Comparison of Pooled and Household-Level Usage Impact Analysis

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ABSTRACT

Members of the energy evaluation community have varying opinions regarding which analytical model yields the most accurate estimate of the impact of an energy efficiency program on usage. While some prioritize a household level analysis approach, others are more likely to use a pooled regression approach.

The Princeton Scorekeeping Method (PRISM) is an example of the house-by-house analysis, where energy usage for each home is analyzed for periods before and after treatment. A regression model is fit for each home in the pre and post period to relate energy consumption to heating degree days. Gross savings is calculated for each home as the difference between pre-and post-treatment weather-adjusted usage. Net savings is calculated by adjusting gross savings by the average change in weather-adjusted usage for a comparison group of non-participating homes. The key advantage of this approach is the availability of household-level savings estimates which can then be analyzed and compared for subgroups of interest. The key disadvantage is that this technique has stringent data requirements that often lead to high attrition, and potentially to biased results.

The pooled analysis approach does not estimate savings for each home, but instead the model directly estimates the program savings as a parameter of the regression model. This model has less stringent data requirements than the house-by-house approach, but does not provide for the same levels of post-estimation analysis of variations in savings by household or treatment characteristics.

This paper will describe models that fall into the house-by-house and pooled approaches, explore the advantages and disadvantages of the two approaches, and compare analysis results using the two methods.

Introduction

Energy efficiency programs provide no-cost or shared-cost services to encourage the adoption of energy efficiency measures. Policymakers and program managers need to understand the impacts that these measures have on energy use to know whether they are obtaining their expected results and investing in cost-effective treatments, and whether they need to consider changes to program design or implementation approaches. Methods used to estimate the impacts of these treatments include modeling predicted impacts, with or without specific retrofit data; metering to directly measure the amount of energy consumed, potentially on a daily or hourly basis; or analyzing billing data obtained from utilities or fuel suppliers.

This paper focuses on two approaches to billing analysis – the house-by-house analysis and the pooled regression approach. Each method has logistical and analytical advantages and disadvantages, and therefore there are situations when one or the other is the preferred approach.

These analysis techniques are discussed in the context of residential energy retrofit programs' impact on energy usage, rather than on peak demand. The methods are applicable to both low-income and general market programs. Additional analysis issues would arise in the study of new construction or commercial efficiency programs, but these programs are not the subject of this paper.

Billing Analysis

The billing analysis approach utilizes actual utility meter readings of customers' energy usage before and after treatments were delivered to estimate the impact of the services on energy usage. Weather data are incorporated into the analysis to control for the change in usage that relates to changes in weather. Comparison groups are often utilized to control for other exogenous factors that can impact energy usage.

Data Requirements

Evaluations do not always include billing analyses because of the data and time that are required. Core data required include energy usage, when the services were provided, and local weather data.

- Energy billing data – These data are necessary to assess the usage change. Required elements include read date, number of days since previous read, and whether it was a real or an estimated read.
- Service delivery date – The service delivery date divides the usage data into the pre- and post-treatment periods.
- Weather data – A local weather station must be selected for each address, and daily weather must be obtained for each location. Weather data are obtained for the pre and post treatment periods and for a longer normalization period to estimate the change in usage that would be predicted from a pre period to a post period, both with average weather conditions.

In addition to the core data requirements, there are supplemental data that can enrich the analysis and enable increased understanding of the characteristics that are related to greater energy savings.

- Energy efficiency measures – Savings from individual energy measures or packages of measures and cost-effectiveness can be estimated when there are a sufficient number of homes that received the treatment. This additional analysis can help to refine measure offerings and/or incentive levels.
- Service delivery agencies/contractors – When there are a large enough sample of jobs per contractor, savings and cost-effectiveness can be computed for each contractor. However, it is important to consider whether there are differences in savings opportunities.
- Housing unit characteristics – These data can allow for an analysis of how housing unit characteristics relate to savings. Useful data may include home type, square footage, main heating fuel, home age, basement or crawl space, pre-treatment air leakage, and pre-treatment usage. Such results can help to identify targets with the greatest savings opportunities.
- Household characteristics – Household characteristics that may be informative include home ownership; presence of children, elderly, or disabled household members; and (for low-income efficiency programs) participation in payment assistance programs.

Challenges

There are several challenges associated with conducting billing impact analysis, including data attrition, sample sizes, and identification of a comparison group.

- Data attrition – Data requirements vary for different billing analysis approaches and attrition will accordingly vary. When attrition is high, there is the concern that the sample included in the analysis is not representative of the population treated, and that estimated savings will not be a good estimate of the savings for the program as a whole.

- Sample size – Depending on the number treated over the analysis period and the level of data attrition, sample sizes may not be as large as desired. This can be problematic due to the variability in energy use and savings, resulting in low precision for savings estimates. While the sample may be large enough to analyze program-wide results, it may not be large enough to estimate impacts for individual measures, contractors, or population subgroups.
- Comparison group – The change in usage for treated housing units between the pre-and post-treatment periods is the gross change. Some of these changes may be due to the program, and some of these changes are due to other exogenous factors, such as changes in household size or composition, energy prices, or availability of more energy efficient equipment. A comparison group should be used to control for these factors. To the extent that the comparison group is similar to the treatment group, the change in usage for the comparison group represents how usage would have changed for the treatment group if households had not received services. The net change is the difference between the change for the treatment group and the change for the comparison group, and represents the actual impact of the program. (This is separate from the net-to-gross analysis for free-ridership and spillover.)

The most robust analysis would randomly assign customers to treatment and control groups, and only offer the program to the control group at least one year later. Such random assignment would provide a greater likelihood that the changes in non-program factors were the same for both groups. However, evaluators rarely have this opportunity, as policy makers and program managers are not willing to restrict program participation.

When random assignment is not possible, customers as similar as possible to the treatment group should be selected for the comparison group, so that the exogenous changes are as similar as possible to the treatment group. Possibilities include:

- Later program participants – Customers who participate in the program one year after the treatment year serve as a good comparison because they have participated in the program. Usage data for the same time period as the treatment group can be analyzed, but we compare pre-treatment data to pre-treatment data.
- Earlier program participants – Similarly to the later program participants, the earlier program participants serve as a good comparison group. The difference for this group is the comparison of post-treatment data to post-treatment data.
- Comparable households – Another possibility is the use of customers who are comparable to the participants. In the case of a low-income program evaluation, non-participant customers who received LIHEAP, a low-income energy assistance grant, could be compared to the treatment group.1

Table 1 provides a summary of the treatment and potential comparison group requirements.

Table 1. Treatment and Comparison Group Example Definition (2012 Program Evaluation)

	Treatment Group	**Comparison Groups – Type of Participant**		
		Later	**Earlier**	**Non**
Participant Year	2012	2013	2011	Non
Participation	Services in 2012.	Services in 2013.	Services in 2011.	No services.
Pre-usage period	Prior to service began.	2 years before service began.	Up to 1 year after service ended.	Same as treatment group.
Post-usage period	After service completion.	1 year before service began.	Up to 2 years after service ended.	Same as treatment group.

[1] However, it can be difficult to determine if these households participated in another energy efficiency program.

Usage Impact Models

Billing data analysis methods can be broadly grouped into two categories – house-by-house savings analysis and pooled analysis.

House-by-House Analysis

This analysis method examines energy usage for each home for periods before and after treatment. Gross savings is calculated for each home as the difference between pre-and post-treatment weather-adjusted usage. Net savings is calculated by adjusting gross savings by the average change in weather-adjusted usage for comparison homes.

The Princeton Scorekeeping Method (PRISM) is an example of the house-by-house analysis technique. This software estimates the Normalized Annual Consumption (NAC) for each home using monthly billing data and daily temperature data (Fels 1986). The model estimates the best fit reference temperature from which heating and cooling degree days are calculated.

PRISM uses regression analysis to fit the model:

$$F_i = \alpha + \beta H_i(\tau) + \varepsilon_i$$

Where,

- F_i = average daily consumption in time interval i
- $H_i(\tau)$ = heating degree days to reference temperature τ in time interval i
- ε_i = random error term

The Normalized Annual Consumption is then calculated using the following equation over a long-term annual average of heating degree days, typically twelve years.

$$NAC = 365\alpha + \beta H_o(\tau)$$

Another degree-day analysis approach to the house-by-house analysis provides very similar results to PRISM and allows for a greater number of homes to be included in the estimation. This method applies the following procedure.

1. Calculate the heating and cooling degree-days that are included in each usage period.
2. Determine whether periods should be classified as baseload periods, heating periods, or cooling periods, based on the number of heating and cooling degree-days in the period.
3. Calculate the total baseload period usage, heating period usage, and cooling period usage.
4. Calculate the relationship between heating usage minus baseload usage and degree- days. Use that slope and the average long-term heating degree-days to calculate normalized heating period usage.
5. Follow the same method to calculate normalized cooling period usage.
6. Add up the baseload usage, heating period usage, and cooling period usage to obtain the normalized annual usage.

There are several strengths of the house-by-house analysis approach.

- A detailed attrition analysis can be performed to demonstrate the percentage of customers included in the analysis, the number excluded for various reasons, the characteristics of those who were excluded, and potential biases that could be introduced based on those characteristics.
- The usage and savings estimates developed for each house can be analyzed using a wide range of statistical techniques.
- Characteristics of high- and low-saving homes can be assessed.
- Regression models can be fit to estimate savings by measure.

- The relationships between usage and a wide range of characteristics of the population and the installed measures can be explored.

However, the house-by-house approach has drawbacks.

- It is less robust where the energy use response to changes in degree days varies and/or the baseload usage varies month-to-month or year to year.
- The approach requires close to a full year of pre- and post-treatment usage data.
- If there is limited or poor quality meter reads for housing units (resulting from either mobility or estimated reads), substantial attrition can potentially bias the analysis.

Given the data requirements for this model, and the analytical power that it affords, the house-by-house approach should be used in the following situations.

- A minimum of close to one year of pre- and post-treatment usage data is available for a significant percentage of treated homes and comparison homes.
- Data are available on treatment, home, or households that can be used to assess factors related to higher or lower energy savings.

Pooled Analysis

Pooled analysis is conducted using a regression model, where savings are not estimated for each home, but instead the model directly estimates the program savings as a parameter of the regression model. The pooled estimates can be calculated using the following regression analysis equation.

$Fit = \alpha i + \beta 1 * Hit + \beta 2 * POSTt + \beta 3 * POSTt * Hit + \varepsilon it$

Where, for each participant 'i' and billing month 't,'

- Fit = average daily usage during the pre- and post-treatment periods.
- αi = average daily non-weather-sensitive baseload usage for each participant in the pre-treatment period.
- $\beta 1$ = average daily usage per HDD in the pre-treatment period.
- Hit = average daily base 60 HDDs.
- POSTt = a dummy variable that is 0 in the pre-period and 1 in the post-period.
- $\alpha i + \beta 2$= average daily non-weather-sensitive baseload usage in the post-treatment period.
- $\beta 1 + \beta 3$= average daily usage per HDD in the post-treatment period.
- $\beta 2$ = average daily baseload savings.
- $\beta 3$ = heating usage savings per HDD.
- εit = estimation error term.

The following would be added in a model of electric usage to estimate the cooling savings as well.

$= \ldots + \beta 4 * Cit + \beta 5 * POSTt * Cit.$

Where, for each participant 'i' and billing month 't,'

- $\beta 4$ = average daily usage per CDD in the pre-treatment period.
- Cit = average daily base 70 CDDs.
- $B4 + \beta 5$= average daily usage per CDD in the post-treatment period.
- $\beta 5$ = cooling usage savings per CDD.

A dummy variable for each billing month can be added to the model to control for exogenous factors specific to each month. Known characteristic variables for participants such as house age and square footage can be added to the model to estimate savings for homes with certain characteristics. Finally, dummy variables for installed measures can be added to the model to estimate measure-specific savings.

The pooled analysis also has several advantages.

- All of the billing data that are available for treatment and comparison homes can be utilized.
- Exogenous factors that are expected to have an impact on usage patterns (e.g., economic factors, energy price changes) can be taken into account directly in the regression model.
- A direct estimate of program savings for the targeted analysis period is furnished.

There are three important weaknesses of the pooled analysis model.

- There are multiple sources of variation in savings, so a fully-specified model requires estimation of many parameters that can make the final results difficult to interpret.
- The underlying relationships are often nonlinear and/or heteroscedastic, requiring an alternative functional form to minimize estimation bias that is difficult to interpret.
- There is limited ability to furnish information on the distribution of savings and to facilitate exploratory analysis of the determinants of program performance.

The pooled analysis technique would be useful in the following situations.

- High attrition results when a year of pre- and post-treatment usage is required.
- Significant attrition bias results from excluding homes with lower data availability.
- Supplemental data on treatment, home, or households are not available for analysis.
- Study sponsors are not interested in sub-group analysis of savings estimates.

Model Results

This section provides a comparison of the results from a house-by-house degree day approach and a pooled regression approach.[2] Table 2 displays results for gas heating homes that received energy efficiency services. The table shows results from the non-weather-normalized data, the house-by-house model, as well as four different regression models. While the non-normalized savings were 70 ccf, the weather-normalized savings estimates were close to one another, ranging from 61 to 66 ccf. Differences between the models were not statistically significant.

Table 2. Program 1 – 2010 Program – Gas Heating Jobs

Model	Obs.	Pre-Use	Post-Use	Savings	
				ccf	%[3]
Not Weather Normalized	1,166	1,060	990	70 (±11)	6.6%
House-by-House Degree Day	1,166	1,052	991	61 (±10)	5.8%
Pooled Regression	1,166	1,030	964	66 (±10)	6.4%
Pooled with Month Dummy Variables	1,166	1,084	1,020	64 (±10)	5.9%
Pooled – all observations	1,439	1,031	966	65 (±9)	6.3%
Pooled with Month Dummies – all obs.	1,439	1,118	1,056	62 (±9)	5.6%

Table 3 displays the same comparisons for another utility gas efficiency program. The post-treatment year's winter was much warmer than the pre-treatment year (and the long-term average),

[2] The heating programs referred to here are comprehensive energy efficiency programs.
[3] Percent of pre-treatment usage.

leading to a large non-normalized savings estimate of 20.2 percent. The weather-normalized savings were close ranging from 63 to 68 ccf with restricted data and from 63 to 74 ccf when models with all observations were also included.

Table 3. Program 2 – 2011 Program – Gas Heating Jobs

Model	**Obs.**	**Pre-Use**	**Post-Use**	**Savings**	
				ccf	**%**
Not Weather Normalized	1,211	1,042	831	210 (±12)	20.2%
House-by-House Degree Day	1,211	1,025	959	67 (±10)	6.5%
Pooled Regression	1,211	999	936	63 (±9)	6.3%
Pooled with Month Dummy Variables	1,211	1,044	976	68 (±10)	6.5%
Pooled– all observations	1,665	1,002	933	69 (±8)	6.9%
Pooled with Month Dummies – all obs.	1,665	1,036	962	74 (±8)	7.1%

Table 4 displays results for another utility gas heating program where a comparison group was available. This case only had 19 homes that could be included. The treatment group results with restricted data were fairly similar, ranging from 106 to 110 therms. However, when the additional ten homes that had usage data available were added to the pooled regression, the savings results appeared much lower, at only 28 ccf. Results that include the comparison group adjustment were similar.

Table 4. Program 3 – 2008 Program – Gas Heating Jobs – Gas Usage

Model	**Obs.**	**Pre-Use**	**Post-Use**	**Savings**	
				Therms	**%**
Treatment Group					
Not Weather Normalized	19	864	780	84 (±64)	9.7%
House-by-House Degree Day	19	831	725	106 (±58)	12.8%
Pooled Regression	19	821	712	109 (±78)	13.2%
Pooled with Month Dummy Variables	19	762	652	110 (±80)	14.4%
Pooled– all observations	29	655	627	28 (±69)	4.3%
Pooled with Month Dummies – all obs.	29	644	616	28 (±70)	4.3%
Comparison Group					
House-by-House Degree Day	274	713	723	-10 (±13)	-1.4%
Pooled Regression	274	703	704	-1 (±14)	-0.0%
Pooled with Month Dummy Variables	274	809	811	2 (±14)	0.2%
Pooled– all observations	874	638	639	-1 (±13)	-0.0%
Pooled with Month Dummies – all obs.	874	747	750	3 (±13)	0.4%
Net Change					
House-by-House Degree Day	293			116 (±51)	14.0%
Pooled Regression	293	711	594	117 (±57)	16.4%
Pooled with Month Dummy Variables	293	809	693	116 (±57)	14.3%
Pooled– all observations	903	639	605	34 (±50)	5.3%
Pooled with Month Dummies – all obs.	903	744	711	33(±50)	4.4%

Table 5 displays results from an electric baseload job analysis. The non-weather normalized savings were low, due to a post-treatment summer with much warmer weather than the previous year. Electric usage data are typically more difficult to model than gas, because there are many more idiosyncratic uses.[4] Table 5 displays results from electric baseload jobs. The table shows greater variation than the gas analysis. When the observations were restricted, savings estimates ranged from 841 to 1,223 kWh, and when all observations are included, savings ranged from 765 to 1,223 kWh. Here, the differences were statistically significant.

Table 5. Program 1 – 2010 Program – Electric Baseload Jobs

Model	Obs.	Pre-Use	Post-Use	Savings	
				kWh	%
Not Weather Normalized	4,055	11,153	10,792	361 (±73)	3.2%
House-by-House Degree Day	4,055	11,370	10,147	1,223 (±78)	10.8%
Pooled Regression	4,055	10,624	9,735	889 (±55)	8.4%
Pooled with Month Dummy Variables	4,055	10,798	9,957	841 (±56)	7.8%
Pooled– all observations	5,375	10,728	9,893	835 (±53)	7.8%
Pooled with Month Dummies – all obs.	5,375	11,190	10,425	765 (±55)	6.8%

Table 6 displays the results from another electric baseload analysis, where the savings were lower and are there was less variation between the model results. These savings results ranged from 610 to 656 kWh when the observations were restricted, and from 575 to 656 kWh when the models with all results were included. These differences were not statistically significant.

Table 6. Program 2 – 2011 Program – Electric Baseload Jobs

Model	Obs.	Pre-Use	Post-Use	Savings	
				kWh	%
Not Weather Normalized	2,440	11,022	9,765	1,257 (±93)	11.4%
House-by-House Degree Day	2,440	10,758	10,148	610 (±99)	5.7%
Pooled Regression	2,440	10,139	9,501	638 (±69)	6.3%
Pooled with Month Dummy Variables	2,440	9,779	9,123	656 (±82)	6.7%
Pooled– all observations	4,654	10,287	9,726	561 (±56)	5.5%
Pooled with Month Dummies – all obs.	4,654	9,853	9,277	575 (±66)	5.8%

Table 7 displays results for the electric analysis on gas heated homes. These results again showed more variation than the gas analysis. While the house-by-house approach estimated savings of 434 kWh for the treatment group, the pooled regression estimated savings of 580 kWh, and then 714 kWh when month dummies were included. However, treatment group savings were approximately the same when all observations were included. The house-by-house approach found greater net savings than the pooled approach. The house-by-house net savings were 1,048 kWh, compared to 568 kWh for the pooled approach and 724 kWh for the pooled approach when month dummy variables were included. However, when the month and year dummies were included, the net savings results were closer.

[4] For example, dehumidifiers, plasma televisions, aquariums, etc.

Table 7. Program 3 – 2008 Program – Gas Heating Jobs – Electric Usage

Model	Obs.	Pre-Use	Post-Use	Savings	
				kWh	%
Treatment Group					
Not Weather Normalized	369	13,487	12,223	1,265 (±320)	9.4%
House-by-House Degree Day	369	13,234	12,799	434 (±320)	3.3%
Pooled Regression	369	12,929	12,350	580 (±209)	4.5%
Pooled with Month Dummy Variables	369	12,828	12,114	714 (±216)	5.6%
Pooled– all observations	466	12,769	12,186	583 (±200)	4.6%
Pooled with Month Dummies – all obs.	466	12,664	11,962	702 (±207)	5.5%
Pooled with Mnth+Yr Dummies – all obs.	466	13,235	12,427	808 (±529)	6.1%
Comparison Group					
House-by-House Degree Day	1,536	14,141	14,754	-613 (±121)	-4.3%
Pooled Regression	1,536	13,875	14,307	-431 (±116)	-3.1%
Pooled with Month Dummy Variables	1,536	14,038	14,337	-299 (±122)	-2.1%
Pooled– all observations	3,696	13,392	14,081	-689 (±104)	-5.1%
Pooled with Month Dummies – all obs.	3,696	13,756	14,288	-531 (±108)	-3.9%
Pooled with Mnth+Yr Dummies – all obs.	3,696	12,772	12,706	66 (±108)	0.5%
Net Change					
House-by-House Degree Day	1,905			1,048 (±293)	7.4%
Pooled Regression	1,905	13,847	13,278	568 (±231)	4.1%
Pooled with Month Dummy Variables	1,905	13,827	13,102	724 (±232)	5.2%
Pooled– all observations	4,162	13,656	13,101	555 (±220)	4.1%
Pooled with Month Dummies – all obs.	4,162	13,741	13,021	721 (±220)	5.2%
Pooled with Mnth+Yr Dummies – all obs.	4,162	12,326	10,989	1,336 (±40)	10.8%

The next tables display results for electric heating jobs. These results were generally less variable than the electric baseload analyses, but more variable than the gas heating analyses. Results ranged from 912 to 1,128 kWh for Program 1, from 1,503 to 1,562 kWh for Program 2, and from 838 to 1,023 kWh for Program 3 with the restricted set of observations. These differences were not statistically significant. Somewhat more of a difference in the regressions that included the full set of observations.

Table 8. Program 1 – 2010 Program – Electric Heating Jobs

Model	Obs.	Pre-Use	Post-Use	Savings	
				kWh	%
Not Weather Normalized	144	17,846	17,779	67 (±541)	0.4%
House-by-House Degree Day	144	19,662	18,534	1,128 (±503)	5.7%
Pooled Regression	144	17,940	17,084	857 (±559)	4.8%
Pooled with Month Dummy Variables	144	19,738	18,826	912 (±586)	4.6%
Pooled– all observations	220	17,830	16,992	838 (±491)	4.7%
Pooled with Month Dummies – all obs.	220	20,846	20,028	818 (±515)	3.9 %

Table 9. Program 2 – 2011 Program – Electric Heating Jobs

Model	Obs.	Pre-Use	Post-Use	Savings	
				kWh	%
Not Weather Normalized	134	18,103	14,298	3,805 (±646)	21.0%
House-by-House Degree Day	134	19,402	17,899	1,503 (±665)	7.7%
Pooled Regression	134	17,020	15,505	1,515 (±543)	8.9%
Pooled with Month Dummy Variables	134	17,177	15,614	1,562 (±647)	9.1%
Pooled– all observations	282	16,884	15,263	1,621 (±391)	9.6%
Pooled with Month Dummies – all obs.	282	18,193	16,374	1,819 (±457)	10.1%

Table 10. Program 3 – 2008 Program – Electric Heating Jobs – Electric Usage

Model	Obs.	Pre-Use	Post-Use	Savings	
				kWh	%
Treatment Group					
Not Weather Normalized	103	23,955	22,730	1,225 (±781)	5.1%
House-by-House Degree Day	103	23,408	22,570	838 (±749)	3.6%
Pooled Regression	103	22,803	21,912	889 (±578)	3.9%
Pooled with Month Dummy Variables	103	22,537	21,514	1,023(±605)	4.5%
Pooled– all observations	136	22,986	22,225	761 (±564)	3.3%
Pooled with Month Dummies – all obs.	136	22,773	21,933	841 (±587)	3.7%
Comparison Group					
House-by-House Degree Day	392	21,690	21,889	-199 (±345)	-0.9%
Pooled Regression	392	21,312	21,430	-118 (±424)	-0.6%
Pooled with Month Dummy Variables	392	23,546	23,714	168 (±110)	-0.7%
Pooled– all observations	3,696	20,414	21,256	-842 (±357)	-4.1%
Pooled with Month Dummies – all obs.	3,696	21,747	22,597	-849 (±369)	-3.8%
Net Change					
House-by-House Degree Day	495			1,038(±773)	4.4%
Pooled Regression	495	21,694	20,721	973 (±777)	4.5%
Pooled with Month Dummy Variables	495	23,501	22,596	905 (±784)	3.9%
Pooled– all observations	1,028	21,309	20,476	833 (±686)	3.9%
Pooled with Month Dummies – all obs.	1,028	22,322	21,533	789 (±690)	3.5%

The next tables examine measure savings estimates. In the house-by-house approach, regressions were run using the installed measures as explanatory variables for the modeled savings, whereas in the pooled regression approach, the measures were included in the original regression analysis. We display the initial model with only the measures as controls ("Basic"), as well as additional models that include whether the home has an electric space heater, home ownership, home age, square footage, and dwelling type ("+Controls").

Table 11 shows that the measures with the larger impacts with greater statistical significance were more consistent across the house-by-house and pooled approaches. For example, the basic house-by-house model estimated savings of 73 ccf for the furnace and 78 ccf for the boiler, compared to estimates of 73 ccf for the furnace and 85 ccf for the boiler when the basic pooled regression approach was used. The gas furnace estimates remained fairly consistent, ranging from 73 to 84 ccf across all of the models explored. Most of the other measures had estimates with large confidence intervals, and varied more across the various models.

Table 11. Measure Saving Estimates

	Program 1–Gas Heat (ccf)–2010					
	House-by-House		**Pooled Regression**		**Pooled –All Cases**	
	Basic	**+ Controls**	**Basic**	**+ Controls**	**Basic**	**+ Controls**
Obs.	1,166	1,166	1,166	1,166	1,439	1,439
Measure						
Blower Door and Air Sealing	15 (±24)	13 (±23)	30 (±24)	20 (±22)	24 (±22)	11 (±22)
Insulation	57 (±24)	54 (±24)	37 (±22)	34 (±22)	36 (±22)	39 (±21)
Gas Furnace	73 (±31)	73 (±33)	73 (±30)	80 (±30)	80 (±30)	84 (±27)
Boiler	78 (±31)	87 (±33)	85 (±27)	53 (±30)	43 (±28)	29 (±28)
Programmable Thermostat	4 (±23)	5 (±26)	9 (±23)	5 (±23)	9 (±22)	6 (±21)
	Program 1–Electric Baseload (kWh)–2010					
Obs.	4,055	4,055	4,055	4,055	5,375	5,375
Air Conditioning	331 (±557)	348(±557)	228 (±448)	204 (±450)	50 (±451)	70 (±453)
Refrigerator	657 (±251)	639(±261)	731 (±200)	726 (±210)	754 (±198)	768 (±207)
Electric Water Heater	1,279 (±629)	1,321 (±628)	561 (±511)	632 (±513)	186 (±486)	302 (±488)

Table 2 shows greater variability on the gas furnace results when comparing the basic house-by-house and pooled regression analyses.

	Program 2–Gas Heat (ccf)–2011					
	House-by-House		**Pooled Regression**		**Pooled –All Cases**	
	Basic	**+ Controls**	**Basic**	**+ Controls**	**Basic**	**+ Controls**
Obs.	1,211	1,211	1,211	1,211	1,665	1,665
Measure						
Blower Door and Air Sealing	30 (±23)	30 (±23)	23 (±20)	23 (±20)	10 (±18)	18 (±18)
Insulation	27 (±22)	25 (±22)	31 (±20)	27 (±19)	30 (±19)	24 (±19)
Gas Furnace	93 (±30)	106 (±33)	75 (±27)	94 (±27)	47 (±25)	75 (±25)
Boiler	63 (±30)	76 (±34)	85 (±27)	75 (±27)	57 (±25)	47 (±27)
Programmable Thermostat	6 (±21)	10 (±22)	10 (±20)	6 (±19)	9 (±19)	4 (±19)
	Program 2– Electric Baseload (kWh)–2011					
Obs.	2,440	2,440	2,440	2,440	4,654	4,654
Air Conditioning	590 (±448)	676 (±452)	596 (±357)	588 (±347)	352 (±320)	323 (±310)

	Program 2–Gas Heat (ccf)–2011					
	House-by-House		Pooled Regression		Pooled –All Cases	
	Basic	+ Controls	Basic	+ Controls	Basic	+ Controls
Refrigerator	410 (±309)	548 (±323)	566 (±245)	718 (±245)	799 (±210)	860 (±210)
Electric Water Heater	-235 (±788)	-271 (±799)	280 (±590)	-142 (±579)	671 (±516)	20 (±503)

Conclusion

This paper compared methods and results from a house-by-house and a pooled regression approach to weather normalization. We found that overall savings results were fairly consistent across the various models and differences between the models were rarely statistically significant. Gas usage results, with less variation in usage by idiosyncratic household patterns, were more consistent across the various models. Electric baseload analysis varied the most across the models. Measure-level results, estimated with a lower level of precision, showed much greater variability across the various models that were estimated. These findings lead to the following recommendations for usage billing analysis.

- Sources and potential biases caused by large data attrition should be explored and explained.
- When additional analysis is desired for many subgroups and data attrition is low, house-by-house analysis may be a favored approach.
- When data attrition is high and only overall usage results are desired, the pooled regression approach may be preferred.

Both approaches have advantages and disadvantages, and when possible, a comparison of the results across various approaches can be beneficial.

References

M. Fels, Ed. 1986. “Measuring Energy Savings: The Scorekeeping Approach,” Special PRISM Issue of *Energy and Buildings*, 9, #1-2, 180 pages.