Energy 271 (2023) 126988

Contents lists available at ScienceDirect

Energy

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

Saving from home! How income, efficiency, and curtailment behaviors shape energy consumption dynamics in US households?

Pranay Kumar [a,*], Holly Caggiano [b], Rachael Shwom [c], Frank A. Felder [d], Clinton J. Andrews [a]

[a] E.J. Bloustein School of Planning and Public Policy, Rutgers University, NJ, USA
[b] Andlinger Center for Energy and the Environment, Princeton University, NJ, USA
[c] Department of Human Ecology, Rutgers, The State University of New Jersey, 55 Dudley Road, New Brunswick, NJ, 08901, USA
[d] Energy Transitions and Electric Power, KAPSARC, Riyadh, Saudi Arabia

ARTICLE INFO

Handling Editor: X Zhang

Keywords:
Energy
Electricity
Efficiency
Curtailment
Behavior
Residential energy consumption

ABSTRACT

The objective of this study is to analyze the role of energy efficiency and curtailment behaviors and examine how these behaviors are mediated by annual household income to explain overall energy consumption dynamics in US households using a nationally representative dataset. Our two-part empirical analysis first explores the role of annual household income on the efficiency and curtailment behaviors while controlling for the physical and demographic variables using structural equation modeling (SEM). Next, we test the extent and direction of self-reported energy efficiency and curtailment behaviors in explaining total energy/electricity consumption of households using cluster analysis and multivariate linear regression methods. We find efficiency behaviors to be positively correlated with the household income. However, the direction of relationship between income and curtailment behaviors appears to vary depending upon specific actions. Our findings also suggest that in comparison to the consistent role of physical factors in the residential energy consumption, the nature and direction of behavioral factors are mixed and vary with specific behaviors and context. Our study builds upon the existing literature on residential energy saving behaviors and provides important insights for tailored, targeted, and effective policies.

1. Introduction

Reducing households' energy consumption while maintaining physical comfort and well-being is important to limit carbon emissions and meet national and global climate policy goals [1–3]. Most nations and governments rely heavily on energy efficiency policies because of their potential socio-economic benefits and important role in the sustainable energy transition [4,5]. Recently, the US federal government announced its plan to reduce GHG emissions by 50–52% from the 2005 level by 2030 [6]. A significant portion of the plan relies on increasing building and transportation energy efficiency with an annual estimated reduction of over 1 Gigaton of CO_2 by 2050 [7]. The residential sector accounts for nearly 21% of total end-use energy consumption and roughly 20% of the GHG emissions in the US [8,9]. The US Department of Energy (DOE) supports several rebates and incentive programs for residential energy efficiency improvements, especially for low-income households with a high energy burden [10,93]. The Inflation Reduction Act (IRA) passed into law recently contains several provisions for funding energy efficiency programs targeted to low- and moderate-income households and tax benefits for energy efficient appliances and home retrofits [11]. Separately, the states also funded energy efficiency programs worth $767.6 billion approximately in 2021 with an expected electricity saving of 26.66 million MWh [12]. In this background, it is not only important to understand what are the physical, socio-economic, and behavioral factors underlying residential energy consumption but also to know their variability across households, regions, and energy sources.

Energy efficiency (EE) is not only considered as one of the lowest cost energy resources with multiple benefits but also an important policy instrument in limiting GHG emissions [13,14]. In the US context, energy efficiency actions spread over a range of sectors and technologies are expected to save energy and reduce emissions in half by 2050 [15,16]. In the residential sector alone, a recent report estimates energy saving potential in the range of 31%–59% and corresponding carbon emissions between 32% and 56% due to deep retrofits [17]. However, some scholars and practitioners have raised concerns regarding the

* Corresponding author.
E-mail address: pranay.kumar@rutgers.edu (P. Kumar).

https://doi.org/10.1016/j.energy.2023.126988
Received 29 November 2022; Received in revised form 16 February 2023; Accepted 16 February 2023
Available online 25 February 2023

conceptual, methodological, and practical limitations of energy efficiency actions in realizing net energy savings, carbon emission reductions, and equitable outcomes [18–22]. Others have argued that the techno-economic construct of energy efficiency alone may not be sufficient to explain and limit residential energy use in line with national and global carbon emission commitments [19,23,24]. Rather, onetime EE investments need to be complemented with a wide range of energy saving behaviors including repetitive energy curtailment (EC) actions aimed at limiting overall consumption based on a deeper understanding of objective, subjective, and contextual factors associated with energy use [3,25–27].

In general, residential energy conservation behaviors have been studied under two broad domains with EE behaviors associated with one time, cost incurring investments in efficient appliances and retrofits and EC behaviors characterized as repetitive, low-cost energy saving efforts [3,26,28,29]. Common examples of EE behaviors include purchasing efficient appliances or upgrading building insulation, while EC behaviors include automating thermostat settings, switching off lights, limiting use of heating systems, and unplugging appliances when not in use [30–34]. Despite the growing body of literature on the role and importance of EE and EC behaviors, there appears to be little consensus on their relative efficacies and tradeoffs [26,32,35]. With few exceptions, these two behaviors have been studied separately, with EE behaviors largely explained by financial motivations and bounded rationality and EC behaviors driven primarily by social psychological factors and pro-environmental concerns [26,36,37]. Still fewer studies examine the interactions between the socio-economic and psychological factors that explain heterogeneity in residential energy consumption across regions and types of energy sources used. Recent studies have begun to explore the dichotomy between EE and EC behaviors and analyzed their combined role in explaining residential energy consumption [32,38–42,95]. However, we are not aware of any study that empirically tests the direction, extent, and combined role of income, EE, and EC behaviors on the estimated energy consumption in the US context while factoring the heterogeneities across households, regions, and energy sources. To address this research gap, we explore the following research questions.

i. How different EE and EC behaviors influence residential energy consumption?
ii. How does household income affect EE and EC behaviors to explain residential energy consumption?
iii. What are the key distinctions in terms of the energy and electricity consumption across US households for different socio-economic, behavioral, and physical factors?

To explore these questions, we use the latest available residential energy consumption survey [43] data drawn from a nationally representative sample of 5400 US residential households. Our empirical analysis is in two parts employing a mix of methods and analytical approaches. We first analyze the direction, extent, and role of reported EE and EC behaviors on the estimated residential energy and electricity consumption using structural equation modeling (SEM). We also test the role of annual household income on EE and EC behaviors. Using cluster analysis, we then identify natural groupings of residential units based on energy purchase costs across the four main geographical regions to control for their possible effects on the total annual energy/electricity consumed. Next, we study the hypothesized roles of the different EE and EC behaviors in explaining residential energy and electricity consumption separately while controlling for the physical, socio-economic, and demographic profiles using multi-variate regression. Our study provides novel insights on the role of self-reported energy efficiency and curtailment behaviors that explain overall energy consumption based on empirical analysis in the US context. By studying residential energy and electricity consumption separately across different geographical regions, our study explores heterogeneity in energy consumption pattern from electricity and other sources that often gets lumped together. We also build upon and add to the existing literature by analyzing the role of household income in mediating different EE and EC behaviors on a national scale.

The remainder of this paper is organized as follows: following a brief overview of the contemporary literature on the theoretical background and empirical findings on residential energy behaviors in section 2, we outline our analytical approach and describe our models in section 3. We present the results of our study in section 4 followed by a discussion in section 5. Section 6 concludes with policy implications and suggestions for future studies.

2. Brief literature overview and research hypotheses

Residential energy consumption behavior is a complex subject studied extensively over decades with lively debates within and across academic disciplines over its variability, measurement, and policy implications [3,25,44]). An indication of the growing research and interest on energy consumption can be ascertained from the volume of publication over decades, starting from 23 in 1951–60 to over 1131 in 2001–10 [45]. In the absence of any overarching model that can comprehensively explain the dynamics of residential energy consumption behavior, scholars have noted the relative strengths and limitations of individual theoretical approaches and highlighted the need for integrating them [3,37]. For a comprehensive review of the different theoretical perspectives and associated debates on the residential energy consumption, see Refs. [27,33] among others. In the following sub-sections, we summarize past research findings on how energy efficiency and curtailment behaviors are related to overall residential energy and electricity consumption and how household income may influence these relationships.

2.1. Heterogeneity in US households' energy consumption

Although residential energy saving is often loosely equated with electricity consumption of the households, the actual mix of different energy sources varies significantly depending on the physical, geographical, and demographic characteristics [1,2]. Past studies have noted significant variation in the electricity consumption versus other energy sources in residential households with gas consumption determined principally by the dwelling's physical characteristics and electricity consumption by socio-economic and demographic factors [2,46]. However, there are no common and specific reasons for this mixed and dynamic pattern that appears to be influenced by multiple factors ranging from individual choices to geographic and economic factors embedded in the larger social, cultural, and historical contexts [47,48]. Residential homes use several energy services powered by different fuels and energy resources across the population over different geographical regions. Despite the predominance of electricity as the most consumed energy source across all US households, natural gas and oil together continue to be used in the cooler Northeast and Midwest regions, forming 70% and 66% of the total energy mix respectively [43].

Past studies have also found huge variations in the amount of energy consumed in physically identical residential households [41]. For example [49], found that despite the dominance of weather effects and building characteristics, occupant behaviors and socio-economic factors were important in influencing energy consumption for heating and cooling services in the US households. Another study compared the role of socio-economic characteristics with physical attributes of Swedish single-family houses. It found that in comparison to the dominance of physical attributes on the heating and cooling loads, residential energy use for the lighting and other appliances was more dependent on the socio-economic characteristics of the households [46]. In general, the nature and role of physical and economic factors underlying residential energy consumption such as, dwelling type, household size, and income have been found to be significant and consistent across the studies. In comparison, occupants' behaviors and their demographic profiles seem to influence energy consumption differently across households and regions [3,26,40].

2.2. Income, efficiency, and curtailment behaviors

Energy conservation policies for the residential sector broadly rely on two types of occupant behaviors–investment in more efficient appliances (EE behaviors), and lesser use of the existing energy services (EC behaviors) [26,39]. With few exceptions, however, combined effects of these two behaviors on residential energy consumption have not been empirically tested using measured values. In the US, a recent study examined the energy use intensity (EUI) of residential households as an indicator of energy efficiency. Using a nationally representative dataset from US, it found that EUI varies with income groups [42]. Another study analyzed the residential energy consumption in terms of fixed and interactive energy efficiency technologies. It found that fixed energy efficiency technologies are more effective than interactive ones [38]. In the past [50], studied energy conservation behaviors as reasoned and unplanned behaviors using survey responses and monthly electricity consumption from apartments in a green building in the northeastern US. The authors found that the value belief norms (VBN) framework correctly predicted the reasoned behaviors but did not adequately explain unplanned actions [50]. Another empirical study using randomized controlled trials on a representative population of Irish consumers investigated the trade-off between the curtailment and efficiency behaviors. Using time of use pricing and feedback information through smart meters, the study found that while the overall and peak electricity usage dropped, the intervention also had an unintended effect of reducing the energy efficient investment of the household [32].

The economics of energy efficiency and energy curtailment differ and thus we hypothesize that household income will impact these behaviors differently. Energy efficiency behaviors are identified with reduction in the energy used for a given service or level of activity – heating, lighting, etc. [51,52]. Alternately, EE actions can also be described as the ratio of energy use per unit of activity or services provided by energy-using technologies, such as buildings, appliances, industrial equipment, and vehicles [4]. However, such claims of energy savings have been contested by some economists, who feel that the real "narrow social optimum" potential which can be realized cost-effectively is far lower than the engineering estimates. They argue that estimation of EE savings is based on technical potential that overstates net benefits [53]. Despite the apparent benefits, it is observed that energy consumers do not adopt efficient products fully in their daily lives. This disconnect between the theoretically available cost-effective EE potential and the actual realized savings, is known as "energy efficiency gap" [54] or paradox [55] and explained primarily by market failures, behavioral anomalies and other personal factors [56]. However, adoption of energy efficient appliances by the households and how they use less energy remains a big unknown that continues to challenge researchers, practitioners, policy makers, and the end users themselves [24,96].

In general, households with higher income are expected to invest more in energy efficient appliances as compared to engaging in curtailment behaviors [26,57]. Drawing from the self-reported behavior of respondents from 22 countries in the European Union [39], studied the role of households' income on the energy efficiency and curtailment behaviors. They found that while income correlated positively with the likelihood of buying energy efficient appliances, it had a negative effect on engaging in curtailment behaviors [39]. Another study on British households found similar results concerning the divergent role of income on self-reported EE and EC behaviors [41]. Further, the annual household income has also been found to be positively associated with the overall energy consumption [38,40]. It thus follows that the relative efficacies, interactions, and the combined role of the household income, EE, and EC behaviors in analyzing the overall residential energy consumption may not be straightforward requiring further investigation [3,58].

2.3. Conceptual model and research hypotheses

In this study, we examine the direction, extent, and combined role of EE and EC behaviors on estimated values of the total residential energy consumption in the US residential households using a mix of methods and analytical approaches. Fig. 1 shows a schematic diagram of the conceptual model used to analyze the research questions and test the hypotheses based on our literature review. By separately examining the outcomes in terms of the total energy and electricity consumption, we explore the consistencies and heterogeneities in the roles of physical, socio-economic, and behavioral factors across US households. We also build upon the current literature by analyzing the role of household income on energy efficiency and curtailment behaviors while controlling for the structural, geographic, and demographic profiles of the residential households.

Fig. 1 above shows the schematic diagram of the conceptual model used to test the following hypotheses.

Hypothesis-1 (H1). Annual household income significantly and negatively affects the energy curtailment behaviors.

Hypothesis-2 (H2). Annual household income significantly and positively affects the energy efficiency behaviors.

Hypothesis-3 (H3). Annual household income significantly and positively affects the total energy/electricity consumption of households.

Hypothesis-4 (H4). Energy curtailment behaviors significantly and negatively affect the total energy/electricity consumption of households.

Hypothesis-5 (H5). Energy efficiency behaviors significantly and negatively affect the total energy/electricity consumption of households.

3. Data, Model description, and variables

3.1. Data

For this study, we accessed the cross-sectional data from the residential energy consumption survey (RECS) for the year 2015 conducted on a nationally representative sample of more than 5400 households by the Energy Information Administration (EIA), U.S. Department of Energy.[1] RECS is conducted in two stages: first, data on the housing characteristics is collected using a household survey; next, the housing

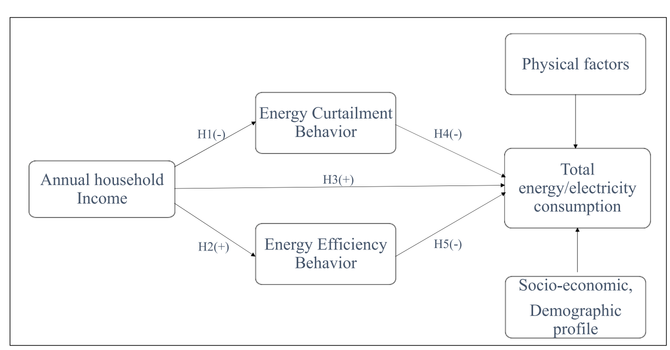

Fig. 1. Schematic diagram of the conceptual model and hypotheses tested.

[1] https://www.eia.gov/consumption/residential/about.php.

information is combined with data from energy suppliers to estimate the total energy consumption and costs [59]. From the RECS data, we observe that whereas close to one-third of the US population predominantly uses electricity for their residential energy needs, most of the population still relies on other sources of energy including natural gas, especially for home heating and cooling applications. Based on the residential household characteristics, i.e., structural-housing type, building vintage, floor area; systems-heating, cooling; devices-appliances, electronics; resident behavior-usage frequency, temperature set points, people, and monthly billing data from energy suppliers, annual energy demand are estimated and disaggregated into end-use estimates. In the most recent [43] data available at the time of this research, household energy consumption was estimated using an engineering model as opposed to the statistical models used in the past surveys.

3.2. Model description-

For the first part of our analysis, we used the SEM method to test the role and extent of the annual household income on the EE and EC behaviors as well as their overall effect on the total energy/electricity consumption. As the model uses more than one simultaneous equation, we used SEM due to their ability to represent complicated relationships between the observed and latent variables with the help of path diagrams [60]. SEMs differ from the usual single equation regression models that have a single dependent variable and multiple covariates as it allows for multiple relationships between endogenous variables with measurement errors subject to multivariate normality assumptions [61, 62].

The mathematical formulation for the structural equation models 1&2 used is as follows:

$\mathbf{Y}_i = \alpha_Y + \mathbf{B}\mathbf{Y_i} + \mathbf{\Gamma}\mathbf{X_i} + \zeta_i$; where

$\mathbf{Y_i}$ represents the set of observed endogenous variables for the ith household, $\mathbf{X_i}$ denotes the set of observed exogenous variables, $\mathbf{B}$ and $\mathbf{\Gamma}$ are the coefficient vectors for the observed endogenous and exogenous variables respectively, α_Y represents the set of constant terms, and ζ_i is the error term [63]. For the SEM 1&2 used in this study, the total annual energy/electricity consumption were estimated on a logarithmic scale and treated as endogenous variables along with the variables representing the EE and EC behaviors. The annual household income, structural, and socio-economic factors were treated as exogenous variables.

Similarly, the mathematical formulation for the multivariate linear regression models 3&4 used is as follows:

$$Y_i = \alpha_i + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \sum_{k=1}^{4} \beta_{ki}\, \mathbf{\Delta_k} + \varepsilon_i; \text{ where}$$

Y_i represents the total energy/electricity consumption of the ith household, X_i represents the structural, behavioral, and socio-economic variables of the households, Δ_k represents the dummy variable with values equal to 1 when the house is located in the cluster region k, and zero for the base (mid-west) cluster region, β_i are the estimated regression coefficients, α_i represents the set of constant terms, and ε_i is the error term.

3.3. Cluster analysis-

Before proceeding with the regression analysis, we used a two-stage clustering technique to identify natural groupings among the variables capturing the total energy consumption and energy costs across the four geographical regions-north east, mid-west, south, and west in the USA. Thereafter, we generated a categorical variable and used it as a proxy variable in the SEM and MLR analysis to control for the possible effects of the geographical location and energy costs on the total residential energy/electricity consumption [64,65]. Using IBM SPSS statistics

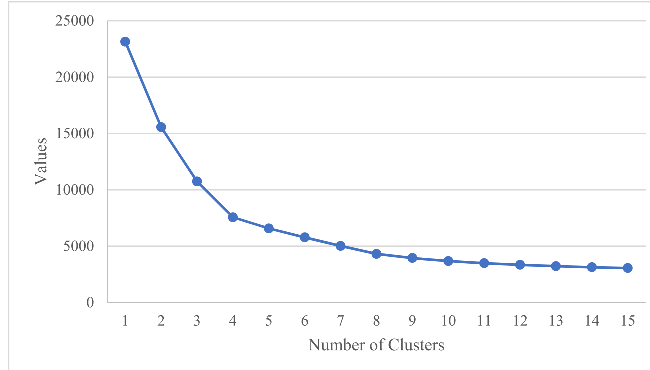

Fig. 2. Screeplot of Schwarz's Bayesian criterion (BIC).

software for Windows (version 28.0), we grouped the energy consumption and costs variables into four clusters broadly overlapping with the geographical regions. Fig. 2 below shows the screeplot of Schwarz's Bayesian criterion (BIC) and the elbow point used to identify the four clusters (summary results and model fitness indices from the cluster analysis are attached at Appendix).

A scatterplot of the total energy consumption versus the energy costs across the four clusters is shown in Fig. 3 below. With the highest mean values of energy consumption and costs, the cluster 2 broadly corresponds to the northeastern geographical region. Similarly, clusters 1 and 3 overlap with the mid-west and southern climate regions respectively. The western region overlaps with cluster 4 with minimum mean energy consumption and cost values.

We checked for the cluster quality using the silhouette measure of compactness[2] (elements within clusters close to each other) and distinction (cluster centers apart from each other) and found the value to be 0.72 (well over the cutoff value of 0.5), suggesting a good fit [65,66]. Based on the cluster results, we generated a categorical variable and used it in the multivariate linear regression analysis as a proxy to control for possible effects of the geographical locations and energy costs on the total residential energy consumed.

3.4. Variables

3.4.1. Dependent variable

To explore possible heterogeneity in the use of electricity versus other energy sources, we separately used the estimated total energy and electricity consumption values from the RECS data as outcome variables (estimated values from utility's data in Btu or kWh for regression analysis and their converted values on a logarithmic scale for the SEM analysis). For this study, we only considered stationary dwelling units comprising of single or multi-family units living in separate houses or in apartments and removed a small number of mobile households in the RECS data for our analysis. The summary statistics of the continuous variables used in our study is shown in Table 1 below. We note that for stationary dwellings, there is a wide variation in the annual energy (electricity) consumed across the households with a minimum of 372 (109), maximum of 490,187 (63,217), and a mean value of 78,716 (10,949) expressed in thousand Btu (kWh).

3.4.2. Independent variables

Following the classification of energy saving behaviors under two broad domains by Ref. [26]; we constructed the energy curtailment and efficiency behavior variables from the questions asked in RECS survey.

[2] Silhouette coefficient s = 1 – a/b for a < b; where a = average distance of any point i to all other points in its cluster and b = min (average distance of i to all points in another cluster) with values between 0 and 1.

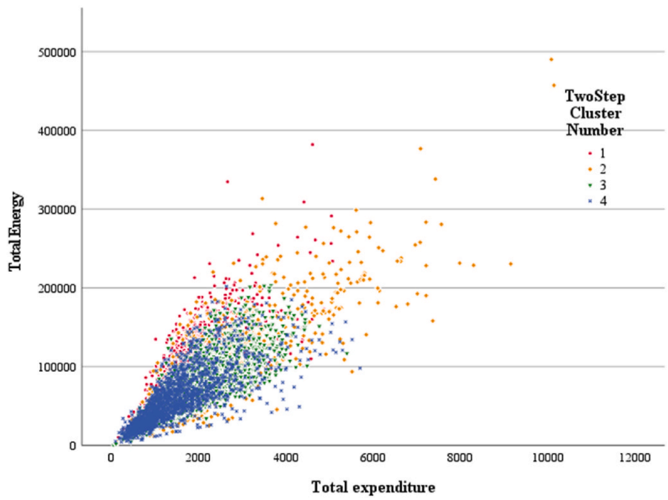

Fig. 3. Scatterplot of the total energy and expenditure across the clustered regions.

Table 1
Summary statistics of continuous variables.

Variable	N	Mean	Std. dev.	Min.	Max.
Total annual energy consumption (1000 Btu)	5400	78,716	47,582	372	490,187
Total annual electricity consumption (kWh)	5400	10,949	7057	109	63,217
Annual Household Income for Stationary homes ($)	5400	65,774	43,747	25,000 or below	150,000 or above
Floor area (square feet)	5400	2130	1294	221	8501
Numbers of household members	5400	2.57	1.42	1	11
Respondent's age	5400	52	17	18	85

Adapted from previous studies, the energy efficiency (EE) behavior was assessed in terms of ownership of *Energy star*[3] qualified appliances measured on a binary scale (no = 0 and yes = 1) [35,38,67]. Similarly, self-reported energy curtailment behaviors were measured on a binary scale (no = 0 and yes = 1) in response to questions on use of control for air-conditioning, central heating, cold water cycle for washing clothes or whether the respondents had seen the smart meter data [26,31,49,68]. To control for possible effects of the geographical locations and energy purchase costs on the total residential energy consumption across the households, we used the cluster regions as a proxy variable [2,49]. Based on our literature review and available data, we also controlled for the role of socio-economic and demographic profiles of the households such as annual household income [38,57,69], number of members in household, age and educational level of the respondent [2,39,70] as well as the physical factors - housing type, building vintage, adequate insulation, total square footage, and presence of heated swimming pool [2,40,49]. The descriptive statistics of the categorical variables used in the study are shown in Table 2 below.

4. Results

For our two-part empirical analysis to test the role of annual income, EE, and EC behaviors on the total energy and electricity consumption as the outcome variables, we relied on a mix of SEM and multivariate linear regression methods using Stata/MP 17.0 Mac (64-bit Intel) software. The path diagrams, regression results, and goodness of fit indices for the models used are shown and described in the sub sections below.

[3] *Energy star* labeled products meet strict energy efficiency criteria set by the US Environmental Protection Agency or the US Department of Energy and use less energy than the standard products.

Table 2
Descriptive statistics of categorical variables.

Variables	Code	Frequency
Cluster region 1 (Midwest)	1	1294
Cluster region 2 (Northeast)	2	821
Cluster region 3 (South)	3	1809
Cluster region 4 (West)	4	1476
Type of house		
Single-family detached house	1	3752
Single-family attached house	2	479
Apartment in a building with 2–4 units	3	311
Apartment in a building with 5 units or more	4	858
Year of construction		
Before 1950	1	855
1950 to 1959	2	537
1960 to 1969	3	548
1970 to 1979	4	860
1980 to 1989	5	811
1990 to 1999	6	718
2000 to 2009	7	857
2010 to 2015	8	214
Heated swimming pool		
No	0	5259
Yes	1	141
Adequate Insulation		
No	0	902
Yes	1	4498
Highest education level of respondent		
Less than high school diploma	1	341
High school diploma	2	1230
Some college or associate degree	3	1813
Bachelor's degree	4	1170
Master's/Professional/Doctorate degree	5	846
Own *Energy star* qualified dishwasher		
No	0	3732
Yes	1	1668
Own *Energy star* qualified refrigerator		
No	0	2852
Yes	1	2548
Own *Energy star* qualified window		
No	0	4019
Yes	1	1381
Own *Energy star* qualified cloth washer		
No	0	2582
Yes	1	2818
Use control for the central heating		
No	0	2375
Yes	1	3025
Use control for the central air conditioning		
No	0	3318
Yes	1	2082
Seen meter data		
No	0	5185
Yes	1	215
Use cold water for cloth washer		
No	0	2582
Yes	1	2818

4.1. SEM analysis

For the hypothesized SEMs 1 and 2, we estimated the path coefficients and significance of the physical, socio-economic, and behavioral factors underlying total energy and electricity consumption of the households respectively using the maximum likelihood iteration method. Figs. 4 and 5 below depict the path diagrams and estimated standardized coefficients for the variables used in the two models.

The SEM estimation results and the model fitness indices for the stationary households are reproduced in Table 3 below. Standardized path coefficients and standard errors for the models 1 and 2 using total

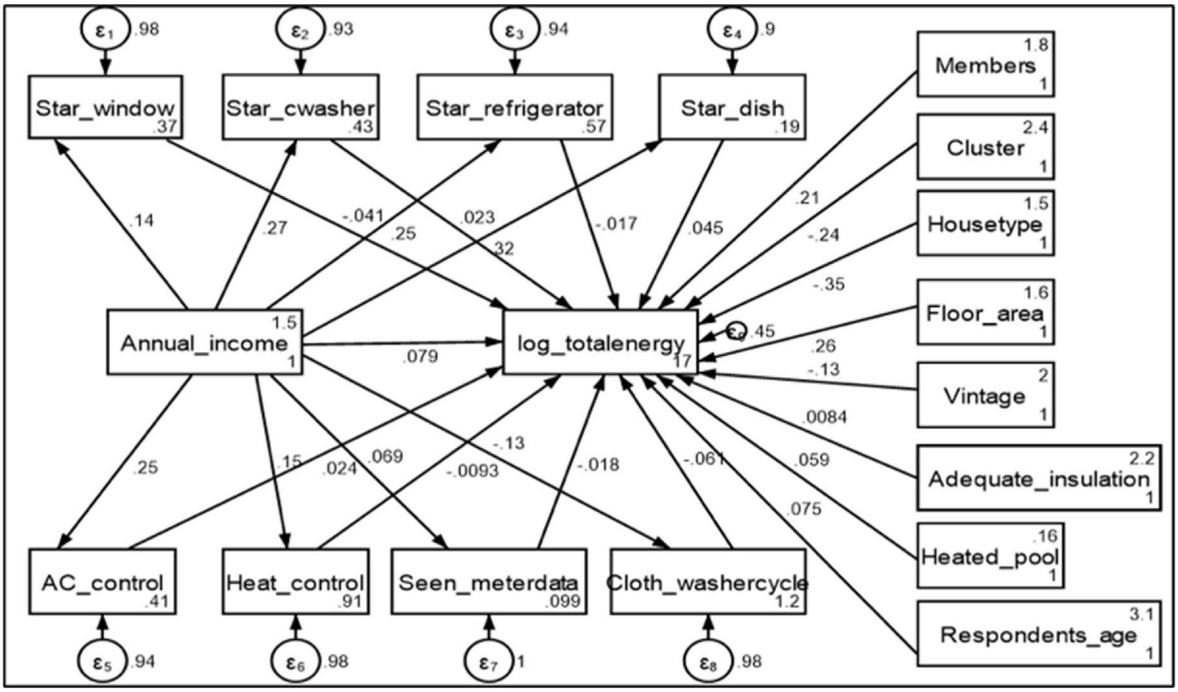

Fig. 4. Path diagram and results of SEM analysis for the total energy consumption on logarithmic scale **(Model 1)**.

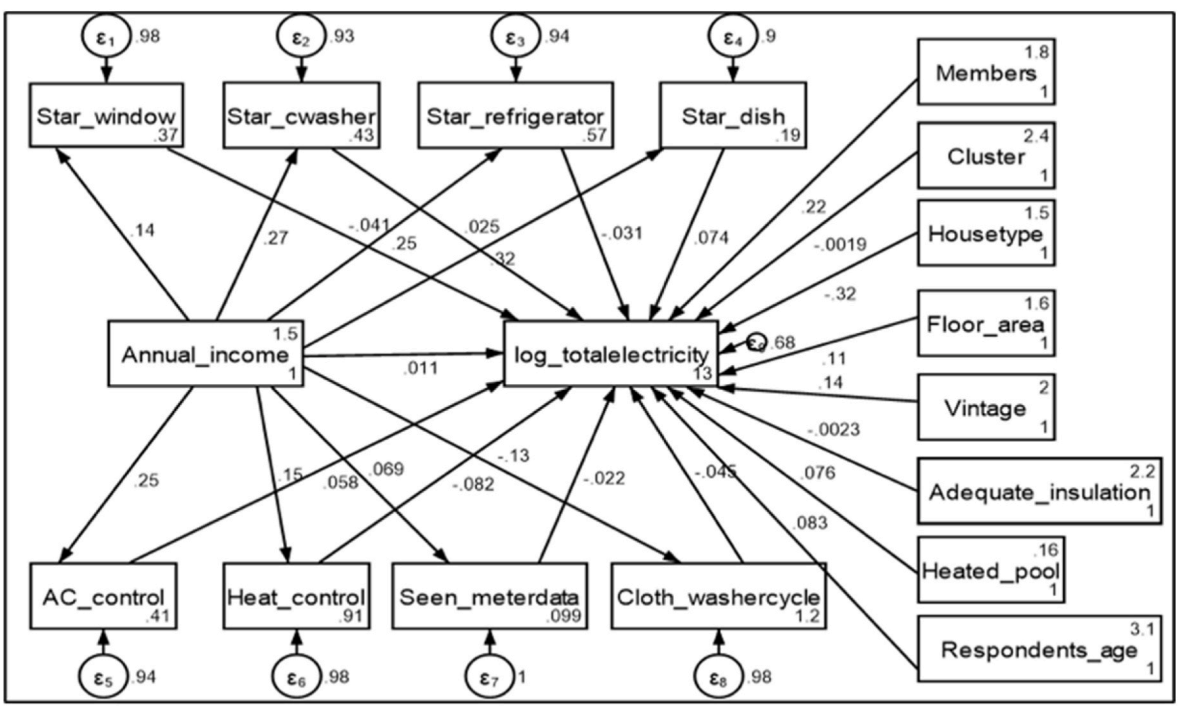

Fig. 5. Path diagram and results of SEM analysis for the total electricity consumption on logarithmic scale **(Model 2)**.

energy and electricity consumption on a logarithmic scale are shown in the second and third columns of the table respectively. The estimated path coefficients were considered significant if the p value was found to be less than 0.05.

The estimated results suggest that annual household income significantly and positively affects the EE behaviors as reflected in the adoption of *Energy star* qualified appliances, namely, windows, refrigerators, cloth washers, and dishwashers. Similarly, annual household income also significantly and positively affects the EC behaviors as reflected in the use of controls for the central air conditioning and heating appliances. Further, residents with higher incomes are less likely to use cold water to wash clothes in comparison to the lower income households as an example of the curtailment behavior. However, the results also highlight a few important differences between the total energy and electricity consumption estimates. For example, the use of control action for central heating is significant only for the electricity consumption and not for the total energy consumed. Further, the total energy and electricity consumption values appear to be oppositely related to the house

Table 3
Standardized path coefficients and standard errors from the SEM analysis.

Path	Model 1 (Energy)	Model 2 (Electricity)
	Standardized coefficients/ standard error	Standardized coefficients/ standard error
Energy star qualified window→ Natural log of total energy/ electricity	−0.041*** (0.015)	−0.041*** (0.02)
Energy star qualified cloth washer→ Natural log of total energy/ electricity	0.022* (0.015)	0.025 (0.02)
Energy star qualified refrigerator→ Natural log of total energy/ electricity	−0.017 (0.015)	−0.031* (0.02)
Energy star qualified dishwasher→ Natural log of total energy/ electricity	0.045*** (0.02)	0.073*** (0.02)
Use control for the central air conditioning→ Natural log of total energy/electricity	0.0240* (0.007)	0.058*** (0.01)
Use control for the central heating→ Natural log of total energy/electricity	−0.01(0.007)	−0.08*** (0.01)
Seen meter data→ Natural log of total energy/electricity	−0.017 (0.031)	−0.021 (0.04)
Use cold water for Clothwasher → Natural log of total energy/ electricity	−0.061*** (0.012)	−0.045*** (0.02)
Annual Household Income for Stationary homes→ Natural log of total energy/electricity	0.079*** (0.00)	0.011 (0.00)
Cluster Variable→ Natural log of total energy/electricity	−0.24*** (0.005)	−0.002 (0.01)
House type→ Natural log of total energy/electricity	−0.34*** (0.007)	−0.314*** (0.01)
Total square footage→ Natural log of total energy/electricity	0.26*** (0.00)	0.11*** (0.00)
Year of construction→ Natural log of total energy/electricity	−0.13*** (0.003)	0.14*** (0.00)
Adequate Insulation→ Natural log of total energy/electricity	0.008 (0.017)	−0.002 (0.02)
Heated swimming pool→ Natural log of total energy/electricity	0.058*** (0.038)	0.075*** (0.05)
Respondent's age→ Natural log of total energy/electricity	0.074*** (0.00)	0.082*** (0.00)
Numbers of household members→ Natural log of total energy/ electricity	0.206*** (0.005)	0.221*** (0.01)
Annual Household Income for Stationary homes→ *Energy star* qualified window	0.14*** (0.00)	0.14*** (0.00)
Annual Household Income for Stationary homes→ *Energy star* qualified Cloth washer	0.271*** (0.00)	0.271*** (0.00)
Annual Household Income for Stationary homes→ *Energy star* qualified refrigerator	0.251*** (0.00)	0.251*** (0.00)
Annual Household Income for Stationary homes→ *Energy star* qualified dishwasher	0.319*** (0.00)	0.320*** (0.00)
Annual Household Income for Stationary homes→ Use control for the central air-conditioning	0.252*** (0.00)	0.252*** (0.00)
Annual Household Income for Stationary homes→ Use control for the central heating	0.146*** (0.00)	0.146*** (0.00)
Annual Household Income for Stationary homes→ Seen meter data	0.069*** (0.00)	0.069*** (0.00)
Annual Household Income for Stationary homes→ Use cold water for Dishwasher	−0.128*** (0.00)	−0.128*** (0.00)
Model fitness		
Description (fit statistic)		
Likelihood ratio		
Model vs. saturated chi2_ms(92)	6569.04	6569.04
p > chi2	0.000	0.000
Baseline vs. saturated chi2_bs(117)	13010.62	10771.65
p > chi2	0.000	0.000
Population error		
Root mean squared error of approximation (RMSEA)	0.11	0.11
Probability RMSEA ≤ 0.05	0.00	0.00
Size of residuals		
Standardized root mean squared residual SRMR	0.093	0.093
Coefficient of determination CD	0.661	0.49

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Standard errors in parentheses.

vintage. Whereas the earlier house constructions have lesser overall energy consumption, their electricity use appears to be higher in comparison to the recently constructed houses.

Both models were tested for their overall fitness with a baseline versus saturated likelihood ratio chi square fitness measure and the p values were found to be less than 0.01. The coefficient of determination values for the two models were found to be 0.66 and 0.49 respectively. However, the root mean squared error of approximation (RMSEA) and the standardized root mean squared residual (SRMR) metrics were found to be marginally acceptable with values 0.11 and 0.093 respectively [71,72]. We followed up and compared the SEM results with multivariate linear regression analysis discussed in the next sub-section.

4.2. *Multivariate linear regression*

Building upon our SEM analysis, we used multivariate linear regression to test the overall role and extent of annual income, EE, and EC behaviors on the total energy/electricity consumption as the outcome variables while controlling for the structural, geographic, and demographic factors. The standardized coefficients and standard errors from the regression results for the models 3 and 4 are shown in the second and third columns of Table 4 below. With an overall F statistic of 240.03 and 140.47 (p values less than 0.0001) for the models 3 and 4, the R squared values were found to explain significant variation in the outcome variable with values 0.54 and 0.36 respectively.

From the regression results, we observe that most of the physical, demographic, and socio-economic factors significantly affect the outcome variables along the expected lines. Cluster region 2 (northeast) has a significantly higher energy consumption with respect to the base region 1 (mid-west). Further, cluster regions 3 (south) and 4 (west) have a significantly lower energy and electricity consumptions with respect to the base (mid-west) region. The estimated coefficients for the respondent's age, number of household members, square footage, and presence of heated swimming pools are all positive and significant across the two models. However, the overall impact of having adequate insulation in the house was not found to be significant. In line with the SEM results, the older house constructions appear to have relatively higher electricity consumption, but their overall energy consumption is lower in comparison to the recently constructed houses. Further, the attached apartment type multi-family dwellings have lower energy and electricity consumptions in comparison to the detached single-family houses. The annual household income has a significant and positive impact on the total energy consumption across the models.

However, the direction and impact of the EE and EC behaviors on the total energy and electricity consumption showed mixed results with respect to our initial hypotheses. Whereas ownership of *Energy star* qualified refrigerators and windows were found to be significant predictors of reduced electricity and energy consumption respectively, the

Table 4
Multivariate linear regression results.

Variables	Model 3	Model 4
	Annual energy consumption (1000 Btu)	Annual electricity consumption (kWh)
Cluster Variable = 1(Base Midwest)	0	0
Cluster Variable = 2 (Northeast)	0.066***(1469.15)	0.021(256.77)
Cluster Variable = 3 (South)	−0.22***(1211.75)	0.27***(211.78)
Cluster Variable = 4 (West)	−0.26***(1274.12)	−0.05***(222.68)
Numbers of household members	0.19***(363.59)	0.23***(63.54)
Respondent's age	0.068***(30.03)	0.07***(5.25)
Heated swimming pool	0.098***(2807.86)	0.11***(490.74)
Adequate Insulation	−0.008(1230.75)	0.008(215.10)
Total square footage	0.34***(.45)	0.18***(.078)
Highest educational level of respondent	−0.002(452.81)	−0.022(79.14)
Year of construction	−0.10***(228.38)	0.07***(39.91)
House type	−0.22***(500.13)	−0.16***(87.40)
Annual Household Income for Stationary homes	0.09***(.0130)	0.07***(.002)
Energy star qualified dishwasher	0.05***(1202.66)	0.08***(210.19)
Energy star qualified lightbulbs	−0.00049(1036.44)	−0.024(181.14)
Energy star qualified refrigerator	−0.021(1107.05)	−0.032*(193.48)
Energy star qualified cloth washer	0.013(1104.37)	0.024(193.01)
Energy star qualified window	−0.058***(1129.51)	−0.008(197.41)
Use cold water for Cloth washer	−0.06***(922.07)	−0.04***(161.15)
Seen meter data	−0.017(2269.30)	−0.014(396.61)
Use control for the central heating	−0.026*(515.81)	−0.062***(90.15)
Use control for the central air conditioning	0.024*(553.84)	0.0153(96.79)
Made changes suggested by home energy auditor	−0.006(1796.89)	−0.007(314.05)
Constant	—— (3,295.20)	—— (575.90)
Observations	5400	5400
R-squared	0.54	0.36

*p < 0.05, **p < 0.01, ***p < 0.001; Standard errors in parentheses.

presence of *Energy star* qualified dishwashers suggests an overall increase in the energy and electricity consumption. Interestingly, the mere fact of respondents having seen the smart meter data or having acted on the recommendations of home energy audit did suggest lesser energy consumption, but the overall impact was not found to be significant. In terms of the EC behaviors, respondents who controlled their central heating plants were found to consume less energy in comparison to those who did not use any control. However, use of controls for the central air-conditioning plants suggested an overall increase in the total energy consumption. In line with the SEM results, the EC behavior regarding use of cold water for the clothes washer cycle had a significantly negative relationship with the energy and electricity consumed.

5. Discussion

A better understanding of residential energy conservation behaviors is necessary to inform tailored, targeted, and effective energy conservation policies. Traditionally, such policies have been dominated by arguments based on the techno-economic conception of energy systems overlooking their social-behavioral dimensions [73–75]. Recently, the role and importance of human behaviors as part of an intervention strategy has attracted the attention of scholars and policymakers due to their potential cost-effectiveness, and acceptability in comparison to price-based solutions [68,76]. Utilities and regulators in US are encouraging behavioral EE programs that include information dissemination, social interactions, and training to reduce energy use. However, reported energy savings from such interventions vary across programs, target audience, and evaluation methods [77]. While individual behaviors are considered important in limiting energy consumption, few scholars have also noted the limitations of behavioral interventions for being reductive, individualistic, and inadequate in capturing energy system dynamics [25,78]. From a long-term sustainable energy policy perspective, it is not only important to choose cost-effective and energy efficient solutions but also make sure that the costs and burdens of the interventions and outcomes are shared equitably. In the past, it has been observed that routine application of energy efficiency policies can sometimes lead to inequitable outcomes [18], widespread protests [79], and in some cases higher per capita carbon emissions in wealthier households, known as "emission paradox" [8]. As such, it is not only important to understand the role of income on the EE and EC behaviors but also useful to consider how they influence overall energy consumption and carbon emissions.

In this study, we conducted empirical analysis to test the role of annual income, self-reported EE, and EC behaviors on the total energy and electricity consumption of US households relying on multiple analytical approaches. However, there are important conceptual and methodological limitations to our study that need to be mentioned. First, our study is based on observed cross-sectional data that suggests correlation instead of cause-effect relationships. Second, we studied the residential energy behaviors primarily from the socio-economic perspectives, largely ignoring the influence of structural and contextual practices that are not captured in the independent variables used [25,50,69,80]. Third, we overlooked the heterogeneity and dynamics of energy behaviors within the members of the residential households [81]. Additionally, our study relies on self-reported EC and EE behaviors in assessing residential energy consumption as against actual measured values. Finally, our study relies on nationally representative annual data from the year 2015 that might not reflect the latest energy consumption pattern and our findings will need to be revisited as new data becomes available.

Despite the above caveats, we find consistent and significant results across the SEM and the multivariate regression models for our hypotheses on the nature and direction of the relationships between the variables used. In line with the previous literature [39,57], the overall results suggest a significant and positive relationship between the annual household income and the EE behaviors supporting hypothesis H2. Further, annual household income is also found to be a significant contributor to the total energy/electricity consumption along expected lines [38,40], supporting hypothesis H3. However, the results are mixed with respect to our hypothesis on the role of annual income on EC behaviors (H1). Whereas the use of cold water for the cloth washing cycle appears to be negatively related to income, the other examples of curtailment behaviors – using control for air-conditioning, heating, or seeing the smart meter data – appear to be positively related to it. It follows that the role of income in influencing EC behaviors may not be consistent across behaviors in partial deviation from the results from an earlier study by Ref. [39] in EU context.

An interesting outcome of our study is regarding the role of the *Energy star* qualified appliances in the overall residential energy consumption levels. Whereas the results for the EE behaviors in terms of the availability of *Energy star* qualified refrigerators and windows were found to be significant in reducing total electricity and energy consumptions along expected lines, the contribution of *Energy star* qualified dishwasher was found to increase the energy consumption contrary to our hypothesis H5. Whereas there may not be two opinions about the technical efficiency of the *Energy star* qualified appliances and their potential in reducing the energy output with respect to a hypothetical counterfactual, our study suggests that overall savings from such appliances vary and differently impact overall residential energy consumption. Possible reasons for this outcome could be due to the mediation and crowding out of the savings by other physical, socio-economic factors or due to rebound effects or negative spillovers behaviors that will need to be studied further [23,82,83]. Further, the results of our analysis were mixed with respect to the role and direction of the specific EC behaviors on the total energy consumption (H4). Use of control for the central heating plants as an example of curtailment behavior was found to be negatively related to the total energy and electricity consumption in line with the expected hypothesis H4. However, the air-conditioning control behavior was not found to be significant for the electricity consumption and was rather positively related to the total energy consumption. Across the models, use of cold water for cloth washer cycle as an example of EC behavior showed a significantly negative relationship with the energy and electricity consumed supporting hypothesis H4.

By treating the total electricity and energy consumption separately as outcome variables across the models, we were also able to highlight important differences in the roles of the structural and behavioral factors. Whereas most of the geographical, physical, and socio-economic factors were found to be significant and consistent in their impact on the outcome variables along the expected lines, the building vintage was found to impact the electricity and energy consumption differently. Whereas the older house constructions had relatively higher electricity consumption, their overall energy consumption was found to be lower in comparison to the recently constructed houses. Although our study differs in terms of geographical scale, vintage classification, and in terms of energy/electricity differentiation, the results are broadly in line with previous study by Ref. [84], who found that older vintage houses in California used lesser electricity during summer. Overall, our results suggest absence of any monocausal relationships with uniform and consistent pattern that can be generalized over different EE and EC behaviors, types of energy sources across the different geographical regions.

6. Conclusion and policy implications

Given the important role and significant potential of residential energy conservation actions in reducing energy consumption and limiting carbon emissions, most nations and governments are relying on energy efficiency policies as a part of their sustainable development objectives. United Nation's 2030 agenda includes doubling the rate of improvement in energy efficiency (SDG 7.3) and enhancing international cooperation in energy efficiency technology and investment (SDG 7. a) as a part of the sustainable development goals [85,86]. Residential energy efficiency programs based on fiscal incentives, building standards, and codes have a long history in the US with significant budgetary allocations at federal and state levels. Recently, US DOE announced several energy efficiency incentives and programs especially for the low and vulnerable populations to balance the social, economic, and environmental aspects of sustainable development. In this context, it is not only important to identify factors underlying adoption of energy efficient appliances and home retrofits but also understand how the overall residential energy conservation behaviors are mediated by their socio-economic profiles, physical factors, and types of energy resources. Despite the growing realization of the importance of behavioral factors in explaining residential energy consumption, empirical evidence on their extent and direction remains limited, contested, and mixed [3,87]. From a policy perspective, comprehensive evaluation of the EE and EC behaviors in the residential context also gets limited due to their explanations from multiple theoretical perspectives, assumptions of monocausal relationships, and reliance on indirect methods that are not tested empirically on a large scale. For tailored and effective energy policies, it is not only important to understand the relative contribution of EE and EC behaviors in reducing total residential energy consumption but also to know how these behaviors are mediated by the external, socio-economic, and demographic profiles [2,39,41]. Our study not only provides novel empirical evidence on self-reported energy efficiency and curtailment behaviors in explaining the estimated energy/electricity consumption but also builds upon the existing literature by analyzing the role of household income on different EE and EC behaviors in the US context. Additionally, by separately analyzing the role of physical, socio-economic, and behavioral factors underlying the energy and electricity consumption, this study reveals important insights about the heterogeneity in residential energy consumption that are often lumped together. Given their significant roles, it will be important to promote both EE and EC behaviors in the context of residential energy conservation policies while taking into consideration different energy sources.

Whereas the EE behaviors appear to be positively correlated with the household income, the direction of relationship between the income and EC behaviors appears to vary depending upon specific EC actions, suggesting heterogeneity across the households and specific behaviors. Instead of a static and consistent relationship between the EE behaviors and energy consumption, our study finds a mixed and dynamic pattern across different EE actions that are also tied to the type of energy sources used. In particular, the overall energy savings from the EE appliances in the households appear to get restricted and sometimes reversed by other socio-economic and behavioral factors. It also suggests a disconnect between some EE actions and final outcomes in terms of the total energy consumption other than the behavior-action gap [88,89] that needs to be analyzed further. Due to the differentiated role of income in the adoption of EE and EC behaviors, routine application of policy instruments, such as, tax rebates or financial incentives tied to the purchase of energy efficient appliances might have unintended consequences. From the considerations of fair and equitable distribution of economic resources across a diverse population, policies to facilitate adoption of energy efficient behaviors will have to be carefully designed to target the intended beneficiaries. Our study also suggests that promotion of energy efficient appliances for the households alone may not be enough to meet the long-term reduction of carbon emission in line with national targets and international commitments. It becomes apparent that the heterogeneities across behaviors, fuel sources, and socio-economic profiles need to be reconciled based on a mix of policy instruments that complement different energy conservation behaviors. In the residential household context, policies promoting EE appliances will need to be supplemented by a wide range of energy curtailment actions built around the idea of overall resource conservation that are economically viable, equitable, and effective for different sections of the society.

In all, we find that in comparison to a consistent and significant role of the structural factors in the residential energy consumption, the nature and direction of the behavioral factors are mixed and vary with specific behaviors. Whereas there may not be a general theory of residential energy savings in terms of a singular, monolithic, and unidirectional relationship, more empirical studies on complexity and the heterogeneity of the households' behaviors will help in evidence-based policy making.

Credit author statement

All authors contributed equally to the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data used in this study is available online.

Appendix

Table A1
Schwarz's Bayesian Criterion (BIC) for Clustering

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change[a]	Ratio of BIC Changes[b]	Ratio of Distance Measures[c]
1	23142.550			
2	15556.601	−7585.949	1.000	1.567
3	10738.697	−4817.904	0.635	1.506
4	7559.190	−3179.507	0.419	3.091
5	6571.350	−987.839	0.130	1.227
6	5777.721	−793.630	0.105	1.043
7	5019.165	−758.556	0.100	1.065
8	4310.476	−708.689	0.093	1.807
9	3945.422	−365.054	0.048	1.287
10	3675.339	−270.083	0.036	1.354
11	3491.647	−183.692	0.024	1.178
12	3344.826	−146.821	0.019	1.111
13	3218.665	−126.161	0.017	1.244
14	3129.145	−89.520	0.012	1.115
15	3055.094	−74.052	0.010	1.049

Note.
[a] The changes are from the previous number of clusters in the table.
[b] The ratios of changes are relative to the changes for the two clusters solution.
[c] The ratios of distance measures are based on the current number of clusters against the previous number of clusters.

Table A2
Frequency distribution of entities across clusters

Cluster Distribution				
N			% of Combined	% of Total
Cluster	1	1327	23.30%	23.30%
	2	840	14.80%	14.80%
	3	1969	34.60%	34.60%
	4	1550	27.30%	27.30%
	Combined	5686	100.00%	100.00%
Total		5686		100.00%

Table A3
Mean and standard deviation of variables across the clusters

Centroids					
		TOTALBTU		TOTALDOL	
		Mean	Std. Deviation	Mean	Std. Deviation
Cluster	1	94244.45771	49104.54295	1780.9135	794.64685
	2	104711.6463	63598.56274	2571.8714	1470.73879
	3	68045.61093	35166.67613	1915.1109	803.47034
	4	61245.40508	35334.95708	1553.8779	877.88074
	Combined	77722.89202	46962.30968	1882.3440	1001.20920

Table A4
Distribution of Clusters across geographic regions

REGIONC									
		1		2		3		4	
		Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Cluster	1	0	0.0%	1327	100.00%	0	0.0%	0	0.00%
	2	794	100.00%	0	0.0%	41	2.0%	5	0.30%
	3	0	0.0%	0	0.00%	1969	98.0%	0	0.0%
	4	0	0.00%	0	0.0%	0	0.0%	1550	99.70%
	Combined	794	100.00%	1327	100.00%	2010	100.00%	1555	100.00%

Model Summary

Algorithm	TwoStep
Inputs	3
Clusters	4

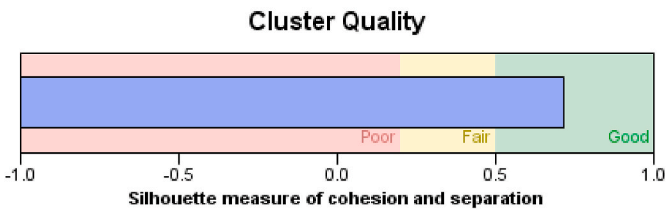

Fig. A1. Cluster summary and quality

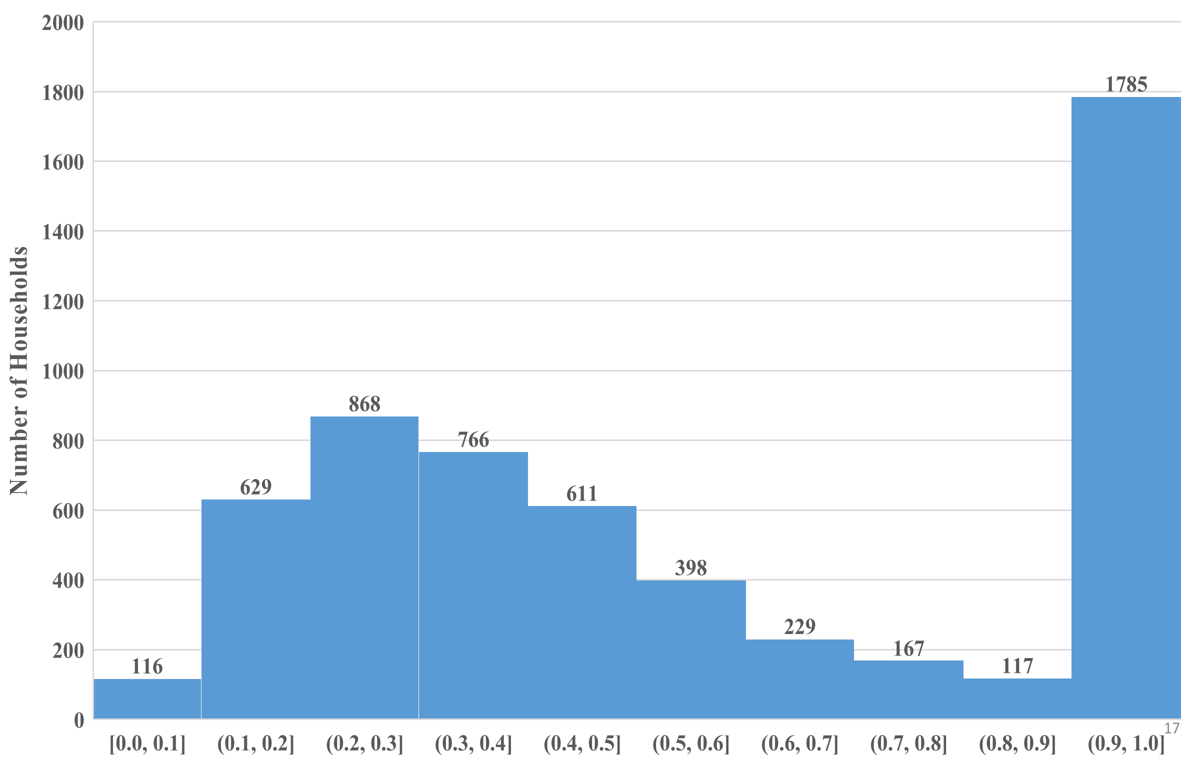

Fig. A2. Distribution of the number of households over the total electricity to energy consumption ratio (Source [43]:

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