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Investigating the factors shaping residential energy consumption patterns in France: evidence form quantile regression

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Abstract

This article provides new evidence on various factors that affect residential energy consumption in France. We model the consumption of residential energy in dwellings and apply a bottom-up statistical approach. Our quantile regression model uses an innovative variable selection method via the adaptive elastic net regularization technique. The empirical estimates are based on responses to the PHEBUS survey. The aim is to untangle the effects of dwelling, socio-economic and behavior-related factors on the household energy consumption, for different levels of energy use. Our findings demonstrate that cross-sectional variation in residential energy consumption is a function of the building's technical characteristics and the household's socio-economic attributes and behavior. The analysis suggests that the effect of the household's dwelling, demographic and socioeconomic attributes on its energy consumption differs across quantiles. We propose some measures and empirical methods that allow a deeper understanding of the factors affecting energy use which should be informative for policy making aimed at reducing residential energy demand.

JEL classification: C2, D1, Q41, Q48

Keywords: Residential energy consumption, Household energy use, Behavior, Energy efficiency, Quantile regression, Adaptive elastic net

1. Introduction

The housing sector is one of the largest energy-consumers. It accounts for up to 30% of total delivered energy consumed worldwide (IEO, 2016) and contributes up to one-third of global annual greenhouse gas emissions. Projections of residential energy demand in future decades are required to estimate and predict future energy needs and environmental effects. In recent years, concern over reducing energy consumption and associated greenhouse gas emissions in the residential dwelling sector has increased greatly. Moreover, the liberalization of energy markets in the European Union let to the creation of more competitive markets and reductions in price by privatization. According to the French ministry for the environment, energy and the sea, new

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suppliers are entering in the French market creating a more competitive market offers – 50 000 to 70 000 suppliers switches each month since the beginning of 2015 (vs. 20 000 to 30 000 two years ago) – leading to more competitive prices and a consumers-switching behavior. Consumers are now free to purchase energy from a supplier of their choice. This process led to price reductions benefitting the consumers.

There is a stream of research which is highlighting the drivers of household energy consumption. Several papers have examined the effects of housing and socio-demographic variables on energy consumption in residential dwellings (Brounen et al., 2012; Estiri, 2015b; Nesbakken, 1999). However, most analyze a small number of causal factors (Belaïd, 2016; Lévy et al., 2014 ; Bakaloglou, and Belaïd, 2018) which led Jones et al. (2015) to highlight the lack of any comprehensive analysis. As a result, our understanding of household energy consumption patterns is limited (Belaïd, 2016; Belaïd and Garcia, 2016; Estiri, 2015a).

The aim of the present study is to examine the predominant drivers of household energy consumption in France, using quantile regression and an innovative variable selection approach employing multi-step adaptive elastic-net (MSA-Enet). This should provide a better understanding of household energy consumption, and allow energy consumption to be modeled based on relevant dwelling and household attributes. We contribute to the literature in this area by providing a first examination of the causal effects of additional dwelling characteristics (dwelling efficiency) and behavioral factors (indoor heating temperature, heating management, and home occupancy).

The literature shows that investigating domestic energy demand is a complex issue and involves many interconnected factors. Household consumption fluctuates according to the household's socio-economic attributes, lifestyle and behaviors, and the physical characteristics of the dwelling. Although certain dwelling-related attributes have been identified (year built, dwelling type, dwelling size, etc.), household characteristics tend to be ignored for methodological reasons, and the complexity, cost and non-availability of individual disaggregated data.

Improving the energy-efficiency of housing stock could be promising for reducing financial costs and environmental damage associated to domestic energy demand. In the last few years, international institutions such as the International Energy Agency (IEA) have highlighted the huge, untapped energy savings potential achievable from good building design and retrofitting (IEA, 2017). The IEA report argues that some 80% of the economic potential of building energy efficiency is unexploited due in the main to non-technical barriers. This untapped potential suggests that building energy efficiency should be at the core of any strategy that aims to tackle carbon emissions and address the energy efficiency paradox in the sector.

Recent efforts to improve the energy performance of existing housing stock have revived interest in household energy demand (Geng et al., 2017). In recent years, patterns of and factors shaping household energy consumption have been subject to intense debate, in academia and the policy arena (Belaïd, 2017; Schulte and Heindl, 2017). The first wave of work on household energy use/demand emerged in the late 1970s, following the first oil crisis (Mazur and Rosa, 1974; Sonderegger, 1978; Dubin and McFadden, 1984).

France is an excellent case to examine the drivers of household energy consumption. In France, residential energy consumption constitutes a large part of total final demand for energy. In 2017, about 30% (38 million tons of oil equivalent) of total French energy consumption was due to the residential sector which includes some 33.5 million housing units. A significant part of this housing stock was built according to no or outdated thermal codes, and thus, with no attention to energy efficiency or environmental issues (French household survey, 2013). Therefore, this sector provides huge potential for delivering long-term significant energy savings and greenhouse gas emissions reductions.

The imperative to improve energy efficiency is increasing. Meeting France's long-term CO_2 emissions reduction target will require significant energy efficiency improvements in its existing residential housing stock which is among the oldest and least energy efficient in Europe. Therefore, a better understanding of the main determinants of residential energy consumption is crucial for the design of effective policies to reduce carbon emissions and energy demand. The French government has begun progressively to focus efforts on improving energy efficiency in the residential dwelling sector, and has set an ambitious energy efficiency target. The latest Energy Transition for Green Growth act (FMEES, 2016) aims to: (i) accelerate refurbishment of existing housing stock (with a goal of 500,000 major renovations per year); and (ii) bring the housing stock to a low energy building standard by 2050.

Given the urgent need to reduce residential sector energy consumption and carbon emissions, it has been suggested that future French energy policy should be aimed at lowering demand from high energy consumers. Therefore, understanding what drives high usage in the residential housing sector is crucial to support decisions about how to reduce energy consumption and carbon emissions.

Our study offers a unique contribution to the available body of literature by developing an empirical model based on rich micro-data from a representative sample of France. First, it introduces a new dimension to the energy debate related to exploring the spectrum of residential energy consumption. Second, we address the gap in the empirical econometric literature related to it's the drivers of residential energy consumption. The proposed quantile model helps to the differentiate the effects of several variables on the entire consumption distribution. In addition, the proposed innovative variables selection technique, not only selects the relevant factors which eases interpretation of the model, it also increases the accuracy and stability of the predictors, which avoids the so-called curse of dimensionality. Third, we investigate an issue that has been rather unexamined in France due to lack of information and unavailability of disaggregated data on household energy usage. Fourth, by disentangling the effects of energy efficiency and energy prices on household energy demand our study adds to recent debate about whether households respond differently to energy efficiency improvements and energy price changes.

This study was undertaken to enhance our knowledge and understanding of the housing, and the socio-economic and behavioral factors affecting energy consumption in the French housing sector. The innovative empirical approach based on quantile regression and MSA-Enet differentiates this study from existing work on residential energy consumption (Lévy et al., 2014; Nesbakken, 1999; Schulte and Heindl, 2017).

The paper is organized as follows: section 2 provides a brief overview of the literature on residential energy consumption. Section 3 presents our hypothesis, the modeling approach employed, and the data. Section 4 summarizes and discusses the main empirical results, and section 5 presents our conclusions and offers some implications for policy based on the model's empirical results.

2. Theoretical background and literature review

The total domestic energy consumed depends on the housing unit and its occupants. According to the existing literature, residential energy consumption is linked to a multitude of inter-related factors including the technical characteristics of the building, household attributes, lifestyle and behavior, energy system, climate, equipment, etc. (Belaïd, 2017). In addition, the economics literature focuses on macroeconomic aspects such as fuel prices and inflation (Summerfield et al., 2010). However, to our knowledge, no serious attempts have been made to consider the impact of these factors on residential energy consumption. Although energy consumption in the residential sector has been studied, none of this work takes account of all of the afore-mentioned causal factors.

Residential energy consumption has been studied for many years. Houthakker (1951) was the first attempt to model household expenditure on electricity as a function of income, and as a function of household total spending. Growing concern over residential energy consumption has resulted in a number of empirical and theoretical studies (Esmaeilimoakher et al., 2016; Estiri, 2015a; Lévy et al., 2014; Schulte and Heindl, 2017), and triggered new theoretical and modeling approaches to analyzing the spectrum of residential energy consumption.

A first literature stream on residential energy consumption and environmental protection, emerged in the late 1970s following the oil crisis. These studies come from different disciplines and are based on different concepts, methods and units of analysis, aimed at reducing or conserving energy (Valenzuela et al., 2014). They were motivated by the recent increased awareness of global warming, climate change, fossil fuel depletion and oil price volatility. However, most previous work is techno-centric and uses an engineering approach.

Much previous research on residential energy consumption and energy efficiency in residential buildings investigates the physical and technical determinants of energy consumption and ignores the role of households' behaviors (Brounen et al., 2012). Most studies examine energy consumption by modeling the physical attributes of buildings (e.g. insulation, square footage, thickness and positioning of windows, etc.). These determinants of energy use show significant differences between real and predicted consumption, sometimes by a factor of 2 or 3 (Hackett and Lutzenhiser, 1991; Sunikka-Blank and Galvin, 2012).

Studies conducted in the USA and the Netherlands show that building characteristics explain 40% to 54% of the variation in energy use (Guerra Santin et al., 2009; Sonderegger, 1978). Summerfield et al. (2010) found that UK households' energy use varied widely within the same building or among buildings with similar physical attributes. Their model is not able to express real energy consumption; it is essential to consider socioeconomic and demographic attributes.

In recent years, there has been an explosion of empirical studies of residential energy consumption. Most use aggregated time series data, only a few micro studies use household-level data (Zhou and Teng, 2013).

Kavgic et al. (2010) highlight the two fundamental approaches to modeling and analyzing various aspects of residential energy consumption: top-down and bottom-up. Top-down models use aggregate data and time series to investigate the inter-relationships between the energy sector and the economy. Bottom-up models use high-resolution data to estimate energy consumption and CO_2 emissions. Bottom up models include two types of sub-models: engineering and statistical.

Although some studies provide theoretical perspectives (Haddad et al, 1995; Kavgic et al., 2010; Swan and Ugursal, 2009) there is no unique model or conceptual framework that provides clarification of residential energy consumption, nor is there a unique method that provides an accurate assessment of individual differences in domestic energy consumption. However, some studies incorporate more than one perspective to try to disentangle the complexity of residential energy consumption and produce consistent findings (Estiri, 2015a; Kavgic et al., 2010; Lévy and Belaïd, 2018; Valenzuela et al., 2014; van den Bergh, 2008).

Studies conducted since the late 2000s, although they provide more clarity do not reach a consensus on the various interconnected factors that cause individual differences in domestic energy consumption. The key explanatory determinants identified include a range of housing attributes (e.g. house size, dwelling type, building age), sociodemographic attributes (e.g. household size, occupation status, income, age of household head), geographical and climate conditions (HDD, CDD, urban area), and external and situational factors (economic, legal, socio-cultural).

The literature reviewed shows that most work on the influence of various factors on residential energy consumption use a standard linear regression approach but do not include all the causal factors. The proposed study adds to the literature by examining a wide range of influencing factors including housing characteristics, socio-economic factors, household behavior, and geographic and climate attributes. Table 1 summarizes selected studies of residential energy consumption.

Table 1. Summary of selected previous study on residential energy consumption

Source	**Type of data /country**	**Method / approach**	**Determinants of residential energy consumption**				
			Energy efficiency	**Housing Technical**	**Socioeconomic & demographic**	**Behaviors & preferences**	**Climate & Geographic**
Nesbakken (2002)	Cross-sectional (Norway)	Discrete continuous model		×	×		×
Labandeira et al. (2006)	Cross-sectional + panel data (Spain)	Almost Ideal Demand Model (Banks et al. 1997) – IV method			×		
Kaza (2010)	Cross-sectional (US)	Quantile regression		×	×		×
Wiesmann et al. (2011)	Cross-sectional (Portugal)	Ordinary least squares (OLS) regression		×	×		×
McLoughlin et al. (2012)	Cross-sectional (Ireland)	Multiple linear regression		×	×	×	
Sanquist et al. (2012)	Cross-sectional (US)	Factor analysis - Multiple linear regression			×	×	×
Brounen et al. (2012)	Cross-sectional (Holland)	Multiple linear regression	×	×	×		×
Labandeira et al. (2012)	Panel (Spain)	Panel Random effects			×		×
Blazejczak et al. (2014)	Panel (Spain)	Dynamic partial adjustment approach			×		×
Estiri (2014)	Cross-sectional (US)	Structural equation modeling		×	×		
Valenzuela et al. (2014)	Cross-sectional (US)	Quantile regression		×	×		×
Romero-Jordán et al. (2014)	Panel (Spain)	Partial adjustment model		×	×	×	×
Huang (2015)	Cross-sectional (Taïwan)	Quantile regression		×	×		×
Estiri (2015b)	Cross-sectional (US)	Covariance Structure Analysis		×	×		
Belaïd (2017)	Cross-sectional (France)	Structural equation modeling		×	×	×	×
Jaffar et al. (2018)	Cross-sectional (Kuwait)	Multivariate regression		×	×	×	
Navamuel et al., (2018)	Cross-sectional (Spain)	Ordinary least squares (OLS) regression		×	×		×

3. Data and method

3.1. Data

Our empirical analysis is based on microdata from the recent household energy consumption survey PHEBUS[1] Administered by the Department of Observations and Statistics (SOeS), part of the French Ministry of Ecology and Sustainable Development. The data used are the latest PHEBUS micro level data released in early 2014. The survey aims to review the *energy performance of French housing units*. PHEBUS is a formal, detailed cross-sectional survey of a nationally-representative sample of the French residential dwelling sector. The first part of the survey involves face-to-face interviews with the responsible household family member; the second part consists of an energy performance diagnosis of the dwelling carried out by certified professionals.

The basic random sample is the result of a complex multistage sampling design. The sample used in this study includes 2,356 households in housing units selected statistically to ensure representativeness of the French principal residence dwelling stock (ca. 27 million housing units). To the best of our knowledge, such a rich, representative, interesting and detailed dataset is unique. The survey affords a detailed overview of dwelling units occupied as the primary residence, and energy performance-related data on residential housing stock.

The PHEBUS database variables include occupant's socio-demographic attributes, technical aspects of the housing unit, energy use and behavior, home appliances, energy type and related consumption. It provides valuable information on dwelling energy performance based on a certified diagnosis. Thus, it is the first data to include both observed and theoretical energy consumption. These data offer new opportunities to understand and control energy consumption in housing. Table 2 presents the summary statistics of the variables employed in the econometric model.

[1] The database is available from the survey operations manager, Service of Observations and Statistics (SOeS) under the French Sustainable Development and Ecology Ministry, subject to prior agreement of the Committee on Statistical Confidentiality.

Table 2. List and description of modeling variables

Variable	Categories	Frequency / Mean
Household socio-economic attributes		
Household income		35593
Energy price		0.15
Age of HRP (Household responsible person)		54
Number of household members (NHM)*	1 person	22.90
	2 persons	36.20
	3 to 4 persons	32.85
	More than 5 persons	8.05
Tenure type (TT)*	Owner	76.15
	Rented	23.85
Employment status (ES)*	Top managerial and intellectual profession	18.17
	Intermediate profession	22.99
	Employees	22.77
	Workers, routine and manual occupations	25.83
	Other	10.25
Actual occupation status (AOS)*	Employed	51.79
	Retired person	38.74
	Unemployed	4.48
	Other	4.99
Gender*	Male	68.40
	Female	31.60
Nationality	French	91.05
	Other	8.95
Dwelling characteristics		
Total square footage (TSF)*		92
Building Proximity to other households (BPH)	Isolated individual house	50.11
	Shared building	49.89
Construction year	Before 1948	26.90
	1948-1974	28.09
	1975-1988	21.36
	1989-2000	12.57
	After 2001	11.08
Heating system (HS)	Shared central	9.69
	Individual central	76.97
	Other	13.34
Heating energy (HE)*	Electricity	34.35
	Gas	38.87
	Oil	15.54
	Wood	5.98
	Other	5.25

Variable	**Categories**	**Frequency / Mean**
Urban structure (US)	Rural commune	24.88
	From 2 000 to 20 000 inhabitants	18.30
	From 20,000 to 200,000 inhabitants	18.21
	More than 200,000 inhabitants	24.92
	Paris conurbation	13.69
Heating degree days (HDD)		1971.06
Household behaviors		
Equipment Rate		6,61
Heating temperature		21.44
Lower the heating of the bedroom	Yes	6.33
	No	31.67
Housing unoccupancy	Less than 4 hours per day	58.18
	4 to 8 hours per day	23.10
	More than 8 hours per day	18.71

**Variable included in the final model*

3.2. Modeling approach and model specification

Our methodological innovation is the bottom-up statistical approach which is based on quantile regression and an innovative variable selection approach via (MSA-Enet). Use of the MSA-Enet (a form of model regularization) allows for parsimony and greater accuracy. It enables examination of the salient drivers of household energy consumption in France using quantile regression model.

3.2.1. Adaptive Elastic Net Selection

To assess the quality of an econometric model and improve its interpretability and performance, two aspects are crucial: (1) parsimony, particularly when analyzing multi-dimensional data, and (2) prediction accuracy. Therefore, when analyzing multi-dimensional data, it is important to decrease the number of factors and reduce the computation load and model complexity. To model energy demand and capture the relevant determinants of domestic energy use, requires an approach that optimizes the model's accuracy and incorporates the complexity of the phenomenon.

An important and still challenging issue well known in the field of modern statistical modeling is variable selection. The statistical literature agrees that in the presence of large numbers of predictors and multicollinearity, a simplistic and standard variable selection approach such as a step-wise approach, performs poorly with respect to both estimating coefficients and standard errors and selecting the repressors, and leads to unstable subset selection and a model with poor prediction accuracy (Zou and Zhang, 2009). To overcome these problems, several techniques have been proposed including the least absolute shrinkage and selection operator (LASSO), ridge regression, and elastic net (Liu and Li, 2017).

The statistical and computational properties of LASSO which allow prediction makes it one of the most popular approaches in recent years (Tibshirani, 1996). However, MSA-Enet which is a new and innovative method, has several advantages over LASSO (Liu and Li, 2017). It is a convex combination of the ridge regression and adaptive LASSO penalties (Zou and Zhang, 2009). Zou and Zhang show that Enet can enhance the prediction accuracy of LASSO, particularly in the case of high correlations among the independent variables. Algamal and Lee (2015) argue that MSA-Enet is more robust, provides more accurate predictions based on its so-called oracle property, and outperforms the other penalization procedures with respect to grouping effects, prediction accuracy, and factor selection. Hu et al. (2018) use real data and numerical simulation to show that MSA-Enet is an alternative method for high-dimensional model selection problems.

Regularized regression of β using the MSA-Enet is defined as follows (Li et al., 2011):

$$\hat{\beta}_{AdaEnetR} = \left(1 + \frac{\lambda_2}{n}\right) \arg\min_{\beta}\left\{L_n(\beta) + \lambda_2 \sum_{j=1}^{Pn} \beta_j^2 + \lambda_1 \sum_{j=1}^{Pn} \widehat{\omega}_j \left|\beta_j\right|\right\} \tag{1}$$

where λ_1 and λ_2 denote the regularization parameters where $\lambda_1 = 0$ leads the MSA-Enet estimate back to the ridge regularization, and $\lambda_2 = 0$ leads to the adaptive LASSO estimate. $X_j = (X_{1j}, \dots, X_{nj})^T, j = 1, \dots, p_n$ are the linearly independent response variables.

The variables selection method proposed not only selects the relevant factors to achieve a model that is easy to interpret, it also provides enhanced prediction accuracy and stability and avoids dimensionality.

3.2.2. Quantile regression

Based upon a new, rich, French micro-level survey combining information on dwelling attributes, occupant characteristics, and behaviors, we employ a bottom-up statistical approach and a quantile regression model.

Most studies of household energy use and its various determinants employ multiple linear regression to examine socio-economic and housing influences (Tso and Guan, 2014).

Energy demand is not homogenous among households and the diversity of household attributes and behavior can result in heterogeneous patterns. Therefore, ordinary least square (OLS), based on the conditional mean is not appropriate to differentiate the rebound effect with respect to the distribution of energy demand across households. Residential energy policies based only on average effects will not be sufficiently rigorous and could be irrelevant. Quantile regression parameters estimate the impact of individual explanatory variables on specific quantiles of the dependent variable (e.g. 10^{th}, 25^{th}, 50^{th} and 75^{th}). In our case, quantile regression allows us to identify the differential impacts of energy efficiency, energy price, household income, etc.

Quantile regression (Koenker and Basset, 1978) extends the well-known mean regression model to conditional quantiles of the response variable, such as the median. The main advantage of quantile regression over OLS is its relative independence of bootstrapped standard errors and heteroskedastic errors and lack of need for a Gaussian error structure. More precisely, the obvious advantages of the quantile regression approach over standard OLS regression are that the quantile regression approach is more robust to the non-normal errors and outliers. Accordingly, quantile regression may provide robust characterization of the data, enabling the model to consider the effect of the explanatory variables across the entire distribution of the dependent factor, not merely on its conditional mean.

Quantile regression is considered to be an extension of standard least squares estimation of conditional mean models to the estimation of a set of models for several conditional quantile functions. In other words, quantile regression developed by Koenker and Bassett (1978) seeks to generalize the idea of univariate quantile estimation to estimation of conditional quantile functions, i.e. the quantiles of the conditional distribution of the dependent variable are formulated as functions of the observed covariates.

The quantile regression model can be considered a location model (Koenker and Bassett, 1978). We assume that:

$$P(y_i \leq \tau|x_i) = F_{\mu_\theta}(\tau - x_i'\beta_\theta|x_i) \tag{2}$$

where $(y_i, x_i), i = 1, \dots, n$ is a sample from some population, and x_i represents a $K * 1$ vector of the regressors.

Relation (1) can be reformulated as:

$$y_i = x_i'\beta_\theta + u_{\theta_i} \text{ with } Q_\theta(y_i|x_i) = x_i'\,\beta_\theta, 0 < \theta < 1 \tag{3}$$

$Q_\theta(y_i|x_i)$ is the conditional quantile of y_i on x_i. It is assumed that u_{θ_i} satisfies the quantile restriction $Q_\theta\left(u_{\theta_i}|x_i\right) = 0$.

$\hat{\mu}_\theta$, termed the θ^{th} sample quantile solves the equation below:

$$\min_b\left\{\sum_{i:y_i \geq b} \theta|y_i - b| + \sum_{i:y_i<b}(1-\theta)|y_i - b|\right\} \tag{4}$$

In our study, the standard log-linear demand equation used to estimate the salient determinants of household energy use can be written as:

$$y_i = x_i'\beta_\theta + u_{\theta_i} \text{ with } Q_\theta(y_i|x_i) = x_i'\,\beta_\theta \tag{5}$$

In our model, y_i is the vector of household electricity demand (in logarithm), x is a vector of all the regressors, β is the vector parameters to be estimated, and u_{θ_i} is a vector of the residuals. The $\hat{\beta}_\theta$ the estimator of $the\ \theta^{th}$ quantile regression minimizes over the objective function below (Cameron and Trivedi, 2013):

$$\min \frac{1}{n_\beta} \left\{ \sum_{i:y_i \geq x_i'\beta} \theta |y_i - x_i'\beta_\theta| + \sum_{i:y_i < x_i'\beta} (1-\theta)|y_i - x_i'\beta_\theta| \right\} =$$

$$\min_\beta \frac{1}{n} \sum_1^n \varphi_\theta(u_{\theta_i}) \tag{6}$$

where $\varphi_\theta(\lambda) = \big(\theta - I(\lambda < 0)\big)$

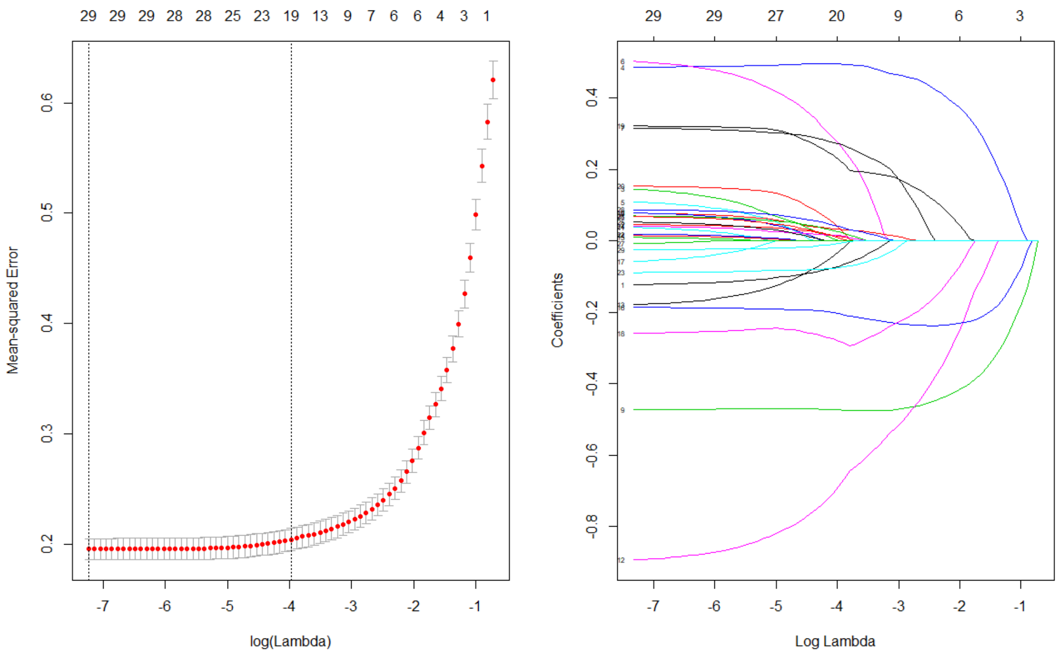
$I(.)$ Is the usual indicator and λ is the check function.

In our case, the dependent variable is household energy consumption defined as total annual demand for energy per household, and measured in kWh.

4. Results and discussion

The final model includes all the variables selected using MSA-Enet. Figure 1 depicts the coefficient shrinkage and the distribution of the sum of the squared errors of the tuning parameter λ. MSA-Enet not only simultaneously assesses the direction of the index and the important factors selected, it also avoids assessment of the unknown link function using the nonparametric method.

Figure 1. distribution of the sum of the squared errors of the tuning parameter λ MSA-Enet shrinkage



We estimate models for the 10th, 25th, 50th, 75th and 90th quantiles. The results help to determine how the variation in predictors affects energy consumption in the tails of the distribution, and indicate the groups of households that consume less or more energy. The empirical results from the quantile regression and OLS are presented Table 3. Almost all of the control factor coefficients in the model are statistically significant at the 1% level. Using OLS, the adjusted R^2 statistic is equal to 0.76, and is relatively high given that the dependent variable was estimated in share form.

Table 3. Estimation results using quantile and OLS regression.

Variable	0.1	0.25	0.5	0.75	0.9	OLS
Energy price	-0.43***	-0.52***	-0.62***	-0.63***	-0.66***	-0.47***
Dwelling efficiency	-0.10***	-0.15***	-0.20***	-0.21***	-0.15***	-0.13***
Household income	0.10	0.09**	0.08	0.01	0.02	0.06***
Age of HRP	0.12	0.18***	0.18***	0.17***	0.11**	0.11***
Number of household members	0.11***	0.09***	0.08***	0.10***	0.07***	0.09***
Owner	-0.07	-0.03	-0.07**	-0.09**	-0.02	-0.10***
Total square footage	0.41***	0.51***	0.51***	0.48***	0.54***	0.48***
Shared central heating	-1.13***	-0.90***	-0.73**	-0.60***	-0.66***	-0.89***
Individual central heating	-0.20***	-0.08*	-0.07	-0.09*	-0.14***	-0.20***
Multi-unit housing (flat)	-0.27***	-0.19***	-0.16***	-0.22***	-0.10**	-0.19***
Wood heating energy	-0.56***	-0.37**	-0.39***	-0.43***	-0.39***	-0.35***
Electricity heating energy	-0.69***	-0.61***	-0.50***	-0.40***	-0.40***	-0.51***
Gas heating energy	-0.26***	-0.16***	-0.20***	-0.20***	-0.21***	-0.18***
Other heating energy	-0.48***	-0.25***	-0.23***	-0.28***	-0.21***	-0.31***
Equipment Rate	0.15**	0.13**	0.10***	0.10***	0.07***	0.12***
Heating temperature	0.37	0.39*	0.73***	0.86***	0.56	0.51***
Lower the heating of the bedroom	-0.06	-0.06**	-0.03	-0.09***	-0.10***	-0.06***
Unoccupied 4 to 8 hours per day	-0.02	-0.04	-0.04	-0.02	0.03	-0.03
Unoccupied more than 8 hours per day	-0.13	-0.16	-0.09**	-0.02	-0.09**	-0.11***
Heating degree days (HDD)	0.21	0.21**	0.24***	0.24***	0.24***	0.30***
Paris conurbation	0.00	0.07	-0.09	-0.05	-0.12**	-0.08*
Rural commune	-0.11	-0.01	-0.01	0.02	0.08	0.01
From 20,000 to 200,000 inhabitants	-0.11**	-0.02	-0.07**	-0.06	-0.02	-0.10***
More than 200,000 inhabitants	-0.18	-0.02	-0.07**	-0.04	-0.01	-0.08***
Prefer comfort to economy	0.14***	0.10***	0.05**	0.05**	0.05	0.06***

****, **, * indicate that estimates are statistically different from zero at 0.01, 0.05 and 0,1 levels, respectively.*

4.1. Energy price

The direction and magnitude of the energy price effect are consistent with the findings in the literature: an increase in the energy price implies a systematic decrease in energy consumption. Here, energy price elasticity is around -0.47 on average (column 6). Otherwise, we find that the magnitude of energy price elasticity varies according to the energy consumption quantile considered. The results in table 3 show that low energy consumers (-0.43 for the 10th quantile) have lower sensitivity to energy price compared to large consumers (-0.66 for the 90th quantile). Our findings are in line with Nesbakken (1999) who argues that energy-price elasticity in residential energy consumption is higher for high-income households. Our results also support the findings in Labandeira et al. (2017) that energy price elasticity demand depends on various factors and is not homogeneous among groups of individuals. They demonstrate that the magnitude of the price elasticity varies depending on type of consumer, sector, energy source, etc. Other studies provide evidence that the response to energy price varies with income level but there no consensus on the relationship (Bakaloglou and Charlier, 2018; Schulte and Heindl, 2017).

4.2. Energy efficiency

As expected, improving the energy efficiency of a dwelling results in a significant decrease in energy consumption. In our case, a 100% increase in energy performance results in a reduction in final energy consumption of 10% to 21%, depending on the energy consumption quantiles considered.

The size of this effect might seem low. However, its magnitude may be due to several factors. First, the scope of energy efficiency and final energy consumption are different. The energy efficiency variable includes only energy used for heating and hot water whereas final energy consumption includes all energy sources; thus, changes in energy efficiency and final energy consumption are not symmetric. In addition, improved energy efficiency has a well-known direct rebound effect, i.e. an increase in demand for energy service because of its reduced cost (this is consistent with our results for the effect of energy price on energy consumption). Thus, a share of the theoretical energy savings we can expect from improving the energy performance of a dwelling is lost (Belaïd et al., 2018). Numerous studies provide evidence of a rebound effect in relation to energy consumption in the residential sector (Galvin, 2015; Khazzoom, 1980; Thomas and Azevedo, 2013), and suggest that enhancing housing energy efficiency has behavioral side effects that may undermine the benefits in terms of energy consumption reduction.

4.3. Socio-economic variables

Table 3 shows that the coefficients of household socio-economic attributes are significant. In relation to the income effect, our results show that the effect is significant only for one quantile. However, in the OLS regression the effect is very weak and significant at the 10% level. This is in line with most previous studies which argue that the income effect is either not significant or is very low, ranging from 0.01 to 0.13 (Labandeira et al., 2006; Bélaïd, 2017, Lévy and Bélaïd, 2018).

Our results show that the coefficient of age of the household head has a positive significant effect on energy consumption except in the 10^{th} quantile. The positive and significant effect of household responsible person (HRP) is in line with energy consumption life cycle theory (Fritzsche, 1981) which suggests that domestic energy consumption increases during child-rearing years and declines when the children leave home.

The results in table 3 show that depending on the quantile, household size affects energy consumption but only to a limited extent. The estimation ranges from 0.07 to 0.11. This finding suggests that an increase in the number of household members contributes to higher levels of energy consumption. The positive and significant effect of family size on household energy consumption is in line with the findings from previous research (Brounen et al., 2012; Estiri, 2015a).

The effect of occupation status is not always significant according to the energy consumption quantiles but is always negative. The results show that owner occupiers consume less energy than tenants. Although the effect of this variable is globally significant, it can be assumed that in the quantile regression it will interact with other characteristics such as income and/or type of dwelling. However, there is no consensus on the effect of type of occupation on domestic energy consumption; some studies report higher consumption in private housing units while others observe significantly lower energy consumption in privately owned houses (Jones et al. 2015). For example, Bélaïd (2016) suggests that tenants consume about 22% less energy than owners.

4.4. Dwelling characteristics

The model shows that size of the dwelling has the expected impact on household electricity consumption. Larger home size leads to increased electricity consumption. Our results show that the effect is positive and significant across all quantiles. The estimations range from 0.41 to 0.54. However, it should be noted that the quantile regression does not add information to the model. Our results coincide with Kaza (2010) and Huang (2015).

The effect of heating system type is significant in all the quantiles. In the case of central heating, the effects range from -0.60 to -1.13 for shared central heating. Several studies examine the influence of different space-heating systems on domestic electricity consumption (Jones et al., 2015). Energy sources can explain energy consumption variability. If we consider all energy types, the effects are systematically higher for lower quantiles. This might suggest that for low energy consumers, energy source is a major explanatory factor in energy consumption variability.

As expected, the effect of housing type is significant for all quantiles but more important for the first quantile compared to the upper ones. The findings suggested that households living in multi-unit housing consume 10%-27% less energy than people living in individual housing units, depending on the quantile. The results are in line with previous findings and confirm the OLS regression. Several studies argue that residential energy consumption increases with the degree of detachment of the housing unit (Jones et al., 2015).

4.5. Dwelling location

Finally, the coefficients of the environmental variables related to dwelling location are significant and have a strong impact on household energy consumption. For example, living in a cooler region involves higher energy consumption (HDD variable). Our results are consistent with previous findings that suggest that climatic conditions have a positive and significant effect on energy consumption (Belaïd et al, 2019). Lin et al. (2014) highlight that climatic conditions are the main variables driving domestic energy consumption. In addition, dwellings located in Paris consume less energy than those located in other areas on average. We interpret this as due possibly to high housing density in the Ile-de-France area.

4.6. Behavioral and preferences variables

Table 3 shows that heating temperature has a positive and significant effect on final energy consumption. Heating energy use accounts for almost 60% of global energy consumption in the residential sectors of western European countries; thus, this effect is consistent with our expectations. The heating temperature effect is stronger in the upper quantiles than in the lower quantiles. The results show a very high elasticity for high energy consumers (0.86 for the 75th quantile of energy consumption) compared to low energy consumers (0.39 for the 25th quantile). We interpret this as possible evidence of household needs and preferences for comfort which contribute to higher energy consumption.

Unsurprisingly, equipment has a positive but differentiated effect on final energy consumption. We show that the magnitude of the effect is decreasing depending on the energy consumption quantiles. Thus, we find a lower effect of equipment rate on energy consumption for high consumers of energy. The marginal effect of new equipment could be smaller if the household already consumes large amounts of energy.

Finally, stated preferences and energy-related behaviors are consistent with the observed effect on the variability of energy consumption. Households declaring lowering the heating temperature in the bedroom consume significantly less energy than others. In addition, we find that the preference for comfort over energy saving is another discriminating factor explaining energy consumption. Our results show that on average, preferring comfort leads to a 5% increase in energy consumption. For both variables, quantile regression is congruent since the effects are different for the extreme energy consumption quantiles. These results are supported by the theoretical frameworks in previous research for household lifestyle and behavior in shaping household energy use (Belaïd, 2017; Sanquist et al., 2012).

5. Conclusion

The residential sector accounts for the major share of total primary energy consumption in most countries. The residential sector is a large energy consumer but also is a major emitter of greenhouse gas emissions. Examining the determinants of energy use in residential dwellings presents significant complexities, shaped by a wide range of inter-related factors including housing characteristics, climate, household attributes, behavior and householders' lifestyle.

Energy policymakers are increasingly concerned about the main drivers of household energy use. Disentangling residential energy consumption is seen as an important step towards the design and implementation of effective policies to improve energy efficiency in this sector.

Based on the results of a new, rich, micro-level survey combining several types of information on dwelling attributes, and occupants' characteristics and behaviors, this article presents new evidence on how various factors affect residential energy consumption in France. First, this paper developed an adaptive elastic net approach, a form of model regularization for the purpose of model selection. It examined the salient drivers of household energy consumption in France using quantile regression model. The proposed methodology provides empirical evidence that adds to the existing knowledge and provides insights into the effect of building and occupant attributes and behavior on domestic energy use.

The findings suggest that overall, most of the model variables are statistically significant at the 1% level. Using OLS, the adjusted R^2 statistic is equal to 0.76 and is reasonably high given that the dependent variable was estimated in share form. Our findings demonstrate that cross-sectional variation in residential energy consumption is a function of both the technical characteristics of the building and the socio-economic attributes and behavior of the household. The analysis suggests that the impact of housing, demographic and socioeconomic attributes on household energy consumption differs across quantiles and OLS. In addition, the direction and magnitude of the effects can vary across quantiles.

The household attributes that seem to have the strongest effect on energy use are age of the household head, household size and occupation status. Household income has a less important effect on energy consumption in French homes. Among housing attributes, we observed significant and positive effect for house size and individual housing unit. Our results confirm previous theoretical frameworks regarding the effect of household behavior and suggest that high heating temperatures and large equipment rate contribute to higher energy consumption.

Our empirical results identify what characterizes high energy consuming households. Strategies to reduce energy consumption in the residential sector should be tailored to the specific profiles of households. Given the need to reduce energy consumption and carbon emissions from the residential sector, the findings in this paper could help the design of energy saving campaigns and future energy policy.

From a policy-making perspective, although study does not assess particular energy reduction scheme or policies, it highlights the need to consider their differential impact on domestic energy consumption. These findings may help policymakers to shape future policy intervention and regulations targeted on reducing housing energy use. Our results underline the importance of residential energy efficiency improvement to achieve the French policy target regarding energy and pollutant emission reduction.

There is remarkable agreement about the considerable promise for reducing the financial costs and environmental damages associated with energy consumption of building energy-efficient technologies. Unfortunately, but these technologies appear not to be adopted to the level that seems substantiated, even on a merely private basis.

In addition to contributing to the energy policy debate, this study adds to ongoing research on residential energy consumption by providing a more elaborated overview of its various facets. Existing French housing stock provides opportunities for energy saving, as underlined by French government debates but requires long-term strategies such as private energy efficiency investments.

Researchers and policymakers developing multiple strategies and intelligent policies to foster improved energy efficiency in the residential sector face various issues related to: (1) regulation reforms (e.g. cost-effective energy pricing, energy efficiency targets by sector, codes/standards with enforcement mechanisms development, etc.); (2) data and information collection (e.g. energy consumption data, case study evidence, etc.); (3) incentive and financial measures (e.g. public sector energy efficiency financing, credits for residential and home appliances, etc.); (4) technical capacity improvements (e.g. certification programs and energy audit/manager training, development of energy management systems, etc.); and (5) institutional reforms (e.g. dedicated entities with energy efficiency mandates, clear institutional roles/accountability, and authority to formulate, implement, evaluate and report on programs, etc.).

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