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Socio-economic status and residential energy consumption: A latent variable approach

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ABSTRACT

Income, housing unit size, number of appliances owned and other components of socio-economic status (SES), are variables generally considered to influence residential energy use. Using structural equation modeling of SES indicators from the U.S. residential energy consumption survey (RECS), we provide evidence that SES, usually modeled as a latent construct with effect indicators, is better conceptualized as including at least some causal indicators. We studied the mediating effect of housing unit size and number of owned appliances on the relationship between SES, household size and residential energy consumption (REC). We found that household size was positively associated with REC, as a direct effect. SES had a strong impact on REC, while being mediated by housing unit size and number of appliances owned. In conclusion, research must take the latent nature of SES into account to uncover its total influence on REC.

1. Introduction

Household consumption of energy for space heating and cooling, lighting, appliances and other energy services is a key driver of energy demand and a major contributor to carbon dioxide emissions, worldwide. Several factors such as climate, building technical and physical characteristics, socio-economic, demographic and psychological characteristics have important influence on residential energy consumption (REC) [1].

Due to the complexity of the factors and the processes that influence REC, there is no single conceptual framework or model that predicts the structure and variability of consumption at the household level [2,3]. Moreover, much empirical research is conducted using some type of multiple linear regression, and often relies on incomplete data sets, convenience samples and different classification [4]. Several studies have shown that income [5-10], family composition [7-9], household size [7-11], housing unit total floor area [7-8,10-13], number of appliances owned [10,11] tend to be positively related to REC. The treatment of socioeconomic and demographics variables in most REC studies is limited to income and household size, although research findings indicate that demographic changes, such as the aging trend of society and income growth will increase energy use and may even offset technical improvements of the building stock [7]. Social sciences can significantly contribute in energy research, and it appears that the time to explore the spaces that exist between the social sciences and energy studies has arrived [14]. Energy studies should be more problem oriented, interdisciplinary and socially inclusive [14,15].

Socio-economic status (SES) is a multidimensional concept [16,17], usually measured as a combination of income, education, occupation and other components. While many of SES components are related to REC, only few studies have included and discussed the direct and indirect effects of SES and household size on REC [18-20].

Estiri [18-19] examined the direct, indirect and total effects of household characteristics on the annual energy consumption, using Structural Equation Modeling (SEM) applied to data from the United States Residential energy Consumption Survey in 2009. Results of this research showed that households with higher SES consume more energy annually because they are living in more energy consumptive housing units. Results of these studies also confirm that considering for the indirect effect of household related attributes, through the selection of the housing units characteristics, the total effect of households on energy consumption is at least as important as the effect of housing units.

Similarly, Belaid [20] used SEM to examine the direct, indirect and total effects of household features on residential energy consumption applied to microdata from the French household energy consumption survey PHEBUS. The results indicate that in addition to their direct impacts, household attributes also have indirect impacts on the total household energy consumption.

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These indirect effects are important in the understanding of the influence on REC. For example, SES may not affect REC directly, but rather may affect REC indirectly by leading households to live in bigger housing units and own a bigger number of appliances. Another critical aspect of incorporating SES in REC studies relates to the modeling of SES. Previous studies in the field of REC have an implicit assumption that any observed variables included in the model are dependent on latent variables, i.e. treated SES as a latent variable of effect indicators, without considering possible causal indicators. However, some of SES components like income or education may be better conceptualized as causal indicators [16,21].

To address these shortcomings, we formulated a model relating the components of SES, including income, family status, education, total heated floor area and number of owned appliances, to REC. We evaluated the impact of two alternative modeling approaches of SES, as a latent variable consisting solely of effect indicators and as a latent variable with both causal and effect indicators. We were able to illustrate associations between SES/household size and residential energy consumption and clarify the mediating effect of housing unit total floor area and number of owned appliances on the relationship between SES, household size and residential energy consumption.

Our results show that, when modeled appropriately, SES can make more of an impact in the residential energy use than what is perceived in current research, so it is worth examining modeling approaches of SES and their effects in REC in more depth.

2. Methods

2.1. Data

In this study, we used publicly available data from the United States Energy Information Administration (EIA) Residential Energy Consumption Survey (RECS) [22]. We used the most recent RECS which have been conducted in 2015. A multistage area probability sample desing was used, where the population was divided into successively smaller statistically selected areas starting from large geographic areas and ending with individual housing units. The population for the 2015 RECS sample design included all housing units occupied as primary residences in the 50 states and the District of Columbia. RECS includes single-family homes, units in multifamily buildings, and mobile homes and excludes vacant, seasonal, vacation homes and group quarters. Thus, the 5686 occupied housing units that consist the 2015 sample, are statistically selected to represent the 118.2 million U.S. housing units that are occupied as primary residences.

For the 2015 survey cycle, EIA used Web and mail forms, in addition to in-person interviews, to collect required information on household energy characteristics.

The RECS consists of the Household Survey, the Energy Supplier Surveys, and EIA's detailed consumption and expenditures estimation. As a result, the data set provides detailed information on occupant socio-demographic characteristics, building physical characteristics, specific energy behaviours and some contextual factors alongside the energy consumption. Fuels used for energy end uses include electricity, natural gas, propane, wood and kerosene.

2.2. Measures

2.2.1. SES

In general, there is no single definition of SES, and there is no one standard for its measurement [23]. A general definition has been proposed by Gralley [24], according which, "SES is an indicator of an individual's social and economic standing in society and often is determined by a combination of ratings on occupational status, income level, and education". For the purposes of this study, where SES is perceived as an important predictor of REC, the following five variables were selected from the REC dataset as indicators of SES: income, family status, education, total heated floor area of the housing unit and number of appliances owned.

Income is a categorical variable that measures gross household income, in \$20k intervals, top-coded at 140k or more.

Family status is a constructed variable coded as 1–0, based on whether or not there are household members with age less than 18 years, respectively. Education is measured through a categorical indicator, expressing the highest education completed by the householder. Values ranged from 1–5, with 1 = Less than high school diploma or General Equivalency Diploma (GED), 2 = High school diploma or GED, 3 = Some college or Associate's degree, 4 = Bachelor's degree (for example: BA, BS), and 5 = Master's, Professional, or Doctorate degree (for example: MA, MS, MBA, MD, JD, PhD).

Total heated floor area is a continuous variable, expressing the total heated floor area of the building, which includes all attached garages, basements and finished/heated/cooled attics. The number of appliances is a constructed measure and represents the sum of the following household appliances: refrigerator, freezer, dishwasher, clothes washer, dryer, color televisions, personal computers and Air Conditioning Units.

As mentioned in the previous section, we distinguish between causal and effect indicators. The SES components of income, education status, and family status are causal indicators of SES. In contrast, the number of owned appliances and the total heated floor area of the housing unit are effect indicators of SES.

2.2.2. Household size

Household size is the number of household members.

2.2.3. Total energy consumption

Total Energy consumption is the total household energy usage for year 2015 (in thousands BTU).

2.3. Analysis

2.3.1. Statistics

To distinguish causal from effect indicators in modeling SES, we conducted vanishing tetrad test (VTA) using SAS macro [25].

A detailed description of Vanishing Tetrad Test can be found in Bollen and Ting [26-28]. Here, we present only a brief overview. VTT is a technique that can be used to assess the fit of structural equation models, as well to assess the fit of models that consist of both causal and effect indicators. A tetrad is formed from four random variables and refers to the difference between the product of one pair of covariances and the product of the other pair. Four variables contain six covariances, and from these, we can create three tetrads. Using Kelley's notation [29], these tetrads are:

$$\begin{aligned} \tau_{1234} &= \sigma_{12}\sigma_{34} - \sigma_{13}\sigma_{24} \\ \tau_{1342} &= \sigma_{13}\sigma_{42} - \sigma_{14}\sigma_{32} \\ \tau_{1423} &= \sigma_{14}\sigma_{23} - \sigma_{12}\sigma_{43} \end{aligned} \quad (1)$$

where σ is the population covariance of the two variables that are indexed below it.

Depending on the structure of a hypothesized model, some of these tetrads are zero, $\tau_{\text{ghij}} = 0$, and these are referred as model implied vanishing tetrads. If nonvanishing tetrads are discovered within the model implied vanishing tetrads, the appropriateness of the model is questioned [26]. Significance testing as described in Bollen and Ting [28] is one method for selecting model implied vanishing tetrads, where $H_{0:}$ $\tau = 0$ (all effect indicators) and H_1: $\tau \neq 0$ (all or some causal indicators). Thus, a significant test statistic supports H_1 and suggests that some of the vanishing tetrads

Table 1
Bivariate correlations between indicators of SES ($N = 5686$).

	1	2	3	4	5
1. Income	1				
2. Family Status	0.12**	1			
3. Education	0.48**	0.03	1		
4. Number of appliances	0.47**	0.24**	0.24**	1	
5. Total heated floor area	0.42**	0.10**	0.23**	0.47**	1

** Correlation is significant at the 0.01 level (2-tailed).

implied by the model are significantly different from zero and indicates poor model fit.

We evaluated the quality of causal indicators using:

(i) the squared correlation between the indicator and the latent variable (ρ^2) [21]:

$$\rho^2_{x_n q} = \frac{[cov(x_q, n)]^2}{var(x_q) var(n)} \quad (2)$$

where $[cov(x_q, n)]$is the covariance of the causal indicator with the latent variable and $var(n)$ and is the variance of the latent variable.

(i) the standardized validity coefficients (Std(β)), available from SEM software output and

(ii) the unique validity variance (U) [21]. The formula for the unique validity variance U_{n1x_q} is:

$$U_{n1x_q} = R^2_{n1} - R^2_{n1(x_q)} \quad (3)$$

where $R^2_{n1}$is the proportion of variance in n_{1i} explained by all variables with a direct effect on the latent variable and $R^2_{n1(x_q)}$is the proportion of variance in n_{1i}explained by all variables with a direct effect excluding x_{qi}. The unique validity variance ranges from 0 to 1 where higher values suggest greater validity than lower ones.

2.3.2. Structural equation modeling (SEM)

We used SEM to estimate the direct, indirect and total effects of the considered variables on total energy consumption. SEM are also referred to as analysis of covariance structures, or causal analysis and their main advantage over other modeling approaches and regression techniques is its ability to include latent variables and to specify the likely causal relations among a set of these variables.

SEMs were fit using statistical software AMOS (Analysis of a Moment structures) [30]. All models were fitted using Maximum Likelihood Estimation. The model fit indices used for judging good fit were: Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker Lewis Index (TLI). The significance of individual paths was tested with p-values less than 0.05.

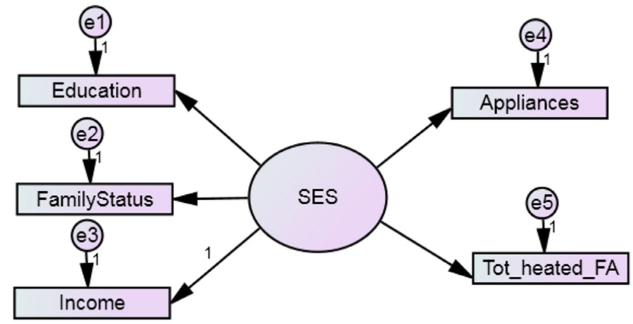
3. Results

3.1. SES measurement models

Table 1 shows the bivariate correlations r between the indicators of SES. We found moderate correlations between income and education ($r = 0.48$), income and number of appliances ($r = 0.47$), and number of appliances and total heated floor area ($r = 0.47$). Also, we see that income has a moderate correlation with total heated floor area ($r = 0.42$). We do not, however, find a clear pattern of correlations among the other variables.

We expect that changes in income, family status and education precede changes in SES, and thus these variables are better conceptualized as causal indicators of SES, while the total heated floor area of a housing unit and the number of owned appliances are affected by SES, and are better conceived as effect indicators of SES.

We consider a set of two models. The first treats all five measures as effect indicators (Fig. 1 Model A). Arrows point from SES



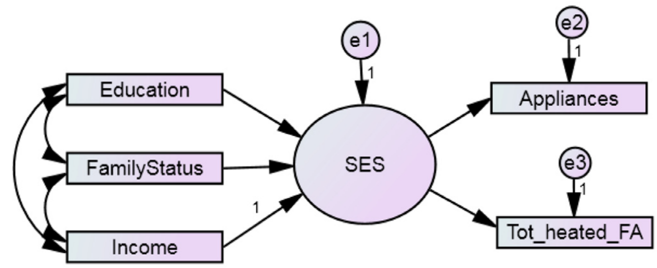


Fig. 1. Measurement models for SES, where observed variables are shown in squares and latent variables are shown in circles.

Table 2
Tetrad test results ($N = 5686$).

	Chi-square	df	p-value
Models			
Effect Indicators	383.51	5	0.000
MIMIC model	79.88	3	0.000
Nested Test effect vs MIMIC	303.62	2	0.000

to observed variables, suggesting that they are caused by SES. The second model treats income, family status and education status as causal indicators and housing unit floor area and number of owned appliances as effect indicators (Fig. 1 Model B). Here, arrows point from income, family status and education to SES, suggesting that these are causal indicators of SES. The arrows point from SES to the total heated floor area and the number of appliances suggest that these are effect indicators of SES. This second model, commonly referred to as multiple indicator-multiple cause (MIMIC) model, is more consistent with our theoretical understanding of the relationships among the indicators of SES.

For these two candidate models, we conducted vanishing tetrad test [25]. The different model structures imply different sets of vanishing tetrads. If an implied vanishing tetrad is significantly different than zero, then this constitutes evidence against the hypothesized model [21].

The model that treats all of the variables as effect indicators has 15 tetrads, all of which vanish. However, only five of the fifteen tetrads are independent, which gives five implied vanishing tetrads to test. For the MIMIC model, there are two implied vanishing tetrads that are a subset of the vanishing tetrads of the all effect indicators model. This indicated that we can perform a nested tetrad test of the MIMIC model within model A.

We find a significant chi-square for both models (see Table 2 for fit statistics). The significant chi-square is evidence that the models do not fit the data well. The chi-square of the nested test between the MIMIC model and the effect indicators model is

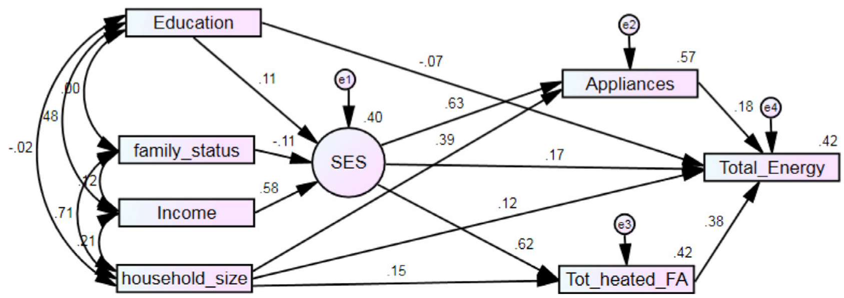


Fig. 2. The relationship among SES, household size and total energy consumption.

Table 3
Measures of Validity; ($N = 5686$).

	ρ^2	Std(β)	U
Income	0.41	0.59	0.28
Family Status	0.07	0.20	0.03
Education	0.11	0.05	0.00

significant, which suggests that the data are best explained by the MIMIC model, i.e. the model with fewer vanishing tetrads.

Income and family status have shared variances with SES of 0.41 and 0.07, and standardized coefficients of 0.59 and 0.20 respectively, all of which are statistically significant (see Table 3). The unique validity variance for education is close to zero, which indicates that education does not explain much of the variance of SES.

The selected MIMIC model was then expanded to test the effects of SES and household size on total energy consumption. Adding household size as a common cause of the number of appliances and the total heated floor area of the housing unit produced a model with parameters shown in Fig. 2.

The fit of model was excellent by several criteria: $x^2(3) = 5.30$, $p = 0.150$, Comparative Fit Index (CFI) $= 1.000$, Tucker Lewis Index (TLI) $= 0.999$ and Root Mean Square of Approximation (RMSEA) $= 0.012$ (90% CI 0.000 to 0.028).

In Fig. 2, the numbers above causal indicators, i.e. income, family status and education, are factor loadings, indicating the strength of relationship between SES and its causal indicators. Income is the strongest predictor of SES. In addition, the existence of a spouse and head's higher education generate higher SES and were also statistically significant.

SES directly positively contributing to the number of owned appliances ($\beta = 0.62$, $P < 0.001$), total heated floor area ($\beta = 0.62$, $P < 0.001$) and total energy consumption ($\beta = 0.17$, $P < 0.001$).

The model implies also indirect pathways, connecting SES with energy consumption via mediating variables. These indirect effects were tested for statistical significance. SES indirectly predicted total energy consumption through the number of appliances ($\beta = 0.63 \times 0.18 = 0.11$, $P < 0.005$) and through the total heated floor area ($\beta = 0.62 \times 0.38 = 0.24$, $P < 0.005$).

The mediating effect of total heated floor area on the relationship between SES and total energy consumption was significant. A 1-SD increase in SES was associated with a 0.24 increase in total energy consumption, resulting from the effect of SES on total heated floor area, which influences total energy consumption in turn ($p < 0.005$).

However, the indirect effect of SES on total energy consumption via the number of appliances is smaller. A 1-SD increase in SES was associated with a 0.11 increase in total energy consumption through the number of appliances.

Household size was found to positively predict the number of appliances ($\beta = 0.39$, $P < 0.001$), total heated floor area ($\beta = 0.15$, $P < 0.001$) and total energy consumption ($\beta = 0.12$, $P < 0.001$). Household size also indirectly predicted total energy consumption through the number of appliances ($\beta = 0.39 \times 0.18 = 0.07$, $p < 0.007$) and through the total heated floor area ($\beta = 0.15 \times 0.38 = 0.06$, $p < 0.004$). The total indirect effect of household size on total energy consumption is thus 0.13 ($p = 0.012$).

As shown in Fig. 2 the strongest direct predictor of total energy consumption is total heated floor area ($\beta = 0.38$, $P < 0.006$) followed by number of appliances ($\beta = 0.18$, $P < 0.009$), SES ($\beta = 0.17$, $P < 0.013$), and then the household size ($\beta = 0.12$, $P < 0.011$).

The model accounted for 42% of the variance in total energy consumption.

We also wanted to evaluate whether education has a direct effect on total energy consumption once its relationship with SES was introduced. The influence of education is mediated by SES. In the education-SES-total energy consumption pathway the direct and indirect impact of education on total energy consumption were -0.07 and 0.06 respectively, over a half of the impact was accounted for by the indirect model, suggesting that SES mediates the effects of education level on total energy consumption. The total effect of education on energy consumption is -0.014 and is negative.

4. Discussion

Our study tested a conceptual model that explains total energy consumption as a function of SES, household size, number of appliances and the total heated floor area of the housing unit.

We evaluated the impact of two alternative modeling strategies of SES in residential energy consumption models, a causal and effect indicators specification versus an effect indicators specification. Previous research regarding SES in residential energy consumption modeling has relied solely on the notion that each item is an effect indicator [18]. In contrast, our findings suggested that SES construct containing at least some causal indicators fits the data better than a construct with only effect indicators. An increase in a person's SES does not result in a corresponding increase in income or education level, neither results in family status change. So, for income, education, and family status, causal indicators are more conceptually attractive and were considered to represent different causes of SES. Conversely, an increase in SES may result in the ownership of a bigger housing unit and the possession of more appliances. Therefore, total heated floor area and the number of owned appliances were deemed to more accurately reflect higher SES, and were modeled as effect indicators.

Our findings also suggested strong effects of SES on the size of the housing unit and the number of owned appliances. The standardized direct effect of SES on total heated floor area was 0.62, whereas the direct effect on the number of owned appliances was 0.63. Both effects were statistically significant and considerable. For each standard deviation (SD) change in the latent SES variable, total heated floor area of the housing unit will increase by 0.62 of a

SD, and the number of appliances should increase by 0.63 of a SD, other things being equal.

Adding household size as a common cause of differences in size of the housing unit and the number of owned appliances produced an excellent model fit. An interesting finding is that the strongest effect on total heated floor area was from SES, almost nine times higher than the respective effect of household size, suggesting that the housing unit total area is determined mainly by SES and wealth of families and not the number of household members. For the number of owned appliances, SES was again the strongest influence, but household size also had a large impact, suggesting that not only households with higher SES but also households with more members possess more appliances.

Similar to previous studies [18-20], we found that the strongest direct influence on total energy consumption was from total heated floor area of the housing unit. The effect from number of owned appliances was the second strongest direct influence, suggesting that as the number of owned appliances is increased, so is the total energy consumption. Consistent with other studies, the positive direct effect of household size suggests that households with more members consume more energy once other influences are controlled. The path from SES to total energy consumption suggests that households with higher SES consume more energy than households with lower SES do even when the other variables in the models are statistically controlled. The direct path from education to total energy consumption is quite small to represent a meaningful effect.

Many more interesting findings are contained in the model beyond the direct effects. The proposed SEM approach allowed us to examine not only the direct but also the indirect and total effects of housing units and household attributes on energy consumption.

In particular, we were interested to determine whether total heated floor area and number of appliances mediated the effect of SES on total energy consumption. SES had a powerful effect on total heated floor area: households with higher SES leave in bigger houses than households with lower SES do. The total heated floor area, in turn, had a strong effect on total energy consumption: bigger houses require much more energy for space heating and cooling and for lighting. Similarly, SES had a powerful effect on the number of the owned appliances: households with higher SES can afford and possess a bigger number of appliances. The number of appliances, in turn, had a moderate effect on total energy consumption: a higher number of appliances consume more energy. Thus, the total effect of SES on total energy consumption is substantial, mediated by total heated floor area and the number of owned appliances.

Our approach is in line with ongoing literature on residential energy consumption [18-20] which confirms the importance of using SEM in revealing the indirect role of households' social characteristics in shaping Residential Energy Consumption.

By accounting for mediation between social, demographic and building characteristics we achieve a deeper understanding of the parameters influencing residential energy consumption and reveal significant indirect effects that have been usually omitted in conventional research. The results documented in this paper showed that the total effect of household SES on energy consumption is considerable and bigger compared to household direct effects.

Such findings have important implications for energy policy and are crucial in the energy efficiency debate. Undoubtedly research and energy policies that promote energy efficiency technology for the physical and technical structures of the buildings, building systems and appliances offer considerable opportunities for energy savings. Though, energy policy could benefit from incorporating socio-economic household-housing dynamics and thus establish efficient and innovating housing and social solutions [31]. Here especially, is where multi-disciplinary approaches that examine behaviour based energy efficiency should add the most insight [32].

5. Conclusions

The objective of this study was to explore conceptual models that explain total energy consumption as a function of SES, household size, number of appliances and the total heated floor area of the housing unit.

There are several reasons why our findings represent important steps forward. We used a latent variable approach for modeling SES as a mixture of causal and effect indicators. While techniques like SEM have been applied to the same dataset in previous studies, SES has been modeled as a reflective construct. We provide evidence that SES is better conceptualized as a causal and effect model.

SES seems to affect total heated floor area and number of appliances which in turn influence total energy consumption, thus suggesting that there may well be indirect effects of SES on total energy consumption. And while these indirect effects are lost in standard multiple regression analysis, they are considerable (and calculable) in SEM.

In conclusion, household size and SES are associated with REC, but research must take their mediating effects into account to uncover their total influences.

Declaration of Competing Interest

Authors declare that there is no competing Interest.

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