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WORKING PAPER

ENERGY CONSUMPTION IN THE FRENCH RESIDENTIAL SECTOR: HOW MUCH DO INDIVIDUAL PREFENCES MATTER?

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The aim of this research is to understand the weight of preference heterogeneity in explaining energy consumption in French homes. Using a discrete-continuous model and the conditional mixed-process estimator (CMP) allows us to tackle two potential endogeneities in residential energy consumption: energy prices and the choice of equipment. As a major contribution, we provide evidence that preferences for comfort over energy savings do have significant direct and indirect impacts on energy consumption, especially for high-income households. Preferring comfort over economy or one additional degree of heating implies an average energy overconsumption of 10% and 7.8% respectively, up to 36% for high-income households. Our results strengthen the belief that household heterogeneity is a substantial factor in explaining energy consumption and could have meaningful implications for the design of public policy tools aimed at reducing energy consumption in the residential sector.

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1. Introduction

Energy efficiency in the residential sector is a significant lever for meeting 2020 EU energy targets. During the past years, driven by its EU commitments, France has set numerous public policies aiming at reducing energy consumption in the residential sector, including thermal regulations for residential construction (RT2000, RT2005, and RT2012[1]) and thermal retrofits[2]. Despite these measures, energy consumption due to space heating in permanently occupied dwellings in France decreased by only 12% between 1990 and 2013 (CEREN[3]), demonstrating that there is still a lot of work to do to achieve national energy goals (-38% by 2020[4]). In order to achieve them, renovation measures and social interventions to encourage more efficient use of energy are potential solutions (Lopes et al. 2012).

Economists have brought to light that 40% of energy consumption in the residential sector is determined by technical factors (Belaïd 2016) but that about 33% is determined by socioeconomic characteristics such as revenue, household age, and tenure status. The role of behavioral characteristics in energy consumption variability (Belaïd 2016; Belaïd and Garcia 2016; Cayla et al. 2011) has also been highlighted. Understanding the determinants of energy consumption has been a recurrent topic of research over the past years and is an important issue in estimating the energy-savings potential of energy policies. Using only engineering models to predict energy consumption has shown limitations in including and modelling the effect of individual heterogeneity (Galvin and Sunikka-Blank 2014) and environmental factors; moreover, the current empirical economics literature on this issue is dense but limited by the availability of appropriate data.

[1] http://www.rt-batiment.fr/batiments-neufs/reglementation-thermique-2012/presentation.html
[2] http://www.planbatimentdurable.fr
[3] http://www.ceren.fr/
[4] Loi Grenelle 1 https://www.legifrance.gouv.fr/affichTexte.do?cidTexte=JORFTEXT000020949548

Improving understanding of the energy consumption spectrum also requires that empirical research go further in the identification of individual determinants. More specifically, analyzing the effect of individual preferences for energy use, from which energy savings and energy-intensive behaviors are derived, is crucial to understand how important household heterogeneity is in explaining variability in energy consumption. The issue has generally been neglected in the economics literature (Lopes et al. 2012), especially because of the lack of relevant data. Thanks to the PHEBUS survey providing information on preference heterogeneity for different kinds of residential energy uses, this research aims at partially filling this gap.

The main hypothesis of this research is that individual preferences regarding household energy use do have a role in explaining energy consumption in French homes. To test this assumption and account for the growing empirical concern of considering the interactions between dwellings and household characteristics when modeling energy demand, we use a discrete-continuous model based on McFadden's pioneering work (1984). In our research, we consider that individual energy consumption preferences may be manifested in two ways. We consider that household preferences for comfort and socioeconomic characteristics influence both the characteristics of their homes (in this case the energy-efficiency level of the dwelling chosen by the household at the time of purchase or rental), and the amount of final energy they consume.

Our research is based on the *PHEBUS*[5] survey, which includes complete thermal data, Energy Efficiency Certificates (energy-efficiency classifications), and socioeconomic characteristics for more than 2000 dwellings as well as newly available information about household behaviors and preferences.

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[5] http://www.statistiques.developpement-durable.gouv.fr/sources-methodes/enquete-nomenclature/1541/0/enquete-performance-lhabitat-equipements-besoins-usages.html

This paper thus contributes to the large literature on the determinants of energy consumption by providing an original analytical framework thanks to the use of an innovative dataset. We provide evidence that individual energy use preferences are a significant driver of energy consumption for high-income households, both directly and indirectly. Our main results show that preferring comfort over economy for two or three types of energy use implies energy overconsumption of 10% on average. If we consider the subpopulation of households belonging to the three highest income deciles, surplus energy consumption from high and medium preferences for comfort lies between 22 and 36%. For low-income households, we find no significant effect of preferences but a lower energy price elasticity. In line with these results, we advise policymakers to consider low-income and high-income households separately when developing and implementing public policy tools to reduce energy consumption in the residential sector. Moreover, through our methodology, we confirm the necessity of accounting for indirect determinants when assessing the drivers of energy demand in the residential sector. The paper is organized as follows. Section 2 presents the literature review. Section 3 describes the model. The data and the results are presented in section 4 and 5 respectively. Section 6 concludes with policy recommendations.

2. Literature review

2.1 Determinants of energy consumption: main direct effects

The final energy consumption of a dwelling is explained by three main determinants: technical building characteristics including local environment, household characteristics (socioeconomic characteristics, individual preferences, income, etc.), and energy price. This literature review also highlights the dearth of studies focusing on the share of energy consumption attributed to individual heterogeneity regarding energy consumption preferences.

Household characteristics

Concerning occupancy status, contrary to the theory that posits that tenants are likely to consume more energy than owners (misaligned incentives), empirical research fails to find a consensus on the effect of tenure status on energy consumption (Belaïd 2016; Charlier 2015; Jones et al. 2015; Yohanis 2012). Family structure and its position in the life cycle, however, do impact energy demand: The number of occupants has a positive impact on energy consumption (Leahy and Lyons 2010; Vaage 2000), and there is a cycle effect of the age of the reference person: energy consumption is comparatively higher for dwellings whose occupants are between 45 and 65 than for other age classes (Belaïd 2016; Brounen and Kok 2011; Brounen et al. 2013).

Regarding income elasticity (see Table 1 below), the effect is positive in most studies, which is consistent with the "normal good status" of energy consumption: income elasticity remains low, often less than 0.15. This low income elasticity is often attributed to the correlation between income and other characteristics such those of the home (Alberini et al. 2011) and occupancy status. Sometimes, however, the effect of household income is more complex. Although the poor use less energy, they have a relatively smaller opportunity to change their equipment. Positive elasticity may involve mainly the purchase of more energy-efficient appliances, which will induce lower energy consumption (Cayla et al. 2011; Labandeira et al. 2006; Nesbakken 2001; Santamouris et al. 2007). Income elasticity may also depend on income level: in 2013, Meier et al. (2013) investigated the relationship between household income and expenditures on energy services in the United Kingdom. As a key result, they find that the income elasticity of electricity and gas demand is contingent on household income. Households with low income exhibit a rather low income elasticity of energy demand (about 0.2). Households at the top end of the income distribution exhibit an income elasticity of up to about 0.6. Finally, in the recent work of Hache et al. (2017), the authors demonstrated with a non-linear approach (CHAID clustering method) that income level and global energy expenditures were intimately related in the french residential sector.

Individual preferences regarding energy use

Individual preferences regarding energy use refer here to the intrinsic disposition of individuals to save energy in their everyday life (Lopes and al. 2012); we do not include here individual preferences that are manifested in one-time actions like the purchase of energy-efficient appliances (cf. section 2.2 on indirect drivers). Depending on their nature, individual preferences can induce a wide range of everyday behaviors, from energy-saving behaviors (energy conservation, restriction) to energy-intensive behaviors. The tendency of households to save energy in the residential sector is a multi-dimensional phenomenon resulting from a trade-off between diverging motivations; it is positively linked with environmental awareness and normative concerns or economic motivation and negatively affected by immediate welfare considerations (Lindenberg and Steg 2007). The work of Hamilton et al. (2013) demonstrates that energy consumption may greatly differ (by up to three times) among dwellings with similar technical characteristics. Thus, assessing the extent of the effect of individual preferences is a crucial step in better understanding the impact of individual heterogeneity on real energy consumption variability.

However, individual preferences have generally been neglected in the economics literature (Lopes et al. 2012) especially because of the lack of appropriate data. Assessing the effect of individual energy use preferences on energy consumption variability is complex, and the estimation strongly depends on the indicator used and the scope considered. Moreover, turning the estimated effect into an energy savings potential that can be targeted by public policies is even more complex: indeed, it can be assumed that only a moderate share of the energy overconsumption induced by individual preferences for intensive energy use is flexible and reversible.

Some scholars approach the issue of preference heterogeneity in energy use by studying the relationship between the effective intensities of energy use for several energy services (i.e. observed energy behaviors like the heating temperature, the running time of appliances, the frequency of realization of some energy services, etc.), household and dwelling characteristics, and energy consumption (Belaïd and Garcia 2016; Santin 2011; Yun and Steemers 2011). Santin (2011) found that the number of hours of heating at maximal temperature explains 10.3% of the variability in heating energy consumption. However, in many cases, scholars often model energy savings behavior as an end in itself and not as a proxy of individual heterogeneity able to explain energy consumption variability. The major results of these studies show that energy savings actions are context-dependent (Belaïd and Garcia 2016; Lopes et al. 2012): living in a energy inefficient dwelling and facing higher energy prices induce more energy-efficient behavior.

The other approach found in the literature is more public policy oriented by giving estimates of the energy savings potential achievable through specific government interventions. Scholars use field experiment studies to assess the effect on energy consumption of information campaigns targeting intensive uses of energy. They test on small samples the effect of energy-behavior advice or information on energy consumption and find that more informative bills and advice on reasonable energy use results in a 10-percent energy savings for electricity (Ouyang and Hokao 2009; Wilhite and Ling 1995). In the literature review of Lopes et al. (Lopes, Antunes, and Martins 2012), the synthesis shows that the savings potential from a change in energy saving behaviors ranges from 1.1% to over 29%.

Technical building characteristics and environment

Technical building characteristics and environment can account for more than half of the energy consumption variability in the residential sector. The size effect is positive if we look at its influence on total consumption but is negative if we consider consumption/m2 (“returns to scale effect”). Some estimations demonstrate that up to 57% of total heating energy consumption can be due to the size effect (Risch and Salmon 2011; Estiri 2015; Baker and Rylatt 2008; Harold, Lyons, and Cullinan 2015). Apartments generally consume less than single-family homes because of their smaller heat loss surface (Rehdanz 2007; Wyatt 2013; Vaage 2000). The influence of the dwelling’s construction date on energy consumption (electricity excluded) is not universal, but generally, older buildings consume more energy than recent ones (Rehdanz 2007; Risch and Salmon 2011; Vaage 2000). Dwelling insulation (attic or cavity walls or global insulation) reduces energy consumption from -10% to -17% (Brounen, Kok, and Quigley 2012; Hong, Oreszczyn, and Ridley 2006). Finally, local climate also has an impact: in western countries, the longer the heating period is, the more energy the dwelling consumes (Kaza 2010; Belaïd 2017).

Energy prices

Price elasticity is always found to be negative, but estimates vary widely from -0.20 to -1.6. Energy price elasticities found in the literature are listed below. However, it is important to stress that the price elasticity of energy demand may depend on the energy considered, the methodology used, and the income level. Concerning its relationship with income, findings are not unanimous. For instance, disaggregation of households by expenditure and socioeconomic composition reveals that the behavioral response to energy price changes is weaker (stronger) for low-income (top-income) households (Schulte and Heindl 2017). However, Alberini et al. (2011) find that the price elasticity of electricity demand declines with income, but that the magnitude of this effect is small.

Table 1: Income and price elasticities in literature

Authors	Country	Price elasticity	Income elasticity
Parti and Parti (1980)	UK	Electricity: -0.758 Gas: -0.311	0,15
Dubin and McFadden (1984)	US	Electricity: -0.26	0,02
Baker et al. (1989a)	UK	Electricity: -0.758 Gas: -0.311	-
Bernard et al. (1996)	Canada	Electricity short-run: - 0.67	0,14
Nesbakken (1999)	Norway	All energies: -0,50	0,01
Vaage (2000)	Norway	Heating energy: -1.24	
Nesbakken (2001)	Norway	All energies: -0,21	0,06
Halvorsen and Larsen (2001)	Norway	Short-run: -0.43	---
Labandeira et al. (2006)	Spain	Electricity: -0.79 Gas: -0.04	
Katrin (2007)	Germany	Oil: [-2.03; -1.68] Gas: [-0.63; -0.44]	
Meier and Rehdanz (2010)	Germany	Oil: -0.4 Gas: [-0.34; -0.36]	
Alberini and Filippini (2011)	US	Electricity: [− 0.860; − 0.667] Gas: [− 0.693; − 0.566]	0,02
Bernard et al. (2011)	Canada	Electricity short-run: [- 0.51]	0,08
Fan and Hyndman (2011)	South Australia	Electricity: [-0.36; -0.43]	
Brounen et al. (2012)	Germany	Electricity: -0.4310 and Space heating: -0.5008	
Meier et al. (2013)	UK	Electricity price on energy spending: 0.7360	[0.2; 0.6]
Filippini et al. (2014)	EU	All energies: [-0.26; -0.19]	
Krishnamurthy and Kriström (2015)	& 11 OECD countries	Electricity: [−0.16; -1.4] France: −0.6523	[0.07; 0.108]
Miller and Alberini (2016)	US	All energies: [-0,56; -0,76]	
Risch and Salmon (2017)	France	All energies: -0,485	0,0295
Schulte and Heindl (2017)	Germany	Electricity: -0.4310 and Space heating: -0.5008	
Campbell (2017)	Jamaica	-0,42	0,42
Damette et al. (2018)	France	Wood [-1.553;-2.394] Electricity: -1.33 Gas: -1.22	[0.0294;0.0443]

2.2 Indirect determinants

For several decades, another way of accounting for the role of preferences or behavior when modeling energy consumption has been to integrate into energy demand models potential interactions between dwelling characteristics or energy-intensive appliances and household characteristics. By doing this, scholars assume the existence of implicit choices and preferences in terms of home characteristics and their effects on energy consumption. In line with this consideration, a large part of this economics literature uses the discrete continuous model (Dubin and McFadden 1984) or, more recently, new approaches such as covariance structure analysis or the structural equation modelling approach.

Models using the discrete-continuous framework assume that household characteristics could play a twofold role in explaining energy consumption: firstly, they influence the choice of home characteristics or appliances (indirect effect on energy consumption); secondly, once the appliances or home characteristics are considered, they also have a direct influence, all things being equal. Thus, scholars consider that energy demand is an indirect product of household choice and consumption behavior (Dubin and McFadden 1984). In 2006, Kriström (2006) explained that households do not demand energy "per se", but demand is combined with other goods such as "capital goods" (housing units, equipment units). Empirical evidence using the discrete continuous framework has confirmed this assumption: for example, Baker et al. (1989b) apply a two-stage model of energy demand to British expenditure data. Durable good appliances are first modelled, which then determines the energy demand of households. Vaage (2000) and Nesbakken (2001) demonstrate that analyzing energy demand conditionally to appliance or heating system choice is relevant in the residential sector. In the case of France, Stolyarova et al. (2015) model two discrete choices: the choice of end-use combinations by energy source or the choice of heating system by dwelling type.

Recently, scholars have demonstrated further interest in tackling the issue of interactions. Ewing and Rong (2008) show that higher-income households are more likely to live in big homes that consume more (Ewing and Rong 2008). More recently, Estiri (2015) spotlights the major interactions between building characteristics and lifecycle and socioeconomic household characteristics and quantifies the direct and indirect roles of each in energy consumption with a covariance structure analysis. He reaches the conclusion that the main effects of socioeconomic and lifecycle characteristics are carried out via building characteristics (expressed with a latent variable that includes surface, number of rooms, and tenure status). Using a general linear model and a path analysis, Yun and Steemers (2011) investigate the significance of behavioral (the proxy used is frequency of AC use), physical, and socioeconomic characteristics on cooling energy consumption. The findings suggest that such factors exert a significant indirect as well as direct influence on energy use, supporting the necessity of understanding indirect relationships. In the same vein, Belaïd (2017) uses a structural equation modelling approach (PLS approach) on French data to elicit the indirect role of household characteristics on building characteristics in order to explain residential energy consumption. His results are consistent with housing consumption theories that socioeconomic household characteristics play an important role in determining the physical attributes of a dwelling. Finally, the importance of accounting for interactions between a dwelling's physical attributes and household characteristics is also supported by the findings of Santamouris et al. (2007) in the UK: their work demonstrates that income explains the presence of several dwelling characteristics, including insulating building envelopes and building age.

3. Data and descriptive statistics

3.1 Data

This research uses data from the "PHEBUS" survey, a national household energy survey conducted by the Department of Observations and Statistics (SOeS), a subdivision of the French

Ministry of Ecology and Sustainable Development. The survey includes 2,040 dwelling energy audits performed by the same company in 2012 to study theoretical energy-efficiency measures; real energy consumption (based on energy bills); and social, economic, and behavioral data of dwelling occupants.

Energy performance certificates and building characteristics

Data sets available through this survey are quite innovative as they provide uniform assessments of Energy Performance Certificates (EPC) for each dwelling. These certificates have been produced by a single organization, which reduces any potential subjective bias in performance assessment. In our database, housing energy efficiency is classified into seven energy classes (according to French legislation): A, B, C, D, E, F, G (from the most energy efficient to the least).

As control variables, we use periods of construction (before 1919, from 1919 to 1945, from 1946 to 1970, from 1971 to 1990, from 1991 to 2005, from 2006 and after) and whether the house is detached.

Household characteristics, preferences, and tenure length

In order to control for household characteristics, we use income, number of persons, length of occupancy since move-in, the number of days of housing vacancy during the heating period, and the number of appliances belonging to each household.

The PHEBUS survey also contains information on household preferences. For each type of end use (heating, hot water, and electricity), it is possible to know whether households favor comfort or energy savings. It is therefore possible to have a scale of preferences. A strong preference for comfort will be measured as a declared preference for each end use, a medium preference as a declared preference for two out of three end uses, and finally a low preference as a single declared preference for comfort. Moreover, other variables can also be used as a proxy for comfort, for example, the heating temperature.

Energy price

Unfortunately, the PHEBUS database does not directly provide energy price information. In order to fill this gap, other information can help determine the energy cost for each household. Indeed, the data set provides information on the type and amount of energy consumed by each dwelling, but also on the type of energy rate (for gas and electricity) and the power required per type of fuel used (electricity, gas, oil). The power required and the type of energy rate depend on the type of fuel used for the heating system and in consequence the energy mix as well as the number of rooms (or the surface area). Thus, it is possible to have different energy rates per energy mix composition and the end use of each type of energy among households. However, no information is provided on the energy rate itself. To complete the PHEBUS data set, we looked into the PEGASE database (provided by the French Ministry of Energy, see appendix A, Table 6) to obtain the energy and subscription cost for each type of energy (oil, gas, electricity, and wood) per the power required and the type of rate in 2011 and 2012. Finally, it is possible to calculate for each household a weighted energy cost depending on the energy mix and the structure of energy consumption. With a weighted energy cost, we have a specific cost of energy for each household. The formula is the following:

$$energy\ price_i = \sum_{j=1}^{n} \frac{volume\ in\ kwh_{ift} \times energy\ price_{ft}}{total\ volume\ in\ kwh_i} \tag{1}$$

where f represents the type of fuel, i the household, and t the type of rate for a specific energy (electricity or gas).

3.2 Descriptive statistics

The main descriptive statistics of the variables used in the model are summarized in appendix B1 (Table 7). Based on these observations, we highlight several trends in our data. The average income, the surface, the occupancy status, etc. seem to be linked in some way with the energy class of each dwelling, which favors the underlying assumption of our model: the potential interactions between home thermal characteristics and household characteristics (Tables 2 and 3). This is consistent with the contribution of Santamouris et al. (2007). We also observe interactions between preferences, income level, and consumption (Table 4 and Table 8a in appendix). Finally, to complete the descriptive analysis, we run some t-tests based on the preference variable, available in appendix in Table 8b. We find that households with high comfort preferences live in dwellings that are statistically more energy efficient. Other t-tests confirm the highly significant relation ($p<0.01$) between energy consumption, high preferences for comfort, and income. The overall descriptive statistics argue in favor of the real need to properly control for thermal, economic, and individual characteristics when modeling energy demand in the residential sector.

Table 2: Descriptive statistics by energy class

Energy class ***Number of observations***	**A** ***5***	**B** ***43***	**C** ***281***	**D** ***564***	**E** ***598***	**F** ***301***	**G** ***248***
Average annual disposable income per household	51068 (22293)	50099 (39645)	46097 (28396)	43970 (25085)	38632 (20893)	37877 (25569)	31201 (18808)
Average number of occupants	3.2 (1.6)	2.9 (1.2)	2.9 (1.2)	2.7 (1.3)	2.5 (1.2)	2.3 (1.1)	2.2 (1.1)
Percentage of individual houses (%)	100	84	79	78	84	81	74
Percentage of renter-occupied dwellings (%)	0	16	18	19	21	25	35
Mean surface (m2)	172 (63.3)	151 (92.2)	127.7 (49.7)	118.7. (45.7)	110 (47.1)	97.5 (40.6)	90.5 (44.0)
Number of years spent in the current dwelling	10.4 (5.8)	10.3 (9.7)	13.1 (11.0)	15.7 (12.8)	18.5 (15.3)	19.5 (16.0)	20.7 (19.9)
Average number of appliances	19,8 (5.4)	22.2 (22.5)	17 (11.3)	16.7 (10.1)	16.6 (18.4)	14.7 (11.5)	12.7 (5.9)

Source: PHEBUS Survey 2012, authors' calculations. () corresponds to standard deviation

Table 3: Individual preferences for comfort over economy by dwelling's energy-efficiency classification

Percentage of households preferring comfort over economy for:	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Heating	80%	63%	58%	57%	58%	51%	55%
Hot water	60%	67%	58%	58%	57%	52%	48%
Specific electricity	40%	37%	44%	43%	41%	37%	39%
High preference for comfort*	20%	30%	31%	30%	31%	27%	26%
Medium preference for comfort*	60%	28%	23%	23%	22%	18%	20%
Low preference for comfort*	0%	20%	21%	20%	21%	24%	25%
No preference for comfort	20%	21%	24%	27%	27%	36%	29%
Heating temperature (in °C)	20.6	20.2	19.9	19.9	20.0	19.7	19.8

**This variable is compounded from PHEBUS data: high preference for comfort means that a household declared that it prefers comfort over economy for all three energy uses: specific electricity, heating, and hot water; medium preference means that this preference for comfort concerns two of the three energy uses; and finally, low preference means that the preference for comfort concerns only one energy use.*

Source: PHEBUS Survey 2012, authors' calculations

Table 4: Energy consumption and preferences according to income

	Energy consump-tion in kwh/m²		High preference for comfort		No preference for comfort		Preference for comfort for heating		Preference for comfort for electricity		Preference for comfort for hot water	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
D1	308.3	171.8	27.47%	44.75%	41.76%	49.44%	42.10%	49.49%	37.57%	48.55%	47.63%	50.07%
D2	309.8	206.4	17.77%	38.32%	30.78%	46.27%	45.88%	49.95%	30.66%	46.22%	50.66%	50.12%
D3	263.0	166.1	29.21%	45.59%	32.83%	47.07%	52.50%	50.06%	37.60%	48.56%	52.40%	50.06%
D4	260.9	140.9	26.70%	44.35%	28.89%	45.44%	53.33%	50.01%	36.19%	48.17%	56.12%	49.75%
D5	264.8	134.5	31.58%	46.60%	27.06%	44.53%	58.70%	49.36%	42.27%	49.52%	53.91%	49.97%
D6	248.7	115.8	27.19%	44.60%	33.22%	47.22%	54.25%	49.94%	33.13%	47.18%	57.27%	49.59%
D7	253.3	132.3	36.13%	48.16%	19.41%	39.65%	62.64%	48.49%	50.54%	50.12%	63.32%	48.31%
D8	241.5	112.4	32.46%	46.94%	18.59%	39.00%	66.07%	47.46%	47.56%	50.06%	60.02%	49.11%
D9	235.7	128.3	33.56%	47.34%	18.73%	39.11%	62.10%	48.63%	51.63%	50.10%	61.16%	48.86%

Source: PHEBUS Survey 2012, authors' calculations

4. Model

4.1 Theoretical background

The main assumption of this research is that individual preference for comfort has a significant positive impact on energy consumption. To test this assumption, we use a discrete continuous choice model framework to take into account the assumed interactions between household characteristics and the dwelling's energy-efficiency level, using a conditional mixed process. We consider that the household's decision is divided in two parts. In the first part, the household decides to live in a housing unit according to its theoretical energy performance; then, in the second part, it decides how much energy to consume according to its preferences. The specification of household fuel demand is based on a utility model with R* the stochastic indirect utility function of the households, which we suppose to be unobserved. Indirect utility V depends on the price of energy P, income Y, and household characteristics (including preferences) T, and is defined conditionally on the choice of energy label classification. We can therefore write:

$$R^*_{ij} = V_{ij}[P_i, Y_i, T_i] + v_{ij} \qquad (2)$$

where j=1, ..., J is the index of category, i=1, ...,N that of the individuals, and v_{ij} the error term. The Roy's identity gives us the household's Marshallian demand function for energy:

$$X_{ij}\left(P_j, Y_i, Z_i\right) = \frac{\partial V_{ij}\left(P_j, Y_i, Z_i\right)/\partial P_j}{\partial V_{ij}\left(P_j, Y_i, Z_i\right)/\partial Y_i} \qquad (3)$$

When simplified, the energy demand function conditional on energy category *j* by household *i* can be written as follows:

$$q_{ij} = \gamma_{ij} z_{ij} + \nu_{ij} w_{ij} + \beta_{ij} P_{2012i} + \eta_{ij} \tag{4}$$

where q_{ij} is the quantity of energy consumed by individual i in an energy classification j, z_{ij} is a vector of individual characteristics (including preferences, income, and mode of occupation), P_{2012i} is the energy price, w_{ij} is a vector of building characteristics (including localization), γ_{ij} and ν_{ij} are vectors of the related parameters, and η_{ij} the error term taking account of the influence of unobservable parameters.

4.2 The econometric methodology: a discrete continuous choice

In using discrete-continuous models, researchers consider that appliance or thermal equipment choices and consumption choice are bound (Dubin and McFadden 1984; Risch and Salmon 2017; Vaage 2000) and use these models to address selectivity biases in data sets with endogenously partitioned observational units (Frondel et al. 2016). In the field of residential energy consumption, the pioneering paper is that of Dubin and McFadden (1984): using heating equipment choice as a discrete step, the authors then study energy consumption determinants. These models are thus often used in the field of energy consumption because of interactions and endogeneity between independent explanatory variables. Generally, the estimation consists of two steps.

In our research, an original data set is used to apply this discrete-continuous choice method because we face two potential problems of endogeneity related to the choice of the dwelling's thermal performance (energy classifications, see figure 1 in the appendix) and endogeneity due to energy prices (proof in appendix section C.1). As a choice variable for the discrete choice, we propose to use theoretical energy performance of the dwelling by energy-efficiency classification. This classification, from an EPC assessment, is chosen as a proxy for the theoretical energy-efficiency level of the dwelling. Thus, we study which characteristics determine a household's probability of belonging to an energy-efficient classification level with an ordered probit. Energy classifications are also introduced in the continuous choice as explanatory variable; this allows us to capture interactions between energy efficiency and households while identifying direct drivers of energy consumption.

Thus, for the discrete choice of the model, we use an ordered Probit because energy performance classifications arise sequentially (Cameron and Trivadi 2010). For individual i, we specify:

$$y_i^* = x_i'\beta + u_i \tag{5}$$

with y^*a latent variable which is an unobserved measure of the dwelling's energy performance; x the regressors. For low y^*, energy performance is very high; for $y^* > \alpha_1$ corresponding to the energy classification threshold A-B to C, energy performance is a little bit lower; for $y^* > \alpha_2$ corresponding to the change from C to D, energy efficiency is even lower, etc. For a m-alternative ordered model (here $m = 6$ because of the 6 energy classifications we consider), we define:

$$y_i = j \quad if \;\; \alpha_{j-1} < y_i^* \leq \alpha_j, \qquad j = 1, \dots, m$$

$$\Pr(y_i = j) = \Pr(\alpha_{j-1} < y_i^* \leq \alpha_j)$$

The regression parameters β and the m-1 threshold parameters $\alpha_1, \dots, \alpha_{m-1}$ are obtained by maximizing the log likelihood with $p_{ij} = \Pr(y_i = j)$. Energy classes are also introduced in the second equation and used as regressors of final energy consumption expressed in kW/m^2/year with other explanatory variables. The model captures the possibility of correlation between unobservable variables in the discrete and continuous stages.

Conditional on the discrete choice, a household decides the quantity of energy to consume. Therefore, in the continuous choice, the total energy consumption (the logarithm of the energy consumption in kWh/m ^{2}) is estimated, conditional on the dwelling's thermal performance (energy-efficiency classification). This is the "energy consumption choice," which we estimate using a least square model. To control endogeneity of the energy price variable in 2012 (P_{2012i}), we introduce as instruments the lag of energy prices (P_{2011i}) and the type of energy rate for electricity.

We therefore have:

$$q_{ij} = \gamma_{ij} z_{ij} + \nu_{ij} w_{ij} + \beta_i P_{2012_i} + \varepsilon_i \tag{6}$$

with

$$P_{2012_i} = \alpha_1 P_{2011_i} + \alpha_2 TARIFF_i + v_{i,k} \tag{7}$$

where q_{ij} is the final energy per square meter consumed and z_{ij} and w_{ij} the regressors. We estimate the model using a double least squares model, which enables us to correct for the endogeneity issue of energy prices.

Finally, we have a system composed of a three-simultaneous-equations model. The model contains variables which are supposed to explain both choices: the choice of a dwelling with a certain energy-efficiency level and the choice of energy use. However, some exclusion (or selection) variables are also introduced in each equation: the duration since move-in and detached house for equation 1 (discrete choice) and the number of appliances and number of days of housing vacancy during the heating period for equation 2 (continuous choice).

4.3 The estimation process

In order to estimate jointly our three equations, we use the conditional mixed process (CMP) proposed by Roodman (2011). A CMP framework can be required to jointly estimate three equations with linkages among their error processes. The CMP also allows relationships among their dependent variables. This process fits a large family of multi-equation, multi-level, conditional mixed-process estimators and is particularly useful in the simultaneous equation framework with endogenous variables (as is the case here), or in a seemingly unrelated regressions (SUR)[6] configuration, where dependent variables are generated by processes that are independent but correlated errors that are not. Thus, the CMP modeling framework is essentially that of SUR, but in a much broader sense. The individual equations need not be classical regressions with a continuous dependent variable; they also may be estimated by ordered Probit. A single invocation of CMP may specify several equations, each of which may use a different estimation technique. Furthermore, CMP allows each equation's model to vary by observation. The main advantage of the CMP estimator to the SUR estimator is *recursivity* and *full observability* that work for a larger class of simultaneous-equation systems. The conditional mixed process is suited for estimations in which there is simultaneity but instruments allow for the construction of a recursive set of equations, as in two-stage least square (2SLS). In this case, the CMP is a limited-information maximum likelihood (LIML) estimator. The use of the maximum likelihood approach to estimate the three equations as a system rather than as a two-step estimator implies efficiency gains.

[6] See Arnold Zellner, 'An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias', *Journal of the American Statistical Association*, 57/298 (1962), 348-68.

5. Results

5.1 Drivers of energy consumption: Discrete-continuous choice model

The results of the two steps are presented in Table 5 below. Complementary results with other measures for preferences and proofs of the quality of estimations are provided in Table 11 in the appendix. Results confirming the existence of endogeneity are provided in section C.1 of the appendix.

Table 5: Results of the discrete-continuous model

	All Sample		Decile 1-2-3		Decile 8-9-10	
	Discrete choice	Continuous choice	Discrete choice	Continuous choice	Discrete choice	Continuous choice
Energy price in 2012	0.153**	-0.552***	-0.0195	-0.437***	0.523***	-0.714***
	(0.0736)	(0.0608)	(0.128)	(0.111)	(0.153)	(0.110)
Income (log)	-0.112**	0.0921**	-0.164	0.0928	0.284*	-0.0775
	(0.0529)	(0.0443)	(0.127)	(0.111)	(0.160)	(0.103)
High preference for comfort for heating	-0.00153	0.102**	0.0974	0.0630	-0.226*	0.181**
	(0.0631)	(0.0518)	(0.114)	(0.0992)	(0.123)	(0.0802)
Medium preference for comfort for heating	-0.0609	0.100*	0.103	-0.0127	-0.360***	0.218**
	(0.0677)	(0.0558)	(0.126)	(0.110)	(0.131)	(0.0896)
Small preference for comfort for heating	-0.0532	0.0621	0.0276	0.0848	-0.365***	0.156*
	(0.0675)	(0.0555)	(0.116)	(0.101)	(0.139)	(0.0947)
Number of appliances (log)		0.146***		0.183***		0.110**
		(0.0324)		(0.0671)		(0.0515)
Number of days of housing vacancy during heating period (log)		-0.0299***		-0.0548***		-0.00775
		(0.00910)		(0.0172)		(0.0152)
Control for individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control for building characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control for localization	Yes	Yes	Yes	Yes	Yes	Yes
Control for building energy class		Yes		Yes		Yes
Control for price endogeneity	Yes	Yes	Yes	Yes	Yes	Yes

N	2,040	2,040	613	613	612	612

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
The thresholds, or cut points, reflect the predicted cumulative probabilities at covariate values of zero. They are all significant at p<0.01

Estimates by subgroup of explanatory variables are given in Table 10 in the appendix in order to confirm the robustness of our results. Marginal effects are given in Table 11.
Individual characteristics include: number of occupants and duration since last move-in;

Building characteristics include: detached or non detached house, building construction period, surface
Localization characteristics include: climate zones. In France metropolitan, three main climate zones are considered, they gather territories with similar temperatures and meteorological conditions (including solar resource). Urban demographic informations are also included in localization.
Building energy class includes EPC energy classes.

5.1.1 Ordered probit (A-B is the reference class)

Results (Table 5) show that household and dwelling characteristics have a significant influence on the propensity to live in an energy-efficient dwelling.

Considering the global sample, income has a significant negative effect: households with higher revenue are more likely to live in energy-efficient homes than poor households. This could be linked with the higher price of real estate with good energy efficiency, i.e. “green value” (Hyland, Lyons, and Lyons 2013). This result is also in line with Santamouris et al. (2007). However, if we consider the subpopulations of the first three income deciles on one hand, and of the three last income deciles on the other hand, income elasticities may differ. We observe that households at the top end of the income distribution are more likely to choose less energy-efficient dwellings; wealthier households generally live in big detached houses which consume more and are less energy efficient. This result is still valid if we remove the individual preferences for comfort.

Variable energy price has a significant positive effect on the probability of belonging to a energy inefficient dwelling in the global model and the model for deciles 8-9-10, meaning that energy is more expensive in dwellings that consume more. This result could be meaningful in the fuel poverty framework.

Concerning other variables, effects for the global sample are summarized below. The age of the reference person has an impact: for the two higher age classes, households are more likely to live in a non-efficient dwelling than those under 44, the effect being higher for households in the last category (over 66 years). Moreover, dwelling occupancy period has a significant link with the energy efficiency of the dwelling. The more recent the move-in date is, the more likely households are to live in efficient dwellings. Two assumptions can be made: the higher availability of energy-efficient dwellings on the current real estate market (new dwellings are more energy efficient because of thermal regulations) and/or the greater attention paid by households to residential energy information (for several years, EPC information has been provided to potential renters and buyers). Some environmental characteristics are also correlated to the energy performance of dwellings. Concerning neighborhood, the less isolated the dwelling (in terms of shared walls), the more energy efficient it is likely to be. Urban area types also have an impact; compared to Paris and big cities, dwellings in rural areas are more likely to be energy inefficient; this result is consistent with (Belaïd 2016). Moreover, energy-efficient dwellings are more likely to be found in cooler climate zones. Finally, size and building type effects are also significant; the bigger the dwelling is, the more energy efficient it is likely to be; living in a bigger house increases the probability of being in an energy-efficient dwelling. A dwelling's energy efficiency is thus not only determined by household characteristics but also by its environmental and technical characteristics.

Finally, preferences for comfort over economy have a significant effect only in the model applied to households in the three lowest income deciles. Households declaring preferring comfort for at least one of the three energy uses considered (heating, hot water, or specific electricity) are more likely to live in more energy-efficient dwellings. For a wealthier household, having a strong preference for comfort raises the probability of living in an energy-efficient dwelling (class B) compared to others from 3.93% to 6.26% (see Table 12 in the appendix).

5.1.2 Direct drivers of energy consumption

Energy price elasticity is significant in our three models, ranging from -0.43 to – 0.714; it is consistent with previous findings presented in our literature review. Results show that the magnitude of the price elasticity differs between low and high levels of revenue. It is lower for low-income households (-0.43) and higher for high-income households (-0.714), meaning that poor households are less responsive to an increase in energy prices. This could be explained by the fact that they are already restricting their energy consumption to their basic requirements; thus, any increase in energy prices does not affect this subsistence consumption. This differentiation in energy price elasticities according to income level is consistent with the work of Schulte (Schulte, 2017).

Income elasticity in the model on the global sample is + 0.09, which is consistent with the findings in the literature for countries with similar climate and development characteristics, which range from 0.02 to 0.15. We do not find significant effects of income in the two other models.

Concerning our core assumption on the effect of individual preferences regarding energy consumption, our model confirms our hypothesis: individual preferences for comfort over economy are highly significant and have a direct positive effect on energy consumption. When the global sample is considered, preferring comfort over economy for two or three energy uses implies energy overconsumption of 10% on average. If we consider the subpopulation of households belonging to the three highest income deciles, the effect is significant and even higher: Energy overconsumption from high and medium preferences for comfort lies between 22 and 36%. Moreover, this result is strengthened by those obtained with the indoor heating temperature (see Table 11 in appendix). One degree Celsius more heat implies an overconsumption of 7.8%. Similar results are presented by SOFRES-ADEME (2009), which obtain an overconsumption of 7%.

This result can be interesting in terms of public policy development (see section 6). If we make a link with the results of the discrete choice presented above and the descriptive statistics (Table 13 in the appendix), we can provide a more complete picture of our findings: first, we demonstrate that richer households are more likely to live in energy-efficient dwellings. Then, for these households, the effect of individual preferences on energy consumption is positive and higher than that for the global population. Preferences for comfort could induce up to +36% of additional energy consumption. This result shows that there is a considerable scope of action for public policies to develop regarding the reduction of energy consumption by behavioral changes for this target population (i.e. wealthier households living in energy-efficient dwellings). Regarding poorer households, we highlight two important facts: they are more likely to live in energy inefficient dwellings where energy is more expensive. Moreover, their response to energy price is low, suggesting that they only address their basic needs regarding energy consumption. The equipment rate of households has also a significant impact on energy consumption. An increase in this rate implies an overconsumption of 14.6%. All these results are consistent with the literature review of Lopes et al. (2012).

Finally, regarding behavioral variables, we see that the duration of absence during the day has, unsurprisingly, a negative significant effect on total energy consumption. The number of appliances is significant and positive in explaining energy consumption.

In terms of dwelling characteristics, energy-efficiency classifications have the expected effects, significant and negative. The more efficient the home is, the less occupants consume energy. This suggests that, in our sample, the EPC measures available in our survey are at least partially representative of the levels of real energy consumption observed. Living in a more energy-efficient dwelling implies a lower effective energy consumption, all things being equal.

6. Conclusion and policy implications

This research provides a new proof of the significant role of individual characteristics in energy consumption. The key result of this research is to give a preliminary estimate of the magnitude of the effect of heterogeneity in preferences to explain energy consumption variability. To sum up, our research makes the following contributions:

- It confirms the role of common drivers of energy consumption for the French residential sector: energy price, income, age, environmental characteristics, energy efficiency of the dwelling, etc. However, our research also supports the existence of a differentiation of energy price elasticity according to household income level.
- It demonstrates that individual preferences for comfort over economy have a significant positive effect on energy demand for the global population: preferring comfort over economy implies on average a 10% increase in individual energy consumption, all else being equal. We show that this effect is higher in magnitude for high-income households, who are otherwise more likely to live in more energy-efficient dwellings.
- We provide new evidence of the importance of taking into account the role of indirect determinants when analyzing the drivers of energy consumption. Regarding our methodology, we applied the very well-known discrete continuous model framework pioneered by McFadden (1984) with a new perspective to account for the complexity of energy consumption. Our modelling of housing choice via the dwelling's energy-efficiency level (energy classification) is an important contribution of this paper. By using a nonlinear methodology to understand the drivers of residential energy demand, our approach, accounting for dwelling/household interactions, is in line with recent work (Estiri 2015, Belaïd 2017). In particular, we provide evidence that basic household and dwelling characteristics (surface, location, etc.) can determine thermal housing attributes, conditioning final energy consumption.

From an energy policy perspective, we have several recommendations. First, better mapping of the match between household socioeconomic characteristics and the energy characteristics of their dwellings could be very useful to develop more effective energy policies aiming at reducing energy consumption. In our analysis, we provide evidence that poorer households are more likely to live in energy inefficient dwellings; this means that poorer people live in dwellings that need to be renovated for improved energy efficiency. For these households, the high investment costs of energy retrofits could be a significant barrier to action, explaining the energy-efficiency gap observed in the literature (Gillingham and Palmer 2014). Otherwise, we have highlighted a lower energy price elasticity for low-income households, implying that they would be less responsive to economic tools like carbon taxation and more affected by its financial consequences. We suggest that policymakers wishing to tax energy be careful not to increase fuel poverty situations for these households.

On the other hand, if we focus on high-income households, attention should be paid to the significant effect of a change in preferences regarding comfort on energy consumption in energy-efficient dwellings: preferences for comfort could induce up to +36% of additional energy consumption. The connection can be made with the famous "rebound effect" (Gillingham, Rapson, and Wagner 2016) that accompanies better energy performance of a dwelling and leads to a reduced amount of energy savings induced by retrofits due to comfort improvement. If financial incentives for energy renovations are given to high-income households, who then decide to favor comfort over economy, implying less energy savings than expected by engineering models, then the allocation of financial incentives could become less cost effective in terms of public expenditures. Conditioning the amount of financial incentives on household's available economic resources, initial energy-efficiency level of the home, and the energy-savings potential of the retrofit measure could constitute an effective way to foster energy-efficient retrofits. Moreover, creating information campaigns promoting reasonable energy use and addressed to intensive energy consumers unaware of environmental impacts would also be an effective tool to reduce energy consumption (Ouyang and Hokao 2009; Wilhite and Ling 1995).

In conclusion, in line with the results of the research of Hache et al. (Hasche and al 2017), we recommend that policymakers aiming at promoting social welfare and achieving effective public policies keep in mind that low-income and high-income households should be considered separately when developing and implementing public policy tools to reduce energy consumption in the residential sector.

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Appendix

A. Energy prices

Table 6: Energy prices provided by PEGASE database

	2011	2012
ELECTRICITY TARIFF		
Electricity. blue rate. base option in euros (tax included)		
Annual subscription cost 3 kVA	64.94606	67.40325
Annual subscription cost 6 kVA	77.45169	80.36592
Annual subscription cost 9 kVA	90.3377	93.76717
Annual subscription cost 12 kVA	142.84527	148.13392
Annual subscription cost 15 kVA	164.85725	171.04758
Annual subscription cost 18 kVA	219.2238	227.44092
Price for 100 kWh (power 3 kVA)	17.02237	17.7994
Price for 100 kWh (power 6 kVA)	16.23193	16.9816
Electricity. blue rate. peak hours rate in euros (tax included)		
Annual subscription cost 6 kVA	93.13223	96.59658
Annual subscription cost 9 kVA	111.76704	115.91475
Annual subscription cost 12 kVA	189.49559	196.56458
Annual subscription cost 15 kVA	223.04773	231.32342
Annual subscription cost 18 kVA	254.38013	263.81675
Annual subscription cost 24 kVA	529.87303	549.78758
Annual subscription cost 30 kVA	652.50116	677.02358
Annual subscription cost 36 kVA	754.42164	782.73067
100 kWh peak-hours	12.91385	13.54292
100 kWh peak-off	8.76965	9.23933
Price for 100 kWh (power 6 kVA)	14.03546	14.70435
Price for 100 kWh (power 9 kVA)	13.02266	13.65389
Price for 100 kWh (power 12 kVA)	12.77758	13.39973
Electricity. blue rate. tempo option in euros (tax included)		
Annual subscription cost 9 kVA	109.04157	113.022
Annual subscription cost 12 kVA	203.35865	210.90942
Annual subscription cost 30 kVA	456.64613	473.54025
Annual subscription cost 36 kVA	566.42158	587.43975
100 kWh blue days and peak-off	6.8142	7.2111
100 kWh blue days and peak-hours	8.20155	8.65528
100 kWh white days and peak-off	9.8401	10.35061
100 kWh white days and peak-hour	11.7537	12.33594
100 kWh red days and peak-off	18.5589	19.40033
100 kWh red days and peak-hour	49.16455	51.17409
Electricity. market rate. in euros (tax included)		
All rates	13.41974	13.82434
DA rate	24.45679	25.13133
DB rate	15.8404	16.3847
DC rate	14.02566	14.45913
DD rate	12.84391	13.2134
DE rate	12.54369	12.91665
GAS RATE		
Natural Gas. price in euros (tax included)		
Annual subscription cost - base rate	43.8933	46.92645
Annual subscription cost - B0 rate	58.0092	61.97075
Annual subscription cost - B1 rate	185.18415	195.4546
Annual subscription cost - B2I rate	185.18415	195.4546

100 kWh PCS - base rate	9.3988	9.96987
100 kWh - B0 rate	8.0742	8.51871
100 kWh- B1 rate	5.58353	5.86163
100 kWh - B2I rate	5.58353	5.86163
Price for 100 kWh B0 rate	11.74238	12.42551
Price for 100 kWh B1 rate	7.08853	7.44654
Price for 100 kWh B2I rate	6.79365	7.13536
DOMESTIC OIL RATE		
Tariff of one ton of propane in tank	1670.297	1791.087
100 kWh PCI (Lower calorific value) propane in tank	12.96815	13.90596
Price of one ton of propane	1670.297	1791.087
100 kWh PCS (Higher calorific value) of propane	12.1036	12.97889
100 kWh PCI of propane	13.06961	14.01476
Bottle of 13 kg butane	30.19	31.75
100 liters of oil at Rate C1	88.79	96.88
100 kWh oil PCI at Rate C1	8.90482	9.71618
WOOD RATE		
One ton of bulk pellets	250	260
One stere of logs	63	67
100 kWh PCI of bulk wood	3.70588	3.94118

Source: PEGASE database, French Ministry of Energy

B. Descriptive statistics – Energy performance class

B.1 Main descriptive statistics

Table 7: Main descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Energy consumption in kwh/m²	170.562	99.901	2.258	814.740
Energy price in 2012	0.094	0.028	0.006	0.382
Energy price in 2011	0.090	0.027	0.006	0.308
Regulated rate with no subsidy	0.703	0.457	0.000	1.000
Regulated rate with subsidy	0.010	0.101	0.000	1.000
Disposable income	40394.0	24639.4	307.0	277601.0
Number of persons	2.544	1.298	1	10
High preference for comfort	0.295	0.456	0	1
Medium preference for comfort	0.218	0.413	0	1
Low preference for comfort	0.215	0.411	0	1
No preference for comfort	0.272	0.445	0	1
Heating temperature	20.458	6.692	8	99.0
Number of appliances	16.082	13.511	1	341.0
Number of days of housing vacancy during heating period	7.783	16.104	0	210.0
Duration since move-in	17.255	15.019	0	89.0
Non-detached house	0.437	0.496	0	1
Surface	111.8	49.3	15.0	600.0
Climate zone H1 - coldest	0.575	0.494	0	1
Climate zone H2	0.361	0.480	0	1
Climate zone H3	0.063	0.243	0	1
Town < 2000 inhabitants	0.274	0.446	0	1
Town between 2,000 and 10,000 inhabitants	0.132	0.339	0	1
Town between 10,000 and 50,000 inhabitants	0.148	0.355	0	1
Town between 50,000 and 200,000 inhabitants	0.110	0.313	0	1
City between 200,000 and 2,000,000 inhabitants	0.243	0.429	0	1
Paris	0.093	0.291	0	1
Period of construction				
Before 1919	0.170	0.376	0	1
1919 to 1945	0.090	0.286	0	1
1946 to 1970	0.174	0.379	0	1
1971 to 1990	0.325	0.468	0	1
1991 to 2005	0.175	0.380	0	1
2006 and after	0.066	0.249	0	1
Energy class				
A	0.024	0.152	0	1
B	0.138	0.345	0	1
C	0.276	0.447	0	1
D	0.293	0.455	0	1
E	0.148	0.355	0	1
F				
G	0.122	0.327	0	1

Table 8a: Analysis of preferences: Correlation between individual preferences and socio-economic characteristics

	Age	Number of consumption units	Revenu	High preferences for comfort	Medium preferences for comfort	Low preferences for comfort
Number of consumption units	-0.4104*					
Revenu	-0.1131*	0.3718*				
High preferences for comfort	0.0242	-0.0262	0.1086*			
Medium preferences for comfort	-0.0568*	0.0687*	0.0602*	-0.3414*		
Low preferences for comfort	-0.0347	-0.0011	-0.0396	-0.3384*	-0.2766*	
Preferences for comfort for heating use	0.0060	0.0224	0.1111*	0.5663*	0.2210*	-0.0947*

Significance level $p<0.05$,

Table 8b: *Analysis of preferences: ttest*

	Obs	Mean		t	Critical probability
		0	1		
Revenue, by Preference for comfort for heating	2038	37271.82	42791.16	t = -5.0449	0.00000
Revenue, by high preference for comfort	2038	38665.47	44532.82	t = -4.9310	0.00000
Revenue, by preference for comfort for hot water	2038	37430.96	44601.38	t = -6.5383	0.00000
Revenue, by preference for comfort for electricity	2038	37265.54	42888.56	t = -5.1529	0.00000
Real energy consumption, by high preference for comfort	2038	164.389	175.3014	t = -2.4484	0.0072
Real energy consumption, by preference for comfort for heating	2038	170.3639	171.0365	t = -0.1386	0.4449
Theoretical energy consumption, by high preference for comfort	2038	208.7363	190.8599	t = 2.9913	0.0014

B.2 Energy class

Figure 1: EPC energy-efficiency classifications

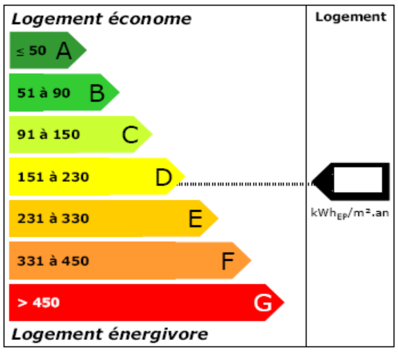

Table 9: Distribution of national dwelling stock into energy-efficiency classifications

Energy Class	Number of observations	At national scale	Share of housing stock (%)
A-B	48	439 585	2
C	281	2 724 895	12.6
D	564	5 483 573	25.4
E	598	6 322 821	28.3
F	301	3 361 569	15.6
G	248	3 257 038	15

C. Regressions

C.1 Quality test of instruments

First, we can perform tests to determine whether endogenous regressors in the model are in fact exogenous. After a 2SLS estimation with an unadjusted VCE, the Durbin (Jiang et al. 2014) and Wu–Hausman (Hausman 1978; Wu 1974) statistics are reported.

We check the consistency of the results with a VCE estimation. In all cases, if the test statistic is significant, then the variables being tested must be treated as endogenous.

Table 10: test of endogeneity

Ho: variables are exogenous	
Durbin (score) chi2(International Energy Agency (IEA)) = 5.27529	p = 0.0216
Wu-Hausman F(1,2016)= 5.25008	p = 0.0220
Robust score chi2(International Energy Agency (IEA)) = 5.42787	p = 0.0198
Robust regression F(1,2025) = 3.497085	p = 0.0616

We now explore the degree of correlation between the additional instruments (energy prices in 2011 and electricity rates) and the endogenous regressor (energy prices in 2012). Our exogenous variable can be considered a valid instrument if it is correlated with the included endogenous regressors but uncorrelated with the error term. Using a Stock and Yogo (2005) test, we can discuss the validity of the instruments. The null hypothesis of each of Stock and Yogo's tests is that the set of instruments is weak. To perform the Wald tests, we choose a relative rejection rate of 5%. If the test statistic exceeds the critical value, we can conclude that our instruments are not weak. In our model, the F statistic is 89361.3 and largely exceeds the critical value. Our instruments are not weak.

Minimum eigenvalue statistic = 89361.3

	5%	10%	20%	30%
2SLS relative bias	13.91	9.08	6.46	5.39
2SLS Size of nominal 5% Wald test	22.30	12.83	9.54	7.80
LIML Size of nominal 5% Wald test	6.46	4.36	3.69	3.32

Finally, to confirm our results, we perform tests of overidentifying restrictions. With the 2SLS estimator, Sargan's (Sargan 1958) and Basmann's (Basmann 1960) χ^2 tests are reported. A statistically significant test statistic always indicates that the instruments may not be valid. Here, the tests are not significant, so our instruments are valid.

Sargan (score) chi2(2) = 0.08529	p = 0.9583
Basmann chi2(2) = 0.084625	p = 0.9586

C.2 Estimations

Table 11: Model estimates by subgroup of variables

	Whole Sample		**With heating temperature**		**Subgroup 1**		**Subgroup 2**		**Subgroup 3**		**Subgroup 4**	
	DC	CC	DC	CC	DC	CC	DC	CC	DC	CC	DC	CC
Energy price in 2012	0.153**	-0.552***	0.139*	-0.521***	0.150**	-0.482***	0.127*	-0.474***	0.135*	-0.491***	0.141*	-0.504***
	(0.0736)	(0.0608)	(0.0739)	(0.0603)	(0.0738)	(0.0412)	(0.0736)	(0.0430)	(0.0737)	(0.0453)	(0.0740)	(0.0472)
Income (log)	-0.112**	0.0921**	-0.0965*	0.0830*	-0.0751		-0.119**	0.0623**	-0.123**	0.0700**	-0.127**	0.0790**
	(0.0529)	(0.0443)	(0.0526)	(0.0435)	(0.0488)		(0.0520)	(0.0312)	(0.0524)	(0.0337)	(0.0524)	(0.0342)
Preference for comfort: high	-0.00153	0.102**			0.0717		-0.00260	0.103***	-0.00201	0.102***	-0.00415	0.104**
	(0.0631)	(0.0518)			(0.0579)		(0.0632)	(0.0381)	(0.0632)	(0.0395)	(0.0631)	(0.0408)
Preference for comfort: medium	-0.0609	0.100*			-0.0200		-0.0605	0.0707*	-0.0636	0.0780*	-0.0554	0.0738*
	(0.0677)	(0.0558)			(0.0622)		(0.0679)	(0.0411)	(0.0679)	(0.0425)	(0.0678)	(0.0439)
Preference for comfort: low	-0.0532	0.0621			-0.0306		-0.0547	0.0424	-0.0577	0.0479	-0.0462	0.0384
	(0.0675)	(0.0555)			(0.0618)		(0.0677)	(0.0408)	(0.0677)	(0.0422)	(0.0677)	(0.0436)
Heating temperature			-0.0463***	0.0789***								
			(0.0164)	(0.0135)								
Number of appliances (log)		0.146***		0.139***				0.131***		0.142***		0.139***
		(0.0324)		(0.0322)				(0.0322)		(0.0324)		(0.0323)
Number of days of housing vacancy during heating period (log)		-0.0299***		-0.0273***				-0.0285***		-0.0296***		-0.0294***
		(0.00910)		(0.00905)				(0.00911)		(0.00915)		(0.00908)
Control for individual characteristics	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Control for building characteristics	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No
Control for localization	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes
Control for building energy class		Yes		Yes		Yes		Yes		Yes		Yes
Control for price endogeneity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2040	2040	613	613	2040	2040	2040	2040	2040	2040	2040	2040

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The thresholds, or cut points, reflect the predicted cumulative probabilities at covariate values of zero. They are all significant at p<0.01.

Table 12: Marginal effects for the ordered probit model

	Outcome 1	Outcome 2	Outcome 3	Outcome 4	Outcome 5	Outcome 6
Whole sample						
	Outcome 1	Outcome 2	Outcome 3	Outcome 4	Outcome 5	Outcome 6
Energy price in 2012	-0.0072	-0.0232	-0.0180	0.0073	0.0159	0.0251
Income (log)	0.0053	0.0170	0.0132	-0.0053	-0.0117	-0.0184
No. of persons	0.0023	0.0073	0.0057	-0.0023	-0.0051	-0.0080
Preference for comfort: high	0.0001	0.0002	0.0002	-0.0001	-0.0002	-0.0003
Preference for comfort: medium	0.0029	0.0092	0.0072	-0.0029	-0.0063	-0.0100
Preference for comfort: low	0.0025	0.0081	0.0063	-0.0025	-0.0055	-0.0087
Control for individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control for building characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control for localization	Yes	Yes	Yes	Yes	Yes	Yes
Decile 1-2-3						
	Outcome 1	Outcome 2	Outcome 3	outcome 4	Outcome 5	Outcome 6
Energy price in 2012	0.0006	0.0024	0.0026	0.0004	-0.0016	-0.0045
Income (log)	0.0048	0.0202	0.0221	0.0036	-0.0133	-0.0375
No. of persons	0.0028	0.0117	0.0127	0.0021	-0.0077	-0.0217
Preference for comfort: high	-0.0029	-0.0120	-0.0131	-0.0022	0.0079	0.0223
Preference for comfort: medium	-0.0030	-0.0127	-0.0139	-0.0023	0.0083	0.0236
Preference for comfort: low	-0.0008	-0.0034	-0.0037	-0.0006	0.0022	0.0063
Control for individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control for building characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control for localization	Yes	Yes	Yes	Yes	Yes	Yes
Decile 8-9-10						
	Outcome 1	Outcome 2	Outcome 3	outcome 4	Outcome 5	Outcome 6
Energy price in 2012	-0.0322	-0.0911	-0.0410	0.0494	0.0607	0.0543
Income (log)	-0.0175	-0.0494	-0.0222	0.0268	0.0329	0.0294
No. of persons	0.0020	0.0055	0.0025	-0.0030	-0.0037	-0.0033
Preference for comfort: high	0.0139	0.0393	0.0177	-0.0213	-0.0262	-0.0234
Preference for comfort: medium	0.0222	0.0627	0.0283	-0.0340	-0.0418	-0.0374
Preference for comfort: low	0.0224	0.0634	0.0286	-0.0344	-0.0423	-0.0378
Control for individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control for building characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Table 13: Distribution of income deciles for each energy-efficiency classification (%).

	A	B	C	D	E	F	G
D1	0	12	4	7	8	14	21
D2	0	5	7	6	11	15	16
D3	0	2	9	10	10	9	13
D8	20	14	14	10	11	6	6
D9	20	16	14	13	7	10	5
D10	20	12	14	13	8	9	5

Legend (upper table): 42% of the dwellings belonging to the energy class B are occupied by households in the three highest income deciles. 50% of the dwellings of energy class G are occupied by dwellings of the three lowest income deciles

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