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

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ABSTRACT

Austin Energy, in Texas, is one of Home Performance with ENERGY STAR's (HPwES's) local sponsors and offers homeowners in their service territory complete home energy assessment and a list of recommendations for efficiency improvements, along with cost estimates. The homeowner can choose to implement only one or the complete set of energy conservation measures. The utility 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.

To determine the benefits of their HPwES program a statistical analysis was conducted using energy consumption data of HPwES homes provided by the utility. This report provides preliminary estimates of average cooling savings per home from the HPwES Loan Program for the period 1998 through 2006, and the estimates are based on electricity billing records provided by the utility for more than 7,000 households.

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. The results from this preliminary analysis suggest that the utility's HPwES program had a 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.

Background

Austin Energy's HPwES program, previously known as the Loan and Whole House program, is a residential energy improvement program for existing homes that focuses on the house-as-a-system and offers homeowners 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.[1] Both incentive programs are only available for improvements made by participating HPwES contractors.

[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

Purpose of This Study

This paper describes 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.

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.

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

The Energy Conservation Measures 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]

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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

[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

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.

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]:

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

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

[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

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).

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):

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

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

[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.

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—

[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.

where *separate* 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.

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.
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 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 above.
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.
5. *Calculate Normalized Consumption and Standard Errors.* The final step is to use the parameter estimates from Step 4 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

[10] The choice of the 8-degree difference 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.

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]

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 the Results section. 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.

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 cooling 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 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

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[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.

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

Table 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]

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

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[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 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.

[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.

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 1 is summarized in Table 2. The different data sets are labeled A, B, C.[17]

Table 2. Sample Sizes Using Statistical Precision of Predicted NCC

Sample Set	Criteria	No. of Households
After initial filters	None	6,667
A	+/- 50%	6,096
B	+/- 20%	4,082
C	+/- 10%	1,234

The subsequent discussion of results will focus only on Sample A. As indicated in Table 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.

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.

Histogram of Percent Changes (Savings)

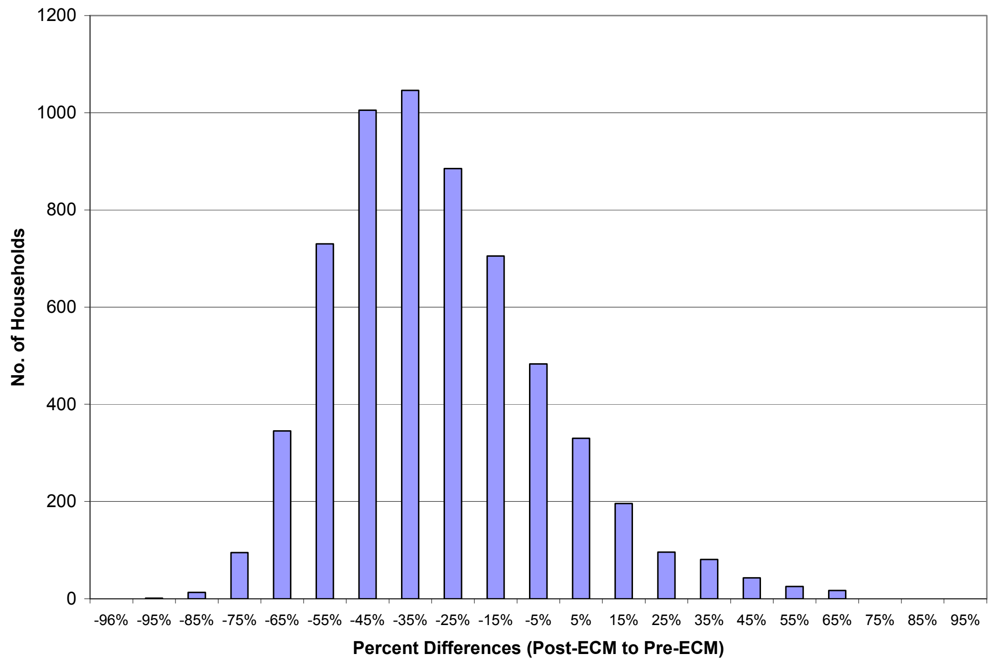
Using the largest sample (A), **Figure 1** shows the distribution of percentage changes in predicted electricity use between the pre- and post-ECM periods. The results yield a very smooth bell-shaped curve centered around a 30% reduction in electricity use after the ECM measure with a slight positive 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%.

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.

[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.

Figure 1. Distribution of Percentage Changes in Predicted Electricity Use Between the Pre- and Post-ECM Periods



Summary measures using median values of the individual-household regression results are shown in Table 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 earlier, the cooling degree days are computed separately for each household based on the estimated reference temperature for that household.

Table 3. Measures of Cooling Consumption and Savings – Median Values[18]

Sample A: Number of Households = 6,096		
Measure	**Median Value**	**Median S.E. of Value**
NCC_pre (kWh/yr)	5192.4	543.5
NCC_post (kWh/yr)	3,429.8	443.2
Delta NCC (kWh/yr)	-1,515.0	773.7
% = Delta NCC/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

[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.

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 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 households for the selected samples (as illustrated in Figure 1 for Sample A).

Summary Results – Means

Table 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%.

Table 4. Measures of Cooling Consumption and Savings Based on Mean Values[19]

Sample A: Number of Households = 6,096			
Measure	**Mean**	**Standard Deviation (Sample)**	**Standard 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
Delta NCC (kWh/yr)	-1,743.6	1,796.0	26.9
% = Delta NCC/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 of households 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 1.

Standard Error of the Mean Values

The final column in Table 4 shows the standard error associated with the *mean* value of savings. 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]

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[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. The adjustment procedure is essentially an analysis of variance where the variance of the point estimates of the saving by households is combined with variance associated with the error from the regression models.

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%.

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 cooling 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 cooling 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 cooling savings for the largest sample of 6,000 households in the analysis was 32%, while the mean cooling 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 cooling savings is that it falls in the range of 25% to 30% with a high level of certainty. In addition, the average household savings would be higher, however the researchers did not have access to gas utility data.

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 above, 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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