renewable Energy Laboratory (NREL) collaborated with the Pacific Northwest National Laboratory (PNNL) to conduct a statistical analysis using energy consumption data of HPwES homes provided by Austin Energy. This report provides preliminary estimates of average savings per home from the HPwES Loan Program for the period 1998 through 2006. The results from this preliminary analysis suggest that the HPwES program sponsored by Austin Energy had a very significant impact on reducing average cooling electricity for participating households. Overall, average savings were in the range of 25%-35%, and appear to be robust under various criteria for the number of households included in the analysis.

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