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Abstract

The main aim of this paper is to defining a multidimensional housing deprivation index and identifying the main determining characteristics of this phenomenon, using Spain as reference. A latent variable model is used in order to overcome some of the traditional difficulties encountered in multidimensional deprivation studies. The construction of a latent structure model has allowed a set of partial housing deprivation indices to be grouped together under a single index. It has also enabled each individual to be assigned to a different class depending on the level and type of deprivation. Results show that the vector of observed variables (having hot running water, heating, a leaky roof, damp walls or floor, rot in window frames and floors, and overcrowding) and the correlations among such variables can be explained by a single latent variable. There are also specific characteristics that differentiate the population affected by housing deprivation.

Keywords: housing, deprivation, poverty, latent class models.
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1. INTRODUCTION

The interest in assessing household's well-being trough direct indicators that complement traditional income measures has increased considerably in recent years. Various attempts have recently been made to put forward new ways of analysing the level of multidimensional deprivation suffered by households [Brandolini and D'Alessio (2000), Chakravarty and D'Ambrosio (2003), Atkinson (2003), Bourguignon and Chakravarty (2003), Dutta *et al.* (2003)]. Housing is undoubtedly one of the main components of material well-being. The right to an adequate dwelling as a basic element of well-being is explicitly recognised among the social rights in most OECD countries. However, no clear consensus has been reached concerning the most appropriate measures to use when assessing to what extent households enjoy the aforementioned right. The difficulties found when trying to obtain accurate definitions are a result of the wide range of questions arising when an attempt is made to fix a level of adequate dwelling or the basic consumption of housing services. What conditions must a dwelling meet? Which of these dimensions are relevant? How are these conditions measured? What combination of conditions allows a minimum level of well-being to be reached? How can these be summed up by a single index?

Of all these questions, perhaps the most relevant refer to aggregation methods and how thresholds are defined. Different criteria and approaches are available to define the basic conditions of a household's well-being. Most of these have to do with a lack of resources and a general insufficiency in a household's basic facilities. The aggregation methods vary from the simple summing up of commodities to more complex methods that use multivariate analysis techniques. These techniques allow us to sum up a wide range of indicators in a multiple deprivation scale. Nevertheless, various difficulties are encountered when trying to obtain objective indices that consistently sum up the insufficiencies suffered by households as well as their weighting. However, the main constraint lies mainly in the recurrent arbitrariness in the setting of deprivation thresholds.

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The main aim of this paper is to make an attempt to overcome these difficulties by defining a multidimensional housing deprivation index and identifying the main determining characteristics behind this phenomenon by using Spain as reference. In order to do so, we use a notion of housing deprivation as an insufficient basic functioning [Sen (1985), (1992), (2000)] A latent variable model is used as a suitable methodological option for such a concept. The main contribution is to provide the possibility of empirically assessing and contrasting whether a specific combination of conditions constitutes an appropriate structure to measure the latent notion of housing deprivation. Constructing a latent structure model allows us to synthesise a group of indices under a single index and provides the possibility of assigning each individual to a different class depending on the level and kind of deprivation. In this way, the arbitrariness encountered when setting deprivation thresholds can be partially overcome.

The structure of the article is as follows. The main approaches used to construct housing deprivation indices are reviewed in the first section. The methodologies of the latent trait and latent class models, which will be the basis of the empirical work, are described in the second section. A model is then estimated using data from the European Union Household Panel in the following section. The socio-economic patterns of the groups affected by this kind of deprivation are analysed afterwards. The paper ends with a brief list of conclusions.

2. THE MEASUREMENT OF HOUSING DEPRIVATION

The construction of social deprivation indices is closely tied to the notion used to identify those suffering from this state. This paper starts off from Sen's notion of functionings [(1985), (1992), (2000)]. We could consider housing deprivation as an insufficient basic functioning of this commodity. A broad interpretation of this concept would include both the problem of individuals or households that do not have access to housing as well as those who, despite having a dwelling, suffer from insufficiencies in this commodity's basic conditions. This paper will focus on the latter.

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The empirical possibilities of approach have been widely discussed in Sen's own studies [(1985, 1992 and 2000)], as well as by others authors [Nussbaum (2000), Schokkaert and Van Ootegem (1990), Balestrino and Carter (1996), Brandolini and D'Alessio (2000), Klasen (2000), Chiappero (1996, 2000) and Robeyns (2000)]. Most of them coincide in pointing out that the main questions broached by any approach focusing on Sen's capabilities and functioning levels concern defining the appropriate space to assess well-being, the set of relevant functionings, the most appropriate criteria to measure them and the aggregation of the indicators used in order to obtain an overall assessment (Chiappero, 2000).

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Regarding the latter, constructing a synthetic deprivation indicator inevitably entails selecting the most relevant characteristics for individual well-being and developing aggregation procedures. An expanding literature on multidimensional well-being has brought forth many methods to establish weighting systems. These vary from simple processes of adding up the commodities not possessed by an individual or households to more complex methods requiring the use of multivariate analysis techniques. In some cases, the idea of unifying indicators is given greater emphasis while more stress is placed on the intersection of vectors in others. From the standpoint of statistical analyses, the main distinction can be made by differentiating the studies that synthesise information by means of arithmetic or weighted means from those that use multivariate analysis techniques.

The arithmetic addition of the commodities not possessed by an individual is the most immediate approach among the many procedures used to aggregate commodities. In a seminal contribution, Townsend (1979) chose twelve different indicators on household's living conditions and constructed a deprivation index based on the arithmetic addition of the commodities that were not present. The condition for choosing these indicators was based on their correlation to income. This method was also used by Mack and Lansley (1985), who included more conditions. All commodities included were considered as a necessity by most of those being surveyed, a negative correlation was necessary between lacking a commodity and income, and information should exist about the reasons behind the lack of commodities[1].

Arithmetic addition implicitly imposes a severe value judgement because it does not differentiate the weighting of each material condition or necessity. A more consistent approach is to use a weighted addition of necessary commodities. It was first proposed by Desai and Shah (1988) and consisted in analysing the times an individual enjoyed a specific commodity. The commodities enjoyed by most of society were given more weight. Various studies have more recently identified individuals suffering from deprivation as those that do not reach a minimum level in at least one of the functionings. The functioning levels reached by most of the population are given more weight [Brandolini and D'Alessio (2000), Böhnke and Delhey (1999), Martínez and Ruiz-Huerta (2000), Muffels and Fouarge (2001), Tsakloglou and Papadopoulos (2002)].

Another way to construct synthetic multidimensional deprivation indices lies on using multivariate analysis techniques. Some studies use main components analysis [Muffels and Vriens (1991), Hutton (1991) and Kamanou (2000)[2]], which enables an index to be created as a lineal combination of partial indicators. Callan *et al.* (1993) and Layte *et al.* (2001) applied factorial analysis to a set of deprivation indicators. Their results showed that there are three different dimensions to deprivation: basic deprivation, secondary deprivation and residential deprivation. They also found that combining income and deprivation indices in the process of identifying disadvantaged households produces differences in the extension and composition of the estimated poor. A less frequent alternative is the use of latent variable models. Gailly and Hausman (1984) used the statistical technique developed by Rasch (1960) that sums up a set of indicators in a multiple deprivation scale. Pérez-Mayo (2002, 2005) also proposed identifying households suffering deprivation or poverty from a multidimensional perspective based on the use of latent class models.

[1] The lack of commodities caused by individual preferences should not be considered as a deprivation situation.

[2] Kamanou (2000) used an alternative version of the main components analysis technique based on a standardised uniform transformation of the set of discrete variables comprising the household wealth index. This approach allows one to take into account differences in the variance of the variables used to construct the index.

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These methods have been also used in Spain for analysing very different topics (Alañon and Gomez-Antonio, 2005).

A third possibility lies in the path opened up by the Fuzzy Sets theory. This theory interprets poverty and deprivation as a phenomena that appear in different degrees and levels that are difficult to separate and identify instead of as an attribute that one lacks or possesses [Cerioli and Zani (1990), Cheli and Lemi (1995) and Chiappero (1994, 1996)]. Chiappero (2000) constructed a multidimensional index of well-being with this methodology based on the capabilities and functioning's approach proposed by Sen. The weighting structure assigned greater weight to those functioning that are reached by a wide majority of the population. Betti, D'Agostino and Neri (2000) used the same technique to construct a poverty index based on an indirect indicator (income) and a set of direct indicators (housing conditions and durable goods).

Therefore there are various options to construct synthetic deprivation indices. Despite its greater complexity, the main advantage of multivariate analysis to aggregate the different functionings -in this case housing conditions- into a single indicator is to minimise value judgements without completely eliminating them. Additionally, since one of the ideas underlying Sen's approach is that functionings are a non-observed concept, some of these models, such as the latent variable model, facilitate an approximation to this notion trough different combination of observable housing conditions.

Some of the aforementioned studies include specific housing indicators among the dimensions of deprivation. In addition to including not having a toilet and bath as components of deprivation, Townsend (1979) analysed the problem of housing in a particular way. He added a wider range of indicators, which included structural problems, the lack of basic facilities (bath, toilet, gas or electric cooker, heating), overcrowding and satisfaction regarding housing conditions. Several of these indicators were also used by subsequent studies following a similar approach [Mack and Lansley (1985), Hausman *et. al* (1989) and Nolan and Whelan (1996)]. Brandolini and D'Alessio (2000)

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specifically defined housing functionings based on indicators such as the lack of heating, overcrowding and subjective quality and location indices to find that the set of housing functionings had the highest correlation with income. Martínez and Ruiz-Huerta (2000), Muffels and Fouarge (2001),and Tsakloglou and Papadopoulos (2002) also proposed a specific dimension of housing deprivation which included the lack of a bath, overcrowding, a leaky roof, damp and rot in window frames and floors.

Among the studies using multivariate analysis techniques, Kamanou (2000) used the main components analysis technique to construct a wealth index based on a set of housing characteristics. Arévalo (1999) used also this technique to construct a housing quality index. Using fuzzy set theory, Chiappero (2000) tried to define a housing functionings based on two indicators: overcrowding and a lack of facilities such as hot running water, heating and a telephone.

To sum up, most of the studies that look into different forms of deprivation and focus on housing include basic facilities (hot running water, heating and bath), structural problems (leaky roof, damp and rot in floors and window frames) and overcrowding as important features of housing deprivation.

The sensitivity of the results to the aggregation procedures are analysed more deeply by studies that primarily focus on housing deprivation. For instance, Whitehead (1998) studied the minimum conditions a dwelling should meet to be considered as adequate. Dale *et al.* (1996) conducted an analysis on the changes in housing deprivation over two decades. One of the criteria used was the association of some housing deprivation components with health. Marsh *et al.* (1999) also looked into the effects of housing deprivation on individuals' health, but used longitudinal data. The criterion they used to select housing indicators was the association with health status and the existing correlations among the indicators.

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A certain consensus regarding the basic dimensions of housing deprivation can be gleaned from this review. These dimensions include: the lack of basic facilities, structural problems and overcrowding. Nevertheless, the set of indicators defined varies among the different studies depending on the criteria used to choose them. Generally speaking, the indicators are usually chosen according to the existing correlation with households' income. In other cases, however, the decision depends on what the individuals state they perceive as basic needs, which generally coincide with the commodities or conditions enjoyed by the majority of society. In other studies the definition of housing deprivation is determined by the housing characteristics more related to individual's health.

3. LATENT VARIABLE MODEL FOR HOUSING DEPRIVATION

Previous section's review allows us to have a wide range of housing characteristics to construct a specific deprivation index. Once these characteristics are chosen there are three questions to be resolved: what method should be used to test if a set of indicators is suitable to define the latent notion of housing deprivation, how are the different insufficiencies to be aggregated, and where the deprivation threshold should be set.

The review above offers different answers concerning the aggregation of indicators. Like income poverty, no clear consensus has been reached regarding how to set a deprivation threshold. Some authors set the threshold based on the insufficiency of a specific number of commodities, others suggest that simply lacking a commodity implies deprivation and yet another group of studies set relative deprivation thresholds that are similar to income thresholds.

Latent trait and class models offer a suitable methodological framework to provide a response to the two-fold problem posed by the aggregation of housing conditions and the setting of a threshold. The notion of housing deprivation fits in well with the idea of an insufficient functioning. Latent variable models use multivariate analysis techniques to measure non-observable

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concepts based on a set of observable variables. They allow the latent concept of multiple housing deprivation to be measured through various basic conditions.

This technique can empirically assess and test whether a specific set of indicators constitutes a suitable structure to measure the same latent concept[3]. Furthermore, these models allow one to synthesise a set of partial indicators on a single phenomenon under a single index based on the correlation of its components and their mutual dependence on the latent variable. These techniques are appropriate for the nature of the set of observed variables and allow different weightings to be assigned to them. More specific latent class models have the advantage of assigning each individual to a different class depending on the level and kind of deprivation suffered. In this way, the arbitrariness of setting thresholds is partially overcome.

The key lies on determining whether the correlations between the observed housing conditions can be explained by a small number of latent variables and to test whether this set of indicators reveals a previously supposed hypothetical structure. Following the lines of the studies reviewed above, the hypothetical structure of housing deprivation could be made up of an insufficiency in hot running water, heating, space, a leaky roof, damp and rot in window frames and floors.

3.1. A Latent Trait Model for Housing Deprivation

Latent trait models are very similar to factorial analysis. However, they can be specifically applied to observed dichotomous variables. When focusing our attention on housing conditions, one can model the probability of a randomly chosen individual suffering deprivation of observed condition x_i, given his/her position with regard to the vector of latent variables y, $P(x_i=1 \mid y)=\pi_i(y)$. This conditional probability can be expressed as a linear function of the latent variables:

[3] An alternative would consist of assessing the consistency of the deprivation indicators by estimating the Cronbach Alpha coefficient. Nevertheless, the use of such methods suffers from some important constraints (Moisio, 2001).

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$$\pi_i(y) = \alpha_{i0} + \alpha_{i1} y_1 + \ldots + \alpha_{iq} y_q + \varepsilon_i \qquad i = 1, .., p \tag{1}$$

The hypothesis of linearity is subject to two important constraints. In (1), $\pi_i(y)$ is a probability that takes on values between zero and one, while no constraints have been imposed on the right-hand side of the equation, which is why it can take on any real value. In addition, it is to be expected that the rate of change in the probability of a positive response (deprivation) is not the same for the whole range of *y*. In this case, a curvilinear relationship could be more suitable. A nexus linking probability and the latent variables needs to be introduced in order take these constraints into account. This nexus should project the range [0,1] in the range $(-\infty,+\infty)$ and should be *s*-shaped. The two commonly used nexus are the logit and probit functions. The latent variable is related to each observed housing condition through a logistic regression model in the model.

The latent variable obtained, which represents housing deprivation, can be discrete or continuous. If the latent dimension or space is considered continuous in the application, the latent trait model will be estimated. If this latent space is considered as discrete, then the latent class model will be estimated. The latent trait model is defined as follows:

$$\text{logit } \pi_i(y) = \log \frac{\pi_i(y)}{1-\pi_i(y)} = \alpha_{i0} + \sum_{j=1}^{q} \alpha_{ij} y_j \tag{2}$$

where

$$\pi_i(y) = \frac{\exp\left(\alpha_{i0} + \sum_{j=1}^{q} \alpha_{ij} y_j\right)}{1+\exp\left(\alpha_i + \sum_{j=1}^{q} \alpha_{ij} y_j\right)} \tag{3}$$

where in the unidimensional case we use instead of the sum the expresion $\exp(\alpha_{i0} + \alpha_i y)$.

In the first model, each observed housing condition would correspond to q+1 parameters (α_{i0} and the discriminating parameters $\alpha_{i1},\ldots, \alpha_{iq}$) to be estimated. If $y_1=\ldots=y_q=0$, $\pi_i(0)=[\exp(\alpha_{i0})/(1 + \exp(\alpha_{i0}))]$. Parameter α_{i0} represents the probability of the average individual suffering deprivation of the observed condition, while α_{ij} with j=1are discriminating parameters. The greater the value of α_{ij} is for an observed condition, the greater will be the difference in the probability of obtaining a positive response from two individuals situated at a certain distance from the latent dimension. The higher the parameter is, the easier will it be to discriminate between two individuals depending on their deprivation concerning each observed condition.

A special case of the one-dimensional latent trait model is the model developed by Rasch when all the discriminating parameters are equal ($\alpha_1= \alpha_2= \ldots= \alpha_p$):

$$\pi_i(y) = \frac{\exp(\alpha_{i0} + \beta_j)}{1 + \exp(\alpha_{i0} + \beta_j)} \tag{4}$$

The latent variable y is substituted by β_j, with j=1,...,n and, as in the general case, α_i represents the probability that the average individual will suffer deprivation of the observed variable. This model meets the requirement that the values obtained for the latent variable based on $\sum_{i=1}^{p} x_{ij}$ are sufficient for β_j and that the total number of positive responses for the observed condition x_i, $\sum_{j=1}^{n} x_{ij}$ are sufficient for α_i.

The assumptions adopted by the latent trait model are conditional independence, the independent nature of the latent variables with standard normal distributions so that $y_j \sim$ N (0,1), j = 1,...,q, and that the link function can be either a logit or a probit function.

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Given that only the observed variables $x_1,\ldots,x_p$ can be known, the estimation of the unknown parameters is based on their joint distribution function:

$$f(x_1,\ldots,x_p)=\int\ldots\int g(x_1,\ldots,x_p \mid y)h(y)dy \tag{5}$$

where we assume the conditions of conditional independence, a Bernoulli distribution for each x_i and independent latent variables:

$$g(x_1,\ldots,x_p \mid y)=g(x_1 \mid y)\ldots g(x_p \mid y)=\prod_{i=1}^{p} g(x_i \mid y),\; g(x_i \mid y)=\{\pi_i(y)\}^{x_i}\{1-\pi_i(y)\}^{(1-x_i)},$$
$$h(y)=h(y_1)\times\ldots\times h(y_q). \tag{6}$$

The parameters α_{i0} and $\alpha_{i1},\ldots,\alpha_{iq}$, included in π_i (y) can be estimated by maximum likelihood. An EM algorithm (Bock, and Aitkin, 1981; Bartholomew and Knott, 1999) is employed to estimate the model using the TWOMISS program (Albanese and Knott, 1990). Estimating the parameters allows us to assign the latent variable values to each individual or household as a function of the presence or lack of the observed conditions. All the information about latent variables is contained in the posterior distribution of such variables given a set of observed responses ($h(y \mid x_1,\ldots, x_p)$), which we will call the response pattern [$x = (x_1,\ldots, x_p)$]. Using the logit link function yields that the posterior distribution depends on the observed variables through q components. These components, called 'sufficient statistics', are given by:

$$X_j=\sum_{i=1}^{q}\alpha_{ij}x_i\,, \qquad j = 1,\ldots,q, \text{ with } q<p \tag{7}$$

The components, which are a weighted sum of the observed responses using as weights the discrimination coefficients (α_{ij}), are used to score the individuals on the latent dimensions. The mean of that distribution, $E(y_j \mid x_1,\ldots, x_p)$, $j=1,\ldots,q$, can also be used to scale individuals.

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In order to validate the model, there are various goodness-of-fit measures [Bartholomew and Tzamourani (1999)]. The most common involve computing a Pearson χ^2 or the LR. Both statistics compare the observed frequency of each response pattern with the expected frequency:

$$\chi^2 = \sum_{r}^{2^p} \frac{\left(O(r) - E(r)\right)^2}{E(r)} \tag{8}$$

$$\mathrm{LR} = 2\sum_{r=1}^{2^p} O(r)\ln\frac{O(r)}{E(r)} \tag{9}$$

where r represents a response pattern, and $O(r)$ and $E(r)$ represent, respectively, the observed and expected frequencies. Both statistics are distributed under the null as a χ^2, with degrees of freedom equal to the number of different response patterns minus one minus the number of independent parameters.

Another option could be to use the relative change in the likelihood ratio statistic when we move from the independence model to the latent variable model in which the discriminating parameters are equal to zero ($\alpha_{i1} = \ldots = \alpha_{iq} = 0$). This comparison offers information on the amount of association among the x variables explained by the latent variables, $T = \frac{G_0^2 - G_1^2}{G_0^2}$, where G_0^2 is the likelihood ratio test of the independence model. A final alternative, which we will also use in our subsequent estimation, is to compute the Pearson's χ^2 statistic for pairs and triplets of responses. These values are equivalent to the residuals and offer us information on how well the model predicts the two and three way margins.

3.2. Types of Housing Deprivation

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Latent Class Models can be considered as a special case of the latent trait model. The main differences between the latent trait and the latent class model consist of, as pointed above, the latent trait model assumes that the latent variables are continuous where the latent class model assumes that the latent space consist of a number of mutually exclusive classes. Additionally, the latent trait model imposes an explicit relationship between the probability of a positive response and the latent variables through the logit model where the latent class model does not impose any functional form on the probability. Despite the differences outlined above the latent class model can be considered as a special case of the latent trait model if it is assumed that the distribution of the continuous latent variables is discretised into a number of points.

One of the advantages of the latent class model is the possibility of stratifying different forms of deprivation. The specific objective of this model is to reduce the dimensions of the observed variables by using a number of mutually exclusive classes. Therefore, we can assign each individual to the relevant class depending on the deprivation suffered in each observed housing condition. The probability of a randomly chosen individual suffering deprivation in one of the observed housing conditions is now defined conditional on the latent class j (j = 1,..., K, where K denotes the number of latent classes):

$$\pi_{ij} = P(x_i = 1 \mid j), \qquad j = 1,\dots,K \tag{10}$$

Each household has a prior probability η_j of belonging to one of the j types of deprivation defined, given that $j = 1,\dots,K$ and $\sum_{j=1}^{K} \eta_j = 1$.

A possible latent class model for housing deprivation should have three components:

1) Prior probabilities η_j, $j = 1,\dots, K$

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2) The conditional probabilities of obtaining a positive response for an observed variable x_i, given latent class j, π_{ij}, where $i = 1,..., p$

3) And the common distribution of all the observed variables:

$$f(x_1, x_2, ..., x_p) = \sum_{j=1}^{K} \eta_j g(x_1, x_2, ..., x_p \mid j) = \sum_{j=1}^{K} \eta_j \prod_{i=1}^{p} \pi_{ij}^{x_i} (1-\pi_{ij})^{1-x_i} \qquad (11)$$

The parameters are estimated through an EM algorithm in order to calculate the model with unobserved variables[4]. The model rests on the assumption of conditional independence. This implies that the vector of latent variables is sufficient to explain all the associations among the housing insufficiencies in each household regarding the different housing characteristics. All the information concerning the assignment of individuals to each latent class can be found in the ensuing distribution of latent classes according to the existence or absence of insufficiencies in the housing variables.

$$P(j \mid x_1,...,x_p), \qquad j = 1,\dots,K \qquad (12)$$

The latent trait and class models meet the requirements set out to construct a housing deprivation index. On the one hand, they allow a set of housing conditions to be synthesised into a single index based on the correlation of these characteristics and their mutual dependence on the latent variable. On the other, these techniques are suitable for the nature of observed conditions and allow us to assign different weightings to them. Lastly, the latent class model has the advantage of assigning each individual to a different class of housing deprivation.

4. AN ESTIMATE INDEX OF HOUSING DEPRIVATION FOR SPAIN

4.1. Choosing Indicators

[4] We use the EM algorithm proposed by Bartholomew and Knott (1999).

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The two fold goals of estimating the extent of housing deprivation in Spain and identifying the socio-economic patterns of this problem make it necessary to search for an adequate data source. It should contain enough information on housing conditions and household characteristics. The *European Community Household Panel* (ECHP) contains valuable information on the facilities and specific problems of each individual's dwelling, in addition to offering a wide range of household socio-economic characteristics. It includes information on basic facilities (having a separate bath or shower, indoor flushing toilet, separate kitchen, hot running water, heating, terrace, courtyard or garden, number of rooms), the presence of specific structural problems (having noise problems, being too dark, a leaky roof, damp walls or floors and rot in window frames or floors), as well as the existence of problems in the surrounding areas such as environmental problems or crime and vandalism.

The unit of analysis used is the household. However, in some cases, the need to analyse personal and socio-economic characteristics associated with running a greater risk of suffering housing deprivation has made it necessary to consider representative individuals of each household, such as the household head. The person providing the greatest amount of resources to the household is defined as such. The data used in this paper are from 1998 and comprise a sample made up of 5476 households. The reason for choosing this year is twofold. On one side, preliminary work with the ECHP showed a high number of transitions between the different states of housing deprivation. Choosing different waves of the ECHP could therefore yield different results. The main reason for choosing an intermediate year (1998) is the fall in the number of observations as new waves of the ECHP were available. On the other side, 1998 results are comparable to those previously obtained in the Spanish literature on housing deprivation[5]. The choice of indicators was made by taking into account three criteria, namely: the correlation between income and housing conditions, the choice of conditions enjoyed by most of society and conditions that harm individual's health.

[5] Ayala, Labeaga and Navarro (2005) estimated to what extent living in poor housing conditions could determine individuals' health status using the 1998 ECHP data.

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Applying the aforementioned criteria allows us to obtain a set of conditions representing a dwelling's functionings. These can be grouped together under the insufficiency of basic facilities (hot running water, heating and overcrowding) and under structural problems (leaky roof, damp walls/floors and rot in window frames and floors). As Table 1 shows, these indicators have a significant relationship with households' equivalent income[6]. The Pearson correlation coefficient is significant and the association coefficient (Cramer's V) is greater than 0.1. The set of indicators chosen also groups together the housing conditions enjoyed by most of society. Apart from heating, between 85% and 90% of Spanish households do not suffer from insufficiencies in the characteristics chosen. Concerning the third criterion, it can also be observed that the households lacking hot running water or heating, or those suffering from structural problems such as damp or rot in window frames or floors also concentrate the greatest health disadvantages[7].

[TABLE 1]

Among the set of housing conditions, the most controversial are the lack of heating and overcrowding. There are doubts about whether the lack of heating in some households really constitutes a problem of deprivation due the benign climate in some regions of Spain. For this reason a specific analysis of households stating that they lacked this commodity was conducted. Results showed that most households lacking heating (around 70%) could not afford it. Nevertheless, an analysis of the relationship between the lack of heating and the geographical location of households revealed that most households located in regions with high temperatures did not have heating. This fact meant that the indicator had to be redefined. We chose to consider that the lack of heating in these regions did not imply a state of deprivation.

Secondly, establishing the space a person needs to live is necessarily a subjective question. An usual practice is defining overcrowding as having less than one room per person or more than one

[6] The modified OECD scale is applied (taking a single-person household as a reference and giving a weighting of 0.5 to the rest of the adults and 0.3 to children under 14 years old).
[7] Health status is defined based on a self-assessment made by the individuals themselves: very bad, bad, regular, good and very good.

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person per room (Dale *et al.*, 1996). A smaller space can lead to health or psychological problems, such as the lack of privacy. In this paper, having a number of rooms less than the number of adults (older than 16 years of age) making up a household is used as a general indicator of overcrowding[8]. However, the contrast between the self-assessment of overcrowding made by households and the indicator above is striking. Only 25% of households that stated they lacked space in their dwellings actually suffered from overcrowding as defined herein. This makes it necessary to interpret the results of this variable with caution. As will be seen further below, it also suggests the need of estimating the sensitivity of alternative measures that take into account the composition and size of the household.

4.2. Results of the Latent Variable Model

The possible combinations of the housing conditions chosen give rise to different levels of deprivation. Applying the latent variable model to ECHP data makes it possible to have a housing deprivation index. The partial indicators chosen make up the supposed *a priori* structure that will be tested.

[TABLE 2]

Estimating the latent trait model shows that the vector of observed variables (having hot running water, heating, a leaky roof, damp walls or floor, rot in window frames and floors, and overcrowding) and the correlations between such variables can be summed up by a single latent variable (Table 2). The goodness-of-fit measurements show an acceptable fit and confirm the assumed *a priori* structure. The last column of the table shows the probabilities of a median individual suffering deprivation of the six housing indicators. The estimates of the discrimination parameters α_{ij} are shown in the fourth column. These represent the weight given to each one of the observed variables. The values of these parameters show that the heating and overcrowding

[8] Another possible way of defining overcrowding could be to consider the number of rooms available corrected by an equivalence scale (Chiappero, 2000).

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indicators receive less weight than the others. Simultaneously, a very small percentage of the population lacks heating or suffers overcrowding conditions. Hence, to a certain extent, we could say that the estimated deprivation index contains an important relative component.

Once the housing deprivation index is obtained, two especially relevant questions arise. Firstly, an attempt is made to analyse whether there are different types of deprivation, such as an insufficiency in basic facilities or the presence of structural problems. Secondly, we could also test whether or not there are differences in the households' personal or socio-economic characteristics. In order to provide a response to the first question, a latent class model can be estimated. This allows us to differentiate the results into four different kinds of housing deprivation (Table 3).

[TABLE 3]

The estimated matrix $\pi(\pi_{i1}, \pi_{i2}, \pi_{i3}$ y $\pi_{i4})$ shows the probability of a randomly chosen household suffering deprivation of each one of the six housing indicators given its situation in the different latent classes. It can be seen that Class 1 includes those households having the lowest probability of suffering housing deprivation. On the other hand, households with the highest probability of suffering multiple deprivation belong to Class 4. It is also very interesting to highlight the difference between households included in Classes 2 and 3. The former includes households having a greater probability of suffering a lack of basic housing facilities (such as hot running water, heating or space) than having structural problems. On the other hand, households included in Class 3 have a very high probability of suffering structural problems and a very small, almost negligible, probability of lacking basic facilities. From the estimated model it can be deduced that 69% of the households included in the sample belong to Class 1 (η_1), 16% belong to Class 2 (η_2), 12% to Class 3 (η_3) and 3% to Class 4 (η_4).

5. DETERMINANTS OF HOUSING DEPRIVATION

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Various questions arise from the previous empirical exercises. Is housing deprivation homogenously distributed among the population? Which demographic groups run a greater risk? How does this risk increase in the face of specific changes in socio-economic characteristics? Table 4 gathers information on the statistical associations among the different housing deprivation indicators and different socio-economic factors. Results show that most of the partial housing deprivation indicators have a significant relationship with the various socio-economic factors included. As was mentioned previously, the housing deprivation indicators have a significant relationship with households' income. Likewise, the main source of household income, the ability to make ends meet, whether the dwelling is rented or owned, its geographical location and the household's composition and size, as well as the household head's educational attainment, state of health, age and civil status all have a significant relationship with the housing deprivation indicators. The relationship with the household head's social relationships, however, is limited.

[TABLE 4]

Generally speaking, the overcrowding indicator yields different results from the rest of the housing conditions. As was mentioned above, establishing the amount of space a person needs to live is an issue permeated by value judgements. It is for this reason that we estimated alternative indicators in order to assess the consistency of the definition initially adopted. Most of the studies focusing on housing deprivation use a value of less than one room per person as a criterion to measure overcrowding. Other studies, however, criticise this definition and propose others that are more sensitive to a household's composition [Murie (1983), Chiappero (2000)]. We defined two new overcrowding indicators:

$$H_d = 1 + \frac{(S - Z)}{2} \quad \text{and} \quad H_v = 2 + \frac{(S - Z)}{2} \qquad (13)$$

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where S represents the size of a household and Z indicates whether it is composed of a couple or an adult. The first indicator would reflect problems of overcrowding when there are two or more people per room. One of the rooms would belong to the couple making up the household or the adult considered as household head. However, this indicator only takes into account the number of bedrooms without designating any room as a "common living area". The second indicator is constructed in the same way as the first. In this case, however, a room is designated as the family's common living area. To a certain extent, these indicators define overcrowding problems more strictly, as the threshold below which a household is considered as overcrowded is having two or more people per room. Estimates carried out with these alternative indicators generally confirm that the singularities of overcrowding, when compared to other housing deprivation indicators, are repeated with these alternative definitions[9]. Due to this, the initial definition will therefore be adopted here with the necessary caution.

Once the intensity of the possible relationships between housing deprivation and the household's characteristics, as well as those of the household head, have been analysed, the most immediate question arising is which categories of the population run a greater risk of suffering this problem. In order to identify the specific effect of each of these variables on housing deprivation, it is necessary to estimate an empirical model that integrates the different dimensions set out previously.

The different classes of deprivation identified by the latent class model were chosen as dependent variable. This variable requires the estimation of a multinomial logistic regression model with four alternatives. Alternative 1 represents the first latent class (very low or negligible levels of housing deprivation). Alternative 2 represents the second latent class (notable insufficiency in basic housing facilities). Alternative 3 represents the third latent class (large presence of structural problems). Alternative 4 represents the fourth latent class (multiple housing deprivation). The probability of a household belonging to a specific class is compared to the probability of belonging to another class, while the former serves as a reference. More precisely:

[9] Other studies have also found that the results of the overcrowding variable are different from the other housing indicators (Marsh *et al.*, 1999).

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$$y_i = \beta' x_i + \varepsilon_i \tag{14}$$

where y_i is a latent variable indicating the probability of belonging to each class, β is the vector of parameters corresponding to the x explanatory variables and ε is the random error, which is assumed to follow a logistic distribution.

This model provides a set of probabilities for the $J+1$ possible alternatives for each household having x_i characteristics. If the J perturbations are independent and distributed identically with a log-Weibull function, $F(\varepsilon_{ij}) = \exp(-e^{\varepsilon_{ij}})$, and the $\beta_1=0$ normalization rule is applied, then:

$$\Pr(Y = j) = \frac{e^{\beta_j x_i}}{1 + \sum_{k=1}^{J} e^{\beta_k x_i}} \quad \text{for} \quad j = 2,\ldots,J, \tag{15}$$

$$\Pr(Y = 1) = \frac{1}{1 + \sum_{k=1}^{J} e^{\beta_k x_i}} \tag{16}$$

The model's coefficients cannot be interpreted in the same way as the ones derived from the probability of suffering a specific kind of deprivation in the face of a change in one of the explanatory variables. They show the effect of the variables on the probability of a specific alternative when compared to the reference. The sign of these coefficients does not necessarily have to coincide with the sign of the marginal effects. The individual characteristics' marginal effects on the probabilities can be estimated as follows:

$$\delta_j = \frac{\partial P_j}{\partial x_i} = P_j\left[\beta_j - \sum_{K=1}^{J} P_K \beta_K\right] = P_j\left[\beta_j - \bar{\beta}\right] \tag{17}$$

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As in the previous analysis, the explanatory variables included in this model offer information on households' economic, work, social and, in general terms, living conditions. More precisely, the variables included are income deciles[10], the main source of income, whether the dwelling is rented, provided free or owned, the region of residence, the household's size and composition, the frequency with which family and friends are visited and the household head's educational attainment, age, sex and civil status.

[TABLE 5]

Table 5 shows the estimated model's variables and significant categories. Similarly to the previous descriptive analysis, it can be seen that household income is one of the variables exerting the greatest influence on the risk of suffering housing deprivation. Belonging to different income deciles causes different effects on the probability of belonging to one or another of the housing deprivation classes[11]. Concerning insufficiencies in basic facilities, the source of income constitutes a significant factor. Households whose primary source of income is made up of welfare benefits have a greater probability of belonging to the aforementioned class when compared to households with earnings as their main source of income.

The factor having the greatest influence in quantitative terms is whether the dwelling is rented, provided free or owned. The relative risk of lacking basic facilities, suffering from structural problems or suffering from multiple housing deprivation is greater for households living in rented or provided free dwellings than those living in owned properties.

[10] We consider income as one of the covariates explaining housing deprivation despite this variable was one of the criteria used to select housing indicators. This procedure allows us to identify income's influence on housing deprivation once we have controlled for other factors. Furthermore, it is also interesting to test whether or not belonging to different income deciles cause different effects on the probability of belonging to a specific class of housing deprivation.

[11] Households with the highest income levels (ninth decile) can serve as an example. They suffer a relative risk of belonging to the second class that is 57% lower than that of the households in the first decile. This percentage falls to 49% for the third class and rises to 81% for multiple deprivation.

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There are also significant differences in the possibility of belonging to one or other category depending on the household's composition. The relative risk run by couples with children of suffering an insufficiency in basic facilities or multiple deprivation as opposed to not suffering any kind of deprivation at all is lower than the risk run by people over 65 years of age living alone. Generally speaking, single people run a greater relative risk of suffering some kind of housing deprivation. The same happens with separated people[12]. Age also constitutes an influencing factor in the probability of suffering structural housing problems. The household head's educational attainment and level of social integration only appear to be significant for the relative risk of lacking basic housing facilities.

Lastly, the regions running the greatest relative risk of suffering housing deprivation differ depending on the kind of housing deprivation considered. Most regions have a lower probability of suffering some kind of housing deprivation than the Northeastern region (Galicia, Asturias and Cantabria), except for the central area (Castilla y León, Castilla-La Mancha and Extremadura), which has a greater probability of suffering structural housing problems.

6. CONCLUSION

Housing constitutes one of the basic commodities that determine the individual's well-being. However, defining what an adequate dwelling is raises numerous questions. Among others, these include what conditions must housing meet, what dimensions are relevant, how should they be measured and what combinations of conditions allow to reach a minimum level of well-being. This paper offers a methodology, the latent variable models, which have been rarely used until now to offer a response to these questions. These models allow responding to the two-fold problem of aggregation and setting a threshold. Assigning each individual to a different class depending on the level and kind of deprivation enables the habitual arbitrariness of establishing thresholds to be partially overcome.

[12] Several studies point out the fact that the lack of the spouse influence on the stability in their income level (Canto, 2002).

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Applying these models to the ECHP data has enabled us to estimate and characterise housing deprivation in Spain. Results of the latent trait model show that a single latent variable allows us to identify the variable underlying housing deprivation, and confirm the assumed *a priori* structure (having hot running water, heating, a leaky roof, damp, rot in window frames or floors and overcrowding). They also corroborate that the set of housing conditions are satisfactory indicators of insufficiencies in the basic functioning of a dwelling. The estimated parameters shows, on one hand, that the lack of heating and, to a lesser extent, overcrowding are generalised problems throughout society. On the other hand, the weighting structure of the model assigns these indicators less importance than bad housing conditions suffered by a small part of population. Results of the latent class model also show that we can differentiate among different kinds of housing deprivation.

Other important implications are the answer provided to the question whether housing deprivation is homogenously distributed among the population or whether there are specific characteristics of deprived households. It appears that the incidence of housing deprivation is strongly tied to a household's level of income. However, the impact of this factor is different according to the class of housing deprivation. The source of income also contributes to explain the risk of suffering housing deprivation, but specifically deprivation of basic facilities. Other important result affecting public policies is that the incidence of the different kinds of deprivation is greater among households that rent dwellings. The household composition is other of the determinant factors of the risk of suffering housing deprivation. Being single person household has more probabilities of being deprived than couples.

These results could lead to a deeper discussion on the design of some policies aimed at aiding disadvantaged households. The heterogeneity found concerning both the kind of deprivation suffered, as well as the different kinds of households affected by each problem puts into question

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traditional general measures. Results suggest the need for designing policies that are differentiated according to the different classes of problems and social groups affected.

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Table 1
Housing Conditions Association with Income and Health Status

Housing Conditions	Frequencies (%)		Cramer's V (χ^2)	
	Deprivation	No Deprivation	Equivalent Income (deciles)	Health Status
Kitchen	1,4	98,6	0,041 (0,411)	0,028 (0,493)
Bath	1,1	98,9	0,080 (0,000)	0,058 (0,000)
Toilet	0,6	99,4	0,056 (0,053)	0,038 (0,156)
Hot Running Water	2,1	97,9	0,109 (0,000)	0,109 (0,000)
Heating	42,3	57,7	0,213 (0,000)	0,083 (0,000)
Garden	24,8	75,2	0,080 (0,000)	0,056 (0,004)
Noise	30,7	69,3	0,041 (0,414)	0,030 (0,461)
Light	14,5	85,5	0,065 (0,000)	0,040 (0,063)
Leaky Roof	8,9	91,1	0,151 (0,000)	0,096 (0,000)
Damp	17,6	82,4	0,175 (0,000)	0,098 (0,000)
Rot in Window Frames or Floor	5,3	94,7	0,122 (0,000)	0,084 (0,000)
Overcrowding	7,5	92,5	0,130 (0,000)	0,040 (0,115)
Pollution	13,5	86,5	0,064 (0,001)	0,028 (0,582)
Crime and Vandalism	17,7	82,3	0,048 (0,122)	0,061 (0,000)

Note: Weighted data based on the variable representing cross-sectional weighting for the last wave or period of the ECHP.

Table 2
Results of the Latent Trait Model for Housing Deprivation (1998)

Indicators	α_{0i}	Standard Error	α_{1i}	Standard Error	Standardised α_{1i}	P(X=1/Z=0)
Hot Running Water	-4.997	0.209	1.612	0.142	0.850	0.007
Heating	-0.395	0.029	0.406	0.044	0.376	0.402
Leaky Roof	-4.521	0.284	2.859	0.246	0.944	0.011
Damp	-3.530	0.352	3.431	0.415	0.960	0.028
Rot in Window Frames or Floor	-4.365	0.181	2.037	0.139	0.898	0.013
Overcrowding	-2.639	0.056	0.205	0.076	0.201	0.067

Tests

% G^2 explained: 89.5
Likelihood Test 90.128
χ^2 (22) of observed responses: 52.904
χ^2 (22) of all responses: 71.736
Total expected frequencies: 5457

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Table 3
Classes of Housing Deprivation

Indicators	$\hat{\pi}_{i1} = P(x_1 = 1 \mid 1)$	$\hat{\pi}_{i2} = P(x_2 = 1 \mid 2)$	$\hat{\pi}_{i3} = P(x_3 = 1 \mid 3)$	$\hat{\pi}_{i4} = P(x_{41} = 1 \mid 4)$
Hot Running Water	0.0000	0.0500	0.0307	0.3366
Heating	0.2963	0.6276	0.5620	0.7166
Leaky Roof	0.0155	0.0764	0.3657	0.8710
Damp	0.0000	0.0587	0.9679	0.9998
Rot in Window Frames / Floors	0.0064	0.0698	0.1799	0.6339
Overcrowding	0.0602	0.0926	0.0641	0.1054
	$\hat{\eta}_1$	$\hat{\eta}_2$	$\hat{\eta}_3$	$\hat{\eta}_4$
	0.6901	0.1660	0.1172	0.0266
Test				
$\chi^2(21)=33.40$ $G^2(21)=46.14$				

Table 4
Housing Conditions and Household Characteristics (Association Coefficients)

Characteristics	Cramer's V (χ^2)					
	Housing Conditions					
	Hot Running Water	Heating	Leaky Roof	Damp	Overcrowding	Rot in Window Frames or Floors
Region	0.085 (0.000)	0.567 (0.000)	0.139 (0.000)	0.242 (0.000)	0.105 (0.000)	0.127 (0.000)
Normalized Equivalent income	0.046 (0.004)	0.153 (0.000)	0.083 (0.000)	0.116 (0.000)	0.103 (0.000)	0.061 (0.000)
Equivalent income (deciles)	0.109 (0.000)	0.213 (0.000)	0.151 (0.000)	0.175 (0.000)	0.130 (0.000)	0.122 (0.000)
Main source of income	0.119 (0.000)	0.135 (0.000)	0.124 (0.000)	0.108 (0.000)	0.103 (0.000)	0.094 (0.000)
Ability to make ends meet	0.141 (0.000)	0.114 (0.000)	0.163 (0.000)	0.171 (0.000)	0.105 (0.000)	0.141 (0.000)
Rental or Owned	0.081 (0.000)	0.103 (0.000)	0.047 (0.000)	0.099 (0.000)	0.022 (0.275)	0.115 (0.000)
Educational attainment	0.091 (0.000)	0.200 (0.000)	0.095 (0.000)	0.117 (0.000)	0.027 (0.264)	0.066 (0.000)
Health	0.109 (0.000)	0.083 (0.000)	0.096 (0.000)	0.098 (0.000)	0.040 (0.115)	0.084 (0.000)
Chronic Illness	0.077 (0.000)	0.065 (0.000)	0.098 (0.000)	0.071 (0.000)	0.042 (0.008)	0.062 (0.000)
Social relationships	0.034 (0.286)	0.035 (0.232)	0.039 (0.133)	0.058 (0.002)	0.046 (0.041)	0.034 (0.291)
Sex	0.058 (0.000)	0.028 (0.039)	0.055 (0.000)	0.061 (0.000)	0.005 (0.714)	0.050 (0.000)
Age	0.094 (0.000)	0.125 (0.000)	0.077 (0.000)	0.052 (0.002)	0.165 (0.000)	0.049 (0.005)
Satisfaction with dwelling	0.170 (0.000)	0.142 (0.000)	0.212 (0.000)	0.268 (0.000)	0.128 (0.000)	0.276 (0.000)
Household size	0.152(0.000)	0.164(0.000)	0.096(0.000)	0.111(0.000)	0.554(0.000)	0.099(0.000)
Household composition	0.154 (0.000)	0.184 (0.000)	0.131 (0.000)	0.132 (0.000)	0.327 (0.000)	0.133 (0.000)
Marital status	0.120 (0.000)	0.132 (0.000)	0.124 (0.000)	0.093 (0.000)	0.127 (0.000)	0.114 (0.000)

Table 5
Results of Multinomial Logistic Model

Variables	Odds-ratio	Standard Error	z	P>z
Class 2				
Income				
Income (decile 7)	.450	.112	-3.180	0.001
Income (decile 8)	.643	.158	-1.790	0.073
Income (decile 9)	.435	.120	-3.000	0.003
Income (decile 10)	.349	.108	-3.380	0.001
Educational Attainment				
Without Studies	1.457	.268	2.050	0.041
Household Size	1.180	.071	2.760	0.006
Household Composition				
Couple 1 child<16	.330	.127	-2.860	0.004
Couple 2 children<16	.464	.169	-2.110	0.035
	.387	.218	-1.680	0.092
	.388	.122	-3.010	0.003
Rented or Owned				
Rented	2.490	.358	6.340	0.000
Provided free	2.944	.512	6.210	0.000
Source of Income				
Other benefits	1.694	.394	2.270	0.023
Social Relationships				
Not very frequent	1.956	.539	2.430	0.015
Regions				
Northeast Region	.359	.064	-5.730	0.000
Madrid Region	.123	.040	-6.410	0.000
Central Region	.437	.070	-5.100	0.000
Eastern Region	.479	.070	-5.010	0.000
Southern Region	.153	.031	-9.170	0.000
Canary Is. Region	.568	.115	-2.770	0.006
Civil Status				
Single	1.613	.322	2.400	0.016
Class 3				
Income				
Income (decile 7)	.357	.115	-3.190	0.001
Income (decile 8)	.378	.123	-2.980	0.003
Income (decile 9)	.510	.160	-2.140	0.033
Income (decile 10)	.316	.127	-2.860	0.004
Educational Attainment				
Without Studies	1.555	.375	1.830	0.068
Household Composition				
Couple without children<65	.391	.175	-2.090	0.037
Rented or Owned				
Rented	1.506	.292	2.110	0.035
Provided free	2.227	.475	3.750	0.000
Social Relationships				
Not very frequent	1.536	.388	1.700	0.090
Regions				
Northeast Region	.483	.131	-2.670	0.008
Madrid Region	.462	.157	-2.260	0.024
Central Region	1.788	.364	2.850	0.004
Age				
Aged 50-65	1.873	.575	2.040	0.041
Civil Status				
Separated	2.351	.937	2.140	0.032
Single	1.850	.471	2.420	0.016

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Table 5 (Continued)

Class 4				
Income				
Income (decile 7)	.410	.200	-1.820	0.069
Income (decile 8)	.192	.127	-2.490	0.013
Income (decile 9)	.186	.124	-2.510	0.012
Income (decile 10)	.268	.171	-2.060	0.039
Household Size	1.210	.124	1.860	0.063
Household Composition				
Couple 2 children<16	.058	.066	-2.480	0.013
	.288	.158	-2.260	0.024
Dwelling Rented or Owned				
Rented	3.020	.774	4.310	0.000
Provided free	2.151	.774	2.130	0.033
Regions				
Northeast Region	.489	.160	-2.180	0.029
Madrid Region	.399	.175	-2.080	0.037
Central Region	.532	.164	-2.040	0.041
Eastern Region	.208	.076	-4.270	0.000
Southern Region	.350	.113	-3.250	0.001
Civil Status				
Divorced	3.951	2.746	1.980	0.048
Single	2.976	1.124	2.890	0.004

Note: Categories of reference: single-person household, resident in northeast region, in first decile of equivalent income, with owned dwelling, with male household head, married, salary earner, sees friends or family most days, university degree, less than 30 years of age.

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