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Objective vs. Subjective Fuel Poverty and Self-Assessed Health

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Keywords	Fuel poverty in Spain; self-assessed health; latent class ordered probit model.
JEL Classification	C01, C25, I14, I32, Q43.

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EPRG WORKING PAPER

Objective vs. Subjective Fuel Poverty and Self-Assessed Health

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Abstract

Policies towards fuel poverty often use relative or absolute measures. The effectiveness of the official indicators in identifying fuel poor households and assessing its impact on health is an emerging social policy issue. In this paper we analyse objective and perceived fuel poverty as determinants of self-assessed health in Spain. In 2014, 5.1 million of her population could not afford to heat their homes to an adequate temperature. We propose a latent class ordered probit model to analyse the influence of fuel poverty on self-reported health in a sample of 25,000 individuals in 11,000 households for the 2011-2014 period. This original approach allows us to include a 'subjective' measure of fuel poverty in the class membership probabilities and purge the influence of the 'objective' measure of fuel poverty on self-assessed health. The results show that poor housing conditions, fuel poverty, and material deprivation have a negative impact on health. Also, individuals who rate themselves as fuel poor tend to report poorer health status. The effect of objective fuel poverty on health is stronger when unobserved heterogeneity of individuals is controlled for. Since objective measures alone may not fully capture the adverse effect of fuel poverty on health, we advocate the use of approaches that allow a combination of objective and subjective measures and its application by policy-makers. Moreover, it is important that policies to tackle fuel poverty take into account the different energy vectors and the prospects of future smart and integrated energy systems.

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1. Introduction

Fuel poverty refers to households that cannot afford to heat their homes to an adequate standard of warmth and meet other energy needs in order to maintain their health and well-being.[1] In recent years, increasing energy prices and reductions in per capita income have exacerbated the occurrence of fuel poverty among households in many EU countries. Fuel poverty was initially analysed in the UK context (Boardman, 1991; or more recently, Hills, 2011; Moore, 2012; Waddams Price *et al*., 2012; Roberts *et al*., 2015). The issue has recently received increasing attention at European level: Ürge-Vorsatz and Tirado Herrero (2012) analyse fuel poverty in Hungary, Boltz and Pichler (2014) for Austria, Heindl (2015) for Germany and Lis *et al*. (2016a; 2016b) in Poland. Contrary to some beliefs, fuel poverty is also a deprivation and health issue in milder climates (Healy, 2004). Some studies have analysed fuel poverty in countries in Southern Europe: Miniaci *et al*. (2014) in Italy, Charlier and Legendre (2016) and Legendre and Ricci (2015) in France, Papada and Kaliampakos (2016) in Greece, or Linares Llamas *et al*. (2017) for Spain are some examples.[2]

A significant challenge from social policy perspective is to define suitable measures of fuel poverty and their relationship with health status of individuals. A negative relationship is normally assumed between them. Empirical evidence of the effect of fuel poverty on physical and mental health has been highlighted by the World Health Organization (WHO) (Braubach *et al*., 2011). People who live in cold homes are more likely to suffer from chronic and severe illnesses such as circulatory and respiratory diseases. Moreover, living in fuel poverty can lead to depression, isolation or affect the formative process of children and young people (Platt *et al*., 1989; Liddell and Morris, 2010; Geddes *et al*., 2011; Ormandy and Ezratty, 2012; among others). In addition, evidence suggests that a reduction in fuel poverty has significant health benefits (Crossley and Zilio, 2017; Curl and Kearns, 2015; or Thomson *et al*., 2001).

When analysing the relationship between fuel poverty and health, the first step is to define a measure of the former. The literature uses two main approaches: i) objective approach based on the relation between household income and energy expenditure. This approach uses measures such as the 10% rule (Boardman, 1991), the Minimum Income Standard (MIS) indicator (Bradshaw *et al*., 2008), the Low Income High Costs (LIHC) or the After Fuel Cost Poverty (AFCP) methodologies (Hills, 2011); ii) subjective approach considering perceptions of whether individuals are able to keep their houses at an adequate temperature (Healy and Clinch, 2002; Waddams Price *et al*., 2012; Thomson and Snell, 2013; Dubois and Meier, 2016; Bouzarovski and Tirado Herrero, 2017).

The appeal of the objective measures of fuel poverty from a social policy point of view is apparent. It can be argued that objective measures of fuel poverty may be more accurate than subjective measures (Hills, 2012; Charlier and Legendre, 2016). However, some studies argue that subjective measures have the advantage of better capturing the 'feeling' of material deprivation perceived by individuals who are unable to keep their homes at a suitable temperature (Fahmy *et al*., 2011; or Thomson *et al*., 2017a). Waddams Price *et al*. (2012) compare two measures of fuel poverty, one objective (based on the 10% rule) and one subjective, and conclude that the two measures are positively related but in a complex way since in many cases they do not coincide. Lawson *et al*. (2015) obtain similar results for New Zealand. Moreover, Waddams and Deller (2017) for UK and Deller (2018) for the EU found that the identification of a common fuel poverty

[1] EU Fuel Poverty Network, http://www.fuelpoverty.eu.

[2] See Thomson *et al*. (2017a) or Bouzarovski and Petrova (2015) for reviews.

metric based solely on spending criteria is problematic due to heterogeneity between countries. More recently, Fizaine and Kahouli (2018) analyse the use of several objective and subjective measures to categorise fuel poverty and find differences in the profiles of the households depending on the measure and threshold utilised. They suggest exploring alternative approaches and particularly the combination of standard indicators, the exclusion of thresholds from expenditure-based measures, and innovative strategies based on more appropriate conceptual frameworks of fuel poverty.

When analysing the effect of fuel poverty on health, several authors have resorted to the use of subjective measures of fuel poverty (Healy, 2004; Thomson *et al*., 2001; 2017a; or Lacroix and Chaton, 2015). Moreover, given that we analyse individuals, it is important to also account for the unobserved heterogeneity among them. This heterogeneity could capture several factors that explain how fuel poverty may affect individual health to differing degrees, more so if health is measured, as the literature suggests, in terms of self-perceived or self-reported health status.

Therefore, we use an objective index in conjunction with a subjective measure of fuel poverty. The latter is used to control for the individual's 'true' underlying personality traits when reporting health status. Hence, assuming that self-reported valuations are related to some underlying personal characteristics, the use of this subjective information may avoid the biases due to individual's unobservable heterogeneity. This enables us to approximate a (self-assessed) health production function (as a function of objective fuel poverty, among other variables) that is adjusted for the influence of subjective personal perceptions. We use an econometric model that combines an ordered probit model jointly with a latent class structure to analyse the effect of fuel poverty on individual self-reported health. By doing so, we aim to identify groups of individuals with similar characteristics and to capture differences in self-reported health status due to those features, assigning each individual to a group without prior knowledge of their group belonging.[3] This type of approach seems suitable to help in the discussion and design of energy and social policies that will likely be adopted in future integrated energy sectors.

The remainder of the paper is as follows. Section 2 describes fuel poverty in Spain. Section 3 presents the proposed model to analyse the effect of fuel poverty on self-reported health while controlling for subjectivity of individuals. Section 4 describes the data used in the study. Section 5 presents the results from the estimation of the models. Section 6 discusses policy issues emerging from the results. Section 7 is conclusions.

2. Fuel Poverty in Spain

Fuel poverty is often related to the cost of fuel, household income and energy efficiency of the dwellings (Boardman, 2010). In the context of increasing energy prices and decreasing income since the financial crisis of 2007-2008, fuel poverty has increased in many countries. The first studies of energy poverty in Spain were by Tirado Herrero *et al*. (2012) revealing the existence of poverty associated with the difficulty to meet basic energy needs, which implies the inability to maintain an adequate temperature at home. Other studies (Tirado Herrero *et al*., 2014; 2016; Romero *et al*., 2014; Scarpellini *et al*., 2015; Phimister *et al*., 2015; Linares Llamas and Romero Mora, 2015; Linares Llamas *et al*., 2017) have also shown an aggravation of the problem in recent years.

[3] Clark *et al*. (2005) use a similar model to capture different relationships between income and self-reported well-being in twelve European countries.

Figure 1 shows the evolution of the GDP per capita in Spain in recent years and compares it with the average for the European Union and OECD economies. Between the years 2007 and 2009, the income differences between GDP per capita series where almost constant. However, while a slow recuperation started in 2009 in the European Union and the OECD, economic recovery in Spain only happened after 2013, although the pre-crisis levels have not been reached yet.

[Insert Figure 1 here]

Bellver *et al*. (2016) analyse the annual electricity bill (including taxes) of an average Spanish household and find an increase of more than 50% from 2004 to 2016. Figure 2 shows the evolution of electricity and natural gas prices for households in Spain and the average of the European Union since 2007.[4] Despite the similar initial prices for electricity and natural gas, Spanish prices have increased more than the average of the European Union. This divergence is especially acute in the peaks of prices of natural gas in the second half of each year after 2011. The growing prices have placed the country among the top 5 of the highest natural gas and electricity prices in the European Union. The conjunction of high energy prices and low GDP per capita along with high unemployment[5] has increased the concerns about the increase in fuel poverty in Spain.

[Insert Figure 2 here]

According to Tirado Herrero *et al*. (2016), in Spain during 2014, 5.1 million people could not afford to keep their homes at an adequate temperature during the winter, implying an increase of 22% compared with 2012. The share of households unable to maintain a suitable temperature in winter rose from 6.2% in 2008 to 11.1% in 2014. Likewise, the percentage of the households allocating more than 10% of their income to domestic energy expenditure (widely used as a measure of fuel poverty) rose from 8% in 2008 to 15% in 2014. In addition, Excess Winter Mortality (EWM) has increased by 20.3% over the 1996 to 2014 period. This figure signifies 24,000 additional annual deaths, of which 7,100 (30% according to WHO) are attributable to fuel poverty.[6]

Despite the emerging evidence, fuel poverty was not a high priority policy in Spain until recently. The public debate and awareness of the problem escalated following the death in late 2016 of an elderly woman in fire in her living room, lit with candles after being disconnected for non-payment of electricity bills.[7] Moreover, complaints from consumers associations about energy price increases during winter in recent years have resulted in a utility being accused of electricity price manipulation (already fined €25 million in November 2015)[8] and proceedings against two other utilities by the Spanish

[4] The electricity price is for the consumption band 2,500-5,000 kilowatt-hour (kWh) and the natural gas price is for the consumption band 20-200 gigajoule (GJ). These are the bands of consumption for medium size household consumers according to Eurostat. Both prices are measured at Purchasing Power Standard (PPS) per kWh and include all taxes and levies.
[5] According to the Economically Active Population Survey (EPA, *Encuesta de Población Activa*) published by the Spanish Statistical Office (INE, *Instituto Nacional de Estadística*), the unemployment rate reached a peak of 27.2% in the first term of 2013, while the youth unemployment rate was 57.2%.
[6] The report also points out that, in the same period, approximately 4,000 persons were killed in traffic accidents in Spain, suggesting the scale of the problem in relative terms.
[7] "Spain anger over 'energy poverty' deaths" – BBC News (20 November 2016) http://www.bbc.co.uk/news/world-europe-38024374.
[8] "Leading Spanish electricity firm Iberdrola accused of manipulating prices" – El País (12 May 2017) https://elpais.com/elpais/2017/05/11/inenglish/1494500623_483653.html.

competition watchdog.[9] These infractions involving some of the largest energy utilities in the country along with 'revolving doors' and political corruption cases, have heated up the fuel poverty debate. A number of urgent measures have since been taken at national and regional level to protect vulnerable households (through new social grants or a ban on disconnection of electricity service to the most vulnerable households). At the end of 2017 a new regulation approved a social bond or discount to protect the most vulnerable electricity consumers.[10]

Romero *et al*. (2014) and Linares Llamas *et al*. (2017) address findings an appropriate measure of assessing fuel poverty for Spain. They compare the widely used measures for this purpose. First, the 10% rule considers that a household in fuel poverty uses more than 10% of their income on fuel costs to maintain an adequate temperature in home. This definition was adopted by the UK government in year 2000 but it was later replaced by the LIHC approach, when the 10% rule presented several weaknesses (some households without economic problems were included in the 'fuel poor' group, and vice versa – i.e., some fuel poor households did not fit into this definition). They also analyse indicators such as AFCP which considers that a household is in fuel-poverty if its income is 60% less than the median income for its household type (after housing and fuel costs); the LIHC indicator which considers that a household is in fuel poverty on the basis of two criteria: a) have energy needs higher than the median for the household type, and b) have an income lower than 60% of the median for the household type (i.e., below the poverty line as used by the OECD). The study also analyses the MIS approach defined as "having what you need in order to have the opportunities and choices necessary to participate in society" (Bradshaw *et al*., 2008, p.1). Thus, if the residual income (after expenditure on energy and housing) is less or equal than the MIS (after housing costs and expenditure on energy services) the household is in fuel poverty. Figure 3 shows the evolution of these indicators. They conclude that the MIS-based approach is the most appropriate for Spain using a false positives analysis based both on the distribution of income and energy consumption. Hence, we use this measure in our empirical analysis.

[Insert Figure 3 here]

3. Methodology - Latent Class Approach to Unobserved Heterogeneity

This paper analyses the effect of several socioeconomic characteristics of individuals on their health paying particular attention to the issue of fuel poverty. We approximate a health production function through an ordered probit model because our dependent variable, i.e., self-assessed health, is categorical. In order to identify different types of individuals and to purge for self-evaluation bias, we use a latent class framework

[9] "Spain's competition watchdog opens proceedings against Gas Natural and Endesa" – Fox Business (18 December 2017) http://www.foxbusiness.com/features/2017/12/18/spains-competition-watchdog-opens-proceedings-against-gas-natural-and-endesa.html.

[10] Real Decreto 897/2017, de 6 de octubre: https://www.boe.es/boe/dias/2017/10/07/pdfs/BOE-A-2017-11505.pdf. The principal novelties with respect to the previous situation is that now the bond is applied as a function of income and specifies in detail the vulnerable consumers, including a category of consumers in a situation of severe social exclusion. Moreover, the channels for informing vulnerable consumers of the social bond have improved and the period for disconnecting the service following non-payment has been extended. Also, a mechanism for avoiding disconnection has been regulated for cases of higher social risk. However, the social bond only applies to electricity, and does not include other services such as natural or butane gas. Moreover, the bond is based on a discount of 25% in the electricity bill, which can reach 40% in the case of the most vulnerable consumers. Linares Llamas *et al*. (2017) have shown that this effectively implies a reduction in the relative price of electricity and discourages energy saving and efficiency.

that allows us to control for unobserved heterogeneity stemming from perceptions and subjective assessments of individuals.

An ordered probit model is a generalisation of a probit in which there are more than two possible outcomes for an ordinal dependent variable (see, e.g., Greene, 2003). The model is constructed around a latent regression as in the following:

$$Y^{*} = X'\beta + \varepsilon \tag{1}$$

where Y^* is an unobserved dependent variable, X is a vector of explanatory variables, β is a set of parameters in the model and ε is a random term normally distributed.[11] What is generally observed instead of Y^* is the categorical variable Y, which can be represented as:

$$\begin{aligned} Y &= 0 \quad if\ Y^{*} \leq 0, \\ Y &= 1 \quad if\ 0 \leq Y^{*} \leq \mu_1, \\ Y &= 2 \quad if\ \mu_1 \leq Y^{*} \leq \mu_2, \\ &\vdots \\ Y &= M \quad if\ \mu_{M-1} \leq Y^{*}, \end{aligned} \tag{2}$$

where the cut points, μs, are unknown parameters to be estimated along with β, and M are the possible outcomes for Y. After normalising the mean and variance of ε to zero and one, the probabilities associated to the alternative values that can take the observed variable Y can be represented as:

$$\begin{aligned} Prob(Y = 0|X) &= \Phi(-X'\beta), \\ Prob(Y = 1|X) &= \Phi(\mu_1 - X'\beta) - \Phi(-X'\beta), \\ Prob(Y = 2|X) &= \Phi(\mu_2 - X'\beta) - \Phi(\mu_1 - X'\beta), \\ &\vdots \\ Prob(Y = M|X) &= 1 - \Phi(\mu_{M-1} - X'\beta), \end{aligned} \tag{3}$$

where Φ represents the cumulative distribution function of a standard normal distribution. For all the probabilities to be positive, the μs should fulfil:

$$0 < \mu_1 < \mu_2 < \cdots < \mu_{M-1}. \tag{4}$$

The non-linear model described before can be estimated through a maximum likelihood approach. The unconditional likelihood function can be expressed in logarithms as:

$$\ln L(\mu, \beta) = \textstyle\sum_{i=1}^{N} \sum_{m=1}^{M} y_{im} \ln[\Phi(\mu_m - x_i{}'\beta) - \Phi(\mu_{m-1} - x_i{}'\beta)] \tag{5}$$

where i denotes each of the N observations in the model and m are the different values that Y can take (i.e., between 1 and M). It should be noted that the β-parameters estimated do not differ across observations, which means that the effect of a specific variable is the same for every individual.

An issue that, if overlooked, can bias the estimates is that of unobserved heterogeneity or unobserved differences among individuals. There are some approaches that can help to control for this problem in the econometrics literature. Some well-known examples are the fixed or random effects models that capture time-invariant unobserved

[11] Other distributions, such as the logistic, could also be adopted for ε. In which case we would obtain an ordered logit model.

heterogeneity through different intercepts in the model. However, this type of models imposes common slopes for all individuals, which means that all of them share the same marginal effects and other economic characteristics.[12] A different approach to address unobserved heterogeneity is to use the latent class models, also known as finite mixture models, which have been largely used in numerous fields of research (see, McLachlan and Peel, 2000).[13] This approach allows the estimation of different parameters for individuals belonging to groups or classes with different features. The log-likelihood function for an individual *i* who belongs to class *j* can be represented as follows:

$$\ln L_{ij}(\mu_j, \beta_j) = \sum_{m=1}^{M} y_{im} \ln\left[\Phi\left(\mu_{jm} - x_i{}'\beta_j\right) - \Phi\left(\mu_{jm-1} - x_i{}'\beta_j\right)\right]. \qquad (6)$$

Note that μ and β are now *j*-specific parameters, which means that the economic characteristics of the health production function vary across classes. Unlike the restricted case in Equation (5) where there was only one class of individuals, here the unconditional likelihood function for individual *i* can be characterised as:

$$L_i(\mu, \beta, \delta) = \sum_{j=1}^{J} L_{ij}(\mu_j, \beta_j) P_{ij}(\delta_j), \qquad 0 \leq P_{ij} \leq 1, \qquad \sum_{j=1}^{J} P_{ij}(\delta_j) = 1 \quad (7)$$

where $\mu = (\mu_1, \dots, \mu_J)$, $\beta = (\beta_1, \dots, \beta_J)$ and $\delta = (\delta_1, \dots, \delta_J)$. This function represents a weighted sum of *j*-class likelihood functions in which the weights are the probabilities of class membership, P_{ij}, which depend on δ, a set of parameters to be estimated jointly with the other parameters in the model. In latent class models, the class probabilities are usually parameterised as multinomial logit models such as the following:

$$P_{ij}(\delta_j) = \frac{\exp(\delta_j' q_i)}{\sum_{j=1}^{J} \exp(\delta_j' q_i)}, \qquad j = 1, \dots, J, \qquad \delta_J = 0 \qquad (8)$$

where q_i can be either a vector of individual-specific variables or an intercept. It should be noted that each individual belongs only to one group, so the above probabilities simply represent the uncertainty of the researcher regarding the true partition of the sample. Consequently, the overall likelihood function is a continuous function of the vector of parameters μ, β and δ that can be expressed as:

$$\ln L(\mu, \beta, \delta) = \sum_{i=1}^{N} \ln L_i(\mu, \beta, \delta) = \sum_{i=1}^{N} \ln\left\{\sum_{j=1}^{J} L_{ij}(\mu_j, \beta_j) P_{ij}(\delta_j)\right\}. \qquad (9)$$

The maximisation of the above likelihood function gives asymptotically efficient estimates of all the parameters in the model under specific assumptions. A necessary condition for parameter identification is that the sample must be generated from different groups of individuals, i.e., there must be heterogeneity. The number of groups or classes, *J*, is chosen in advance by the researcher. Nevertheless, there are statistical tests, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which can be used to choose the appropriate number of classes once the finite mixture models have been estimated. These criteria imply the minimisation of indices that balance the lack of fit due to a small number of classes and overfitting due to an excessive number of classes. For that aim, these criteria use the value of the likelihood function and penalise with different weights the augment in the number of parameters in the models. Models with lower values of the indices are usually preferred.[14]

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[12] An extension of the random effects model is the random parameters model in which both the intercepts and the slopes are allowed to vary across individuals according to a specific distribution.

[13] Some applications are Orea and Kumbhakar (2004) [banking], Bago d'Uva (2005) [health], Fernández-Blanco *et al*. (2009) [movie demand], Álvarez and del Corral (2010) [dairy farming] or Llorca *et al*. (2014) [electricity].

[14] See Section 5 for more details about the statistical tests applied in this paper.

As noted in the above, the prior probabilities in Equation (9) reflect the uncertainty of the researcher about allocation of each of the individuals to different J classes. Nevertheless, the estimated parameters can then be used to compute posterior class membership probabilities which can be defined as:

$$P(j|i) = \frac{L_{ij}(\hat{\mu}_j, \hat{\beta}_j) P_{ij}(\hat{\delta}_j)}{\sum_{j=1}^{J} L_{ij}(\hat{\mu}_j, \hat{\beta}_j) P_{ij}(\hat{\delta}_j)} \tag{10}$$

We observe that the posterior probabilities depend not only on the estimated δ parameters but also on the values of the likelihood functions which in turn depend on the estimated μ and β parameters. This means that latent class models use the goodness of fit of each estimated probit as additional information to identify groups of individuals. Moreover, this also means that even in the case in which separating variables are not included (or available) in the probabilities of class membership, the procedure is able to classify the individuals into the different classes based on the previously mentioned goodness of fit.

In 'standard' probits, the estimated function is the same for the whole sample, so the estimated parameters and marginal effects are identical for every individual. In the Latent Class Ordered Probit Model (LCOPM) presented here, we obtain 'as many probits' as number of classes. As a consequence, given the uncertainty introduced in the class membership probabilities, the question about the true membership of individuals in different classes arises, which influences the computation of the parameters for each individual. In that sense, there are two possible strategies to identify the individual specific parameters (Greene, 2005). The first strategy is to only consider the specific parameters of the class with the largest posterior probability for each individual. The second strategy is to compute individual specific parameters as a weighted average by using the value of the parameters of each of the classes and the posterior probabilities of belonging to them obtained from Equation (10).[15]

4. Data

We use the longitudinal data from the Life Conditions Survey[16] which contains information about income and living conditions of Spanish individuals and households who are followed up over 4 years. This information is collected by INE, the Spanish Statistical Office. Our sample is an unbalanced panel of 53,918 observations (24,990 people from 11,039 households) for the period 2011-2014.

The dependent variable is the general health status reported by the individuals. The original variable in the survey ranges between 1 (*very good health*) and 5 (*very poor health*). Figure 4 presents a histogram of the distribution of responses in our sample. Responses related to self-reported health status of surveyed individuals may not always correspond with the objective clinical condition of the individuals. In that sense, Greene *et al*. (2015) have proposed a model to identify potential inflation of responses, i.e., whether people tend to report that their health is good or very good. In a random sample of Australian population they found around 10% probability of inaccurate reporting in the *good* and *very good* categories. However, this misreporting issue that, if overlooked, can

[15] It should be mentioned that both computation strategies produce similar results when the posterior probabilities of the most likely class for each individual are large (i.e., they are close to 100%). This similarity between outcomes obtained through both approaches is also suggested by other studies such as Greene (2002) or Alvarez and del Corral (2010).

[16] In Spanish: *Encuesta de Condiciones de Vida* (ECV).

bias the results is expected to be correlated with unobserved heterogeneity and individual perceptions to some extent. Therefore, this problem is, at least, partially controlled through the latent class approach proposed here, in which a subjective measure of fuel poverty is introduced in the class membership probabilities. For the purpose of convergence in the estimations, we have rescaled the variable to a new variable with three categories in which 0 represents *good heath*, 1 stands for *fair health* and 2 represents *poor health*. The asymmetry of responses towards a positive assessment of health is observed after the transformation of the variable.

[Insert Figure 4 here]

The variables used in the analysis to explain self-reported health status are: chronic condition of the individuals (*CC*: takes value 1 when the individual has no chronic disease and 0 otherwise), *age* (included through a quadratic polynomial), employment situation (*employed*: takes value 1 when the individual is employed and 0 otherwise; *self-employed*: takes value 1 when the individual is self-employed an 0 otherwise), *gender* (takes value 1 for woman and 0 for man), marital status (*married*: takes value 1 if the individual is married and 0 otherwise; *SDW*: takes value 1 if the individual is separated, divorced or widowed and 0 otherwise), education (*SE1*: takes value 1 if the education level of the individual is the first stage in secondary education and 0 otherwise; *SE2*: takes value 1 if the education level of the individual is the second stage in secondary education and 0 otherwise; *PSE_NHE*: takes value 1 if the education level of the individual is post-secondary education – no higher education – and 0 otherwise; *HE*: takes value 1 if the education level of the individual is higher education and 0 otherwise), net disposable income (*income*: it is measured in 2016 EUR), type of dwelling (*flat*: takes value 1 if the dwelling is a flat and 0 otherwise), housing condition (*leak*: takes value 1 if there are no leaks, dampness in walls, floors, ceilings or foundations, or rot in floors, window frames or doors in the dwelling, and 0 otherwise), Fuel Poverty Index (*FPI*: defined later), material deprivation (*MD*, defined later), and two sets of dummies: one for the years of the survey and the other for the autonomous communities.[17] Our objective measure of fuel poverty, *FPI* can be expressed as:

$$FPI = \frac{MIS - AHEE + HSEE}{Net\ disposable\ income} \tag{11}$$

As explained in Section 2, this method of computing a fuel poverty index is based on Romero *et al*. (2014) and has also been applied by Rodríguez-Álvarez *et al*. (2016) and allows obtaining a ratio that reflects the 'risk' of being in fuel poverty. *FPI* uses the *MIS* of each autonomous community, which represents the minimum living costs that allow the members of a household to reach a socially acceptable living standard and an active participation in the society. As this measure includes energy expenditure and with the aim of obtaining a household-specific measure, we subtract the Average Household Expenditure on Energy (*AHEE*) of each autonomous community[18] and we add the Household-Specific Energy Expenditure (*HSEE*). This adjusted measure is then divided by the net disposable income. Higher values of this ratio should reflect a higher likelihood of being fuel poor.[19] According to the definition by the OECD, "measures of material

[17] Our sample covers the 17 Spanish autonomous communities and the 2 autonomous cities on the north coast of Africa (Ceuta and Melilla).

[18] *AHEE* was obtained from the Household Budget Survey (EPF, *Encuesta de Presupuestos Familiares*).

[19] This ratio can be seen as an adaptation of the MIS-based indicator to identify fuel poor households (see Moore, 2012): [Fuel costs] > [Net household income] – [Housing costs] – [MIS]. According to this criterion, a household is in fuel poverty if this inequality is fulfilled. Equivalently, in our case, households with a *FPI* greater than 1 could be rated as fuel poor.

deprivation provide a complementary perspective on poverty to that provided by conventional income measures. Material deprivation refers to the inability for individuals or households to afford those consumption goods and activities that are typical in a society at a given point in time, irrespective of people's preferences with respect to these items" (OECD, 2007, p.68). We identify material deprivation through a dummy, *MD*, which takes value 1 for households in a situation of material deprivation according to the Eurostat criteria.[20]

Apart from the provision of other energy services, fuel poverty is frequently related to keeping a dwelling at an adequate temperature (Boardman, 1991). In our analysis, another variable, *affordability*, has been included to account for the subjective perception of fuel poverty that may be correlated with self-assessed health to some extent. This variable has been introduced as a separating variable for the class membership probabilities in our model.[21] It is a dummy variable that takes value 1 when the household cannot afford to keep their home at an adequate temperature during winter and 0 otherwise. Table 1 presents the descriptive statistics of the variables used in the analysis. It should be noted that for the dummy variables the mean represents the proportion of individuals that present the condition coded as 1.

[Insert Table 1 here]

5. Results

We approximate our health production function through three different models. The first is an ordered probit model in which a set of socioeconomic variables are introduced as determinants of individuals' health. The other two models use the same explanatory variables but are based on a latent class framework that allows us to control for unobserved heterogeneity. One of these two models includes the subjective measure of fuel poverty as a separating variable. Table 2 presents the parameter estimates of these alternative models.[22] It should be noted that the information provided by the βs in these models, by itself, is of limited interest, as they represent the direct effect of the explanatory variables on Y^* (see Equation 1), which is an abstract construct. As we are interested in the effect of the variables on the probabilities of reporting different health status, we compute the marginal effects of some relevant variables on these probabilities.

[Insert Table 2 here]

In the ordered probit model, we observe that most of the coefficients are statistically significant. Apart from two of the year dummies, only the coefficient of *SDW* is not significant. It should be noted that once other characteristics are controlled, the worsening of each of the variables that are directly related to overall poverty (*income* and

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[20] "People in households who cannot afford at least 3 of the following 9 items: coping with unexpected expenses; one week annual holiday away from home; avoiding arrears (in mortgage or rent, utility bills or hire purchase instalments); a meal with meat, chicken, fish or vegetarian equivalent every second day; keeping the home adequately warm; a washing machine; a colour TV; a telephone; a personal car" (Guio *et al*., 2012, p.9).

[21] It was also included in the behavioural function in some ancillary models not presented in the paper. The issue is discussed in footnote #26.

[22] The coefficients of the dummies for the autonomous communities are not shown in Table 2 as they do not provide relevant information for the objective of this paper. However, it is noteworthy that all of them, except the coefficient for the Canary Islands are statistically significant in the probit model evidencing clear differences across communities. Similar results are obtained for the latent class models. The reference autonomous community is Galicia. The coefficients are available upon request.

MD) and fuel poverty (*leak* and *FPI*) has a detrimental effect on health. As previously mentioned, Table 2 provides the parameter estimates of the two latent class models. Each of these models has two classes and includes the same variables in the probit as the first model presented.[23] The main difference between the two LCOPM models is that one introduces the separating variable, *affordability*, in the class membership probabilities to allocate the individuals to the classes, while the other simply uses the goodness of fit of the model. It is reasonable to assume that (self-reported) affordability to keep the house adequately warm during winter is also correlated with unobservable conditions that can make individuals sensitive when assessing their health.

The results of the two latent class models are very similar. Again, most of the coefficients are statistically significant. As in the probit model, the coefficients for *SDW* and for some of the year dummies are not significant. Other coefficients are not significant in one of the classes (*flat* and *FPI* in Class 1, and *married* in Class 2), while *PSE_NHE* is not significant in any of them. Therefore, not all the coefficients that relate to poverty are significant in the two classes. One of the relevant features of these estimates for the LCOPMs is the difference in the magnitude of the coefficient for *income* between the two classes, i.e., the coefficient in Class 1 is about 50% higher than the coefficient in Class 2. In Class 2, income is a weaker determinant of self-reported health.[24] At the same time, a notable result is that objective fuel poverty appears to negatively affect self-reported health in Class 2, but shows no significant effect in Class 1. If we focus on the latent class model that incorporates the separating variable in the class membership probabilities, we can state that individuals who report that they cannot afford to keep their house adequately warm in winter (i.e., they are in subjective fuel poverty) tend to be in Class 1. For these individuals, the coefficient for *FPI* is not significant and therefore, as we will see later, an increase in objective fuel poverty does not seem to have a negative effect on health.[25] In Class 2, the coefficient for *FPI* shows a significant and positive value implying that objective fuel poverty implies a higher probability of reporting poor health.[26]

Before continuing with the interpretation of the results, we compare the alternative estimated models and choose the preferred one based on information criteria. Table 3 shows the values for several information criteria that assist us to make appropriate decisions. As mentioned earlier, these criteria use the value of the likelihood function and apply different weights to penalise the increase in the number of parameters in the models

[23] Models with further classes do not converge. As suggested by Orea and Kumbhakar (2004), we consider this as evidence that a model with three classes (or more) is over-specified.

[24] *Income* is particularly relevant as it is related to fuel poverty. It should be emphasised that there is not a large correlation between and within the variables related to overall poverty (*income* and *MD*) and fuel poverty (*FPI*, *leak* and *affordability*) in our sample.

[25] We can interpret this as that these individuals tend to report poor health regardless of the objective conditions under which they live. We return to this point later.

[26] If the same model is estimated while also additionally including *affordability* in the probit, i.e., in our health production function, we obtain similar results. *FPI*'s coefficient is still not significant in Class 1 while it is significant and positive in Class 2. The coefficient of *affordability* shows a positive value in Class 1, which means that, as expected, subjective fuel poverty increases the possibility of reporting poor health. This has also been found for France by Lacroix and Chaton (2015). However, in Class 2 the coefficient of *affordability* is not significant. In other specifications where additional variables are included, we observe similar features when the models are estimated: the coefficient for *FPI* is not significant in Class 1 and significant and positive in Class 2. This reinforces the idea that objective conditions of households may not be relevant by itself for those who state that they live in poor conditions, i.e., they tend to report poor health regardless. In Class 2, on the contrary, subjective fuel poverty does not affect the reported health. In that case, if people report poor health, we can link that assessment to the objective fuel poverty conditions under which they live. These alternative specifications have been rejected on statistical grounds and are not reported here.

(for further information, see Fonseca and Cardoso, 2007). The criteria that we have used are the well-known AIC and BIC, in addition to some variants of these criteria that have also been presented for robustness: the corrected AIC (AICc); the modified AIC (AIC3); the AICu, which imposes larger penalties when overfitting and particularly when incrementing sample size; and the consistent AIC (CAIC). We highlight again that models that show lower values of the criteria are usually preferred. It can be seen that progressing from the model with one class (i.e., the standard ordered probit) to the latent class model with two classes (LCOPM) represents a significant improvement in terms of fitness. Moreover, all the criteria show their lowest value for the LCOPM model that incorporates *affordability* as separating variable and hence we clearly choose this as our preferred model.

[Insert Table 3 here]

Table 4 shows the main characteristics of the two groups of individuals identified by our preferred LCOPM model.[27] We observe that the 'partition' of the sample is not even, with 12.5% of the observations being assigned to Class 1 and 87.5% assigned to Class 2. It is also evident that average health in Class 1 is poorer than in Class 2 and in the whole sample. Class 1 has more individuals with leaks or dampness in their homes. Moreover, in Class 1 material deprivation is more prevalent and more people who cannot afford to keep their homes warm during the winter, as expected from the coefficient of *affordability* variable in the class membership probabilities in Table 2. Additionally, the average net disposable income is lower in Class 1 than in Class 2. However, it should be noted that, perhaps surprisingly, the average value of *FPI* in Class 1 (0.43) is lower than in Class 2 (0.46). This finding suggests that objective fuel poverty does not necessarily correspond to low income and to subjective fuel poverty although, as Waddams Price *et al*. (2012), we observe a positive correlation between the subjective and objective measures of fuel poverty.[28]

[Insert Table 4 here]

We observe differences related to health status of individuals within different classes. Figure 5 presents a histogram of health status in the observations allocated to the two classes in our preferred model. The shape of the histogram in Class 2 is similar to that for the whole sample (Figure 4). Class 2 contains most of the observations of the sample and in particular about 90% or more of those who rate their health as 1 (*very good*), 2 (*good*), 4 (*poor*) or 5 (*very poor*) have been allocated to this class. For Class 1, the histogram has a shape similar to a normal distribution (Figure 5a). It should be noted that despite the smaller number of observations in this class, 40% of the total number of observations in which the health is rated as 3 (*fair*) and 12% in which the health is rated as 4 (*poor*) are allocated to this class. Some authors have identified incentives for misreporting when individuals respond to questions related to their health (see, Kerkhofs and Lindeboom, 1995). Given the informative nature of our survey,[29] we associate a

[27] Observations have been allocated to the class that shows the higher posterior probability.

[28] Using our total sample, we observe that 6.5% of the observations are in a situation of objective fuel poverty (*FPI*>1, which is equivalent to the fulfilment of the inequality in footnote #19) and 8.2% are in a situation of subjective fuel poverty. According to the 10% threshold criteria, this figure increases to 10.6%. Additionally, these criteria do not necessarily identify the same households. We find that 18.6% of the observations in an objective fuel poverty situation are also in subjective fuel poverty, while 14.7% of the observations in subjective fuel poverty are rated as being in an objective fuel poverty situation using the *FPI*. These figures confirm the complexity of the relationship between objective and subjective fuel poverty (see Waddams Price *et al*., 2012).

[29] This means that the responses are not attached to the reception of benefits, allowance or assistance.

misreporting with an 'assessment bias' probably due to a higher sensitivity of the individuals. Subjectivity of individuals (i.e., unobserved heterogeneity) should be, at least partially, controlled for through our latent class model that incorporates the perception of fuel poverty as a separating variable.

[Insert Figure 5 here]

Finally, Figure 6 shows the marginal effects of the variables related to general and fuel poverty in our preferred LCOPM model and the ordered probit. These marginal effects represent changes in the probability of declaring each of the *health status* categories when there is a change in an explanatory variable, i.e., $\partial P(Y=m|X)/\partial X$. From the two top charts in Figure 6, we observe similar changes in the probabilities: an increase in income and having a home without leaks or damp augments the probability of declaring good health (between 1 and 7 percentage points) and reduce the probability of reporting fair or poor health. The probit model produces marginal effects that are between the marginal effects of the two classes of the LCOPM for every health status category and for every variable, evidencing the bias in models that do not account for unobserved heterogeneity among individuals.

In the two charts at the bottom of Figure 6, we expect a similar 'behaviour': an increase in objective fuel poverty should imply in every case an increment in the probability of declaring poor health, as observed for material deprivation.[30] However, we find that only the marginal effects for *FPI* in the probit and Class 2 show the expected marginal effects, i.e., an increase in the probability of declaring fair health (0.99 and 1.33 percentage points, respectively) or to a much lesser extent poor health (0.15 and 0.02 percentage points, respectively) when fuel poverty increases. On the contrary, the marginal effects in Class 1 are negligible for every health status category.[31]

[Insert Figure 6 here]

These results indicate that objective measures of fuel poverty are not necessarily good 'thermometers' for self-reported health for an overall sample unless the subjectivity (i.e., unobserved heterogeneity) of individuals is also controlled for. Disentangling the specific effect on health from diverse causes (material deprivation, low income, objective fuel poverty, poor conditions of dwelling, etc.) for individuals who perceive themselves to be in a situation of fuel poverty is a challenge but if they are not considered separately, this can bias the results for the whole sample.

6. Policy Discussion

The extension of the link between perceived health and (objective/subjective) fuel poverty analysed in this paper has not been explored previously and can help target the affected individuals and groups more accurately. Classifying households using a subjective measure of fuel poverty yields different results than when using objective measures, even when there is a positive correlation between both measures. Waddams Price *et al*. (2012) discuss the possibility that this difference in the classification may be due to a possible rationing of energy for those who are subjectively but not objectively (using the 10% threshold criterion) fuel poor. However, contrarily to one might expect they find that income and energy expenditure in both groups are substantially different

[30] Recall that *MD* takes a value of 1 when the household is in material deprivation and for that reason a change from 0 to 1 implies a higher likelihood of having fair (*Y=1*) or poor health (*Y*=2).

[31] Indeed, this variable was not significant in Class 1 of the 2 latent class models (see Table 2).

and hence they conclude that both approaches to measure fuel poverty are positively related but in a convoluted way.

In our analysis we found that the use of objective or subjective measures may also bias the results when analysing the effect of fuel poverty on health. In general, we can state that if objective measures of fuel poverty are used, we need to control for the effect of subjectivity. These results can serve to guide energy policies oriented to tackle fuel poverty, since it is increasingly recognised that subjectivity is a relevant feature when analysing this problem. The results support this affirmation and could be considered to contribute to mitigate the mismatch between the definition of fuel poverty and eligibility for assistance that frequently arises and increases the total costs of tackling the problem of fuel poverty (Boardman, 2010).

Thomson *et al*. (2017b) stress the need to improve the quality of existing data on fuel poverty to monitor this issue. They advocate the creation of a dedicated household survey on fuel poverty that could improve our knowledge about energy expenditure and its seasonal and annual variations, and a deeper understanding of the related problems (e.g., through changing the responses from binary to a Likert-type scale in the existing surveys). Using this type of information will help to better target fuel poor households. Moreover, it is useful to evaluate the policies that are implemented. Dubois (2012) proposed a three-step approach (targeting, identification and implementation) to identify the efficiency of fuel poverty policies. In some cases, measures that can be socially acceptable may not be effective or efficient. Al Marchohi *et al*. (2012) find that in Flanders, the provision of free electricity has not been an appropriate measure because it has not taken into account fuel poverty among the households. They suggest that energy demand and income level should be considered in policy design, and suggest that policies promoting rational use of energy in fuel poor households (i.e., investment in energy efficiency) should be more effective than corrected price mechanisms.

Finally, it is imperative to avoid that the burden of the internalisation of external costs of carbon emissions from climate change policies mainly fall on the most vulnerable member groups of the society. A likely effective long-term solution to tackle fuel poverty could be to invest in energy efficiency retrofit of residential buildings (Boardman, 2010; Ürge-Vorsatz and Tirado Herrero, 2012). The suitability of this type of programmes should be analysed taken into account not only the more visible benefits, such as lower energy consumption and carbon emissions, but also, as done by Clinch and Healy (2001), other benefits such as avoided morbidity and increased comfort derived from fuel poverty mitigation. Therefore, a joint consideration of goals will help to share resources and contribute to fulfil a broader number of environmental, energy, economic and health policy objectives. The perspective of an integrated energy sector with a high penetration of distributed generation and a prominent role of consumers through demand response, storage and energy efficiency also seems to suggest the use of a holistic approach to address the issue of fuel poverty. Nevertheless, the phenomenon of rebound effect[32] should be taken into account in design of policies as there is likely a large latent demand for energy services not fully covered yet for fuel poor households. Therefore, these policies should be accompanied by campaigns that promote an efficient use of appliances and resources.

[32] Rebound effect implies that a portion of the expected savings from energy efficiency enhancement may not be realised due to an increase in demand for energy services derived from the lower use cost of the service whose energy efficiency has improved (see, Orea *et al*., 2015).

7. Concluding Remarks

In recent years, energy price rises and household income reductions have aggravated the fuel poverty issue in many countries. Fuel poverty occurs when a household cannot afford basic levels of energy services such as space heating, space cooling, lighting or cooking. The issue is generally related to fuel expenditure, income level and energy efficiency of dwellings. Thus fuel poverty can also be a social policy problem even in countries with mild climate. In Spain, in 2014, 5.1 million people could not afford to heat their homes to an adequate temperature, a 22% growth from 2012. It is accepted that fuel poverty has a negative effect on health. The WHO identifies several diseases and health issues related to fuel poverty, mainly cardiovascular and respiratory problems, less resistance to infections and poor mental health (anxiety and stress). Nevertheless, there are difficulties in defining and measuring the effect of fuel poverty on health and well-being. Notwithstanding its significance and the compelling need for tackling this issue, fuel poverty has not been a high priority policy.

In this paper we analyse the effect of fuel poverty on self-assessed health controlling for the subjectivity of individuals' perception of their health. We apply a latent class ordered probit model to a sample of Spanish households for the period 2011-2014. The latent class approach allows us to control for unobserved heterogeneity in perceptions among the individuals. In addition, by including a subjective measure of fuel poverty in the probabilities of class membership, this approach allows us to purge the influence of 'objective' fuel poverty on self-assessed health that is based on personal perceptions. We find that poor housing conditions, low income, material deprivation and 'objective' fuel poverty have a negative impact on health.

We find that individuals who rate themselves to be in fuel poverty tend to be in Class 1 and their average self-reported health (in addition to other variables related to poverty) is worse than in Class 2. For the individuals in Class 1, an increase in objective fuel poverty shows negligible effect on the probability of declaring poor health. Nevertheless, in Class 2, objective fuel poverty has, as expected, a clear detrimental effect on health. These puzzling results reflect the difficulties of identifying fuel poverty and its effect on health. Moreover, this may also indicate that objective measures of fuel poverty are not always good determinants of self-reported health, especially where they may be needed most, i.e., for general, large and heterogeneous samples, unless individual perceptions are controlled for in some way.

Subjectivity and perception of health are important when analysing the effects of fuel poverty on individual health and hence we advocate the use of approaches that allow a combination of objective and subjective measures and its application by policy-makers. Research to explore the link between fuel poverty and health while taking into account the role of individual perceptions on assessments can inform the design of better policies aimed at tackling fuel poverty and improving public health. Moreover, it is important that policies oriented to tackle fuel poverty take into account the different energy vectors and the prospects of future smart and integrated energy systems.

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Table 1. Descriptive statistics

Variable	Mean	S.D.	Min.	Max.
Health status	2.19	0.88	1	5
CC	0.70	0.46	0	1
Age	49.9	18.6	16	88
Employed	0.33	0.47	0	1
Self_employed	0.07	0.25	0	1
Gender	0.51	0.50	0	1
Married	0.57	0.50	0	1
SDW	0.13	0.34	0	1
SE1	0.28	0.45	0	1
SE2	0.22	0.41	0	1
PSE_NHE	0.00	0.05	0	1
HE	0.20	0.40	0	1
Income	30,827	21,476	485.20	387,200
Flat	0.62	0.49	0	1
Leak	0.84	0.36	0	1
FPI	0.45	0.64	0.01	30.41
MD	0.10	0.29	0	1
Affordability	0.08	0.27	0	1

Note: Health status is the original variable coded from 1 to 5

Table 2. Parameter estimates of the models

	Probit			LCOPM (without sep. variable)						LCOPM (with sep. variable)					
				Class 1			Class 2			Class 1			Class 2		
Variable	**Est.**		**Est./s.e.**	**Est.**		**Est./s.e.**	**Est.**		**Est./s.e.**	**Est.**		**Est./s.e.**	**Est.**		**Est./s.e.**
Health production function															
Intercept	0.886	***	22.10	1.826	***	22.46	0.479	***	6.22	1.828	***	22.55	0.479	***	6.22
CC	-1.549	***	-109.29	-1.830	***	-64.51	-1.614	***	-56.18	-1.830	***	-64.53	-1.613	***	-56.06
Age	0.024	***	38.53	0.031	***	28.65	0.032	***	18.09	0.031	***	28.91	0.032	***	17.93
$(Age/100)^2$	-2.197	***	-9.63	-2.831	***	-6.78	-1.820	***	-3.46	-2.858	***	-6.88	-1.768	***	-3.34
Employed	-0.223	***	-12.15	-0.330	***	-10.60	-0.179	***	-4.07	-0.330	***	-10.62	-0.175	***	-3.98
Self_employed	-0.189	***	-6.52	-0.290	***	-6.15	-0.123	*	-1.89	-0.290	***	-6.15	-0.120	*	-1.84
Gender	0.098	***	7.02	0.122	***	5.01	0.169	***	6.14	0.123	***	5.09	0.167	***	6.09
Married	-0.061	***	-2.91	-0.115	***	-3.43	-0.037		-0.84	-0.117	***	-3.49	-0.041		-0.93
SDW	-0.009		-0.36	0.047		1.00	-0.026		-0.52	0.043		0.92	-0.033		-0.68
SE1	-0.167	***	-9.36	-0.176	***	-5.34	-0.243	***	-7.24	-0.172	***	-5.25	-0.245	***	-7.29
SE2	-0.324	***	-15.19	-0.345	***	-9.30	-0.480	***	-10.75	-0.342	***	-9.24	-0.474	***	-10.66
PSE_NHE	-0.306	**	-2.28	-0.346		-1.41	-0.324		-1.19	-0.341		-1.37	-0.319		-1.18
HE	-0.428	***	-18.43	-0.445	***	-11.51	-0.719	***	-13.11	-0.440	***	-11.39	-0.715	***	-13.15
ln Income	-0.066	***	-3.81	-0.102	***	-3.20	-0.069	**	-2.01	-0.097	***	-3.06	-0.065	*	-1.88
Flat	-0.040	***	-2.71	-0.009		-0.33	-0.091	***	-3.31	-0.008		-0.29	-0.093	***	-3.37
Leak	-0.149	***	-8.41	-0.170	***	-5.26	-0.176	***	-5.10	-0.165	***	-5.17	-0.169	***	-4.87
ln FPI	0.042	**	2.54	-0.003		-0.11	0.103	***	3.10	-0.004		-0.15	0.105	***	3.16
MD	0.300	***	13.76	0.349	***	8.90	0.288	***	6.64	0.287	***	7.47	0.250	***	5.43
Year_2012	-0.020		-0.87	0.006		0.15	-0.029		-0.60	0.002		0.04	-0.025		-0.51
Year_2013	0.020		0.90	0.189	***	4.78	-0.070		-1.53	0.189	***	4.79	-0.071		-1.58
Year_2014	0.072	***	3.19	0.210	***	5.10	0.030		0.67	0.213	***	5.18	0.027		0.60
μ_1	1.320	***	114.80	1.579	***	61.45	1.836	***	50.88	1.578	***	61.51	1.842	***	50.75
Class membership probabilities															
Prior Prob.				0.368	***	27.56	0.632	***	47.41	0.368			0.632		
Intercept										-0.585	***	-10.15			
Affordability										0.545	***	5.77			
Log-likelihood	-26,950.032			-25,951.464						-25,934.998					

Significance code: * p<0.1, ** p<0.05, *** p<0.01

Table 3. Model selection tests

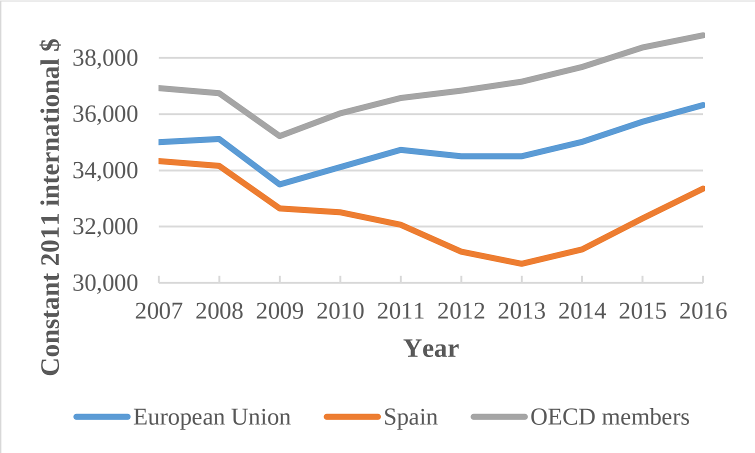
Model	Log LF	k	AIC	AICc	AIC3	ACIu	BIC	CAIC
Probit	-26,950.03	40	53,980.06	53,980.12	54,020.06	54,021.14	54,335.87	54,375.87
LCOPM (2C)	-25,951.46	81	52,064.93	52,065.17	52,145.93	52,147.24	52,785.44	52,866.44
LCOPM (2C with sep. variable)	-25,935.00	82	52,034.00	52,034.25	52,116.00	52,117.31	52,763.40	52,845.40

Notes: The number of observations in all the models is 53,918

Table 4. Features of the classes in the LCOPM model (with sep. variable)

	Number of obs.	Health status	Income	Leak	FPI	MD	Affordability
Total	53,918 (100%)	2.19	30,827	15.81%	0.45	9.61%	8.22%
Class 1	6,749 (12.5%)	2.72	29,636	17.66%	0.43	11.47%	10.77%
Class 2	47,169 (87.5%)	2.11	30,998	15.54%	0.46	9.34%	7.85%

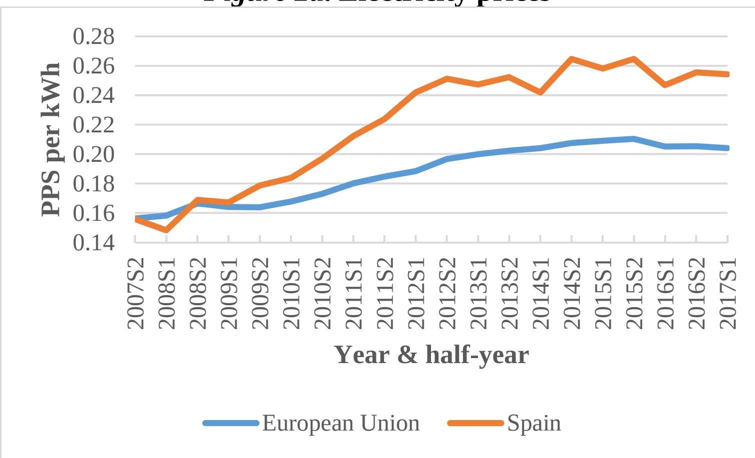
Figure 1. Evolution of GDP per capita (at Purchasing Power Parity)



Source: World Bank

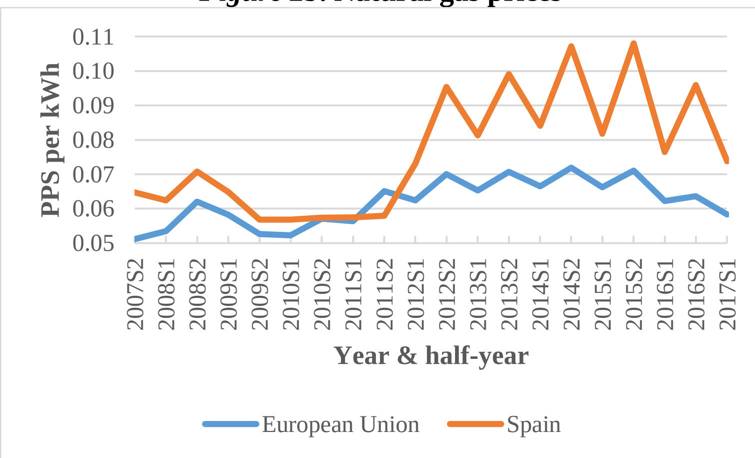
Figure 2. Evolution of energy prices for household consumers

***Figure 2a*. Electricity prices**



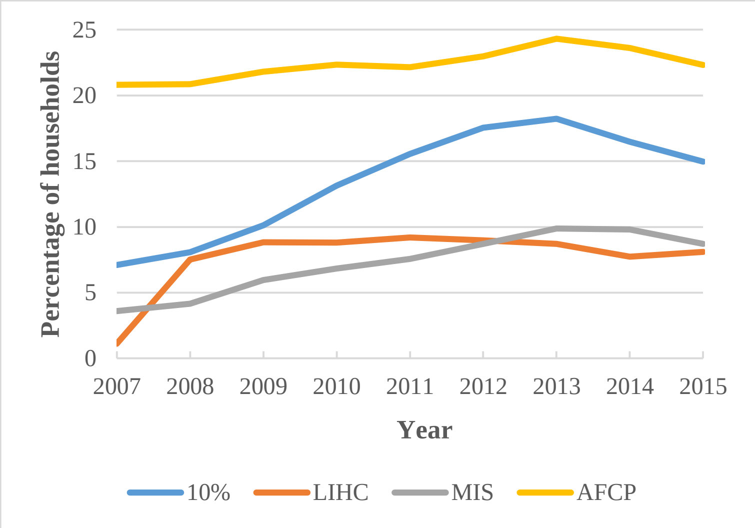
Source: Eurostat

***Figure 2b*. Natural gas prices**



Source: Eurostat

Figure 3. Fuel poverty evolution in Spain under alternative indicators



Source: Linares Llamas *et al*. (2017)

Figure 4. Histogram for variable *Health status* (total sample)

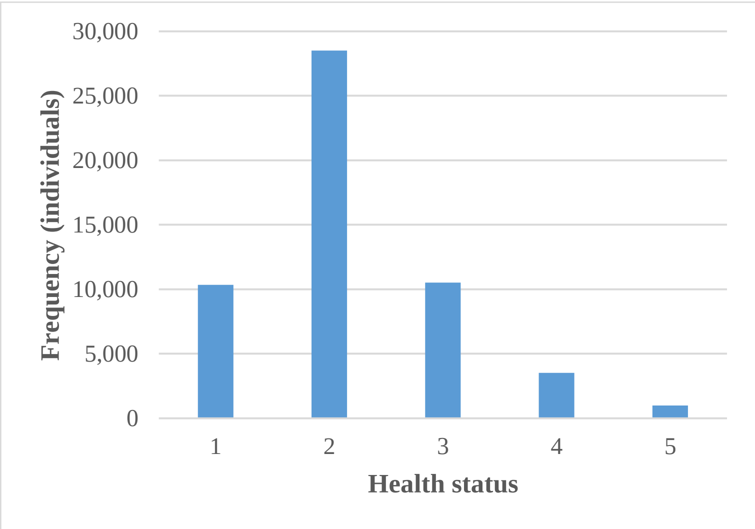


Figure 5. Histogram for variable *Health status* in each class

Figure 5a. Class 1

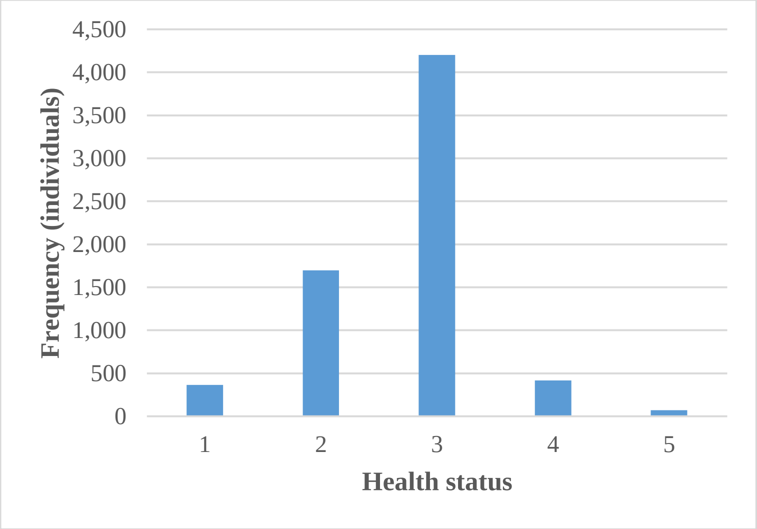


Figure 5b. Class 2

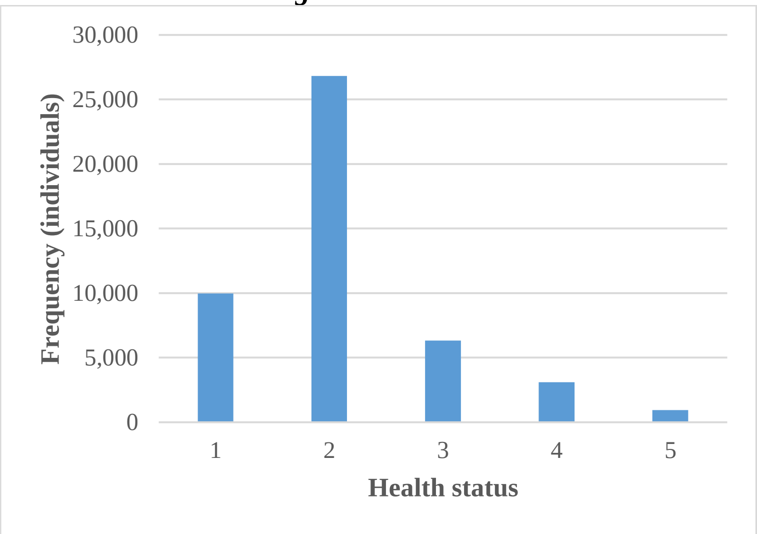
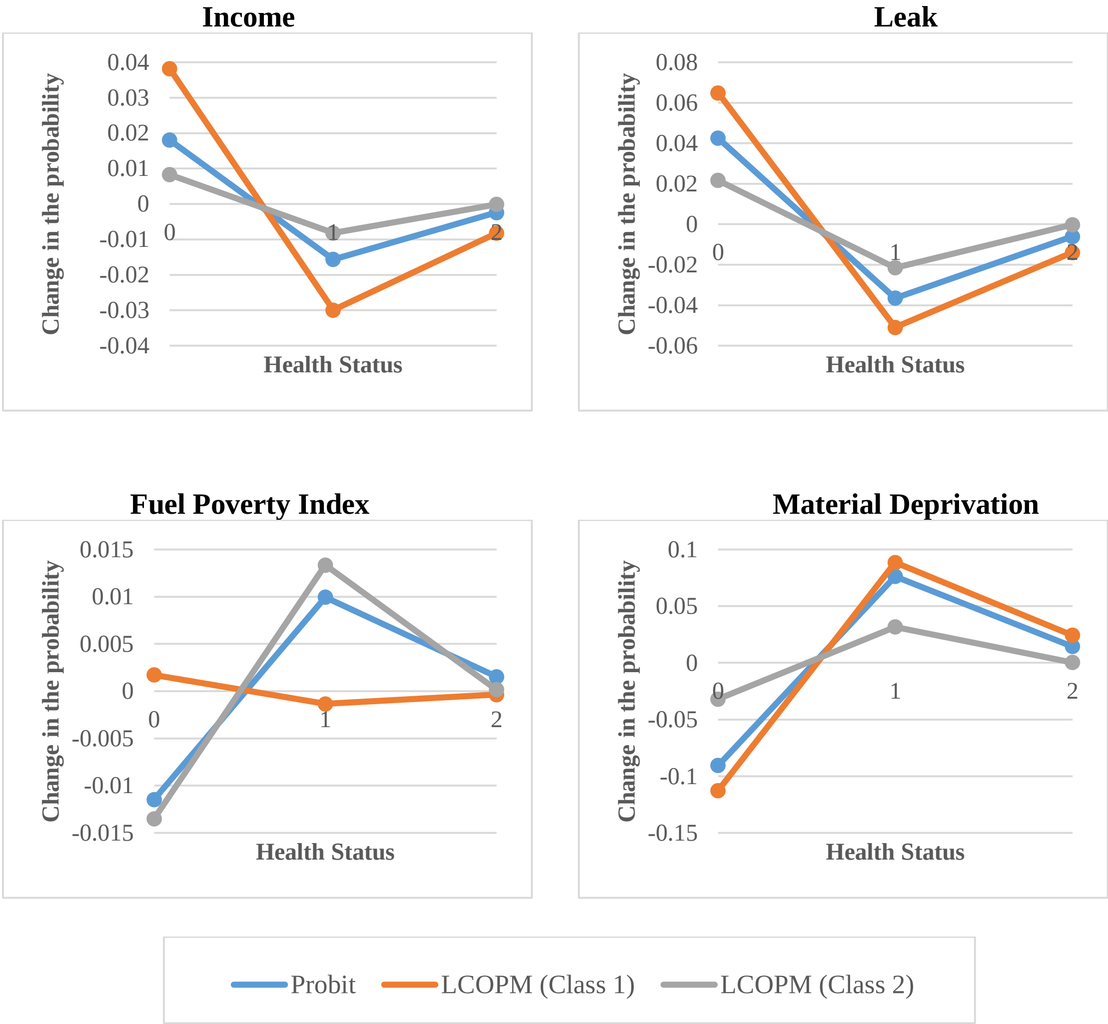


Figure 6. Marginal effects of poverty-related variables



Note: Leak and material deprivation are dummies, so the marginal effect represents changes in the probabilities of reporting different health status when there is a change from 0 to 1 in the explanatory variable. Income and the Fuel Poverty Index are continuous and changes in the probabilities are linked to increases of 1% in these variables.