Title:

Cross comparison of empirical and simulated models for calculating residential electricity consumption

Authors:

Pamela Torres
The University of Texas at Austin
Civil Architectural and Environmental Engineering

Michael Blackhurst
The University of Texas at Austin
Civil Architectural and Environmental Engineering

Nour Bouhou
The University of Texas at Austin
Civil Architectural and Environmental Engineering

Corresponding Author:

Pamela Torres
Pjt19@utexas.edu
571-294-4621
The University of Texas at Austin
Civil Architectural and Environmental Engineering
301 E. Dean Keaton, Stop 1752
Austin, TX 78712

Acronyms

CCSP U.S. Climate Change Science Program

EIA Energy Information Administration

ICC Intraclass Correlation Coefficient

ME mixed-effects model

MLR multiple linear regression

PS Pecan Street Research Institute

RECS Residential Energy Consumption Survey

1. Introduction

Many local, state and regional agencies have historically relied on simulated residential energy end-use consumption data for decision support, particularly for demand-side management [1,2,3,4,5,6]. Perhaps the most utilized end-use consumption estimates are published in the Residential Energy Consumption Survey (RECS), which the U.S. Energy Information Administration (EIA) has provided since 1979.

RECS is a nationwide cross-sectional survey that uses multiple sources to simulate and generate non-linear statistical models that estimate costs and usage for heating, cooling, appliances and other end uses [7]. EIA conducts in-person interviews to collect energy characteristics on housing unit (including dimension measurements), use patterns, and household demographics. EIA uses geographic indicators from other government agencies, such as cooling and heating degree-days (CDDs, HDDs), to complete the characteristics profile of each household.

Follow-up surveys with energy suppliers are conducted to obtain more accurate total annual energy consumption and expenditures. EIA [7] states that they received complete or partially complete data for 90% of the households surveyed and 90% participation of the energy suppliers. Missing and inconsistent data are edited using a variety of statistical adjustments. In brief, business end-uses are removed and total annual consumption is estimated where records are incomplete. End-use regression models and previous RECS publications are also used to quality assure and complete household records. Additionally, base-sampling weights for each household are calculated in order

to scale sampled household estimates to national values from the RECS sample. Although energy data are collected on a monthly basis, RECS produces only annualized consumption and expenditures estimates for each reference year.

Consumption and expenditures for specific end-uses must be estimated by disaggregating total household consumption and expenditure estimates. The EIA [8] uses five separate and independently fitted nonlinear regression models - one for each of the main fuels (electricity, natural gas, propane, fuel oil, and kerosene) - for end-use disaggregation. Most of the independent variables are housing unit characteristics: physical home characteristics such as age and size of home; demographic information such as number of household members and income bracket; and equipment-related characteristics such as quantity or size. For example, total electricity use is an additive model of nonlinear models of space heating, air conditioning, refrigerator and other such appliances. The nonlinear models of individual end-uses (e.g. space heating or air conditioning) may include additional exogenous independent variables, such as cooling-degree days. Missing measurement data (i.e. non-energy data) is imputed using a statistical process called hot-deck imputation, where missing data is randomly assigned to the same data value as a similar household.

Final end-use estimations are based on an iterative procedure that uses nonlinear regression model techniques (SAS proc nlin with the Marquardt option). The estimation process uses end-use estimates from prior RECS publications, increasing or decreasing previous estimates based upon new information. Some adjustments are made using EIA expert judgment. For quality control, the estimated summation of estimated end-uses may be further adjusted based upon the observed total consumption.

There are many examples of decision support and research using RECS. Recent examples include highlighting regional demand differences influenced by space conditioning balance points [9, 10] and econometric analysis of residential energy consumption [11, 12, 13, 14, 15, 16, 17, 18]. The U.S. Climate Change Science Program (CCSP) [19] recently used RECS data to estimate the future energy consumption for the buildings sector. Similarly, the U.S. Department of Energy has also produced multiple documents referencing studies reliant on RECS data. The National Action Plan for Energy Efficiency Leadership Group recommends RECS as a data source for demand-side

analyses [20]. Several respective applications include residential energy efficiency simulations [21] and saving potentials due to smart metering [22].

Recently, however, some studies reveal discrepancies in the RECS data. For example Kaza [23] shows that the 2005 RECS space-conditioning end-uses account for almost half of the energy consumption, while his analysis shows space-conditioning accounts for only 37% of the energy use. Kaza attributes this overestimation to the sampling weights used by the EIA that are not reflective of variability and lacks sample stratification method. More recently, Ewing and Rong [24] and Tso and Guan [25] performed multilevel regression analysis to capture the natural hierarchical structure of RECS, concluding that despite their more sophisticated and encompassing model, RECS fails to collect enough information to fully describe households' behaviors. Tso and Guan highlight inconsistencies with their results (e.g. less drafty homes consume more energy than more drafty homes), and suggest that increased precision of models requires more specific information of householders' end-use behaviors.

With emerging sources of high-resolution empirical data describing energy consumption and respective predictors, it is increasingly possible to explore, compare and validate the predictive power of RECS. Such analyses are important to identify any inappropriate assumptions supporting the RECS data that may consequently affect downstream decision-making processes. The purpose of our analysis is to develop empirical models of residential air conditioning demands and apply these models to both the RECS database (estimated) and a separate high-resolution dataset (observed) to develop insights into potential opportunities to improve RECS and similarly derived energy use estimates.

2. Methods

2.1 Data Description

Observed electricity consumption data were obtained from the Pecan Street Research Institute (PS). PS is a 501(3)c non-profit that has partnered with The University of Texas at Austin and industry leaders to advance understanding of resource consumption in homes. The information is gathered through a series of home inspections, drawings, two household surveys, energy audits, and metered energy consumption (electricity, water and natural gas) that encompass occupant characteristics (e.g. income, education, age, household size), physical

descriptors of the home (e.g. floor area, home vintage, insulation) and behavioral and technology penetration choices (e.g. number of different energy efficient technologies, frequency of use of different technologies, indoor temperature settings). Though PS currently has over 1,000 participants located throughout Austin, Texas, only 126 homes have completed comprehensive audits, which do not include demographic information such as income, education, household members, etc. Annual consumption for PS sample reflects the period between May 1, 2013 and April 30, 2014, which was selected to maximize the PS sample size with a complete annual record.

The 2009 RECS provides complete data for 12,083 households. To have comparable data sets, the RECS data was filtered to only provide urban, single-family detached homes in Texas, reducing the original 12,083 homes to 464 homes. Tso and Guan [25] and Kaza [23] both suggest models beyond multiple linear regression analysis, due to geographical factors that may influence consumption behaviors, i.e. households that share common social standards and a common environment may have similar consumption patterns despite different household features. Tso and Guan [25] state that most sampling designs of RECS (that obtain population represented samples) adopt multistage stratified sampling schemes, creating a multilevel structure where observations are not independently and identically distributed. The models specified by PS data, though obtained by multiple linear regression analyses, allow for natural clustering addressed by Tso and Guan because homes are geographically similar. However, in order to compare values across different models, the models specified by RECS data were also obtained using multiple linear regression analyses. The multilevel structural issue is addressed by matching 126 RECS homes to the 126 PS homes using one-to-one propensity score matching [26, 27, 28, 29, 30] based on total electricity consumption, cooling-degree days (CDD), and floor area.

While the PS data provides continuous insulation R-values, the RECS data provide a qualitative assessment of overall home insulation (poor, fair, good, adequate, and excellent). Both RECS and PS insulation values were transformed into binary values, where homes are either adequately insulated (input = 1) or not (input = 0). The critical value for the continuous values of the PS data was calculated to be R-values above 17 [31].

Similar to Steemer and Yun [17], the distribution of each data set was checked for normality. The PS air conditioning electricity consumption is slightly positively skewed (0.42) and has greater than normal kurtosis

(3.74). Nevertheless, a transformation was not pursued because doing so increases skewness and kurtosis significantly (minimum skewness of -1.77 and kurtosis of 6.31). No significant outliers were identified.

Though traditional analyses include income and education, energy audit data available for PS homes does not provide that information. Nevertheless, the exclusion of these indicators were not of great concern due to recent studies that consistently show the lack of statistical significance of income and education as directly impacting energy consumption [18, 23, 32].

Table 1 provides descriptive statistics of each sample. The following observations from Table 1 are noted:

- *Building Characteristics:* RECS and PS homes are similar in size and the majority of them have slab-on-grade foundation. Yet, RECS homes are slightly older homes by about a decade.
- *Cooling Technologies:* Both RECS and PS show that a great majority of homes cool their homes through central AC (75 percent and 92 percent, respectively), and very few have window AC units. However, RECS reports 10 times more window AC units than PS. Additionally, PS homes report using heat pumps three times more than RECS.
- *Insulation Technologies:* RECS homes have more than twice the total window area than PS homes, yet less efficient windows, 37 percent compared to 70 percent in PS homes. Both RECS and PS have comparable adequate insulation. PS homes report having more than twice as many programmable thermostats as RECS homes.
- *Technology Penetration:* Most technologies have similar penetration patterns, except for efficient dishwashers and clothes washers, where RECS reports about two times greater technology penetration than PS.

2.2 Methodology

Explanatory variables were chosen parsimoniously, comparing purposeful selection results [33] to traditional methods of forward selection, backward elimination, and stepwise selection [34, 35]. A p-value of 0.10 was used for the entry and removal of variables for the forward selection and backward elimination methods. Selected

models were compared to address (1) individual adequacy as well as the overall performance of the combined variables and (2) potential overfitting and irrelevant noise variables or highly inflated R^2 values [35].

Bendel and Afif [36] suggest that models with 80 degrees of freedom should be subject to preferred significance level of entry of a variable of 0.25 and that the significance level of removal be half of the entry level. Considering 126 households and a maximum of 13 allowable independent variables to achieve a numerically stable model, our stepwise selection method set an entry level of 0.25 and a removal level of 0.10. We did not consider interaction terms for our purposeful selection model and limited the final number of predictors to 12 terms due to sample size restriction. Finally, a robust regression was implemented, instead of the more common least square regression, as an additional measure to counteract the shortcomings of a small sample size and to ensure constant variance of error terms [37].

The above procedures were used to derive two independent linear models of electricity demand; one using PS data (Equation 1) and the other using RECS data (Equation 2). Variables such as conditioned square-footage and window area are represented per 1000 and 100 square-feet, respectively, to provide estimates within the same magnitude as other binary variables. Additionally, these models were modified to quantify the statistical significance between estimate values across data sources (Equation 3 and Equation 4); that is, pooling PS and RECS homes (total of 252 households) and creating an interaction term between PS homes and each indicator. Thus, the coefficient for the interaction terms provide the magnitude and significance of the demand differences among PS homes (PS = 1) compared to RECS homes (PS = 0).

$$\begin{aligned} AC\_KWH = & \beta_0 + \beta_1 \text{conditioned\_sqft\_per1000} + \beta_2 \text{total\_window\_sqft\_per100} \\ & + \beta_3 \text{window\_double\_triple\_pane} + \beta_4 \text{has\_heat\_pump} + \beta_5 \text{adequate\_insulation} \\ & + \beta_6 \text{cooling\_system\_central\_ac} + \varepsilon \end{aligned}$$

(Specified using PS data)

Equation 1

$$\begin{aligned} AC\_KWH = & \beta_0 + \beta_1 \text{conditioned\_sqft\_per1000} + \beta_2 \text{foundation\_slab} + \beta_3 \text{total\_window\_sqft\_per100} \\ & + \beta_4 \text{window\_double\_triple\_pane} + \beta_5 \text{thermostats\_programmable} \\ & + \beta_6 \text{cooling\_system\_window\_units} + \beta_7 \text{cooling\_system\_central\_ac} \\ & + \beta_8 \text{has\_heat\_pump} + \varepsilon \end{aligned}$$

(Specified using RECS data)

Equation 2

$$\begin{aligned} AC\_KWH = & \beta_0 + \beta_1 conditioned\_sqft\_per100 + \beta_2 total\_window\_sqft\_per100 \\ & + \beta_3 window\_double\_or\_triple\_pane + \beta_4 has\_heat\_pump + \beta_5 adequate\_insulation \\ & + \beta_6 cooling\_system\_central\_ac + \beta_7 PS + \beta_8 PS \cdot conditioned\_sqft\_per100 + \beta_9 PS \\ & \cdot total\_window\_sqft\_per100 + \beta_{10} PS \cdot window\_double\_triple\_pane + \beta_{11} PS \\ & \cdot has\_heat\_pump + \beta_{12} PS \cdot adequate\_insulation + \beta_{13} PS \cdot cooling\_system\_central\_ac \\ & + \varepsilon \end{aligned}$$

(Specified using PS data)

Equation 3

$$\begin{aligned} AC\_KWH = & \beta_0 + \beta_1 conditioned\_sqft\_per100 + \beta_2 foundation\_slab + \beta_3 total\_window\_sqft\_per100 \\ & + \beta_4 window\_double\_triple\_pane + \beta_5 thermostats\_programmable \\ & + \beta_6 cooling\_system\_window\_units + \beta_7 cooling\_system\_central\_ac \\ & + \beta_8 has\_heat\_pump + \beta_9 PS + \beta_{10} PS \cdot foundation\_slab + \beta_{11} PS \cdot home\_vintage + \beta_{12} PS \\ & \cdot total\_window\_sqft\_per100 + \beta_{13} PS \cdot window\_double\_triple\_pane + \beta_{14} PS \\ & \cdot thermostats\_programmable + \beta_{15} PS \cdot cooling\_system\_window\_units + \beta_{16} PS \\ & \cdot cooling\_system\_central\_ac + \beta_{17} PS \cdot has\_heat\_pump + \varepsilon \end{aligned}$$

(Specified using RECS data)

Equation 4

While each model specification was tailored to a specific data set (PS or RECS), we compare results from both modeling estimates to highlight model sensitivity to specific indicators. Post-estimation diagnostics were conducted to verify the goodness of fit criteria- residuals appeared random and independent, based on both a graphical and a normal distribution evaluation. No significant outliers were identified.

In addition to the robust multiple linear regression (MLR) models described above, we also applied a mixed effects (ME) model to the PS data. We used the same predictor variables described in Equation 1 and 2 in the ME model (using monthly consumption, rather than yearly consumption) to test the significance of seasonality. We also derived a separate analysis based solely on PS data to (1) disaggregate seasonality from repeated choices within the same household- an analysis similar to that of Revelt and Train [38]- and (2) understand potential

consumption predictors that are provided by the PS audits but that are not currently surveyed in RECS.

The power behind mixed effects models lies on not only accounting for fixed effects of independent variables (e.g. conditioned floor area, home vintage, etc.), but also accounting for the unobservable preferences associated with repeated choices made by the same household (i.e. fixed/normal distribution of random effects). We use a household identifier that is randomly assigned by PS as the random effect variable.

The Intraclass Correlation Coefficient (ICC) was used as a diagnostics for the appropriateness of the ME models.

We define ICC as $ICC = \sigma_{\text{households}}^2 / (\sigma_{\text{households}}^2 + \sigma_{\text{residuals}}^2)$, which describes how strongly monthly consumption demands within the same household resembles each other, controlling for homes that naturally and consistently consume more than others. The ICC for all models were between 0.3 and 0.4, indicating fair agreement, verifying the appropriateness of constructing an ME model. Thus, if we did not use ME models and treated households as a fixed effect, our models could misrepresent the randomized effects of individual household consumption demands.

We built Mixed effects models (Equation 5 and 6) that estimate air condition demand as a function of CDD as well as the predictors used in Equation 1 and 2. We did not consider HDD since central Texas does not experience harsh winters like other parts of the nation and because most heating systems are not electrical (about 7 percent of the homes in our sample have electric heating- central heat-pump or electric strip heater), thus have very little influence on electricity demand.

$$\begin{aligned} AC\_KWH = & \beta_0 + \beta_1 cooling\_degree\_days\_base65 + \beta_2 conditioned\_sqft\_per100 \\ & + \beta_3 total\_window\_sqft\_per100 + \beta_4 window\_double\_triple\_pane \\ & + \beta_5 has\_heat\_pump + \beta_6 adequate\_insulation + \beta_7 cooling\_system\_central\_ac + \beta_i R_i \\ & + \varepsilon_{it} \end{aligned}$$

(Specified using PS data)

Equation 5

$$\begin{aligned}
AC\_KWH = & \beta_0 + \beta_1 cooling\_degree\_days\_base65 + \beta_2 conditioned\_sqft\_per100 + \beta_3 foundation\_slab \\
& + \beta_4 total\_window\_sqft\_per100 \\
& + \beta_5 window\_double\_triple\_pane + \beta_6 thermostats\_programmable \\
& + \beta_7 cooling\_system\_window\_units + \beta_8 cooling\_system\_central\_ac \\
& + \beta_9 has\_heat\_pump + \beta_i R_i + \varepsilon_{it}
\end{aligned}$$

(Specified using RECS data)

Equation 6

Where:

β_0 through β_9 are the coefficient estimates for fixed effect (i.e. same beta values for all homes)

β_i is the individual household coefficient estimate for random effects

R_i represents the household identification number

ε_{it} represents error terms

Though PS and RECS share multiple independent variables, the PS energy audits provide variables not sampled by EIA, and more importantly, provides engineering values (e.g. R-values, blower door test results, HVAC capacity, etc.). Thus, we performed an additional analysis (not comparative with RECS) that includes the additional fields provided by the PS energy using a mixed-effects model mimicking the purposeful selection methods to derive Equation 7. Similar post-estimation analyses were pursued to ensure normality and independence.

$$\begin{aligned}
AC\_KWH = & \beta_0 + \beta_1 cooling\_degree\_days\_base65 + \beta_2 conditioned\_sqft\_per100 \\
& + \beta_3 cooling\_system\_window\_unit + \beta_4 cooling\_system\_central\_ac + \beta_5 efficient\_ac \\
& + \beta_6 tsolar\_screening\_film\_sqft\_total\_per100 + \beta_7 total\_window\_sqft\_per100 \\
& + \beta_8 window\_sqft\_northward\_per100 + \beta_9 window\_sqft\_southward\_per100 \\
& + \beta_{10} window\_single\_pane + \beta_{11} window\_double\_or\_low\_e + \beta_6 adequate\_insulation \\
& + \beta_5 has\_heat\_pump + \beta_i R_i + \varepsilon_{it}
\end{aligned}$$

(Specified using PS data)

Equation 7

Table 2 summarizes the different models developed, the corresponding equations, methods used to develop these models, and the motivation behind each derivation.

3. Results

Figure 1 compares results of the model derived from PS data (Model 1 results) and the model derived from RECS data (Model 2 results). Five predictors overlap across models: conditioned area, window area, double or triple pane windows, central air conditioning, and existence of a heat pump. RECS values (black bars) varied the most across models, whereas PS values remained similar. Strikingly, the RECS model shows that there is a statistically significant difference (0.10 level) between PS homes and RECS homes, where PS homes consume over 2300 kWh per year more than RECS homes (Table 3).

Furthermore, we analyzed the correlation between each predictor and compared them across data sources for further insight (Figure 2). Both PS and RECS homes show positive and statistically significant correlation between conditioned area and most other variables; yet, there is a stronger relationship between conditioned area and window area within the PS homes. An unexpected difference exists between window area and other insulation technologies (window pane type, adequate insulation, programmable thermostat, and type of cooling system)- while RECS homes show positive and statistically significant correlations (11 combinations of 15 possible combinations), PS homes exhibit less statistically insignificant correlations (7 combinations out of 15 possible combinations). This further supports possible overestimation of RECS values.

3.1 PS Derived Model

Though the model derived from PS data did not show overall statistically significant differences between data sources (indicator PS_or_RECS, where 1 signifies PS data and 0 signifies RECS data), having a heat pump and adequate insulation were individual indicators that are statistically significantly different to the 0.05 level and provide contradictory information (second column in Table 3). As shown in Figure 1 (top), RECS estimates show an increased consumption of almost 200 kWh per year for adequately insulated homes and an average saving of 400 kWh per year for homes using heat pumps, *ceteris paribus*. By contrast, PS yields an average savings of almost 1000 kWh per year for adequately insulated homes and an increase of over 2600 kWh per year for homes using

heat pumps, *ceteris paribus*. Combined, this creates a statistically significant differential of over 3000 kWh per year and 1100 kWh per year for heat pumps and adequate insulation, respectively. Furthermore, both of these indicators are individually not statistically significant with RECS homes, but are individually statistically significant to the 0.05 level with PS homes.

Another indicator that has statistical significance to the 0.10 level with PS homes (but not statistically significant with RECS homes) is having central air-conditioning as the primary cooling system, compared to the alternative grouped category of window units, other technologies, or no cooling system. It should be noted that central air-conditioning makes up 92% of the cooling systems used by PS homes, compared to 76% used by RECS homes. Nevertheless, consumption is about three times greater in PS homes than RECS homes. The only indicator that is statistically significant within RECS homes is the conditioned square-footage.

When the PS data is decomposed into monthly consumption, controlling for weather by using CDD, the PS homes show that having central air conditioning and a heat pump are no longer statistically significant. However, the insulation performance is statistically significant to the 0.10 level, revealing an average savings of almost 700 kWh per year (about 58 kWh per month).

3.2 RECS Derived Model

In addition to some of the indicators present in the PS model, the RECS model also incorporates the type of home foundation, the type of windows, programmable thermostats, and differentiation between cooling technologies (central air conditioning, window unit, dependent on heat pumps). As shown in Figure 1 (bottom), the variables that show statistical significance within the RECS homes are home square-footage, and the type of cooling system—central air or window units. The PS homes, however, only show statistical significance of the type of home foundation and existence of heat pumps. The RECS model does not yield any indicators that are statistically significant across both PS and RECS homes.

Overall, PS and RECS homes are statistically significantly different to a 0.10 level (third column in Table 3), where PS homes consume on average 2300 kWh more than RECS homes. Comparatively, though the models specified by PS data are not statistically significantly different, PS homes showed over 700 kWh per year less demand than RECS

homes, opposite in sign (where PS homes experience a reduction in demand and RECS experience an increase in demand) and almost three times smaller in magnitude. Furthermore, four of the eight indicators are statistically significantly different (type of foundation, central air conditioning, window air conditioning units, and existence of heat pumps), compared to two of six indicators in the PS model (existence of heat pumps and adequate insulation) mentioned in the previous section.

A monthly decomposition, i.e. MEM, of cooling demands for PS homes using the RECS model (Model 2, Equation 6) reveals statistical significance of the existence of heat pumps and having slab-on-grade foundation. Heat pumps consume about 90 kWh per month (over 1000 kWh per year) compared to the yearly value of over 2600 kWh from the MRL model.

3.2 Mixed-Effect Model

By expanding the pool of possible indicators to include all PS energy audit fields, a more comprehensive mixed-effects model was derived (Table 4). The indicators that are statistically significant include: having a central air conditioning system, efficiency of the central air conditioning systems, total window square-footage, southward-facing window square-footage, adequate insulation and existence of a heat pump. The strongest driver of consumption is having a heat pump (93 kWh per month), while the strongest indicator of reduced consumption is having an efficient central air conditioning system (88 kWh per month), both consistent with previous work. Other indicators that show a reduction of consumption include: southward-facing window square-footage and adequate insulation.

4. Discussion and Policy Implications

Our results show that there are some discrepancies between estimated and empirical values of electricity demands within space cooling technologies. Although the two independent models derived using RECS and PS data had some indicators in common, there were few that showed statistical significance across models and across data sources. Even when total electricity consumption, weather (CDD), and floor area are normalized across sources via propensity score matching, the RECS model reveals a statistically significant difference between data sources, possibly indicating underestimation of cooling demands (an average difference of over 2,300 kWh per

year). Additionally, using PS-derived models yields smaller R^2 values (0.21 for PS data and 0.19 for RECS data) when compared to RECS-derived models (0.57 for PS data and 0.36 for RECS data). This may indicate overestimation within RECS models for air conditioning demands, since the models show that they reasonably account for variation. Intriguingly, PS data provides stronger R^2 values despite the data source used to derive the model, indicating a more robust model.

Errors associated with the RECS end-use disaggregation methods are either empirical (per estimation and quality assurance techniques for total household consumption and expenditures) or are methodological per the regression models used for end-use disaggregation. By conducting similar end-use disaggregation techniques on two separate samples - homes with estimated data versus homes with complete empirical records – the EIA could better understand how to improve end-use disaggregation techniques.

RECS currently does not survey for household technical factors we find important for air conditioning consumption. The binary category of adequate insulation for PS homes was based on R-values greater than 17, whereas RECS surveys provided homeowners' best estimate. Insulation responses are almost identical across data sources, yet the RECS model does not require adequate insulation as part of the final model. In addition, RECS data does not show statistical significance and even indicates an increase in demand in the PS model. RECS results challenges current literature on the effects of adequate insulation [6, 16, 18, 23, 39]. Consistent with observations made by Tso and Guan [25], including engineering values instead of subjective estimates could readjust and address these types of discrepancies and contradictions.

Furthermore, results highlight the possible inadequacy of RECS estimations when comparing results across data sources, since RECS-derived model imposed on RECS data neglects the significance and even wrongly captures the effect of heat pumps and triple-pane windows; heat pumps decrease electricity demand whereas triple-pane windows increase electricity demand. Also, it yields three statistically significant indicators (conditioned floor area, central air condition and window cooling units), whereas only two predictors are significant if the model is applied to the PS data (slab-on-grade foundation and heat pumps). Slab-on-grade foundation raises questions of adequacy, since there is no previous research, to our knowledge, specifying foundation type as a significant predictor of energy demand. The anomalies presented by heat pumps and triple-pane windows may explain the

‘appearance’ of foundation type as a statistically significant indicator when the RECS-derived model is imposed on PS data.

We recognize the EIA has limitations on data collection and processing. However, improved empirical descriptors of homes are increasingly available, many from utility-funded energy audits. Given the EIA currently collects total consumption from utilities, perhaps end-use disaggregation could be improved by collecting energy audit data for specific end-uses with few additional resources. Some select predictors are available through property tax records, which could similarly improve empirical estimates of end-use disaggregation.

A comparison between MLR and MEM also shows the overvaluing of indicators and statistical significance. Though the MLR PS model (Table 2) reveals three statistically significant indicators, only one remains statistically significant in the MEM PS model: adequate insulation. The MLR PS model shows an average annual decrease in demand of 973 kWh, while the MEM PS model translates to an average annual decrease of 696 kWh (58 kWh per month). Similarly, the MLR RECS model (Table 3) reveals a yearly difference of almost 200 kWh with respect to a slab-on-grade foundation (MLR yearly estimate = -892 kWh and MEM yearly estimate = -696 kWh) and more than double with over 1,500 kWh with respect to having a heat pump (MLR yearly estimate = 2,662 kWh and MEM yearly estimate = 1,100 kWh). Providing monthly consumption would provide more accurate information on the predictive power of indicators, taking into account the effect of seasonal patterns. This is further supported by the R^2 estimations for both ME models (0.49 for both). Since there is no conventional determination R^2 for mixed models, we calculate pseudo- R^2 values by assessing the correlation between the observed and predicted responses.

Further insight gained from the MEM, similar to conclusions reached by Min, Hausfather, and Lin [39], is the added benefits of including special factors, such as home orientation. Specifics on home orientation could capture the impact of urban form on residential electricity demands, especially if coupled with quantitative values (e.g. the direction and square-footage of windows). This is especially important in view of Baker and Steemers [40] findings that urban form can affect energy consumption by a factor of up to 2.5.

Moreover, leveraging engineering values over householder's best estimate provides stronger and more statistically significant indicators to understand cooling demands. For example, even if a home has an adequate insulation, having a standard air conditioning system can possibly erode any benefits of reduction in demand. Similarly, having an efficient conditioning system could offset the increased demand due to heat pumps. EIA could provide many benefits by publishing data on a monthly basis, given it already collects monthly electricity consumption.

5. Conclusions

Space conditioning technologies and their presence can provide useful insight into understanding residential demand electricity consumption, given space-conditioning claims nearly 50% of energy use and 45% of energy expenditure [22]. However, some of the most widely used end-use data are estimates derived from non-linear regression models. Our results indicate that adequate insulation could be overlooked, overvalued, or misrepresented by current estimation methods. It also highlights a need for higher-resolution values reported to account for seasonality. Providing more accurate predictors that drive space-cooling demands could potentially allow policy-makers the opportunity to couple incentives or efforts to offset electricity demands associated with specific technologies.

Several questions remain for future research, in particular regarding other end-use demands. Additionally, examining the interaction between end-uses appears to be promising field of research. Moreover, technology interactions within individual end-uses could provide insight on synergistic efforts and how future policies can improve these interactions.

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Table 1. Summary statistics for PS and RECS variables; “Building” parameters describe the physical characteristics of the households; “Insulation/Cooling” describes factors that have an effect on energy demanded by a home’s cooling system; and “Other Technologies” includes information on technologies present in the household and how occupants use each technology. The last column “PS:RECS” represents the mean ratios between both models. It should be noted that binary values such as having adequate insulation (input = 1) can be interpreted as an overall penetration rate (i.e. adequate_insulation = 0.76, thus about 76% of the homes have adequate insulation).

Characteristics	Variable	RECS		PS		Ratio
		Mean	Stdv.	Mean	Stdv.	
Exogenous	cooling_degree_days	2863	609	2870	0	1.00
Building	conditioned_sqft	2154	936	1991	711	0.92
	foundations_slab	0.80	0.40	0.84	0.37	1.05
	home_vintage	37	24	27	26	0.72
Insulation / Cooling	adequate_insulation	0.76	0.43	0.83	0.38	1.08
	cooling_system_central_ac	0.76	0.43	0.92	0.37	1.21
	cooling_system_window_unit	0.20	0.40	0.02	0.14	0.10
	has_heat_pump	0.03	0.18	0.10	0.29	3.00
	number_ac_window_units	0.52	1.24	0.10	0.30	0.18
	number_of_digital_thermostats	0.96	0.60	0.83	0.67	0.87
	thermostats_programmable	0.39	0.49	0.87	0.33	2.24
	total_window_sqft	516	108	242	104	0.47
	window_double_triple_pane	0.37	0.49	0.70	0.46	1.87
Other Technologies	num_frig	1.2	0.4	1.1	0.3	0.95
	efficient_frig	0.52	0.50	0.40	0.49	0.77
	refrigerator_vintage	7.2	5.2	7.5	3.7	1.05
	num_freez	0.25	0.49	0.30	0.50	1.18
	dishwasher_used	0.52	0.50	0.96	0.20	1.83
	efficient_dishwasher	0.26	0.44	0.13	0.34	0.51
	clothes_washer_vintage	7.2	5.3	7.4	3.2	1.04
	efficient_clothes_washer	0.48	0.50	0.28	0.45	0.58
	clothes_dryer_vintage	7.4	5.7	7.6	4.5	1.04

Table 2. Summary of the models specified by data source, application of model, equations associated with each model, and the motivation of each application.

	Model Specified Using PS or RECS	Model Applied To	Corresponding Equation	Motivation of Application
Model 1	PS	RECS Yearly	1	Show indicators that affect AC consumption in RECS
		PS Yearly	3	Compare statistical significance of indicators when same model is applied to PS data
		PS Monthly	5	Compare statistical significance of indicators when same model is applied to PS monthly data
Model 2	RECS	RECS Yearly	2	Compare statistical significance of indicators when same model is applied to RECS monthly data
		PS Yearly	4	Show indicators that affect AC consumption in PS
		PS Monthly	6	Compare statistical significance of indicators when same model is applied to PS monthly data
Model 3	PS Monthly	PS Monthly	7	Derive model that also incorporates indicators not captured by RECS

Table 3. Comparison of statistically significant differences across indicators of Model 1 and Model 2 (excluding PS monthly ME model). The second column is the results of the PS MLR model imposed on both RECS and PS homes (Equation 3). The third column is the results of the RECS MLR model imposed on both RECS and PS homes (Equation 4).

PS vs. RECS	Specified Using PS data			Specified Using RECS data		
Variable	$\hat{\beta}$	Stdv.	P> t	$\hat{\beta}$	Stdv.	P> t
PS_or_RECS	-755	1261	0.55	2395	1441	0.1
Conditioned Area ft ²	-300	490	0.54	-290	520	0.58
On-Slab Foundation				-1126	631	0.08
Window Area ft ²	273	301	0.37	199	312	0.53
Double/Triple Pane	-721	539	0.18	-736	533	0.17
Adeq. Insulation	-1166	581	0.05			
Prog. Thermostat				-40	563	0.94
Window Cooling Unit				-3484	1046	0
Central AC	1057	990	0.29	-1737	1005	0.09
Heat Pump	3073	1376	0.03	3078	1519	0.04

Table 4. Summary of the model derived from PS homes, using a MEM to account for seasonal demands, providing a means of controlling for seasonal effects, where pseudo- R^2 is 0.51 and ICC is 0.33

Variable	PS MEM		
	$\hat{\beta}$	Stdv.	P> t
conditioned_sqft_per100	2.4	3.2	0.45
cooling_system_central_window_unit	22	48	0.64
cooling_system_central_ac	51	27	0.06
efficient_ac	-88	30	0.00
total_window_sqft_per100	59	21	0.01
window_sqft_northward_per100	25	18	0.17
window_sqft_southward_per100	-69	28	0.02
window_single_single_pane	-47	54	0.38
window_double_or_low_e	-48	55	0.38
adequate_insulation	-61	31	0.05
has_heat_pump	93	53	0.08

Figure(s)

* Significance level to 0.10; ** Significance level to 0.05; ***Significance level to 0.01

Figure 1. Model 1 (top) was specified using PS data. The model was applied to RECS yearly cooling demands (black, where R^2 is 0.18), PS yearly cooling demands (dark grey, where R^2 is 0.21) and PS monthly cooling demands (light grey, where pseudo- R^2 is 0.49 and ICC is 0.36). Model 2 (bottom) was specified using RECS data. The model was applied to RECS yearly cooling demands (black, where R^2 is 0.35), PS yearly cooling demands (dark grey, where R^2 is 0.57) and PS monthly cooling demands (light grey, where pseudo- R^2 is 0.49 and ICC is 0.36). The original PS MEM results are in per monthly values; however, for comparison purposes these monthly values were transformed into yearly values (multiplied by 12) to ease comparison across RECS yearly MLR and PS yearly MLR analysis. Conditioned area is measured on a per 1000 ft² and window area on a per 100 ft² to provide estimates within similar orders of magnitude. The error bars represent the standard deviation associated with each variable. Significance levels are represented above/below each variable. Not all variables appear in both models, thus the blank columns.

	PS	RECS	Conditioned Area	On-Slab Foundation	Window Area	Double/Triple Pane Window	Adequate Insulation	Prog. Thermostat	Window AC Units	Central AC	Has Heat Pump
Conditioned Area				0.30 ***	0.35 ***	0.31 ***	0.20 **	0.32 ***	-0.35 ***	0.36 ***	0.11
On-Slab Foundation			0.22 **		0.03	0.14	0.19 **	0.27 ***	-0.50 ***	0.42 ***	0.09
Window Area			0.71 ***	0.13		0.26 ***	0.07	0.08	-0.08	0.04	0.12
Double/Triple Pane Window			0.31 ***	0.19 **	0.29 ***		0.20 **	0.23 **	-0.18 **	0.24 ***	0.23 ***
Adequate Insulation			0.22 **	0.14	0.18 **	0.24 ***		0.29 ***	-0.28 ***	0.30 ***	-0.01
Prog. Thermostat			0.26 **	0.23 **	0.20 **	0.27 ***	0.14		-0.40 ***	0.41 ***	0.04
Window AC Units			-0.03	0.06	-0.11	0.10	0.06	0.06		-0.89 ***	-0.09
Central AC			0.29 *	-0.15	0.33 ***	-0.04	0.09	-0.06	-0.20 **		0.10
Has Heat Pump			0.16 *	0.07	0.06	0.10	-0.14	0.12	0.29 ***	-0.64 ***	

* Significance level to 0.10; ** Significance level to 0.05; ***Significance level to 0.01

Figure 2. Correlation comparison across cooling technologies and behaviors for PS and RECS. The lower left section represents correlations among PS homes, while the upper right section represents correlations among RECS homes.