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Fuel Poverty and Health: a Panel Data Analysis

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Protecting and improving health and mitigation of climate change have a shared agenda. In this paper, we contribute to the literature by assessing the link between fuel poverty and health over a lengthy recent period. Using dynamic probit models, we examine the influence of fuel poverty on health. We control for state dependency of health as we regard health status to be closely related to previous health trajectories. Considering that unobserved heterogeneity might influence health status and fuel poverty simultaneously, we have corrected for the endogeneity bias that could affect our results. We conclude that being fuel-poor increases the risk of bad health by slightly more than a factor of 7 for those whose health is already poor and by 1.82 for those in good health. For policy makers, combatting fuel poverty reduces sources of discomfort which might also severely affect the health of a dwelling's inhabitants.

Keywords: Fuel poverty; Health; Dynamic Probit; Panel dataset

JEL codes: C33; I14; Q41

1/ Introduction

Protecting and improving health and mitigation of climate change have a shared agenda. Public policies intended to respond to climate change can help reduce health problems. Various policies can reduce greenhouse gas emissions and produce important health co-benefits (Zivin & Neidell, 2013) notably through retrofitting of housing (WHO Regional Office for Europe,

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2004). In northern countries, many households live in homes that have poor thermal conditions and are therefore expensive to heat, accounting for a substantial share of emissions which in turn contribute to climate change. Inadequate thermal performance and ventilation of existing buildings are two of the biggest challenges for the European housing sector with respect to the sustainability and health of the built environment. Moreover, recent research has demonstrated that it is possible to improve indoor environmental quality, health and well-being of building occupants along with improved energy efficiency (Pampuri, Caputo, & Valsangiacomo, 2018; Prasauskas et al., 2016; Rashid & Zimring, 2008; Stabile, Buonanno, Frattolillo, & Dell'Isola, 2019).

Low-income households may have difficulty paying for energy due to the poor thermal conditions of the buildings they occupy combined with rising energy prices, and therefore restrict their energy consumption. These households are considered to be fuel-poor (Boardman, 1991, 2010; Hills, 2011, 2012) and are subject to increased health problems due to the inferior energy performance of the buildings they live in. Thus, in this paper we contribute to the literature exploring the impact of being fuel poor on health. The literature on the relationship between fuel poverty and health is quite limited, while research into the determinants of health is extensive.

Indeed, the economic and epidemiologic literature on the nexus between air pollution and health is vast (Contoyannis & Jones, 2004; Neidell, 2004). Local air quality exposure is a significant driver of health problems (Currie, Neidell, & Schmieder, 2009; Jans, Johansson, & Nilsson, 2018). By reducing air pollution levels, countries can reduce the burden of disease from stroke, heart disease, lung cancer, and both chronic and acute respiratory diseases, including asthma (WHO, 2013, 2018). The relationship between socioeconomic characteristics and health is well-established. . Negative health behaviors and psychosocial characteristics are clustered in low socioeconomic status groups (Lynch, Kaplan, & Salonen, 1997). The notion that low socioeconomic status, mainly due to low income, causes poor health is widely supported by empirical research (Contoyannis, Jones, & Rice, 2004): poverty is associated with poor health even in advanced industrial societies (Benzeval & Judge, 2001). Education has been also found to have a positive association with physical and mental health (the so-called *education-health gradient*) because individuals invest in their health more effectively and allocate their resources better (Cutler & Lleras-Muney, 2006). Older people are often in poor health also (Ohrnberger, Fichera, & Sutton, 2017). While many studies have focused on the drivers of health, they have largely neglected to evaluate the magnitude of fuel poverty on health. Assessing the impact of fuel poverty on health is necessary for the development of health-related housing policies. Highlighting this impact would point to the need for coordinated policies. Indeed, housing improvement policies and energy performance are costly, but these costs should also be compared with the gains, particularly in terms of health savings.

Additionally, a better understanding of the profile of households in poor health can help policy makers prevent other households from falling into this state and reduce future health expenditures. In this context, our objective is to contribute to the literature by assessing the link between fuel poverty and health over a lengthy recent period (2008-2016). Identifying a precise, direct and mid-term link between fuel poverty and health seems crucial in the design of relevant public policies. Implementing an effective policy implies anticipating both intermediate and final objectives: tackling fuel poverty as the intermediate objective and improving public health as the final objective. Thus, we use panel data (EU-SILC) to consider individual health and household fuel poverty trajectories, but also to avoid obtaining results affected by 1-year climate variables. We focus on the French situation where the direct medical cost related to poor housing is estimated to be 930 million euros (Eurofound, 2016). The indirect annual costs are estimated to be 20.3 billion euros. Using dynamic probit models, we tested the influence of fuel poverty on health. We controlled for state dependency of health as we consider health status to be closely related to health status in the previous year. We also controlled for initial conditions (Heckman, 1981). Considering that unobserved heterogeneity might have an impact on health status and fuel poverty simultaneously, we corrected for the endogeneity bias that could affect our results. In order to improve the living conditions of households in fuel poverty, both short- and long-term policies are needed. Supplementing the household income and reducing energy costs will help in the short term, but improving the energy efficiency of housing (e.g. modernizing heating systems, installing thermal insulation) is the long-term solution to address fuel poverty and its health consequences. Energy-efficient housing not only has benefits for the health of occupants, but also for society as a whole.

The next section presents the existing literature on the relationship between energy efficiency and health. The theoretical background is then introduced. Data are presented in the fourth section, and the empirical strategy is introduced in the fifth section. The results are presented in Section 6, along with a key policy recommendation. We conclude in Section 7.

2. Methods

2.1 Literature on energy efficiency and health

The literature extensively documents the impact of cold, damp housing and mold on health (Maidment, Jones, Webb, Hathway, & Gilbertson, 2014; Peat, Dickerson, & Li, 1998; Platt, Martin, Hunt, & Lewis, 1989). There is much evidence that poor housing conditions, combined with financial constraints may worsen both mental and physical health (Hills, 2012; Hunt, 1988; Maidment et al., 2014; Platt et al., 1989; University College, Team, & Earth, 2011). Persistently low temperatures in housing lead to respiratory tract infections and coronary problems, increased blood pressure, worsening arthritis, along with more frequent accidents in the home and adverse effects on children's education and nutrition (National Heart Forum, 2003). Dampness and mold that accumulate in cold homes increase respiratory symptoms including asthma, coughing and wheezing (Dales, Zwanenburg, Burnett, & Franklin, 1991; Jaakkola, Hwang, & Jaakkola, 2005; Peat et al., 1998). In their meta-analysis Fisk, Lei-Gomez, and Mendell (2007) conclude that dampness and mold are associated with increases of 30–50% in respiratory and asthma-related health problems. Cold and damp housing may also affect well-being and cause stress and depression in its inhabitants (Khanom, 2000; Lowry, 1991; Shortt & Rugkåsa, 2007). Poor-quality housing can expose households to cancer risks , due to exposure to radon, or to formaldehyde from combustion or off-gassing (Braubach, Jacobs, & Ormandy, 2011).

Thus, improving energy efficiency reduces health problems. In an experiment conducted in south Devon in the UK, Barton et al. (2007) concluded that improving heating and insulation reduces chest problems and asthma symptoms, at least in the short term. After conducting a fuel poverty program in 54 rural homes in Ireland, Shortt and Rugkåsa (2007) showed that the installation of central heating systems and development of energy-efficiency awareness led to a significant decrease in both the numbers of householders reporting arthritis/rheumatism and other forms of illness. A pilot study in Cornwall established that installation of central heating was an effective measure for reducing nocturnal cough and asthma in children, and consequently time lost from school (Sorrell, Dimitropoulos, & Sommerville, 2009). Other studies have demonstrated the general impact of fuel poverty on health (Liddell & Morris, 2010).

Public policies such as retrofitting and saving energy pursue an intermediate objective which is the reduction of fuel poverty, but also have an impact on public health as a final objective. For households, retrofitting increases comfort, as housing conditions are improved. The quality of the dwelling might be improved through heating upgrades (Chapman, Howden-Chapman, Viggers, O'Dea, & Kennedy, 2009), better insulation (Bourdon, Van Mien, & Normand-Cyrot, 1992; Homøe, Christensen, & Bretlau, 1999; Vandentorren et al., 2006), draftproofing/sealing around doors or windows (P. Howden-Chapman et al., 2005; Philippa Howden-Chapman, Phipps, & Cunningham, 2007), glazing improvements (Iversen, Bach, & Lundqvist, 1986) or a combination of different measures (Lloyd, Callau, Bishop, & Smith, 2008).

The literature includes many case studies which were carried out with experimental data. Some of them explore the direct impact of retrofitting plans, housing improvements and/or energy-saving programs on health[4] (Chapman et al., 2009; Philippa Howden-Chapman et al., 2007; Lloyd et al., 2008) (Chapman et al., 2009; Ezratty, Duburcq, Emery, & Lambrozo, 2009; Thomson & Snell, 2013). Others do not measure the impact on health but assess domestic energy use after retrofitting in order to estimate the likely health impact of an intervention from an intermediate outcome, such as temperature or air quality and carbon emissions (Rosenow & Galvin, 2013). Some studies evaluate the actual impact of energy consumption and fuel poverty (Rosenow & Galvin, 2013) (Grimes et al., 2016; Webber, Gouldson, & Kerr, 2015).

Case studies and experiments make it possible to precisely evaluate the impact of policies on a given region at a particular point in time, thus providing useful guidance for designing or improving public policy. However, they fail to establish a clear causal relationship between fuel poverty and health in the absence of any retrofitting, energy-saving measures or housing improvements. When non-experimental studies confirm a link between fuel poverty and health (Chaton & Lacroix, 2018; Lacroix & Chaton, 2015; Liddell & Morris, 2010), the results are based on cross-sectional data, ignoring the effects of health trajectories and climate hazards on

[4] See Maidment et al. (2014) for a meta-analysis including 36 studies which evaluate the relationship between household energy-efficiency interventions and the health of the occupants

fuel poverty. The effects of climate hazards are then determined by conducting an evaluation ex-ante, and/or ex-post and by carrying out a non-experimental study.

2.3 Data

In this study, we wish to shed light on the potential causal effect of energy precariousness on the health of individuals. Thus, econometric analysis was conducted using the French portion of the EU-SILC[5] database (European Union – Community Statistics on Income and Living Conditions). We chose data from 2008 until 2016, which is the last survey to date. This time frame was selected since the year 2008 marked significant changes, such as improving the accuracy of household resources using data from public institutions, and specifying the type of energy used inside dwellings instead of a global indicator, which is fundamental to the construction of relevant fuel poverty indicators (Hills, 2011, 2012). The database also includes some health indicators, such as self-assessed health condition, the presence of chronic diseases and handicaps, potentially unfulfilled needs to see a specialist and the reasons for this, and other health-related variables, thus providing a good set of tools for describing and controlling the effect of fuel poverty on health. The database also contains many variables characterizing socio-economic status, demographic status and living conditions related to housing and energy use of individuals, thus provides a solid basis for assessing health and fuel poverty under the many aspects and definitions reviewed in the literature. The entire sample consisted of 239,477 observations over nine years.

Our health indicator is the self-assessed health status of the respondents; this will be our binary dependent variable, with 1 for poor health. Some 8.3% of individuals declared a status of poor health over the period studied. While a categorical self-assessed health variable is a wide measure of one's mental and physical condition, its reliability could be questionable (Crossley & Kennedy, 2002). However it remains one of the best tools available to measure health as it predicts future mortality and morbidity adequately (Idler & Kasl, 1995; Lundberg & Manderbacka, 1996). We also use a stated binary variable for chronic disease as a control (robustness check); 37.3% of individuals in the sample report a chronic disease. A chi square test of independence shows that having a chronic disease is not independent from declaring a

[5] The EU-SILC project was established in response to a request from the European Commission and is led by Eurostat. The French part of the project is called SRCV (*Statistiques sur les Ressources et Conditions de Vie*)

status of poor health. Among people who declared a status of poor health, 94% had a chronic disease. In this study, we are interested in the possible continuity of health status. In our sample, the 95.9% of individuals who reported a status of good health, reported this over the entire period. Only 4.1% of individuals saw their health deteriorate, whereas 41% reported a status of poor health at the beginning of the period and saw their health improve.

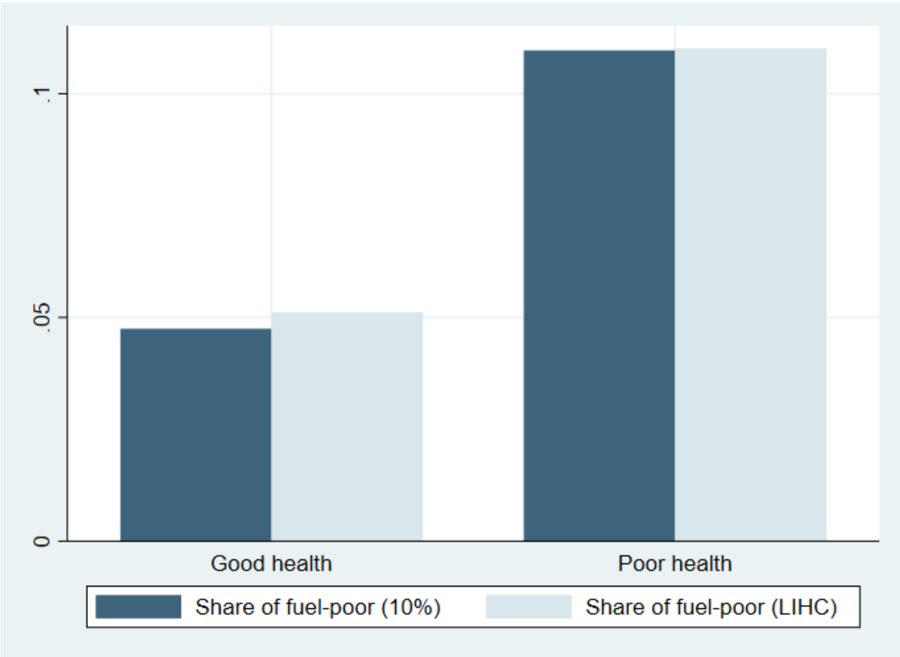
To measure fuel poverty, we chose to apply the most common indicators of fuel poverty defined and used in the literature (which will be our main predictors): the 10% ratio[6] (Boardman, 1991) and Low Income High Costs (LIHC)[7] (Hills, 2011, 2012). Both of these measures are calculated based on the standard of living[8] (SL) of the households observed rather than the disposable income of the household. The 10% ratio permits comparisons and serves as a reference. We built it by aggregating electricity, natural gas and other heating expenditures whether or not included in the rent, and calculating its share of the SL which gives us the energy effort rate of individuals, and compared it to the 10% threshold, resulting in a binary variable (1=fuel poor, 0=not fuel poor). There is some criticism in the literature about this measure of fuel poverty, mainly due to the fact that high income individuals who spend a lot on energy can be considered to be fuel poor while being nowhere near fuel poverty socially speaking (Healy & Clinch, 2002), so we have also compared our results with the LIHC indicator[9]. We did this by comparing an individual's SL to a poverty threshold[10] on the one hand and then comparing the individual's fuel expenditures to an expenditure threshold[11]. If one has a SL below the poverty threshold, and spends more on energy than the expenditure threshold, the individual is then considered to be fuel poor (1=fuel poor, 0=not fuel poor). In our sample 4.78% are fuel poor according to the 10% ratio and 5.74% according to the LIHC.

We tested the independence of fuel poverty (10% definition) and health status. The chi square test allows us to reject the hypothesis of independence between fuel poverty and poor health at the 1% level. Similar results are obtained if we consider another definition of fuel poverty or

[6] Based on the first measure used in the UK, 10% representing the ratio between the double median of heating energy expenditure of the population and their income. If one's own ratio is over this threshold, then the individual is considered to be fuel poor.
[7] The LIHC is used in the analysis to prove the robustness of results obtained later.
[8] Disposable income / consumption unit (OECD equivalent scale)
[9] Due to the cultural heterogeneity of European countries, as well as EU resistance to acknowledge a pan-European definition of fuel poverty (Thomson et al., 2017), the debate on how to measure it precisely and exhaustively is still raging. Our objective in this paper is not to discuss measurement of fuel poverty, but to determine if fuel-poor individuals have a worse health status that those who are not fuel-poor.
[10] This particular threshold is fixed at 60% of the median of income after energy costs by consumption unit.
[11] Which is the median fuel expenditure among the observed population.

another measure of health i.e. having a chronic disease. Generally speaking, more fuel-poor households are in poor health (Figure 1).

Figure 1 Health status according to fuel poverty definition



Finally, we introduced variables for controlling for health status: socio-demographic characteristics and local conditions (weather and pollution).

Degree level and home ownership are especially used as proxies to better control the standard of living and the wealth of individuals.

Health status might also be linked to climate (WHO, 2013). Our dataset gave us access to information about the climate zone where each household is located. This was matched with meteorological data of Meteo France (unified degree days[12]) to provide a proxy for the actual meteorological conditions. Finally, we approximated the income variable with level of education to avoid multicollinearity with fuel poverty (based on income). The descriptive statistics are presented in Table 1, and all variables are defined in Appendix 1.

[12] Unified Degree Days express the severity of cold weather in a specific time period taking into consideration actual outdoor temperature and an average reference temperature previously recorded.

Table 1 Descriptive statistics

Variable		Mean	Std Dev	Min	Max	Observations
Poor health	overall	0.084	0.277	0.000	1.000	N = 187817
	between		0.246	0.000	1.000	n = 53430
	within		0.166	-0.805	0.972	
Chronic disease	overall	0.372	0.483	0.000	1.000	N = 187803
	between		0.423	0.000	1.000	n = 53438
	within		0.264	-0.516	1.261	
Fuel poverty 10%	overall	0.048	0.213	0.000	1.000	N = 239477
	between		0.178	0.000	1.000	n = 67030
	within		0.137	-0.841	0.937	
Fuel poverty LIHC	overall	0.057	0.233	0.000	1.000	N = 239477
	between		0.197	0.000	1.000	n = 67030
	within		0.153	-0.832	0.946	
Pollution	overall	0.121	0.326	0.000	1.000	N = 239477
	between		0.273	0.000	1.000	n = 67030
	within		0.213	-0.768	1.010	
Number of children	overall	1.282	1.298	0.000	11.000	N = 239475
	between		1.290	0.000	11.000	n = 67030
	within		0.297	-2.718	4.949	
Age	overall	40.507	23.586	0.000	102.000	N = 239475
	between		23.840	0.000	101.000	n = 67030
	within		1.565	13.507	54.507	
Undergraduate degree	overall	0.082	0.274	0.000	1.000	N = 239477
	between		0.257	0.000	1.000	n = 67030
	within		0.099	-0.807	0.971	
Homeowner	overall	0.676	0.468	0.000	1.000	N = 239477
	between		0.463	0.000	1.000	n = 67030
	within		0.138	-0.213	1.564	
Medical density	overall	302.65	39.64	243.70	403.00	N = 239477
	between		38.77	243.70	403.00	n = 67030
	within		10.50	203.73	392.98	
Dark dwelling	overall	0.077	0.267	0.000	1.000	N = 239452
	between		0.232	0.000	1.000	n = 67026
	within		0.166	-0.812	0.966	
Electricity price	overall	0.162	0.035	0.000	0.200	N = 239477
	between		0.028	0.000	0.200	n = 67030
	within		0.025	0.007	0.329	
Gas price	overall	0.051	0.037	0.000	0.130	N = 239477
	between		0.033	0.000	0.130	n = 67030
	within		0.021	-0.054	0.165	
Unified degree days	overall	1928	355	1054	2683	N = 219431
	between		297	1054	2683	n = 61324
	within		214	906	2904	

2.4 Empirical model

This paper presents an approach based on traditional consumer theory where representation of individual preferences is based on the bundle of goods they have chosen to maximize their utility or well-being. Theoretical foundations are presented in appendix (Appendix 2).

We estimate the impact of fuel poverty on the probability of being in poor health controlling for other characteristics (based on equation 3, section 2). We use panel probit models and propose four configurations, first to control for state-dependence of health (Contoyannis et al., 2004), and second to control for endogeneity of fuel poverty (Awaworyi Churchill & Smyth, 2018).

So, we have as the first model specification (Model 1):

$$h*_{it} = \alpha X_{it} + \beta W_{it} + \gamma FP_{it} + u_i + v_{it} \quad (4)$$

With:

$$i = 1, \dots, N \; and \; t = 1, \dots, T$$
$$h_{it} = 1 \text{ if } h_{it}^{*} > 0 \text{ and } 0 \text{ otherwise}$$

h_{it} represents the health status of the individual i in t, equal to 1 for good health at time t, X_{it} is the vector of observed variables (including age, level of education, etc.), W_{ij} is a vector of living conditions including local air pollution and climate, FP_{it} is the fuel poverty regressor, equal to 1 for a fuel-poor individual, according to the 10% threshold., u_i the individual-specific effect assumed to be unrelated to control variables, and v_{it} the idiosyncratic error term.

However, health status has a certain degree of persistence over time (Contoyannis et al., 2004), which leads to the first configuration being biased. To account for this state-dependence (Carro & Traferri, 2014; Halliday, 2008), we include a lagged health status variable representing the health of individuals in the previous year.
So, we propose a dynamic random effect model:

$$h_{it}^{*} = \delta h_{it-1} + \alpha X_{it} + \beta W_{it} + \gamma FP_{it} + u_i + v_{it} \tag{5}$$

h_{it-1} representing the lagged health status.

The use of a lagged variable presents the initial conditions problem (Heckman, 1981). The historic stochastic process of health status is not observed at the beginning. The initial values of this variable cannot be considered exogenous (Akay, 2009). Health during childhood, or other exogenous parameters affect the entire health trajectory for example (Contoyannis et al., 2004; Halliday, 2008). So, we can express health at the first period in the panel as following:

$$h_{i0}{}^{*} = \gamma Z_{i0} + \theta u_i + \varepsilon_i \tag{6}$$

With Z_{i0} including exogenous attributes affecting health status in the first period. The initial conditions problem leads y_{i0} then to be correlated with the unobserved heterogeneity. Consequently, in equation (2) we have $E(u_i|y_{i0}) \neq 0$ when $\theta \neq 0$.

In order to treat the initial conditions problem, we use the inverse of Mills' ratio[13] within the Orme's two-step method (Arulampalam & Stewart, 2007; Orme, 1997). We estimate a probit of the probability of being in good health in the first year in the panel. The medical density[14] i.e. the ratio of physicians (practitioners or specialists) to the population in a geographic area, is used as an exogenous instrument (Z_{i0}) to explain the health status at time t_0 (Chaix, Veugelers, Boëlle, & Chauvin, 2005; Macinko, Starfield, & Shi, 2003).

Our second specification, correcting the initial conditions problem, might be expressed as follows (Model 2):

$$h_{it}^{*} = \delta h_{it-1} + \alpha X_{it} + \beta W_{it} + \gamma FP_{it} + \sigma E[u_i|y_{i0}] + u_i^{*} + v_{it} \tag{7}$$

in which $E[u_i|y_{i0}]$has been estimated in the first step as:

[13] Which is a monotone decreasing function of the probability of the selection of an observation in the sample (Heckman, 1979)

[14] Data from the French Atlas of Medical Demography[14], carried out annually by the French Medical Board, adjusted by national territory divisions have been used to construct the variable of medical density.

$$E[u_i|y_{i0}] = E[u_i|\theta u_i + \varepsilon_i \geq -\gamma Z_{it}] = \frac{\phi(\gamma Z_{it})}{\Phi(\gamma Z_{it})}$$

The third specification of the model accounts for the potential endogeneity of fuel poverty as we cannot rule out that unobserved heterogeneity simultaneously affects health and fuel poverty (Awaworyi Churchill & Smyth, 2018). We adopt a two-step instrumental method (Heckman, 1979) by first estimating fuel poverty. Electricity and natural gas prices are used as instruments as they are the most commonly used sources of energy for heating (Ambrosio, Belaid, Bair, & Teissier, 2015). Energy prices are often recognized as one of the most important determinants of residential energy demand (see Labandeira, 2017 Labandeira, Labeaga, and López-Otero (2017) for a literature review) and as a consequence of energy expenditures, a main component of fuel poverty (Charlier & Kahouli, 2019; ONPE 2014). We extrapolate the fuel price rate of each individual using the surface area of their dwelling and their fuel bills. In order to estimate fuel poverty more precisely, we also introduce a variable to consider energy efficiency from the solar exposure of the dwelling (Charlier & Kahouli, 2019), a binary variable if the dwelling is dark.

The predicted value of fuel poverty is thus obtained using equation 8:

$$FP_{it}^{*} = \theta_1 X_{it} + \theta_2 W_{it} + \theta_3 Gas\_p_{it} + \theta_4 Elec\_p_{it} + \theta_5 GasElec\_p_{it} + \theta_6 D_{it} + u_i' + v_{it}' \quad (8)$$

With $p_{it} = 1$ if $p_{it}^{*} > 0$ and 0 otherwise.

Gas_p_{it}, $Elec\_p_{it}$ are the gas price and the electricity price, $GasElec\_p_{it}$ the interaction parameter between both energy prices to account for potential multicollinearity between evolution of energy prices[15] and D_{it}, a dummy variable indicating if the dwelling is dark.

The third specification of the model is a dynamic probit model, with correction of the endogeneity bias caused by the fuel poverty variable (Model 3):

[15] Before 2008, energy prices rose rapidly and fell sharply during the 2009 crisis, which explains why energy expenditures were quite low during this period compared to the previous. However, since 2010, the price of oil increased as did household energy expenditures, reaching a peak in 2013. Then, considering France had recorded several mild winters, the share of energy expenditure in the overall budget continued to grow ((ONPE, 2018))

$$h_{it}^{*} = \delta y_{it-1} + \alpha X_{it} + \beta W_{it} + \gamma \widehat{FP}_{it} + \sigma E[u_i|y_{i0}] + u_i^{*} + v_{it} \quad (5)$$

Finally, the fourth specification controls the sensitivity to the choice of health variable. We estimate the third model and replace the health variable with a binary variable for chronic disease (Model 4). Then, we apply bootstrap techniques in each step to avoid bias (Efron & Tibshirani, 1993; Horowitz, 2003).

3. Results and discussion

The main results are reported in Table 2. For the sake of clarity, the results of the initial conditions equation and the endogeneity treatment of fuel poverty equation are reported in the Appendix (See Appendix 3).

The results of the four models are reported in Table 2, but there is no doubt that only models 3 and 4 contribute to correctly identifying the causal effect of fuel poverty on health. We will therefore discuss these results directly.

The estimates confirm the negative impact of fuel poverty on health status, as expected in the theoretical model, and as previously established in different cross-sectional case studies (Table 2, Models 1 to 4).

The impact of fuel poverty appears to be strong (Table 2, Model 3): being fuel poor increases the risk of bad health by more than a factor of 7 (Table 3, Model 3) for those already in poor health, and by a factor of 1.82 for those who were in good health in the previous year. Finally, to test the robustness of the results established by Models 1 to 3, we use an objective measure of health, the existence of chronic diseases (Model 4). This last model confirms that being fuel poor multiplies the risk of chronic disease by more than a factor of 6.14 (Table 3, Model 4) for those in good health (no chronic disease) in the previous year, and by 7.88 for those who already declared at least one chronic disease. If we account for the unobserved heterogeneity affecting exposure to fuel poverty and deteriorating health simultaneously, we can conclude there is a very strong causal relationship between both phenomena.

The empirical strategy adopted first shows that the nature of the health variable has to be accounted for, and second that neglecting endogeneity of fuel poverty would lead to a

significant underestimation of the health risk. The entire health trajectory of each individual has to be controlled: the intermediate estimate consisting of the control of initial conditions shows that medical density is a good instrument to explain the health of individuals before their entry in the panel (Table 6, Appendix 3A). Medical density significantly decreases the probability of being in poor health and of having a chronic disease.
The effects of path dependency in health are evident in Tables 2 and 3, and confirms the necessity to control initial conditions: being in poor health in the previous period significantly increases first the risk of poorer health and secondly the impact of fuel poverty. A self-perpetuating spiral, reinforced by energy insecurity, is then triggered.

The first step in Models 3 and 4 which provides the estimated fuel poverty probability also allows us to conclude that energy prices are good instruments and strongly affect exposure to fuel poverty (Table 7 in Appendix 3B). When electricity and gas prices increase, the risk of fuel poverty increases significantly for each individual. Having a dark dwelling also significantly increases the probability of being poor. This step enables us to provide a good prediction of fuel poverty: the correct prediction rate is about 87%.

To test the robustness of the results established in the Models 3 and 4, we introduced an alternative indicator of fuel poverty: the low-income high cost indicator. According to this definition, households are fuel-poor if they have an income after fuel costs that is below the poverty threshold[16] as well as fuel costs above the median population fuel cost. These estimates are reported in the Appendix (Table 8 in Appendix 3C). We have validated the results and particularly the size of the effect: being fuel poor leads to an increase in the risk of bad health by more than a factor of 2 for a person previously in good health and by more than 8 for those already in poor health (Table 9 model 3). The risk of declaring a chronic disease increases by a factor of 4.38 for a healthy person (Table 9 Model 4).

[16] This poverty threshold is set at 60% of the population income, from which fuel costs have been deducted.

Table 2 results - probability of being in poor health

	Model 1	*Model 2*	*Model 3*	*Model 4*
To be in poor health (lag)		1.611***	1.609***	
		(0.0328)	(0.0328)	
Fuel poverty 10%	0.252***	0.198***		
	(0.0332)	(0.0630)		
Number of children	0.0824***	0.0353***	0.0188**	0.00461
	(0.0127)	(0.0118)	(0.00857)	(0.00607)
Unified Degree Days (log)	0.0527	0.0306	-0.0280	-0.0823***
	(0.0466)	(0.0361)	(0.0371)	(0.0252)
Age	0.0529***	0.0216***	0.00139	-0.000319
	(0.00100)	(0.00651)	(0.00272)	(0.00190)
Pollution problem	0.186***	0.142***	0.0202	0.0708***
	(0.0247)	(0.0515)	(0.0273)	(0.0179)
Undergraduate degree	-0.365***	-0.186***	0.0287	0.0160
	(0.0469)	(0.0718)	(0.0397)	(0.0176)
Homeowner	-0.642***	-0.281***	-0.0208	0.00102
	(0.0274)	(0.0915)	(0.0392)	(0.0158)
Mills' ratio		-0.0219	-0.836***	-0.895***
		(0.293)	(0.119)	(0.0994)
Predicted fuel poverty 10%			21.39***	25.15***
			(3.357)	(2.964)
Chronic disease (lag)				1.548***
				(0.0210)
Constant	-5.568***	-3.068***	-0.242	0.526*
	(0.362)	(0.828)	(0.431)	(0.286)
Observations	173,88	122,362	122,347	122,32
Number of individuals	49,422	37,855	37,855	37,861

Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

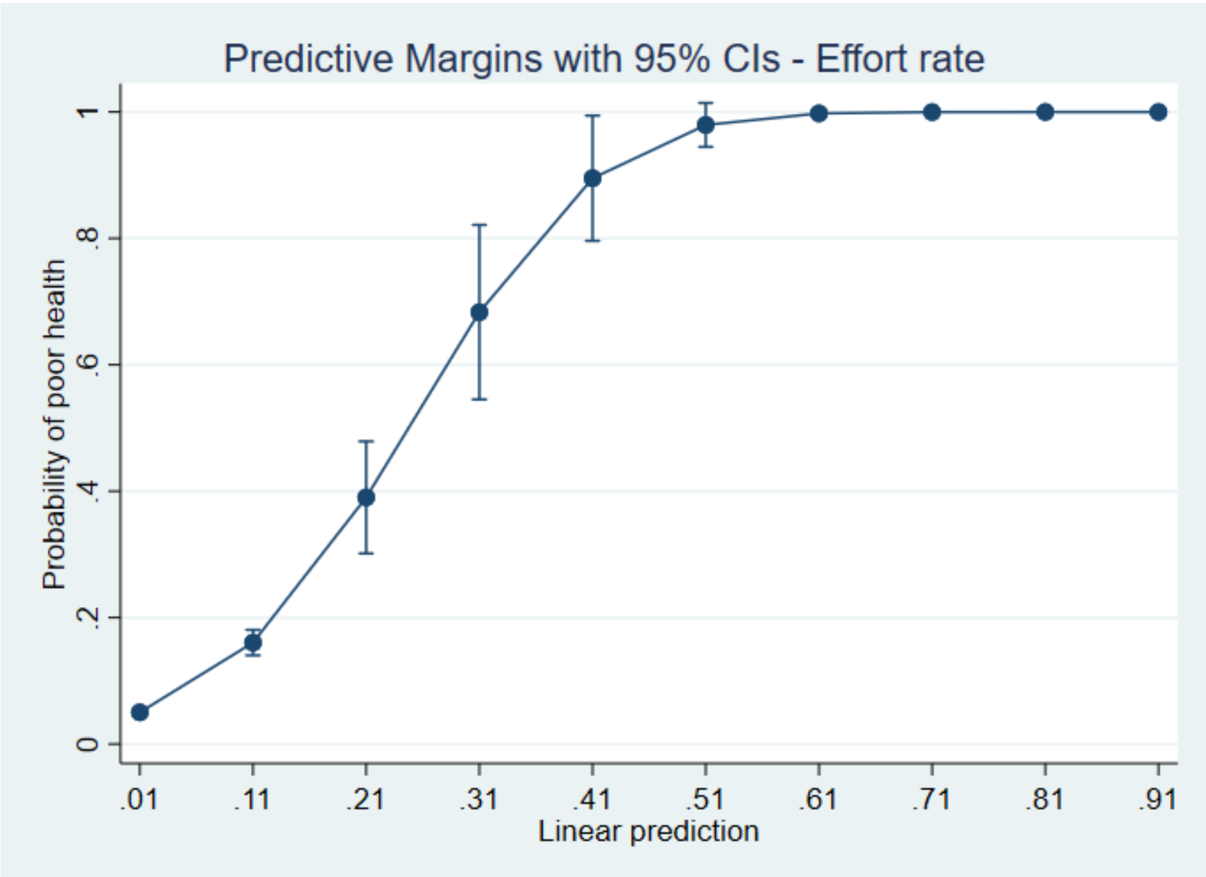
Table 3 Marginal effect of fuel poverty (10%) on poor health

Model 1	0.019***	
	Good health in t-1	Poor health in t-1
Model 2	0.017***	0.065***
Model 3	1.82***	7.05***
Model 4	6.14***	7.88***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Finally, using the same methodology, we wanted to identify the threshold where the effort rate significantly increases the probability of being in poor health . Results for predictive values are presented in Figure 2 below. We note that from a predicted effort rate of 25%, the probability of being in poor health is greater than being in good health.

Figure 2: Predictive margins for effort rate – linear prediction



The concept revealed in Figure 2 is confirmed when replaced in Model 3 (the most complete, the variable of fuel poverty multiplied by the effort rate). The results are reported in Table 4:

when the effort rate increases marginally, the risk of declaring a state of poor health increases by 5.5.

Table 4 Results - probability of being in poor health

Poor health (lag)	1.613***
	(0.0329)
Predicted effort rate	5.505***
	(1.522)
Number of children	0.0158*
	(0.00936)
Unified Degree Days (log)	-0.0245
	(0.0408)
Age	0.00172
	(0.00370)
Pollution problem	0.0203
	(0.0334)
Undergraduate degree	0.0514
	(0.0482)
Homeowner	-0.0560
	(0.0537)
Mills' ratio	-0.853***
	(0.165)
Panel-level variance (log)	-1.727***
	(0.132)
Constant	-0.433
	(0.526)
Observations	122,345
Number of individuals	37,855

Robust standard errors in parentheses – Bootstrap 5000 replications
**** p<0.01, ** p<0.05, * p<0.1*

Our results reinforce the estimates provided by the National Housing Federation in 2010: the cost for treating ill health resulting from poor housing conditions has been estimated at GBP 2.5 billion per year in the UK. Eurofound (2016) models the cost of housing inadequacies and estimated that in France, 930 million euros in medical expenses would be saved by repairing inadequate housing. The previous reports combined with our results lead us to conclude that spillover effects exist in public policy: implementing policies which promote energy efficiency, such as encouraging investment in retrofitting are useful tools for tackling fuel poverty and also reduce medical spending.

Retrofitting policies, in this sense, go beyond the simple monetary benefits: a household could occupy an energy-inefficient dwelling and cope with it by means of a high income. Retrofitting measures would still be highly beneficial to them due to improvement of the environment. In the context of continuous increases in energy prices in Europe as shown by Eurostat (2019), investment opportunities created by the need for energy efficiency are vast and highly profitable (Amstalden, Kost, Nathani, & Imboden, 2007). Retrofitting plans and energy efficiency measures have an impact on fuel poverty through different channels. First, they directly and robustly improve living conditions (reduce cold, dampness, mold). Second, they lead indirectly to a decrease in energy costs, particularly because the housing becomes less energy-intensive. Finally, reducing residential energy consumption/demand reduces carbon dioxide emissions, which is an important component of the preservation of climate and natural resources, and the environment as a whole. "*For example, cleaner energy systems could reduce carbon emissions, and cut the burden of household air pollution, which causes some 4.3 million deaths per year, and ambient air pollution, which causes about 3 million deaths every year*" (WHO, 2018).

More broadly, our results beg the question whether it is possible to achieve energy transition without considering the impact of fuel costs on fuel poverty and the indirect impact on public health. Achieving energy transition without incurring excessive economic and social costs requires anticipating long chain reactions.

7/ Conclusion

Fuel poverty has been treated extensively in recent literature. But very few studies target the causal link between fuel poverty and poor health. Numerous papers focus on specific experiments assessing the link between some timely retrofitting policies and the health of occupants (Chapman et al., 2009; Ezratty et al., 2009; Philippa Howden-Chapman, 2015; Philippa Howden-Chapman et al., 2007; Lloyd et al., 2008; Thomson & Snell, 2013). To the best of our knowledge only two papers (Lacroix & Chaton, 2015; Liddell & Morris, 2010) describe non-experimental and cross-sectional research on the relationship between fuel poverty and health. Our study aims to go beyond the limits of this previous work, namely the overly specific aspects of experimental studies and the non-generalizable results of cross-sectional research that neglect climate hazards and the path dependency of health.

In the present paper, we estimate the causal effect of fuel poverty on health status. To do this, we used panel data from the EU-SILC over a lengthy recent period (2008-2016) and estimated probit panel models in four steps. We begin with a simple probit model without controlling for state dependency of health and endogeneity of fuel poverty, and finish with a dynamic probit model controlling for both biases.

We conclude that fuel poverty has a significant impact on health. Being fuel poor increases the risk of bad health by slightly more than a factor of 7 for those already in poor health (1.82 for those in good health) and by 7.88 the risk of having a chronic disease for those who already have a chronic disease (6.14 for those previously in good health). In terms of policy recommendations, we stress the importance of energy-efficiency retrofits. This type of policy will not only make it possible, to improve the housing conditions of households and their well-being, but also to reduce their energy bills and thus their exposure to fuel poverty. Indirectly, our work suggests that such policies could also have a positive impact on health spending.

Lessons learned from our empirical strategy also allow us to conclude that neglecting path dependency of health and endogeneity of fuel poverty leads to a substantial underestimation of the impact on health. By controlling both biases, we first show that medical density must be accounted for to achieve a good understanding of the health history of each individual. Secondly, as energy prices are good instruments for controlling endogeneity, our results question the inextricably linked issues of energy transition, combatting fuel poverty and safeguarding public health. Is it possible to achieve energy transition without excessive economic and social costs, i.e. without increasing fuel poverty and damaging public health?

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References

Akay, A. (2009). The Wooldridge Method for the Initial Values Problem is Simple: What about Performance? , 42.

Ambrosio, G., Belaid, F., Bair, S., & Teissier, O. (2015). Observatoire de la Precarite Energe tique. 59.

Amstalden, R. W., Kost, M., Nathani, C., & Imboden, D. M. (2007). Economic potential of energy-efficient retrofitting in the Swiss residential building sector: The effects of policy instruments and energy price expectations. *Energy Policy, 35*(3), 1819-1829. doi:10.1016/j.enpol.2006.05.018

Arulampalam, W., & Stewart, M. B. (2007). *Simplified Implementation of the Heckman Estimator of the Dynamic Probit Model and a Comparison with Alternative Estimators*.

Awaworyi Churchill, S., & Smyth, R. (2018). *Energy Poverty and Health: Panel Data Evidence from Australia*.

Barton, A., Basham, M., Foy, C., Buckingham, K., Somerville, M., & Torbay Healthy Housing, G. (2007). The Watcombe Housing Study: the short term effect of improving housing conditions on the health of residents. *Journal of epidemiology and community health, 61*(9), 771-777. doi:10.1136/jech.2006.048462

Benzeval, M., & Judge, K. (2001). Income and health: the time dimension. *Social Science & Medicine, 52*(9), 1371-1390. doi:https://doi.org/10.1016/S0277-9536(00)00244-6

Boardman, B. (1991). *Fuel Poverty: From Cold Homes to Affordable Warmth*. London: Belhaven Press.

Boardman, B. (2010). *Fixing Fuel Poverty: Challenges and Solutions.* London: Earthscan.

Bourdon, P., Van Mien, H. D., & Normand-Cyrot, D. (1992). Power Plants: Nonlinear Modelling. In D. P. A. Borne (Ed.), *Concise Encyclopedia of Modelling & Simulation* (pp. 358-363). Oxford: Pergamon.

Braubach, M., Jacobs, D. E., & Ormandy, D. (2011). *Environmental burden of disease associated with inadequate housing: a method guide to the quantification of health effects of selected housing riss in the WHO European Region*. Copenhagen: World Health Organization, Regional Office for Europe.

Carro, J. M., & Traferri, A. (2014). STATE DEPENDENCE AND HETEROGENEITY IN HEALTH USING A BIAS-CORRECTED FIXED-EFFECTS ESTIMATOR: STATE DEPENDENCE AND HETEROGENEITY IN HEALTH. *Journal of Applied Econometrics, 29*(2), 181-207. doi:10.1002/jae.2301

Chaix, B., Veugelers, P. J., Boëlle, P.-Y., & Chauvin, P. (2005). Access to general practitioner services: the disabled elderly lag behind in underserved areas. *European Journal of Public Health, 15*(3), 282-287. doi:10.1093/eurpub/cki082

Chapman, R., Howden-Chapman, P., Viggers, H., O'Dea, D., & Kennedy, M. (2009). Retrofitting houses with insulation: a cost-benefit analysis of a randomised community trial. *Journal of Epidemiology & Community Health, 63*(4), 271-277.

Charlier, D., & Kahouli, S. (2019). From Residential Energy Demand to Fuel Poverty: Income-induced Non-linearities in the Reactions of Households to Energy Price Fluctuations. *Energy Journal, 40*(2), 101-137.

Chaton, C., & Lacroix, E. (2018). Does France have a fuel poverty trap? *Energy Policy, 113*, 258-268. doi:https://doi.org/10.1016/j.enpol.2017.10.052

Contoyannis, P., & Jones, A. M. (2004). Socio-economic Status, Health and Lifestyle. *Journal of Health Economics, 23*(5), 965-995. doi:http://www.sciencedirect.com/science/journal/01676296

Contoyannis, P., Jones, A. M., & Rice, N. (2004). The dynamics of health in the British Household Panel Survey. *Journal of Applied Econometrics, 19*(4), 473-503. doi:10.1002/jae.755

Crossley, T. F., & Kennedy, S. (2002). The reliability of self-assessed health status. *Journal of Health Economics, 21*(4), 643-658. doi:10.1016/S0167-6296(02)00007-3

Currie, J., Neidell, M., & Schmieder, J. F. (2009). Air Pollution and Infant Health: Lessons from New Jersey. *Journal of Health Economics, 28*(3), 688-703. doi:http://www.sciencedirect.com/science/journal/01676296

Cutler, D. M., & Lleras-Muney, A. (2006). Education and Health: Evaluating Theories and Evidence. *National Bureau of Economic Research Working Paper Series, No. 12352*.

Dales, R. E., Zwanenburg, H., Burnett, R., & Franklin, C. A. (1991). Respiratory Health Effects of Home Dampness and Molds among Canadian Children. *American Journal of Epidemiology, 134*, 473–503.

Efron, B., & Tibshirani, R. J. (1993). *An introduction to the Bootstrap*: Boca Raton, FL: Chapman & Hall.

Eurofound. (2016). *Inadequate Housing in Europe : costs and consequences*. Retrieved from

Ezratty, V., Duburcq, A., Emery, C., & Lambrozo, J. (2009). Liens entre l'efficacité énergétique du logement et la santé des résidents : résultats de l'étude européenne LARES. *Environnement, Risques & Santé, 8*(6), 497-506.

Fisk, W. J., Lei-Gomez, Q., & Mendell, M. J. (2007). Meta-analyses of the associations of respiratory health effects with dampness and mold in homes. *Indoor Air, 17*, 284-296. doi:https://doi.org/10.1111/j.1600-0668.2007.00475.x

Grimes, A., Preval, N., Young, C., Arnold, R., Denne, T., Howden-Chapman, P., & Telfar-Barnard, L. (2016). Does Retrofitted Insulation Reduce Household Energy Use? Theory and Practice. *Energy Journal, 37*(4), 165-186. doi:10.5547/01956574.37.4.agri

Halliday, T. J. (2008). Heterogeneity, state dependence and health. *Econometrics Journal, 11*(3), 499-516. doi:10.1111/j.1368-423X.2008.00256.x

Healy, J. D., & Clinch, J. P. (2002). *Fuel poverty in Europe A cross-country analysis using a new composite measurement*. Retrieved from http://hdl.handle.net/10068/504189

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica, 47*(1), 153. doi:10.2307/1912352

Heckman, J. J. (1981). The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time - Discrete Data Stochastic Process. In C. M. Press (Ed.), *chapter Structural Analysis of Discrete Data with Econometric Applications*: Cambridge MIT Press.

Hills, J. (2011). *Fuel Poverty: The problem and its measurement*. Retrieved from

Hills, J. (2012). *Getting the measure of fuel poverty*. Retrieved from

Homøe, P., Christensen, R. B., & Bretlau, P. (1999). Acute otitis media and sociomedical risk factors among unselected children in Greenland. *International Journal of Pediatric Otorhinolaryngology, 49*(1), 37-52. doi:https://doi.org/10.1016/S0165-5876(99)00044-0

Horowitz, J. L. (2003). The Bootstrap in Econometrics. *Statistical Science, 18*(2), 211-218. doi:10.2307/3182851

Howden-Chapman, P. (2015). How real are the health effects of residential energy efficiency programmes? *Social Science & Medicine, 133*, 189-190. doi:10.1016/j.socscimed.2015.03.017

Howden-Chapman, P., Crane, J., Matheson, A., Viggers, H., Cunningham, M., Blakely, T., . . . Waipara, N. (2005). Retrofitting houses with insulation to reduce health inequalities: Aims and methods of a clustered, randomised community-based trial. *Social Science & Medicine, 61*(12), 2600-2610. doi:10.1016/j.socscimed.2005.04.049

Howden-Chapman, P., Phipps, R., & Cunningham, M. (2007). Warmer houses reduce children’s asthma. *Build August/September 2007,* p 40-41.

Hunt, V. D. (1988). 8 - Definitions A to Z. In V. D. Hunt (Ed.), *Robotics Sourcebook* (pp. 73-295): Elsevier.

Idler, E. L., & Kasl, S. V. (1995). Self-Ratings of Health: Do they also Predict change in Functional Ability? *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 50B*(6), S344-S353. doi:10.1093/geronb/50B.6.S344

Iversen, M., Bach, E., & Lundqvist, G. R. (1986). Health and comfort changes among tenants after retrofitting of their housing. *Environment International, 12*(1), 161-166. doi:https://doi.org/10.1016/0160-4120(86)90026-7

Jaakkola, J. J. K., Hwang, B.-F., & Jaakkola, N. (2005). Home Dampness and Molds, Parental Atopy, and Asthma in Childhood: A Six-Year Population-Based Cohort Study. *Environmental Health Perspectives, 113*, 357-361. doi: https://doi.org/10.1289/ehp.7242

Jans, J., Johansson, P., & Nilsson, J. P. (2018). Economic Status, Air Quality, and Child Health: Evidence from Inversion Episodes. *Journal of Health Economics, 61*, 220-232.

Khanom, L. (2000). Impact of fuel poverty on health in TowerHamlets. In *Cutting the Cost of Cold - Affordable Warmth for Healthier Homes*. London: Routledge.

Labandeira, X., Labeaga, J. M., & López-Otero, X. (2017). A meta-analysis on the price elasticity of energy demand. *Energy Policy, 102*, 549-568. doi:https://doi.org/10.1016/j.enpol.2017.01.002

Lacroix, E., & Chaton, C. (2015). Fuel poverty as a major determinant of perceived health: the case of France. *Public Health, 129*(5), 517-524. doi:10.1016/j.puhe.2015.02.007

Liddell, C., & Morris, C. (2010). Fuel poverty and human health: A review of recent evidence. *Energy Policy, 38*(6), 2987-2997. doi:10.1016/j.enpol.2010.01.037

Lloyd, C. R., Callau, M. F., Bishop, T., & Smith, I. J. (2008). The efficacy of an energy efficient upgrade program in New Zealand. *Energy and Buildings, 40*(7), 1228-1239. doi:https://doi.org/10.1016/j.enbuild.2007.11.006

Lowry, S. (1991). *Housing and Health*: British Medical Journal.

Lundberg, O., & Manderbacka, K. (1996). Assessing reliability of a measure of self-rated health. *Scandinavian Journal of Social Medicine, 24*(3), 218-224. doi:10.1177/140349489602400314

Lynch, J. W., Kaplan, G. A., & Salonen, J. T. (1997). Why do poor people behave poorly? Variation in adult health behaviours and psychosocial characteristics by stages of the socioeconomic lifecourse. *Social Science & Medicine, 44*(6), 809-819. doi:https://doi.org/10.1016/S0277-9536(96)00191-8

Macinko, J., Starfield, B., & Shi, L. (2003). The Contribution of Primary Care Systems to Health Outcomes within Organization for Economic Cooperation and Development (OECD) Countries, 1970–1998. *Health Services Research, 38*(3), 831-865. doi:10.1111/1475-6773.00149

Maidment, C. D., Jones, C. R., Webb, T. L., Hathway, E. A., & Gilbertson, J. M. (2014). The impact of household energy efficiency measures on health: A meta-analysis. *Energy Policy, 65*, 583-593. doi:10.1016/j.enpol.2013.10.054

Neidell, M. J. (2004). Air Pollution, Health, and Socio-economic Status: The Effect of Outdoor Air Quality on Childhood Asthma. *Journal of Health Economics, 23*(6), 1209-1236. doi:http://www.sciencedirect.com/science/journal/01676296

Nijman, T., Verbeek, M., & van Soest, A. (1991). The efficiency of rotating-panel designs in an analysis-of-variance model. *Journal of Econometrics, 49*(3), 373-399. doi:10.1016/0304-4076(91)90003-V

Ohrnberger, J., Fichera, E., & Sutton, M. (2017). The dynamics of physical and mental health in the older population. *The Journal of the Economics of Ageing, 9*, 52-62. doi:https://doi.org/10.1016/j.jeoa.2016.07.002

ONPE (2014). *Définitions, indicateurs, premiers résultats et recommendations - Premier rapport de l'ONPE*. Retrieved from

ONPE. (2018). *Tableau de bord de la précarité énergétique*. Retrieved from

Orme, C. D. (1997). *The Initial Conditions Problem and Two Step Estimations in Discrete Panel Data Models*: Mimeo, University of Manchester

.

Pampuri, L., Caputo, P., & Valsangiacomo, C. (2018). Effects of buildings' refurbishment on indoor air quality. Results of a wide survey on radon concentrations before and after energy retrofit interventions. *Sustainable Cities and Society, 42*, 100-106. doi:https://doi.org/10.1016/j.scs.2018.07.007

Peat, J. K., Dickerson, J., & Li, J. (1998). Effects of damp and mould in the home on respiratory health: a review of the literature. *Allergy, 53*, 120-128.

Platt, S. D., Martin, C. J., Hunt, S. M., & Lewis, C. W. (1989). Damp housing, mould growth, and symptomatic health state. *BMJ 298*, 1673–1678. doi:https://doi.org/10.1136/bmj.298.6689.1673

Prasauskas, T., Martuzevicius, D., Kalamees, T., Kuusk, K., Leivo, V., & Haverinen-Shaughnessy, U. (2016). Effects of Energy Retrofits on Indoor Air Quality in Three Northern European Countries. *Energy Procedia, 96*, 253-259. doi:https://doi.org/10.1016/j.egypro.2016.09.134

Rashid, M., & Zimring, C. (2008). A Review of the Empirical Literature on the Relationships Between Indoor Environment and Stress in Health Care and Office Settings: Problems and Prospects of Sharing Evidence. *Environment and Behavior, 40*(2), 151-190. doi:10.1177/0013916507311550

Rosenow, J., & Galvin, R. (2013). Evaluating the evaluations: Evidence from energy efficiency programmes in Germany and the UK. *Energy and Buildings, 62*(0), 450-458.

Shortt, N., & Rugkåsa, J. (2007). The walls were so damp and cold" fuel poverty and ill health in Northern Ireland: results from a housing intervention. *Health Place, 13*(1), 99-110.

Sorrell, S., Dimitropoulos, J., & Sommerville, M. (2009). Empirical estimates of the direct rebound effect: A review. *Energy Policy, 37*(4), 1356-1371.

Stabile, L., Buonanno, G., Frattolillo, A., & Dell'Isola, M. (2019). The effect of the ventilation retrofit in a school on CO2, airborne particles, and energy consumptions. *Building and Environment, 156*, 1-11. doi:https://doi.org/10.1016/j.buildenv.2019.04.001

Thomson, H., & Snell, C. (2013). Quantifying the prevalence of fuel poverty across the European Union. *Energy Policy, 52*, 563-572. doi:10.1016/j.enpol.2012.10.009

University College, L., Team, M. R., & Earth, F. o. t. (2011). *The health impacts of cold homes and fuel poverty*. London: Friends of the Earth & the Marmot Review Team.

Vandentorren, S., Bretin, P., Zeghnoun, A., Mandereau-Bruno, L., Croisier, A., Cochet, C., . . . Ledrans, M. (2006). August 2003 Heat Wave in France: Risk Factors for Death of Elderly People Living at Home. *European Journal of Public Health, 16*(6), 583-591. doi:10.1093/eurpub/ckl063

Webber, P., Gouldson, A., & Kerr, N. (2015). The impacts of household retrofit and domestic energy efficiency schemes: A large scale, ex post evaluation. *Energy Policy, 84*(0), 35-43. doi:http://dx.doi.org/10.1016/j.enpol.2015.04.020

WHO. (2013). *Review of evidence on health aspects of air pollution – REVIHAAP project: final technical report*. Retrieved from

WHO. (2018). Ambient (outdoor) air quality and health.

WHO Regional Office for Europe. (2004). Paper presented at the Fourth Ministerial Conference on Environment and Health, Budapest, Hungary.

Zivin, J. G., & Neidell, M. (2013). Environment, Health, and Human Capital. *Journal of Economic Literature, 51*(3), 689-730.

Appendix 1

Table 5 Description of variables

Variables and Header	Description	Source	Expected effect on health status
Dependent variables			
Health status	Dummy: 1 if in poor health, 0 otherwise	EU-SILC	
Chronic disease	Dummy: 1 if individual has a chronic disease, 0 otherwise	EU-SILC	
Control variables for fuel poverty			
Fuel poverty LIHC	Equalized net income ≤ 60% (Equalized median net income) and Equalized fuel expenditures ≥ Required national median fuel expenditures Equalized fuel expenditures are calculated by dividing fuel expenditures by the number of consumption units in the case of the LIHC (cu) indicator Equalized net income =(Disposable income - Housing costs - Domestic fuel costs) divided by number of consumption units	EU-SILC	+
Fuel poverty 10%	(Actual) Fuel costs Divided by Equalized disposable income (before housing costs) (cu) Dummy: 1 if fuel-poor household, the ratio is greater than 10%, 0 otherwise	EU-SILC	+
Control variables for health condition -Climate and environmental characteristics			
Unified degree days	Continuous - A degree day is a measure of heating need. The air temperature in a building is on average 2–3 C higher than that of the air outside. A temperature of 18 C indoors corresponds to an outside temperature of about 15.5 C. If the air temperature outside is below 15.5 C, then heating is required to maintain a temperature of about 18 C. If the outside temperature is 1 C below the average temperature it is accounted as 1 degree-day. The sum of the degree days over periods such as a month or an entire heating season is used in calculating the amount of heating required for a building.	Meteo France – Merged with EU-SILC climate zone	+
Pollution	Pollution and environmental problems of other pollutants related to industry or road traffic dust, bad odors or water pollution Dummy: 1 if local air pollution, 0 otherwise	EU-SILC	+
Control variable for health condition - Socio-demographic characteristics			
Number of children	Number of children in the household	EU-SILC	-/+
Age	In years	EU-SILC	+
Homeowner	Dummy: 1 if a homeowner, 0 otherwise	EU-SILC	-
Undergraduate degree	Dummy: 1 if a homeowner, 0 otherwise	EU-SILC	+
Medical density	Number of doctors by region	Atlas de la démographie médicale en France	-
Control variable for fuel poverty - instruments			

Variables and Header	Description	Source	Expected effect on health status
Electricity price	kWh/€. Electricity price is deducted from the surface area, the share of energy expenditures dedicated to electricity. Assumptions are made using EDF and ENGIE websites.	Authors' calculation EU-SILC and PEGASE	
Gas price	kWh/€. Gas price is deducted from the surface area, the share of energy expenditures dedicated to gas. Assumptions are made using EDF and ENGIE websites.	Authors' calculation. EU-SILC and PEGASE	
Solar exposure and natural lighting - DARK	Dummy: 1 if dark, 0 otherwise	EU-SILC	

Appendix 2: **Theoretical foundations of the empirical strategy**

This paper presents an approach based on traditional consumer theory where representation of individual preferences is based on the bundle of goods they have chosen to maximize their utility or well-being. So, we characterize individual preferences as $U(G, H)$.

G as a whole spectrum of other goods that has nothing to do with medical services and products, but which definitely contribute to quality of life. Let H be the care demand that is directly derived from a health status h. We assume that a person in good health has a relatively low health care demand. Then the budget constraint of the individual is simply $m = p_h H + p_g G$, where m is just the income of the individual, p_g the price of other goods prices and p_h the price of medical care.

The specification of household medical care demand is based on a utility model with R* the stochastic indirect utility function of the households, which we assume to be unobserved. Indirect utility V depends on the price of medical care p_h and income m, household characteristics X, fuel poverty condition FP, climatic and environmental conditions W, and is defined conditionally on health status j.

Therefore, we have:

$$R_{ij}^{*} = V_{ij}[p_{hi}, m_i, X_i, W_i, FP_i] + v_{ij} \tag{1}$$

where j=0,1 is health status, i=1, ..., N that of the individual, and v_{ij} the error term. The Roy's identity gives us the household Marshallian demand function for medical care:

$$H_{ij}(p_{hi}, m, X_i, W_i, FP_i) = \frac{\partial V_{ij}(p_{ei}, m_i, X_i, W_i)/\partial p_{hi}}{\partial V_{ij}(p_{ei}, m_i, X_i, W_i)/\partial m_i} \tag{2}$$

p_h is the numéraire in the model and equal to 1. In France, the government assumes responsibility for health expenditures, especially for the poorest households.

On simplification, the medical care demand function conditional on health status j by household i can be written as follows:

$$q_{ij} = \alpha_{ij}X_{ij} + \beta_{ij}W_{ij} + \gamma_{ij}FP_{ij} + \eta_{ij} \quad (3)$$

where q_{ij} is the quantity of medical care consumed by household i in health status j, X_{ij} is a vector of household characteristics, W_{ij} is a vector of climatic and environmental conditions, FP_{ij} is the fuel poor variable, α_{ij}, β_{ij} and γ_{ij} are vectors of the related parameters, and η_{ij} the error term taking into account the influence of unobservable parameters. In our empirical strategy, we analyzed health status denoted h depending on the same vector variables with a particular focus on fuel poverty exposure.

Appendix 3: Results

3A – Estimated results for controlling initial conditions

To ensure that medical density is a good variable to explain the initial health status, we perform a Wald test. Based on the p value, we are able to reject the null hypothesis, indicating that the coefficient for medical density is not equal to zero, meaning that including this variable creates a statistically significant improvement in the fit of the model at the 1% level.

Table 6 Estimated results for controlling initial conditions

	Poor health			Chronic disease		
	Coef.	St.Err.	Sig	Coef.	St.Err.	Sig
Fuel poverty 10%	0.246	0.032	***	0.170	0.027	***
Number of Children	0.039	0.009	***	-0.038	0.006	***
UDD (log)	-0.071	0.052		-0.053	0.037	
Age	0.027	0.001	***	0.027	0.000	***
Pollution problem	0.203	0.024	***	0.174	0.018	***
Undergraduate degree	-0.261	0.038	***	-0.079	0.022	***
Homeowner	-0.382	0.019	***	-0.176	0.014	***
Medical density	-0.001	0.000	***	-0.001	0.000	***
Constant	-1.882	0.428	***	-0.752	0.306	**
Observations		45918			45921	
Pseudo R-squared		0.117			0.115	
Chi-square		3249.936			6953.236	
Percent correctly predicted		90.9%			69.5%	
Wald test	chi2(1) = 7.71 p= 0.0055			chi2(1) = 62.54 p= 0.0000		
LR test	chi2(1) = 7.74 p= 0.0054			chi2(1) = 62.71 p= 0.0000		

*** $p<0.01$, ** $p<0.05$, * $p<0.1$- Bootstrap 5000 replications

3B – Estimated results for binary probit regression on fuel poverty

It is quite difficult to test the consistency of instruments. But it is possible to test whether parameters are significant and significantly improve the fit of the model. In our estimates, energy prices are significant, especially the price of gas which is significant at 1%. It is also possible to perform a Wald test, and a likelihood-ratio test. The Wald test performs simple and composite linear hypotheses about the parameters of the most recently fit model. Based on the *p* value, we are able to reject the null hypothesis, indicating that the coefficients for gas price, electricity price and the interaction parameter for energy prices are not simultaneously equal to zero, meaning that including these variables creates a statistically significant improvement in the fit of the model. Finally, the likelihood-ratio test performs a likelihood-ratio test of the null hypothesis that the parameter vector of a statistical model satisfies some smooth constraint. Adding the energy price parameters as predictor variables together (not just individually) results in a statistically significant improvement in the model fit.

Table 7 Estimated results for binary probit regression on fuel poverty

	Fuel poverty 10%			Fuel poverty LIHC		
	Coef.	St.Err.	*p* value	Coef.	St.Err.	*p* value
Number of Children	-0.156	0.012	***	0.049	0.010	***
UDD (log)	0.511	0.050	***	0.183	0.044	***
Age	0.014	0.001	***	0.005	0.001	***
Pollution problem	-0.075	0.028	***	-0.028	0.024	
Undergraduate degree	-0.446	0.047	***	-0.498	0.044	***
Homeowner	-0.020	0.026		-0.417	0.022	***
Dark dwelling	0.308	0.030	***	0.185	0.027	***
Electricity price	1.821	0.328	***	0.938	0.293	***
Gas price	1.860	1.024	*	5.793	0.906	***
Interaction parameter	0.997	5.949		-19.134	5.285	***
Constant	-7.877	0.388	***	-4.527	0.339	***
Observations		219,404	***			
Wald test on electricity price, gas price, darkness and interaction parameter	chi2(4) =	247.62 p=	0.0000	chi2(4) = 198.44	p=	0.0000
LR test	chi2(3) =	120.62 p=	0.0000	chi2(3) =	143.45 p=	0.0000
Percent correctly predicted	87.2%			86.7%		

*** *p<0.01,* ** *p<0.05,* * *p<0.1* - Bootstrap 5000 replications

3C – Results : probability of being in poor health using the LIHC indicator

Table 8 Results - probability of being in poor health using the LIHC indicator

	Model 1	*Model 2*	*Model 3*	*Model 4*
Poor health (lag)		1.611***	1.609***	
		(0.0328)	(0.0328)	
Fuel poverty 10%	0.252***	0.198***		
	(0.0332)	(0.0630)		
Number of children	0.0824***	0.0353***	0.0188**	0.00461
	(0.0127)	(0.0118)	(0.00857)	(0.00607)
Unified Degree Days (log)	0.0527	0.0306	-0.0280	-0.0823***
	(0.0466)	(0.0361)	(0.0371)	(0.0252)
Age	0.0529***	0.0216***	0.00139	-0.000319
	(0.00100)	(0.00651)	(0.00272)	(0.00190)
Pollution problem	0.186***	0.142***	0.0202	0.0708***
	(0.0247)	(0.0515)	(0.0273)	(0.0179)
Undergraduate degree	-0.365***	-0.186***	0.0287	0.0160
	(0.0469)	(0.0718)	(0.0397)	(0.0176)
Homeowner	-0.642***	-0.281***	-0.0208	0.00102
	(0.0274)	(0.0915)	(0.0392)	(0.0158)
Mills' ratio		-0.0219	-0.836***	-0.895***
		(0.293)	(0.119)	(0.0994)
Predicted fuel poverty 10%			21.39***	25.15***
			(3.357)	(2.964)
Chronic disease (lag)				1.548***
				(0.0210)
Constant	-5.568***	-3.068***	-0.242	0.526*
	(0.362)	(0.828)	(0.431)	(0.286)
Observations	173,88	122,362	122,347	122,32
Number of individuals	49,422	37,855	37,855	37,861

**** p<0.01, ** p<0.05, * p<0.1* - Bootstrap 5000 replications

Table 9 Marginal effects of fuel poverty (LIHC) on poor health

Model 1	0.02***	
	Good health in t-1	Poor health in t-1
Model 2	0.02***	0.09***
Model 3	2.30***	8.89***
Model 4	4.38***	5.62***

**** p<0.01, ** p<0.05, * p<0.1* - Bootstrap 5000 replications