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ABSTRACT

A Life-Cycle Theory Analysis of French Household Electricity Demand

This paper develops a pseudo-panel approach to examine household electricity demand behavior through the household life cycle and its response to income variations to help strengthen the energy policy-making process. Our empirical methodology is based on three rich independent microdata surveys (the National Housing Surveys), which are representative of the French housing sector. The resulted sample covers the 2006-2016 period. Using within estimations, this paper finds striking evidence that the income elasticity of French residential electricity demand is 0.22, averaged over our four cohorts of generations. In light of other works, our estimate stands in the lower range. The empirical results also show that residential electricity consumption follows an inverted U-shaped distribution as a function of the age of the household's head. Most notably, it appears that households at the mid-point of their life cycle are relatively the largest consumers of electricity. This outcome has important implications for policy-making. Any public policy aimed at reducing household energy consumption should consider this differentiation in consumption according to the position of households over the life cycle, and therefore target as priority households at the highest level of consumption.

JEL Classification: C23, D12, Q21, Q41

Keywords: residential electricity demand, pseudo-panel, energy policy, France

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1. Introduction

Since 1990, the final national consumption of electricity in France, adjusted for climate variations, has increased by almost half. This steady growth, mainly attributable to the residential and tertiary sectors, was continuous until the economic crisis of 2008. Since then, consumption has tended to stabilize. Residential buildings account for 37% of total electricity consumption, ahead of the tertiary sector (32%) and industry (27%) (INSEE, 2019). Increasing awareness of climate change in recent years has given rise to a large number of energy demand studies. These studies share a common purpose, which is to understand the main factors shaping energy demand or one particular energy source (Bernard et al., 1996; Belaïd, 2016). Studies are mostly carried at a rather aggregate level by sectors such as commercial, industrial, and residential. The present analysis belongs to this methodological stream.

To achieve a significant residential energy demand reduction, it is crucial to understand how households use energy (Belaïd, 2017; Belaïd et al., 2019). Starting from this conjecture, this study aims at providing a better understanding of how energy use in households varies during the household life cycle and its response to income variations. More precisely, we explore how changes in household age affect domestic electricity consumption. Although the picture is more complicated, because various factors such as individual preferences and societal transformation may play an essential role in shaping household electricity consumption, we focus on the role of individual's heterogeneity in terms of age and generation to capture the evolution of their energy consumption patterns. This analysis will help understand how domestic energy uses can be reduced to benefit consumers and meet the government's energy reduction targets. Although the concept of the household life cycle is not new and has been widely used in marketing as a driver of consumer behavior and a prominent principle in market segmentation, the recent literature on residential electricity demand neglects forward-looking to the effect of the demographic and generational effect on household electricity consumption (Chalal et al., 2017).

In European Union countries, the residential sector is one of the largest consumers of electricity, accounting for about a third of the total final electricity demand (Eurostat, 2016). In France, the residential sector occupies the same weight in the national electricity consumption as in Europe: in 2017, it accounted for more than one third (nearly 36%) of final electricity consumption in France, which represented a total of 151.1 terawatt-hours (EDF, 2020). Considering that French energy consumption in the residential sector has remained stable since 2000, at a constant climate, electricity remains the most consumed energy by the residential sector (33% of national energy consumption), ahead of natural gas (28%), renewable energies (22%) and oil (13%) (Commissariat général au développement durable, 2019). Therefore, untangling domestic electricity use dynamics is of great importance in conceiving future energy policies to enhance energy service use efficiency. The benefits of energy efficiency can be manifold, including improving the durability of the energy system, contributing to strategic economic and social development goals, fostering environmental objectives, enhancing prosperity, and alleviating fuel poverty (Belaïd, 2018; Belaïd et al., 2018). Starting from this conjecture, in this paper, we develop the first model examining income elasticity and life cycle variation for residential electricity demand in France. Our research hypotheses are:

- H_1: Household income has a significant and positive effect on residential electricity consumption;
- H_2: Residential electricity consumption follows an inverted U-shaped distribution as a function of the age of the household's head.

This research contributes to the existing literature in different ways. First, it is a pioneering effort to fill the literature gap related to the household life cycle impact on domestic electricity demand. The economic effects of an aging population have been extensively studied and, following the pioneering contributions by Modigliani (1966) and Jappelli and Modigliani (1998), life-cycle theory shows that the age structure of the population plays an essential role in shaping the aggregate consumption and savings. One rational explanation of this theory is that households tend to adapt their consumption behavior to the various needs of diverse life-cycle stages. Nonetheless, as far as we know, somewhat surprisingly, little consideration has been devoted to the energy-related behavior from the life-cycle theory perspective in the energy economics literature (Bardazzi and Pazienza, 2017). Second, by using a pseudo-panel approach, which considers the lack of information availability, variability, and dynamic adjustment process, the proposed methodology overcomes the shortcoming of standard single cross-section methods. In fact, although the cross-sectional analysis of electricity consumption is helpful to highlight how households with distinct features compare, it is unable to disentangle behavioral differences or changes and structural heterogeneity in consumption patterns. Third, this research is stimulated not only to enrich the scant empirical studies investigating the residential electricity demand but also tempts to shed light on several unanswered questions from energy policy perspectives. For example, how does understanding age structure help to improve the implementation of energy-efficiency policies? Finally, the French National Housing Surveys (henceforth NHSs) provide a rather unique data and experiment, and it is of some interest to explore whether the observed electricity patterns can be explained in terms of household income and various life-cycle stages.

Using the NHSs provided by the French National Institute of Statistics and Economic Studies (INSEE) for the years 2006, 2010, and 2016[1] and pseudo-panel econometric methods, we find via within estimations an income elasticity of residential electricity of 0.22, averaged over our four cohorts of generations. The effect of equivalent income is significant and positive, which confirms our first research hypothesis (H_1). In light of the existing literature, our estimate stands in the lower range. We also find evidence that our second research hypothesis (H_2) is supported by data: residential electricity consumption does follow an inverted U-shaped distribution as a function of the age of the household's head. Our results are robust to a change in the estimation method.

The remainder of this paper is organized as follows: Section 2 explores the existing literature about the link between age, income and domestic electricity consumption and, more broadly, energy consumption; Section 3 introduces the data and the econometric methodology; Section 4 discusses results and provides robustness checks; finally, Section 5 concludes.

2. Literature review

In a context of growing concern about energy transition emerging from public policymakers, understanding household lifestyle in terms of energy use has become essential. Lévy et al. (2014) study the factors of household energy consumption. Their socio-economic approach allows them to highlight how energy consumption is influenced by households' social, demographic, and economic

[1] These are the three most recent waves of the survey.

characteristics as well as their dwelling characteristics. This survey indeed uses the same data as we do: the NHSs provided by the INSEE. They find that dwelling characteristics and location being equal, (i) energy use intensities per person vary according to their position in the life cycle; whereas (ii) energy use per square meter are relativity stable. These main findings promote the need for understanding the dynamics of household energy use all along with their life as well as the importance of dwelling socio-economic characteristics.

For several decades, research has paid growing attention to energy use variations over a lifetime. Bodier (1999) underlines that, even if former studies have shown that consumption declines with age, the distortion of the population structure in favor of higher standards of living induces uncertainty about households' future consumption. In order to remove this uncertainty, Bodier suggests distinguishing the effect of age and the effect of belonging to a specific generation via delineating cohorts of generations. A cohort is a set of households that are grouped together according to specific membership criteria that remain the same for all surveys in order to form a fairly homogeneous group (Bernard et al., 2011). All in all, Bodier observes that the way income, in a broader sense, is spent varies as the household gets older. In terms of energy consumption, she stresses a phenomenon of "domestic downturn" in aging households hence an increase in energy expenditures at home; of 1.2 points in average precisely. More recently, the CREDOC (2008) defined seven cohorts of generations, as suggested by Bodier (1999):

- The "rationing" generation born between 1917 and 1926;
- The "refrigerator" generation born between 1927 and 1936;
- The "electric robot" generation born between 1937 and 1946;
- The "hypermarket" generation born between 1947 and 1956;
- The "home delivery" generation born between 1957 and 1966;
- The "low cost" generation born between 1967 and 1976;
- The "Internet" generation born between 1977 and 1986.

Following Bodier (1999), the CREDOC designs these cohorts of generations in order to isolate the age effect from the generational effect. The CREDOC also admits that the oldest generations spend more on energy than the most recent ones. A possible explanation comes from dwelling quality. Indeed, the most recent dwellings are better insulated and use less energy because their construction is now subject to thermal regulations designed to support energy consumption reduction in the residential sector. In 2013, buildings built before 1919 consumed on average 1.45 times more than buildings built after 2006 (Commissariat général au développement durable, 2015).

Nevertheless, the eldest are less likely to live in recent dwellings: in 2006, only 11% of individuals aged 60 or over living in a dwelling built after 1982, whereas this proportion was equal to 29% for individuals aged between 20-60. The older the building, the stronger this phenomenon: 24% of individuals older than 60 years lived in a dwelling built before 1914 against 18% for individuals aged between 20-60 (INSEE, 2017a). Therefore, this observation is illustrated by more considerable energy expenditure for older people than for middle-aged people.

Bardazzi and Pazienza (2017) apply the same methodology to understand energy consumption profiles linked with the life cycle and generations. Just as Bodier (1999) and the CREDOC did, cohorts of generation are created. Bardazzi and Pazienza (2017) write that "consumption behavior at different ages for the same cohort cannot be analyzed because, in repeated cross-sections, families are not followed over time as in panel data". They recommend to define birth cohorts as the unit of analysis and specify that "generations encounter different historical and social conditions as they age and therefore, it is reasonable for them to have diverse behavioral attitudes."

The significance and the magnitude of the effect of the household reference person age on energy consumption is often discussed and remains debated in the literature. Interestingly, Longhi (2015) and Jones et al. (2015) suggest that "the energy consumption of households whose reference person is aged between 50 and 65 years is high, whereas one of the households whose reference person is aged above 65 years is low", which indicates a decreasing relationship between age and energy consumption from the age of 50 onwards. Similarly, Estiri and Zagheni (2019) find that residential energy consumption increases over the United States life course until it decreases. It might be due to the fact that mid-aged people have more children (Brounen et al., 2012; Bedir et al., 2013; Estiri and Zagheni, 2019). Alternatively, ageing could have an indirect impact on households' energy use through a decline in household size, which undoubtedly results in a decrease in energy use at the household level (Huebner and Shipworth, 2017). The aging of the society was also found to yield a decrease in electricity demand in Japan, known for its aging population (Ota et al., 2018). However, some studies (Abrahamse and Steg, 2009; Huebner et al., 2015) find no evidence of a significant relationship between the reference person's age and households' energy demand. York (2007) even finds that an increase in the proportion of the elderly population is associated with an increase in energy demand in 14 EU countries. A potential reason is that elderly people are expected to "spend more time at home rather than on outside activities due to their preferences for a sedentary lifestyle" (Ota et al., 2018).

Our research question is also profoundly linked to housing dynamics. The progression of households is actually influenced by economic resources and stages in the life cycle: these stages are linked to family status (*e.g.*, from a couple to a family) and age. Indeed, Fritzsche (1981) finds that "total energy consumption increases with succeeding stages of the life cycle up to the point when the children leave the family". He also writes that middle-aged, married households with children "have higher energy consumption levels than households at earlier and later life-cycle stages." Previous studies suggest several possible explanations. In fact, a change in family size can affect residential mobility as Stephan and Crawford (2016) demonstrate that life cycle energy is correlated with house size. Dolling (1975) goes further, stating that, everything else being equal, a decrease in family size can result in residential mobility towards smaller dwellings. On this point, Huebner and Shipworth (2017) find that downsizing could realize significant energy savings. Broadly speaking, it means that living in a smaller dwelling generally reduce expenditure on energy. Another alternative states that parents still live in the same dwelling when children leave the family. This decrease in family size does incur a decrease in energy consumption. However, by remaining in this too large dwelling, energy consumption does not drop as much as it should. Thus, Lévy and Belaïd (2018) reckon that the energy consumption reduction at end-of-life is not as sharp as the increase at the beginning of life.

Previous research does not reach a consensus on the income elasticity of domestic energy demand either. However, Bardazzi and Pazienza (2017) find that income elasticity estimates tend to be smaller when using microdata sets. Longhi (2015) states that changes in household socio-economic circumstances translate into changes in energy consumption "but their impact is small compared to that of dwelling characteristics and especially household size." Table 1 presents selected empirical studies seeking to identify the income elasticity of residential electricity demand.

Table 1

Literature review on the estimation of the income elasticity of residential electricity demand

Author	Country	Period	Income elasticity estimate
Gomez et al., 2013	Spain	2001-2010	0.27
Zhou and Teng, 2013	China	2007-2009	0.14-0.33
Miller and Alberini, 2016	USA	1997-2009	0.06-0.18
Schulte and Heindl, 2017	Germany	1993-2008	0.41
De Abreu Pereira Uhr et al., 2019	Brazil	2008-2013	0.32
Csereklyei, 2020	Europe	1996-2016	0.61

The present research is in line with aforementioned studies. We follow Bodier (1999) and the CREDOC's works by opting for cohorts of generations in order to isolate the age and generation effects. By doing so, we seek to confirm Lévy et al.'s (2014) findings about the importance of the position in the life cycle in energy consumption, everything else being equal. Finally, we aim at estimating the income elasticity of residential electricity demand and comparing our results with those of the previous literature.

3. Data and empirical strategy

3.1. Data source and description

Aggregate time series seem appropriate to study energy consumption, as they are reliable and offer good coverage of data. Forecasting is also possible using this type of data. However, Dubin and McFadden (1984) work on their shortcomings: aggregate time series lack from energy price variability between individuals living in the same territory. Moreover, the dynamic adjustment process is not explicitly given in this type of data as it encompasses users who may be at a different stage of the decision process. In that respect, authors draw attention to "the estimation biases that may result from neglecting the simultaneous nature of the decisions to acquire a particular space heating system and to use it for instance". A solution to tackle this last issue is to make use of panel data. Nevertheless, it is worth noting that panel data are not always available since they are highly costly to obtain (Bernard et al., 2011).

Thus, we take advantage of the availability of three NHSs provided by the INSEE to carry out an analysis taking the time dimension into account. 2006, 2010, and 2016 surveys are used. Carried out by INSEE since 1955 every 4 to 6 years, the NHS is an official detailed cross-sectional survey on a nationally-representative sample of housing units of around 40,000 dwellings. The primary sample results from a multistage sampling design. Households are randomly selected: every quarter, one-sixth of the sample is renewed, representing 65,000 new households, and the other five-sixths are conserved to ensure a better precision of dynamics and trends. Finally, it represents a sample of 100,000 people per year. Because of this particular data collecting process, the NHSs are not panel data because some of the people may drop out of the sample. However, it is not problematic: thanks to the random selection of households, the sample is still representative of the French population.

The NHSs are the primary statistical source for describing the stock of ordinary housing, occupancy conditions, and household spending on its principal residence in a particularly detailed manner. Their main objective is to study the state and structure of the housing stock in France and the conditions under which households occupy their primary residence. The survey consisted of more than 1,000 questions on several themes (Belaïd, 2016):

- Occupant characteristics: age of reference person in the household, number of household occupants, resources received by the different members of the household;
- Quality of the housing: conditions of the residence and the building, size, noise, exposure, location, environment, neighbors, security, quality of existing equipment (heating installation, sanitary facilities, annexes), use of clean energies;
- Expenses associated with housing (rent, rental or condominium charges, prices and financing of recently bought housing, loan repayments by first-time buyers, work, repair, and maintenance) and assistance to occupants;
- Legal arrangements for occupying the residence: form and origin of ownership, rental legislation, aid from the State;
- Difficulties accessing housing, household solvency, the functioning of rental relationships; etc.

Figure 1 illustrates the evolution of residential electricity consumption in kilowatt-hour according to age for the three used NHSs. This figure offers us a first clue about the nature of the relationship between age and residential electricity consumption, namely that this relationship is an inverted U which reaches its maximum between age 40 and 50. Figure 2 presents the evolution of the equivalent annual income expressed in euros according to age for the three NHSs. Similarly to domestic electricity use, an inverted U-shaped relationship is observed between equivalent income and age. Moreover, this figure demonstrates a general increase in the level of equivalent income of French households since the 2016 curve is, for all ages, always above the 2006 and 2010 curves.

Table 2 gives the list and description of variables included in our model as well as the definition of other socio-demographic variables and dwelling characteristics. Frequencies and means are given by NHS. The average annual residential electricity demand is 4,406, 4,211, and 4,276 kWh in 2006, 2010, and 2016, respectively. On average, respondents are in their early fifties. The share of owners surveyed in the three NHSs varies from 53 to 61% between 2006 and 2016 and is close to national figures: in 2013, 57,9% of French households owned their home (INSEE, 2017a). Moreover, the first impressions derived from the observation of Figure 2 are confirmed by summary statistics since, over time, the average annual equivalent income of French households went from 16,612 in 2006 to 22,500 euros in 2016, *i.e.,* a 35%-increase within a decade. The French national institute for statistical and economic studies confirms this stable and constant increase in disposable income over the past decade (INSEE, 2019). Finally, the average dwelling size in the total sample is around 91 squared meters. In metropolitan France in 2013, the average housing surface area was 90.9 squared meters (INSEE, 2017a), which is very close to our sample. This underlines the representativeness of the three NHSs used in this study.

Figure 1

Residential electricity consumption (kWh) according to age in 2006, 2010 and 2016

Reading note: respondents of the 2006 NHS had an average annual electricity consumption of 5,317 kWh at age 50.

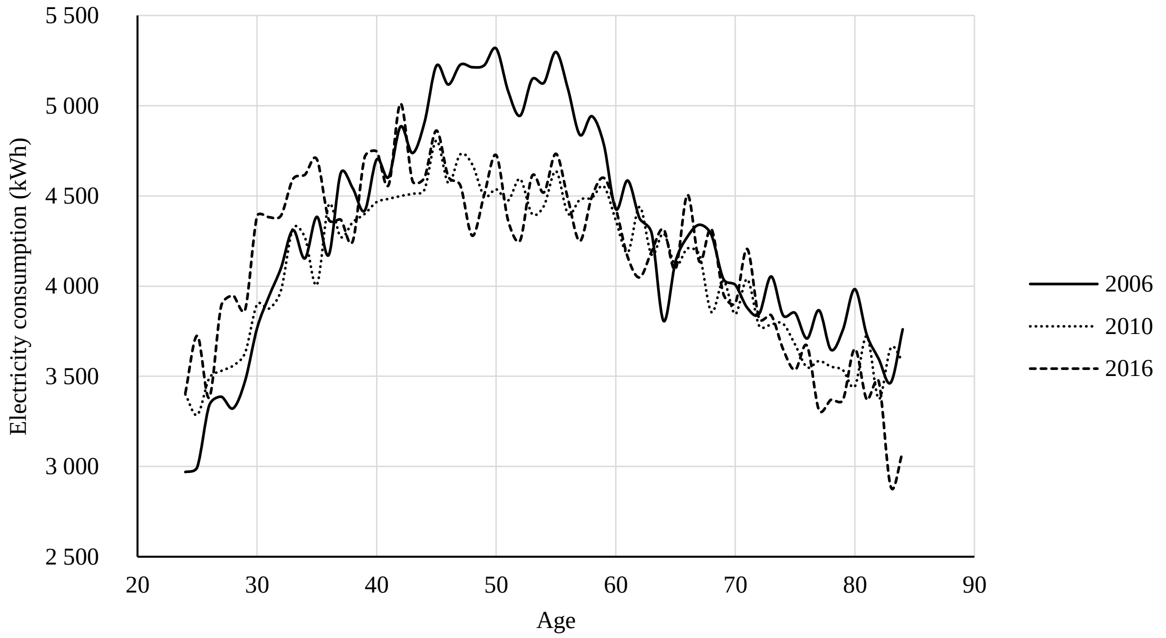


Figure 2

Households' equivalent income (euros) according to age in 2006, 2010 and 2016

Reading note: respondents of the 2006 NHS had an average annual equivalent income of 15,696 euros at age 30.

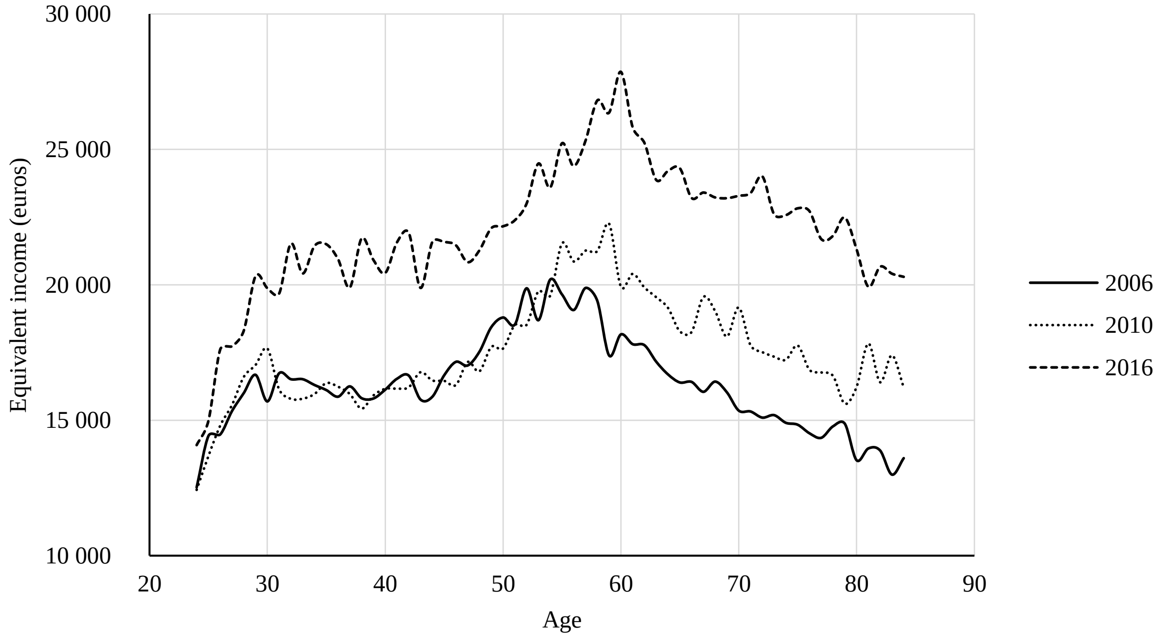


Table 2

List and description of variables by NHS

Variable	Definition	Frequency/Mean in 2006 NHS	Frequency/Mean in 2010 NHS	Frequency/Mean in 2016 NHS
Household socio-economic attributes				
Annual residential electricity consumption	In kilowatt-hour	4,406.27	4,210.88	4,275.55
Age of the reference person	In years	50.92	49.73	53.83
Equivalent income	Total net income of the reference person adjusted for its size, in euros	16,612.12	17,445.06	22,500.12
Gender of the reference person	Man	77%	63%	62%
	Woman	23%	37%	38%
Employment status	Employees and workers	32%	37%	31%
	Farmers and artisans	6%	5%	5%
	Top managerial profession and intermediate profession	27%	28%	28%
	Retired and other	36%	30%	36%
Actual occupancy status	Owner	60%	53%	61%
	Tenant	36%	44%	38%
	Other	3%	3%	2%
Number of dependent children in the household	From 0 to 9	0.74	0.83	0.70
Dwelling characteristics				
Urban unit	Rural commune (less than 5,000 inhabitants)	25%	16%	21%
	From 5,000 to 50,000 inhabitants	23%	17%	18%
	From 50,000 to 200,000 inhabitants	13%	15%	13%
	More than 200,000 inhabitants	38%	52%	48%
Dwelling size	In square meters	93.25	88.60	92.98

3.2.Empirical strategy

The difficulty stems from the fact that the French NHSs are not panel data (the same sample of individuals at different dates) but repeated independent cuts. Thus, it seems necessary to turn towards other methods. Pseudo-panel methods are an alternative to using panel data when only repeated cross-sectional data are available. The use of these methods does not necessarily imply a loss in precision estimation compared to results obtained with genuine panel data. Indeed, pseudo-panel estimates are often close to estimates based on genuine panel data (Gardes et al., 2005). The main threat in panel data analysis is attrition, i.e., when surveyed people drop out of the sample. Here, the French NHSs suffer from attrition due to their data collection process. However, this issue is attenuated since individuals are not the same from one period to another (Bernard et al., 2011). Hence, there is a trade-off between more complete pseudo-panel data subject to measurement errors and more precise information subject to attrition. Baltagi (2005) explores methods for incomplete panels.

The two main econometric methods for panel data analysis are random effects and fixed effects. The first assumes that the random effect terms are orthogonal to the regressors, whereas the second does not. We perform two tests to choose between these two econometric specifications: the Hausman test and the Mundlak test (Hausman, 1978; Mundlak, 1978). Both tests indicate that random effects are inconsistent and provide evidence in favor of fixed effects (see Appendices A and B). Consequently, in what follows, we opt for the fixed effects methodology, also referred to as the within estimation.

Researchers commonly use pseudo-panel methods, notably for life-cycle analyses (Nijman and Verbeeket, 1992a), price, or income elasticity estimates. These methods make it possible to overcome the problem of unobserved heterogeneity by getting rid of the individual effect, or fixed effect, a constant component over time, specific to each individual. The idea behind this is to reduce oneself to a similar configuration, not following individuals themselves, but stable groups of individuals called cohorts (Deaton, 1985). Determining these groups is essential to the smooth running of the pseudo-panel analysis. Cohorts must be stable over time and identified by characteristics observed in the data. A cohort fixed effect replaces the individual fixed effect. Variables are then be averaged within each cohort on the respective dates. In the case of linear models, classic estimation models with fixed effects based on panel data are then easily adaptable, as shown below.

Let the regression model in a "classic" panel data be, where $i = 1, \dots, N$ and $t = 1, \dots, T$:

$$Y_{i,t} = X'_{i,t}\beta_0 + \alpha_i + \varepsilon_{i,t} \qquad (1)$$

It is easy to adapt this regression model to pseudo-panel data:

$$Y^*_{i,t} = X'^*_{i,t}\beta_0 + \alpha_{c,t} + \varepsilon_{c,t} \qquad (2)$$

, where $c = 1, \dots, C$, $i = 1, \dots, N$, $t = 1, \dots, T$ and for all variable Z, $Z^*_{c,t} = E[Z_{i,t}|i \in c, t]$. Cohort means are actually used as if they were observations in a genuine panel.

For our reference model, we follow the most common grouping criterion in literature: year of birth (Deaton, 1985). This criterion appears natural because it is invariant and represents a stable population over time. We also decide to create three other types of cohorts according to aggregation criteria in order to verify the stability of our results (successive generations from 3 to 5 years, generations of 5 years shared between baccalaureate graduates and non-graduates). Grouping successive generations together make it possible to obtain large cohorts and thus reduce potential bias associated with incorrectly approximating expectation by the intra-cohort empirical mean but at the risk of aggregating heterogeneous behaviors and significantly reducing the number of observations. A quick glance at Table 3, which displays the number of observations by cohort, stresses that even with the strictest aggregation criterion, we have a large number of individuals to calculate intra-cohort averages. We can, therefore consider that the risk of obtaining biased estimators is low (Nijman and Verbeek, 1992a-b). Furthermore, in order to work on a stable sample, some operations on the database are carried out before estimation. Following Bodier (1999), we limit our sample to 24-85 years old. As a result, the aggregation criteria being the year of birth, we can assume that the very "young" and the very "old" generations are not well represented in the sample. Elderly people are less likely to be surveyed (as there are no surveys in retirement homes), and this is the same for young people (when they are still living with their parents, for example).

Table 3

Number of observations by cohort

Cohort	Number of observations
Generations of 1 year	183
Generations of 3 years	63
Generations of 5 years	39
Generations of 5 years with a diploma	78

Once the cohorts are correctly completed, the model to estimate becomes:

$$\overline{Y_{c,t}} = \overline{X'_{c,t}}\beta_0 + \overline{\alpha_0} + \overline{\varepsilon_{c,t}} \qquad (3)$$

, where $c = 1, \ldots, C$, $t = 1, \ldots, T$ and $\overline{X'_{c,t}}$ is the empirical mean observed in the sample of $X_{i,t}$ in cohort c at period t. By demeaning variables, fixed effects are eliminated. Consequently, a classic way of estimating β_0 is by calculating the within estimator in the same way as with panel data. Strict exogeneity of the error term is required. Parameters are estimated by Pooled OLS (Wooldridge, 2012). Adapted to our framework, the pseudo-panel model that is estimated formally writes as follows:

$$\overline{\log(elec_{c,t})} = \beta_0\overline{age_{c,t}} + \beta_1\overline{age^2_{c,t}} + \beta_2\overline{\log(income_{c,t})} + \overline{\alpha_c} + \overline{\varepsilon_{c,t}} \qquad (4)$$

, where $elec$ is the annual residential electricity consumption expressed in kWh, age is the age of the reference person, and $income$ is the reference person's level of equivalent income. ε is the normally distributed and heteroskedastic error term (see Appendices C and D). The subscript $c = 1, \ldots, C$ refers to cohorts and $t = 1, \ldots, T$ denotes the year. Under this form, the value of β_2 provides a proxy of the income elasticity of annual residential electricity consumption.

We assume that age is a quadratic profile on electricity consumption. This hypothesis comes from the life cycle theory and the literature on the subject (Brounen et al., 2012). This choice is also motivated by the non-linearity of the relationship between a household's life-cycle and its energy consumption, as underlined by Fritzsche (1981).

It is worth noting that pseudo-panel methods introduce a constraint on the choice of candidate explanatory variables for the model. Consequently, it is challenging to introduce categorical variables into the analysis because their intra-cohort mean does not make quantitative and qualitative sense. As a result, if we consider a variable using three modalities (*e.g.*, 1 for married, 2 for divorced, and 3 for single), its average within the cohort considered at period t will be a decimal number between 1 and 3 that will be uninterpretable. Similarly, cohort aggregation can artificially create variability and give the impression that the parameters associated with fixed characters of individuals are identifiable (in a pure panel setting, all effects constant over time are captured by the fixed individual effect). A simple example is to consider a sex indicator, a characteristic that is invariant overtime on an individual level. In the pseudo-panel setting, this variable becomes "the proportion of men (or women)" in cohort c at the time of t. However, the temporal variations observed are only due to sampling error. For these reasons, we choose of focusing our main econometric specification using the within estimator on the effect of the life cycle and income on electricity consumption, two continuous variables.

The Ramsey's (1969) regression specification error test data is implemented. This test investigates if non-linear combinations of the regressors have any power in explaining the dependent variable. If they do, the model is misspecified in the sense that a polynomial or another non-linear functional form might better approximate the data generating process. This test, applied to equation (4) estimated by the within estimator on cohort 1, presents a p-value of 0.0722, indicating that there is not enough evidence to reject the null hypothesis that the model is specified. Therefore, the selected model, including the age, the age squared, and the equivalent income as explanatory variables to understand the evolution of French annual domestic electricity consumption, is correctly specified at a 10% significance level.

Table 4 reports descriptive statistics by cohort for the main variables of interest. Even if the number of observations in each cohort differs (see Table 3), means and other descriptive indicators over cohorts are relatively stable, which shows that cohorts look alike and are well defined.

Table 4

Descriptive statistics for the main variables of interest by cohort

Cohort	Variable	Mean	Standard Deviation	Minimum	Maximum
Generations of 1 year (183 obs.)	Electricity consumption	3,332.18	439.58	2,235.00	4,311.50
	Age	54.02	17.65	24.00	84.00
	Equivalent income	15,570,54	2,586.87	10,732.27	22,236.13
Generations of 3 years (63 obs.)	Electricity consumption	3,311.38	4,39.92	2,369.79	4,209.64
	Age	53.69	18.22	24.00	84.00
	Equivalent income	15,441.25	2,619.22	10,818.62	21,644.75
Generations of 5 years (39 obs.)	Electricity consumption	3,289.13	451.84	2,369.79	4,170.54
	Age	52.77	18.64	24.00	83.00
	Income	15,375.45	2,665.01	10,732.27	21,229.83
Generations of 5 years with a diploma (78 obs.)	Electricity consumption	3,375.03	483.14	2,167.68	4,436.44
	Age	52.77	18.51	24.00	83.00
	Equivalent income	17,290.54	5,800.99	9,638.48	31,235.03

3.3. Robustness checks

In order to test the robustness of the results, we consider another empirical strategy. Moffitt (1993) proposes an alternative based on instrumental variables techniques. He shows that the within estimator of the pseudo-panel model is equivalent to the double least squares estimator on stacked data where all explanatory variables of the model are instrumented by the product of all cohort indicators with time indicators.

As previously discussed, our main econometric specification only focuses on the effect of age and income on the French annual domestic electricity use in order to check the validity of our two research hypotheses H_1 and H_2. However, the literature strongly emphasizes the effect of socio-demographic variables and housing characteristics on energy consumption in the residential sector (Belaïd and Garcia, 2016; Bazzardi and Pazienza, 2017; Chalal et al., 2017; Belaïd et al., 2020a). Individual preferences are also found to matter in explaining energy consumption in the residential sector, particularly in France (Bakaloglou and Charlier, 2018; Belaïd et al., 2020b). Therefore, as a supplementary robustness analysis, the square of equivalent income of the reference person of the household, socio-demographic variables, and dwellings characteristics are added to our primary econometric model, along with Moffitt's (1993) instrumental variables techniques. Including the square of income in the model allows us to capture non-linear effects, as it is already the case for age.

4. Results and discussion

4.1. Within estimator results

Columns 2 to 5 of Table 5 below present the results of the pseudo-panel model estimation (4) according to the cohorts considered. The results of the estimation on the cross-sectional data of the three stacked surveys are also presented in column 1. First, it is worth noting the similarity of the results between the different specifications.

Second, equivalent income, *i.e.*, the total net income of the household adjusted for its size, is found to have a significant and positive impact on residential electricity consumption. This holds for all cohorts and for the stacked cross-sectional data, which confirms our first research hypothesis H_1. Being specified in logarithm, the coefficient in front of equivalent income can directly be interpreted as an elasticity: for individuals in cohort 1, a 1%-increase in equivalent income leads to a 0.16%-increase in annual electricity consumption. Averaging the parameter estimates for equivalent income across the four cohorts yields an income elasticity of nearly 0.22. Omitting the different time periods studied, this result is close to that of Zhou and Teng (2013) and Gomez et al. (2013) for Chinese and Spanish cases, respectively. However, in light of other works, our estimate stands in the lower range (see Table 1).

Third, in line with our expectations, the coefficient associated with age is significantly positive, and the one associated with age squared is significantly negative. Numerically, this result indicates that electricity consumption increases throughout the life cycle up to a certain age and then decreases. This result is also remarkable and graphically visible. Indeed, Figure 3 presents the log of annual residential electricity consumption as a function of age by cohort as estimated by the within estimator. Each curve is concave, rising from the age of 24 to around 45 and declining thereafter, to the point where electricity consumption at the end of life is less than that at the beginning of life. Therefore, our second research hypothesis H_2 is confirmed: residential electricity consumption does follow an inverted U-shaped distribution as a function of the age of the household's head in France.

Fourth, to determine the inflection point of the model, *i.e.*, the age at which household electricity consumption decreases, it is necessary to solve the following equation:

$$\frac{\partial E[\log(elec)]}{\partial age} = 0 \Leftrightarrow \beta_0 + 2\beta_1 age = 0 \Leftrightarrow age^* = -\frac{\beta_0}{2\beta_1} \qquad (5)$$

According to this model, domestic electricity consumption peaks at age 44~45 for individuals in cohorts 1 and 4 and at age 43~44 for individuals in cohorts 2 and 3. The estimated age at which electricity consumption begins to decrease is slightly higher with cross-sectional data than with pseudo-panel methods as it is ~50 years. From a family life cycle, this echoes with Fritzsche (1981) saying that total energy consumption follows the life cycle "up to the point when the children leave the family". Likewise, Bardazzi and Pazienza (2017) write that household electricity use reaches a peak when the household head is about 45 years old, and the family is its largest size, and then it decreases "as the youngsters move out and the household's members become older." In France in 2016, women were, on average, 28.5 years old when they had their first child (Eurostat, 2018a). Besides, in 2017, French young people were on average, 24 years old when leaving the parental household (Eurostat, 2018b). Therefore, our model predicting that household electricity demand reaches a peak when the household head is approaching 50, *i.e.*, when children are around 20~22 years old, seems plausible and consistent.

Finally, we can note that the estimators' accuracy decreases as the cohort grouping criterion expands (the standard deviations of columns 3 and 4 are more significant than those of column 2). This is simply because the number of observations and variability are decreasing.

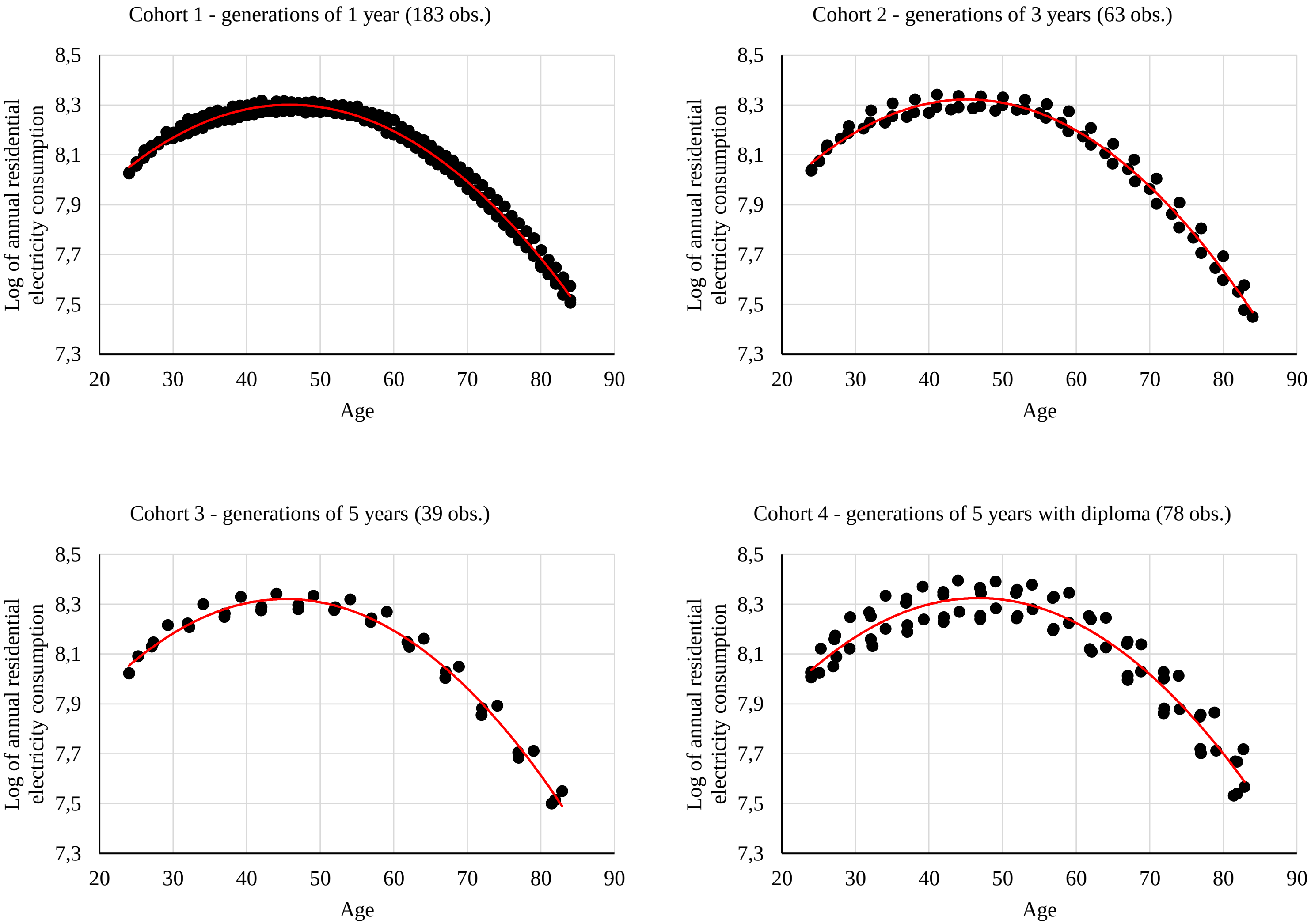
Table 5

Estimate effect of age, age squared, and equivalent income on residential electricity consumption, within estimator

Logarithm of electricity consumption in kWh/year		Within estimator			
		Generations of			
	Cross-sectional data	1 year	3 years	5 years	5 years with a diploma
Age	0.0382*** (0.00104)	0.0436*** (0.00441)	0.0437*** (0.00713)	0.0453*** (0.00896)	0.0444*** (0.00632)
Age squared	-0.000384*** (0.00000966)	-0.000487*** (0.0000352)	-0.000501*** (0.0000553)	-0.000520*** (0.0000686)	-0.000503*** (0.0000515)
Equivalent income (log)	0.123*** (0.00361)	0.158** (0.0761)	0.235* (0.126)	0.254* (0.147)	0.231* (0.0982)
Intercept	6.091*** (0.0412)	5.792*** (0.064)	5.090*** (1.046)	4.879*** (1.208)	5.103*** (0.834)
Observations	83,999	183	63	39	78
Note: standard errors in parentheses; *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$					

Figure 3

Log of annual residential electricity consumption as a function of age by cohort, within estimator



4.2. Robustness analysis results

Table 6 below reports the results of the performed estimations by instrumental variables on the four cohorts as robustness checks. As a reminder, this method developed by Moffitt (1993) consists of instrumenting the explanatory variables by a set of indicators that are the product between cohort and time indicators. Columns 1, 3, 5, and 7 report the estimation results of equation (4) by cohort, *i.e.*, where age, age squared, and equivalent income are the only regressors. Columns 2, 4, 6 and 8 present parameter estimates by cohort when the square of equivalent income, socio-demographic variables and dwelling features are added to the model. These new variables are defined and described in Table 2. The first step equations are not reported below for a sparing presentation.

First, the advantage of this estimation method is that it makes it possible to work on individual data directly, which makes the estimation more accurate for all specifications considered. Indeed, standard deviations in parenthesis in columns 1, 3, 5, and 7 in Table 6 are always strictly smaller than those of Table 5, hence indicating a gain in estimation accuracy using the instrumental variables method suggested by Moffitt (1993). Moreover, estimating equation (4) using this new approach produces a double least square estimator equivalent to the within estimator (Table 5), which confirms our first analysis and the stability of its results. Once again, results across cohorts remain stable. This new approach yields the same results concerning our first research hypothesis $H_{1,}$ stating that income has a significant and positive effect on residential electricity consumption. Averaged over our four cohorts of generations, the income elasticity of residential electricity demand is now found at 0.16, a lower value than that estimated by the within estimator. However, this lower result remains close to those reported by Zhou and Teng (2013) and Miller and Alberini (2016). This new estimation method also confirms our second research hypothesis $H_{2,}$ stating that residential electricity consumption follows an inverted U-shaped distribution as a function of the age of the household's head. Indeed, for all cohorts, coefficients associated with age are positive, and the ones associated with age squared negative, all of them being statistically significantly different from zero at a 1% significance level. Therefore, it appears once again that households at the mid-point of their life cycle are relatively the largest consumers of electricity. Any public policy aimed at reducing household energy consumption should consider this differentiation in consumption according to the position of households over the life cycle, and therefore target as priority households at the highest point of the consumption curve (*i.e.*, households located in the middle of their life cycle).

Second, a model including the square of equivalent income, socio-demographic variables, and dwelling characteristics is estimated (columns 2, 4, 6, and 8). On the one hand, our second research hypothesis $H_{2,}$ still holds empirically, although some parameters associated to age lose their significance. Nevertheless, the predicted age at which households consume the most electricity varies greatly by cohort: it is 44 for cohort 1 and 47 for cohort 4, which is comparable to results obtained by the within estimator; however, it is 34 for cohort 2 and 39 for cohort 3, two surprisingly low values. Indeed, the life cycle theory reckons that household energy consumption increases with age up to the point when the children leave the family (Fritzsche, 1981). Then, knowing that in France in 2016, mothers had their first child at age 28.5 on average (Eurostat, 2018a), it seems surprising that these children leave the family cocoon when their parents are in their mid-thirties. On the other hand, our first research hypothesis H_1 that income has a significant and positive effect on residential electricity consumption is no longer valid since parameters estimates associated with income and income squared a not significant. Estimations of the income elasticity are also not stable; they completely change and go beyond unity, ranging from 0.89 to 2.98. This would suggest that electricity consumption responds to an increase in income in a proportion greater than the increase in income itself. Income elasticities for electricity demand larger than unity have already been found by scholars (Alter and Syed, 2011; Jamil and Ahmad, 2011) but, to our knowledge, the literature on the French case has never led to such conclusions. On the contrary, previous research on French data finds a low or non-significant income elasticity, hence a weak income response of residential electricity demand. Belaïd (2016) states that, in France, "energy consumption is a normal good, but remains weakly responsive to an increase of income per consumption unit". Moreover, it should be noted that almost none of the socio-demographic variables or dwelling characteristics enter the model significantly.. There is evidence that the number of dependent children has a positive impact on household demand for electricity., as it has often been highlighted by the literature (Bedir et al., 2013; Brounen et al., 2012), but this effect is not always significant in our case.

The size of the dwelling also positively impacts household electricity use, although this effect is minimal and non-significant.

To sum up, the variability entailed by the inclusion of socio-economic attributes and dwelling characteristics in the model is potentially due to collinearity or endogeneity problems. Indeed, to account for the varying financial needs of households of varied size and composition. , one of our main variables of interest, equivalent income, is already adjusted by assigning different weights to each household member. The equivalized income calculated using the OECD equivalence scale[2].

. Thus, including the number of children in the household, or any variable describing the household's composition, particularly distorts our results. It is also for these reasons that most of the variability applies to income outcomes, while the results for age are only slightly affected.

[2] According to the OECD scale, weights in consumption units are 1 for the first adult, 0.5 for each subsequent adult and 0.3 for each child in the household, where a child is defined as a person under 14 years old.

Table 6

Estimate effect of age, age squared, equivalent income, socio-demographic variables and dwelling characteristics on residential electricity consumption, instrumental variables estimation

Logarithm of electricity consumption in kWh/year	Instrumental variables estimation							
	Generations of							
	1 year		3 years		5 years		5 years with a diploma	
	1	2	3	4	5	6	7	8
Age	0.0451***	0.0231***	0.0449***	0.0199**	0.0456***	0.0174	0.0449***	0.0167***
	(0.00221)	(0.00522)	(0.00223)	(0.00805)	(0.00226)	(0.0110)	(0.00224)	(0.00606)
Age squared	-0.000510***	-0.000262***	-0.000514***	-0.000293***	-0.000519***	-0.000223**	-0.000522***	-0.000177***
	(0.0000194)	(0.0000431)	(0.0000195)	(0.0000724)	(0.0000197)	(0.000107)	(0.0000197)	(0.0000552)
Equivalent income (log)	0.135***	0.885	0.160***	1.765	0.150***	2.983	0.194***	1.787
	(0.0339)	(1.046)	(0.0356)	(1.851)	(0.0366)	(3.219)	(0.0348)	(1.094)
Equivalent income squared (log)	-	-0.0450	-	-0.0774	-	-0.149	-	-0.107*
		(0.0559)		(0.0972)		(0.163)		(0.0574)
Gender of the reference person								
Woman	-	-0.0481	-	0.000780	-	-0.252	-	-0.138
		(0.107)		(0.185)		(0.284)		(0.148)
Employment status								
Farmers and artisans		-0.232		2.399		5.603		-0.467
		(1.260)		(2.934)		(7.026)		(2.890)
Top managerial profession	-	-0.482	-	0.809	-	4.202	-	-1.578
		(1.212)		(2.710)		(6.934)		(2.910)
Retired and other		-0.420		1.169		4.375		-1.608
		(1.206)		(2.741)		(6.983)		(2.896)
Actual occupancy status	-			-0.209	-		-	

Tenant		-0.0998		(0.293)		-0.517		-1.115***
		(0.145)		-1.073		(0.665)		(0.315)
Other		-0.597		(0.850)		-1.003		-1.607*
		(0.408)				(1.616)		(0.841)
Number of dependent children (log)	-	0.0774***	-	0.0900*	-	0.0298	-	0.0000615
		(0.0262)		(0.0460)		(0.0618)		(0.0330)
Urban unit								
Rural commune		-0.0616		-0.435		-0.732		-0.214
		(0.146)		(0.301)		(0.505)		(0.244)
5,000-50,000 inhabitants	-	-0.208	-	-0.186	-	-0.700	-	-0.234
		(0.172)		(0.402)		(0.542)		(0.284)
50,000-200,000 inhabitants		-0.323*		-0.749*		-1.410		0.0264
		(0.171)		(0.385)		(1.070)		(0.377)
Dwelling size (log)	-	0.00406**	-	0.00195	-	0.00161	-	0.00325
		(0.00193)		(0.00369)		(0.00744)		(0.00409)
Intercept	5.900***	3.546	5.677***	-2.955	5.725***	-10.60	5.311***	3.204
	(0.304)	(5.195)	(0.319)	(9.930)	(0.329)	(20.46)	(0.320)	(5.794)
Observations	183	183	63	63	39	39	78	78
Note: standard errors in parentheses; *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$								

5. Conclusions and Policy Implications

This study uses the French National Housing Surveys from 2006, 2010, and 2016 to identify the different factors that affect electricity demand in the residential sector. Micro-level data provide us with richer sources of information. This paper seeks to identify the key factors conditioning domestic electricity demand, which represents the basis of the design of effective energy efficiency policies. To untangle electricity demand patterns across generations, this article develops a pseudo-panel methodology creating four generational cohorts, as suggested by Bodier (1999). Our criterion is the year of birth (Deaton, 1985) as it is invariant and represents a stable population over time. After exploring the methodology of pseudo-panel data, we run a within estimation which leads us to retain our two research hypotheses, being H_1, household income has a significant and positive effect on residential electricity consumption; and H_2, residential electricity consumption follows an inverted U-shaped distribution as a function of the household's responsible-person age. Our econometric investigation reveals an average income elasticity of the residential electricity demand of nearly 0.22 across our four cohorts. This result stands in the lower range compared to previous studies in different countries. Besides, we find evidence that electricity consumption peaks at age 43~45 in the life cycle. Eventually, it corresponds to when children leave the family house, hence a change in family size, which goes in line with Fritzsche (1981). Our results are also plausible and consistent with family dynamics in France. In the future, as the age at first childbirth in France has been rising steadily since 1974, from 24.0 to 28.5 years of age (INSEE, 2017b), we can expect electricity consumption to increase longer throughout life and start decreasing from a later age.

Our research findings should be useful to energy policymakers to help them better identify their target: households that are the most likely to be receptive to such policies are those positioned at the highest point of the consumption curve, *i.e.*, in their mid-forties. It is necessary to take into account the differentiation in consumption according to the position of households over the life cycle.

As always, our estimates must be interpreted with caution. The current analysis control only for heterogeneity at household-head age and family size level. However, household composition and the different weights in electricity demand attributed to different family members may impact the household's global electricity demand. Due to data limitations, it was simply not possible to capture such heterogeneity or give different weights to different family members in our survey, and we had to settle for controlling only for household-age and household composition. Overcoming this issue requires additional detailed information regarding household members' attributes and their electricity use. To further untangle the various source of heterogeneity on domestic electricity consumption in relation to the life cycle theory, the role of age and composition of family members would be a worthwhile perspective to explore in futures studies. Finally, it might also be useful to extend the theoretical and the empirical framework proposed in this analysis to explore the life cycle theory framework in the context of the other energy demand, including gas and renewable energies.

Appendix

A. Hausman test for cohort 1

The Hausman test permits to choose between fixed effects and random effects. The null hypothesis is that the two estimation methods are both suitable and deliver consistent estimators, which should therefore yield similar coefficients, whereas the alternative hypothesis is that fixed effects are suitable but not random effects. If this is the case, differences between the two sets of coefficients would be expected. A large and significant Hausman statistics means a large and significant difference (Hausman, 1978).

Table 7

Hausman test for equation (4) estimated on cohort 1

Logarithm of electricity consumption in kWh/year	Fixed effects	Random effects	Difference
Age	0.0436	0.0424	0.00122
Age squared	-0.000487	-0.000415	-0.000072
Equivalent income	0.158	-0.0991	0.2571

Here, for cohort 1, the Hausman test statistics is found at 19.92 and is statistically significant (p-value of zero). Therefore, the null hypothesis that the two methods are suitable is rejected in favor of the alternative hypothesis that fixed effects are suitable and random effects are not.

B. Mundlak test for cohort 1

The Mundlak test permits to check the validity of the assumptions on which random effects are based upon, being that there is no correlation between time-invariant effects and regressors. The null hypothesis states that the panel-level averages of time-varying covariates are jointly zero and the alternative hypothesis states that at least one of the panel-level averages is different from zero. The test follows a three-step procedure:

- Compute the panel-level average of time-varying covariates;

- Regress the dependent variable on the set of covariates and their panel-level averages with random effects;
- Compute the test-statistics and conclude.

If the null hypothesis is rejected, *i.e.*, that panel-level averages are not jointly zero, then it indicates that there is a correlation between the time-invariant unobservable and other covariates. In this case, the violation of the hypothesis on which random effects are based upon implies the inconsistency of random-effects parameters. Therefore, the fixed effects should be favored (Mundlak, 1978).

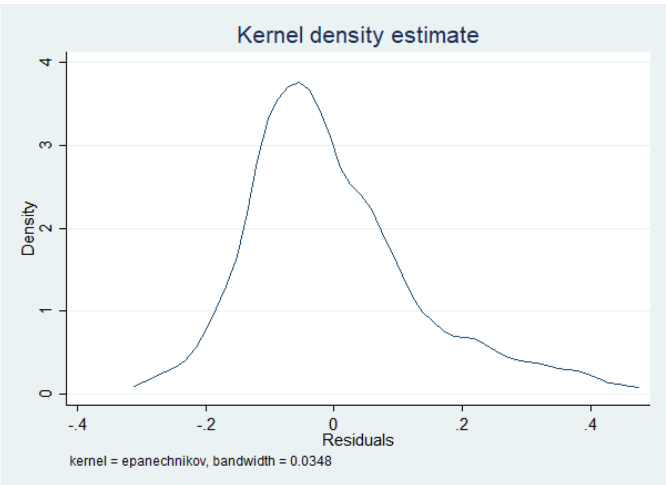
Here, for equation (4) estimated on cohort 1, the test statistics of 28.83 is large and statistically significant (p-value of zero), so the null hypothesis that panel-level averages of time-varying covariates are jointly zero is rejected, meaning that there is evidence that time-invariant unobservables are correlated to regressors. Therefore, the random effects assumption is not satisfied, making the estimators inconsistent. Consequently, fixed effects should be favored.

C. Normality of residuals

Figure 4 is the Kernel estimation of the density of the residuals from the estimation of equation (4) performed on cohort 1, cross-sectional data, with Epanechnikov Kernel and an optimal bandwidth of 0.0348. A quick glance at it confirms the normality of residuals.

Figure 4

Kernel density estimation of residuals from the regression estimation of equation (4) on cohort 1, cross-sectional data



D. Breusch-Pagan heteroskedasticity test

The Breusch-Pagan heteroskedasticity test investigates the presence of heteroskedasticity in the model. Heteroskedasticity happens when the error term's variance is not constant across individuals, which, if omitted, can yield non-robust standard errors. This test's null hypothesis is that there is homoskedasticity and the alternative hypothesis is that there is not (Breusch and Pagan, 1979). This test follows a three-step procedure:

- Run an OLS regression of the independent variable on the dependent variables and compute squared residuals;
- Run the auxiliary regression, that is to say, regress the squared residuals on the set of dependent variables;
- Compute the test-statistics and conclude.

Here, for the estimation of equation (4) on the cross-sectional data of the three stacked surveys (*i.e.*, parameter estimates derived from column 1 of Table 5), a p-value of 0.2612 is obtained. Therefore, the null hypothesis is not rejected, which indicates that the residuals of equation (4) are homoskedastic.

E. Number of observations by cohort

Table 8

Complete number of observations in cohort 1

Generation (year of birth)	2006 NHS	2010 NHS	2016 NHS	Generation (year of birth)	2006 NHS	2010 NHS	2016 NHS
1917	100			1954	551	670	467
1918	136			1955	617	677	497
1919	168			1956	608	797	472
1920	290			1957	590	781	507
1921	286			1958	589	718	487
1922	326	220		1959	626	736	499
1923	353	270		1960	580	806	476
1924	331	254		1961	607	726	481
1925	346	277		1962	625	765	489
1926	378	280		1963	589	803	488
1927	390	322		1964	621	808	475
1928	376	331		1965	599	837	477
1929	361	321	143	1966	579	836	463
1930	445	381	211	1967	522	849	473
1931	452	376	232	1968	538	865	443
1932	416	403	263	1969	590	807	494
1933	395	354	228	1970	542	887	477
1934	402	380	272	1971	539	895	486
1935	381	379	257	1972	550	813	455
1936	422	416	275	1973	464	778	442
1937	424	366	269	1974	410	758	414
1938	398	412	272	1975	331	603	352
1939	404	356	300	1976	293	564	356
1940	378	360	264	1977	290	499	363
1941	338	377	258	1978		537	361
1942	406	394	291	1979		495	353
1943	407	410	335	1980		473	360
1944	402	448	304	1981		418	325
1945	457	444	340	1982		328	290
1946	543	559	461	1983			238
1947	592	599	458	1984			239
1948	607	635	445	1985			207
1949	579	609	470	1986			186
1950	557	629	465	1987			172
1951	573	684	423	1988			140
1952	617	619	480	1989			103
1953	564	602	458				

Table 9

Complete number of observations in cohort 2

Generation (year of birth)	2006 NHS	2010 NHS	2016 NHS
1917-1919	404		
1920-1922	902	220	
1923-1925	1,030	801	
1926-1928	1,144	933	
1929-1931	1,258	1,078	586
1932-1934	1,213	1,137	763
1935-1937	1,227	1,161	801
1938-1940	1,180	1,128	836
1941-1943	1,151	1,181	884
1944-1946	1,402	1,451	1,105
1947-1949	1,778	1,843	1,373
1950-1952	1,747	1,932	1,368
1953-1955	1,732	1,949	1,422
1956-1958	1,787	2,296	1,466
1959-1961	1,813	2,268	1,456
1962-1964	1,835	2,376	1,452
1965-1967	1,700	2,522	1,413
1968-1970	1,670	2,559	1,414
1971-1973	1,553	2,486	1,383
1974-1976	1,034	1,925	1,122
1977-1979	290	1,531	1,077
1980-1982		1,219	975
1983-1985			684
1986-1988			498
1989-1991			103

Table 10

Complete number of observations in cohort 3

Generation (year of birth)	2006 NHS	2010 NHS	2016 NHS
1917-1921	980		
1922-1926	1,734	1,301	
1927-1931	2,024	1,731	586
1932-1936	2,016	1,932	1,295
1937-1941	1,942	1,871	1,363
1942-1946	2,215	2,255	1,731
1947-1951	2,908	3,156	2,261
1952-1957	2,957	3,365	2,374
1958-1961	2,992	3,767	2,450
1962-1967	3,013	4,049	2,392
1968-1971	2,731	4,303	2,373
1972-1076	2,048	3,516	2,019
1977-1981	290	2,422	1,762
1982-1986		328	1,160
1987-1991			415

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