Quantifying Household Energy Performance Using Annual Community Baselines

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1. Introduction

This paper describes an approach using metered data to estimate annual community energy consumption baselines for single-family detached homes in the Gainesville Regional Utility (GRU) service area of Alachua County, Florida, United States. Further, it details methods using these baselines to make direct comparisons of individual households' energy consumption and evaluate the performance impacts of three prescriptive demand side management (DSM) programs. This approach demonstrates the potential for application to a range of energy efficiency programs and utility service areas to improve impact evaluations and estimates of energy savings.

1.1 Building-Sector Energy Efficiency

Housing has an important role to play in decreasing overall energy consumption and associated Greenhouse Gas (GHG) emissions. Over the last decade the residential building sector accounted for over 20% of total U.S. energy consumption (EIA, 2009, p. 38), and this is an important sector to evaluate given that "single-family detached homes are the most energy-intensive housing type" (EIA, 1999). Despite residential energy intensity decreasing 9% from 1985 to 2004, total residential household and per capita energy use rose as house sizes increased while household occupancy decreased (DOE, 2008, p. 12). For all buildings (residential and commercial) GHG emissions averaged a 2.1% annual growth rate over approximately the same period (McMahon, McNeil *et al.*, 2007, p. 95).

Because of the building sector's size and relatively inefficient energy consumption patterns, it is a high-priority target for policies aiming to mitigate climate change and improve energy security. Improvements in energy efficiency "probably offer the greatest potential to provide [GHG emissions mitigation] wedges" for the United States (Pacala and Socolow, 2004, p. 969). Many estimates of the potential for reducing household energy consumption indicate that the residential building sector is and will continue to be a critical player in achieving this potential (Dietz *et al.*,

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2009; Horowitz, 2007). Some studies have projected that a whole-building systems integration of current best practices can reduce residential energy intensity between 30-40% at little or no additional cost, and possibly up to 70-90% in optimal situations (Affordable Comfort Inc., 2007; McMahon, McNeil *et al.*, 2007, p. 95; DOE, 2008, p. 12).

Federal and state governments promote energy efficiency in the residential sector with a variety of programs, some flexible and others highly prescriptive. For new residential construction the best known examples are the US Environmental Protection Agency's (EPA) ENERGY STAR® Homes program, which essentially requires a home to be ~15% more energy efficient than one built to code[1], and the US Department of Energy's (DOE) Building America Builders Challenge, which requires homes to be ~30% more energy efficient than houses built to code[2]. These two programs set performance thresholds rather than directly requiring specific practices and/or materials and both are flexible in the sense that builders can choose through design and product specification how to achieve the required efficiency targets. For existing housing the best known program is the DOE's Weatherization Assistance Program (WAP), a highly prescriptive retrofit program that ranks explicit residential retrofits and funds them in priority order[3].

Both the ENERGY STAR and Builders Challenge programs rely on Home Energy Rating System (HERS) Index scores as performance measures. A HERS rater uses an energy efficiency software package, EnergyGauge®[4], to perform an energy analysis of a home's design and specified components (windows, insulation, etc.). The rater then conducts on-site inspections, typically including a blower door test (to measure the air infiltration of the house) and a duct test (to measure leakage in Heating, Ventilation and Air Conditioning (HVAC) duct systems). Results of these tests, along with inputs derived from the plan review, are evaluated in reference to a similar home built to code and are then used to generate a home's HERS Index score[5]. ENERGY STAR and Builders Challenge program designations are awarded before a new home is occupied on the basis of HERS Index score meeting specific thresholds. Smith and Jones (2003) found that annual household energy consumption for ENERGY STAR qualified homes was significantly lower (~12% less) than conventionally built homes. However, post-occupancy household energy consumption data are seldom used to evaluate the success of these energy efficiency programs in achieving actual absolute or relative energy savings.

1.2 Demand Side Management (DSM) Program Goals and Outcomes

Historically, utility demand-side management (DSM) programs were designed to encourage consumers to modify their level and pattern of electricity usage in an effort to delay investments in new power plants and to manage costly peak electric demand (EIA, 1999). More recently, DSM programs have become linked to public policy concerns such as reducing financial burdens on low income households and reducing GHG emissions. Today, a fundamental goal of many DSM programs is to change patterns of energy use, thereby reducing absolute energy consumption and associated GHG emissions. Investor-owned utilities in Florida must submit DSM plans to the Public Service Commission as part of their responsibilities as regulated monopolies. Both investor-owned and municipal utilities are required to report DSM impact annually to the DOE Energy Information Administration (EIA) via Form EIA-861 (EIA, 2007). As DSM programs have moved more directly into the public policy sphere, utilities have shown a growing interest not only in implementing programs with meaningful energy consumption impacts, but also in maintaining the perception of successful programs.

Utility energy conservation programs (as well as national, state and local governments) are relying increasingly on incentives linked to "green certification" protocols to reduce residential energy use. Programs like ENERGY STAR are perceived to increase brand power for premium product pricing while encouraging reduced energy consumption:

> "If you purchase an energy-efficient product, you may be eligible for a federal tax credit…ENERGY STAR distinguishes energy efficient products which, although they may cost more to purchase than standard models, will pay you back in lower energy bills within a reasonable amount of time, [even] without a tax credit"[6].

Like many other power providers, GRU links one of its largest DSM rebates directly to the Home Performance with ENERGY STAR Program, "a whole-house approach developed to assist residential electric customers in upgrading existing homes to reduce energy use [and] lower their bills"[7].

All of the described programs' performance baselines rely on projected energy savings that are calculated from the energy efficiency characteristics of applied upgrades (such as programmable thermostats, ceiling fans and water heaters). The methods used to project energy savings can range from simplistic, such as a directly comparison of incandescent and compact fluorescent lamp energy use over a given period of time, to sophisticated, holistic processes using simulation modeling and direct testing, such as HERS Index scoring. Essentially, all program rebates, tax credits and energy efficiency designations are awarded on the front-end with no validation of post-occupancy energy consumption required.

This has led to a tendency in the building industry to rely on program labels and designations rather than on direct measurement of actual performance. There is growing concern that voluntary programs, such as the United States Green Building Council's (USGBC) Leadership in Energy and Environmental Design (LEED) programs, can mask a lack of energy-focused design behind other non-energy criteria, inaccurately estimate the actual energy in occupied buildings, and/or fail to acknowledge that performance persistence may degrade over time (Stein and Meier, 2000; Cannon *et al.*, 2008; Gifford, 2008; Jones and Vyas, 2008; Lstiburek, 2008; Malin, 2008; Del Percio, 2009; Scofield, 2009). These concerns are likely to be exacerbated if caps on GHG emissions are imposed.

Utilities can address these concerns directly, especially as they relate to DSM programs. Since they collect monthly energy consumption data (essential to their customer billing functions), they can directly quantify individual household energy consumption patterns and changes attributable to DSM programs. Property appraiser data also are available that provide basic building characteristics of individual homes, which are important factors affecting residential energy consumption and efficiency potential. By merging utility and property appraiser data, direct comparisons of individual households' energy consumption can be made and impacts of various prescriptive DSM programs can be evaluated.

1.3 Energy Use and Performance Baselines

Utilities reward customers with cash rebates for energy-efficiency upgrades that are presumed to reduce actual energy use and reduce GHG emissions, and DSM program performance is often evaluated based on its relative cost-effectiveness (e.g., cents per kWh saved or GHG emissions avoided) (Gillingham *et al.*, 2006). At the same time, "utility energy efficiency programs are taking center stage in ongoing discussions about U.S. energy policy and how best to combat climate change" (Arimura *et al.*, 2009, p. 24). In this context, the appropriate construct, interpretation, and application of energy performance baselines and specification of models to estimate savings are important (Parfomak and Lave, 1996; Schiller, 2007). The Model Energy Efficiency Program Impact Evaluation Guide emphasizes this point:

> "A major impact evaluation decision is selecting the baseline. The baseline defines the conditions, including energy consumption and related emissions that would have occurred without the subject program. The selection of a baseline scenario always involves uncertainty because it represents a hypothetical scenario" (Schiller, 2007, p. 4-2).

Sophisticated engineering, econometric, and mixed-model approaches have been developed to minimize uncertainty in specification of baseline scenarios and improve methods for evaluation of DSM program impact. Using these standard approaches, utility analysts and independent consultants are analyzing metered consumption data, estimating energy demand response to specific DSM programs, and calculating associated energy savings (Gillingham *et al.*, 2006). When funding is sufficient, the analyses attempt to quantify free rider, spillover, and rebound effects. However, the relatively high cost of complex modeling approaches (Schiller, 2007) and the variability of estimates across utilities justify continued pursuit of simple, valid, transparent and replicable methods for establishing energy performance baselines and measuring program impacts. In this paper, we describe a regression analysis approach that aims to satisfy these key methods criteria – simple, valid, transparent, and replicable – while generating robust estimates for the measures of interest.

Engineering Models

Empirical models are commonly used to project or estimate energy savings from DSM and other utility conservation and efficiency programs. Engineering models (such as the EnergyGauge® software that underpins the HERS Index) are typically constructed at a micro scale and are particularly useful for delineating the upper bounds of energy-efficiency potential for structural, mechanical, and electrical features of a home. Output from such models serves as benchmarks for measuring changes in performance after an appliance or equipment upgrade and/or for evaluating a new home's actual performance. They are particularly useful when constructed and applied at a whole-house systems level. Energy performance measures derived from engineering models alone, however, are limited in scope of application. They typically do not account for variability driven by factors independent of the home's engineered design and building features (such as occupant demographics and behavior). Furthermore, they cannot be easily scaled up to provide valid expectations about and estimates of performance at the community or utility level.

Econometric Models

Conversely, econometric models are typically constructed at a macro scale using self-reported electric utility data on energy consumption and savings (e.g., those supplied to the Energy Information Administration (EIA) via Form EIA-861[8]). These models often include data on critical energy demand determinants such as service population characteristics, utility rates, and climate data to estimate DSM program impacts within and across samples of utilities. While such econometric approaches are well-established and typically robust, they are designed for use at a macro level and are dependent on the quality of data that have already been aggregated by individual utilities (e.g., Horowitz, 2007; Arimura *et al.*, 2009), and they may not generate appropriate estimates of energy savings and cost-effectiveness when scaled down to the individual household or DSM-program level. Furthermore, methods used by individual utilities to calculate energy savings vary and the original data used to estimate key model parameters are often not readily accessible to the empirical research community. Finally, given uncertainties surrounding the original estimates of key independent variables (e.g., energy savings) applied in large scale econometric models, it is difficult to know whether changes in energy consumption via DSM programs are being measured using the most suitable performance baselines.

Are reported energy savings generated from and used by engineering and econometric models consistent in magnitude and precision with actual efficiency gains or are they simply gross estimates of change relative to a static baseline? Complex modeling that adjusts consumption measures for a wide range of independent variables can perform well in terms of producing precise, robust estimates of savings and isolating DSM program impacts (Parfomak and Lave, 1996; Gillingham *et al.*, 2006). Access to data that would improve or allow scaling of these analytical methods, however, is often expensive (Schiller, 2007). Central to the premise of this paper, we think that a more appropriate baseline for adjusting actual energy consumption data can be constructed to facilitate cost-efficient analyses at the utility scale. We propose that with this alternative baseline methodology, valid energy savings and impact assessment results can be achieved using a parsimonious – yet still logical and functional – approach to modeling residential energy use.

1.4 Annual Community Baselines (ACB) Approach

To improve estimates of energy savings, we propose using a "micro" scale multivariate regression methodology based on a census of utility and property appraiser household data. We have applied this approach in the GRU service territory to: 1) establish new measures of energy performance by constructing annual community energy consumption baselines against which actual (metered) household-level energy consumption (ekWh) is compared for the years 2004-2009, and 2) estimate energy savings attributable to each of three DSM programs implemented in 2007 using ACB estimates as the foundation for year-over-year performance comparisons.

Our proposed methodology is unique in that it: 1) defines a new household-level energy consumption baseline measure that we think produces more accurate performance measures, 2) uses a census of publicly-available data for the population of interest, merging metered utility data with property appraiser data; and 3) uses these census data with the new baseline measure to construct a simple model for evaluating changes in household-level energy consumption over time. These performance measures are then applied to estimate what we think are improved measures of energy savings attributable to each of the three DSM programs evaluated in this study.

The critical element that distinguishes our proposed energy performance measures is that they are calculated and interpreted using annual, population-level, comparison-group baselines that effectively normalize for community energy consumption patterns in any given year. Year-over-year changes in household consumption are evaluated relative to the community baseline, so residuals estimated from the ACB regression directly reflect our definition of meaningful and relevant energy performance measures (i.e., energy savings). Furthermore, because the annual performance measures themselves are derived from a regression-adjusted baseline approach, the data are normalized in such a way that year-over-year performance of individual households or groups of homes can be compared directly. This prevents the performance impacts of DSM and other energy conservation programs from being overstated or obscured as a result of non-program effects (such as economic conditions, rebound, free riders and free drivers, spillover and so on). In light of debate surrounding the need to account for these effects, which are "notoriously difficult to measure", we think that this feature of our model is particularly valuable (Heins, S. 2006; Herring, 2006).

2. Analysis Design and Methods

In developing our ACB model, we first considered the primary determinants of energy use of residential customers in a given utility service area, expressed generally in equation (1), and evaluated whether each was relevant and necessary for inclusion in the detailed analysis.

$$E_{t,u} = f\left(H_{t,u}, S_{t,u}, D_{t,u}, B_{t,u}, P_t, C_t\right) \quad (1)$$

Absolute energy use (*E*) of a given residential unit (*u*) in a specified time period (*t*) is a function of: 1) home building structural attributes (*H*) such as conditioned area and wall type; 2) number and type of energy systems or components within the home (*S*) such as HVAC systems, kitchen appliances, and electronics; 3) resident demographics (*D*) such as the number of occupants and their income and education level; 4) resident behavior (*B*) such as thermostat settings and length of showers; 5) electricity and natural gas prices (*P*); and 6) weather and climate variability (*C*).

2.1 Scope

One of our central aims is to develop a reliable protocol for measuring energy savings that uses commonly-available data sources, is practical in application, and is readily portable. A census of the available and reliable data is included without restrictions on or distortions of subpopulations within. It is designed to quantify true programmatic impacts on the community and utility service area within the context of evolving social norms and economic drivers related to energy consumption. Selection of independent variables for estimating annual baselines represents the simplest form that can be used to produce valid, statistically sound results. It is important to note that the ACBs are complementary to, but not direct substitutes for conventional "business-as-usual" baselines; they provide another layer of information that we argue is critical for effective construction of baselines or reference scenarios.

The ACB technique provides a measure of savings in terms of reduced energy consumption that is a function of but not synonymous with "increased efficiency". In addition, this technique applies specifically to site energy use of buildings, not accounting for primary energy associated with losses in production and transmission from source to site. To translate analysis outcomes to reflect utility scale impacts, factors related to operational efficiencies must be considered but are beyond the scope of this paper.

2.2 Data

Sources

To construct and test our model, data were requested and obtained from three sources: the Alachua County Property Appraiser (ACPA); Gainesville Regional Utilities (GRU), and the National Climatic Data Center (NCDC). ACPA provided data on the physical characteristics, location, and sales of all properties in Alachua County, Florida as of November 2009. GRU provided two distinct datasets. The first included monthly, account-level, electric, natural gas and water consumption data for each residential and commercial customer from 1996 through 2009[9]. The second GRU dataset included information about all DSM program participants through September 2009. Monthly heating and cooling degree day data for 1996 through 2009 were obtained from the NCDC.

In identifying data to use in the analysis, fields were selected based on availability, accuracy, and their known relation to residential energy consumption. Monthly, account level, electric and natural gas data linked to the premise, customer identification number, and physical address were selected from the GRU database. Physical address, building type, US Department of Revenue (DOR) tax code, parcel number, number of bedrooms, number of bathrooms, conditioned floor area, year built and residential neighborhood listing were selected from the ACPA database. Physical address was used to link and merge the two databases to create an analysis dataset. GRU DSM program data including the type of incentive, installation date, and incentive amount were tagged to the analysis dataset by premise and customer numbers. Table 1 lists the fields included in each of the original databases.

Table 1: Original databases from which full analysis dataset was generated

ACPA Database	GRU Consumption Database	GRU Rebate Database	NCDC Database
Parcel Number	Premise Number	Premise Number	Heating Degree Days
Physical Address	Customer Number	Customer Number	Cooling Degree Days
Building Type	Physical Address	Rebate Type	Year
DOR Code	Meter read date	Rebate Amount	Month
Number of Bedrooms	Service Type	Installation Date	
Number of Bathrooms	Billed Consumption		
Conditioned Area			
Year Built			
Neighborhood Code			

Cleaning and Screening

The 2009 ACPA database listed 51,746 single family residential units. Of the ACPA units 35,091 were identified by physical address to be GRU customers during calendar year 2009. For purposes of this study these single-family homes formed a census list from which annual subsets were created for calendar years 2004 through 2009 (excluding 2007). For each annual subset, homes were screened to ensure that there were at least 350 and no more than 380 days of electric consumption data on record and that the necessary property appraisal data were available.

Monthly electric and natural gas consumption were combined and expressed in units of equivalent kilowatt hours (ekWh) to quantify total annual energy use. Annual consumption data were normalized to represent the full calendar year by taking average daily use for the number of days recorded and multiplying by 365. Residential units consuming less than 3,000 ekWh per year or more than 65,000 ekWh per year were removed from the dataset as either unoccupied homes or outliers. A schematic representation of the screening process and listing of the full populations of single-family residential units that met all screening criteria to be included in five calendar year databases from 2004 through 2009 (excluding 2007) are shown in Figure 1.

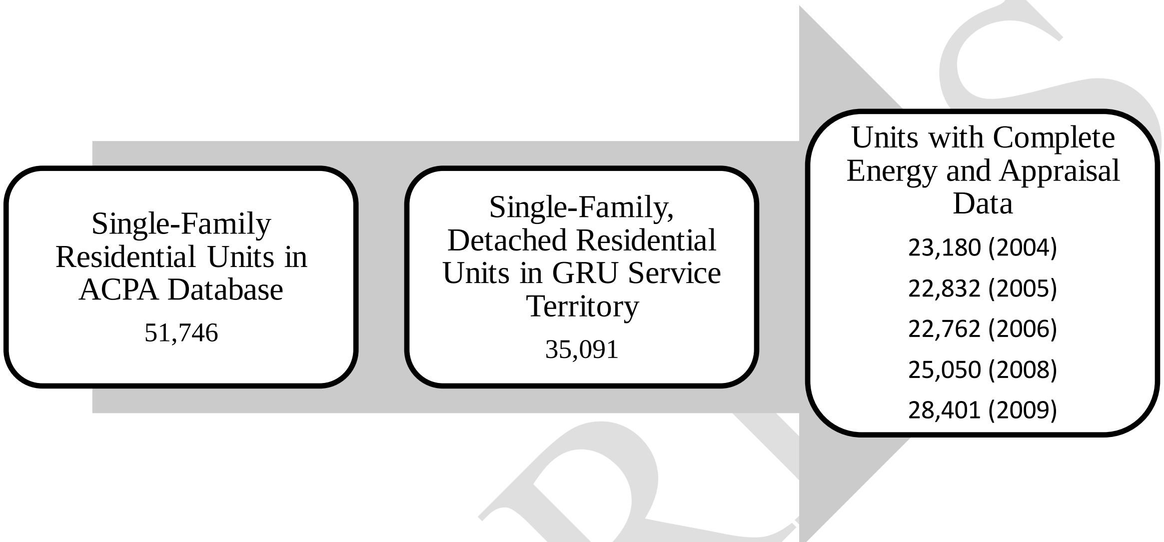

Figure 1: Diagram of initial data screening process to ensure no missing data or unoccupied homes.

2.3 ACB Model Specification

Each calendar year dataset was analyzed independently using multivariate regression, equation (2), to estimate predicted home energy use values for each residential unit in the census.

(2) $$EC_{t,u} = \beta_0 + \beta_1(Size\ Factor_{t,u}^{PC}) + \beta_2(Age_{t,u}) + \beta_3(Neighborhood_u) + \epsilon_{t,u}$$
where $Size\ Factor_{t,u}^{PC} = f(conditioned\ area, \#\ of\ bedrooms, \#\ of\ bathrooms)$

Annual energy consumption (*EC*) is the dependent variable with size factor (conditioned area, number of bedrooms and number of bathrooms), year built, and neighborhood code as independent variables. The number of bedrooms and bathrooms, and square feet of conditioned area are important explanatory factors for energy use because they are indicators of the number of people living in each home and HVAC demand, respectively. Using a principal components analysis (PCA), we transformed these highly correlated, yet distinct measures of home size into a single "size factor" predictor variable. Year built is also considered an important energy use predictor variable as it captures the building code under which the home was constructed and the common building practice used in that particular time period. To transform it to a more meaningful continuous value for use in regression, the year built variable was converted to home age by subtracting year built from the analysis year (2010). The property appraisal neighborhood code was selected as a geographic indicator for resident behavior and demographic variables (census block or zip code may substitute if necessary but may increase error in the model) and as an indicator of the materials, construction techniques and workmanship used in subsets of houses. These factors (size factor, age, and neighborhood code) were used to complete a regression analysis giving predicted energy use values for each home in each of the analysis years. These predicted values represent the Annual Community Baseline for absolute energy consumption ($\widehat{EC}_{t,u}$) in each year for each residential unit.

Residuals, $\hat{\varepsilon}_u$, derived from this ACB regression (equation (2)) are then interpreted as annual energy performance measures for each residential unit in each year; mathematically, they are calculated as actual minus predicted energy use

(3) $$\hat{\varepsilon}_{t,u} = (EC_{t,u} - \widehat{EC}_{t,u})$$

Overall annual performance of a given subset (*n*) of residential units in a given year (*t*) is calculated as the mean of the individual performance indicators (i.e., residuals) for that particular subset

(4) $$\overline{\hat{\varepsilon}_{t,u}} = \left(\sum_{u=1}^{n} \hat{\varepsilon}_{t,u}/n_t\right)$$

The absolute and relative year-over-year differences in the residuals for individual homes or subgroups of homes, equations (5a) and (5b), respectively, are then calculated to estimate changes in household energy performance over time

(5a) $$\Delta\hat{\varepsilon}_{t,u} = \left(\hat{\varepsilon}_{t_{post},u} - \hat{\varepsilon}_{t_{pre},u}\right)$$

(5b) $$\Delta\left(\hat{\varepsilon}_{t,u}/\widehat{EC}_{t,u}\right) = \left(\hat{\varepsilon}_{t_{post},u}/\widehat{EC}_{t_{post},u}\right) - \left(\hat{\varepsilon}_{t_{pre},u}/\widehat{EC}_{t_{pre},u}\right)$$

A second regression is used to estimate the magnitude and statistical significance of change in energy use (i.e., savings) for any given subset of the population relative to the census savings

(6) $$ES_{D,post-pre} = \gamma_0 + \gamma_1(Dummy) + \varepsilon$$

For this regression, equation (6), which essentially applies a basic analysis of variance statistical test, the changes in residuals between one year and the next for each residential unit (calculated using equations (5a) and (5b)) are used as the dependent variables and a dummy variable is used as the explanatory variable to distinguish the population sub-group of interest (coded '1') from all other residential homes in the population (coded '0'). The parameter coefficient, γ_1, estimated for the rebate dummy tells us the magnitude and direction of change in energy use, or energy savings, $ES_{D,post-pre}$ (such that a negative coefficient represents a decrease in energy use/increase in performance/positive energy savings for sub-group of interest while a positive change represents an increase in energy use/decrease in performance/negative energy savings). The p-test on the F-statistic for this regression provides a measure of statistical significance for these energy savings estimates.

2.4 Application of ACB to DSM

GRU's DSM programs were considered individually (single upgrades) for their numbers of participating households during calendar year 2007. Three programs were selected for evaluation: the Duct Sealing Rebate Program, the Refrigerator Buyback Program, and the Super SEER A/C Program. The Duct Sealing Rebate Program incentivizes customers to repair leaky ductwork to reduce pressure differential and associated air infiltration. The Refrigerator Buyback Program pays customers to dispose of secondary and unnecessary refrigerators and freezers to reduce energy consumption. The Super SEER A/C Rebate Program offers customers assistance in upgrading to HVAC equipment with a Seasonal Energy Efficiency Ratio (SEER) of 16+ or higher. GRU data were used to identify households that: 1) participated in one of the three selected programs during 2007; and 2) had not participated in any other GRU DSM programs. Homes that met these criteria were tagged; the number of tagged homes for each DSM program is shown in Table 2. For purposes of this analysis, the calendar year databases covering 2004 through 2009 (excluding 2007) were aggregated into a single database.

Table 2: Population sizes of residential units for rebate analysis

Rebate Type	N
Duct Sealing Rebate	123
Refrigerator Buyback	294
Super SEER A/C Rebate	148
Total	565

In addition to ACB, three conventional techniques were used to estimate energy savings attributable to the rebate programs. Energy savings estimates from the conventional techniques were then compared to those of the ACB approach to evaluate its relative effectiveness. For the purposes of this analysis, as in equation (6), 2006 performance is used as the reference or pre-installation standard, 2007 is the DSM intervention year, and 2008 and 2009 are the post-installation years. (Note that the term "baseline year" in this context refers to the conventional definition of the conditions that exist prior to an efficiency upgrade or other change: pre-installation. In this context, the ACB baseline year and reporting period years are all estimated using ACB regression, so this analysis technique actually includes four "baselines". Time Series, Time Series with Weather Normalized Annual Consumption (NAC), Time Series and Comparison Group, and Annual Community Baseline analyses were tested. (Explanations of these approaches were adapted from Schiller, 2007.)

- **Time Series** analysis was used to estimate savings by taking the difference between post upgrade energy use and pre upgrade energy use.

  Time Series Estimate = Post - Pre

- **Time Series NAC** used data normalized with heating and cooling degree data to calculate savings by taking the difference between post upgrade and pre upgrade energy use.

  Time Series NAC = $Post_{NAC}$ - Pre_{NAC}

- **Time Series and Comparison Group** analysis uses a difference in difference technique to estimate energy saving. The difference between average annual consumption of the census before and after upgrades to the sample population is subtracted from the post and pre upgrade consumption of the participants.

Time Series and Comparisons = (Post$_{participant}$ - Pre$_{participant}$) - (Post$_{census}$ - Pre$_{census}$)

- **Annual Community Baseline** uses multivariate regression to create predicted home energy use values for each home in the census. Homes that participated in rebate programs were compared by taking the difference of their residuals (actual minus predicted values) before and after energy conservation upgrades. (These savings estimates were then used in a second regression analysis to estimate program impact, so they are similar to the commonly-used difference-in-difference approach, but with an additional difference adjustment using the first regression expression residuals) (Meyer, 1995).

ACB Analysis = (Actual$_{post}$ - Predicted$_{post}$) - (Actual$_{pre}$ - Predicted$_{pre}$)

3. Results and Discussion

Each annual baseline graphed in Figure 2 represents the ordered range of expected energy use for DSM participant homes. The figure displays variability in expected consumption among homes and across years (as we expect from variability in climate, economic conditions, etc. across years, but also from changes in performance). Although these baselines only represent the DSM homes' performance baselines, they have been adjusted through the regression analysis using the entire census of homes. This effectively expands the number of comparables for each home to the maximum extent possible within the census. The area under each baseline represents the total energy consumption predicted for the DSM group in a given year. If the full census ACBs were plotted, their shapes would be similar to those shown in Figure 2 and the area under each baseline would represent the actual energy consumption for the given year.

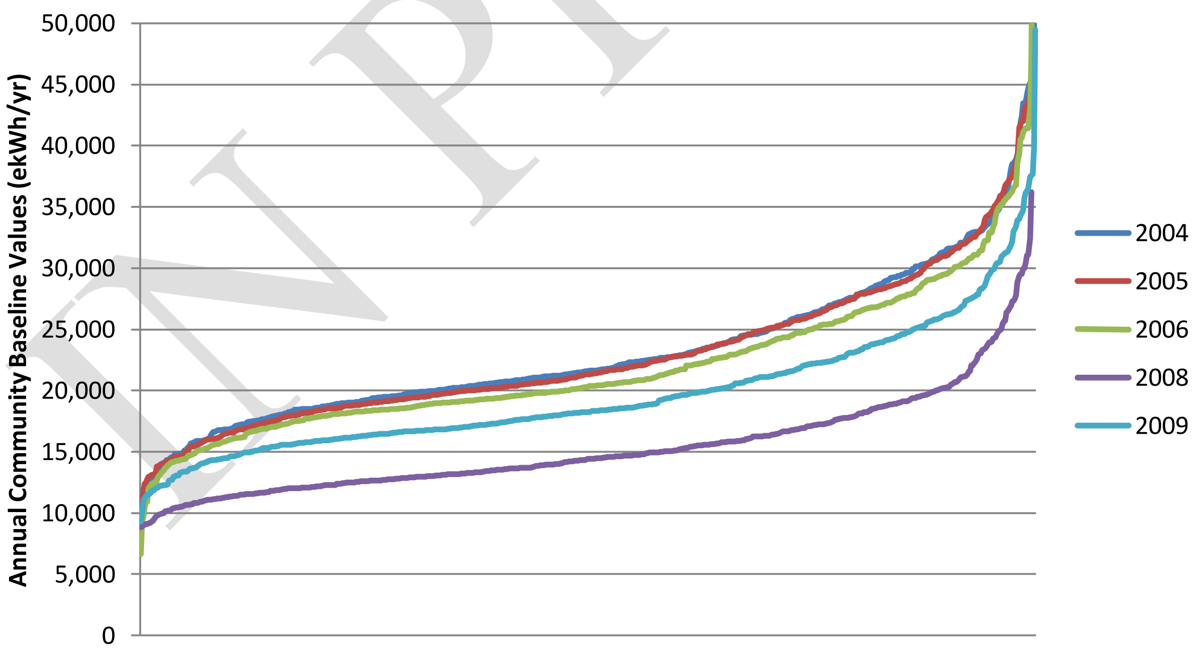

Figure 2: Annual energy use baseline value ranges presented by year for 2007 GRU rebate participants.

In Table 3, for each of the rebate programs the “Difference” values are equal to the average residuals in absolute terms while the “% Difference” are the residuals specified in relative terms so that it easier to interpret them as performance measures in a given year (i.e., the degree to which homes are consuming above or below the baseline). These values only compare within years between each DSM group and the entire population as represented by the baseline. In the years prior to 2007, the DSM participant homes were consuming more energy on average as determined by the ACB than their peer groups. In post-installation years (2008 and 2009) DSM participants reduced their consumption to points close to or below the baselines. These numbers are only annual performance indicators, not estimates of change in performance or programs savings. They can be compared across time within the context of the shifting annual baselines, but they alone cannot be used to estimate the effect of DSM participation on change in energy use and performance.

Table 3: DSM program participants’ actual energy use (ekWh) relative to ACB-predicted energy use, 2004-2009.

Program		2004	2005	2006	2007	2008	2009
Duct Sealing Rebate	Actual	23,966	23,905	23,169		14,853	19,324
n = 123	Baseline	23,152	22,812	21,879		15,281	19,593
	Difference	814	1,093	1,290		-428	-268
	% Difference	3.52%	4.79%	5.89%		-2.80%	-1.37%
Refrigerator Buyback	Actual	23,326	23,817	22,999		15,401	19,822
n = 294	Baseline	23,017	22,682	21,891		15,467	19,502
	Difference	308	1,135	1,108		-66	320
	% Difference	1.34%	5.00%	5.06%		-0.43%	1.64%
Super SEER A/C Rebate	Actual	23,030	22,569	21,922		14,348	18,466
n = 148	Baseline	22,437	22,046	21,115		14,804	19,010
	Difference	593	523	808		-456	-544
	% Difference	2.64%	2.37%	3.83%		-3.08%	-2.86%

Figures 3-5 provide a visual representation of results in Table 5 and illustrate how the relative performance of DSM program participants changes from year to year. Notice that in all three figures, DSM participants’ performance improved after 2007 relative to previous years, which indicates that the DSM programs *may* have had a significant effect on performance in 2008 and 2009. It is also worth noting that year over year changes in relative performance of the DSM participant groups are small relative to the changes in the ACBs.

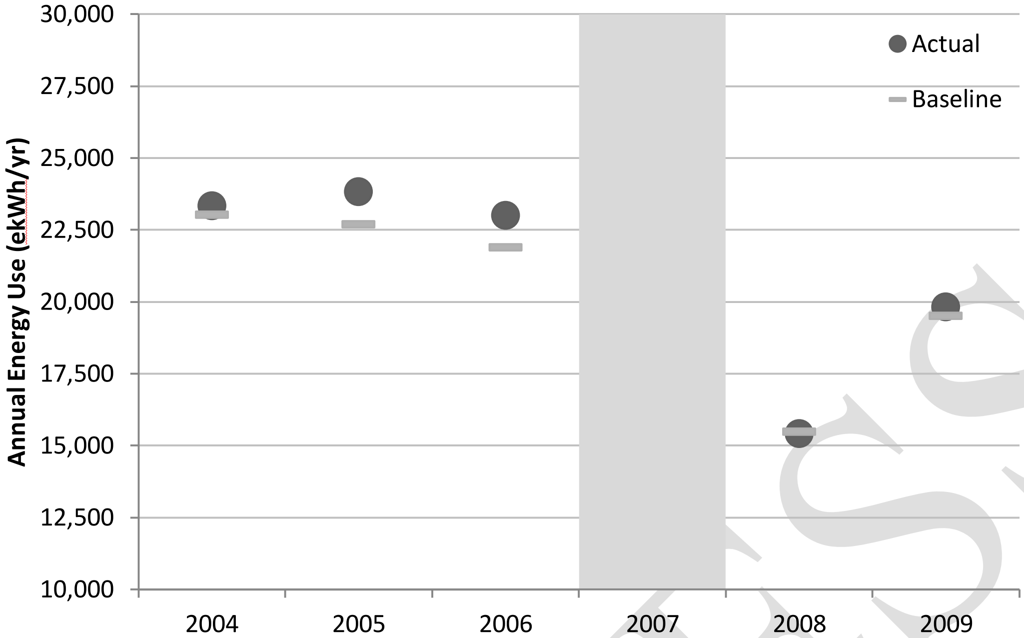

Figure 3: Average annual energy use for 2007 GRU Duct Sealing Rebate Program Participants as compared to their average Annual Community Baselines.

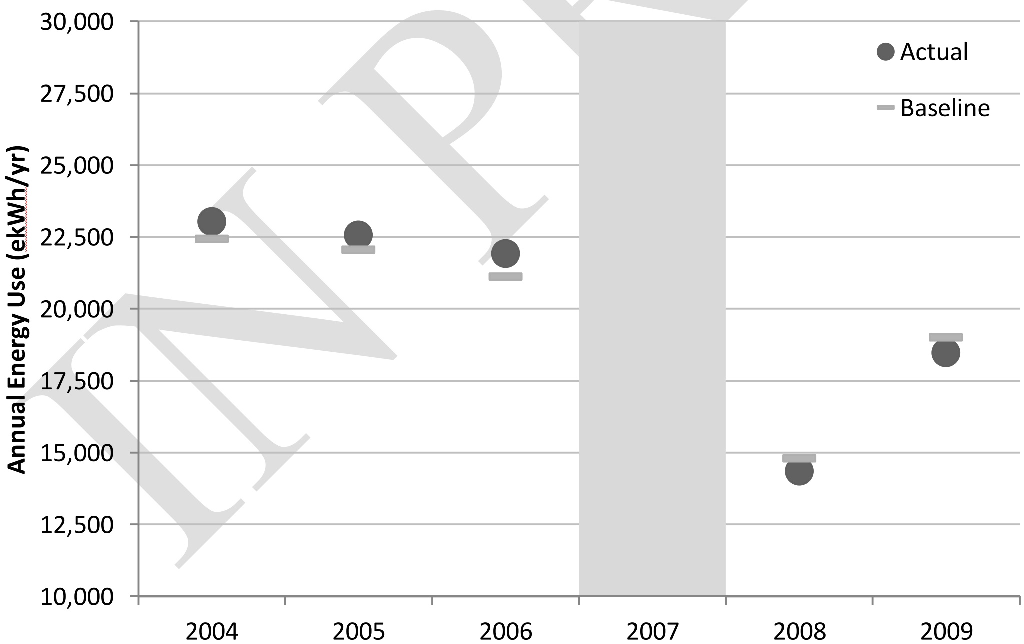

Figure 4: Average annual energy use for 2007 GRU Refrigerator Buyback Program participants as compared to their average Annual Community Baselines.

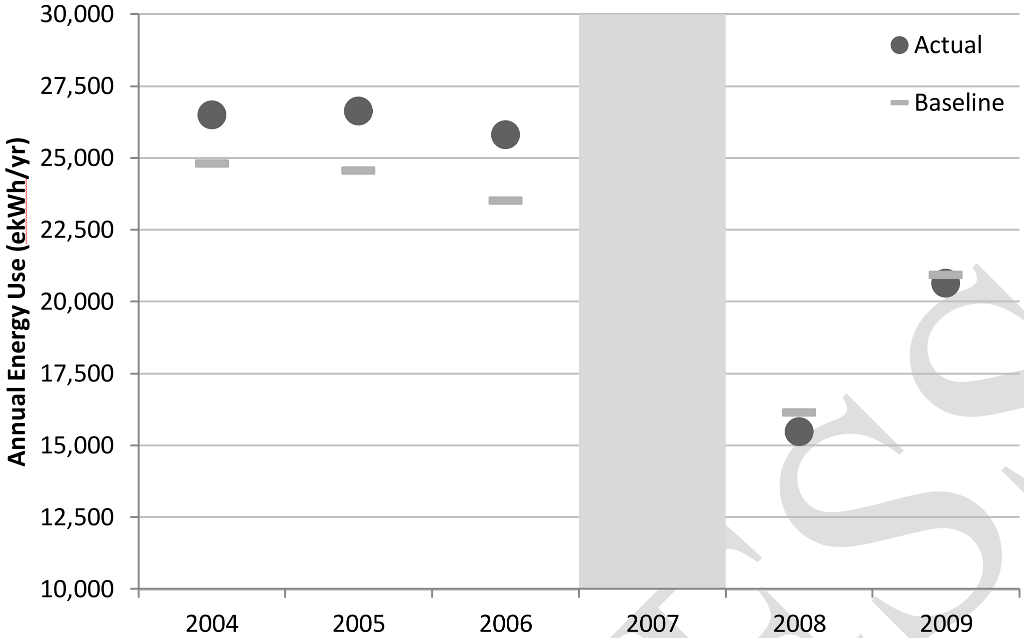

Figure 5: Average annual energy use for 2007 GRU Super SEER A/C Rebate Program Participants as compared to their average Annual Community Baselines.

Table 4 shows the estimates of energy savings attributable to each DSM program using each of the four analysis techniques. Recall that in all analyses, 2006 represents the pre-installation or reference year and 2008 and 2009 are the reporting period years. Results suggest that conventional analysis approaches are likely to overestimate savings significantly, ranging from an average across reference years and techniques of 2.5 times higher when applied to the Super SEER A/C Rebate to 4.9 times higher when applied to the Duct Sealing Rebate. Overall, ACB appears to give more stable savings estimates when compared across the two post-installation year analyses. For example, if time series analysis is used, an average savings of 10,351 ekWh/yr would be reported attributable to the Super SEER A/C Rebate program for the 2008 reporting period while the estimate for 2009 drops ~56% to 4,476 ekWh/yr; future reporting period estimates should improve our confidence in making this claim. Time series analysis results in the largest discrepancy in savings estimates for the two reporting periods, followed by time series analysis of weather normalized annual consumption (NAC). Although commonly used in the utility industry, these two techniques are understood by experts to be weak, if not unacceptable, for reports of program impacts (Schiller, 2007).

Table 4: Estimates of energy savings (ekWh/yr) across DSM programs using conventional techniques and ACB.

Program	Sample Size	Analysis Year	Time Series	Time Series NAC	Time Series Comparison	ACB
Duct Sealing Rebate	123	2008	-8,066***	-6,846***	-1,599***	-1,136**
		2009	-3,016**	-4,493**	-1,039**	-572
		Difference in estimates	5,050	2,353	560	564
Refrigerator Buyback	294	2008	-7,622***	-6,463***	-1,155***	-959***
		2009	-3,450***	-4,828***	-1,473***	-1,220***
		Difference in estimates	4,172	1,635	318	261
Super SEER A/C Rebate	148	2008	-10,351***	-9,122***	-3,884***	-2,786***
		2009	-4,776***	-6,316***	-2,799***	-2,191***
		Difference in estimates	5,575	2,806	1,085	595

Note: * indicates statistical significance at 10%, ** at 5%, and *** at 1% level.

Time series with comparison groups was the third comparison technique applied. In this case the entire census was used as the comparison group and DSM participant homes were evaluated based on census average energy use before and after program implementation. When homes are compared with others in the same geographic and utility service area, effects of energy prices and weather are inherently incorporated (because in any given time period, all homes experience the same prices and weather), so data are not normalized using price or climate data for this and the ACB analysis. Although this technique can provide more realistic estimates of savings than time series or time series NAC, results are highly dependent on data screening methods used to create comparison groups. Figures 6-8 graph the results in Table 6 as estimated energy savings across the four analysis techniques; they reinforce the potential for wide variation in deemed program impact as a result of the analysis technique used to adjust actual energy use and estimate savings.

Table 5 shows estimates for energy savings associated with the three DSM programs derived using ACB analysis. Estimates are presented in terms of both absolute and relative (percentage) savings. Table 5 also includes estimates for the effect (i.e., magnitude and significance) of the DSM on changes in annual performance and estimates the extent to which energy savings are directly attributable to the DSM program. Both the Refrigerator Buyback and the Super SEER A/C Rebate programs showed statistically significant changes in energy use associated with the efficiency upgrades.

(It should be noted that the Duct Sealing Rebate Program returned marginally significant savings in 2008 and savings that were not statistically significant in 2009.)

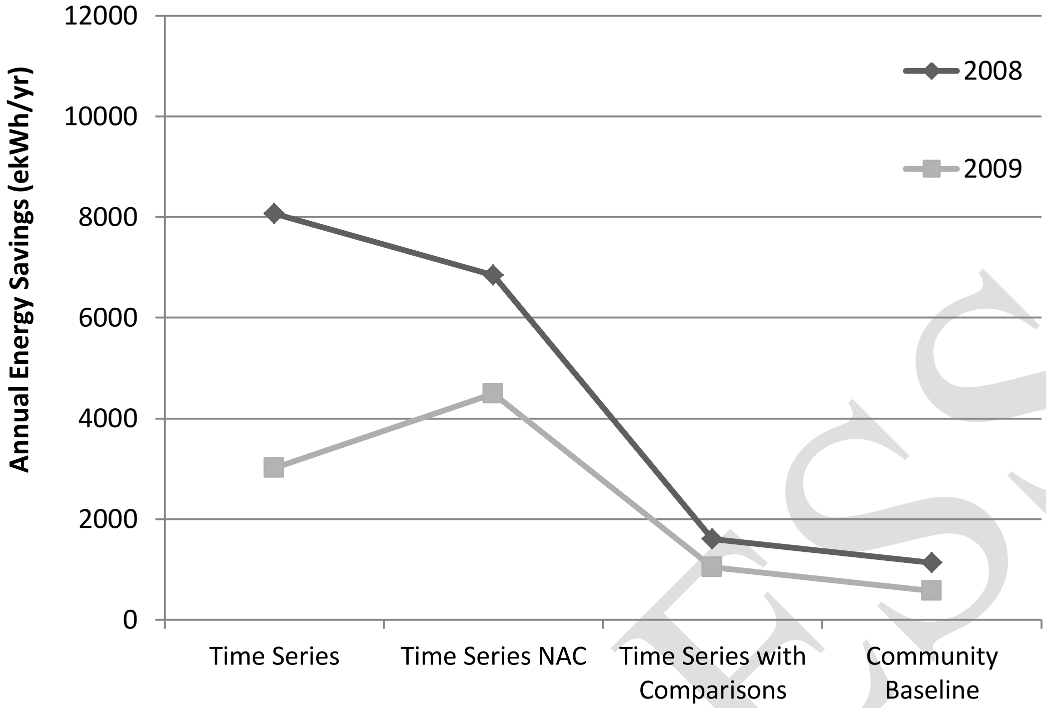

Figure 6: 2007 GRU Duct Sealing Program savings estimates using various analysis methods

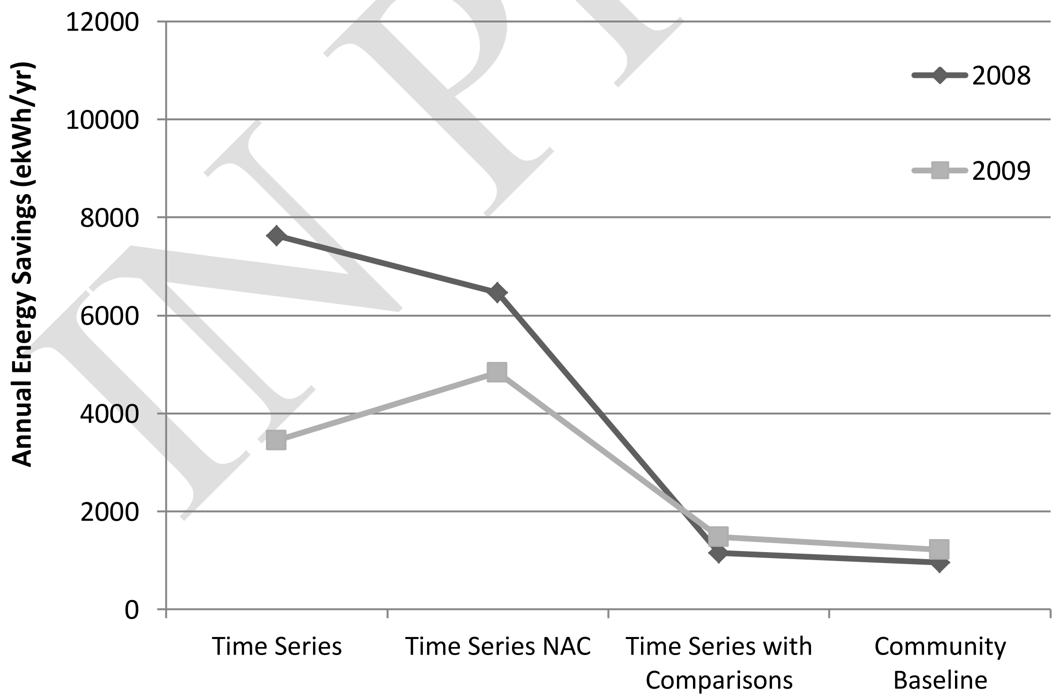

Figure 7: 2007 GRU Refrigerator Buyback Program savings estimates using various analysis methods.

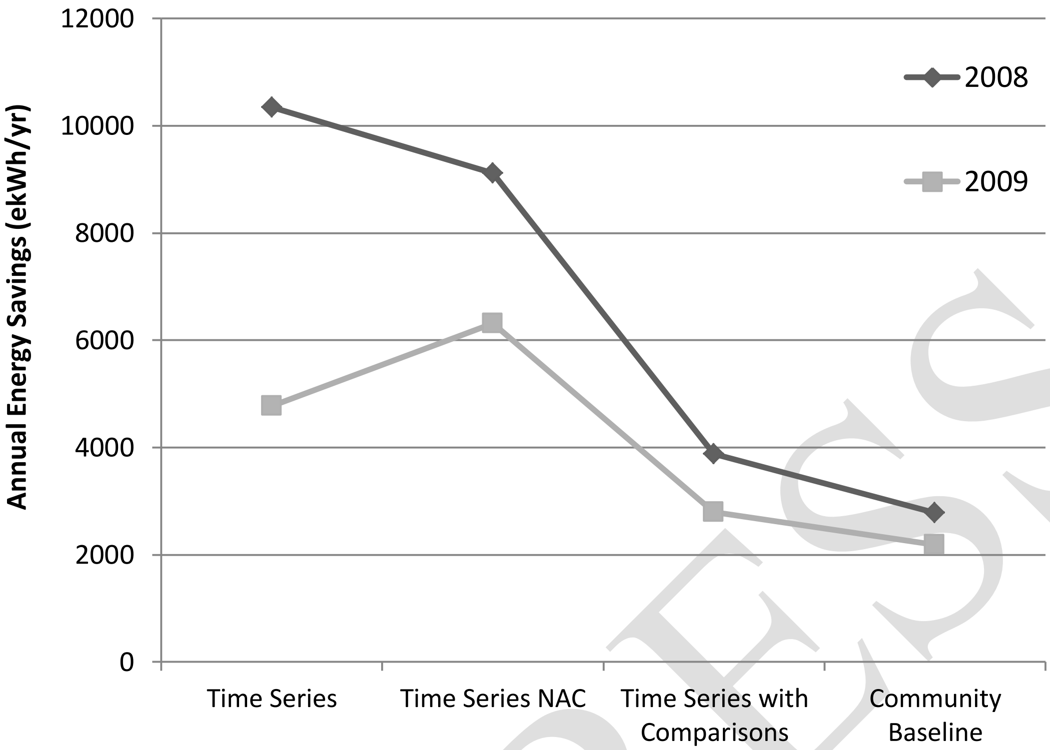

Figure 8: 2007 GRU Refrigerator Buyback Program savings estimates using various analysis methods

Table 5: Results of Rebate Savings Analysis using ACB technique, given as absolute and relative savings (ekWh).

Program	Sample Size	Analysis Year	ACB Savings (absolute)	ACB Savings (relative)
Duct Sealing Rebate	123	2008	-1,136**	-5.1%*
		2009	-572	-1.5%
Refrigerator Buyback	294	2008	-959***	-5.5%***
		2009	-1,220***	-6.4%***
Super SEER A/C Rebate	148	2008	-2,786***	-12.6%***
		2009	-2,191***	-8.9%***

Note: * indicates statistical significance at 10%, ** at 5%, and *** at 1% level.

4. Conclusions

Estimates of potential savings from energy efficiency programs are the key drivers for homeowner decision making and demand side management program design. If careful attention is not given to data screening, baseline development, model specification and final analysis, flawed estimates can lead to unexpectedly long payback periods for both utilities and their customers. Deemed savings for building retrofits are generally based on engineering analyses and typically do not take into account occupant behavior and other factors likely to affect performance. Savings measured using simple time-series modeling techniques do not properly account for environmental, economic, and social trends. Advanced econometric and mixed models that attempt to compare residential performance across geographic regions based on utility reported savings are typically at an aggregate level and may have flawed input that can distort impact estimates.

The proposed method of Annual Community Baseline analysis offers a tool that can provide accurate estimates of year-over-year changes in household energy consumption that in turn, can be used to fairly evaluate the impact of various energy conservation efforts. The ACB regression analysis approach is a relatively inexpensive, simple, rigorous, transparent, and replicable method for generating robust estimates of performance impacts of any energy conservation program. For utilities ACB analysis can be used to more effectively compare and prioritize their demand side management programs as shown in this study. We believe that ACB can provide an effective means to accurately depict real-world energy savings impacts and that it can work equally well for evaluating weatherization in existing homes or "green" certification programs applied to new housing.

Notes

1. ENERGY STAR is a labeling program of the U.S. Environmental Protection Agency designed to promote the adoption of energy efficient technologies in lighting, appliances, electronics, equipment, homes, and industrial buildings to reduce greenhouse gas emissions. See www.energystar.gov for more information.
2. Builders Challenge is a program of the U.S. Department of Energy that provides incentives – research results and marketing tools – for homebuilders to construct homes that excel in energy performance. The program's goal is to expand the market for "cost-neutral, net-zero energy homes" in the U.S. market. See www1.eere.energy.gov/buildings/challenge for more information.
3. The Weatherization Assistance Program (WAP) is a funding program administered through the U.S. Department of Energy Office of Energy Efficiency & Renewable Energy to help low-income families reduce their energy bills through improvements in home energy efficiency. See http://www1.eere.energy.gov/wip/wap.html for more information.
4. EnergyGauge® is a software tool for analyzing buildings' energy use performance, compliance with building codes, and economics of energy efficiency upgrades. See http://www.energygauge.com for more information.
5. The HERS® Index is a relative energy use index for rating buildings. A "HERS Index of 100 represents the energy use of the "American Standard Building" and an Index of 0 (zero) indicates that the Proposed Building uses no net purchased energy (a Zero Energy Building)". For additional details, see www.natresnet.org.
6. ENERGY STAR "Federal Tax Credits for Energy Efficiency" at http://www.energystar.gov/index.cfm?c=tax_credits.tx_index.
7. Gainesville Regional Utilities (GRU) "Home Performance with ENERGY STAR® Program" at http://www.gru.com/YourHome/Conservation/Energy/Rebates/homePerformance.jsp.

8. All electric utilities in the United States, its territories, and Puerto Rico are required to submit Form EIA-861 (Annual Electric Power Industry Report) each year to the U.S. Department of Energy, Energy Information Administration. It can be viewed/downloaded at http://www.eia.doe.gov/cneaf/electricity/forms/eia861/eia861.pdf. Instructions for completing the form, including details about how energy savings should be measured, can be viewed/downloaded at http://www.eia.doe.gov/cneaf/electricity/forms/eia861/eia861instr.pdf.

9. Due to data reliability and availability issues in 2007, these consumption data were not used in this study. Homes that were upgraded in 2007 were analyzed based on their metered consumption in years before (2006) and after (2008 and 2009) the upgrades.

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