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Dorothée Charlier, Bérangère Legendre

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Carbon Dioxide Emissions and aging: Disentangling behavior from energy efficiency

Dorothée Charlier[1] and Bérangère Legendre[2]

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Abstract

Demographic aging affects Western societies and calls for the adaptation of a number of economic structures, such as pension systems. But this trend requires us to take into account the behavioral changes inherent in aging if we are to develop sustainably, specifically concerning resource consumption and carbon dioxide emissions in the context of global warming. The aim of this research is to assess the impact of aging on emissions by disentangling the pure effect of behavioral patterns and the effect of home energy efficiency. Showing that a selection bias arises through the choice of home, we isolate the pure effect of the behavior of older people. We use a discrete-continuous model to address potential endogeneity in a residential energy consumption model due to the choice of home energy characteristics. As a key contribution, we provide evidence that age does have a significant but indirect impact on carbon dioxide emissions, through the choice of dwelling.

Keywords: energy consumption; carbon dioxide emissions; aging; empirical analysis; endogeneity

JEL codes: Q41, J14

[1] Corresponding author, Université Savoie Mont-Blanc. IREGE. 4 chemin de Bellevue. 74940 Annecy le vieux.
[2] Université Savoie Mont-Blanc. IREGE. 4 chemin de Bellevue. 74940 Annecy le vieux.

1/ Introduction

Increasing longevity worldwide is now a well-known phenomenon, and began several decades ago in Europe. The average age in France was 38.6 years in 2000 and is now 41.7 years. In Germany, the average age in 2000 was 40.1 and in 2020 the average age there is expected to be 45.7 years. Aging is also particularly striking in Italy, where the average age rose from 40.3 to 47.3 between 2000 and 2020. In 2010, 16.2% of the European population was over 65 years old. In 2017, those over 65 represent 18.2% of the population. Population aging raises questions about how sustainably our societies are developing. Beyond the conventional questions about the viability of pension systems (Blake and Garrouste, 2019 [9]), especially pay-as-you-go (PAYG) pension systems, the question of sustainable development is emerging, particularly with regard to the use of finite resources (Fisher, 1971 [21],Guesnerie, *et al.*, 2012 [24]). Aging is likely to lead to profound changes in energy consumption habits (Erlandsen and Nymoen, 2008 [23]). Indeed, individuals are living longer, leading to changes in household composition and housing choices. Households through their consumption emit carbon dioxide emissions (Stern, 2008 [47]).The literature reports that older households have a higher demand for electricity and heating, mainly due to daily occupancy time, but also because they have more pronounced preferences for thermal comfort (Bardazzi and Pazienza, 2017 [2]). Thus, aging can influence emissions (O'Neill, *et al.*, 2010 [38]).

At the same time, the question of greenhouse gas emissions is raised, and consequently that of global warming. Lashof and Ahuja (1990) [31] showed that both are closely linked. If age actually increases household consumption and carbon dioxide emissions[3], then the ecological footprint of societies will deteriorate due to demographic trends. The pioneering work of Ehrlich and Holdren (1971) [19] shows that CO_2 emissions can be explained by the size and the affluence of the population (GDP per capita).

Many studies highlight the individual (or household) socioeconomic characteristics that can affect household consumption and greenhouse gas emissions (Zheng, *et al.*, 2011 [51]) on the one hand and on the other hand the technical characteristics related to housing that also play an important role (Nesbakken, 1999 [36],Nesbakken, 2001 [37]). It is therefore difficult to

[3] The link between energy consumption and CO_2 emissions is clearly established at both the macroeconomic and microeconomic levels. The latest IEA report states that "Driven by higher energy demand in 2018, global energy-related CO_2 emissions rose 1.7% to a historic high of 33.1 Gt CO_2".

disentangle the exact determinants of energy consumption and greenhouse gas emissions. Furthermore, many of these characteristics are closely related to the age of individuals, and therefore to the demographics of a population (Biesiot and Noorman, 1999 [8],Gatersleben, *et al.*, 2002 [23]). The findings of these studies are quite worrying in the context of global warming, which is now well established in the international community.

Bardazzi and Pazienza (2017) [2] summarize the human and non-human factors affecting the energy consumption of older people. Human factors include behaviors and households and individual attributes, inextricably linked to age. People are not interested in consuming energy per se, but in the services provided, and the demand for these services can be influenced by social norms, cultural practices or socio-demographics (Quigley and Rubinfeld, 1989 [40],Shove, 2003 [46]). Elderly households are smaller households, leading to a loss of economies of scale (Brounen, *et al.*, 2012 [10]). Household size is one of the most important factors impacting per capita energy expenditure and carbon footprint (Longhi, 2015 [33],Schroder, *et al.*, 2015 [45]). According to Longhi (2015) [33], moving from a one to a two individual household leads to a sharp decrease in per capita expenses: by 51% for gas and by 41% for electricity.

A household's environmental footprint tends to increase with income (Büchs and Schnepf, 2013 [11],Longhi, 2015 [33]). Retired households usually have lower incomes, because pensions are lower than income from employment. However, they also accumulate greater wealth over their life cycle. Thus, for the elderly, the question of how household income is related to CO_2 emissions is related to choices over the short and long term. The type of home is a long-term choice, while choice of appliances has direct consequences in the short term. Energy cannot be consumed as an end in itself but in conjunction with other choices. These are dependent on the type and range of appliances owned, as well as building characteristics, which influences heating, cooling, lighting, and humidity control. Thus, demand is reflected by how much appliances are used. Structural factors relating to convenience, lifespan, and choice can be also reflected in the types of homes and appliances the elderly possess.

Culture is a behavioral attribute reported in the literature to also explain consumption and the ecological footprint of the elderly (Bardazzi and Pazienza, 2017 [2],Carlsson-Kanyama, *et al.*, 2005 [12],Hamza and Gilroy, 2011 [25]) Dietz, *et al.*, 2013 [19]. According to Hamza and Gilroy (2011) [25], baby boomers have a high demand for domestic thermal comfort, but also for consumables in the home. Consequently they may have less environmentally-friendly attitudes than younger people.

Documenting the impact of demographics Brounen, *et al.* (2012) [10] provided forecasts of energy demand, taking into account the irreversible aging trend. They emphasize the need to account for the impact of demographic characteristics, especially the growing number of elderly aged 65 or older. In Holland, energy use will increase, because the elderly consumes more energy for heating than other types of households. According to them, the academic literature has neglected the behavioral components of energy consumption, which are directly linked to household demographics, compared to the technical literature.
Belaïd and Garcia (2016) [7] showed that people between the ages 45 and 56 adopt more energy-saving behaviors. But older people tend to prefer energy comfort. In addition, age seems to have a negative impact on environmental behavior which accentuates the difference in behavior between 45 and 56. There is greater behavioral inertia on the part of older people (Hines, *et al.*, 1987 [26]). Wei, *et al.*, 2018 [52] stressed that the participation of the elderly population in the labor market has the potential to considerably mitigate the negative impact of aging on the economy, even if this effect can differ across regions.

Housing attributes are “non-human factors” (Bardazzi and Pazienza, 2017 [2]). The period of construction, dwelling type and size strongly impact energy consumption (Brounen, *et al.*, 2012 [10],Meier and Rehdanz, 2010 [34],Rehdanz, 2007 [41]) Costa and Kahn, 2011 [16]. Behavior doesn't explain everything. Today, fuel poverty especially affects a proportion of older people (Legendre and Ricci, 2015 [32]) living in homes whose energy efficiency can be questioned. Many studies also reveal that energy consumption in the home and CO_2 emissions are not independent of the quality of the building. Brounen et al. (2012) estimate the impact of the technical characteristics of dwellings and the impact of the demographic attributes of households on the consumption of gas and electricity separately and propose then models combining both. This overlooks the notion that housing choice is probably not independent from individual and household attributes, including demographics.

Some of the existing work raises the question of the exogeneity of the technical characteristics of housing. Thus, one of the contributions of our research is to take this important assumption into account. Indeed, Dubin and McFadden (1984) [17] concluded that households choose their housing according to its characteristics. Dubin and McFadden (1984) [17], (Nesbakken, 1999 [36])],Nesbakken (2001) [37] and assume for example that appliance or heating system choices and consumption choices are bound. Age could play a twofold role in explaining CO_2 emissions: first, it influences the choice of home characteristics or appliances (indirect effect on CO_2 emissions); second, once the appliances or home characteristics are considered, age also has a direct influence through consumption behavior. Estiri (2015) [20] reached the conclusion that 80% of the effects of household socioeconomic characteristics are observed via building characteristics.

The physical attributes of dwellings can therefore no longer be considered to be exogenous variables in explaining energy consumption and greenhouse gas emissions. Methodologically, this raises the question of the selection bias in the studies cited above. In choosing housing according to its characteristics, households self-select, then adopt a consumption pattern that is known to be directly influenced by their age. They therefore make a two-step decision. We can then consider that there are determinants impacting housing demand, but not energy consumption or domestic emissions. Technically, this requires finding robust instrumental variables that allow an appropriate methodology to be implemented. The framework of conditional demand analysis employing the two-step discrete-continuous model first put forward by Dubin and McFadden (1984) [17] has been used to model energy consumption. Using those models, researchers address selectivity biases in data sets with endogenously partitioned observational units (Bakaloglou and Charlier, 2019 [1],Frondel, *et al.*, 2016 [22]). These models are thus often used in the field of energy consumption due to the interactions and endogeneity between independent explanatory variables. Identifying good instruments with sufficient explanatory power is extremely difficult, which may explain why existing research favors a single model or two different econometric models to highlight the human and non-human determinants of energy consumption and greenhouse gas emissions.

In this paper, we fill the gap in the literature on both of these topics by disentangling the impact of age on housing characteristics, and the impact of age on behavior. We aim to correct for selection bias in the impact of aging on energy consumption, which is overlooked in the literature. Based on the existing energy consumption literature, the main assumption of this study is that age has a significant but indirect positive impact on CO_2 emissions. We assume that the household's decision is divided into two parts. In the first, the household decides to live in a housing unit according to its theoretical energy/climate performance (depending on its technical characteristics). In the second, it decides how much energy to consume according to the occupants' age. Properly disentangling these aspects, particularly by correcting for selection bias and the effect of age on dwelling choice and consumption will be of great help in designing energy policy relevant to aging societies. Is it more appropriate to address consumption behavior, through financial incentives for example, or to focus on the structural attributes of housing? Is it necessary to combine both types of measures or is it ineffectual to target them simultaneously?

The dataset is presented in Section 2. Section 3 sets out the empirical strategy. The results and the discussion are presented in Section 4, and Section 5 concludes.

2/ Data

The survey

In the present study we use the PHEBUS survey, conducted by the French Ministry of Ecology and Sustainable Development. This national household survey is furnished by the Ministry's Department of Observations and Statistics (SOeS). Energy audits performed in 2012 on 2,040 individual dwellings are reported, providing enough data to study theoretical energy-efficiency and real energy consumption (based on energy bills). Social, economic and behavioral variables of the occupants are also recorded.

Consequently, the survey provides cross-sectional annual data (2012) and is representative of the French dwelling stock according to region, climate zone, dwelling type and building construction date. The survey was conducted using face-to-face interviews. The richness and originality of the database lie in the information about the Energy Performance Certificate (EPC), collected through audits carried out by an independent auditor. An individual auditor visited dwellings to collect technical data and evaluate the theoretical CO_2 emissions calculated from engineering models with the assumption of standardized behaviors. The mode of data collection, the expertise of the auditors and the precision of the information collected on the energy attributes of the dwelling make this survey a unique and exceptional source of data for researchers. Very few surveys provide this level of detail on dwellings and at the same time on the socioeconomic characteristics of the inhabitants. The survey also included behavioral questions.

Theoretical and effective carbon dioxide emissions

Housing energy needs are usually measured by the theoretical CO_2 emission of the dwelling and are also measured using the EPC. Indeed, according to the literature, technical building characteristics (insulation, year of construction, appliances, energy mix) can account for more than half of the energy consumption/CO_2 emissions variability in the residential sector (Baker and Rylatt, 2008 [2],Costa and Kahn, 2011 [16],Estiri, 2015 [24],Harold, *et al.*, 2015 [30],Risch and Salmon, 2017 [48]). Newer buildings tend to consume less energy due to thermal regulation (Koirala, *et al.*, 2013 [28]). Such improvements are as a result of changes in building techniques and regulations. The theoretical CO_2 emissions are estimated using the 3CL method[4] :

$$C02 = C02ch + C02ecs + C02cool \tag{1}$$

Where $C02ch$ is the theoretical heating CO_2 emissions of the dwelling, $C02ecs$ the theoretical CO_2 emissions for hot water use and $C02cool$ the theoretical CO_2 emissions for cooling use.

The main assumptions in the calculation are the following. The heating needs depend on building insulation, appliances, dwelling characteristics and location as well as energy mix. The meteorological data used are the heating degree hours of the *département* (county) of reference to assess the heating needs of the building. Although France is not a geographically large country, there are significant differences in climate between areas along the coast, mountainous areas and areas with a more continental climate. Therefore, we take into account the administrative division of the country by integrating differences by *département*. Degree hours used are an average for the last 30 years for each *département*. Regarding heating management, 19°C is the conventional target heating temperature used in the calculation. The entire dwelling surface is considered to be heated permanently during the heating season. Moreover, hot water needs are set according to the habitable area and the *département* where the dwelling is located.

The link between energy consumption and CO_2 emissions is clearly established at both the macroeconomic and microeconomic levels. The latest IEA report states that "Driven by higher energy demand in 2018, global energy-related CO_2 emissions rose 1.7% to a historic high of 33.1 Gt CO_2".
CL-DPE_vf.pdf (Last accessed February 2019).

Ultimately this engineering calculation provides the theoretical CO_2 emissions for each dwelling, expressed in kg CO_2. This method thus makes it possible to classify the dwellings by energy label, ranging from the rank A for the best performing dwellings to the rank G for the most inefficient dwellings (see appendix A).

Actual carbon dioxide emissions

Information on actual CO_2 emissions for each dwelling was also available in the PHEBUS survey using real energy consumption and applying a conversion factor. CO_2 is emitted as a result of combustion of fossil fuels (oil, natural gas, and coal), solid waste, biomass (e.g., wood products), and from industrial processes (e.g., cement kilns). Also, CO_2 can be removed from the atmosphere (or sequestered) when it is absorbed by plants as part of the biological carbon cycle. To compute CO_2 emissions, we use common energy consumption in kilowatt hours according to each type of fuel and we apply a conversion factor to obtain CO_2 emissions in kg[5]. Energy sources in French dwellings include electricity (31%[6]), gas (40%), domestic fuel (16%), wood (3.5%), district heating (5%), etc.

Household characteristics, preferences, and duration since move-in

Income, number of persons, gender, duration since move-in, the number of days of housing vacancy during the heating season, and the behavior of occupants characterize households (Dietz, *et al.*, 2013 [19],Quigley and Rubinfeld, 1989 [46]). Studies also seem to show that gender has an effect on emissions: men consume more energy (Barla, *et al.*, 2011 [3],Bel and Rosell, 2017 [5]). Moreover, information on stated household behavior is available from the PHEBUS survey. For each behavior (opening windows during the heating season, turning off the heating when unoccupied, etc.), we know whether the household stated having the behavior or not. It is possible also to obtain some information about heating preferences. Households answered the following question: "When it comes to heating, do you give priority to comfort or saving energy?".

[5] The typical conversion factors are 0.09 for electricity, 0.206 for gas, 0.271 for oil, 0.343 for coal and 0.0018 for wood (IPPC, 2013 [27]); 0.09 kg of CO_2 for 1 kilowatt hour of electricity consumed.

[6] The percentage corresponds to the percentage of households that consume this source of energy as the main source of heating energy. Source: Phebus 2012

The effect of income elasticity is positive in most studies. This is consistent with the "normal good status" of energy consumption: income elasticity often lies between 0.01 and 0.15 (Bakaloglou and Charlier, 2019 [1],Cayla, *et al.*, 2011 [13],Charlier and Kahouli, 2019 [14],Labandeira, *et al.*, 2006 [30],Nesbakken, 1999 [36],Santamouris, *et al.*, 2007 [43]).

Energy prices

Prices are believed in economics to influence household's energy demand (Dietz, *et al.*, 2013 [16],Quigley, 1984 [39]). Price elasticity is always found to be negative, but estimates vary widely from -0.20 to -1.6 depending on energy type, methodology used, level of aggregation of data, evaluation method, country, etc. (see the meta-study of (Labandeira, *et al.*, 2017 [29]). The PHEBUS database does not provide energy price information directly but provides information on the type and amount of energy consumed by each dwelling according to each type of fuel, and also on the type of contract (for gas and electricity) and the power required per type of fuel used in kVA (electricity, gas, oil). The power required depends on the type of fuel used for the heating system (i.e. the energy mix) as well as the number of rooms (or the surface area) and the number of appliances. This information can help us bridge this gap. Finally, the PHEBUS data set also provides information on the quantity consumed in peak hours and in off-peak hours. Thus, to complete the PHEBUS data set, we looked at the PEGASE database (provided by the French Ministry of Energy, see Table B1 in appendix B) to obtain the energy and subscription cost for each type of electricity and gas per the amount of power required and the type of contract in 2011 and 2012.

Climate data for 2012 – Unified degree days

As explained above, the dataset also provides the *département* where each dwelling is located. Climate has an impact of energy consumption (Deschênes and Greenstone, 2011 [15]). This information was matched with 2012 meteorological data from Météo France (annual heating degree days by *département*) in order to have a proxy for the actual 2012 meteorological conditions and to control for different climates within the same country. As theoretical CO_2 emissions (based on the EPC) integrates climate data from the past 30 years, using the actual heating degree days for 2012 is assumed to influence the gap between theoretical CO_2 emissions and effective CO_2 emissions. We are then able to understand significant differences over a year between theoretical and actual emissions. Narayan and Smyth (2005) [35], using aggregate time series data, showed that residential electricity demand in Australia notably depends on the number of heating-degree and cooling-degree days. In the absence of information about cooling degree-days, a proxy for air conditioning is considered.

2.2 Descriptive statistics

The main descriptive statistics are provided in Table 1. The data are at the household or dwelling level. Age and gender are determined according to the reference person in the household. The average age in the sample is 56 years old. There were very few households residing in Label A dwellings in 2012, with a significantly higher concentration in Labels C, D and E: 19.2%, 21% and 20.2% respectively. The poorer labels, F and G still accounted for 22.6% of the sample. These statistics remain consistent with those in the distribution by construction period. 86.7% of households had an adjustable thermostat, and only 7.9% of households had air conditioning. Households owned an average of 15 appliances and were absent from their dwelling for one week per year. A further 16% reported problems being cold due to heating restrictions, 13.5% open windows when the heating is on, and almost a third never turn off the heating.

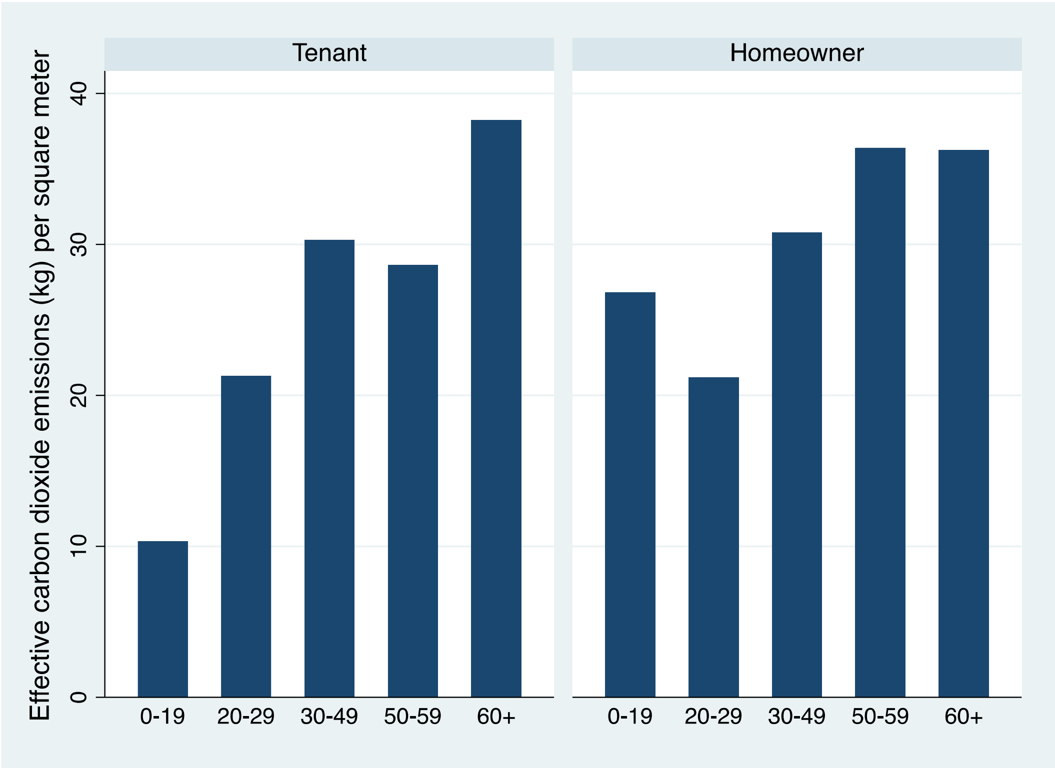
Table 1. Descriptive statistics

VARIABLES	N	mean	sd	min	max
Effective CO_2/m_2 (kg of CO_2)	2009	33.788	33.475	0.746	739.8421
Theoretical CO_2/m_2 (kg of CO_2)	2009	38.701	32.201	0.71	344.61
Disposable income (in euros)	2009	40472	24648	3244	277601
Age (in years)	2009	56.086	15.201	13	98
Number of persons	2009	2.540	1.288	1	10
Unified degree days	2009	2342.69	705.08	0	3153.1
Male	2009	0.701	0.458	0	1
Electricity price (euros per kWh)	2009	0.024	0.032	0	0.0939
Gas price (euros per kWh)	2009	0.136	0.029	0.0652	0.416
Climate label					
A	2009	0.066	0.249	0	1
B	2009	0.104	0.305	0	1
C	2009	0.192	0.394	0	1
D	2009	0.210	0.407	0	1
E	2009	0.202	0.402	0	1
F	2009	0.124	0.330	0	1
G	2009	0.102	0.303	0	1
Period of construction					
Before 1919	2009	0.167	0.373	0	1
1919-1945	2009	0.092	0.289	0	1

1946-1970	2009	0.172	0.377	0	1
1971-1990	2009	0.328	0.469	0	1
1991-2005	2009	0.176	0.381	0	1
After 2006	2009	0.066	0.249	0	1
Adjustable thermostat	2009	0.867	0.340	0	1
Air conditioning	2009	0.079	0.270	0	1
Number of appliances	2009	14.976	5.872	1	55
Rural	2009	0.274	0.446	0	1
2,000 to 4,999 inhabitants	2009	0.094	0.291	0	1
Vacancy period (days)	2009	6.829	45.608	0	999
Cold problems due to heating restriction	2009	0.161	0.368	0	1
Open windows during the heating season	2009	0.135	0.342	0	1
Do not turn down the heating (windows open)	2009	0.277	0.448	0	1
Never turn down the heating	2009	0.329	0.470	0	1
Never turn down heating during periods of inoccupancy	2009	0.114	0.318	0	1

To examine the relationship between average age and occupancy status (the dwellings that consume the most energy are often inhabited by tenants), we look at average emissions by age group and occupancy status (Figure 1). Although renter households aged 60 and over consume slightly more on average than owners, there is no marked contrast between the two occupancy statuses.

Figure 1: Effective carbon dioxide emissions, age and housing occupancy status



If we look specifically at the distribution of households according to age for the different climate labels (Figure 2), it is quite clear that the average age is higher in dwellings with a higher emissions profile. Average age generally increases according to climate label (results reinforced in Table 2).

Figure 2: Climate label category and mean of age

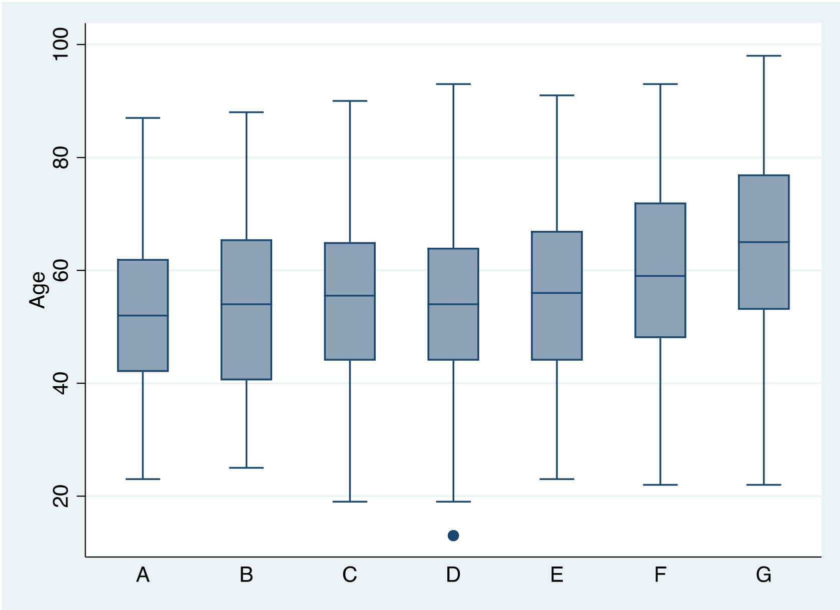


Table 2. Age and energy consumption variables

	N	Age		*t*-test
		Mean	**Std. Dev**	***t***
Entire sample		**56.08**	**15.20**	
Building characteristics				
Period of construction				
Before 1919	335	57.14	0.91	-1.39
1919-1945	184	55.19	1.17	0.86
1946-1970	345	59.20	0.87	-4.19 ***
1971-1990	658	59.29	0.53	-6.67 ***
1991-2005	354	50.47	0.68	7.77***
After 2006	133	45.71	1.10	8.28 ***
Climate label				
A	133	51.97	1.16	3.24 **
B	208	53.72	1.03	2.37 **
C	386	54.68	0.74	2.03**
D	421	54.35	0.71	2.62**
E	406	55.90	0.74	0.28
F	250	59.38	0.99	-3.66***
G	205	63.71	1.13	-7.69***
Detached dwelling	1,131	58.35	0.42	-7.68***
Not a detached dwelling	878	53.17	0.54	
Location				

Rural	550	55.60	0.40	-2.34**
2,000 to 4,999 inhabitants	188	54.47	1.05	1.53
5,000 to 9,999 inhabitants	78	57.81	1.60	-1.02
10,000 to 19,999 inhabitants	139	55.08	1.32	0.81
20,000 to 49,999 inhabitants	159	55.91	1.25	0.15
50,000 to 99,999 inhabitants	114	54.88	1.45	0.87
100,000 to 199,999 inhabitants	107	55.81	1.59	0.19
200,000 to 1,999,999 inhabitants	487	56.43	0.70	-0.57
Paris	187	54.07	1.13	1.90*
Appliances				
Portable air conditioner	159	56.56	1.15	-0.41
No portable air conditioner	1850	56.04	0.35	
Adjustable thermostat	1742	56.93	0.36	0.98
No thermostat	267	55.96	0.99	
Behavior and preferences				
Preference for thermal comfort	1138	56.11	0.46	-0.09
No preference for thermal comfort	871	56.05	0.50	
Cold problems due to heating deprivation	324	53.11	0.85	3.86
No cold problems due to heating deprivation	1685	56.66	0.37	
Open windows when the heating is on	271	53.49	0.96	3.03***
Do not open windows when the heating is on	1728	56.49	0.36	
Do not turn down the heating when windows are open	557	57.27	0.66	-2.17**
Turn down the heating when windows are open	1452	55.63	0.40	
Never turn down the heating	661	55.60	0.62	0.99
Turn down the heating	1348	56.32	0.41	
Never turn down the heating during periods of inoccupancy	230	53.31	1.03	2.96***
Turn down the heating during periods of inoccupancy	1779	56.45	0.36	

Difference between average numbers is statistically significant at the * 90%, ** 95%, and *** 99% level

In Table 2, we identify differences in average age between different population groups. We specifically examine building characteristics (period of construction, climate category, type of housing, energy efficiency), location, appliances (air conditioning and adjustable thermostat), preferences for thermal comfort, heating deprivation and behavior during the heating season. What is clear is differences are mainly in average age by building type and location (especially in rural areas) and there are no differences in average age by type of behavior. From a descriptive point of view, it does not appear that people having preference for thermal comfort are older. Neither do they adopt behaviors that result in more emissions. On the contrary, we even find that people who turn off the heating when windows are open are slightly older on average. The same observation is made for closing the windows when the heating is on.

This result is corroborated in Figure 3: it is clear that the average stated winter heating temperature in dwellings is the same regardless of age group. Older people do not seem to have a stronger preference for thermal comfort. People older than 60 are also less likely to own appliances than people aged 30 to 60 (Figure 4). This higher rate of appliance ownership for the 30 to 60 age group may be explained by the presence of children in the household.

Figure 3: Stated indoor heating temperature in winter by age class

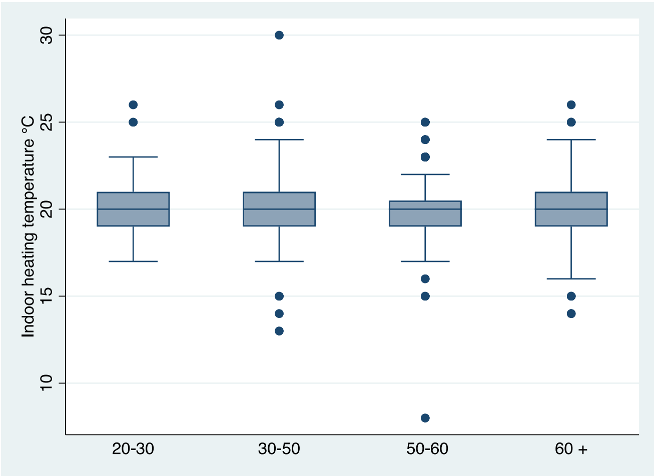
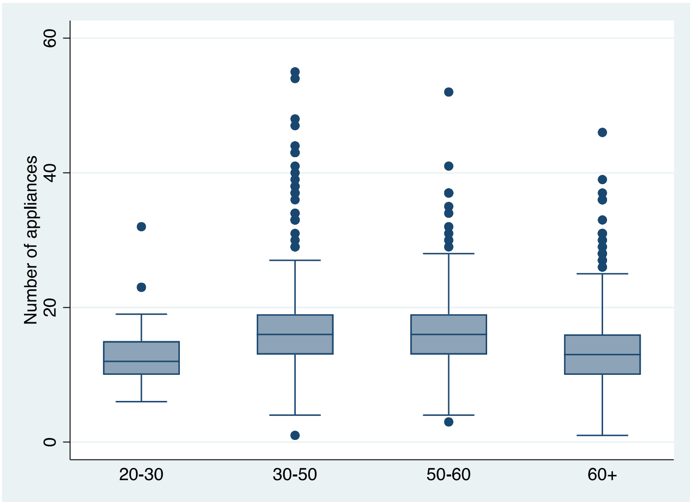


Figure 4: Number of appliances by age class



These descriptive statistics are very interesting because they suggest that the potential impact of demographic aging on energy consumption and greenhouse gas emissions (Figure 2) does not operate via the specific consumption behavior of older people (Figures 3 and 4). Therefore, further investigation is needed to understand the channels by which aging affects consumption and emissions.

3/ Theoretical foundations & empirical approach

3.1 Theoretical background

For several decades, conditional demand analysis employing the two-step discrete-continuous model initiated by Dubin and McFadden (1984) [17] has been used to model energy consumption[7]. In discrete-continuous models, researchers assume that appliance or thermal equipment choices and consumption choice are bound (Dubin and McFadden, 1984 [17],Nesbakken, 2001 [37]) and use these models to address selectivity biases in data sets with endogenously partitioned observational units (Frondel, *et al.*, 2016 [22]). These models are thus often used in the field of energy consumption due to the interactions and endogeneity between independent explanatory variables. Models using the discrete-continuous framework assume that age could play a twofold role in explaining CO_2 emissions: first, it influences the choice of home characteristics or appliances (indirect effect on CO_2 emissions); second, once the appliances or home characteristics are considered, they also have a direct influence, all things being equal.

Recently, there has been interest in examining the issue of interactions. For instance, Estiri (2015) [20] called attention to the major interactions between building characteristics and life-cycle and socioeconomic household characteristics. He concluded that the main effects of socioeconomic and life-cycle characteristics are observed via building characteristics (expressed with a latent variable that includes surface area, number of rooms, and tenure status). In the same vein, Belaïd (2017) [6] employed a structural equation modeling approach (PLS approach) using French data to determine the indirect role of household characteristics on building characteristics in order to explain residential energy consumption. His results are

[7] Modeling energy consumption is similar to modeling CO_2 emissions in that the latter is derived from energy consumption.

consistent with consumption theory in that that household socioeconomic characteristics play an important role in determining the physical attributes of a dwelling. Both examples allow exceeding the limits identified in previous papers but not treated methodologically. For example, Brounen et al. (2012) emphasize that "the energy consumption of the elderly […] is highly responsive to thermal quality of homes as reflected in period of construction" but do not control for the endogeneity of age or period of construction.

Here, we estimate effective CO_2 emissions conditional on housing choice determined by its energy efficiency determined by theoretical CO_2 emissions. Using a continuous variable instead of a discrete variable to determine household choices is a distinct advantage. It allows us to confirm the econometric quality in this initial step, by adopting traditional parametric statistics tests. The main assumption of this research is that age has a significant indirect but positive impact on CO_2 emissions. We assume that the household's decision is divided into two parts. In the first, the household decides to live in a housing unit according to its theoretical energy/climate performance and in the second, it decides how much energy to consume according to age.

To test this hypothesis, we used an endogenous choice model framework to account for the assumed interactions between household characteristics and the dwelling's energy-efficiency level. The specification of household fuel emissions is based on a utility model with R* the stochastic indirect utility function of the households, which we assume to be unobserved. This specification is derived from Bakaloglou and Charlier (2019). Indirect utility *V* depends on the price of energy *P*, income *Y*, household characteristics (including age) and behavior/preferences *Z* and building characteristics (including location) *W* and is defined conditionally on the choice of climate performance. Therefore:

$$R_{ij}^{*} = V_{ij}[P_i, Y_i, Z_i, W_i] + v_{ij} \tag{2}$$

where *j* is the energy performance, *N* that of the individuals, and v_{ij} the error term. The Roy's identity gives us the household's Marshallian demand/emission function for energy:

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

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

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

where q_{ij} is the quantity of greenhouse gas emissions by household i according to climate performance j, z_{ij} is a vector of household characteristics (including age, income, number of persons and behavior), P_{2012i} is the energy price, w_{ij} is a vector of building characteristics (including location), γ_{ij} and ν_{ij} are vectors of the related parameters, and η_{ij} the error term taking into account the influence of unobservable parameters.

3.2 Econometric methodology: an endogenous choice

In our research, an original data set was used to consider the potential problem of endogeneity related to the choice of the dwelling's thermal performance. As a choice variable, we used the theoretical climate performance of the dwelling according to theoretical climate certificate (continuous variable). Thus, we studied which characteristics determine the choice of a theoretical energy-efficient dwelling. Using this information in the first step, enables us to capture interactions between energy efficiency and households while identifying direct drivers of CO_2 emissions. Thus, for the first stage, we use a simple regression. For individual i, we specify:

$$qt_{ij} = \gamma_{ij} z_{ij} + \nu_{ij} w_{ij} + \beta_{ij} P_{2011i} + ELEVATOR_{ij} + LENGTH_{ij} + \eta_{ij}$$

(5)

where qt_{ij} is the theoretical CO_2 emissions of a dwelling j for households i, z_{ij} is a vector of household characteristics (including age, income, number of persons and behavior), P_{2011i} is the energy price in 2011[8], w_{ij} is a vector of building characteristics (including location), γ_{ij} and ν_{ij} are vectors of the related parameters, ELEVATOR and LENGTH are variables used as instruments and η_{ij} the error term taking into account the influence of unobservable parameters.

In order to obtain a proxy for theoretical CO_2 emissions, an instrument should be identified that explains the efficiency or obsolescence of the housing, but not the actual emissions (conditional on theoretical emissions). Thus, to the best of our knowledge, there is no theoretical evidence

[8] We assume that households base their energy demand on the energy cost of the previous year. We also control for potential endogeneity due to energy prices in the model. Proof of the absence of endogeneity is available on request.

of the quality of the latter. From an intuitive point of view, the most recently built dwellings are those equipped with an elevator. On the other hand, a household that moved into a dwelling two decades ago does not live in a recently built dwelling. In addition to presenting the intuitive evidence, we will demonstrate in the next section that these two instruments are statistically valid.

Theoretical CO_2 emissions are also introduced in the second equation (the second stage) and used as regressors of effective CO_2 emissions with other explanatory variables. The model captures the possibility of correlation between unobservable variables in both stages. Conditional on the first stage, a household decides on the quantity of CO_2 emissions to emit (derived from energy consumed). Therefore, in the second stage, the total CO_2 is estimated, conditional on the dwelling's thermal performance (energy-efficiency certificate) and a set of explanatory variables (energy price, income, individual behavior, housing characteristics, etc). This is the *CO_2 emission choice*.

We therefore have:

$$q_{ij} = \gamma_{ij} z_{ij} + \nu_{ij} w_{ij} + \widehat{qt}_{ij} + \ \beta_i P_{2011_i} + \varepsilon_i \qquad (6)$$

where q_{ij} is the final effective CO_2 emissions per square meter (in log) consumed, $\widehat{qt}_{ij}$ the predicted theoretical CO_2 emissions (in log) and z_{ij} ,w_{ij} the regressors and P_{2011_i} the energy prices (gas and electricity prices) in 2011. An interaction parameter is also introduced between both prices to control for multicollinearity. We estimate the model using a maximum likelihood estimator (compared to a two stage least-squares model). Evidence that using a maximum likelihood estimator is better than a two stage least square method is provided in next section. A system composed of the two simultaneous equations (5) and (6) yields the model.

4/ Results

4.1 Results

Table 4: Results for entire sample

	(1)	(2)		(3)	
	OLS	With endogeneity control – 2SLS		With endogeneity control – Maximum likelihood	
VARIABLES		First stage	Second stage	First stage	Second stage
Socio-demographic characteristics					
Disposable income	-0.00213	-0.0981***	0.0948*	-0.0985***	0.0965*
	(0.0380)	(0.0360)	(0.0572)	(0.0358)	(0.0588)
Age	0.00652***	0.00438***	-0.00240	0.00408***	-0.00255
	(0.00141)	(0.00160)	(0.00253)	(0.00152)	(0.00272)
Number of persons	0.103***	-0.0371**	0.133***	-0.0362**	0.133***
	(0.0177)	(0.0169)	(0.0254)	(0.0168)	(0.0261)
Male	0.0581	-0.0363	0.0900	-0.0357	0.0906
	(0.0423)	(0.0387)	(0.0568)	(0.0384)	(0.0585)
Prices					
Electricity price in 2011	0.383***	1.289***	-0.943***	1.289***	-0.966***
	(0.142)	(0.132)	(0.322)	(0.131)	(0.362)
Gas price in 2011	0.0124	0.332**	-0.391*	0.333**	-0.398*
	(0.150)	(0.145)	(0.212)	(0.145)	(0.226)
Interaction parameters between prices	0.0529	0.262***	-0.246**	0.263***	-0.251**
	(0.0769)	(0.0739)	(0.116)	(0.0735)	(0.126)
Climate and location					
Unified degree days	7.34e-05***	7.60e-05***	-1.71e-05	7.69e-05***	-1.87e-05
	(2.48e-05)	(2.54e-05)	(3.92e-05)	(2.54e-05)	(4.16e-05)
Rural	0.322***	0.147***	0.145*	0.149***	0.142*
	(0.0522)	(0.0465)	(0.0789)	(0.0463)	(0.0819)
2,000 to 4,999 inhabitants	0.371***	0.212***	0.124	0.214***	0.120
	(0.0688)	(0.0696)	(0.113)	(0.0692)	(0.116)
Appliances					
Adjustable thermostat	-0.326***	0.328***	-0.636***	0.329***	-0.641***
	(0.0717)	(0.0653)	(0.128)	(0.0651)	(0.136)
Portable air conditioner	-0.0121	-0.181**	0.185	-0.183**	0.188
	(0.0783)	(0.0862)	(0.118)	(0.0858)	(0.121)
Vacancy and behavior					
Vacancy period (days)	-0.000865	-0.000521	-0.000271	-0.000527	-0.000261
	(0.000543)	(0.000324)	(0.000726)	(0.000320)	(0.000766)
Cold problems due to heating restriction	-0.0348	0.268***	-0.282***	0.270***	-0.287***
	(0.0518)	(0.0474)	(0.0843)	(0.0471)	(0.0910)
Never turn down the heating	0.0443	0.0380	-0.000123	0.0379	-0.000901
	(0.0385)	(0.0370)	(0.0523)	(0.0368)	(0.0543)

Never turn down the heating during inoccupancy	-0.0661	-0.111**	0.0774	-0.113**	0.0799
	(0.0571)	(0.0529)	(0.0803)	(0.0526)	(0.0855)
Open windows during the heating season	0.0634	-0.0918	0.142*	-0.0926	0.143*
	(0.0515)	(0.0567)	(0.0810)	(0.0565)	(0.0828)
Do not turn down the heating	0.0992**	-0.0500	0.152***	-0.0493	0.153***
	(0.0428)	(0.0400)	(0.0582)	(0.0397)	(0.0591)
		Building efficiency			
Theoretical CO_2/m_2	0.299***		1.291***		1.309***
	(0.0281)		(0.193)		(0.227)
		Instruments			
Duration since move-in		0.00703***		0.00759***	
		(0.00158)		(0.00127)	
Elevator		-0.321***		-0.283***	
		(0.0541)	.4721494	(0.0512)	
Error term correlation					-0.6947***
					(0.0752)
Constant	2.153***	5.997***	-3.696***	6.001***	-3.799**
	(0.517)	(0.472)	(1.352)	(0.470)	(1.527)
Observations	2009	2009	2009	2009	2009

Bootstrapped standard errors in brackets, 5000 replicates.
Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively.

It is possible to compare the three estimates. We have demonstrated the necessity of considering the endogeneity of the dwelling's efficiency. Disregarding this endogeneity permits consideration of a direct causal impact of age on carbon emissions (Table 4, Column 1). With each additional year of life there is an increase of 0.65 % in effective CO_2 emissions per square meter. However, such an approach ignores the selection bias and consequently hides a more complex reality. Demographics affect emissions through different channels that we disentangle by assuming a parameter of building energy where households first choose their housing and second adopt a consumption behavior while living in this housing (Table 4, Columns 2 and 3).

We find that the age explains the choice of theoretical dwelling efficiency and not effective CO_2 emissions. Each additional year of life increases theoretical CO_2 emissions from 0.41% to 0.44% per square meter. Risch and Salmon (2017) [42] found a positive effect of age on heating with gas or oil (leading to the greatest emissions) and a negative effect of age on heating with electricity (leading to the lowest emissions), which is consistent with our results. The age of the head of household increases the theoretical emissions per m_2. Thus, our results differ from those of Brounen, *et al.* (2012) [10]: energy usage does not increase because the elderly prefer to consume more. These key results confirm assumptions obtained using descriptive statistics. The elderly are less mobile: moving to another dwelling decreases with age, which probably explains why older people live in less efficient housing. Our results show that the increased emissions related to older households are simply due to their dwellings, which are on average older and therefore less efficient.

Moreover, the effect of age on effective emissions is no longer significant in the main equation, once the housing energy-efficiency choice is made. Ignoring the endogeneity of the heating system therefore leads to the interpretation that age has a direct impact on effective CO_2 emissions. However, this is not the case. Age plays an endogenous role in the choice of housing, which explains the emissions. But once energy efficiency of housing is taken into account, age as such no longer explains the variability of emissions. These results differ from those of Belaïd and Garcia (2016) [7]. Older people do not consume more energy (leading to greater emissions). We did not find greater behavioral inertia on the part of older people (Hines, *et al.*, 1987 [26]) nor a tendency to consume more energy for heating.

In order to demonstrate that socio-demographic characteristics need to be taken into account to explain effectives emissions, we regress effective CO_2 emissions by theoretical emissions, without any other control variable (Appendix Table C1). Results show that considering theoretical emissions only is not sufficient to explain effective CO_2 emissions: The R^2 is quite low and equal to 0.13 (close to the 0.16 of Brounen et al., 2012). This demonstrates that the considerable variability in CO_2 emissions in the residential sector remains unexplained once controlling for building weatherization and location. Once again, controlling endogeneity is essential to avoid miscalculation of parameters and misunderstanding results. The impact of the theoretical CO_2 emissions parameter seems limited if we only consider the OLS estimate: each 1% increase in CO_2 leads to an increase of effective emissions by 0.37 %. This parameter becomes quite elastic after correcting for endogeneity, reaching 1.13% or 1.15% depending on methodology. The same results with other controls (0.30% vs 1.30%) are shown in Table 4.

The parameter of household size is one of the most important factors influencing CO_2 emissions. According to the literature, economies of scale emerge with larger households. Our results indeed confirm that adding one inhabitant increases the dwelling's theoretical efficiency: CO_2 emissions decrease significantly from 3.6% to 3.7% per square meter. At first glance, it would appear that larger households are looking for theoretically more efficient housing, confirming then the potential existence of economies of scale. However, after having chosen the theoretical efficiency level of their dwelling, consumption behaviors tend to show CO_2 emissions per square meter increasing with the number of household members. The final effect of household size therefore seems difficult to determine: increased theoretical efficiency within larger households is offset by effective consumption behaviors. Nevertheless, this result tends to support our findings: older households have fewer members, leading them to live in less efficient housing, although they consume more moderately.

Carbon dioxide emissions (or energy) is a normal good with an income elasticity between 0.095 and 0.097 (Bakaloglou and Charlier, 2019 [1],Cayla, *et al.*, 2011 [13],Labandeira, *et al.*, 2006 [30]). An environmental footprint tends to increase with income (Büchs and Schnepf, 2013 [11],Longhi, 2015 [33]). It is also a typical good, commonly described in the literature, but with a higher price elasticity for electricity (the most expensive energy in France) than for gas (respectively between -0.94 and -0.97 for electricity and between -0.39 and -0.40 for gas). Our results are consistent with the literature (Labandeira, *et al.*, 2017 [29]). Having an adjustable thermostat leads to lower effective emissions, which is in line with expectations. Having a portable air conditioner has a negative effect on the theoretical emissions of dwelling whereas it does not have an impact on effective emissions.

Opening windows explains greater emissions as does not turning the heating down during the heating season. In general, the parameter describing building energy efficiency especially after controlling for endogeneity is quite strong. Once again, ignoring this methodological problem can lead to an underestimation of theoretical efficiency, although this is not sufficient to explain all variability.

Table 5: Results by age

	Under 60		Over 60	
VARIABLES	First stage	Second stage	First stage	Second stage
Socio-demographic characteristics				
Disposable income	-0.101**	0.143*	-0.0884	0.0445
	(0.0449)	(0.0868)	(0.0611)	(0.0783)
Number of persons	-0.0481***	0.161***	0.00810	0.0745
	(0.0184)	(0.0399)	(0.0508)	(0.0613)
Male	0.0119	0.0204	-0.125*	0.180**
	(0.0475)	(0.0786)	(0.0704)	(0.0884)
Prices				
Electricity price in 2011	1.243***	-1.315**	1.340***	-0.661*
	(0.181)	(0.652)	(0.184)	(0.357)
Gas price in 2011	0.300	-0.461	0.349	-0.388

	(0.193)	(0.339)	(0.213)	(0.288)
Interaction parameters	0.258***	-0.339*	0.253**	-0.187
	(0.0984)	(0.201)	(0.108)	(0.152)
Climate and location				
Unified degree days	9.95e-05***	-4.41e-05	2.89e-05	1.00e-05
	(3.04e-05)	(7.21e-05)	(4.28e-05)	(4.94e-05)
Rural	0.0982*	0.125	0.213***	0.189*
	(0.0594)	(0.115)	(0.0737)	(0.105)
2,000 to 4,999 inhabitants	0.218***	-0.0164	0.189	0.296*
	(0.0828)	(0.177)	(0.124)	(0.162)
Appliances				
Adjustable thermostat	0.368***	-0.696***	0.264**	-0.652***
	(0.0800)	(0.236)	(0.110)	(0.166)
Portable air conditioner	-0.317***	0.396*	-0.0377	0.0473
	(0.103)	(0.226)	(0.140)	(0.138)
Vacancy and behavior				
Vacancy period (days)	0.00206	-0.00538	-0.000554	-0.000407
	(0.00199)	(0.00359)	(0.000388)	(0.000250)
Cold problems due to heating restriction	0.234***	-0.299**	0.313***	-0.275**
	(0.0572)	(0.137)	(0.0842)	(0.118)
Never turn down the heating	-0.00842	0.0686	0.0905	-0.0660
	(0.0467)	(0.0770)	(0.0598)	(0.0744)
Never turn down the heating during inoccupancy	-0.215***	0.258	0.0139	-0.0683
	(0.0681)	(0.162)	(0.0798)	(0.107)
Open windows during the heating season	-0.103	0.155	-0.125	0.208*
	(0.0634)	(0.124)	(0.111)	(0.117)
Do not turn down the heating	-0.118**	0.235**	0.0355	0.108
	(0.0520)	(0.106)	(0.0617)	(0.0782)
Building efficiency				
Theoretical CO_2/m_2		1.581***		1.099***
		(0.458)		(0.171)
Instruments				
Duration since move-in	0.00701***		0.00864***	
	(0.00202)		(0.00160)	
Elevator	-0.170***		-0.433***	
	(0.0637)	.4721494	(0.0740)	
Error term correlation		-0.781***		-0.581***
		(0.105)		(0.0912)
Constant	6.073***	-5.830**	6.379***	-2.204
	(0.611)	(2.973)	(0.734)	(1.501)
Observations	1,205	1,205	804	804

Bootstrapped standard errors in brackets, 5000 replicates.
Significance at the 10%, 5% and 1% levels are indicated by *, ** and *** respectively.

After having examined the impact of age on theoretical and actual emissions, we examined whether different CO_2 emission profiles emerge among individuals under 60 and individuals over 60 (see Table 5). We believe that older households live in housing chosen in earlier decades, and that given their low mobility, their past choices particularly affect their current ecological footprint, which is less true for younger and more mobile households. Results presented in Table 4 appear to confirm our first assumption.

Income significantly affects both choice and effective CO_2 emissions before the age of 60 but not after. There is a life-cycle effect. Income and number of inhabitants suggest a social environment which differentiates people under 60 from people over 60. In addition, price elasticity is quite inelastic for electricity for the elderly and not significant for gas, which differs significantly from the youngest age category. Energy can be considered to be a good that prevents problems such as poor health, and the elderly cannot adjust their consumption after a change in energy prices (Warriner, 1981 [48]). These people may therefore be more vulnerable (as long as their income does not change) to problems of fuel poverty (Legendre and Ricci, 2015 [32]). Two points can be made. First, the inelasticity of emissions to price shows that in times of increasing energy prices, older people will have to give up other consumption to maintain a temperature compatible with the desired or necessary level of comfort. However, we can also question this inelasticity and argue that retired people, whose incomes have fallen, have already adopted a restricted consumption behavior, leaving no room for further adjustment of the quantity of energy consumed. The phenomenon of fuel poverty already highlighted in the literature can be exacerbated by the fact that older households have less air conditioning than other types of households, and live in poorly insulated dwellings, causing problems of overheating during the increasingly frequent summer heat waves.

After the age of 60, the effect of gender is marked. If the head of the household is male, the household consumes more energy, which is consistent with a body of literature showing that women care more about the environment. Most studies report a positive relation between being male and CO_2 emissions: the proportion of high consumers of energy among males being much greater than among females (Barla, *et al.*, 2011 [3],Bel and Rosell, 2017 [5]). The literature also reports that women prefer a higher ambient temperature than men (Brounen et al., 2012). Finally, it is again shown that there is no marked difference in behavior between those over 60 and those under-60: those under 60 never turn off the heat during the heating season. More people over 60 open windows during the heating season but this result is slightly significant at only 10% and is consistent with health recommendations on airing your home for 15 minutes a day.

5.1 Quality tests of instruments and quality of estimates

We propose three estimates, the results of which have been presented above: a simple first approach using OLS, and then two two-step estimates, one using a 2SLS methodology, and one using maximum likelihood, involving use of both the instruments. To validate the consistency of the instruments, we employ a three-step methodology. First, we conduct a significance test and a Wald test to ensure the quality of instruments in the endogenous estimate. Having an elevator has a negative effect on theoretical energy efficiency. Clearly, elevators are more numerous in recently built buildings[9] and therefore denote better energy efficiency. In contrast, the greater the length of time since moving in, the higher the theoretical emissions. Buildings that consume more energy are not of recent construction as a result of due to energy efficiency regulations. It is reasonable to assume that a household who moved in a decade ago, moved into an older building as the newer buildings did not exist yet.

Second, we carry out validity tests for the instruments (identification and exogeneity) using the Durbin (1954) [18] and Wu (1974) [50] tests of endogeneity and the Wooldridge (1995) [49] robust score test. In all cases, if the test statistic is significant, then the variables being tested must be treated as endogenous. We perform tests to determine whether endogenous regressors in the model are in fact exogenous. After 2SLS estimation with an adjusted VCE, the Wooldridge (1995) [49] robust score test and a robust regression-based test are determined. The results are compared with a model without a robust VCE. We tabulate the Sargan (1958) [44] and Basmann (1960) [4] χ^2 tests noting that a statistically significant test statistic always indicates that the instruments may not be valid.

Table 3: Statistics after 2SLS regression

	Statistics	*p*-value
Durbin (score) $X_2(1)$	39.8229	0.0000
Wu-Hausman $F(1.1988)$	40.2035	0.0000
Sargan (score) X_2 (3)	0.781634	0.3766
Basmann X_2 (3)	0.773765	0.3791
Robust score X_2 (1)	44.5898	0.0000
Robust regression F (1.1988)	49.061	0.0000
Score X_2 (1)	.961447	0.3268

[9] The most recent French Law (November 2018) on housing, development and digital technology requires, among other things, the provision of an elevator for all buildings of three or more stories.

Finally, we validate the correlation error terms. It is statistically significant which demonstrates the relevance of considering potential endogeneity in the model. We were concerned that the errors in effective emissions per square meter and the choice of energy efficiency of the building (theoretical emissions) would be correlated. Table 4 in the next section shows that the errors are indeed negatively correlated (-0.6947) and it is significant. Unobserved heterogeneity that describes effective CO_2 emissions is negatively correlated to unobserved heterogeneity explaining the choice of the dwelling's energy efficiency.

We subsequently compare the estimated results using 2SLS, and the results obtained using a maximum likelihood. Using this last methodology to estimate the coefficients of the main equation, the endogenous regressor equations, and the variance and correlation parameters enables us to improve the quality of the estimates compared to the 2SLS procedure. When employing the linear prediction (fitted values) to estimate covariate effects, the maximum likelihood method allows prediction of the mean of the response conditional on the covariates and instruments in contrast to the 2SLS method. Using both methods, we predicted the conditional mean (3.14). But comparing both methods, we note that the conditional mean is a better predictor of CO_2 emissions than the linear prediction by comparing the mean squared errors (respectively 0.441. vs 1.042).

5. Discussion and conclusion

An aging population calls into question the sustainability of a society. The issue of sustainable development is emerging, particularly regarding exhaustible natural resources. Aging is likely to lead to profound changes in energy consumption habits. Indeed, individuals are living longer, leading to changes in household composition and housing choices.

Two categories of variables have an impact on energy consumption: on the one hand the technical and non-human attributes of the dwelling, and on the other energy consumption behavior. A good understanding of the determinants of energy consumption has become essential both to reduce dependence on certain types of energy and to preserve the environment, which is threatened by global warming. Much progress has been made in the energy economics literature through the acquisition of microeconomic data to study behavior and housing, but also through methodological progresses to take into account the links between human and non-human factors affecting energy consumption.

In this paper, we contribute to the emerging debate on the ecological footprint of different generations by analyzing household energy consumption by age, using cross-sectional data. We do so by integrating the literature on the determinants of energy consumption with the latest methodological advances allowing us to affirm that CO_2 emissions respond to a strong logic of self-selection by households according to age. We therefore show that age has a significant impact on the theoretical emissions of housing. Older households having lived in their dwelling for a longer period of time, and older buildings are less energy efficient on average. The higher emissions related to older households are therefore indirectly due to the past choice they made when they chose their dwelling and its technical characteristics. But once this self-selection through choice is controlled, age no longer has an impact on the actual emissions related to the dwelling. Our results therefore contradict some existing studies which conclude that there is an exaggerated preference for greater energy consumption among older people. We have therefore disentangled two potential channels of impact of age on emissions, the housing efficiency channel and the behavioral channel, but have shown that only the former has a significant impact.

Government agencies typically play a role in influencing the behavior of economic agents by providing information or raising awareness such as in the case of limited rationality or a lack of information. In a second stage, incentives are intended to act directly on consumers' budget trade-offs, particularly when the incentives are financial. Finally, the last stage, which is not the preferred option of economists, is to regulate and constrain behavior when faced with irreversible phenomena (such as destruction of biodiversity).

The literature submits that the elderly have less economical consumption patterns than younger generations. Such conclusions suggest that the elderly should be the target of policies encouraging more moderate energy consumption. Our results challenge this notion. They shed new light on economic policy: policies that encourage more moderate consumption, especially for elderly people, are not needed to conserve resources (which does not mean they are never useful). In contrast, a sustained policy of housing renovation, particularly for older people, is necessary to limit the increased emissions linked to demographic aging which in turn leads to aging of the building stock. This type of policy could also be part of a set of social measures targeting the elderly, whose consumption is inelastic to price. Thus, better-insulated housing will make it possible to limit the impact of energy price rises on the well-being of the elderly.

Demographic aging presents many challenges for Western societies, which were the first to be confronted by it. But beyond changes in energy consumption patterns, there will be marked changes in housing-related choices and behavior in the coming decades, particularly due to the increasing number of elderly with disabilities or other health problems. Policies related to housing improvements will certainly have to include improved energy efficiency to limit emissions and increase the thermal comfort of the aging population, but they will also have to enable people to maintain their independence and remain in their own homes as long as possible. Policies related to the loss of autonomy of older people place great emphasis on maintaining the independence of the elderly. Placement in specialized institutions should take place only when all alternatives have been exhausted. This approach is also in line with the wishes of the elderly, who often find it very traumatic to leave their home.

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Appendix

Appendix A: Energy and climate performance certificates

Energy certificate

- **A** ≤ 50 kWh pe/m²/year
- **B** 51 to 90 kWh pe/m²/year
- **C** 91 to 150 kWh pe/m²/year
- **D** 151 to 230 kWh pe/m²/year
- **E** 231 to 330 kWh pe/m²/year
- **F** 331 to 450 kWh pe/m²/year
- **G** > 450 kWh pe/m²/year

Climate certificate

- **A** ≤ 5 kg. $_{CO2}$/m²/year
- **B** 6 to 10 kg. $_{CO2}$/m²/year
- **C** 11 to 20 kg. $_{CO2}$/m²/year
- **D** 21 to 35 kg. $_{CO2}$/m²/year
- **E** 36 to 55 kg. $_{CO2}$/m²/year
- **F** 56 to 80 kg. $_{CO2}$/m²/year
- **G** > 80 kg. $_{CO2}$/m²/year

Appendix B:

Table B1- *Energy prices from the PEGASE database*

	2011	2012
ELECTRICITY TARIFF		
Electricity: blue rate – base option in euros (tax included)		
Annual subscription cost 3 kVA	64.94606	67.40325
Annual subscription cost 6 kVA	77.45169	80.36592
Annual subscription cost 9 kVA	90.3377	93.76717
Annual subscription cost 12 kVA	142.84527	148.13392
Annual subscription cost 15 kVA	164.85725	171.04758
Annual subscription cost 18 kVA	219.2238	227.44092
Price for 100 kWh (power 3 kVA)	17.02237	17.7994
Price for 100 kWh (power 6 kVA)	16.23193	16.9816
Electricity: blue rate - peak hours rate in euros (tax included)		
Annual subscription cost 6 kVA	93.13223	96.59658
Annual subscription cost 9 kVA	111.76704	115.91475
Annual subscription cost 12 kVA	189.49559	196.56458
Annual subscription cost 15 kVA	223.04773	231.32342
Annual subscription cost 18 kVA	254.38013	263.81675
Annual subscription cost 24 kVA	529.87303	549.78758
Annual subscription cost 30 kVA	652.50116	677.02358
Annual subscription cost 36 kVA	754.42164	782.73067
100 kWh peak-hours	12.91385	13.54292
100 kWh off-peak	8.76965	9.23933
Price for 100 kWh (power 6 kVA)	14.03546	14.70435
Price for 100 kWh (power 9 kVA)	13.02266	13.65389
Price for 100 kWh (power 12 kVA)	12.77758	13.39973
Electricity: blue rate - tempo option in euros (tax included)		
Annual subscription cost 9 kVA	109.04157	113.022
Annual subscription cost 12 kVA	203.35865	210.90942
Annual subscription cost 30 kVA	456.64613	473.54025
Annual subscription cost 36 kVA	566.42158	587.43975
100 kWh blue days and off-peak	6.8142	7.2111
100 kWh blue days and peak-hours	8.20155	8.65528
100 kWh white days and off-peak	9.8401	10.35061
100 kWh white days and peak-hour	11.7537	12.33594
100 kWh red days and off-peak	18.5589	19.40033
100 kWh red days and peak-hour	49.16455	51.17409
Electricity: market rate-in euros (tax included)		
All rates	13.41974	13.82434
DA rate	24.45679	25.13133
DB rate	15.8404	16.3847
DC rate	14.02566	14.45913
DD rate	12.84391	13.2134
DE rate	12.54369	12.91665
GAS RATE		
Natural Gas: price in euros (tax included)		
Annual subscription cost - base rate	43.8933	46.92645
Annual subscription cost - B0 rate	58.0092	61.97075
Annual subscription cost - B1 rate	185.18415	195.4546
Annual subscription cost - B2I rate	185.18415	195.4546
100 kWh PCS - base rate	9.3988	9.96987
100 kWh - B0 rate	8.0742	8.51871
100 kWh- B1 rate	5.58353	5.86163
100 kWh - B2I rate	5.58353	5.86163
Price for 100 kWh B0 rate	11.74238	12.42551
Price for 100 kWh B1 rate	7.08853	7.44654

Price for 100 kWh B2I rate	6.79365	7.13536

Appendix C – Results

Table C-1: Theoretical and effective CO_2 emissions

N=2009		With endogeneity control – 2SLS		With endogeneity control – ML	
VARIABLES	OLS	Second stage	First stage	Second stage	First stage
Theoretical CO_2/m^2	0.367***		1.126***		1.155***
	(0.0249)		(0.132)		(0.133)
Duration since move-in		0.0108***		0.00987***	
		(0.00135)		(0.00128)	
Elevator		-0.327***		-0.412***	
		(0.0715)		(0.0628)	
Constant	1.935***	3.123***	-0.573	3.145***	-0.668
	(0.0895)	(0.0327)	(0.431)	(0.0306)	(0.436)
Error term correlation					-0.655***
					(0.0644)
R^2	0.131		0.042		
Wald $X^2(1)$ – p-value		73.12 p = 0.0000		74.98 p = 0.0000	

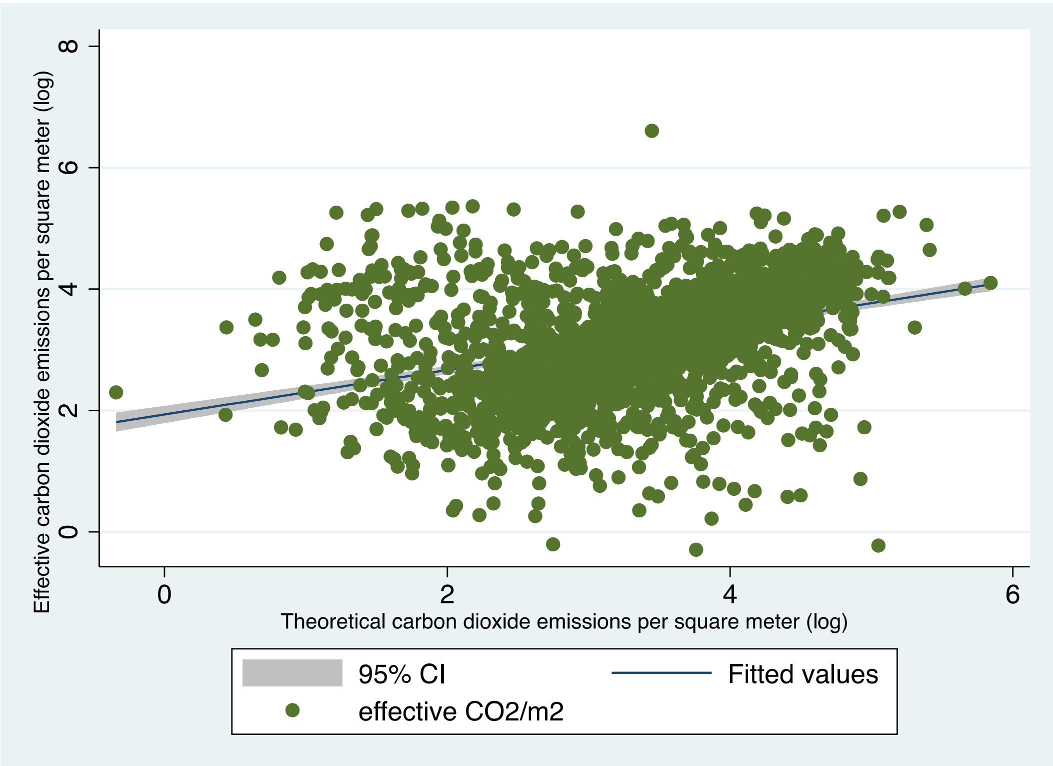

Table C-2: Robustness checks 1 (effect of age on the second stage)

	Benchmark		Sub-regression 1		Sub-regression 2		Sub-regression 3		Sub-regression 4	
VARIABLES	First stage	Second stage	First stage	Second stage	First stage	Second stage	First stage	Second stage	First stage	Second stage
Age	0.00438***	-0.00240	0.00520***	-0.00441	0.00371**	-0.00248	0.00384***	-0.00262	0.00401***	-0.00252
	(0.00160)	(0.00253)	(0.00166)	(0.00292)	(0.00144)	(0.00246)	(0.00147)	(0.00268)	(0.00149)	(0.00258)
Socio-demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prices	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Climate and location	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes
Appliances	Yes	Yes	No	No	No	No	No	No	Yes	Yes
Vacancy and behavior	Yes	Yes	No	No	No	No	No	No	No	No
Theoretical emissions	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Instruments	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Error term correlation		-0.6947***		-0.771***		-0.734***		-0.742***		-0.711***
		(0.0752)		(0.0615)		(0.0587)		(0.0704)		(0.0720)
Observations	2009	2009	2009	2009	2009	2009	2009	2009	2009	2009

Table C-3 Robustness checks 2

	Sub-regression 1		Sub-regression 2		Sub-regression 3		Sub-regression 4		Sub-regression 5		Sub-regression 6	
VARIABLES	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
Socio-demographic caracteristics												
Age	0.00629***	-0.0116***			0.00520***	-0.00441						
	(0.00151)	(0.00306)			(0.00166)	(0.00292)						
disposable income			-0.121***	0.0778	-0.130***	0.106						
			(0.0405)	(0.0561)	(0.0406)	(0.0649)						
Nb of pers			-0.0215	0.134***	0.00299	0.115***						
			(0.0175)	(0.0233)	(0.0188)	(0.0276)						
Man			-0.108**	0.173***	-0.113**	0.194***						
			(0.0448)	(0.0616)	(0.0446)	(0.0705)						
Prices												
electricity price in 2011							1.345***	-0.876***				
							(0.139)	(0.260)				
gas price in 2011							0.385***	-0.322				
							(0.148)	(0.202)				
Interaction paremeters							0.285***	-0.216**				
							(0.0751)	(0.107)				
Climate and localization												
Unified DD									0.000103***	-9.23e-06		
									(2.94e-05)	(3.30e-05)		
Rural									-0.200***	0.337***		
									(0.0488)	(0.0647)		
2,000 to 4,999 inhabitants									-0.0327	0.256***		
									(0.0731)	(0.0873)		
Appliances											0.505***	-0.603***
Heating controller											(0.0700)	(0.117)
											-0.294***	0.151
mobile cooling system											(0.100)	(0.102)
Vacancy and behavior												
												-
Vacancy period (days)												0.000854*
											-2.93e-05	**

											(0.000434)	(0.000308)
Cold problem due to heating restriction											0.358***	-0.277***
											(0.0511)	(0.0704)
Never turn down heating											0.0243	0.0189
											(0.0417)	(0.0458)
Never turn down heating during inocupancy											-0.177***	-0.0101
											(0.0597)	(0.0740)
Open window during heating period											-0.128**	0.143**
											(0.0618)	(0.0689)
Do not turn down the heating											0.0507	0.104**
											(0.0447)	(0.0507)
Building efficiency												
Theoretical CO2/m2		1.641***		1.328***		1.489***		1.170***		1.028***		1.012***
		(0.236)		(0.151)		(0.217)		(0.131)		(0.120)		(0.117)
Instruments												
Duration since move-in	0.00699***		0.00992***		0.00757***		0.00951***		0.0106***		0.0115***	
	(0.00122)		(0.00119)		(0.00125)		(0.00115)		(0.00129)		(0.00134)	
Elevator	-0.330***		-0.353***		-0.323***		-0.439***		-0.389***		-0.378***	
	(0.0656)		(0.0646)		(0.0690)		(0.0456)		(0.0679)		(0.0613)	
Error terms correlation	-0.808***		-0.722***		-0.771***		-0.647***		-0.589***		-0.564***	
	(0.0526)		(0.0563)		(0.0615)		(0.0583)		(0.0709)		(0.0713)	
Observations	2,009	2,009	2,009	2,009	2,009	2,009	2,009	2,009	2,009	2,009	2,009	2,009