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Modeling the residential electricity demand in the US

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Abstract

In this paper, we estimate a demand model for electricity in the US residential sector using both the 2009 and 2015 (RECS). We find socio-economic characteristics and building patterns of households as the main drivers of residential electricity demand in the US. Also, controlling for regional and climatic effects is found to enhance the performance of the estimated models. Our results are further complemented with plausible scenario analyses and robustness checks.

Key words: Electricity consumption, US residential sector, Demand analysis

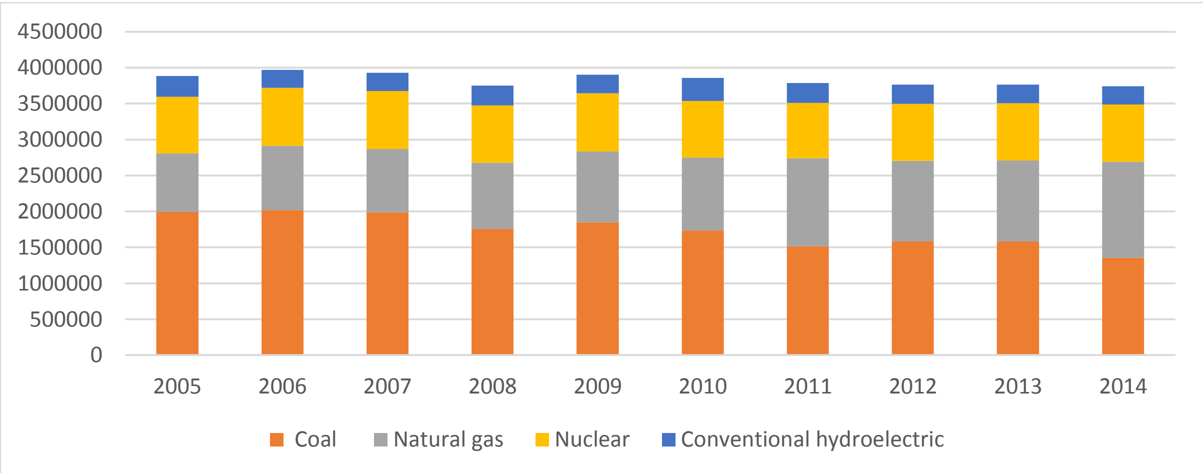
Modeling the residential electricity demand in the US

1.0 Introduction

The debate on how best to use energy will continue to attract the attention of policy makers, investors and researchers as long as energy remains a key input to everyday activities both at the micro [households and firms] and macro [industrial and public sector] levels. The US Energy Information Administration (US EIA) recently projects that world energy consumption will grow by 56% between 2010 and 2040, from 524 quadrillion British thermal units (Btu) to 820 quadrillion Btu.[1]

In this paper, we focus essentially on US electric energy - a secondary source of energy - obtained from primary energy sources including fossil energy (66%) [mainly coal (38%), natural gas (27%) and oil (1%)], renewable sources (13%) [with geothermal (0.4%), hydropower (6%), solar (0.6%), wind (4%), wood (1%) and other Bio (1%)], nuclear (19%) and others (2%)[2]. More noticeably, US electric energy has continued to rely on fossil fuel contributing about two-third of the energy required to generate electricity yearly with coal taking the lion share consistently (see Fig. 1).

Figure 1: Electricity generation from major sources[3]

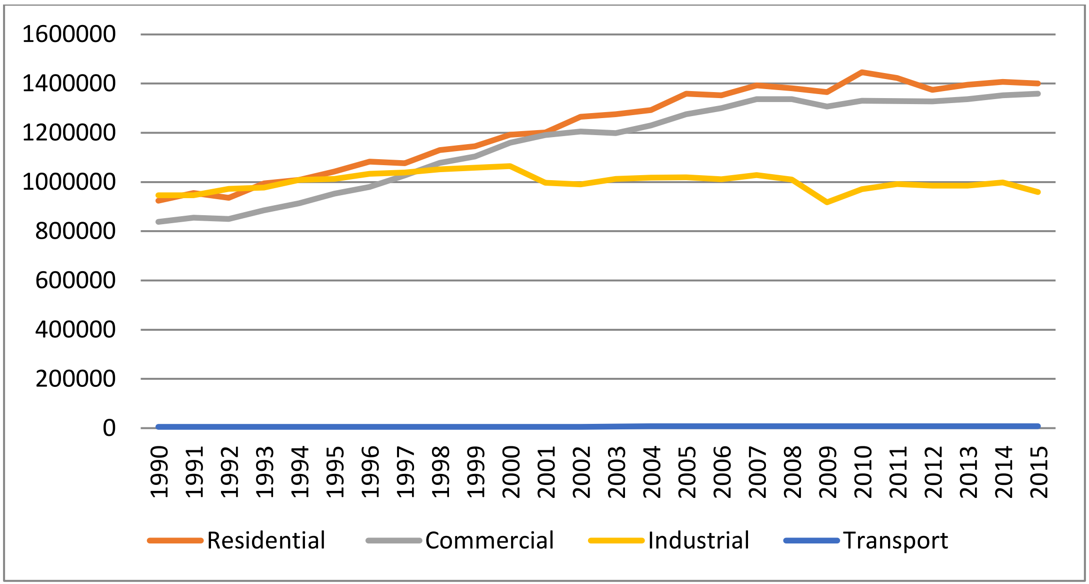


Source: US EIA, 2015.

[1] See the 2013 International Energy Outlook.
[2] Others include miscellaneous generation, pumped storage, and net imports. The statistics reported here are for the year 2014 obtained from US EIA, Electricity Net Generation, March 2015. The statistics in parentheses represent the amount of electric energy obtained from the primary energy sources.
[3] Data used for charts, graphs and descriptive statistics in this paper were obtained from the US EIA website.

In general, electricity obtained from these primary sources is delivered to the different sectors of the economy namely residential (33.93%), commercial (32.61%), and industrial [including transportation] (24.25%).[4] However, our interest lies in electricity consumption at the residential sector which has relatively remained dominant in the consumption of electricity in the US in recent years (see Figure 2). The sector overtook the industrial sector (as leading electricity consuming sector) in 1992 and has consistently maintained the lead up till the time of this review (2015).

Fig. 2: Electricity Consumption in the US by Sector



Source: US EIA, 2015.

The interest in this sector is motivated by the availability of robust database for energy consumption at the household level for US.[5] It appears to be the richest and consistently maintained survey globally wherein every segment of the country is captured in the survey. In addition, the survey provides all the relevant energy characteristics of the households including the housing unit, usage patterns, and household demographics thus making it convenient to subject US households' energy use to empirical scrutiny. Also, the survey is complemented with data from

[4] The statistics in parentheses denote the proportion of electricity consumed by each sector from the total for the year 2014. The statistics were obtained from US Department of Energy through the US EIA.

[5] The database is described as the Residential Energy Consumption Survey (RECS) and it is administered by US EIA.

energy suppliers to these homes to estimate energy costs and usage for heating, cooling, appliances and other end uses— information critical to meeting future energy demand, improving efficiency and building design.

In this paper, we consider both the 2009 (thirteenth) and 2015 (fourteenth) RECS data. However, for the purpose of empirical analyses, the former is employed since the micro-data required for such analyses are not readily accessible this time for the 2015 RECS survey. Nonetheless, both surveys are used to render some useful stylized facts about the behaviour of US households in relation to electricity consumption. We hope that as the 2015 dataset becomes available, future studies can reexamine the plausibility and robustness of the regression estimates obtained from the 2009 survey.

In the literature, the use of electricity related data for quantitative analyses is not new [see Suganthi & Samuel, 2012; Romero-Jordan et al., 2014 for a survey of the literature]. However, the use of micro-level data to analyze the demand for electricity both in the developed [including US] and developing countries is scarce in the literature. For instance, Lutzenhiser et al. (1987) note that while we know a good deal about aggregate, societal level consumption, the consumption of individual households is quite variable, even when controlling for weather, system efficiencies, family size, and so on. In addition, despite the sophistication of US energy supply, the demand-side of the system remains a poorly-understood sink into which utilities and governments are required to deliver ever increasing amounts of energy (Lutzenhiser, 1992). This is the motivation for this research. Thus, the study is intended to contribute to the scarce literature on household level analyses of electricity demand as well as complement the extant literature on the macroeconomic perspective. In order to ensure the prediction accuracy and stability of the model, the study employs the least angle regression (lars) approach which produces interpretable models and also exhibits stability.

The remainder of the paper is organized as follows. Section 2 renders some stylized facts about US residential energy demand using 2009 and 2015 RECS data. Section 3 deals with the methodological framework of the study while section 4 discusses empirical results with scenario analyses and policy implications. Section 5 concludes the paper.

2.0 The 2009 and 2015 RECS: A comparison

In this section, we capture certain peculiarities in the U.S residential energy sector by considering data obtained from the 2009 and 2015 RECS. Specifically, we carry out a comparison between both surveys to identify changes in residential energy demand between both periods. However, it should be noted that our analysis is limited to discussions on housing characteristics alone as data on consumption & expenditure and micro data for the 2015 RECS are not available at the time of this study.

First, we examine the structural and geographical characteristics of houses across regions in both surveys. The 2015 RECS presents data on 118.2 million housing units as compared with 113.6 million housing units presented in the 2009 survey. Of the 118.2 million housing units surveyed in 2015 RECS, 95.1 million housing units representing about 80% of total primary occupied housing units in U.S are situated in urban regions while the remaining 23.1 million housing units representing approximately 20% are resident in rural settlements. This is a slight change from 78% and 22% for houses situated in the urban and rural areas respectively recorded in the 2009 RECS.

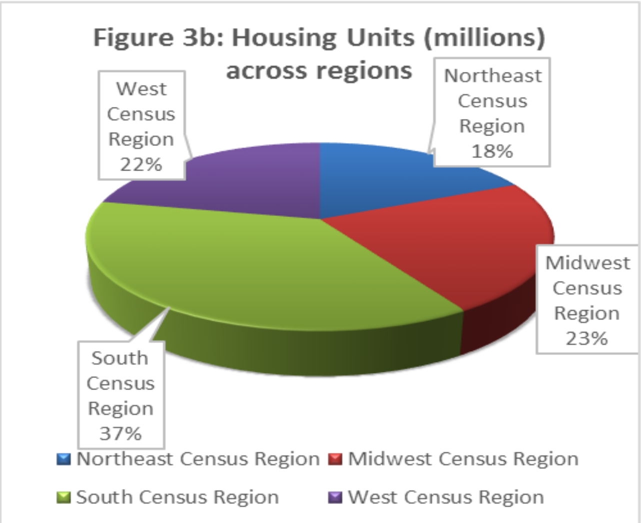
Furthermore, we discover some similarities in both surveys as we notice that a larger concentration of houses in the U.S is domiciled in the South Census Region. In the 2009 survey, 37% of total primary occupied housing units in the U.S are domicile in the South Census region whereas this increases to 38% of total primary occupied housing units in 2015. In the 2015 RECS, the Midwest, West and Northeast regions account for 22%, 22% and 18% of total primary occupied housing units in the U.S respectively which is slight change form 23%, 22% and 18% recorded for the three regions respectively in the 2009 survey (see figure 3b and 4b). In addition, both surveys suggests that single-family detached houses account for over 60% of total primary occupied housing units in the U.S and remains dominant across regions (see figure 3c and 4c).

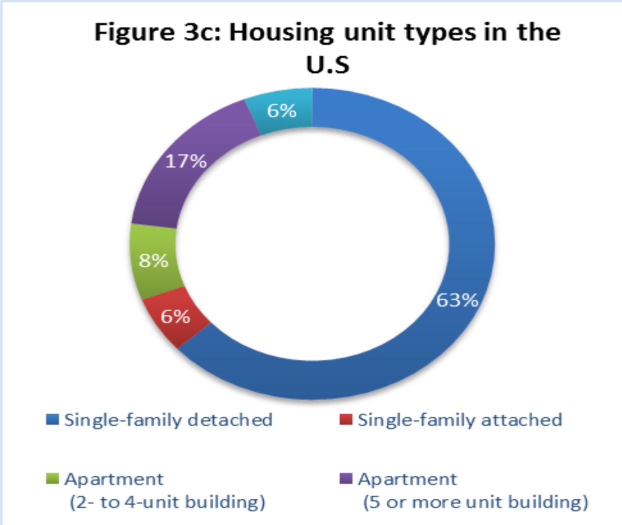
Figures 3d and 4d present a description of electricity end usage across regions as recorded in the 2009 and 2015 RECS respectively. From the latter, the South Census region accounts for most houses in the U.S, most houses in this region use electricity for air conditioning while the least use of electricity are for space and water heating, this is also applicable across regions. However, evidence suggest that household electricity use for other purposes supersedes all other electricity end usage across regions in the 2009 RECS (see figure 3d). According to the 2009 RECS, about 113.6 million houses use electricity for other purposes, 94 million houses use electricity for air conditioning, 71.1 million houses use electricity for cooking, while 57.9 and 47 million houses make use of electricity for space and water heating respectively. On the other hand, 2015 RECS suggests about 103.1 million houses use electricity for air conditioning, 74.4 million housing units use electricity for cooking, while 58.8 and 54.1 million houses make use of electricity for space and water heating respectively. Overall, it is expected that the South region consumes most electricity while the Northeast region consumes the least (see figure 4d).

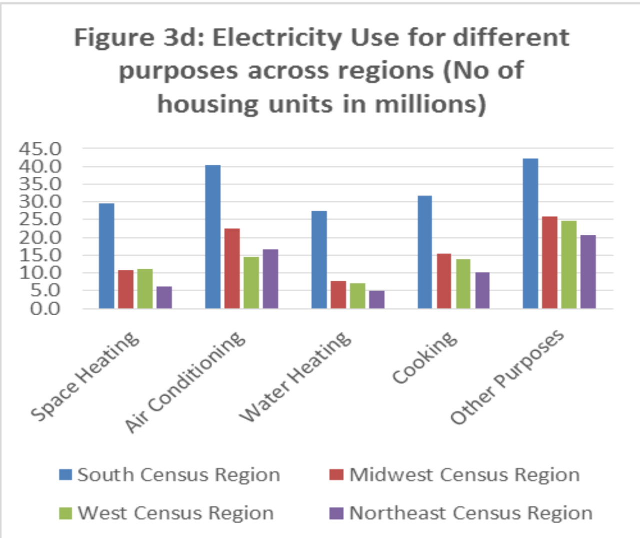
In terms of main heating fuel and equipment (see figure 3e and 4e), evidence from 2015 RECS suggests that use of natural gas is predominant as it serves as main heating fuel 48% of U.S. households while about 36% of U.S. households make use of electricity as the main energy source for heating. Fuel oil, propane and wood also serve as main heating fuel for 5%, 5% and 2% of primary housing units in the U.S while about 4% do not make use of any heating equipment. This is slightly different from information obtained from the 2009 RECS, as 48% of households made use of natural gas as their main heating fuel while fuel oil and kerosene served as main heating fuel for 7% of households (see figure 3e).

Figure 3a: Structural and geographic characteristics by housing type (2009)

	Number of housing units (million)					
	Housing type					
	Total U.S.	**Single-family detached**	**Single-family attached**	**Apartment (2-4 unit building)**	**Apartment (5 or more unit building)**	**Mobile home**
All homes	113.6	71.8	6.7	9.0	19.1	6.9
Census region						
Northeast	20.8	10.9	1.8	3.1	4.4	0.5
Midwest	25.9	18.0	1.2	1.9	3.7	1.1
South	42.1	27.6	2.1	2.2	6.2	3.9
West	24.8	15.4	1.5	1.7	4.7	1.4
Urban/rural classification						
Urban	88.1	51.3	6.3	8.5	18.5	3.5
Rural	25.5	20.5	0.4	0.5	0.7	3.5







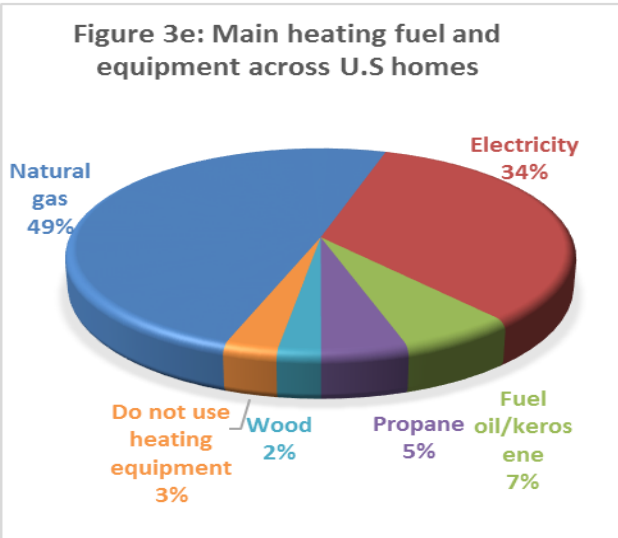


Figure 4a: Structural and geographic characteristics of U.S. homes by housing type (2015)

	Number of housing units (million)					
	Housing type					
	Total U.S.	Single-family detached	Single-family attached	Apartment (2- to 4-unit building)	Apartment (5 or more unit building)	Mobile home
All homes	118.2	73.9	7.0	9.4	21.1	6.8
Census region						
Northeast	21.0	10.8	1.9	3.2	4.7	0.5
Midwest	26.4	18.2	1.3	2.0	4.0	1.0
South	44.4	28.7	2.3	2.4	7.2	3.9
West	26.4	16.2	1.6	1.9	5.3	1.4
Urban/rural classification						
Urban	95.1	55.7	6.7	8.8	20.9	3.0
Rural	23.1	18.2	0.3	0.6	0.2	3.8

Figure 4b: Housing Units (millions) across regions

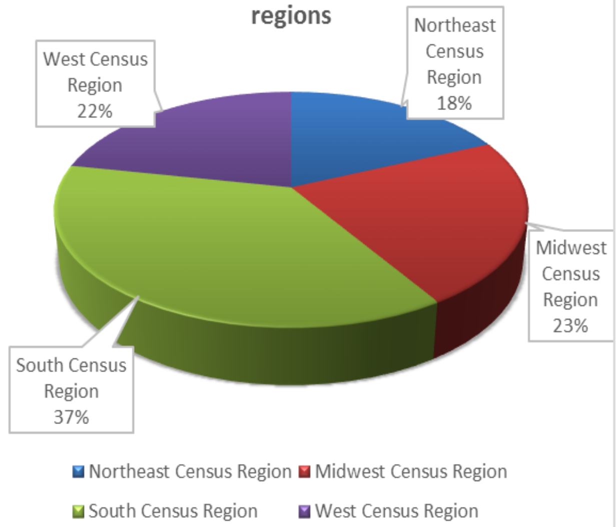


Figure 4c: Housing unit types in the U.S

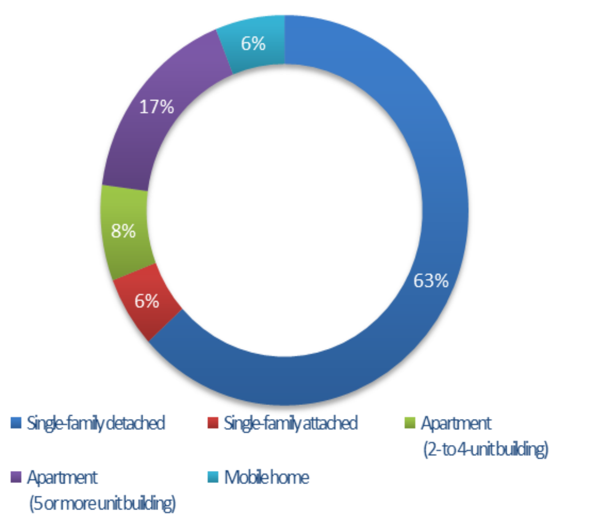


Figure 4d: Electricity Use for different purposes across regions (No of housing units in millions)

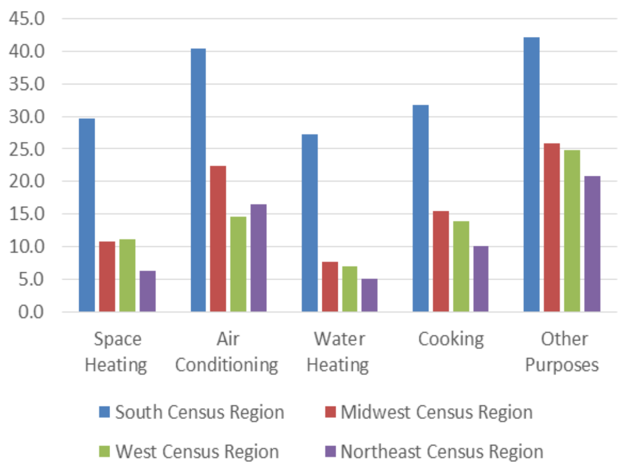
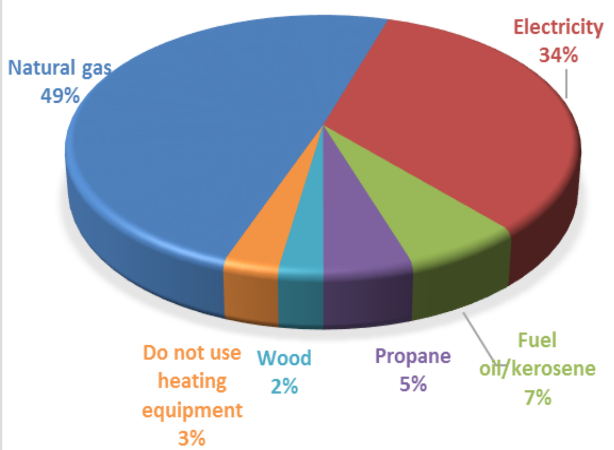


Figure 4e: Main heating fuel and equipment across U.S homes



3.0 The Model

There is no generally accepted theoretical framework for modeling energy use at the household level for some obvious reasons. Different theoretical explanations have been rendered by different disciplines [such as sociology, anthropology, economics and engineering] to analyze the subject. For instance, in economics, the demand for energy (or any other good/service) is usually modeled as a function of income and price which makes it easy to calculate income and price elasticity of energy demand. The economic theory of energy demand relies on rationality principle which assumes optimal outcomes based on rational choices which are usually determined by price (and consequently income). In engineering, they hold the view that building technology [starting from the design, space, geography to household equipment] influences energy use at the household level. Since the choice of building technology is determined by price and income (thus linking engineering with economics - ergonomics), the need to be more conscious of energy requirement of a particular type of building is increasingly gaining prominence. However, psychology deviates from the principle of economic rationality but assumes prominent role for consumer's energy conservation behavior in energy demand modeling. This approach seems to have lost relevance perhaps due to the inability to link conservation behaviour to changes in energy-consumption (see Lutzenhiser, 1992). In relation to sociology and anthropology, household energy demand is considered a social problem. In other words, the way individuals consume energy, perceive energy conservation, and utilize energy-related technology vary among groups differentiated by social class.

On this basis, our model hinges on an eclectic approach involving various perspectives of energy demand use at the household level. Essentially, we estimate possible variations in electricity consumption across different income groups (economics and sociology perspectives), building environment such as building design, climate and region effects (engineering, sociology and anthropology perspectives), and household characteristics such as household size, age, education, employment status, gender and poverty level (economics and sociology). The functional representation of our model is given below:

$$kwh = f\left(\text{buildg\_env, hh\_soc\_eco}\right) \tag{1}$$

$$\text{buildg\_env} = f\left(\text{region,climate, room size,cool\_deg,heat\_deg}\right) \tag{2}$$

$$\text{hh\_soc\_eco}=f\left(\text{income,age,poverty,employment,education,hh\_size, gender}\right) \tag{3}$$

where kwh represents electricity consumed by the sampled households, measured both in kilowatts-hours and British thermal units (Btu). We use the former measure for the main analyses while the latter measure is used for robustness checks. The predictors of electricity demand are grouped into two: the building environment category and the household socio-economic characteristics category. The former category $(\text{denoted by buildg\_env})$ captures room size, cooling degree days (cool_deg), heating degree days (heat_deg), climatic condition of the geographical location of the housing unit (climate) and region of the housing unit (region) [see e.g., De Cian et al., 2007; Dolinar et al., 2010; Eskeland and Mideksa, 2010; Shaeffer et al., 2012; Taseska et al., 2012; Xu et al., 2012; Karimpour et al, 2015]. The second category involving socio-economic characteristics of households $(\text{denoted by hh\_soc\_eco})$ includes income, age, employment status(employment), level of poverty(poverty), level of education(education), household size (hh_size) and gender [see e.g., Labanderia et al., 2006]. A review of prominent papers that have also engaged some of the predictors identified here is well documented in Salisu and Ayinde (2016).

Also, the main analysis is further partitioned into two: the non-probability model (where electricity is used in its continuous form) and the probability model (where electricity consumption is expressed in discrete form). The latter is recoded into Very high to Very Low [Grades 1 to 5] where '1' represents the lowest and '5', the highest (see Table 4) [see e.g., Jung, 1993]. This consideration allows us to determine the probability of a household transiting from high electricity user to low (and vice versa) after controlling for relevant covariates as previously mentioned. Meanwhile, electricity consumed in 2009 was not exactly measured in the survey; rather, it was indirectly computed using the amount of the monthly electricity bill. Thus, it may be necessary to model energy demand using the probabilistic approach that gives the likelihood of attaining a specified level of consumption The estimation procedure for the ordered household electricity consumption follows the ordered logistic regression while the non-probability model follows linear regression model and estimated with ordinary least squares since all the variables are indicator variables. For the ordinal logistic regression, we compute the odds ratios for all the variables and energy consumption outcomes. Also, some scenario analyses using specific values for some variables are conducted to elicit information on the likelihood of having a particular outcome given certain conditions.

$$kwh_i = x_i'\alpha + e_i \tag{4}$$

$$kwh_i^* = j \quad \text{if} \quad u_{j-1} < kwh_i \le u_j \tag{5}$$

The probability that observation *i* will select alternative *j* is:

$$\begin{aligned} p_{ij} = p\left(kwh_i^* = j\right) &= p\left(u_{j-1} < kwh_i \le u_j\right) \\ &= F\left(u_j - x_i'\alpha\right) - F\left(u_{j-1} - x_i'\alpha\right) \end{aligned} \tag{6}$$

For the Ordered logit, *F* is the logistic cumulative density function usually expressed as:

$$F\left(z\right) = e^z / \left(1 + e^z\right) \tag{7}$$

The cut-off points (i.e. choice rule) for the different outcomes are defined based on the thresholds as follows:

$$\begin{aligned} &kwh_i^* = 1 \quad \text{if} \quad kwh_i \le 10000 \\ &kwh_i^* = 2 \quad \text{if} \quad 10000 < kwh_i < 20000 \\ &kwh_i^* = 3 \quad \text{if} \quad 20000 < kwh_i < 30000 \\ &kwh_i^* = 4 \quad \text{if} \quad 30000 < kwh_i < 40000 \\ &kwh_i^* = 5 \quad \text{if} \quad 40000 < kwh_i < 50000 \end{aligned} \tag{8}$$

Where kwh_i^* is the discrete version of kwh_i. Using the generic representation, the respective probabilities for the five categories are derived as:

$$\begin{aligned}
&\Pr\left(kwh_i^* = 1\right) = 1 - F\left(u_1 - x_i'\alpha\right) \\
&\Pr\left(kwh_i^* = 2\right) = F\left(u_2 - x_i'\alpha\right) - F\left(u_1 - x_i'\alpha\right) \\
&\Pr\left(kwh_i^* = 3\right) = F\left(u_3 - x_i'\alpha\right) - F\left(u_2 - x_i'\alpha\right) \\
&\Pr\left(kwh_i^* = 4\right) = F\left(u_4 - x_i'\alpha\right) - F\left(u_3 - x_i'\alpha\right) \\
&\Pr\left(kwh_i^* = 5\right) = F\left(u_5 - x_i'\alpha\right) - F\left(u_4 - x_i'\alpha\right)
\end{aligned} \tag{9}$$

Where u_1 to u_5 denote the thresholds from 10,000 to 50,000. There will be one set of coefficients (odds ratios) for all the categories with four intercepts but there will be five sets of marginal effects, one for each category. On the basis of our classification of electricity consumption at the household level, the odds ratio (OR) evaluates the relative odds that households' electricity consumption will increase (from low to high) or decrease (from high to low) given the predictors of electricity consumption considered in our main model. On the other hand, the marginal effect measures the change in the probability of an outcome occurring as a result of a unit change in a particular (continuous) explanatory variable or a discrete change in a qualitative regressor.

For computational ease, we recode some of the variables of interest for the study. We categorize them into a more compact form drawn from the EIA format (see Table 3).

Table 3: Variables Ordering and Codes

Variable	Code – [Name]	Variable	Code – [Name]
Gross Income	1 – [Low Income] 2 – [Medium-Low] 3 – [Medium] 4 – [Medium-High] 5 – [High]	Employment Income	1 – [Not Received] 2 – [Received]
		Investment Income	1 – [Not Received] 2 – [Received]
Supplemental Security Income	1 – [Not Received] 2 – [Received]	Cash Assistance	1 – [Not Received] 2 – [Received]
Age Group	1 –[Below 26 years] 2 – [26-40 years] 3 – [41-55 years] 4 – [56-70 years] 5 – [71-95 years]	Highest Education Level	1 – [Uneducated]] 2 – [College/No Degree] 3 – [Degree] 4 – [Doctorate]
Number of Rooms	1 – [Below 7 Rooms] 2 – [7-12 Rooms] 3 – [13-25 Rooms]	Household Size	1 – [Below 7 members] 2 – [7-25 Members]
Employment Status	1 – [Unemployed] 2 – [Employed – Full-	Sex of Householder	1 – [Female] 2 – [Male]

	Time & Part-Time]		
Poverty 100%	1 – [Above Line] 2 – [Below Line]	Poverty 150%	1 – [Above Line] 2 – [Below Line]
Heating Degree Days	1 - [Below 3001] 2 – [3001-6000] 3 – [6001-9000] 4 – [9001-12525]	Cooling Degree Days	1 - [Below 2001] 2 – [2001-4000] 3 – [4001-5480]
Census Region	1 – [Northeast] 2 – [Midwest Census] 3 – [South Census] 4 – [West Census]	Climate Region	1 - [Very Cold/Cold] 2 – [Hot-Dry/Mixed Dry] 3 – [Hot-Humid] 4 – [Mixed-Humid] 5 – [Marine]
kwh[6]	(1/10000=1) (10001/20000=2) (20001/30000=3) (30001/40000=4) (40001/50000=5)		

Source: Authors' compilation from EIA codebook[7]

4.0 Discussion of results

4.3.1 Odds Ratio for Electricity Consumption

As described earlier, we recoded the continuous electricity consumed at the households into five groups from high to low and we further test whether the cut-off points for these outcomes are distinct. On the basis of the ordered logistic regression, we find that the five categories are distinct and can therefore be treated as separate distinct outcomes in the analyses of residential electricity consumption in the US (see Table 3). We are aware of the different regression estimates that can be obtained from the ordered logistic regression: the Log odds, Odds ratio and marginal effects. However, for ease of interpretation, we report and consequently interpret the odds ratio for the overall model (comprising all the effects) and marginal effects for the lowest and highest electricity consumption levels.[8] The results are presented in Table 4.

The odds ratio for each socio-economic, demographic and geographic factor is evaluated and reflects the likelihood that a household will transit from a low to a high consumer of electricity. Beginning with the income group of the households,

[6] The kwh is recoded for the purpose of logistic regression.
[7] Available at www.eia.gov/consumption/residential/data/2009/xls/recs2009_public_codebook.xlsx
[8] All the other estimates can be produced using the attached program file.

the odds ratio result reports that the higher the gross income received by a given household, the higher the probability of a household increasing electricity consumption from low to high. In addition, the probability is greater for high income earners than for low income earners judging by the differential intercept coefficients for the different income groups. For instance, all the households in the different categories that received annual gross income above $20,000 are significantly more likely to report a higher electricity consumption than those who received gross annual incomes of less than $20,000. Similarly, households that received employment income in 2009 have significant tendency (*OR*=1.604; *p-value*<0.01) to consume more electricity than households that do not receive employment income. Contrary to the estimated OR for the gross income and employment income, the OR for all other forms of income (supplemental security, welfare benefits/cash assistance and investment income), did not provide a significant difference in electricity consumption by US households. Thus, the OR did not provide statistical support for probability of increasing electricity consumption from low to high level when supplemental security, cash assistance and investment income is received by households.

The OR analyses further indicate that households below the poverty line (poverty100% and poverty150%) are significantly more likely to increase their consumption of electricity than households above the poverty line. Also, households with the employed heads are at about 26.9% [(0.731-1)*100= -0.269] significantly less likely to increase their electricity consumption level than households with unemployed heads.

The OR did not provide any evidence to support significant variations in electricity consumption by gender or household heads. The results indicate that households with male heads statistically do not increase their electricity consumption level than households with female heads. On the other hand, the age of every household head matters in terms of increasing the amount of electricity consumed. The odds ratio depicts that household heads older than 25 years but less than 71 years are significantly more likely to consume more electricity than households with less than 26 years. However, there is no significant likelihood (*OR*=1.315; *p-value*>0.1) that household in the age category between 71 and 95 years will consume more or less electricity than households in age category below 26 years.

Highest education level completed by householders appears to have no effect on the probability of increasing electricity consumption from low to high. The results from the OR analysis provide no significant evidence to support differences in electricity consumption by highest educational level attained by householders. Thus, the probability of increasing the level of electricity consumption from low to high when householders attain higher educational levels is negligible. As expected, the OR results suggest that each `additional household occupant significantly increases the probability (*OR*=3.525; *p-value*<0.1) of the household transiting from low to high electricity consumer while controlling for all other variables.

In general, the OR analyses further indicate that households having a total number of rooms between 7 and 25 rooms are significantly more likely to attain a higher consumption level than households with below 7 rooms. In terms of Heating Degree Days, with the exception of periods of 9001-12525 HDD (*OR*=6.414; *p-value*<0.01), there is no significant likelihood that in days between 3001 and 9000, the consumption level will increase (from low to high) or decrease (from high to low) as compared to days below 3001 HDD. However, with the consideration of climate region in our model, the OR analysis suggests an increased tendency (*OR*=1.483; *p-value*<0.1) for households to attain a higher consumption level of electricity for 3001-6000 HDD as compared to days below 3001 HDD. Also, cooling degree days appear to have no significant impact on the probability of increasing the level of electricity consumption by US households.

In terms of Census region, the odds ratio result reports that the probability of increasing the level of electricity consumption (from low to high) is more visible for households in the Midwest and South Census than households in the Northeast region. However, there is no significant likelihood (*OR*=1.300; *p-value*>0.1) that householders in the West Census region will attain a higher status than households in Northeast region in relation to electricity consumption. Lastly, concerning climate regions, compared to households domiciled in very cold/cold climate regions, the result shows that all households in other climate region categories are significantly more likely to report a higher level of electricity consumption than those domiciled in very cold/cold climate regions. This may possibly be due to the fact that most households in the very cold/cold climate regions make use of other energy sources for heating.

Table 4: Odds Ratio and Marginal Effects

Variables	Odds Ratio	Marginal Effects (Low)	Marginal Effects (High)
Gross Income			
Medium low	2.751	-0.209	0.003
	(0.513)***	(4.94)**	(4.09)**
Medium	5.529	-0.300	0.007
	(1.182)***	(6.91)**	(4.52)**
Medium High	6.848	-0.320	0.009
	(1.581)***	(7.32)**	(4.32)**
High	9.571	-0.345	0.013
	(2.210)***	(8.06)**	(4.65)**
Other Income			
Employment Income	1.604	-0.061	0.003
	(0.204)***	(3.70)**	(3.08)**
Supplemental security Income	1.207	-0.024	0.001
	(0.199)	(1.14)	(1.12)
Cash Assistance	1.000	-8.01e-06	3.77e-07
	(0.367)	(0.00)	(0.00)
Investment income	0.956	0.006	-0.000
	(0.102)	(0.42)	(0.42)
Poverty			
[Above Poverty Line]			
Below 100%	1.599	-0.061	0.003
	(0.303)**	(2.48)*	(2.25)*
Below 150%	2.114	-0.097	0.005
	(0.355)***	(4.44)**	(3.47)**
Status of Employment			
[Ref: Unemployed]			
Employed	0.731	0.041	-0.002
	(0.076)***	(2.99)**	(2.63)**
Sex	0.988	0.002	-0.000
	(0.078)	(0.15)	(0.15)
Age Group			
[Ref: Below 26 years]			

26-40 years	1.795	-0.093	0.003
	(0.279)***	(3.41)**	(3.32)**
41-55 years	2.207	-0.119	0.004
	(0.349)***	(4.35)**	(3.94)**
56-70 years	2.235	-0.120	0.004
	(0.369)***	(4.30)**	(3.80)**
71-95 years	1.315	-0.048	0.001
	(0.264)	(1.36)	(1.31)
Highest Education Level [Ref: Uneducated]			
College/No Degree	1.661	-0.068	0.003
	(0.573)	(1.26)	(1.78)
Degree	1.120	-0.017	0.001
	(0.394)	(0.31)	(0.34)
Doctorate	0.729	0.055	-0.001
	(0.268)	(0.92)	(0.75)
Household size	3.525	-0.105	0.015
	(2.439)*	(3.20)**	(1.04)
Number of Rooms [Below 7 Rooms]			
7-12 Rooms	4.553	-0.172	0.013
	(0.431)***	(16.45)**	(5.10)**
13-25 Rooms	25.746	-0.223	0.082
	(14.279)***	(18.32)**	(1.88)
Heating Degree Days [below 3001]			
3001-6000	1.395	-0.043	0.002
	(0.319)	(1.46)	(1.38)
6001-9000	1.213	-0.026	0.001
	(0.468)	(0.52)	(0.47)
9001-12525	6.414	-0.143	0.027
	(3.576)***	(5.41)**	(1.63)
Cooling Degree Days [below 2001]			
2001-4000	1.020	-0.003	0.000
	(0.235)	(0.08)	(0.08)
4001-5480	1.154	-0.018	0.001
	(0.296)	(0.56)	(0.55)
Census Region [Ref: Northeast Region]			
Midwest Census Region	1.227	-0.026	0.001
	(0.347)	(0.69)	(0.77)
South Census Region	1.117	-0.015	0.001
	(0.324)	(0.37)	(0.40)
West Census Region	0.585	0.087	-0.002
	(0.205)	(1.53)	(1.35)
Climate Region [Ref: Very Cold/Cold}			
Hot-Dry/Mixed Dry	4.440	-0.219	0.008
	(1.703)***	(3.38)**	(2.69)**
Hot-Humid	2.672	-0.166	0.004
	(0.986)***	(2.37)*	(2.65)**
Mixed-Humid	2.496	-0.158	0.004
	(0.704)***	(2.69)**	(3.23)**
Marine	4.336	-0.217	0.008***

	(1.924)***	(3.44)**	(1.85)
Cut Point			
Low to Medium-Low	2.651		
	(0.559)***		
Medium-Low to Medium	5.514		
	(0.570)***		
Medium to Medium-High	7.718		
	(0.579)***		
Medium-High to High	9.443		
	(0.603)***		
No of Obs.	2,541	2,541	2,541

Note: Standard errors are in parenthesis. ***, ** and * signify statistical significance of coefficients at 1%, 5% and 10% respectively. The reference category (ref) for each variable category is reported under each variable name. Odds Ratio depicts the estimation results of the best mode (that is, model that considers both census region and climate region effects). The marginal effects for low electricity consumption and high electricity consumption are reported in (Low) and (High) respectively.

4.3.2 Marginal Effects for High and Low Electricity Consumers

For ease of interpretation and policy relevance, we focus on the two extreme scenarios for the marginal effects: the lowest outcome (kwh*=1) and the highest outcome (kwh*=5) [see Table 3 and Footnote 7]. Four striking findings are discernible from the results. Firstly, by increasing the level of household income from low to high, the probability of attaining the highest outcome also improves after controlling for other relevant covariates [check the column for Marginal effects (High)]. Conversely, by increasing the level of household income from low to high, the probability of attaining the lowest outcome deteriorates after controlling for other relevant covariates [check the column for Marginal effects (Low)]. Secondly and in a similar fashion, households with employment income have a higher probability of achieving the highest outcome relative to households without employment income. On the other hand, households with employment income have a lower probability of achieving the lowest outcome relative reference category. Thirdly, households below the poverty line 100% and 150% have a higher (lower) likelihood of reporting the highest (lowest) outcome relative to the benchmark category. Fourthly, households in dry, humid and marine regions have a higher (lower) probability of reaching the highest (lowest) consumption category of electricity relative to the cold/very cold region. In other words, the latter category is likely to be slower (faster) than the former in reaching the highest (lowest) outcome.

We further complement the results of the marginal with some scenario analyses as discussed in the section that follows.

4.4 Scenario Analyses for High Electricity Consumers

Unlike the marginal effects which evaluate the regressors at their means (with exception of discrete regressors), the scenario analyses conducted here capture the effect of some regressors, evaluated at different values, on the predicted probabilities of achieving the highest outcome of electricity consumption (see Table 5). The considered scenarios focus on households' income, employment income, the number of household members, total number of rooms in the dwellings, as well as households below and above the 100% and 150% poverty level, when other variables are held at their means.

For an average household, the predicted probability of reporting the highest outcome increases with income. For instance, the predicted probability of attaining the highest outcome is 0.0016 for low; it is 0.0087 for medium while the high income group has the highest predicted probability value of 0.0150. When employment income is considered, the probability is 0.0043 when such household does not receive employment income. This value increases to 0.0068 when there is employment income. Hence, employment income increases the likelihood of reporting the highest outcome by US households. The increase in the number of members in a household is also an important factor in the amount of electricity consumed by such household. The predicted probability increases with the number of household members as well as number of rooms.

Table 5: Scenario Analyses: Predicted Probability of Demanding High Electricity

Scenario	Prob.	Scenario	Prob.
Gross Income		***No. of Household Member***	
Low	0.0016	*7 and Below*	0.0061
Medium-Low	0.0044	*More than 7*	0.0212
Medium	0.0087	***No. of Rooms***	
Medium-High	0.0108	*Less than 7*	0.0036
High	0.0150	*Between 7 and 12*	0.0164
Employment Income		*More than 12*	0.0859
Absent	0.0043		
Present	0.0068		

5.0 Policy implications and concluding remarks

The empirical analyses of electricity consumption carried out in this paper are based on the 2009 RECS data. The findings of this study identified some of the key factors that influenced the demand for electricity by US households. As evident in the literature and based on our empirical analyses, we find that there is tendency for high electricity consuming households to demand for more electricity over time. Hence, the findings of this study are of vital relevance to policy makers and stakeholders in the US energy sector in planning and making energy-related decisions.

First, our empirical findings reveal that socio-economic characteristics of households are important drivers of electricity demand. Similarly, we find that the dwellings characteristics – in terms of household size and number of rooms among others, influence the likelihood that households will demand for high amount of electricity. Hence, these factors can keenly influence how the residential demand for electricity evolves over time. Therefore, the socio-economic and demographic distributions of households should be adequately mapped out and stratified accordingly in order to identify where there is need for more production and distribution capacity based on high demand.

Second, our findings show that households with income below the poverty threshold of 100% and 150% are likely to consume more electricity than households above the poverty line. The presence of energy subsidies for poor and disadvantaged households seems to encourage more consumption of electricity by these categories of households. Whilst the policy of energy subsidy enables the accessibility to energy by all, however, adequate infrastructural support must be in place to ensure that the benefits are accrued to the targeted group. What is obtainable is that most the poor and vulnerable households are not connected to electricity grid and they only account for small proportion of total electricity use. Hence, proper policy mechanisms must be in place to ensure that public funds are not just squandered and the objectives of energy for all are still not achieved.

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