Energy 66 (2014) 722–731

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

A multilevel regression approach to understand effects of environment indicators and household features on residential energy consumption

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ARTICLE INFO

Article history:
Received 26 June 2013
Received in revised form
13 January 2014
Accepted 16 January 2014
Available online 22 February 2014

Keywords:
Residential energy consumption
Multilevel regression
Area variations

ABSTRACT

Modeling residential energy consumption survey (RECS) data is a complex socio-technical problem that involves macroeconomics, climate, physical characteristics of housing, household demographics and usage of appliances. A multilevel regression (MR) model is introduced to calculate the magnitude and significance of effects of environment indicators and household features on residential energy consumption (REC). MR helps construct a conceptual framework and organize explanatory variables. The benefit of this approach is that based on stratified sampling schemes, MR extracts area effects from total variations of REC and explains the remaining variations with manifest variables and their interactions. Using the US 2009 RECS micro data consisting of 10,838 unique cases, 26 primary determinants of REC are found to be division groups, housing type, house size, usage of space heating equipment, household size and use of air-conditioning, etc. MR helps to quantify 82% of area effects and 47% of household effects. Proportion of the overall explained variance proportion is 53% compared to <40% using OLS regression models.

1. Introduction

The residential sector accounted for 22% of the total energy consumption in the US during 2011. This proportion was less than 10% in the late 1940s. Total residential annual energy consumption increased from 5989 trillion BTU in 1950 to 21,619 trillion BTU in 2011. National and global energy markets are challenged by explosively growing population, fast penetration of modern home appliances, global energy shortages and increasing energy prices. Thus, understanding energy consumption behaviors in the residential sector is important for all other sectors in US. Yet, the Energy Information Administration (EIA) [1] claimed that total U.S. energy consumption in homes has remained relatively stable for years, and the average per-household energy consumption has a decreasing trend. This decrease is due to the increased energy efficiency and offsets the increase in the number and average size of housing units. With a decreasing trend of average household residential energy consumption (REC), it is of interest to explore the latest residential energy consumption survey (RECS) micro dataset in the US.

Besides, due to area variations or regional effects, energy policies such as tier-based policies can easily become ineffective. Regional effects to REC stem from environment, energy and residents. Sailor [2] in 2001 pointed out previous literature exhibited a narrow regional focus and related climate changes to residential electricity consumption of eight states in the US. In the few literature that explicitly consider regional effects on energy consumption, Wang and Wang [3] in 2011 confirmed the existence of regional interaction of biomass consumption in the US by using spatial autoregressive model. Their results show that regional interaction becomes weaker with the farther neighbor states. Thus, we speculate that regional effects might be significant on REC. Besides, regional effects as a key factor of energy plantation, architecture design, city planning and infrastructure, and future energy assessing, do not draw enough attention from REC researchers. It requires sufficient evidence to support governmental policy making, to improve the operations made by industrial practitioners, and to help households understand how they consume energy in homes. Hence, it is of interest to find an advanced statistical modeling approach which can extract area variations and identify key impact factors, to improve modeling approaches of REC.

In this paper, we propose a cross-sectional analysis of household energy consumption in the US by using micro-level data. Instead of

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http://dx.doi.org/10.1016/j.energy.2014.01.056
0360-5442/

focusing on residential electricity consumption e.g. [2,4,5] or local area research e.g. [6] or national research without identifying regional effects e.g. [7], we uses a new approach, i.e. a multilevel regression (MR) model, which explicitly considers regional effects within a national sample. The MR model we build is a combination of bottom–up [8,9,10] and top–down model [11,12,13]. It is because we utilize individual household feature data provided by the EIA along with techno-socio-macroeconomic data provided by the BEA. This approach chimes in with the idea that total energy demand can be explained by a wide array of structural indicators, such as the general degree of economic welfare, the extent of electrification, the availability of other energy carriers, the prevalence of energy efficient technologies, the prevailing climate and cultural habits [14–18].

1.1. Contribution

The prime purpose of this paper is to provide a better data-based REC modeling strategy to improve residential energy policy making. We introduce multilevel regression analysis to split total variations of REC among households into area variations and household variations. This is the first known application of MR models for study of REC with the US 2009 RECS micro dataset. Multilevel regression analysis stems from multiple linear regression analysis, which is popular in modeling REC. Multilevel regression analysis can address the problem of clustering of households in modeling REC, which multiple linear regression analysis cannot. Clustering of households has strong impacts on research problems with datasets collected by complex multistage stratified sampling in national surveys. For example, one consequence is that relationships between explanatory variables and response variable are heterogenous among clusters. To handle clustering of households, multilevel regression analysis incorporates information on how consumption disparities are attributed to households and areas they live in. It quantifies the clustering extent of REC among areas, and permits examining cross effects of area-level and household-level factors.

Based on multilevel regression analysis, we propose a conceptual framework for modeling REC. This conceptual framework emphasizes the hierarchical structure within RECS micro dataset. Households are geographically nested into different areas. Households form first hierarchy, whilst areas form second hierarchy. In the context of the US 2009 RECS, as shown in Fig. 1, objects in level 1 are individual households; objects in level 2 of the model refer to clusters of individual households according to their geographical location by divisions or reportable domains, as shown in Figs. 2 and 3. Hence, the data structure brought by multistage stratified sampling schemes is considered. Response variable is REC of individual households. Explanatory variables in the regression model are arranged in accordance with objects that they measure. Level-1 explanatory variables refer to household features, including microclimate, housing construction, socio-demographic and usage of appliances factors. Level-2 explanatory variables are environment indicators, which refer to variables measuring geographical groups of households; they are common to all households living in the same region.

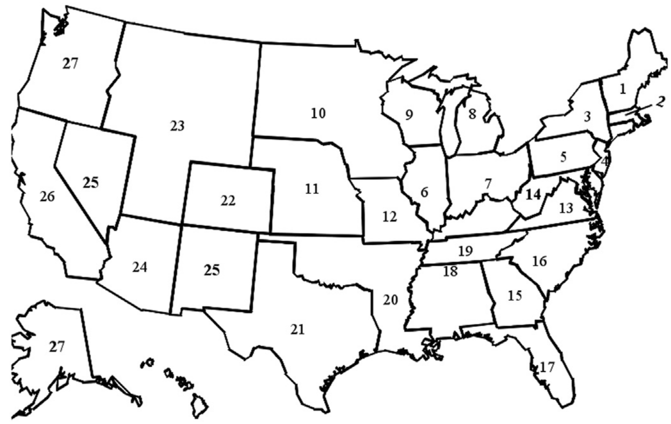

Fig. 2. Reportable domains of US.

We confirm the necessity of using multilevel regression analysis by a finding that clustering effects or regional effects can explain nearly 20% of variances of REC among households. The MR model we have identified can explain 82% of clustering effects, and 47% of variations of household effects. Proportion of the overall explained variance is around 53%. We found 26 significant determinants of REC including division groups, housing type, house size, usage of space heating equipment, household size and use of air-conditioning (AC) etc. Households living in northern parts of the US consume more energy than those living in southern US do. Especially, households living in divisions 1 and 2 consume more energy than others. After ruling out regional effects, ceteris paribus, house size has the largest impact on household energy consumption. For each square feet increase of mean house size, the expected household energy consumption increases by 488,791 kWh/year. Though the highest education of householder, the member(s) who owns the living unit, turns out to be not significant, it mediates house size with a U-shape relationship on REC. We find that single-family detached (SFD) housing is the most energy consuming housing type throughout all divisions in the US. For an extra person living in a house, while compared to divisionwise averages, the expected household energy increases by 219,811 kWh/year. Moreover, program-controlled space heating equipment does help save 11,227 kWh/year compared to those without program control. Basically, our MR model not only avoids biased estimations resulting from traditional linear regression models but also proves that REC disparities among households located in a vast area can be carefully examined by levels of hierarchy.

1.2. Structure of the paper

Section 2 introduces the epistemology of modeling RECS data with multilevel regression analysis. It deliberates on the motivation for applying multilevel regression analysis to explain REC, the advantages of using multilevel regression analysis, and a conceptual framework to analyze the 2009 RECS US micro dataset. The

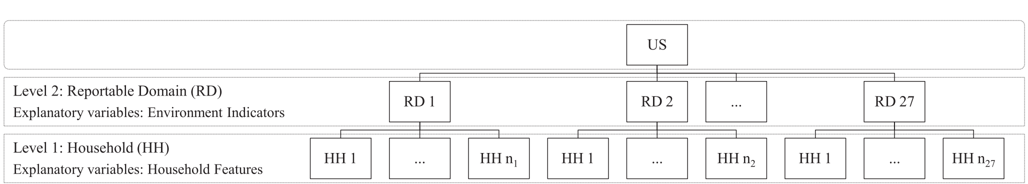

Fig. 1. The conceptual framework of modeling REC with multilevel regression analysis.

Fig. 3. Divisions of US.

methodology is described in Section 3 and 4. Section 3 focuses on data description and preparation, while Section 4 concentrates on MR model development and model precision. Section 5 discusses the empirical results of the MR model, and demonstrates effects of important environment indicators and household features on REC. Section 6 is a methodological discussion of analyzing REC with multilevel regression. In Section 7, policy implications and conclusions are provided to show how multilevel regression methods can minimize adverse effect of energy policies on a mixture of households nested nationwide.

2. The epistemology of multilevel regression modeling of REC

2.1. Background of using multilevel regression analysis

Area variations can crucially confound interpretation of analysis results and implementation of energy policies if their impacts were not excluded in the model. Previous literature has alerted practitioners to be careful with area variations when applying their results; but it hardly provides information on how to incorporate area variations for making energy policies. In fact, analysis results are not reliable without quantifying area variations in the modeling process.

For analysis of RECS data, an important but long neglected aspect is that the quantitative differences of consumption between households can partly be attributed to the areas in which they live. Social scientists usually describe a society in hierarchical structures. Countries such as the US have multilayers: cities, states and divisions, etc. Most sampling designs of RECS concerning this multilevel structure adopt multistage stratified sampling schemes to obtain population represented samples. Households who live in different areas may have different consumption behaviors, even though with similar household features. This is so because of impacts of environment indicators, including different cultural, economic, political, historical or geographic influences. With similar reasons such as energy infrastructure, energy sources, energy carriers, energy prices, climates, socio-macroeconomics, and living quarter construction [19], households sharing a common environment may to some extent have similar consumption patterns, even with different household features. This contextual phenomenon expresses itself as the clustering of households' consumption patterns within neighboring areas. Due to this clustering, we can split variations of REC among households into two sources: environment indicators and household features.

Traditional analyses of REC which neglect multilevel structure of RECS dataset probably lead to questionable estimation and inferences. This neglect might be due to the contradiction between multilevel structure and assumptions, e.g. observations are independently and identically distributed, that traditional statistical methods tend to hold. Methods, including multiple linear regression analysis and generalized linear models, require that observations are not associated with each other. However, there is a non-ignorable chance that this assumption is violated, that is, observations from some households are associated due to multilevel structure and clustering of RECS data. Therefore, traditional statistical methods are no longer appropriate for analyzing RECS data. The presence of clustering or the multilevel structure of RECS data is, in turn, the main reason for applying multilevel regression analysis.

Multilevel regression analysis is an extension of multiple linear regression analysis. Multiple linear regression analysis is popular in modeling REC. For instance, Ranjan and Jain [20] developed linear multiple regression models of energy consumption for different seasons. Bianco and Manca [21] used linear regression models to investigate the annual consumption of electricity up to 2030, considering the annual GDP and population time series. Sanquist et al. [7] used multiple linear regression models to examine the relationship between lifestyle factors and electricity consumption. Regarding the limitations of multiple linear regression analysis, some researchers have proposed the use of models stemming from multiple linear regression analysis to examine relationships between influencing factors and REC. For instance, Kaza [22] stated that linear regression models with ordinary least squared estimates do a poor job in analyzing REC when the variability is high in the sample, especially when policy makers target high-income households. He used quantile regression models instead. He built a series of regression models for groups of households clustered by amounts of energy consumption. Regional effects still get involved in the modeling process and disturb interpretation of estimated effects of specific factors. Conversely, our attempt can extract area variations from total REC variations, and simultaneously explain the remaining variances by introducing household features into the model.

Multilevel regression analysis is consistent with the traditional multiple linear regressions, as discussed by Gelman and Hill [23]. The estimated effects are set to be zero if group or area variations are small. Then the MR model is reduced to traditional multiple regression models. Additionally, unlike Principal Component Analysis followed by linear regressions for explaining energy consumption e.g. [24], neither Neural Networks for predicting energy consumption, e.g. [25–28], the parameter estimates are simple to understand in multilevel regression. Hence, multilevel regression is a flexible statistical tool.

One advantage of using multilevel regression modeling is that it helps avoid the Robinson effect [29], known as aggregation/disaggregation bias, which refers to the fact that conclusions drawn from one hierarchy are not applicable in another hierarchy. In terms of the Robinson effect, it seems impossible to draw conclusions for regions or nations based on individual end-use data. Instead of applying representative weight to combine results of individual samples [30], we recommend multilevel regression analysis. Multilevel regression analysis is explicitly designed for avoiding the Robinson effect [31]. It provides a tool to analyze hierarchically structured data, modeling REC with variables at both micro (household) and macro (environment) levels simultaneously.

Another advantage of using multilevel regression to model REC is ruling out the impacts of heterogeneity of relationships between explanatory variables and response variable among different clusters of households. Heterogeneity of relationships can cause questionable parameter estimations. Traditional statistical models cannot explicitly control for these heterogenous relationships. Wang et al. [31] commented the inappropriateness of extant approaches for handling heterogeneity of relationships between explanatory variables and response variable in datasets with clustering. They also point out that it is impractical to run separate regressions for each group, particularly, when the number of groups is large, and the number of observations per group is small. Therefore, we adopt multilevel regression analysis because it is a standard analysis tool for understanding unobserved heterogeneity in relationships between variables measured on individuals clustered within higher order units [32–34]. The heterogeneity in MR models is expressed in terms of random intercepts and slopes, i.e. continuous latent variables that vary between clusters [35].

There are other advantages of using multilevel regression analysis. It allows transformation of response variables, such as discrete outcomes, to model nonlinear relationships. It can handle repeated measurements from panel studies. Subgroups with small sample size can benefit from estimates from subgroups with large sample size with some Bayesian methods. Larger number of subgroups leads to more reliable group effect estimations. It is easy to implement multilevel regression analysis with statistical packages in SAS, HLM, and R, etc.

2.2. MR models

Since its introduction, a variety of names have been used for MR models, such as random coefficient model [36,37], variance component model [38], hierarchical linear model [39,40], or mixed-effects or mixed models [41,42]. As MR models have been successfully adapted to diverse fields such as education [43] and epidemiology [44] to handle hierarchically structured data collected by multistage stratified sampling schemes and to help decision and policy making, we have great expectations of its application for modeling RECS micro datasets.

There are 27 reportable domains in 2009 survey data. Following Hox's [45] notation, our model could be contextually written as

$$Y_{ij} = \gamma_{o0} + \sum_{p}\gamma_{p0}X_{pij} + \sum_{k}\sum_{l}\gamma'_{kl}X_{kij}X_{lij} + \sum_{q}\gamma_{0q}Z_{qj} + \sum_{p}\sum_{q}\gamma_{pq}X_{pij}Z_{qj} + \sum_{p}u_{pj}X_{pij} + u_{0j} + e_{ij} \quad (1)$$

In Eq. (1), Y_{ij} is the annual energy consumption of household i, $i = 1,\dots,n_j$, in reportable domain j, $j = 1,\dots,27$, n_j, is the number of household in reportable domain j. X_{ij} is the matrix of level-1 explanatory variables, while Z_j is the matrix of level-2 explanatory variables. Y_{ij}, X_{ij} and Z_j are what we can observe and measure.

Other parameters in Eq. (1) need to be estimated. On one hand, for fixed effects, γ_{o0} is intercept. γ_{p0} is slope of explanatory variables X_{pij} in level 1; γ'_{kl} are slopes of two-way interaction terms in level 1. γ_{0q} is slope of level-2 explanatory variable Z_{qj}. γ_{pq} is slope of interaction of level-1 explanatory variable X_{pij}, and level-2 explanatory variable Z_{qj}. On the other hand, for random effects, errors of the lowest level, e_{ij}, are assumed to have a normal distribution with a mean of zero and a common variance σ_e^2. Residual terms in the highest level, u_{pj} and u_{oj}, are assumed to be independent of error e_{ij}, and to have a multivariate normal distribution with mean values of zero. The variance of the residual error u_{0j} is the variance of the intercepts between clusters, symbolized by $\sigma_{u_o}^2$. The variances of the residual term u_{pj} are the variances of slopes between the groups, symbolized by $\sigma_{u_p}^2$. The covariances between the residual error terms are generally not assumed to be zero.

2.3. A conceptual framework based on MR models

According to the structure of MR models, we propose a conceptual framework for analysis of REC. As shown in Fig. 1, the conceptual framework contains two hierarchies. Units in level 1 are individual households, while units in level 2 are clusters of households grouped by reportable domains. Explanatory variables in corresponding hierarchies are introduced to explain variations among units within respective hierarchies. Level-1 explanatory variables are household specific. Level-2 explanatory variables are cluster-average or remain the same for all households in the same cluster. According to Swan and Ugursal's review [30], level-1 explanatory variables usually include physical characteristics of the dwellings, occupants, and climatic conditions; level-2 explanatory variables usually contain macroeconomic indicators, and energy retail prices, etc.

3. Methodology

3.1. The dataset

Our MR model relies on three principle sources: the 2009 RECS micro dataset, the 2009 Annual Energy Review published by the EIA, and the macroeconomic statistics published by Bureau of Economic Analysis (BEA). To meet future energy demand and improve building design and efficiency, the RECS is conducted every four years and is an important information source of energy characteristics of housing units, usage patterns and household demographics [46]. The 2009 RECS micro dataset is our primary data source. It consists of observations from 12,083 housing units selected to represent the 113.6 million housing units that are occupied as a primary residence. This dataset was collected using a complex multistage, area-probability sample design regarding the hierarchical structure of residences in the US. 27 reportable domains, shown in Fig. 2, along with 10 divisions, shown in Fig. 3, are defined as geographic clusters of households. As shown in Fig. 3, from number 1 to 10, these divisions are New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain North, Mountain South and Pacific division. To reflect energy retail prices in divisions, we select divisionwise average energy prices in 2009 from 2009 Annual Energy Review. Consumption capacity of households in different divisions is calculated by a division's average per capita personal disposable income in 2009, according to the information published by BEA and the subsample sizes in 2009 RECS.

The relevance of this dataset for introducing multilevel regression methods to model REC can be emphasized in several aspects. One advantage is that the US RECS micro datasets are typically representative of datasets generated from RECS conducted in other countries such as UK and New Zealand. Additionally, this dataset provides the latest information on what factors impact how US households consume energy. Analysis of this dataset leads to updates of policy makers and researchers' beliefs based on past information. Hence, based on this dataset, we provide a paradigm for modeling REC with MR models.

3.2. Variables

3.2.1. Response variable

Response variable in our model is annual energy consumption per household (TOTKWH), measured in kWh, in 2009.

3.2.2. Level 2 variables (environment indicators)

CENPDPI is division-average per capita disposable personal income in 2009, centered by the grand mean of 10 divisions.

CENPRICES are division-average energy prices measured in US dollars in 2009, centered by the grand mean of 10 divisions.

DIVISION GROUP is a categorical variable grouping divisions into six categories, including *division 1*; *division 2*; *division 3 and 8*; *division 4*; *division 5, 6, and 7*; *division 9 and 10*.

3.2.3. Level 1 variables (household features)

3.2.3.1. House characteristics. CENCDD65/CENHDD65 measures cooling/heating degree days (CDD/HDD) in 2009; base temperature 65 °F, centered by division averages.

HOUSING TYPE is a categorical variable measuring types of housing, including *mobile home*; *SFD house*; *single-family attached (SFA) house*; *apartments in buildings with 2 to 4 units*; *apartments in buildings with 5 or more units*.

URBAN is a binary indicator measuring whether a household is located within the Metropolitan Statistical Area as defined by the U.S. Office of Management and Budget in 1993.

CENYEARMADE records the year when the house was constructed, centered by division averages.

CENTOTSQFT measures house size by square feet, centered by division averages.

WALLTYPE is a categorical variable measuring major outside wall materials, including *brick*; *wood*; *siding* (*aluminum*, *vinyl*, *steel*); *stucco*; *composition* (*shingle*); *stone*; *concrete/concrete block*; *glass*; *other*.

CRAWL is a binary variable measuring whether housing units are built over a crawl space.

DRAFTY is a categorical variable measuring households' perceptions of housing insulation and drafts in winter, including *drafty all the time*; *drafty most of the time*; *drafty some of the time*; *never drafty*.

3.2.3.2. Household characteristics. KOWNRENT classifies housing units as *owned*, *rented*, or *occupied without payment of rent*.

INCOME is a categorical variable that measures gross household income in 2009, including *Less than $30,000*; *$30,000–$54,999*; and *$55,000 or more*.

EDUCATION is a categorical variable that measures the highest level of education completed by householder; including *no schooling completed*; *kindergarten to grade 12*; *high school diploma or GED*; *some college, no degree*; *associate's degree*; *bachelor's degree*; *master's degree*; *professional degree*; *doctorate degree*.

RACE is a categorical variable that measures householders' races, including *white alone*; *black or African/American alone*; *American Indian or Alaska native alone*; *Asian alone*; *native Hawaiian or other Pacific islander alone*; *some other race alone*; *2 or more races selected*.

CENMEMBER measures number of members in a household, centered by division averages.

ATHOME is a binary variable that measures whether a household has a member at home on typical weekdays.

3.2.3.3. Adoptions of end-use appliances. THERMHEAT is a categorical variable that measures households' adoption of space heating equipment, including *use with program control*; *use without program control*; *own but never use*; *no space heating equipment*.

AGEHEAT is a categorical variable that measures age of space heating equipment, including *no space heating equipment*; *less than 2 years old*; *2–4 years old*; *5–9 years old*; *10–14 years old*; *20 years or older*.

OTHHEAT is a categorical variable that measures whether main space heating equipment heats other homes or farms.

SIZHEAT is a categorical variable that measures the portion of space heating provided by main space heating equipment, including *almost all of all heat*; *about three-fourths of all heat*; *closer to half of all heat*.

CENH2O measures number of water heaters, centered by division averages.

THERMAC is a categorical variable that measures households' adoption of AC equipment, including *use with program control*; *use without program control*; *own but never use*; *no AC equipment*.

TYPEAC is a categorical variable that measures type of AC equipment used in a household, including *central system*; *window/wall units*; *both a central system and window/wall units*; *not applicable*.

USEAC is a categorical variable that measures frequency of use of central AC are used in summer 2009, including *turned on only a few days or nights when really needed*; *turned on quite a bit*; *turned on just about all summer*; *not applicable*.

3.3. Preparing the data for analysis

3.3.1. Dealing with outliers

We rule out households who run a business or have unusual non-REC at home. Exclusion of this part of the sample helps ensure the reliability of the model, which focuses on REC. Within each cluster, extreme outliers who lie outside 6-sigma area are deleted. The remaining sample size is 10,838 households.

3.3.2. Centering continuous variables

Grand-mean centering and group-mean centering are two popular methods of centering continuous variables in MR models. Group-level continuous variables can only be centered by the grand mean of the overall sample. Household-level continuous variables can be centered by group means. To minimize variability introduced into the modeling approach, we center household-level continuous variables by division averages.

3.3.3. Scaling sample weights

RECS incorporate unequal sample weights to obtain population representative samples. MR models that take no account of unequal sample weights lead to biased estimates [47–49]. Hence, it is of importance to consider sample weights of observations when analyzing multilevel structured data. We adopt two methods recommended by Carle [49] to calculate appropriate weights. Asparouhov [50] pointed out that scaled weight A often provides the least biased estimates for point estimates while scaled weight B may generally provide the least biased estimates for residual between-cluster variance, and as cluster size increase ($n > 20$), scaled weight A appears to have increasing advantage. However, bias decreases substantially for both methods as cluster sizes become sufficiently large.

Two kinds of weights are calculated as follows.

$$\text{Scaled weight A}: w_{ij}^{a} = w_{ij}\left(n_j/\textstyle\sum_i w_{ij}\right);$$
$$\text{Scaled weight B}: w_{ij}^{b} = w_{ij}\left(\textstyle\sum_i w_{ij}/\sum_i w_{ij}^{2}\right).$$

where w_{ij} is the unscaled weight for individual i in cluster j.

4. Model development

4.1. Processing the dataset in SAS 9.3

GLIMMIX procedure in SAS 9.3 is used to estimate parameters in our MR models. GLIMMIX procedure helps obtain the best linear unbiased predictors. A major benefit of using GLIMMIX procedure is its simplicity. It is easy to switch estimation methods between maximum likelihood (ML) and restricted maximum likelihood (REML), which are the two primary estimation methods of MR models. We assume that, with GLIMMIX procedure, the distribution of the response variable is conditional on normally distributed random effects [51].

4.2. Model identification

The key to identify a MR model is to first quantify clustering effects of observations, which is measured by intraclass correlation coefficient (ICC). With a null model, ICC is calculated by $\sigma^2_{u_0}/(\sigma^2_{u_0}+\sigma^2_e)$, ranged between 0 and 1. ICC is the proportion of between-group variance in total variations, since, in null model, $\sigma^2_{u_0}$ is between-group variance while σ^2_e is within-group variance. ICC is 0 when no clustering effect exists among groups of households. ICC is 1 when variations of response variable can be fully explained only by clustering effects of households. As ICC approaches 1, multilevel regression analysis becomes more useful. Besides ensuring the degree of freedom within model, a critical standard to identify a final MR model is to minimize information criteria. Minimizing information criteria to some extent corresponds to maximizing likelihood functions. GLIMMIX procedure provides information criteria AIC, AICC, BIC, CAIC, and HQIC. The smaller the information criteria are, the better the model performs. AIC is Akaike's information criteria [52] which accounts for the number of parameters in the model. BIC is Schwarz's Bayesian criterion [53]. HQIC was introduced by Hannan and Quinn [54] while CAIC was introduced by Bozdogan [55]. BIC, HQIC and CAIC consider number of parameters and sample size.

Step 1 Null model is built to calculate ICC. In null model with scaled weight A, as Table 1 shows, ICC = 15%. In null model with scaled weight B, ICC = 18%. Both ICCs imply that clustering effect is greater than 10% such that multilevel regression analysis is needed to control for this clustering effect.

Step 2 Introduce level-2 explanatory variables to explain the clustering effect. Four candidate variables are proposed. Division-average per capita yearly income in 2009 and CENPDPI represent the general level of macroeconomics. CENPRICES represent the average prices of energies in different divisions. DIVISION GROUP describes the geographical clustering and energy-source clustering of divisions. All candidate variables aim to capture regional effects from a top-down perspective. Selection of variables is based on information criteria, such as AIC and BIC; and the significance level of corresponding effect. A level-2 variable is selected if it decreases AIC or BIC by 10 or more. Three variables, CENPDPI, CENPRICES, and DIVISION GROUP, are selected.

Step 3 Introduce level-1 explanatory variables and examine all possible interaction terms to explain within-household variations. Based on the US 2009 RECS micro dataset, all possible household features are used as candidate variables. Selection of variables is based on information criteria, such as AIC and BIC; and the significance level of corresponding effect. A term is selected if it decreases AIC or BIC by 10 or more, and its estimated effect is significant at 10%. All reasonable two-way interaction terms are considered. If a two-way interaction term is significant at 10%, both variables are included in the final model. All candidate variables aim to capture household behaviors from a bottom-up perspective. When selection involves random effects, REML estimators are used. When selection only involves fixed effects, ML estimators are used. Twenty-four terms are selected as fixed effect and HOUSING TYPE is selected as a random effect.

Step 4 Introduce cross-level interaction terms into the model. A cross-level interaction term refers to a two-way interaction term of a level-1 variable and a level-2 variable. All possible cross-level interaction terms are considered based on the results of Step 2 and Step 3. Selection of interaction terms is based on information criteria, such as AIC and BIC; and the significance level of corresponding effect. A cross-level interaction term is selected if it decreases AIC or BIC by 10 or more, and its estimated effect is significant at 10%. Interaction between HOUSING TYPE and DIVISION GROUP is selected.

Table 1
Comparison of fit statistics of OLS and multilevel regressions.

Fit statistics	OLS	REML			
	Scaled weight A	Scaled weight A		Scaled weight B	
	Full model	Null model	Full model	Null model	Full model
AIC	230,478	236,960	228,725	236,957	228,726
BIC	231,295	236,962	228,727	236,960	228,729
CAIC	231,407	236,964	228,729	236,962	228,731
HQIC	230,754	236,960	228,725	236,958	228,727

4.3. Model fit statistics

As shown in Table 1, OLS represents the traditional regression model, while REML represents MR models with REML estimators and scaled weight A. Null models are without explanatory variables, as benchmark models for model comparisons. Full models are with explanatory variables we identify from model identification step. When information criteria differ a lot between models generated with two scaled weights, MR models are no longer appropriate. We can observe in Table 1 that fit statistics including AIC, BIC, etc. are very close for MR models with both scaled weights. This closeness confirms that we have a valid full MR model. As suggested by Raftery [56], larger than 10 BIC differences across models imply very strong evidence that the model with smaller BIC fits the data better than the other model does. When we compare BIC differences between null model and full model corresponding to different scaled weights, BIC differences are 8235 and 8231, respectively. Further, we found that MR models are with 2568 and 2566, smaller BIC differences compared to the traditional regression model. Thus, we can conclude that our full MR model is valid and it outperforms traditional regression model.

The goodness-of-fit in MR models is measured by proportions of explained variance within the corresponding levels. Explained variance proportions can be treated as *R*-square in corresponding levels. Explained variance proportions are calculated by $[1-\widehat{\sigma}_{u_0}(\text{full model})/\widehat{\sigma}_{u_0}(\text{full model})]$ for level 2, while $[1-\widehat{\sigma}_e(\text{full model})/\widehat{\sigma}_e(\text{full model})]$ for level 1. Our full MR model remarkably explains around 82% of variations in level 2, whilst it explains around 47% of variations in level 1. This means our final model explains 82% of regional effects or clustering effects of REC among households along with 47% household variations. The overall explained variance proportion is around 53%. It can be calculated by a weighted combination of level-1 and level-2 explanatory variance proportions and with corresponding weights (1-ICC) and ICC.

5. Results and discussions

5.1. Parameter estimations

The prime focus of this paper is to apply multilevel regression analysis to extract regional or clustering effects on REC and to examine significant environment indicators and household features that influence REC. Many conclusions can be drawn according to Type III tests of fixed effects, along with Table 2. Except for energy

Table 2
Parameter estimates of final model parameters.

Effect	Categories	Categories	Estimate	*P* (Sig.)	Standard error
Intercept			25,520	***	332
CENPDPI			−126,207	*	53,720
CENPRICES			−27,559		52,772
DIVISION GROUP (*9 and 10*)	1		262,585	**	71,077
	2		319,967	***	74,023
	3 and 8		146,507	*	69,935
	4		161,468	*	79,776
	5, 6 and 7		−88,831		82,127
HOUSING TYPE (*Apartment in building with 5+ units*) × DIVISION GROUP	Mobile home	1	45,674	**	15,279
		2	36,498	*	16,075
		3 and 8	85,817	***	15,524
		4	103,408	***	19,659
		5, 6 and 7	115,406	***	26,138
		9 and 10	59,315	*	24,430
	Single-family detached house	1	283,319	***	52,702
		2	287,189	***	50,271
		3 and 8	461,817	***	50,530
		4	389,039	***	65,458
		5, 6 and 7	437,550	***	57,727
		9 and 10	231,781	**	61,979
	Single-family attached house	1	90,606	***	21,974
		2	68,076	*	28,251
		3 and 8	97,291	***	20,925
		4	71,749	**	24,120
		5, 6 and 7	66,842	**	24,533
		9 and 10	52,151	-	28,558
	Apartment in building with 2–4 units	1	147,760	***	33,043
		2	85,444	**	29,715
		3 and 8	116,513	***	19,501
		4	52,876	**	20,490
		5, 6 and 7	50,649	*	24,370
		9 and 10	44,144		30,012
CENTOTSQFT			488,791	***	76,500
CENTOTSQFT × EDUCATION (*Doctorate degree*)	No schooling completed		20,787		14,533
	Kindergarten to Grade 12		25,399		21,910
	High school diploma or GED		−8000		35,901
	Some college, no degree		−16,254		34,447
	Associate's degree		−6405		24,411
	Bachelor's degree		−3823		40,752
	Master's degree		−7187		26,855
	Professional degree		41,828	*	17,935
CENYEARMADE			−167,813	***	11,229
CRAWL (*Yes*)	No		−63,181	***	13,337
URBAN (*Yes*)	No		−61,722	***	10,712
CENCDD65			33,560	-	19,274
CENHDD65			45,428		36,570
WALLTYPE (*Others*)	Brick		−116,770		65,995
	Wood		−117,286	*	58,909
	Siding (aluminum, vinyl, steel)		−178,401	*	71,579
	Stucco		−87,203		55,240
	Composition (Shingle)		−28,146		21,550
	Stone		−37,647	*	17,020
	Concrete/concrete block		−56,311		33,690
	Glass		5962		9707
DRAFTY (*Never*)	All the time		55,311	***	10,399
	Most of the time		34,247	**	10,155
	Some of the time		45,533	***	10,309
CENMEMBER			219,811	***	10,579
ATHOME (*Yes*)	No		−78,869	***	10,058
RACE (*2 or more races selected*)	White alone		−107,183	**	33,452
	Black or African/American alone		21,537		28,839
	American Indian or Alaska native alone		−29,615	*	11,634
	Asian alone		−69,659	**	18,664
	Native Hawaiian or other pacific islander alone		−24,082	*	10,910
	Some other race alone		−44,916	**	14,592
KOWNRENT (*Occupied without payment of rent*)	Owned by someone in the household		5181		40,681
	Rented		−56,312		41,013
INCOME (*$55,000 or more*)	Less than $30,000		−17,063		29,557
	$30,000– $54,999		−16,793		30,384
EDUCATION (*Doctorate degree*)	No schooling completed		14,828		17,596

Table 2 (*continued*)

Effect	Categories	Categories	Estimate	*P* (Sig.)	Standard error
	Kindergarten to Grade 12		26,230		30,429
	High school diploma or GED		5854		44,131
	Some college, no degree		16,649		41,087
	Associate's degree		−470		29,952
	Bachelor's degree		10,181		39,009
	Master's degree		1051		27,061
	Professional degree		22,159		16,600
THERMHEAT (*No space heating equipment*)	Use with program control		313,332	***	24,241
	Use without program control		324,559	***	24,370
	Own but never use		119,306	***	16,461
CENH2O			76,875	***	9963
TYPEAC (No AC equipment)	Central system		135,171	***	18,585
	Window/wall units		60,054	***	13,412
	Both a central system and window/wall units		51,737	***	10,130
USEAC (*Turned on just about all the time*)	Turned on only a few days / nights when really needed		−83,886	***	11,773
	Turned on quite a bit		−5297		10,979
CENHDD65 × THERMHEAT (*Own but never use*)	Use with program control		111,011	***	24,092
	Use without program control		113,068	***	21,541
	Own but never use		33,952	*	14,050
AGEHEAT (*15–19 years old*)	No space heating equipment		−64,242	**	16,662
	Less than 2 years old		−11,493		12,917
	2–4 years old		−27,638	*	13,953
	5–9 years old		−9998		15,439
	10–14 years old		6602		15,598
	20 years or older		19,832		14,423
OTHHEAT (*No space heating equipment*)	No		−79,487	*	27,836
	Yes		47,288		26,299
SIZHEAT (*No space heating equipment*)	Almost all of all heat		9434		10,456
	About three-fourths of all heat		−13,748		9860
	Closer to half of all heat		−20,534	*	9674
HOUSING TYPE (*Apartment in Building with 5+ Units*) × INCOME (*$55,000 or More*)	Mobile home	Less than $30,000	5930		22,251
		$30,000–$54,999	3788		16,037
	Single-family detached house	Less than $30,000	−102,559	***	24,508
		$30,000–$54,999	−79,928	*	28,132
	Single-family attached house	Less than $30,000	−3400		17,101
		$30,000–$54,999	849		17,150
	Apartment in building with 2–4 units	Less than $30,000	3333		22,143
		$30,000–$54,999	−36,453	*	18,053

-: Significant at 10% level, *: significant at 5% level, **: significant at 1% level, and ***: significant at <1% level.
Reference groups are in brackets.

retail price (CENPRICES) and the highest education level of householder (EDUCATION), all effects we demonstrate in Table 2 are significant at 10% according to Type III tests. We discuss parameter estimation results in this section from two aspects: environment indicators (regional effects) and household features (household effects).

Interpretation of parameter estimates needs carefulness in multilevel regressions. Since continuous variables are centered by observed divisionwise averages, parameter estimates for these variables implies effects of fluctuations from divisionwise averages. For categorical variables, baselines are chosen such that we can detect differences among categories, but no precise measurements are involved.

5.1.1. *Regional effects on REC*

As shown in Fig. 3, divisions 1, 2, 3, 4 and 8 located in the north US are mostly cold and very cold areas, while divisions 5, 6, 7, 9 and 10 located in the south and west US are mostly warm and humid areas. These climatological and geographical differences imply that households living in divisions 1, 2, 3, 4 and 8 have higher heating demand for residential energy in order to maintain comfortable living environments. As shown in Table 2, for DIVISION GROUP, the estimated effects of divisions 1 and 2 are significantly larger than other categories. This can be attributed to the fact that energy efficiencies in divisions 1 and 2 are substantially lower than energy efficiencies of other divisions. This is because though natural gas and electricity are primary energies in the US, whereas fuel oil covers a relatively high proportion (>16%) of REC in divisions 1 and 2 compared to other divisions. Interactive effects between housing type and division groups are remarkable. SFD households located in any division have significantly larger energy consumption than other types of housing. This is a little different from Kaza's [22] findings with 2005 RECS micro dataset, that SFD REC is only significantly different from multifamily units in large apartment buildings. This may because we have ruled out impacts of regional effects on REC.

5.1.2. *Household effects on REC*

As mean house size increases by one square foot from corresponding divisionwise average of house size, the expected mean household consumption increases by 488,791 kWh/year. It is important to note that though householders' highest education itself is not a significant factor that affects REC, house size is mediated by the highest education of the householders. A possible reason is that education level might not directly impact households' energy consumption; it may have an indirect impact on REC in that a U-shape relationship exists between house size and highest education of householders. If a house is built one-year later from corresponding divisionwise average of year of construction, the expected mean household energy consumption drops by

167,813 kWh/year. For a house built on a crawl place, the expected mean household energy consumption increases by 63,181 kWh/year. For a house located in an urban area, the expected mean household energy consumption increases by 61,722 kWh/year. This result contradicts Ewing and Rong's [57] statement that compact urban forms have substantial energy savings. This may due to compactness in urban area intensifies impacts between households such that increasing amounts of energy are required to offset this impact in the US.

As shown in Table 2, for each extra person living in a house, compared to corresponding divisionwise average household size, the expected household energy consumption increases by 219,811 kWh/year. Energy consumption of households with no member staying at home all day on a typical weekday is lower by 78,869 kWh/year. It is noticed that householders who are white alone, Asian alone or some other race alone consume less energy on average. We track interaction effects of householders' race with other reasonable variables, e.g. household size, but we did not find any significant effects on REC.

Households' usage of space heating equipment has a stronger positive impact on REC than their usage of AC equipment on REC. This is probably because an AC is more likely to rely on electricity, which is more energy efficient. Households use space heating equipment with program control saving 11,227 kWh/year on average, compared to those without program control. It is also noted that for each increment of heating degree days, expected household energy consumption of households using space heating equipment with program control can decline by 2057 kWh/year compared to those without program control. Houses with only central AC systems on average consume 75,117 kWh/year more than those with window or wall unit ACs. This is likely due to central AC systems having large coverage of houses and they lower residents' attempt to turn them off when not in use, compared to window or wall unit ACs.

6. Methodological discussion of multilevel regression

Our approach aims to draw researchers' attention to consider regional effects on REC and we propose using multilevel regression analysis to explain REC along with regional effects. Multilevel data, as defined by Hox and Maas [58], are data that have a hierarchical or nested structure, usually individuals within groups. REC data are usually multilevel data due to area geographically groups households. The critical part of utilizing multilevel regression for explaining multilevel data of REC is to identify a hierarchical structure. In practice, a reasonable hierarchical structure can be easily identified from the RECS data.

Area variations and clustering effect of households are counterparts in research of REC. Researchers should expect increasing heterogeneity of REC as the research area goes vast, that is, an increasing ICC is expected. We calculate the ICC based on the hierarchical structure before building regression models. ICC provides a way to quantify the heterogeneity of geographical clusters. A large-than-10 ICC urges the control of regional effects. Calculating ICC is equivalent to running an Analysis of Variance with random effects with reportable domains as the factor. Our case shows a not-less-than 15% ICC. That means, around 15% variations of REC among households can be explained by regional effects.

Alternatively, a linear regression model with no consideration of these regional effects probably leads to biased estimates. Or, a linear regression model with reportable domain as an explanatory variable can merely quantify differences among reportable domains as a qualitative variable. Multilevel regression approach is better than both approaches as we have demonstrated above.

To carefully examine REC, we adopt the natural hierarchical structure, namely 27 reportable domains and 10 divisions in the US, of the original US 2009 RECS dataset. With the multilevel regression, 27 reportable domains are like 27 pools that observations come from. Whereas, if we adopted linear regression, there would be only one pool that observations come from. Our MR model shows that division-level explanatory variables account for 82% of area variations, which reveals a high efficiency of explaining area variations. With ICC equals to 15% (calculated by weight A) and 18% (calculated by weight B), the division-level explanatory variables respectively accounted for 12.3% and 14.8% total variations of REC among households. Namely, to a great extent, regional effects on REC can be disparted from household effects on REC with a set of appropriate environment indicators. After extracting the regional effects, household features and the interaction between HOUSING TYPE and DIVISION GROUP explain 47% of remaining REC variance. Summarizing, 53% of total variance of REC is explained with our model.

7. Policy implications and conclusions

In this paper, a MR model is used to determine the explanatory power and significance of environment indicators and of household features on REC. Using multilevel regression analysis, it is possible to extract regional effects and segregate direct and indirect impacts of household features on REC. This is the first time that researchers do not have to alert practitioners that analysis results are derived from national level data and application to division level needs careful adjustment. Due to the flexibility of multilevel regression analysis, researchers and practitioners can easily apply it to analyze energy datasets with multilevel structure.

Key findings of this research are that we confirm statistically significant impacts of division groups, SFD housing, house size, usage of space heating equipment, household size and usage of AC on REC. This implies that regional effects are critical in analyzing national RECS data. SFD housing needs further investigation owing to its remarkable impact on REC; it is the predominant type of housing of REC in the US. Our results do confirm that program-controlled usage of space heating equipment help save energy. However, we find that program control does not have the same effect when it comes to usage of AC. In addition, central AC system provides convenience for maintaining coolness of the entire house. Sometimes households no longer turn their ACs off such that more energy is consumed.

We utilize the latest US RECS micro dataset in this paper. 82% and 47% of the variance proportions is explained, but we still cannot explain nearly 45% of REC variations of households. This leads to the notion that regional effects, house and household characteristics, and ownerships and usages of appliances are not enough for full projections to REC. We infer that RECS does not collect enough information to fully describe households' behaviors. Improving precision of the model requires specific information of households' end-use behaviors. Moreover, as shown in Table 2, the only respondent-reported variable, DRAFTY, has a contradictory result that households reporting drafty some of the time in winter consume more energy than those reporting drafty most of the time. This implies that RECS designers should improve the design of RECS such that more precise information can be collected in future.

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