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From Residential Energy Demand to Fuel Poverty: Income-induced Non-linearities in the Reactions of Households to Energy Price Fluctuations

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Abstract :

The residential energy demand is growing steadily and the trend is expected to continue in the near future. At the same time, under the impulse of economic crises and environmental and energy policies, many households have experienced reductions in real income and higher energy prices. In the residential sector, the number of fuel-poor households is thus expected to rise. A better understanding of the determinants of residential energy demand, in particular of the role of income and the sensitivity of households to changes in energy prices, is crucial in the context of recurrent debates on energy efficiency and fuel poverty. We propose a panel threshold regression (PTR) model to empirically test the sensitivity of French households to energy price fluctuations-as measured by the elasticity of residential heating energy prices-and to analyze the overlap between their income and fuel poverty profiles. The PTR model allows to test for the non-linear effect of income on the reactions of households to fluctuations in energy prices. Thus, it can identify specific regimes differing by their level of estimated price elasticities. Each regime represents an elasticity-homogeneous group of households. The number of these regimes is determined based on an endogenously PTR-fixed income threshold. Thereafter, we analyze the composition of the regimes (i.e. groups) to locate the dominant proportion of fuel-poor households and analyse their monetary poverty characteristics. Results show that, depending on the income level, we can identify two groups of households that react differently to residential energy price fluctuations and that fuel-poor households belong mostly to the group of households with the highest elasticity. By extension, results also show that income poverty does not necessarily mean fuel poverty. In terms of public policy, we suggest focusing on income heterogeneity by considering different groups of households separately when defining energy efficiency measures. We also suggest paying particular attention to targeting fuel-poor households by examining the overlap between fuel and income poverty.

Keywords : Residential energy demand, Income non-linearities, Price elasticity, Fuel poverty, Panel threshold regression, France

1 Introduction

The residential sector accounted for 25.40% of energy consumption in Europe in 2014 (EUROSTAT, 2017). The energy demand of this sector is still growing steadily in line with society's increasing economic affluence. This trend is expected to continue in the near future (Meier et al., 2013). As a consequence, enhancing our understanding of the determinants of residential energy demand and characteristics of households is important for the field of economics as well as for policy analysis. Although the question of the determinants of energy demand in the residential sector has been abundantly analyzed (Meier and Rehdanz (2010), Cayla et al. (2010, 2011), Newell and Pizer (2008), Braun (2010), Rich and Salmon (2017)), studies of the overlap between those determinants and the characteristics of households, particularly their fuel poverty profiles, are – to date – few and far between. In fact, on the one hand, there is ample literature on the determinants of residential energy demand which identifies variables explaining energy consumption by focusing mainly on the role of prices and income (*cf.* Section 2.1). On the other hand, the incipient literature on fuel poverty published over the last decade occupies an increasingly important space in the current energy landscape and focuses on the definition of fuel poverty, its measurement, and how to tackle it (*cf.* Section 2.2). Nevertheless, to develop public policies with the double objective of enhancing energy efficiency and fighting fuel poverty in the residential sector, there is a crucial need to understand to what extent households respond to these policies and if there are any heterogeneities in households' responses according to their fuel poverty profile. This goal can not be reached unless the issue of the determinants of residential energy demand and fuel poverty are jointly analyzed. At the European level, each government defines, in line with European objectives, it own policies that are adapted to the specific national context to address the issues of residential energy efficiency and fuel poverty. However, learning (and even spillover) from these heterogeneous national policies can be very useful and goes in hand in hand with interlocked European objectives. In this context, one of the objectives of the EU Energy Poverty Observatory (EPOV) created in January 2018 is to "*improve transparency by bringing together the disparate sources of data and knowledge that exist in varying degrees across the whole of the EU*" to "*promote informed decision making by local, national and EU-level decision makers*"[3] .

In terms of national efforts, the French government has and continues to take action to improve energy efficiency in the residential sector and to combat fuel poverty. More precisely, when adopting the Energy Transition for Green Growth (ETGG) Act on 17 August 2015, the French government set ambitious medium- and long-term objectives for its national energy policy. This policy deals with all sectors of the economy and mainly seeks to enhance energy autonomy, decrease greenhouse gas emissions by, among others, enhancing energy efficiency, and provide the necessary tools to stakeholders to support green growth[4]. In a context of a steady increase in energy prices, and to ensure social acceptability and enhance the implementation of ETGG measures, the French government included a social component in the ETGG Act, calling for, among others, the prevention of fuel poverty, a situation under which some households have serious difficulties in meeting

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[3] Source: `https://www.energypoverty.eu/about/role-and-mission`.

[4] In particular, the Energy Transition for Green Growth (ETGG) the Act of 17 August 2015 established six targets:

— contribute to the target of a 40% decrease in EU emissions by 2030,
— reduce national consumption of fossil fuels by 30% by 2030,
— reduce the share of nuclear energy in electricity production to 50% by 2025,
— increase the share of renewable energies in final energy consumption and in electricity production to 32% and 40%, respectively, by 2030,
— halve national final energy consumption by 2050,
— cut waste going into landfills by 50% by 2050.

their energy needs[5].

Currently, ONPE (2016) estimates the number of fuel-poor households at 3.8 million in France. With the expected large-scale diffusion of renewable energies and the associated carbon price increase from €56 per tonne by 2020 to €100 by 2023 driven by the ETGG Act, the cost of energy will plausibly increase and the conditions of access to energy will change. Therefore, some groups of the population are expected to find it difficult, or even impossible, to satisfy their energy needs, thereby exacerbating fuel poverty in both the residential and transport sectors. In this context, the government aims to ensure that the implementation of the targets of the ETGG Act will not increase the number of people suffering from fuel poverty. Hence, in addition to the several short- and long-term measures devoted to eliminating fuel poverty since the beginning of the 1980s (Dubois, 2012), the government continues to address the issue throughout the implementation of ETGG measures. In particular, regarding fuel poverty in the residential sector, curative measures have been implemented to help fuel-poor households to pay their energy bills, *i.e.* income support through an Energy Voucher (as of January 2018), affordable fuel pricing, and assistance with solvency in the event of arrears. French authorities have also implemented preventive policies that focus on the improvement of dwelling energy efficiency, *i.e.* dwelling insulation, double glazing, etc.

The recognition of these measures as tools to fight fuel poverty has usually been accompanied by debates on their efficiency. For example, curative measures such as social tariffs for electricity are usually particularly criticized for their lack of clarity from the perspective of the fuel-poor population as well as their lack of indexation on energy price fluctuations. Moreover, although recent in France, dwelling renovation measures are advocated to represent a more promising strategy to resolve the fuel poverty problem in more durable manner than curative measures.

Here, we argue that – regardless of the type of measure – the implementation of suitable public policies devoted to fighting fuel poverty in the residential sector requires an in-depth understanding of the determinants of residential energy consumption, particularly in the case of fuel-poor households, which are the primary target of the social component of the ETGG Act. No policy measure can be efficient unless households respond to it. Therefore, in this paper, by considering conventional determinants of residential energy demand, we focus on the non-linear effects of income on the reactions of households to energy price fluctuations. We give special attention to studying the sensitivity of fuel-poor households compared with that of non-fuel-poor households, as measured by the elasticity of heating energy prices. We integrate a new dimension in our analysis by considering the impact of income on the reaction of households to energy price variation, given other socio-economic and dwelling characteristics. Differences in the sensitivity of households, or alternatively, between the elasticities of energy prices, indeed depend on income level. By extension, we also look at implications of income-induced non-linearities in terms of the nature of the relationship between income poverty and fuel poverty: does income poverty necessarily translate into fuel poverty?

We carried out our research within the theoretical frameworks of the well-established literature on residential energy consumption and the more recent body of literature on fuel poverty. Our empirical approach uses the panel threshold regression (PTR), which belongs to the class of regime-switching models and makes it possible to test for non-linearities.

As far as we know, a study of income-induced non-linearities in terms of the distinction between people's reactions – in particular, on how fuel-poor households react to price fluctuations compared with non-fuel-poor households – has never been carried out before, although this issue is crucial for the implementation of policies that aim to eliminate fuel poverty and enhance energy efficiency

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[5] A detailed definition of fuel poverty is given in Section 2.2.

in the residential sector. This fresh approach brings three new contributions to the field. Firstly, this study explores this distinction between fuel-poor and non-fuel-poor reactions to changes in energy prices. Secondly, we shed light through our empirical analysis on the issue of whether income poverty is different from fuel poverty or immediately translate into fuel poverty (Watson and Maître, 2015). In particular, we assume in our empirical analysis that the problem of generalized poverty, as measured by the income level, is a determinant of fuel poverty and we look if effectively fuel-poor households determined under each PTR regime (elasticity) are income poor. Thirdly, this is the first panel empirical analysis on the fuel poverty issue. As far as we know, all previous empirical analyses dealing with fuel poverty have been conducted using a cross-section analysis, usually due to a lack of empirical data.

The paper is structured as follows. In Section 2.2, we detail two brief reviews of the literature on residential energy demand and fuel poverty measures. In Section 3, we conduct an empirical analysis that focuses on the income-induced non-linearity of household reactions to energy prices to determine if fuel-poor households are more or less sensitive to energy price variations than non-fuel-poor households and if they are also income-poor. We start in Sub-section 3.1 by presenting the econometric framework and data. Then, in Sub-section 3.2, we present and discuss our results. Finally, in Section 4, we discuss the policy implications of our results and conclude.

2 Literature reviews

In this section, we present two brief literature reviews on the two conceptual frameworks within which our empirical analysis is constructed, namely the well-established residential energy consumption literature and the more recent fuel poverty literature. Therefore, in Sub-section 2.1, we present a summary of the literature on the determinants of residential energy consumption by focusing on the estimations of energy prices and income elasticities. Then, in Sub-section 2.2, we first define fuel poverty and give a quick summary of conventional indicators used to measure it. We will use some of these indicators in our empirical analysis in Section 3 to determine the proportion of fuel-poor households in each PTR regime. We conclude this section by stressing the need to connect these two bodies of literature to understand sources of income-induced non-linearities in households' reactions to energy price variation, particulary in terms of household fuel poverty.

2.1 Determinants of residential energy demand

The literature dealing with the determinants of residential energy consumption is abundant and well established. Nevertheless, the difference between the reaction of fuel-poor and non-fuel-poor households has never been analyzed before. In other words, all studies to date have assumed that there is a linear relationship between these determinants and household demand for energy. These determinants can be classified into five groups.

Energy prices

Energy prices are usually recognized as one of the most important determinants of residential energy demand. The high number of estimations of price elasticity dealing with different time periods, different geographical areas, different econometric specifications, and different underlying theoretical frameworks highlights the considerable variability in estimations (Halvorsen and Larsen (2001), Nesbakken (2001), Meier and Rehdanz (2010)). These estimations show elasticity values ranging from 0.2 to 1.4 for own-price elasticity of demand for electricity, and from 0.04 to 1.6 for own-price elasticity of demand for natural gas (in absolute value) (Rich and Salmon, 2017).

In Table 1 below, we give a brief literature review on estimations of price elasticities regarding the demand for energy of the residential sector.

Household characteristics

Household characteristics mainly include the size of the household, *i.e.* single *vs* married, with or without children, the age, the type of housing tenure, the socio-economic situation and the income. Among these characteristics, estimations usually focus on the impact of household income, because – in the context of continuous increases in energy prices – households are frequently obliged to set up some consumption trade-offs depending on their budget. In particular, it is usually expected that an increase in income will cause an increase in energy demand.

Most estimations report a positive, but low, income elasticity ranging from 0.02 to 0.6 meaning that energy consumption responds weakly to an increase in income. Conversely, some studies report negative income elasticity, which may reflect energy savings induced by the use of more efficient energy equipment that a household purchases after an increase in income. As we have done for price elasticity, we give a brief literature review in Table 1 on the estimations of income elasticities regarding the demand for energy in the residential sector.

Interestingly, some studies, for example Cayla et al. (2010, 2011), underscore the role of household income as a determinant of the (French) residential energy consumption. They argue that households with lowest income are not in a position to make investments in more efficient heating equipment. This argument clearly emphasizes the key role of income in the decision process of the households with regard to its energy demand. It also points out the need to understand how households react to price variations by distinguishing between low- and high-income groups, or alternatively, fuel-poor and non-fuel-poor households.

Regarding the impact of other household characteristics, Meier and Rehdanz (2010), Santin et al. (2009) show that the age of the reference person and household size have a positive impact on energy consumption *ceteris paribus*. The effect of housing tenure is however rather ambiguous. In fact, some studies find that home-owners tend to consume more energy than tenants (Sardianou (2008), Vaage (2000)), but other studies find either the opposite result (Rehdanz, 2007) or a statistically non-significant effect (Meier and Rehdanz, 2010).

Dwelling and appliance characteristics

Several studies have tested for the impact of dwelling characteristics such as the dwelling type, *i.e.* apartment or detached house, its surface, its year of construction and its other technical characteristics, *i.e.* insulation, exposure, and daylight, on the residential energy demand. In this context, Santin et al. (2009) and Rehdanz (2007) argue that energy consumption of recent buildings constructed under strict thermal regulations is lower than that of older buildings in which energy efficiency was not a priority. In this context, Leth-Petersen and Togeby (2001) show that in Denmark, thermal building regulations play a key role in improving residential energy efficiency. Conversely, Sardianou (2008) found no evidence of the impact of buildings' thermal quality on energy consumption. He also found that there is no significant impact of housing type on the level of energy consumption. Nesbakken (2001) and Vaage (2000) report the opposite result.

In regard to dwelling characteristics, several studies have analyzed the impact of the type of appliances, particularly the type of heating system and fuel on residential energy consumption [6] (Bernard et al. (1996), Nesbakken (1999, 2001), Vaage (2000), Newell and Pizer (2008), Braun (2010)). More specifically, the aim of these studies is to analyze determinants of heating energy consumption as well as the impact of heating fuel costs on the choice of the type of heating system. For example, Vaage (2000) shows that the probability of choosing electricity as the only fuel for heating increases with income, and that the choice of electricity as heating fuel is more common in flats and new buildings. By extension, Nesbakken (1999) found that households having only electric heaters use far less energy than households using other types of heating systems.

Climate characteristics

Climate characteristics, in particular outside temperature, may have an impact on the level of residential energy consumption. During the winter, in a cold region, it is expected that heating needs increase. In this context, Nesbakken (1999), Meier and Rehdanz (2010), Vaage (2000) report a significant impact of outdoor temperature on residential energy consumption. The same also holds in (very) hot regions where the use of an air-conditioner depends on the temperature outside.

We present in Table 1 below a brief summary on price and income elasticities in residential energy demand. These elasticities are of primary interest in our estimations in Section 3.

Table 1 – Brief literature review on estimations of elasticities of energy prices and income in the residential sector

Reference	Country	Type of energy	Price elasticity	Income elasticity
Parti and Parti (1980)	UK	Electricity	-0.75	0.15
		Gas	-0.311	0.15
Dubin and McFadden (1984)	US	Electricity	-0.26	0.02
Baker et al. (1989)	UK	Electricity	—	-0.75
		Gas	—	-0.31
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	Electricity	[-0.43 [a]; -0.44 [b]]	—
Leth-Petersen and Togeby (2001)	Denmark	Oil	-0.08	
		District heating	-0.02	
Labandeira et al. (2006)	Spain	Electricity	-0.79	—
		Gas	-0.04	—
Rehdanz (2007)	Germany	Oil	[-2.03 ; -1.68]	
		Gas	[-0.63 ; -0.44]	
Killian (2008)	US	All energies	-0.45	—
Meier and Rehdanz (2010)	Germany	Oil	-0.4	—
		Gas	[-0.34 ; -0.36]	—
Alberini et al. (2011)	US	Electricity	[-0.86; -0.66]	0.02
		Gas	[-0.693 ; -0.566]	
Bernard et al. (2011)	Canada	Electricity	-0.51 [a]	0.08
Fan and Hyndman (2011)	Southern Australia	Electricity	[-0.36 ; -0.43]	—
Brounen et al. (2012)	Germany	Electricity	-0.43	—
	Germany	Space heating	-0.50	—
Meier et al. (2013)	UK	Electricity	-0.73	[0.2 ; 0.6]
Filippini et al. (2014)	EU	All energies	[-0.26 ; -0.19]	—
Krishnamurthy and Kriström (2015)	OECD [c]	Electricity	[-0.16 ; -1.4]	[0.07 ; 0.10]
Miller and Alberini (2016)	US	All energies	[-0.56 ; -0.76]	—
Rich and Salmon (2017)	France	All energies	-0.485	0.0295
Schulte and Heindl (2017)	Germany	Electricity	-0.4310	—
		Space heating	-0.50	—

a. Short-run.
b. Long-run.
c. 11 countries.

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[6] Usually (space) heating represents at least half of the household energy bill. For instance, in the UK in 2013, on average, around 51% of the theoretical household bill was devoted for space heating costs, 34% for lighting and appliance usage, 12% for water heating, and 3% for cooking costs (DECC, 2014).

2.2 Fuel poverty definitions and measures

Fuel poverty refers to a multidimensional concept that considers three main factors, namely the household's financial situation, the dwelling characteristics, *i.e.* energy efficiency, and energy prices (EPEE (2006), Devalière (2007), Palmer et al. (2008), Blavier et al. (2011)). A household is considered fuel-poor when it lives in an energy-inefficient dwelling and is unable to heat the home at an appropriate standard level of warmth [7] due to insufficient financial resources.

Despite the spread of fuel poverty in Europe and its recognition by governments as a social, public health and environmental policy issue in a context of ever-increasing energy prices, the European Union (EU) has not yet adopted a common definition of fuel poverty nor common indicators to measure it [8]. The UK government was the first to acknowledge the phenomenon and set up measures to fight it. In fact, the fuel poverty concept was born in the UK in the 1970s under the leadership of activist organizations that called the issue to the attention of authorities and the general population in light of the winter mortality induced by the steady rise in energy prices preventing some households from heating their dwellings at an appropriate standard level of warmth (Dutreix et al. (2014), ONPE (2014, 2015)). Two decades later, Boardman (1991), based on an earlier contribution by Isherwood and Hancock (1979), defined an indicator that has since been used in the 2001 UK Fuel Poverty Strategy to measure fuel poverty [9].

In France, the official definition of fuel poverty was published in the National Environmental Commitment Act (no. 2010-788 of 12 July 2010, "Loi Grenelle 2") amending the Housing Rights Act (no. 90-449 of 31 May 31 1990, "Loi Besson") [10]. According to this definition, a fuel-poor household represents a person who has difficulties inside his/her dwelling to have access to energy to satisfy his/her basic needs due to insufficient financial resources or inadequate dwelling characteristics *i.e.* energy inefficiency, presence of dampness and rot. Although it provided an official general framework for defining the fuel-poor, the French definition of fuel poverty remains impractical. In particular, it does not establish any clear-cut operational criteria to ensure the reliable identification of fuel-poor households and, therefore, frustrates the appropriate implementation of policies to fight fuel poverty (Host et al., 2014). Nevertheless, recently inspired by developments in the UK, the French national observatory of fuel poverty ("*Observatoire National de la Pauvrete Energetique*"; ONPE) suggests to use different objective and subjective indicators to measure the magnitude of fuel poverty (ONPE (2014, 2015)).

The recent literature on fuel poverty identifies three types of measures: objective factual measures, subjective self-reported measures and composite indices. Objective factual measures draw on measurable and observable criteria and are based on consumption theory. We distinguish between

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[7] According to the World Health Organization (WHO), an appropriate standard level of warmth is equal to 21°C for the main living area and 18°C for other occupied rooms (ONPE, 2015).

[8] However, the European Fuel Poverty and Energy Efficiency (EPEE) project conducted between 2006 and 2009 used a descriptive approach to analyze fuel poverty in some European countries, *i.e.* Belgium, France, Italy, Spain and the United Kingdom. It was based on three criteria: the ability to pay to keep one's home warm, the existence of dampness, leaks, mold in the dwelling and arrears on electricity, gas and water bills (EPEE, 2006).

[9] According to Fahmy et al. (2011), "*the Warm Homes and Energy Conservation Act, effective from November 2000 and introduced with cross-party support, represents the first formal acknowledgement of fuel poverty as a social policy issue requiring governmental intervention. This Act mandated the UK Government and Devolved Administrations to develop and implement a strategy to reduce fuel poverty, resulting in the 2001 UK Fuel Poverty Strategy. This official document committed the UK government and its devolved administrations for the first time to the ambitious goal of eliminating fuel poverty (DETR, 2001). Fuel poverty reduction targets include eliminating fuel poverty in England amongst "vulnerable" households by 2010, i.e. older persons, sick and disabled households and families with children, and amongst all households by 2016. These targets were reaffirmed in the 2007 Energy White Paper DTI (2007), and broadly similar targets are in place within the devolved administrations (DSDNI (2004), Scottish Executive (2002), WAG (2003))*".

[10] La "Loi Besson" no. 90-449 of 31 May 1990 stipulates that anyone encountering difficulties, particularly due to insufficient financial resources or inadequate living conditions, can benefit from public aid, according to the rules defined in the Act, for access to decent and independent housing with water, energy and telephone services - Translated from French (JORF, 1990).

expenditure-based measures, the restriction-behavior approach and consensual social measures. In particular, considering a given household, objective factual measures take into account the amount of expenditures devoted to satisfying fuel needs with respect to the total available financial endowments. We distinguish between the 10% indicator, the After-Fuel-Costs Poverty (AFCP) indicator and the Low-Income/High-Costs (LIHC) indicator. Subjective fuel poverty indicators are based on personal opinions, interpretations, points of view and judgment. They are usually constructed by referring to households' self-reported answers to questions asked by social investigators in a survey. The most frequently asked questions include "*Do you suffer from thermal discomfort?*", "*Have you had difficulty in paying your utility bills (in the past)?*", "*Can you afford your energy bills?*", or "*Are you satisfied with your heating equipment?*". Finally, composite indices were created as a compromise between the simplicity of one-dimensional indicators and the need to account for the multidimensional nature of fuel poverty. They represent an attempt to overcome the shortcomings of one-dimensional indicators and, at the same time, produce a result that condenses the information into single and easy-to-interpret metrics (Thomson and Snell, 2013). In particular, based on a set of sub-indicators, these indices aim to associate several attributes of fuel poverty that cannot be reliably depicted in a single indicator.

In Table 2, we give an overview of existing fuel poverty measures, their advantages, and their drawbacks. For each type of indicator, we also give the main references. Some of these references, mainly in the case of objective and subjective measures, have been behind the emergence and the widespread recognition of associated indicators (Boardman (1991), Healy and Clinch (2002), Hills (2011, 2012)).

Within this framework, the main issue behind measuring fuel poverty, or alternatively, identifying the fuel-poor households is to set up suitable public policies devoted to eliminating this problem in particular in the residential sector. Nevertheless, once correctly identified, the question of the effectiveness of these policies is, in reality, still pending. It depends on the role of income as a determinants of households energy spending and how these households react to energy price variations. To bridge the gap between the impact of income as determinants of residential energy demand and fuel poverty, we drop the linearity assumption between income and energy consumption and wonder if, given these non-linearities, fuel-poor households less or more sensitive to price variations?

Table 2 – Brief literature review on fuel poverty measures, their advantages and their drawbacks

Main references	Definition	Advantages	Drawbacks
1. Objective factual measures			
Expenditure-based measures			
UK Government based on Boardman (1991)	The 10% indicator: — Calculation : $I = \frac{\text{Theoretical fuel costs}}{\text{Equivalized income before housing costs}}$ — Rule: — if $I \geqslant 10\% \Rightarrow$ the household is fuel-poor, — if $I < 10\% \Rightarrow$ the household is not fuel-poor,	— The comparison between theoretical and actual energy consumption takes into account self-imposed under-heating.	— Based on an obsolete UK energy expenditures threshold dating from 1988, — Based on theoretical rather than actual energy expenditures, — Does not take into account restriction practices, — Does not take into account the income level of affluent households, — Does not take into account restricted expenditures.
Hills (2011)	The After-Fuel-Costs Poverty (AFCP) indicator: Fuel poverty if [Equivalized (Income − Housing costs − Domestic fuel costs)] < [60% equivalized (Median income − Housing costs − Domestic fuel costs)]	— Takes into account some constrained expenditures, *i.e.* housing costs, — Identifies the aggravating effect of fuel poverty on monetary poverty.	— May classify some households with very low income as fuel-poor regardless of their fuel needs, — Possible confusion between fuel and monetary poverty.
Hills (2011, 2012)	The Low-Income/High-Costs (LIHC) indicator: Fuel poverty if [Equivalized net income < 60% (Equivalized median net income)] and Equivalized fuel expenditures ⩾ Requires national median fuel expenditures	— Definition of two thresholds that distinguish fuel poverty from monetary poverty to ensure reliable identification of fuel-poor households.	— Not based on constrained income, — Does not take into account heating restriction behavior practiced in some households.
Restriction-behavior measure			
ONPES cited in Dutreix et al. (2014) and ONPE (2014)	The restriction behavior indicator: Theoretical fuel consumption − Actual fuel consumption	— Helps target households that have a cost analysis suitable for dwelling fuel investment.	— Theoretical energy expenditures are usually difficult to assess.
Consensual social measures			
Also *cf.* summary of Healy and Clinch (2002) and Nussbaumer et al. (2012) presented in the “Composite indices” section in this table)			

cf. next page

Table 2 – Continued

Main references	Definition	Advantages	Drawbacks
Healy and Clinch (2002) and Nussbaumer et al. (2012)	Possibility of using different objective indicators: — Presence of damp walls and/or floors, — Lack of central heating, — Presence of rotten window frames, — Access to electricity distribution, — Household appliance ownership.	— Captures the multidimensional nature of fuel poverty especially when included in composite indices.	— Results may be irrelevant if used irrespectively of other objective measures.
	2. Subjective self-reported measures		
Healy (2003), EPEE (2006), and INSEE ENL (2006)	Possibility to ask different questions: — Do you suffer from thermal discomfort? — Have you experienced difficulty paying utility bills (in the past)? — Can you afford your energy bills? — Are you satisfied with your heating equipment?	— Can be supplemented with qualitative surveys/interviews to better understand the characteristics of fuel-poor households.	— Results should be interpreted with caution, — Possible contrasting results compared with those of objective measures mainly with respect to the identification of fuel-poor households.
	3. Composite indices [11]		
Healy and Clinch (2002)	Composite weighted index based on the combination of six consensual social indicators which — are split into two sub-groups: subjective self-reported and objective factual indicators, — pertains to household finances (fuel and utility bills), the state of the building (presence of dampness or rot) and the dwelling's heating system.	— Associates objective and subjective criteria, — Suitable for cross-country comparisons.	— Assignments of weights to each indicator incorporated in the composite indice is somewhat arbitrary, — Results vary depending on the weight assigned to each indicator.
Thomson and Snell (2013)	Composite weighted index, based on the combination of three proxy indicators, namely the presence of arrears on utility bills in the last 12 months, the presence of a leaky roof, damp walls or rotten windows and the ability to pay to keep the home adequately warm.	— Suitable for cross-country comparisons.	— Assignments of weights to each proxy indicator is somewhat arbitrary, — Results vary depending on the weight assigned to each indicator.
Fabbri (2015)	Composite index, the so-called Building Fuel Poverty Index (BFP), aims to assess the relationship between building energy performance, dwelling habits and fuel poverty.	— Focuses on the role of dwelling energy efficiency as a driver of fuel poverty, — Identifies subjects who can afford to pay for building energy refurbishment.	— Generally not straightforward to apply to countries other than Italy.
Okushima (2017)	Composite index, the so-called Multidimensional Energy Poverty Index (MEPI), which is composed of three attributes of energy poverty, namely energy costs, income and dwelling energy efficiency.	— Considers the multidimensional nature of energy poverty which matches the original concept of energy poverty by Boardman (1991).	— Does not take into account the subjective dimension of fuel poverty.

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[11] References cited in this part of the table present indices that were constructed for developed countries. Therefore, if applied to a developing country, some refinements are necessary, especially with regard to the definition of the dimensions of poverty. In fact, when considering energy poverty in developing countries, most existing studies focus on the question of energy access, not on thermal comfort.

3 Are fuel-poor households more sensitive to energy price variations than non-fuel-poor households?

In Sub-section 3.1, we start by presenting the econometric framework and the data that we used for our estimations. Then, in Sub-section 3.2, we turn to presenting and discussing our empirical results.

3.1 Econometric framework and data

We used a Panel Threshold Regression (PTR) model that was introduced by Hansen (1999). This model aims to estimate and test the threshold effects in non-dynamic panels. After identifying the threshold variable, the model can divide observations into different groups according to the estimated value of this threshold variable. Time series and cross-sections are used to identify the regimes for each group. Based on this procedure, it is then possible to test and estimate the threshold effects without assuming homogeneity of the estimated function. Each group has its own estimated coefficients and each group defines one regime of the model. The PTR model assumes a transition from one regime to another based on the value of a threshold variable. In a two-regime model, if the threshold variable is below a certain value, the estimated function will be defined by one sub-model, whereas if the threshold variable exceeds the threshold parameter, it is defined by another sub-model. At each date in the threshold model, observations are divided into a small number of groups having the same estimated coefficients. The heterogeneity of groups is then endogenously determined by the threshold model and not specified *ex ante*, *i.e.* exogenously, by splitting the whole sample into n groups (or regimes).

Applied to our research, the main advantage of the PTR model is to be able to test for non-linearities, as represented by different values of elasticities, inherent to the impact of the income level on the household demand for heating energy. In other words, the PTR can identify groups of households that react differently to price variations according to their financial endowment. Each group belongs to a different regime and is characterized by its own price elasticity of energy demand, and each regime is defined according to the value of the income threshold variable. In other words, the PTR describes the structural break in the relationship between energy prices and (heating) energy consumption and "*specifies that individual observations can be divided into classes based on the value of an observed threshold variable*" (Hansen, 1999).

Therefore, by using a PTR model, we developed an original approach to endogenously distinguish between groups of households reacting differently to price variations according to their income level. Our aim is to look at the household composition of each group to determine if there is a clear-cut difference in the sensitivity of fuel-poor households compared with that of non-fuel-poor households: do fuel-poor households belong to the group of high or low price elasticity? The advantage of this approach is that it does not exogenously divide the whole sample of households into groups of fuel-poor and non-fuel-poor by using the conventional indicators of fuel poverty (*cf.* results of the benchmark model in Table 7). Instead, the PTR regression is applied to the whole sample of households and thereby distinguishes between households reaction by considering the estimated value of the threshold variable, *i.e.* income. Thus, knowing the value of the threshold variable, we compared the elasticity of each group and determined the dominant household profile in each regime, *i.e.* fuel-poor or not. By extension, we also analyzed for each group (regime) if fuel-poor households are necessarily income poor.

If we consider two groups (regimes), the general form of the PTR model is written as follows:

$$y_{it} = \mu_i + \beta_1 x_{it} I\left(q_{it} \leqslant \gamma\right) + \beta_2 x_{it} I\left(q_{it} > \gamma\right) + \xi_{it} \tag{1}$$

for $i = 1, ..., N$ and $t = 1, ..., T$, where N and T denote the cross-sections and time dimensions of the panel, respectively. y_{it} represents the dependent variable and is scalar, x_{it} is a k-dimensional vector of time-varying exogenous variables, μ_i represents the fixed individual effect, $I\left(.\right)$ is the indicator function, and u_{it} are the errors. Note that the estimation of a threshold model requires the use of a balanced panel.

Applied to our study, the PTR specification is written as follows:

$$\begin{aligned} LnEC_{it} = \mu_i + \alpha X_{it} & \quad + \\ \beta_1 P.I\left(LnINC_{it} \leqslant \gamma_1\right) & \quad + \\ \beta_2 P.I\left(\gamma_1 < LnINC_{it} \leqslant \gamma_2\right) & \quad + \\ \beta_3 P.I\left(\gamma_2 < LnINC_{it}\right) + \xi_{it} & \end{aligned} \tag{2}$$

where subscripts $i = 1, ..., N$ represent the household and $t = 1, ..., T$ indexes the time. μ_i is the household-specific fixed effect. EC_{it} denotes the dependent variables, namely the heating energy consumption per m^2. X_{it} is a vector of exogenous control variables where associated slope coefficients are assumed to be regime independent. $I(.)$ is the indicator function indicating the regime defined by the threshold variable, INC, and the associated threshold level γ. Only the price variable P_{it} depends on the threshold variable stressing that the reaction of households to fluctuation of prices depends mainly on their financial endowments. Finally, ξ_{it} denotes the error term that allows for conditional heteroscedasticity and weak dependence.

Based on insights detailed in Sub-section 2.1, in the PTR, we incorporated the following exogenous control variables classified into three homogeneous families:

— household characteristics: disposable income (INC), poverty threshold ($POOR$), number of persons (NB), type of housing tenure (TEN), and the financial ability for a household to maintain an appropriate level of warmth (TEM).

— dwelling characteristics: dwelling type ($DWTY$), ownership of heating system ($OWHS$), difficulty in heating the dwelling to an appropriate level of warmth ($DIFFH$), presence or absence of roof leaks, damp walls/floors/foundations, rot in window frames or floor ($LEAK$), and exposure and daylight ($DARK$).

— Climate characteristics ($CLIMHFR$): (inner) Paris ($CLIMFR1$), Parisian Region ($CLIMFR2$), East and Center-East ($CLIMFR3$), North and South ($CLIMFR4$), and West, South-West and Mediterannean region ($CLIMFR5-8$).

For the $CLIMHFR$ variable, we adopted the official classification of France into eight zones having different climate characteristics, *i.e.* $FR1$ to $FR8$ (*cf.* Appendix A).

To ensure the suitability of our model, in particular the choice of exogenous variables, we started by estimating a linear panel model with fixed effects and thus created a benchmark model to verify that our results do not distort those previously obtained in the literature dealing with the determinants of energy consumption in the residential sector. This benchmark model also allowed us to focus on issues that were depicted in the PTR model and are different from the linear model. In this benchmark analysis, we estimated the linear model by considering two groups of households determined exogenously based on the 10% and LIHC (m^2) indicators of fuel poverty. We therefore identified a group of non-fuel-poor households and a group of fuel-poor households. We wrote the linear panel specification as follows:

$$\begin{aligned} LnEC_{it} = \mu_i + \theta_1 P + \theta_2 LnINC_{it} + \theta_3 POOR_{it} + \theta_4 NB_{it} + \theta_5 TEN_{it} + \theta_6 TEM_{it} & + \\ \theta_7 DWTY_{it} + \theta_8 OWHS_{it} + \theta_9 DIFFH_{it} + \theta_{10} LEAK_{it} & + \\ \theta_{11} DARK_{it} + \theta_{12} CLIMFR1_{it} + \theta_{13} CLIMFR2_{it} & + \\ \theta_{14} CLIMFR3_{it} + \theta_{15} CLIMFR4_{it} + \xi_{it} & \end{aligned} \tag{3}$$

where subscripts $i = 1, ..., N$ represent the household that is fuel-poor if it belongs to the fuel-poor group or non-fuel-poor if it belongs to the non-fuel-poor group. We detail in Appendix B how we determined groups of fuel-poor households, or alternatively, how we calculated the fuel poverty rate, using the 10% and LIHC (m^2) indicators to obtain samples based on which the linear model was estimated.

Before estimating coefficients of the linear benchmark model, we started by choosing between estimating a fixed-effects or a random-effects model. We performed the Hausman (1978) test for fixed effects. Under the null hypothesis that individual effects are random, fixed- and random-effects estimators are similar because both are consistent. Under the non-null model, these estimators are different. Our results led to the rejection of the null hypothesis that individual effects are random, because we did not obtain consistent estimates. We therefore used a panel linear model with fixed effects [12].

In our models, *i.e.* the PTR and linear fixed-effects models, a possible endogeneity issue may arise. In fact, there is an open debate in the empirical literature on whether the direction of causality runs from energy prices to energy consumption or *vice versa*. In the case of the linear fixed-effects model, to take into account the endogeneity of energy prices, we used Instrumental Variables (IV), *i.e.* the two-stage least-squares within estimator [13], and as instruments, we used energy prices lagged by one period as well as a dummy variable taking the value 1 when households benefit from the basic energy tariff, *i.e.* the blue tariff (*cf.* Table C.1 from Appendix C). For the PTR model, we followed Polemis and Stengos (2017) and we used lagged values of prices as a regressor and checked the sensitivity of our results against that choice. Our findings were robust to changes in the time lag of prices, with similar results regardless of the use of current or lagged values of prices as an independent variable. Therefore, we feel that the issue of endogeneity is not severe in our case. However, to ensure the reliability of our results, we nevertheless used lagged prices as regressor rather than current prices (*cf.* Appendix E for more details on how we dealt with the endogeneity).

For our estimations, we used three databases, namely the EU-SILC database [14], the PHEBUS

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[12] The output of the random-effects estimation is available upon request.

[13] See Baltagi (2008) for more information on panel-data models with endogenous covariates.

[14] The "*EU Statistics on Income and Living Conditions (EU-SILC)*" covers four topics, *i.e.* people at risk of poverty or social exclusion, income distribution and monetary poverty, living conditions and material deprivation. It includes several European countries. For more information on the methodological and practical framework for the computation and production of the EU-SILC database as well as information on quality and methodological limitations, interested readers can consult `http://ec.europa.eu/eurostat/statistics-explained/i`

database [15] and the PEGASE database [16]. Our main source of data was the EU-SILC database. All variables were extracted from it except energy prices, P. We constructed the variable P based on the PHEBUS and PEGASE databases. In Appendix C, we detail the methodology that we used.

Variables and data sources are summarized in the first four columns of Table 3. The last column of the same table presents the expected effects of variables. We estimated models on a balanced sample composed of 827 households observed for the time period from 2008 to 2014. All non-dummy variables used in estimations were log-transformed.

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[15] The "PHEBUS" database ("*Performance de l'Habitat, Equipements, Besoins et Usages de l'énergie*") is especially devoted to the in-depth analysis of the fuel poverty issue in France. This database was compiled from April to October 2013 by the Ministry of Ecology, Sustainable Development and Energy ("*Ministère de l'Ecologie, du Développement durable et de l'Energie*"; MEDDE)), the General Commission for Sustainable Development ("*Commissariat Général au Développement Durable*" (CGDD)), and the Department of Observation and Statistics ("*Service de l'observation et des statistiques*"; SOeS). It has two parts: (1) a face-to-face interview with the occupants of the home about their energy consumption, expenditures and attitudes and (2) an energy-efficiency diagnosis of the dwelling. In particular, "PHEBUS" contains information describing the household, *i.e.* the amount of energy expenditures, attitudes toward energy consumption, disposable income, age, etc., and dwelling characteristics, *i.e.* surface, type of heating system, level of energy efficiency, etc. Therefore, it can study households' energy consumption in detail and the associated question of fuel poverty. The "PHEBUS" database covers the year 2013.

[16] The PEGASE database ("*Petrole, Electricite, Gaz et Autres Statistiques de l'Energie*") stores and distributes French energy statistics collected by the Department of Observation and Statistics ("*Service de l'Observation et des Statistiques*"; SOeS)). The new methodology of dissemination of detailed statistics is based on a Beyond 20/20 format which is also used by the International Energy Agency (IEA) and the French National Institute of Statistics and Economic Studies (INSEE; *"Institut National des Statistiques et des Etudes Economiques"*). It mainly provides long-term data series. The annual energy statistics summarize the consumption of different types of energies. This database presents the annual series in units (per kWh for gas or electricity). All statistics can be downloaded free of charge and reused with any license or payment of royalties, provided the acknowledgement of the source. More details on the PEGASE database are available on `http://www.statistiques.developpement-durable.gouv.fr/donnees-ligne/r/pegase.html`

Table 3 – Variables, data sources, and expected effects

Variable	Header	Description	Source	Expected effect
Endogenous variable				
Residential energy consumption [a]	EC	kWh per m^2	EU-SILC	—
Threshold variable				
Disposable income	INC	€	EU-SILC	—
Regime-dependent exogenous control variables				
Energy prices	P	kWh/€. To treat endogeneity, we used lagged values of P as a regressor and checked the sensitivity of our results to that choice	Authors calculation. EU-SILC, PHEBUS and PEGASE. *Cf.* Appendix C.	Decrease
Regime-independent exogenous control variables				
Household characteristics				
Poverty threshold [b]	$POOR$	Dummy: 1 if poor, 0 otherwise	EU-SILC	Decrease
Number of persons in household	NB	1, 2, 3,...	EU-SILC	Increase
Type of housing tenure	TEN	Dummy: 1 if home-owner, 0 otherwise	EU-SILC	
Financial ability to maintain an appropriate level of warmth	TEM	Dummy: 1 if yes, 0 otherwise	EU-SILC	Not clear
Dwelling characteristics				
Dwelling type	$DWTY$	Dummies: 1 if apartment, 0 otherwise	EU-SILC	Decrease
Ownership of heating system	$OWHS$	Dummy: 1 if yes, 0 otherwise	EU-SILC	Increase
Dwelling difficult to heat	$DIFFH$	Dummy: 1 if yes, 0 otherwise	EU-SILC	Increase
Roof leaks, damp walls/floors/foundations, rot in window frames or floor	$LEAK$	Dummies: 1 if leaks and rot, 0 otherwise	EU-SILC	Increase
Exposure and natural lighting	$DARK$	Dummy: 1 if dark, 0 otherwise	EU-SILC	Increase
Climate characteristics				
Climate zone FR1	$CLIMFR1$	Dummy: 1 if located in Paris, 0 otherwise	Offical definition	Increase
Climate zone FR2	$CLIMFR2$	Dummy: 1 if located in Parisian region, 0 otherwise	Offical definition	Increase
Climate zone FR3	$CLIMFR3$	Dummy: 1 if located in North, 0 otherwise	Official definition	Increase
Climate zone FR4	$CLIMFR4$	Dummy: 1 if located in the East or Center-East, 0 otherwise	Official definition	Increase

a. As an acceptable proxy of residential energy consumption, we used heating energy consumption. Usually space heating represents at least half of the household energy bill. For instance, in the UK in 2013, on average, around 51% of the theoretical household bill was devoted to space heating costs, 34% for lighting and appliance usage, 12% for water heating, and 3% for cooking costs (DECC, 2014).

b. This variable is calculated based on the official definition of income, or equivalently, monetary poverty in France. It states that an individual (or household) is considered poor when living in a household whose standard of living is below the poverty line. In France, the poverty line is determined regarding the distribution of living standards of the entire population. In particular, it generally uses a threshold at 60% of the median of living standards. It however publishes poverty rates according to other thresholds (40%, 50% or 70%). Source: `https://www.insee.fr/fr/metadonnees/definition/c1653`.

3.2 Findings and discussion

In this section, we present the results of the PTR fixed-effects model by referring to those of the benchmark fixed-effects linear model.

Table 4 – Tests for threshold effects

	Threshold variable: household income (INC)
Test for single threshold [a]	
F_1	13.30
P-value	0.037
(10%, 5%, 1% critical values)	(10.545, 12.361, 16.710)
Test for second threshold [a]	
F_2	5.318
P-value	0.649
(10%, 5%, 1% critical values)	(10.376, 13.237, 16.874)

a. P-value and critical values were computed from 1000 and 2000 bootstrap replications. F_1 denotes the Fisher-type statistic associated with the test of the null hypothesis of no threshold against one threshold and F_2 corresponds to the test of one threshold against two thresholds.

Table 5 – Threshold estimates and confidence interval

	Estimate	95% confidence interval
$\hat{\gamma}_1$	10.421	[10.370, 10.438] [a]

a. The confidence interval for the threshold parameters corresponds to the no-rejection region of the 95% confidence level associated with the likelihood ratio statistic for the test on the values of the threshold parameters (Hansen, 1999). This confidence interval cannot be symmetric.

Before estimating a PTR model, the first step consists in determining the number of groups (regimes) or, equivalently, testing for the existence of threshold(s). We used the sequential procedure as proposed by Hansen (1999) and the model was estimated, allowing for zero, one, two, and three thresholds, sequentially. For each specification, the test statistics F_1 and F_2, along with their bootstrap P-values were determined. The results of these tests, and the threshold variable income INC, are reported in Table 4.

When testing for the presence of a single threshold, we found that F_1 was significant, with a bootstrap P-value equal to 0.03. This provides the first evidence that the relationship between energy consumption (m^2) and energy prices is not linear. The test for a double threshold, F_2, was not significant, with a bootstrap P-value equal to 0.64. We, therefore, stopped the sequential procedure at this stage and concluded that there is only one threshold. The estimations of the value of the threshold and associated confidence interval are given in Table 5 [17]. It showed that the threshold was equal to 10.421. The asymptotic confidence interval for the threshold is narrow, *i.e.* [10.370, 10.438], indicating little uncertainty on this division of households according to this estimated value of the threshold. Thus, the two groups of households indicated by the point estimates were those with a high income level *i.e.* €33,223, given the mean level of income of the sample, *i.e.* €25,826.

After demonstrating the existence of a threshold and determining its value, we estimated six threshold models. In Model 1, we included all control variables. In Model 2, we omitted climate characteristics from the list of control variables. In Model 3, we also omitted dwelling characteristics. In Model 4, we did not include any control variables and only kept price as an explanatory variable. In Model 5, we included year fixed effects. Finally, Model 6 included the monetary

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[17] The threshold variable was trimmed by 5% on both sides to screen for the threshold estimator.

poverty variable. Our aim was to test how the choice of control variables affects the stability of coefficients, in particular the relationship between energy prices and heating energy consumption (m^2).

The estimates of the coefficients and the corresponding t-statistic are given in Table 6. Those of primary interest are those associated with the energy prices variable. Our results corroborate previous estimates of price elasticity in the residential sector. Our elasticity estimates are however slightly lower than those reported in the literature (see Table 1). Regardless of the model used, our estimates suggest that price elasticity is negative for both classes of households ranging from -0.0611 to -0.119 (Model 1). This means that when energy prices increase by 10%, energy expenditures decrease by 6.11% to 11.9%, depending on household income level. More precisely, households having an income lower than the threshold value, *i.e.* $INC \leqslant$ €33,223, have a higher price elasticity equaling 11.9%. These results regarding price elasticity estimations were stable regardless of the PTR model we used.

Once PTR income threshold and, thus, the number of household groups (regimes) as well as price elasticities estimated, we turned to the study of the profile of households belonging to each group in terms of fuel and income poverty. Depending on these profiles, we propose an economic interpretation for the estimated elasticities by referring to the existing literature when relevant.

To determine if a household is fuel-poor or not, we used the usual indicators of fuel poverty namely the 10% and LIHC (m^2) (*cf.* section 2.2). As for income poverty, we refer to the conventional definition of income poverty according to which a household is income-poor when its standard of living is below the threshold of 60% of the median of living standards (*cf.* footnote number [b] from Table 3). To determine if a household belonging to one group or the other is income-poor or not, we only needed to compare its income level with the threshold of 60% of the median of living standards for a households with two children, *i.e.* €25,584 per year[18]. We particularly note that the PTR income threshold, *i.e.* €33,223, is not an income poverty threshold nor a fuel poverty threshold. It is a just a PTR threshold indicating the income level at which income non-linearities in reaction of households to variations in energy prices are triggered.

— regime (group) 1 (income $<$ €33,223 and income elasticity $=$ 11.9%)

Households belonging to this regime have an income level less than €33,223; 56.01% are fuel-poor households and 43.99% are not fuel-poor. Overall, 27.25% of fuel-poor households are income-poor and 20.21% of non fuel-poor households are income-poor. This means that almost one-third of the proportion of fuel-poor households is income-poor, and an income-poor household can be non-fuel-poor. In other words, income poverty does not necessarily translate into fuel poverty. It is often associated with income poverty due to the fact that the latter is usually used to capture the monetary aspect of fuel poverty. However, although low income can be a driver of fuel poverty, fuel poverty also has other determinants such as the energy inefficiency of building and home appliances. In addition, from a purely quantitative view, if there is indeed a relationship between income and fuel poverty, this relationship is not always symmetrical and/or significant. For instance, Palmer et al. (2008) show for example that most fuel-poor households are income-poor but most income-poor are not fuel-poor. Phimister et al. (2015) show that in a study in Spain, only

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[18] In France, for an individual, the income poverty threshold in 2016 is equal to €1015 per month and €12,180 per year. For a household with 2 children, it is equal to €2132 per month and to €25,584 per year (`https://www.inegalites.fr/Les-seuils-de-pauvrete-en-France`). In our case, to determine if a household is income-poor or not, we needed to compare its income to the income poverty threshold of a household with two children. Our sample involves data on equivalized income per consumption unit (cu) where the average level of cu is equal to 1.8 ($\simeq 2$).

28.5% of income-poor are affected by fuel poverty while 79.6% of fuel-poor are income-poor.

In terms of elasticity, households belonging to this group have a higher price elasticity equaling 11.9%, compared to those belonging to the other regime. Since our results show that the fuel poverty situation of these households is not necessarily income-induced and needs to be understood by looking at other determinants of fuel poverty[19], we expect that their higher elasticity reflects their capacity to adjust to an increase in energy prices by following different strategies, by inventing solutions for coping with the restrictions and finding other ways to satisfy energy needs (Heindl and Schuessler, 2015).

— regime (group) 2 (income > €33,223 and income elasticity = 6.11%):

21.52% of households belonging to group 2 are fuel-poor and only 15.23% of these fuel-poor are income-poor. Also, 5.34% of non-fuel-poor households belonging to this group (79.48%) are income-poor. With regard to the causal relationship between income and fuel poverty, these results corroborate the fact that income poverty does not necessarily imply fuel poverty and that it is crucial to search for determinants of fuel poverty in socio-economic sources other than the income. Fuel poverty is a multidimensional phenomenon that, in particular, cannot be reduced to income poverty.

As for elasticity, households belonging to this regime have a lower elasticity compared to this of households belonging to the first group. Since these households belong to a high-income category, we may conjecture that the lower elasticity reflects not a limited adjustment capacity as it is usually interpreted in the case of low-income households but rather a deliberated preference for thermal comfort. Indeed, energy for heating is a typical and a normal good[20] but also can be considered as a necessity good[21]. In formal terms, the necessity goods are products and services that consumers will buy regardless of the changes in their income levels making, therefore, these products less sensitive to price change. Like any other normal good, an income rise will lead to a rise in demand, but the increase for a necessity good is less than proportional to the rise in income, so the proportion of spendings on these goods falls as income rises. Since households will buy this necessity good regardless of the changes in its income level, this makes this product less sensitive to price change. Households can decide to slightly adjust their consumption but not to considerably limit it. In our case, we may conjecture that households will make the choice to consume less another type of good (non energy goods) in order to ensure an adequate level of thermal comfort.

It is important to note here that our PTR income threshold does not distinguish between low- and high-income households. Therefore, comparing our price elasticities with those in the existing literature dealing with low- and high-income households is not relevant. However, our PTR income threshold is just a linearity breakthrough threshold. In our sample, results give an income threshold level that is rather high compared to official income poverty threshold. This level may be specific to the particular database, time period, or French-specific characteristics. These specificities can be tested for by applying the same methodology to a different database. More fundamentally, our results indicate that the PTR threshold level could be interestingly compared with the income or poverty thresholds based on which public policies are defined (Fizaine and Kahouli, 2018).

Regarding the control variables, our results show that when focusing on household character-

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[19] This aspect clearly goes beyond the scope of our empirical model and of this article.

[20] According to the economic theory, a negative price elasticity means that the good is a normal good, *i.e.* when the price increases, the demand decreases, which our results corroborate.

[21] According to the economic theory, necessity goods have a positive income elasticity belonging to [0,1]. Our income elasticity results corroborates the fact the energy is a necessity good. In fact, as displayed in Table 6 and whatever the model we use, the energy income elasticity is between 0 and 1. Taking for example the Model 1 as a baseline, the income elasticity is equal 0.087.

istics, the most important determinants of heating energy expenditures are income, the number of persons living in the household, and housing tenure. In particular, as expected and frequently reported in the literature, income elasticity is positive and equal to 8.7% (see Table 1). Similarly, our results show that the number of persons in a household increases energy consumption and being a home-owner lowers it (Rehdanz, 2007).

When looking at dwelling characteristics, our results show that the variables significantly correlated to energy consumption are mainly the dwelling type and the ownership of heating system. Living in an apartment rather than a detached house results in lower energy consumption. Otherwise, the ownership of heating system is, as expected, positively correlated with energy consumption [22]. However, interestingly, our results show that poor natural lighting and insulation problems have no significant impact on energy consumption. Finally, the impact of climate zone on heating expenditures was statistically significant. Energy needs of households living in cold regions are more important, *i.e.* north-eastern and western (Atlantic coast and some southern regions) France.

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[22] It would have been interesting to follow the literature and to test for the effect of the type of heating system and of the heating oil (Newell and Pizer (2008), Braun (2010)). However, we were not able to find such data in our initial database.

Table 6 – Regression estimates for the single threshold model - Balanced panel 2008-2014

Variable	Model 1 [a]	Model 2 [b]	Model 3 [c]	Model 4 [d]	Model 5 [e]	Model 6 [f]
c^g	3.053	3.017	3.250	4.058	3.056	3.96
	(9.450)*** [h]	(9.390)***	(10.370)***	(7.247)***	(9.43)***	(38.95)**
$LnINC$	0.087	0.092	0.078		0.091	
	(2.770)***	(2.940)***	(2.530)**		(2.86)**	
$POOR$						-0.076
						(-2.14)**
NB	0.051	0.055	0.059		0.051	0.041
	(4.980)***	(5.280)***	(5.790)***		(4.88)***	(3.54)***
TEN	-0.160	-0.162	-0.157		-0.174	-0.154
	(-5.27)***	(5.610)***	(-5.770)***		(-5.56)***	(-5.08)***
TEM_{it}	-0.036	-0.038			-0.035	-0.034
	(-0.70)	(-0.740)			(-0.69)	(-0.68)
$DWTY$	-0.065	-0.040			-0.073	-0.067
	(-1.990)**	(-1.30)			(-2.22)**	(-2.05)**
$OWHS$	0.126	0.120			0.126	0.126
	(2.200)***	(2.080)**			(2.38)**	(2.19)**
$DIFFH$	0.073	0.073			0.073	0.070
	(2.400)***	(2.410)**			(2.38)**	(2.30)**
$LEAKS$	0.050	0.053			0.051	0.050
	(1.260)	(1.310)			(1.27)	(1.22)
$DARK$	0.063	0.062			0.062	0.063
	(1.330)	(1.310)			(1.29)	(1.31)
$CLIMFR1$	0.129				0.131	0.134
	(3.290)***				(3.32)***	(3.44)***
$CLIMFR2$	0.171				0.033	0.035
	(3.620)***				(0.99)	(1.07)
$CLIMFR3$	0.171				0.170	0.168
	(3.620)***				(3.59)***	(3.55)***
$CLIMFR4$	-0.014				-0.013	-0.012
	(0.04)				(-0.30)	(-0.28)
Regime 1: $LnP.I\,(LnINC \leqslant 10.411)$	-0.119	-0.125	-0.122	-0.126	-0.117	-0.115
	(-5.16)**	(-5.39)**	(-5.24)***	(-5.43)***	(-4.94***)	(-4.96)***
Regime 2: $LnP.I\,(LnINC > 10.411)$	-0.061	-0.069	-0.067	-0.084	-0.060	-0.081
	(-2.30)**	(-2.61)**	(-2.53)**	(-3.36)***	(-2.20)***	(-3.23)***
			Diagnostics			
Number of observations	4962	4962	4962	4962	4960	4962
Number of households	827	827	827	827	827	827
R^2	0.032	0.029	0.024	0.008	0.036	0.034
F-statistic	13.30	12.71	12.14	12.81	12.87	12.80
Year fixed-effects	No	No	No	No	Yes	No

a. Model with exogenous control variables.
b. Model without climate variables.
c. Model with only household characteristics as control variables.
d. Model without control variables.
e. Model with year fixed effects.
f. Model with monetary poverty.
g. Individual-specific effects.
h. *** Significant at P<1%, ** P<5%, and * P<10%.

Results of the benchmark linear model are presented in Table 7. Model 7 gives the results for the estimation based on the whole sample and Models 8 and 9 give the results of estimations on groups of fuel-poor and non-fuel-poor households, where these groups were exogenously determined based on the 10% and the LIHC (m^2) conventional indicators of fuel poverty, respectively.

The results of Model 7 corroborate those of the PTR regression. In particular, it confirms the negative elasticity between energy prices and consumption: when energy prices increase by 10%, heating consumption decreases by 10.6%. As for the other determinants of energy consumption related to household characteristics, our results underscore the role of income as a determinant of energy consumption, as already argued by Cayla et al. (2010) and Cayla et al. (2011) in a study on the French residential sector. Income elasticity is statistically non-significant in the benchmark model. Otherwise, as in the PTR model, the other most important household characteristics that have a significant impact on residential energy consumption are the size of the household, or alternatively the number of persons, and the type of housing tenure. Energy consumption increases with the number of persons and decreases when the household is the home-owner.

Regarding the relationship between dwelling characteristics and energy expenditures, results show that there is a statistically significant impact of dwelling type, the difficulty heating it to a comfortable level of warmth, and the ownership of the heating system. They therefore confirm the results of the PTR model, in particular, that energy consumption in apartments is lower than that in detached houses. Moreover, as in the PTR model, technical aspects of the dwelling, for example poor insulation, *i.e.* roof leaks, damp foundations, or rot in window frames or floor as well as poor natural lighting, have no statistical significant impact on energy consumption. Finally, when examining the impact of the climate, although results show some evidence of a negative and statistically significant impact of living in a cold regions, in particular in western France, the relationship between climate characteristics and energy consumption was not stable.

The results of Models 8 and 9, based on exogenously determined groups of fuel-poor and non-fuel-poor households, reveal three main findings. The first finding is that the negative price elasticity of energy demand is higher for fuel-poor households than for non-fuel-poor households. It ranged from 55.99% for fuel-poor households determined based on the 10% indicator to 66.4% for fuel-poor households determined based on the LIHC m^2 indicator. Fuel-poor households are, therefore, more sensitive to variation in energy prices. We advance the same arguments as in the case of the PTR model to explain this result. The second finding is that only household characteristics play a significant role in explaining energy consumption, at the expense of dwelling and climate characteristics. In particular, we note that for fuel-poor households determined using the 10% indicator, income had a significant impact on energy consumption: income elasticity was equal to 35.7%. However, in the case of the LIHC (m^2) indicator, income becomes statistically non-significant. Similarly, being a home-owner had a statistically significant impact on energy expenditure, but this impact was statistically non-significant when the group of fuel-poor is based on the LIHC (m^2) indicator. The third finding is that in the case of non-fuel-poor households, dwelling and climate characteristics have a more significant impact on energy consumption. In particular, the dwelling type, the ownership of heating system, and the difficulty in heating the dwelling had a significant and typically signed impact on energy consumption. Similarly, climate characteristics had a significant impact on energy consumption. Living in a cold region increases energy needs.

In summary, the linear benchmark model results show that the main determinants of energy consumption in the case of fuel-poor households are energy prices and income, whereas in the case of non-fuel-poor households, dwelling as well as climate characteristics play an important role.

To summarize, in light of our main question, the results derived from the PTR and the linear

Table 7 – Results of the linear panel benchmark model - Balanced panel 2008-2014

		10% indicator		LIHC (m^2) indicator	
	Model 7 [a]	Model 8		Model 9	
Within estimates		Poor	Not poor	Poor	Not poor
c [b]	3.731	-0.433	3.634	3.647	3.466
	(9.234)*** [c]	(-0.23)	(13.21)***	(1.01)	(13.00)***
LnP	-0.106	-0.5499	-0.082	-0.664	-0.079
	(2.8760)***	(-2.500)***	(-3.510)***	(-2.660)**	(-3.380)***
$LnINC$	0.0204	0.357	0.035	0.057	0.051
	(1.160)	(2.470)***	(1.180)	(0.360)	(1.980)**
NB	0.0527	0.096	0.056	0.042	0.053
	(4.210)***	(0.850)	(5.22)***	(0.210)	(4.890)***
TEN	-0.161	-0.669	-0.155	-0.410	-0.164
	(-4.230)***	(-2.28)**	(3.180)***	(-1.16)	(-5.270)***
TEM	-0.035	0.206	-0.021	0.178	0.020
	(0.480)	(0.55)	(-0.400)	(0.420)	(0380)
$DWTY$	0.069	0.849	-0.083	0.716	-0.094
	(1.990)**	(1.83*)	(-2.52)**	(1.550)	(-2.830)***
$OWHS$	0.124	-0.474	0.138	0.051	0.135
	(2.01)**	(-1.06)	(2.330)**	(0.120)	(2.240)**
$DIFFH$	0.070	0.159	0.082	0.438	0.093
	(2.030)**	(0.67)	(2.600)**	(1.670)*	(2.920)***
$LEAKS$	0.049	-0.272	0.054	-0.257	0.052
	(1.210)	(-0.94)	(1.090)	(-0.770)	(1.240)
$DARK$	0.061	-0.392	0.049	-0.144	0.063
	(0.340)	(-0.86)	(1.17)	(-0.270)	(1.270)
$CLIMFR1$	0.126	0.562	0.119	-0.621	0.138
	(2.870)***	(0.584)	(3.03)***	-(0.780)	(3.550)***
$CLIMFR2$	0.039	-0.324	0.163	-0.621	0.043
	(1.100)	(1.160)	(3.30)	(-0.81)	(1.25)
$CLIMFR3$	0.172	0.175	0.163	0.044	0.150
	(3.120)***	(0.297)	(3.30)***	(0.120)	(3.030)***
$CLIMFR4$	-0.011	0.398	-0.016	-0.274	0.001
	(0.880)	(0.342)	(-0.35)	(-0.730)	(0.030)
R^2	0.326	0.372	0.319	0.250	0.326
Number of observations	4962	371	4591	398	4564
Number of households	827	298	529	330	497

a. We note that we have also run benchmark regressions (models (7), (8) and (9)) by introduced year fixed effects. Results still valid compared to the case where year fixed effects are introduced. Therefore, in order to save space, we do not report results of regressions with year fixed effects. They are available open request.

b. Individual-specific effects.

c. *** Significant at P<1%, ** P<5%, and * P<10%.

models show that:

- — regarding the determinants of residential energy demand: price remains an important determinant of residential energy consumption. However, there are significant income-induced non-linearities in the demand for residential energy. In other words, the price elasticity of households depends on their income, and in turn, their sensitivity to policy measures targeting energy efficiency in the residential sector, in particular, those based on carbon pricing.
- — regarding fuel poverty: fuel poverty in the residential sector is a multidimensional phenomenon and income is far from the only determinant. Other determinants such as dwelling energy inefficiency or energy price increases seem to play a key role in pushing households into fuel poverty. Other socio-economic variables as well as other variables describing the dwelling help to draw a more precise profile of fuel-poor households.

4 Conclusion and policy implications

In this paper, by considering conventional determinants of residential energy demand, we first focused on analyzing the income-induced non-linearities in households' reaction to energy price fluctuations as measured by the price elasticity of heating energy consumption. Then, by looking at the composition of groups of households, we analyzed their fuel and income poverty profile and focused on studying the sensitivity to energy price variation of fuel-poor households compared with that of non-fuel-poor households. Compared to other contributions dealing with the demand of energy in the residential sector, we included a new dimension by seeking to determine whether there are income non-linearities in the reactions of households to energy prices, given other socio-economic and dwelling characteristics.

We argue that before implementing public policies devoted to eliminating fuel poverty in the residential energy sector, it is necessary to understand how sensitive households – in particular fuel-poor households – are to these public policies. In this context, we consider that the non-linearity of their sensitivity is tightly linked to their financial resources. We directly draw on the recurrent debates on the overlap between fuel poverty and income poverty: is fuel poverty a distinct type of deprivation or rather an aspect of low living standards induced by low income? In other words, does income poverty necessary translate into fuel poverty?

From an empirical point of view, we used a PTR model to test for income-induced non-linearities in the sensitivity of French households to energy price fluctuations. The novel aspect of this model is that it can endogenously identify groups of households that react differently to price fluctuations according to their income level. We compared results of the PTR model to those of a standard panel model estimated for two groups of households determined exogenously based on the conventional 10% and LIHC (m^2) indicators of fuel poverty, namely a group of fuel-poor households and a group of non-fuel-poor households.

Our results show that there is heterogeneity in households' reactions to energy price fluctuations. In particular, we identified two groups of households reacting differently and, by analyzing the composition of groups, demonstrated that fuel-poor households belong mostly to the group of households that have the highest energy price elasticity, *i.e.* the most sensitive households. Such high sensitivity, equivalent to the capacity of a household to handle problematic situations – such as an increase in prices – to satisfy its energy needs, is supported by high income level. We stress that, in our sample, the set of fuel-poor households that have higher elasticity do not necessarily correspond to low-income households, because only one-third of them are income-poor.

In terms of public policies, we argue that:

- policy markers aiming at implementing effective public policies in the residential energy sector and promoting social welfare should consider different groups of households separately, depending on their income level.

This distinction should not be based only on the separation between low- and high-income households. We suggest that, given the importance of income as a determinant of fuel poverty, one relevant criterion is to examine income-induced non-linearities to set income threshold(s) for which we can observe an elasticity change, or equivalently, a change in the capacity to adjust to price increases. More fundamentally, our results renew the debate on the relevance of the choice of thresholds when defining fuel- and income-poverty indicators. How should these thresholds be defined? Energy expenditures generally increase with income. However, their magnitude increases with income thresholds, because it reflects the changing nature of residential energy consumption (electricity and gas in our case) when income changes. There is, therefore, a need to consider different income groups (Hache et al., 2017). As shown by our results, it is not only the lowest income households that may be of particular interest (the PTR income threshold operates at an income level that is higher than the income-poverty threshold). Policies should account for this threshold effect across the whole range of households when attempting to determine a precise socio-economic profile of households facing energy problems. In particular, certain policy measures, such as those targeting fuel poverty and energy efficiency in the residential sector, need to consider a differentiated and targeted approach towards different income groups (Meier et al., 2013).

— since fuel poverty represents a serious threat to the efficient implementation of policy measures devoted to enhancing energy saving and efficiency in the residential sector, particular attention should be paid to how to target fuel-poor households. For example, fuel-poverty does not always arise from income poverty and there is a need to examine the overlap between fuel poverty and income poverty.

In particular, the recent creation in January 2018 of the Energy Voucher in France as a new measure to fight fuel poverty and to replace social tariffs of electricity and gaz – in addition to other measures[23]– calls into question its attribution based only on income by assuming that income poor households are also fuel-poor[24]. The Energy Voucher is attributed to the poorest 15% of households, *i.e.* less than €7700/*cu* per annum to help them to pay their energy bills. It is based only on an income criterion which, in light of our results, appears unwise. Income poverty does not translate into fuel poverty, although there is a significant probability that the poorest 15% of households are also fuel-poor, because the income threshold of 15% is very low. We suggest that exploring solutions to the fuel-poverty problem should be carried out in conjunction with those that define the public policies devoted to fighting income poverty.

We finish this article by suggesting some avenues of further research. From an econometric point of view, one way to enhance our understanding of the income-induced non-linearities in the demand for residential energy, or equivalently, distinction between income groups is to use a Panel Smooth Transition Regression (PSTR) model (González et al., 2005). PSTR is an extension of the PTR model and considers a smooth – rather than abrupt – transition between regimes to explain the mechanism of going from one regime to another. A brutal transition means that the link between energy consumption and income can be divided only into a (small) finite number of regimes. This assumption reduces the possibility of heterogeneity within regimes and may constitute a drawback to a detailed classification of households in economic and policy contexts that usually highlight the high variability of household profiles. Within the framework of a PSTR model, the transition from one regime to another operates in a gradual way with no constraints on the number of regimes. This may be a valuable source of information on how to make a distinction between households in the context of their residential energy demand as well as how to identify fuel-poor households.

From a policy point of view, we suggested above that tackling the fuel poverty issue should be carried out in conjunction with income poverty. Once causality relationship have been identified, a central question is therefore how to finance measures devoted to overcome fuel poverty and/or income poverty (throughout the paper, we have assumed that fuel poverty is multidimen-

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[23] A complete list of French policy measures devoted to fight fuel poverty is available by following this link `http://www.onpe.org/notes_de_lobservatoire/17_fiches_descriptives_des_dispositifs_daides_existants`.

[24] `https://www.ecologique-solidaire.gouv.fr/sites/default/files/Rapport%20evaluation%20cheque%20energie.pdf`

sional and not only due to income poverty). When the target is fuel poverty, making all energy consumers contribute *via* direct taxation or taxation of their energy consumption may be unfair to fuel-poor households. These households should be identified in advance and either exonerated from tax or compensated *ex post*. Solutions for this issue are still pending and call for carrying out redistributive and welfare economic analyses.

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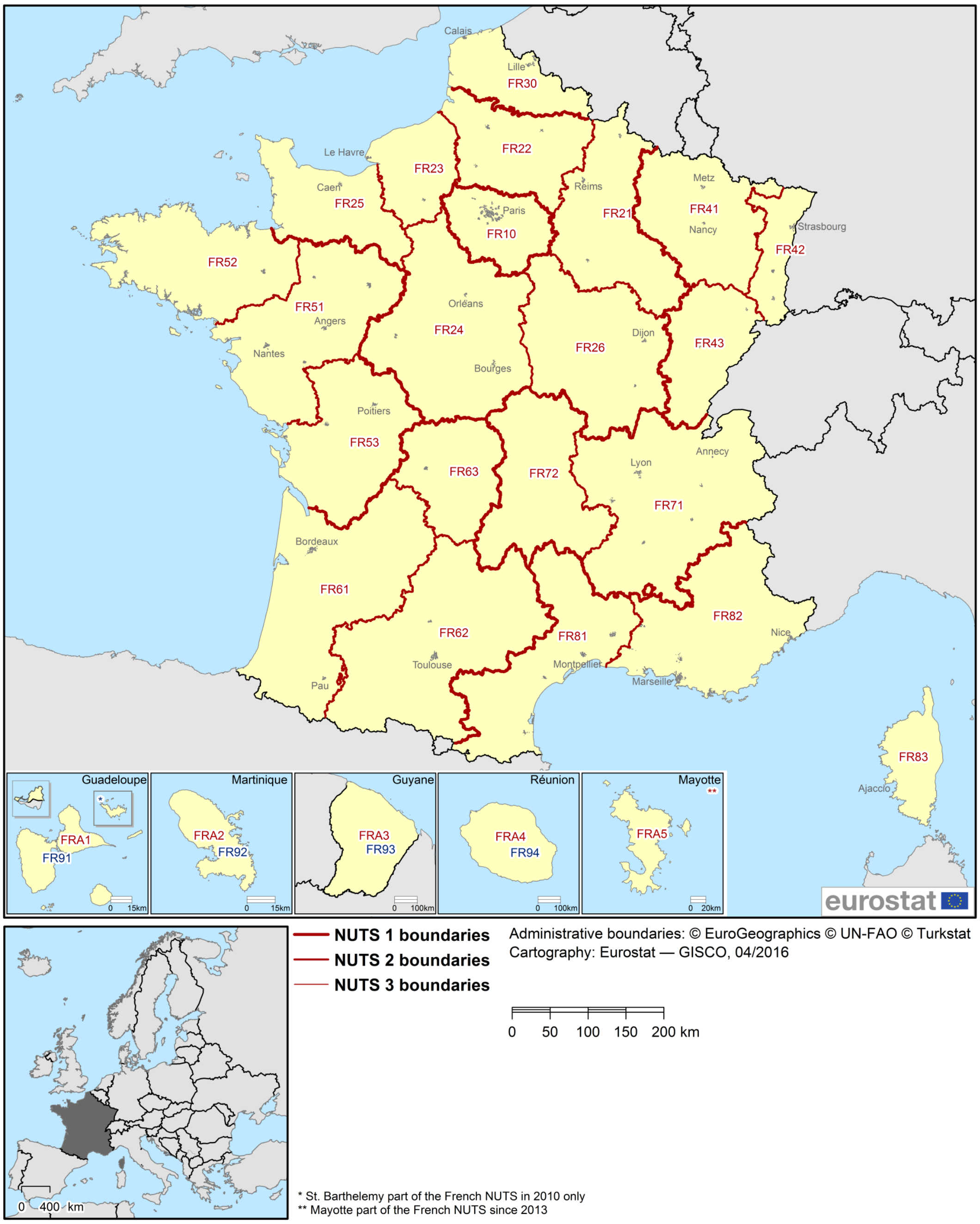
A Official definition of French climate zones



Administrative boundaries: © EuroGeographics © UN-FAO © Turkstat
Cartography: Eurostat — GISCO, 04/2016

* St. Barthelemy part of the French NUTS in 2010 only
** Mayotte part of the French NUTS since 2013

Figure A.1. Official definition of French climate zones

B Calculation of fuel poverty rates

The EU-SILC database covers the period from 2004 to 2014. Nevertheless, to calculate annual fuel poverty rates, we considered only the period from 2008 to 2014. From 2004 to 2008, the quality of data describing energy expenditures is very poor. For example, in 2006, 10,036 households were surveyed on their energy expenditures, but only 2146 of 7890 observations were reported [25].

B.1 Calculation of fuel poverty rates according to the 10% indicator

The 10% indicator is calculated according to the following formula (*cf.* Table 2 from Sub-section 2.2):

$$\mathrm{I} = \frac{\text{(Actual) Fuel costs}}{\text{Equivalized disposable income (before housing costs)}} \tag{B.1}$$

- if I $>$ 10% $\Rightarrow$ the household is fuel-poor.
- if I $\leqslant$ 10% $\Rightarrow$ the household is not fuel-poor.

One drawback of the 10% indicator is that it overestimates the extent of fuel poverty within the general population by including households with a high level of income. To overcome this criticism, the ONPE (2014, 2015) studies suggest including in the calculation only those households having an income (*cu*) lower than the threshold of the third decile of income (*cu*).

Therefore, in our study, households were first sorted according to their income (*cu*) and then divided into 10 equal groups each one containing 10% of the global population to create deciles. Then, the annual threshold of the third income (*cu*) decile was determined. Only households having an income (*cu*) level lower than this threshold were considered as fuel-poor. To consolidate our calculation, we compared our threshold with national thresholds. In particular, Table B.1 below presents thresholds of the third income (*cu*) decile that we calculated compared to the national thresholds calculated by the French National Institute of Statistics and Economic Studies (INSEE) (2014) [26] from 2008 until 2014.

Thus, a household is fuel-poor if:

Table B.1 – Threshold of the third decile of income (*cu*)

Year	EU-SILC sample threshold	National threshold [a]
2008	€15,539	€17,230
2009	€15,957	€17,160
2010	€16,300	€17,000
2011	€16,428	€16,830
2012	€16,986	€16,770
2013	€17,079	€16,850
2014	€17,254	€17,150

a. These thresholds do not represent the exact value of national threshold of the third decile of income (*cu*), but rather the standard of living of a population having an income level situated between the national third and fourth deciles of income. They are calculated in constant €2013.

$$\frac{\text{(Actual) Fuel costs}}{\text{Equivalized disposable income}} > 10\% \tag{B.2}$$

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[25] *Cf.* Dictionary of codes 2006, p. 124.

[26] `https://www.insee.fr/fr/statistiques/2417897`. Accessed in July 20, 2017.

and

$$\begin{aligned}\text{Equivalized disposable income } (cu) &= \frac{\text{Disposable income}}{\text{Number of consumption units}} \qquad \text{(B.3)}\\ &< \text{Threshold of the third decile of income}\end{aligned}$$

Our results show that 7.5% of households in our initial sample are fuel-poor according the 10% indicator.

B.2 Calculation of fuel poverty rates according to the LIHC indicators

Based on Table 2 from Sub-section 2.2, we calculated the LIHC indicator according the following formula:

$$\begin{cases}\text{Equivalized net income} \leqslant 60\% \text{ (Equivalized median net income)}\\ \text{Equivalized fuel costs} \geqslant \text{Required national median fuel costs}\end{cases} \qquad \text{(B.4)}$$

Equivalized fuel costs are calculated by dividing fuel costs by the number of consumption units in the case of the LIHC (cu) indicator and by the surface area of the dwelling in the case of the LIHC (m^2) indicator:

— LIHC (cu) indicator:

$$\text{Equivalized fuel costs } (cu) = \frac{\text{Fuel costs}}{\text{Number of consumption units}} \qquad \text{(B.5)}$$

— LIHC (m^2) indicator:

$$\text{Equivalized fuel costs } (m^2) = \frac{\text{Fuel costs}}{\text{Surface in } m^2} \qquad \text{(B.6)}$$

Equivalized net income is calculated as follows:

$$\text{Equivalized net income } (cu) = \frac{\text{Disposable income - Housing costs - Domestic fuel costs}}{\text{Number of consumption units}} \qquad \text{(B.7)}$$

In our sample, the value of 60% of Equivalized median net income and values of the Equivalized median fuel costs in the case LIHC (m^2) for the period going from 2008 to 2014 are given in Table B.2.

Our results show that 8.81% of households in our initial sample are fuel-poor according the LIHC (m^2) indicator and 8.02% according to the LIHC (cu) indicator.

Table B.2 – Equivalized median income and fuel costs

Year	60% of equivalized median disposal income	Median of equivalized fuel costs
2008	€11,654	€702
2009	€12,076	€761
2010	€12,314	€771
2011	€12,460	€801
2012	€12,786	€800
2013	€12,728	€860
2014	€12,698	€870

C Methodology used to calculate energy prices

The EU-SILC database does not provide data on energy prices. Only information on electricity and gas expenditures are available. Therefore, to estimate the effect of energy price fluctuations on household energy consumption, we needed to complete our database and calculate energy prices per household. To do so, we considered two crucial points.

First, the energy tariff in France depends on the power needed for space and water heating, appliances, lighting and cooking, etc. This power itself depends on the structure of the energy mix in the dwelling (share of gas and electricity) and the size of the dwelling (surface area). For instance, the electricity tariff is not the same for a dwelling using gas for heating and a dwelling using electricity for a given surface area. Such information on tariffs is available in PHEBUS database.

Second, we needed to associate the energy tariff (divided by the price of the base fee and the unit cost of kWh) with each dwelling (household), which depends on its surface area and its energy mix. For each household, we must determine an electricity tariff and a gas tariff. From a practical point of view, to include energy prices in the the EU-SILC database, we used the three following steps:

- First, we split the EU-SILC database into categories according to the surface of the dwelling (10 classes), the share of electricity expenditures (10 classes from 0% to 100%) and the share of gas expenditures (10 classes from 0% to 100%).
- Second, we split the PHEBUS database into the same categories. Because for each category of household, the tariff for electricity and gas is given in PHEBUS database, we incorporated this information (tariffs) into the EU-SILC database. This step let us attribute an electricity and gas tariff for each housing unit in the EU-SILC database.
- Finally, we used information provided in the PEGASE database to assign to each energy tariff in the EU-SILC database an energy price covering base fees and consumption.

The merging process is summarized in Figure C.1 below. Otherwise, Table C.1 reports official electricity and gas tariffs in France as well as associated prices that we used in our final compiled database.

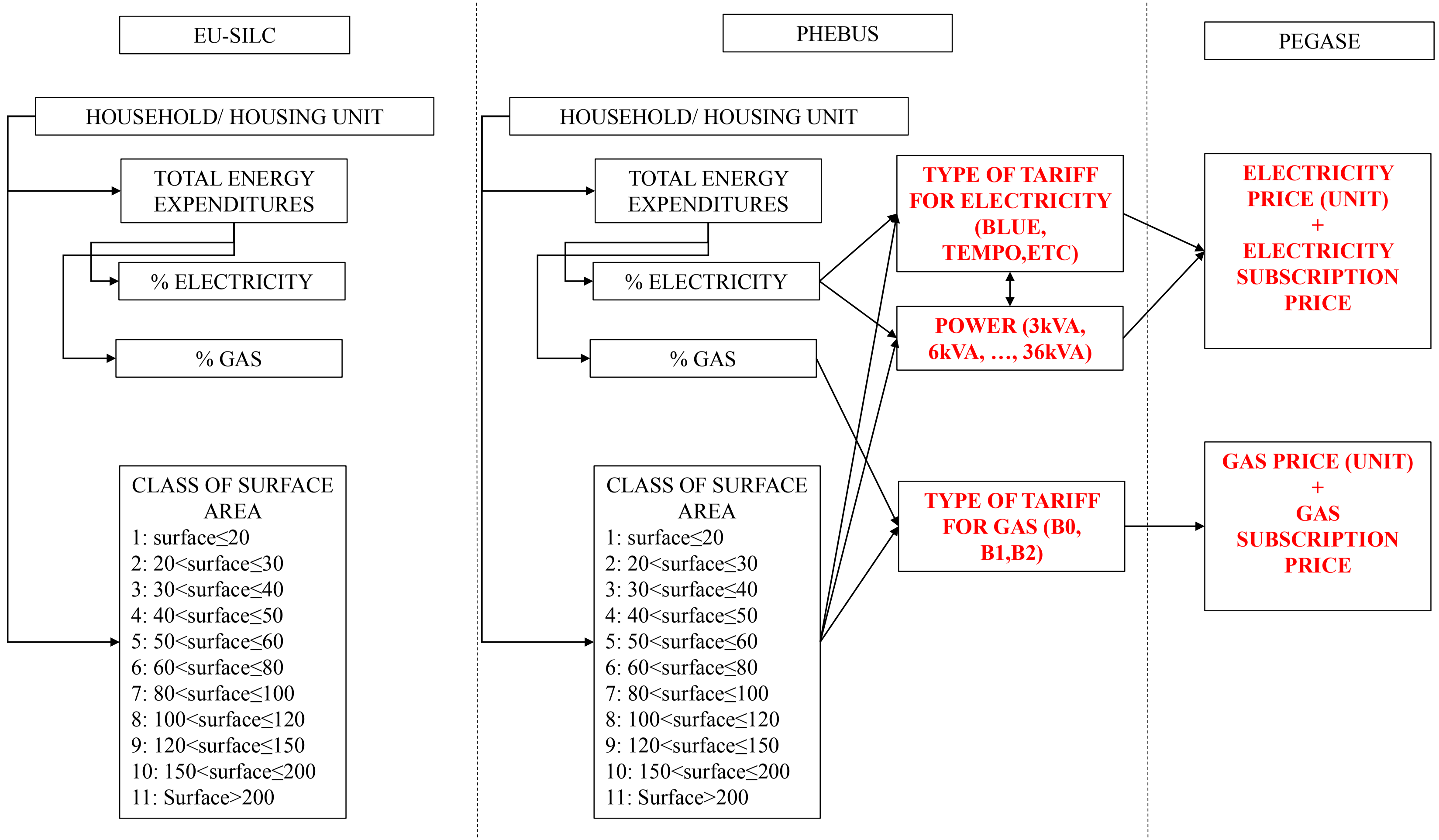

Figure C.1. Summary of the merging process used to calculate energy prices. Source: Authors calculations.

Table C.1 – Energy tariffs from 2006 to 2014 used to calculate the energy prices. Source : PEGASE database (http://www.statistiques.developpement-durable.gouv.fr/donnees-ligne/r/pegase.html)

	2006	2007	2008	2009	2010	2011	2012	2013	2014
Electricity tariffs									
Electricity, blue tariff, base option in € (tax included)									
Annual distribution fees 3 kVA	23,89798	24,11667	24,51333	42,33033	68,02905	64,94606	67,40325	62,84999	53.84
Annual distribution fees 6 kVA	60,83597	61,34167	62,26667	68,86288	79,60103	77,45169	80,36592	84,32679	87.55
Annual distribution fees 9 kVA	120,05802	121,10083	122,80917	112,76375	96,8435	90,3377	93,76717	103,98908	115,99
Annual distribution fees 12 kVA	172,32332	173,72167	176,01917	173,81625	161,82429	142,84527	148,13392	162,46268	178,57
Annual distribution fees 15 kVA	224,58528	226,34083	229,235	220,40483	192,97068	164,85725	171,04758	187,11733	204,78
Annual distribution fees 18 kVA	276,85058	278,96167	282,445	266,99758	238,81541	219,2238	227,44092	233,87278	235,52
Price for 100 kWh (power 3 kVA)	14,98	15,17667	15,395	15,11583	16,5125	17,02237	17,7994	18,38731	18,66
Price for 100 kWh (power 6 kVA)	14,22083	14,3925	14,60083	15,0075	15,56917	16,23193	16,9816	18,1521	19.32
Electricity, blue tariff, peak hours tariff in € (tax included)									
Annual distribution fees 6 kVA	105.4267	106.3325	107.84667	106.18071	101.25412	93.13223	96.59658	97.36873	94.19
Annual distribution fees 9 kVA	189.26538	190.7625	193.51667	178.57946	140.10612	111.76704	115.91475	122.31733	126.30
Annual distribution fees 12 kVA	273.10902	275.19417	279.1225	261.51175	220.06033	189.49559	196.56458	205.38349	204.64
Annual distribution fees 15 kVA	356.94765	359.62417	364.73833	337.03417	270.04042	223.04773	231.32342	240.47863	237.16
Annual distribution fees 18 kVA	440.79128	444.06	450.35	412.55075	318.97905	254.38013	263.81675	273.0081	266.76
Annual distribution fees 24 kVA	737.63455	743.4875	754.14917	690.63436	580.88412	529.87303	549.78758	560.82791	559.77
Annual base fees 30 kVA	1034.47698	1042.915	1057.94833	963.22013	766.4663	652.50116	677.02358	679.4427	661.39
Annual base fees 36 kVA	1331.32437	1342.3525	1361.75333	1235.80483	942.68368	754.42164	782.73067	784.14173	760.87
100 kWh peak-hours	10.64083	10.78583	10.9375	11.26	11.8775	12.91385	13.54292	14.55315	15.61
100 kWh off-peak hours	6.48167	6.56917	6.66	6.98417	7.54833	8.76965	9.23933	10.00336	10.76
Price for 100 kWh (6 kVA power)	12.10417	12.25417	12.43	12.7075	13.1625	14.03546	14.70435	15.64518	16.50
Price for 100 kWh (9 kVA power)	11.775	11.92417	12.09583	12.2175	12.30417	13.02266	13.65389	14.66745	15.68
Price for 100 kWh (12 kVA power)	11.14083	11.28	11.44167	11.62833	11.90583	12.77758	13.39973	14.38309	15.32
Electricity, blue tariff, tempo option in € (tax included)									
Annual distribution fees 9 kVA	162.63282	164.06417	166.5075	145,57613	115,00574	109,04157	113,022	120,17613	125,36
Annual distribution fees 12 kVA	222.63263	224.57167	227.93833	222.68442	214.26835	203.35865	210.90942	212.62099	200.96
Annual distribution fees 30 kVA	409.58732	413.17417	419.31083	444.52454	479.03303	456.64613	473.54025	546.94455	638.80
Annual distribution fees 36 kVA	550.46912	555.39417	563.89417	577.58796	594.67214	566.42158	587.43975	674.79218	783.84
100 kWh blue days and off-peak hours	4.485	4.53667	4.59333	5.02333	5.62496	6.8142	7.2111	7.92828	8.63
100 kWh blue days and peak hours	5.56333	5.63083	5.70583	6.295	7.11058	8.20155	8.65528	9.49	10.33
100 kWh white days and off-peak hours	9.1325	9.2575	9.38083	9.18	8.86254	9.8401	10.35061	11.22325	12.12

Cf. next page

Table C.1 – Continued

	2006	2007	2008	2009	2010	2011	2012	2013	2014
100 kWh white days and peak hours	10.82083	10.97	11.1275	11.05417	10.90929	11.7537	12.33594	13.3671	14.47
100 kWh red days and off-peak hours	16.9325	17.16917	17.42167	17.76167	18.17804	18.5589	19.40033	20.73046	22.21
100 kWh red days and peak hours	47.34917	48.02667	48.73	49.69417	50.88158	49.16455	51.17409	54.34604	58.21
Electricity, market tariff, in € (tax included)									
All tariff		11.4164	11.23334	11.48405	12.44275	13.41974	13.82434	14.67013	15.35
Tariff DA		23.22329	23.03031	22.62814	23.33377	24.45679	25.13133	28.20565	26.77
Tariff DB		14.2505	14.09432	14.0427	15.0075	15.8404	16.3847	17.74836	17.84
Tariff DC		12.17538	12.07868	12.06498	13.12644	14.02566	14.45913	15.5346	16.00
Tariff DD		10.67828	10.55988	10.92719	11.83248	12.84391	13.2134	14.30701	14.74
Tariff DE		9.95671	10.15655	10.48225	11.48295	12.54369	12.91665	13.01667	13.64
					Gas tariffs				
Natural Gas, price in € (tax included)									
Annual distribution fees - base tariff	25.32	25.32	29.99365	34.5618	39.81045	43.8933	46.92645	52.961	62.37
Annual distribution fees - tariff B0	35.95	35.9544	41.9046	47.88645	53.35665	58.0092	61.97075	66.6338	74.27
Annual distribution fees - tariff B1	125.21	125.2074	141.581	160.149	175.41225	185.18415	195.4546	209.10455	220.71
Annual distribution fees -tariff B2I	187.62	187.62	194.37333	171.5446	175.41225	185.18415	195.4546	209.10455	220.71
100 kWh PCS - base tariff	7.11333	7.1999	8.18655	7.96583	8.46893	9.3988	9.96987	10.36132	10.21
100 kWh - tariff B0	5.90333	5.992	6.85797	6.8117	7.2669	8.0742	8.51871	8.78259	8.51
100 kWh- tariff B1	4.22	4.3056	4.86664	4.61108	4.89583	5.58353	5.86163	5.88729	5.65
100 kWh - tariff B2I	4.05667	4.1382	4.78892	4.6081	4.89583	5.58353	5.86163	5.88729	5.65
Price for 100 kWh tariff B0	8.27333	8.3753	9.62172	9.85603	10.62315	11.74238	12.42551	12.94149	13.00
Price for 100 kWh tariff B1	5.29	5.3821	6.08373	5.88843	6.27773	7.08853	7.44654	7.54033	7.33
Price for 100 kWh tariff B2I	5.10667	5.1955	5.94003	5.66641	5.99843	6.79365	7.13536	7.20735	6.98

D Descriptive statistics and correlation between variables

Table D.1 – Descriptive statistics and correlations between variables

	EC	INC	TEN	NB	OWH	$TYPH$	$LEAK$	$DARK$	TEM	$DIFFH$	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	P
Statistical measures																			
Mean	99.74	25,826	0.659	2.380	0.948	0.311	0.119	0.0764	0.933	0.274	0.144	0.199	0.0781	0.0973	0.155	0.113	0.109	0.0992	0.105
Median	87.25	20,852	1	2	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0.114
Minimum	0.0393	124	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.66e-05
Maximum	658.3	577,813	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.184
Standard deviation	68.76	23,553	0.474	1.233	0.222	0.463	0.323	0.266	0.250	0.446	0.351	0.400	0.268	0.296	0.362	0.316	0.311	0.299	0.0357
Skewness	1.438	10.38	-0.672	0.639	-4.036	0.817	2.361	3.191	-3.463	1.014	2.033	1.505	3.145	2.718	1.902	2.451	2.515	2.682	-1.006
Kurtosis	6.670	192.4	1.451	2.326	17.29	1.667	6.573	11.18	12.99	2.027	5.134	3.265	10.89	8.390	4.616	7.006	7.325	8.195	3.172
Observations	827	827	827	827	827	827	827	827	827	827	827	827	827	827	827	827	827	827	827
Correlation																			
EC	1.0000																		
INC	-0.0223	1.0000																	
TEN	-0.0877	0.1862	1.0000																
NB	0.0674	-0.0098	0.0351	1.0000															
OWH	0.0429	0.0449	0.0089	0.0513	1.0000														
TYP	0.0002	-0.0413	-0.4453	-0.2050	0.0380	1.0000													
$LEAK$	0.0690	-0.0820	-0.1434	0.0311	-0.0730	0.0262	1.0000												
$DARK$	0.0396	-0.0609	-0.1144	-0.0204	-0.0704	0.0148	0.1864	1.0000											
TEM	-0.0367	0.1062	0.1060	0.0355	0.0461	-0.0378	-0.1454	-0.1050	1.0000										
$DIFFH$	0.0893	-0.1022	-0.0731	-0.0279	-0.0236	-0.0704	0.2517	0.1924	-0.2690	1.0000									
Z_1	0.0700	0.1369	-0.0975	0.0110	0.0182	0.3263	-0.0114	-0.0101	0.0132	-0.0560	1.0000								
Z_2	0.0094	-0.0356	0.0167	0.0211	0.0175	-0.0970	0.0124	0.0047	0.0300	0.0173	-0.2043	1.0000							
Z_3	0.0690	-0.0587	-0.0244	0.0399	-0.0275	-0.0773	0.0288	0.0109	-0.0276	0.0522	-0.1191	-0.1452	1.0000						
Z_4	0.0056	-0.0241	-0.0211	0.0054	0.0296	0.0213	-0.0085	-0.0395	0.0134	0.0311	-0.1344	-0.1638	-0.0955	1.0000					
Z_5	-0.0849	-0.0235	0.0591	-0.0199	0.0382	-0.1399	-0.0187	0.0095	0.0159	-0.0273	-0.1757	-0.2141	-0.1249	-0.1408	1.0000				
Z_6	-0.0148	-0.0233	0.0325	-0.0476	-0.0372	-0.0764	0.0080	0.0354	-0.0225	0.0397	-0.1459	-0.1778	-0.1037	-0.1169	-0.1529	1.0000			
Z_7	-0.0460	0.0241	0.0239	0.0136	-0.0232	0.0377	-0.0336	-0.0168	0.0070	-0.0278	-0.1429	-0.1742	-0.1016	-0.1146	-0.1498	-0.1244	1.0000		
Z_8	0.0079	-0.0156	-0.0005	-0.0215	-0.0290	0.0106	0.0232	0.0047	-0.0474	-0.0146	-0.1358	-0.1655	-0.0965	-0.1089	-0.1423	-0.1182	-0.1158	1.0000	
P	0.2746	0.0097	-0.1505	-0.0197	0.0438	0.2731	0.0039	-0.0057	-0.0115	-0.1319	0.1402	-0.0459	-0.0024	-0.0826	-0.0341	-0.0036	-0.0417	0.0574	

E Endogeneity correction: Instrumental variables estimation

To take into account potential endogeneity of the energy price variable, we used an instrumental variables with fixed effects. We relied on the two-stage least-squares within estimator (Baltagi, 2008). As instruments, we used the lag of energy prices and a dummy variable taking the value 1 when households benefit from the basic energy tariff called the blue tariff in France and 0 otherwise.

We can test for both under-identification and weak identification. The under-identification test is an LM test of whether the equation is identified, *i.e.* that the excluded instruments are relevant, meaning correlated with the endogenous regressors. Weak identification arises when the excluded instruments are only weakly correlated with the endogenous regressors (Stock and Wright (2000), Stock and Yogo (2005)).

We explored the degree of correlation between instruments and the endogenous regressor. 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 the Stock and Yogo (2005) test, we can gauge the validity of the instruments. The null hypothesis of each Stock and Yogo (2005) test is that the set of instruments is weak. To perform the Wald tests, we chose 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 Cragg-Donald Wald F statistic is 237.22 and largely exceeds the critical value (10%, 19.93; 15%,11.59; 20%, 8.75; 10%, 7.25). Our instruments are not weak. Results are corroborated with the Anderson Rubin test.

In an instrumental variables (IV) estimation, it also is important to conduct a test on whether the excluded instruments are valid IVs or not, *i.e.* whether they are uncorrelated with the error term and correctly excluded from the estimated equation. We performed the Sargan test of the null hypothesis that the excluded instruments are valid instruments. The p-value of χ_2 is equal to 0.949 for a Sargan statistics equal to 0.005. The instruments are therefore valid instruments and the energy prices is endogenous. Finally, we applied a bootstrap correction on the variance covariance matrix to avoid bias in the interpretation of coefficient's significance level. The results are presented in Table E.1 below. Results show that we need to introduce the lag of energy prices to avoid endogeneity.

Table E.1 – IV estimation

	Energy consumption in kWh per m^2
LnP	-0.482*
	(-1.98)
$LnINC$	0.0361
	(1.21)
NB	0.0649***
	(4.69)
TEN	-0.189***
	(-4.94)
TEM	-0.0613
	(-0.97)
$DWTY$	0.0587
	(0.78)
$OWHS$	0.144*
	(2.09)
$DIFFH$	0.00649
	(0.14)
$LEAKS$	0.0512
	(1.06)
$DARK$	0.0796
	(1.38)
$CLIMFR1$	0.151**
	(3.22)
$CLIMFR2$	0.0261
	(0.64)
$CLIMFR3$	0.189***
	(3.33)
$CLIMFR4$	-0.0699
	(-1.15)
c	2.679***
	(3.74)
Observations	4962

*** Significant at P<1%, ** P<5%, and * P<10%.

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