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Abstract

We analyse the changes in multidimensional deprivation in very heterogeneous rural areas in Spain during the economic crisis using multigroup latent class models. Decomposition analyses of material deprivation are conducted by considering intra-area and inter-area components. Counterfactual distributions are implemented to identify the factors behind the change in deprivation in the different areas. We find that the economic crisis negatively affected direct indicators of the living standards in rural areas. A wide range of differences appears when specific rural areas are studied going beyond the usual dilemma between rural and urban areas. Our results also belie the common stereotype that the greatest incidence of monetary poverty in rural areas is offset by better living conditions.

Keywords: rural areas, multidimensional deprivation, latent class model, EU-SILC.
JEL: I32, R13

INTRODUCTION[1]

Among the variety of elements that influence the development and profiles of multidimensional deprivation, the spatial dimension has received less attention than other determining factors. This is especially noticeable in the case of rural areas, where the evidence on multidimensional deprivation is scarce. This relatively marginal consideration is due to several reasons.[2] First, in most high-income countries the contribution of the primary sector to the GDP and employment has continued to decrease. Second, depopulation and ageing in these areas have limited the analysis of living conditions to the issues of the adequacy of social benefits and access to basic public services.

There are also methodological problems and a limited availability of data to measure deprivation in rural areas. The definition of appropriate thresholds for sparsely populated areas remains a challenge for applied research and the difficulties in transferring the indices used in national studies to rural areas are considerable. As noted by Haase and Walsh (2007), the concepts built for data analysis at the individual level should not be applied as such at the spatial level. The difficulties of adapting the usual methodological decisions to more disaggregated territorial areas add to the heterogeneity of rural areas themselves, due to both the diversity of patterns of productive specialization and differences in the socio-demographic structure, with varied population sizes and densities. Given the lack of availability of sufficiently disaggregated data, overly simplistic classifications –which only discriminate between urban and non-urban based on a population threshold– are often used.

As a result, few research studies provide information on the differences in the extent and characteristics of multidimensional deprivation in heterogenous rural areas. Some of the questions arising from the analysis of income poverty in these areas have not been tested yet in the case of multidimensional deprivation. Among many other issues,

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[2] We focus here on deprivation in rural areas in rich countries. For a detailed review of the problems of poverty and inequality in rural areas of developing and emerging countries see Rodríguez-Pose and Hardy (2015).

this is the case of a general deterioration of poverty over time in rural areas compared to urban areas (Ulimwengu and Kraybill, 2004, Fisher and Weber, 2005, European Commission, 2008), how some non-observable characteristics in rural areas increase local poverty rates and the individual probabilities of being poor (Weber *et al.,* 2005), or the likelihood of spatial traps of poverty (Birk *et al.*, 2002) determining both a higher incidence of poverty and the fact that national policies are significantly less effective in these areas (Weber *et al*., 2004; Simmons *et al*., 2007; Mammen *et al.,* 2011).

This higher occurrence of income poverty in rural areas is confirmed and often opposed to the hypothesis that situations of multidimensional deprivation are, on the contrary, lower in these areas where the effects of recessionary economic cycles also tend to be less adverse. However, due to the above mentioned constraints, the implementation in rural areas of the new methods for measuring multidimensional deprivation has been very limited. Mosley and Miller (2004) found that, for the US case, indicators were worse in large cities and non-urban areas. In the case of Spain, some studies showed some growth in the differences in income per capita, poverty and multidimensional deprivation between urban and rural areas (Jurado and Pérez-Mayo, 2008). With data reflecting the effect of the crisis, profound changes in the extent of material deprivation in rural areas have been found (Ayala *et al.,* 2015).

Is multidimensional deprivation less sensitive to recessions in rural than urban areas? Was the impact of the economic downturn different across heterogenoeus rural areas in terms of multidimensional deprivation? Does an individual with certain characteristics more likely to experience deprivation depending on the area where she/he resides? This paper aims to provide an answer to these three questions by analyzing the changes in multidimensional deprivation in Spanish rural areas at the height of the last economic crisis. Spain is a country with a broad heterogeneity in rural areas, and it was one of the OECD countries where the effects of the economic crisis were the most adverse. It is also a country with very large territorial differences in access to essential public services (Herrero-Alcalde and Tranchez-Martín, 2017).

The paper contributes to the previous literature in mainly two ways. First, we solve the problem of measuring multidimensional deprivation in disaggregated areas using a extended version of a latent class model. These models can partially solve the problem of measurement error that are usually serious in most of the statistical approaches that look at this issue. Second, a decomposition analysis of material deprivation are conducted by considering between-areas components and estimating counterfactuals to identify the major factors behind the change in deprivation in the different areas under analysis. Both empirical strategies allow to identify whether an individual with certain characteristics is more likely to experience multidimensional deprivation if he/she resides in a different type of habitat.

The paper is structured as follows. First, the data used in the study and the demarcation criteria of the habitats are presented. Second, the latent class method used to measure multidimensional deprivation is introduced. Third, a detailed analysis of deprivation during the crisis period is performed. Fourth, the observed changes are decomposed into categories of habitats. The study ends with a brief summary of conclusions.

1. DATA

1.1. Data on Living Conditions

The European Union Statistics on Income and Living Conditions (EU-SILC) established by Eurostat in 2004 is the main source of statistics for studies on multidimensional deprivation in EU countries. In this study, the Spanish version of the survey (ECV) is used for the years 2005 and 2012. This was the period of deepest economic recession, with a national unemployment rate that rose from 8.4% in the third quarter of 2005 to over 26% by the end of 2012. The individual is used as the unit of analysis, and the samples include 36,678 and 33,573 observations for 2005 and 2012, respectively[3]. The data come from specific information produced for this paper by the National Institute of Statistics (INE), which for the first time includes differentiation of heterogenous rural areas, allowing a much more precise analysis of their living conditions.

The structure and design of the survey make it possible to collect very detailed information on income, both its values and components, household members, and

[3] Income data collection in this survey completely changed in 2013. The 2012 wave was chosen for sake of comparability.

certain demographic and material characteristics of households, including the subjective evaluation of the level of financial constraints. Thus, it is possible to estimate multidimensional deprivation indicators from the information on material well-being provided by the survey.[4]

1.2. Definition of rural areas

The territorial nature of deprivation initially requires the definition of what areas are considered urban and rural. Several studies use the OECD (1994) classification as a criterion, which is mainly based on population density and which considers localities with a density of less than 150 inhabitants per km^2 to be rural areas. From this information, the Spanish provinces (NUTS3) can be grouped in three clusters depending on their population densities. However, given the wide area of the municipal boundaries and the population distribution in Spain, the application of this criterion raises several problems. Many cities belong to a low-density municipality due to the extension of its municipal boundary. According to the above criterion, they would be classified as predominantly rural areas.

One option is that provided by Eurostat in the ECV, in which there is a variable that represents the degree of urbanisation with three possible categories combining total population and population density: densely populated areas, semi-urban or intermediate areas, and sparsely populated areas. Although this classification has the clear advantage of being directly available in the same dataset used in the analysis without the need for recoding, it suffers some of the problems of the previous classification. Other studies have chosen to define a classification considering the municipal population. EDIS *et al.* (1999) and Jurado and Pérez-Mayo (2008) applied the same classification, which divides the municipalities into four clusters only depending on the number of inhabitants. However, a purely population-based criterion makes this classification insufficient for the study of heterogeneous rural areas.

To compensate for the limitations noted above, in this paper we use a classification based on eight categories or area groupings, according to the criteria defined by Pereira

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[4] A more detailed description of using the EU-SILC database to measure material deprivation can be found in Perez-Mayo (2005) and Ayala et al. (2011).

et al. (2004). In addition to the size and density of the population, the productive specialization of the various rural areas is also considered:

1) Urban areas: more than 160 inhabitants per km^2 or more than 500,000 inhabitants;
2) Other intermediate areas: between 80 and 160 people per km^2 or more than 10% of the utilized agricultural area under irrigation;
3) Scattered rural communities: areas with 30 or more small villages;
4) Arable crops and agricultural smallholdings: over 40 % of utilized agricultural area is devoted to cereal and holdings with more than 200 hectares account less than 50% of the agricultural land;
5) Arable crops and agricultural large holdings: over 40 % of utilized agricultural area is devoted to cereal and holdings with more than 200 hectares accounts 50% or more of the agricultural land;
6) Permanent pastures (including meadows) and agricultural smallholdings: over 40% of utilized agricultural area is devoted to grazing and holdings with more than 200 hectares account less than 50% of the agricultural land;
7) Permanent pastures (including meadows) and agricultural large holdings: over 40 % of utilized agricultural area is devoted to grazing and holdings with more than 200 hectares account 50% or more of the agricultural land;
8) Mountain areas: areas with more than 50% of their land area above 1,000 metres or with more than 48% of their land with a slope greater than 3%.

This classification of areas, which is much more disaggregated than the previous ones, considers a greater heterogeneity in the deprivation analysis than that used in previous studies. If this classification is applied to data from the last Census of Population and Housing (2011), it is possible to work with 326 areas, with data from more than 8,000 municipalities.

When individuals and households from the survey's microdata are grouped according to the above criteria, some categories have a low representation in the sample. Because of this restriction, some clusters that are relatively homogeneous in their main characteristics have been combined, changed from eight into the following six categories (percentage of the total population in brackets): urban areas (69.4%), other intermediate areas (15.8%), scattered rural communities (1.8%), arable crops and permanent pastures (including meadows) smallholdings (3.9%), arable crops and permanent pastures (including meadows) large holdings (5.7%), and mountain areas (3.4%).

One way to verify the heterogeneity in living conditions in the different areas defined is to check whether situations of income poverty differ from one another, estimated as the population percentage with an income per equivalent adult of below 60% of the median. Table 1 shows the poverty rates in the different areas for the two years under study. It can be observed how, according to the national threshold, almost 20% of the population earned an income of less than 60% of the national median in 2005. After the first years of the crisis, the rate significantly increased to 22.2%. However, this increase was not equally distributed among the different areas. The most prominent characteristic is the difference between urban and rural areas. Before the economic crisis, the rates in urban areas were more than 10% lower than the national average, in stark contrast to each rural area defined. In some, such as arable crops and large holdings and permanent pastures and large holdings, the rates were nearly 70% higher than the average. However, these differences narrowed with the prolonged economic crisis, though the best relative situation of urban areas remained.

[TABLE 1]

Table 1 also illustrates the wide range of variation among rural areas. In 2005, the highest poverty rates were recorded in arable crops large holdings and in permanent pastures large holdings. During the crisis, the rates in scattered rural communities significantly decreased and more moderately decreased in arable crops of both types, in permanent pastures large holdings and in mountain areas, though they increased in other intermediate areas and particularly in urban areas. The issues of job losses and falling wage income were particularly concentrated in the latter, whereas in most rural areas stability in income of much of the population due to the maintenance of the purchasing power of pensions favoured the drop in relative poverty rates.

2. A LATENT CLASS MODEL FOR MULTIDIMENSIONAL DEPRIVATION IN HETEROGEOUS AREAS

2.1. Latent class model

The literature provides a wide range of possibilities to build a synthetic index of multiple deprivation. The very choice of a synthetic indicator is, in fact, the result of a concrete decision, given that most datasets provide a full battery of indicators of deprivation; and the first choice is whether to use a synthetic measure or the joint consideration of the different items. Some studies follow a *counting approach* (Berthoud and Bryan (2011), and Chzhen *et al.* (2016)), where individuals are identified as deprived if they show deprivation in one or more indicators. Similarly, the official indicator of the European Union, as shown by Guio (2009) and Guio and Marlier (2013), estimates material deprivation as severe when households report deprivation in a number of the indicators of the selected set.

To summarize the information contained in several partial indicators of deprivation or material deprivation, it is first necessary to determine the weighting that each of them should have. The simplest method is to assign the same weighting to all partial indicators, as initially proposed by Townsend (1979). This option is found not only in pioneering studies on multidimensional deprivation but also in the methodology used by Eurostat in its official indicator of severe material deprivation. The main disadvantage of this approach lies in its simplicity. However, this uniform weighting has the advantage of a possible minor arbitrariness. Although it is considered that not all indicators are equally important, there may be no information on the need for the goods and services considered. The researcher's decision regarding the degree of need may cause biases in the results, which in some cases can be lower if uniform weighting is chosen.

Some alternatives to estimate the importance of each attribute from the information collected in the observed values have been proposed. According to most proposals, an indicator reflects greater deprivation when the item is more widespread in the general population. An alternative proposal presented by Guio and Marlier (2013) and Boarini and Mira D'Ercole (2013) is the use of the declared importance for each indicator of deprivation from the Eurobarometer or other surveys. These authors understand that this declared relevance can be equivalent to the social perception of the importance of each item. Other authors propose alternative and more complex procedures applied to the observed frequencies, like multivariate statistical techniques.

The methodological approach followed in this paper belongs to the group of latent variable models. Specifically, a latent class model is proposed, which helps estimate or measure a variable that is not directly observable as deprivation, based on the information in a set of directly observable indicators. The latent class model is chosen for two reasons. These models use the information gathered in discrete variables to identify groups in the population, defined as classes or categories of the unobservable variable. Simultaneously, it can be observed that the indicators used are mostly dichotomous or binary variables that indicate deprivation or not in a particular aspect of the living conditions of households. In addition, the identification of different groups in the population according to their level or profile of deprivation helps solve, or at least reduce, the problem of arbitrariness produced by the choice of deprivation threshold. Our measurement procedure is similar to those used in Perez-Mayo (2005), Ayala and Navarro (2007) or Ayala et al. (2011).

As a starting point, assume that there is a set of p partial indicators of deprivation (x_1, ..., x_p), with a number of categories I_1,..., I_p. There is an x_q latent variable with a total of J classes representing multidimensional deprivation.[5] Given these assumptions, it is possible to build the basic equations of the model as follows:

$$\pi_{i_1 \dots i_p} = \sum_{j=1}^{J} \pi_{i_1 \dots i_p j}, \qquad [1]$$

where

$$\pi_{i_1 \dots i_p j} = \pi_j \pi_{i_1 \dots i_p | j} = \pi_j \pi_{i_1 | j} \dots \pi_{i_p | j}. \qquad [2]$$

[5] Here we summarize the basic points in the development of the latent class model. For a more developed formalization of the model adapted to the case of multidimensional deprivation see Pérez-Mayo (2005, 2007).

and $\pi_{i_1 \ldots i_{pj}}$ represents the likelihood of the joint distribution ($x_1,\ldots,x_p;x_q$). Moreover, π_j is the likelihood of belonging to the j latent class, and $\pi_{i_1 \ldots i_p|j}$ is the likelihood of having a specific response pattern, given that $x_q=j$. The remaining parameters π are probabilities given the former ones.

These parameters are estimated by using the expectation-maximization (EM) algorithm proposed by Dempster *et al.* (1977), which is a cycle of estimations and likelihood maximizations until convergence is reached, under the following restrictions:

$$\sum_{i_1=1}^{I_1} \pi_{i_1|j} = \cdots = \sum_{i_p=1}^{I_p} \pi_{i_p|j} = 1 \text{ and } \sum_{j=1}^{J} \pi_j = 1 \qquad [3]$$

Once the process is finished, the maximum likelihood estimates are obtained:

$$\hat{\pi}_{i_1|j} \ldots \hat{\pi}_{i_p|j} \text{ and } \quad \hat{\pi}_j \qquad [4]$$

from which it is possible to calculate the joint probabilities:

$$\hat{\pi}_{i_1 \ldots i_{pj}} \text{ y } \hat{\pi}_{i_1 \ldots i_p} = \sum_{j=1}^{J} \hat{\pi}_{i_1 \ldots i_{pj}} \qquad [5]$$

Although the joint and conditional probabilities would have already been estimated, the analysis do not end yet because the class sizes must be computed. From the probabilities estimated in the previous steps, the conditional probabilities of belonging to each latent class given the $(i_1,\ldots,i_p)$ categories of the observed indicators $x_1,\ldots,x_p$ are:

$$\hat{\pi}_{j|i_1 \ldots i_p} = \frac{\hat{\pi}_{i_1 \ldots i_{pj}}}{\sum_{j=1}^{J} \hat{\pi}_{i_1 \ldots i_{pj}}}. \qquad [6]$$

It is a three-steps process because the joint and conditional probabilities are estimated first and, afterwards, the Bayes theorem is applied to reverse the direction of conditionality. The last step consists of assigning each observation (household or individual) to the most likely latent cluster given their response patterns (the modal conditional probability). Therefore, since those modal probabilities are used, the classification error –that is, the probability of being misclassified- should be taken into account by using the following expression for all the observations:

$$E = \sum_{i_1=1}^{I_1} \Lambda \sum_{i_p}^{I_p} \pi_{i_1 \mathrm{K}\, i_p} \varepsilon_{i_1 \mathrm{K}\, i_p} \qquad [7]$$

where $\varepsilon_{i_1 \mathrm{K}\, i_p}$ is the individual likelihood of being misclassified.

Once deprivation is estimated, the discussion of the actual role of the spatial dimension can be included in the analysis by means of the multi-group latent class models or simultaneous latent-class analyses across groups (Kankaras and Vermunt, 2014). Those models are an extension of the expression [1] to datasets where an observed covariate divides them into some groups. In fact, the database can be splitted into some clusters –spatial areas- before and, therefore. These models check the existence of measurement equivalence across groups. Such assumption is related to the level of by-group similarity of response patterns given the latent class membership. Figure 1 helps to understand the alternative models that can be found by depending on the influence of spatial areas in latent and response probabilities.

[FIGURE 1]

Naming A the variable representing the spatial areas, D the latent variable that provides the estimated level of deprivation and I the set of observed variables or indicators, Figure 1(a) shows the complete homogenous model because there is no link between A and D or I. This absence of links means that the response and latent probabilities are independent of the group –in this case, spatial area– the individuals belong to. Therefore, comparison between groups is impossible and non-required because neither response patterns nor latent probabilities depend on the spatial areas the individuals live. The other extreme case presented in Figure 1(c) is the unrestricted structural latent class model which assumes full heterogeneity by allowing all the parameters to be different across groups. Hence, since all measurement model parameters are group-specific, group comparability is very difficult.

Comparability is the main objective when structural latent class models are applied. Comparing the latent classes across groups involves imposing across-groups restrictions on the model parameters (Figure 1b). This constraint involves that the conditional response probabilities are equal across groups -in our case, response patterns are the same in each area. However, sometimes only some of the parameters are restricted to be equal. These alternative models are called partially homogenous (Clogg and Goodman, 1985).

Although measurement equivalence can be assessed by using one of three types parameterizations of the multigroup latent model[6], using linear-logistic parameters make easier to consider several versions of partial homogeneity. The probabilistic parameterization can be used when the only goal is testing the assumption of measurement equivalence and all the variables are nominal by equating the class-specific response probabilities across groups (Clogg and Goodman, 1985; Hagenaars and McCutcheon, 2002). On the contrary, by using the linear-logistic parameters, the conditional response probabilities of each indicator i_k in equation [2] given j-th latent class and a-th spatial area can be expressed as:

$$\pi_{i_k|ja} = \frac{exp\left(\alpha_{i_k|a}+\beta_{i_kj|a}\right)}{\sum_{i_k} exp\left(\alpha_{i_k|a}+\beta_{i_kj|a}\right)} \quad [8]$$

In this case, the unrestricted latent model involves different intercepts and slopes across groups while the partially homogeneous model allows the former to vary across groups and it requires that the latter are group-equal. Finally, the structural homogeneous (measurement equivalence) model, which considers that groups directly have influence in latent variables and the response patterns are assumed to be equal across groups, can be computed from equation [8] with the same intercepts and slopes in every group.

2.2. Application of the latent class model to the ECV

[6] This model can be expressed by using conditional probabilities, log-linear parameters, or linear-logistic item parameters (Kankaraš, Moors and Vermunt, 2010).

To estimate the latent class model and measure the degree of material deprivation in the ECV, deprivation indicators must first be selected. The variables chosen as indicators to estimate deprivation are related to the common living conditions of households –the ability to pay unexpected expenses, the inability to afford a one-week annual holiday, a meal with meat, chicken, fish or vegetarian equivalent every second day, having a car or computer, and being confronted with payment arrears[7]– together with deficiencies in housing conditions, such as trouble keeping the adequate heating of a dwelling in winter. These indicators are selected because they are part of the set of items used by both Eurostat and the Spanish National Statistics Institute (INE) in their indicators of severe material deprivation and material deprivation, respectively. In addition to the indicators noted above, this paper includes two other indicators that have already been used by other authors (Martínez and Navarro, 2015): housing cost overburden and the degree of overcrowding. These are two potentially relevant indicators in the case of Spain.

[TABLE 2]

Having described the indicators to be used in the estimation, it is necessary to decide which model will be selected.[8] The choice of the best model will determine the number of groups (classes) of the latent variable (multiple deprivation) that can be identified in the population. The results in Table 2 show that the most appropriate model is that which identifies three population groups according to their level of deprivation. According to the most common indicator, the L^2 statistic, not only the hypothesis of independence –the results confirm that there are latent groups in the population– but also the remaining estimated models should be rejected. The BIC prioritizes models with the lowest values, which in this case are those that consider three and four population groups. This choice is also supported by the increased likelihood when the number of classes is extended: moving from the model of independence to a two-class model improves the likelihood by almost 79%; and in the three- and four-class models, the likelihood increases by 85% and 87%, respectively. To discriminate between these two models, the information from the indicator of classification error (E) is used. The

[7] It is assumed that a household is confronted with payment arrears if it occurs in at least in one of the following payments: rental housing, mortgage, supplies, and other loan-related payments
[8] Latent Gold 4.5 software was used to estimate the models and probabilities.

two-point improvement in the likelihood by using the four-class instead of the three-class model contrasts with the increased classification error, which rises from 14% to 20%.

Therefore, the selected model is that which involves three different underlying groups in the population. It seems reasonable to consider an intermediate group of individuals who show deprivation in some indicators but who do not belong to extreme categories. This is complemented by the analysis of profiles and conditional likelihoods by adopting the four-class model in two intermediate categories with the same profile and slight differences in likelihoods within the profile. The gains in explanatory capacity lead to improvements in explaining the problem.

[TABLE 3]

To contribute to comparability in the two years that constitute the time reference of the analysis, the same methodological options are applied to data for the year 2012. Again, the results in Table 3 show that the three-class model is preferred due to the balance between improvement in explanatory power and classification error. Although the four-class model presents a smaller and therefore more appropriate BIC statistic, it does not significantly improve the explanation of the data observed, and it has a slightly higher classification error. Furthermore, the analysis of the estimated profiles for this latter model does not show relevant information that supports theoretical conclusions that are different from those of the three-class model.

3. MULTIDIMENSIONAL DEPRIVATION IN RURAL AREAS

3.1. Deprivation in rural areas before the crisis

Prior to the crisis, a small group of the population (5.3%) showed a severe degree of deprivation, whereas more than half of all individuals could be described as 'non-deprived' (Table 4). The remaining population can be identified as in a situation of moderate deprivation after the analysis of conditional likelihoods or profiles (the likelihood of experiencing deprivation in an indicator, given the belonging to a particular group of deprivation). This intermediate group can be defined as a vulnerable group that can meet basic needs, though there is deprivation or risk of deprivation in some goods or activities.

[TABLE 4]

Table 5 reports that, in terms of the urban-rural dichotomy, deprivation is in general less relevant in urban areas, though this is not the case in mountain areas and in smallholdings. The fact that severe material deprivation is greater than in urban areas only in areas where large holdings predominate also stands out. Therefore, the situation before the crisis was characterized by a slightly higher incidence of deprivation in general in rural areas but with a lower intensity than that of urban areas[9].

[TABLE 5]

Another striking feature from the comparison of the different geographical areas is the diversity of results in rural areas, with indicators of severe material deprivation in large holdings being four times higher than in smallholdings and mountain areas. Both findings reinforce the idea of the singularity of rural areas in the assessment of living conditions and of a marked heterogeneity among the different areas.[10]

[TABLES 6a and 6b]

Tables 6a and 6b report the results of estimating the different structural latent class models before and after the crisis. Leaving aside the full homogeneous model –no relationship between spatial areas and latent classes and response patterns– the statistics are very similar for the rest of the models, and the increase in explaining power of the structural homogeneous stands out. Therefore, the assumption of structural homogeneity, that is, the influence of spatial areas on deprivation while the reference framework for response pattern is national, can be accepted. Living in a specific area affects the relative risk of being deprived whenever deprivation is measured, so that

[9] If each combination of observed indicators was assigned to one latent class based on the modal probabilities instead of the average risks or probabilities, the incidence rates would be slightly different from the reported data because of classification error.

[10] Due to space constraints, it was not possible to include a detailed comparison of the results using national and area reference frameworks. These results are available from the authors upon request.

some rural areas show higher relative risks that the urban areas, the usually accepted fact in the political discussion.

3.2. Deprivation in rural areas after the crisis

The severity of the crisis in Spain, with a deep deterioration in household income and a dramatic growth in the unemployment rate to greater than 25%, caused a rapid growth in the incidence of monetary poverty. It went from a rate below 20% in 2005 to 22.2% in 2012, despite the continued lowering of the threshold due to a reduction in the median income. As shown in previous sections, this growing relative poverty affected rural areas to a lesser extent, except in a few cases in which the opposite evolution occurred. Therefore, it seems appropriate to analyse whether a similar process occurred in the case of multidimensional deprivation.

[TABLE 7]

By using the same methodology as with the data for 2005, the results in Table 7 show an important change in the incidence of deprivation in the entire country. Although the percentage of non-deprived remained stable during the crisis, there was a marked change in the deprivation profiles. Severe deprivation situations gained weight and affected 10% of the population, more than twice as high as in the pre-crisis situation at the expense of fall in moderate deprivation. That is, deprivation does not become wider but deeper.

[TABLE 8]

Unlike what was observed in the case of monetary poverty, material deprivation (moderate plus severe) slightly decreased in all areas except for large holdings (Table 8). A significant increase also occurred in the most severe forms of deprivation, particularly in smallholdings and mountain areas. Moreover, only in arable crops and permanent pastures large holdings material deprivation became more extensive and more severe than what it was before the economic crisis. Rural areas, which are typically regarded as a haven against changes in macroeconomic conditions, may have been less resistant to the effects of the economic downturn in terms of living conditions than in terms of insufficient household income.

4. DECOMPOSITION OF THE CHANGE IN MULTIDIMENSIONAL DEPRIVATION IN EACH AREA

The variations observed in the extent and structure of deprivation in each type of geographic area during the crisis period may be due to two causes. The changes in each area after the crisis may be caused because the incidence of each partial indicator of deprivation has changed and because the likelihood of belonging to the group of greater deprivation is different in both periods. To analyse the weight of each possible determinant, we evaluate the changes in deprivation between the two time references by drawing upon an approach that is similar to that originally proposed by Datt and Ravallion (1992) regarding monetary poverty. These authors decompose variations in poverty rates between the initial and final periods into two components, growth and inequality.

The variation in the incidence of deprivation during the economic crisis can be expressed as a linear combination of changes explained by different patterns of response, on the one hand, and by the different probability structures, on the other hand. Assume that the deprivation rate in period t is expressed as follows:[11]

$$p^t = \frac{\sum n^t_{i_1 \dots i_p 1}}{N} \qquad [9]$$

If estimated rates are used instead of observed, as $\hat{n}^t_{i_1 \dots i_p 1}$ equals $n^t_{i_1 \dots i_p} \hat{\pi}^t_{i_1 \dots i_p}$, that is, the product of the frequency of each response pattern by the conditional likelihood of suffering from high deprivation given this response pattern, the estimated deprivation rate can be written as follows:

$$\hat{p}^t = \frac{\sum n^t_{i_1 \dots i_p} \hat{\pi}^t_{1|i_1 \dots i_p}}{N} \qquad [10]$$

[11] Sub-index 1 is used for the latent class to identify the class characterized by a higher level of deprivation.

To simplify the expression and its implementation, it is preferable to work with relative frequencies rather than absolute frequencies, such that:

$$\hat{p}^{t} = \sum f^{t}_{i_1 \ldots i_p} \hat{\pi}^{t}_{1|i_1 \ldots i_p} \qquad [11]$$

By applying expression [12] to the years considered, the variation in the incidence of deprivation between 2005 and 2012 can be expressed as follows:

$$\hat{\mathrm{p}}^{12} - \hat{\mathrm{p}}^{05} = \sum \mathrm{f}^{12}_{\mathrm{i}_1 \ldots \mathrm{i}_\mathrm{p}} \hat{\pi}^{12}_{1|\mathrm{i}_1 \ldots \mathrm{i}_\mathrm{p}} - \sum \mathrm{f}^{05}_{\mathrm{i}_1 \ldots \mathrm{i}_\mathrm{p}} \hat{\pi}^{05}_{1|\mathrm{i}_1 \ldots \mathrm{i}_\mathrm{p}} \qquad [12]$$

This expression does not make it possible to independently analyse the effects of changes in partial deprivations and likelihood structures. To that end, by adding and subtracting, the following term $\sum f^{12}_{i_1 \ldots i_p} \hat{\pi}^{05}_{1|i_1 \ldots i_p}$is included to the right of expression [12]:

$$\hat{p}^{12} - \hat{p}^{05} = \sum f^{12}_{i_1 \ldots i_p} \hat{\pi}^{12}_{1|i_1 \ldots i_p} - \sum f^{12}_{i_1 \ldots i_p} \hat{\pi}^{05}_{1|i_1 \ldots i_p} + \sum f^{12}_{i_1 \ldots i_p} \hat{\pi}^{05}_{1|i_1 \ldots i_p} - \sum f^{05}_{i_1 \ldots i_p} \hat{\pi}^{05}_{1|i_1 \ldots i_p} \qquad [13]$$

By grouping the common terms, the above expression can be rewritten as follows:

$$\hat{p}^{12} - \hat{p}^{05} = f^{12}_{i_1 \ldots i_p} \sum \left(\hat{\pi}^{12}_{1|i_1 \ldots i_p} - \hat{\pi}^{05}_{1|i_1 \ldots i_p} \right) + \hat{\pi}^{05}_{1|i_1 \ldots i_p} \sum \left(f^{12}_{i_1 \ldots i_p} - f^{05}_{i_1 \ldots i_p} \right) \qquad [14]$$

The first component of the expression reflects the influence of the changes in the probability structure weighted by the relative incidence in 2012, and the second shows the effect of changes in the relative incidence weighted by the structure of likelihoods in 2005. If the linear-logistic parametrization is used instead of the probabilistic one, the estimated deprivation rate in year *t* can be expressed as $\hat{p}^{t} = \overline{F(X^{t\prime} \beta^{t})}$, where the right term is the average probability of being deprived and the response pattern are represented in X^{t}. By using this in the previous expression, it can be written as:

$$\hat{p}^{12} - \hat{p}^{05} = \overline{F(X^{12\prime}\beta^{12})} - \overline{F(X^{05\prime}\beta^{05})}$$

$$= \underbrace{\overline{F(X^{12\prime}\beta^{12})} - \overline{F(X^{12\prime}\beta^{05})}}_{probabilities} + \underbrace{\overline{F(X^{12\prime}\beta^{05})} - \overline{F(X^{05\prime}\beta^{05})}}_{indicators} \quad [15]$$

Equation [15] is very similar to the Oaxaca-Blinder decomposition proposed for wage discrimination and used for deprivation differences in Ayala et al (2011).

[TABLE 9]

Table 9 shows the results of decomposition. This table first shows the differences in the incidence of deprivation and then shows the component due to changes in patterns and the part of the change observed due to the variation in conditional likelihoods. One must bear in mind that the estimated incidence of deprivation depends on both the observed indicators of deprivation and conditional likelihoods of presenting these types of deprivation due to belonging to a particular latent group.

The first of these components shows what part of the observed difference is exclusively due to changes in the indicators of deprivation, such as being confronted with payment arrears or keeping the adequate heating of a dwelling. That is, it expresses how much deprivation would have changed if the conditional likelihoods or likelihoods of response had remained constant. The component presented in the last column of Table 9 shows the effect caused only by the conditional likelihoods. It answers the question of what would have occurred if the distribution of observed deprivation had remained constant and if only its relative importance had changed -the conditional likelihood. It is important to make this distinction to discover the extent to which the increase observed in the crisis is due to changes in the living conditions of individuals or the different level of relative importance of such conditions.

The analysis shows how, despite the prominence of the effect of changes in the likelihood structures, the incidence of each partial deprivation has a positive sign. That is, deprivation would have increased in most areas even though the relative importance of each indicator had been maintained. Thus, the important effect of the economic crisis on multidimensional deprivation is identified. The exception, albeit with a very slight value, is found in scattered rural communities. However, the changes in the relative weights of the deprivation indicators lead one to consider a greater degree of deprivation.

Moreover, the analysis also helps to check again the impact of the crisis on deprivation in rural areas, generally with higher increases, though with marked heterogeneity, than that observed in urban areas. Therefore, it can be stated that the crisis has affected rural areas in their direct living standards indicators. Simultaneously, the results obtained belie the common stereotype that the greatest incidence of monetary poverty in rural areas is offset by better living conditions.

5. CONCLUSION

The changes in rural areas in recent decades have affected the income and living conditions of household residents in these habitats. This evolution, marked by the gradual ageing of the population and its exodus to cities, in addition to the situation of the productive activity of the primary sector, has led to very heterogeneous situations in rural areas. This variety barely corresponds to the assumed uniformity from which this reality is typically analysed.

In this paper we have analysed the heterogeneity in situations of multidimensional deprivation in various types of habitats and the different levels of intensity of the effects of the crisis in each area. The wealth of information shows that there are notable differences in the extent of these issues both between urban and rural areas and within the latter.

Unlike what some studies on monetary poverty show, it appears that there is a lower incidence of severe material deprivation in certain rural areas, though there is a wide variety of experiences, which makes it difficult to speak of consistent results. In almost all of the rural habitats considered, the incidence of moderate deprivation is greater than in urban areas, except in smallholdings and mountain areas. Severe deprivation is higher in urban areas, with the exception of large holdings. This diversity should be considered when developing and designing public initiatives that consider the multidimensionality of deprivation.

Both the estimation of various types of deprivation indicators and the decomposition analysis of their changes over time make it possible to affirm that the crisis has had a particularly significant impact on some of these areas. Severe deprivation has increased in almost all rural areas, though the relative improvement in household income –due to the greater stability of social security transfers– has reduced the incidence of monetary poverty. In any case, rural areas have not been spared from the impact suffered by most of the population. More difficulties added to those already occurring before the sharp slowdown in economic activity.

The economic crisis has negatively affected direct indicators of the living standards in rural areas. Moreover, the observed results belie the common stereotype that the greatest incidence of monetary poverty in rural areas is offset by better living conditions. To be effective, the necessary reduction of the problems of multidimensional deprivation should address the marked heterogeneity of the effects by types of rural areas, which makes it necessary to consider the complexity of each area and the diversity of the demographic and economic structures of each environment.

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Table 1. Poverty rates by types of area

Areas	Poverty rate 2005	Poverty rate 2012
Urban areas	17.4	20.5
Other intermediate areas	23.0	25.5
Scattered rural communities	22.4	15.5
Arable crops and permanent pastures smallholdings	28.4	27.1
Arable crops and permanent pastures large holdings	33.2	31.5
Mountain areas	23.1	22.0
TOTAL	19.9	22,2

Table 2. Latent class models for deprivation, 2005

Model	L^2	Df	Prob	E	$\Delta\%L^2$	BIC
Independence	27994	502	$1.6x10^{-5535}$	0.000	0.0000	22708
2 classes	5888	492	$7.6x10^{-910}$	0.073	0.7897	707
3 classes	4130	482	$1.7x10^{-570}$	0.141	0.8525	-945
4 classes	3526	472	$4.1x10^{-460}$	0.204	0.8741	-1444

Table 3. Latent class models for deprivation, 2012

Model	L^2	df	Prob	E	$\Delta\%L^2$	BIC
Independence	34371	502	$5.2x10^{-6898}$	0.000	0.0000	29140
2 classes	4990	492	$1.6x10^{-732}$	0.046	0.8548	-137
3 classes	2910	482	$3.1x10^{-342}$	0.127	0.9153	-2112
4 classes	2299	472	$1.6x10^{-237}$	0.130	0.9331	-2619

Table 4. Latent profiles of deprivation, 2005

		No deprivation	Moderate deprivation	Severe deprivation
Latent class likelihood		0.5521	0.3949	0.0530
	Conditional likelihoods			
Payment arrears	Non-deprived	0.9827	0.9081	0.5156
	Deprived	0.0173	0.0919	0.4844
Paid holidays	Non-deprived	0.8820	0.2100	0.0834
	Deprived	0.1180	0.7900	0.9166
Keeping adequate heating	Non-deprived	0.9784	0.8651	0.4829
	Deprived	0.0216	0.1349	0.5171
Unforeseen expenses	Non-deprived	0.9434	0.3350	0.0404
	Deprived	0.0566	0.6650	0.9596
Eating meat or fish every other day	Non-deprived	0.9980	0.9716	0.7855
	Deprived	0.0020	0.0284	0.2145
Having a computer	Non-deprived	0.9834	0.7773	0.4924
	Deprived	0.0166	0.2227	0.5076
Owning a car	Non-deprived	0.9943	0.9130	0.5082
	Deprived	0.0057	0.0870	0.4918
Housing cost overburden	Non-deprived	0.9506	0.9123	0.7385
	Deprived	0.0494	0.0877	0.2615
Overcrowded household	Non-deprived	0.9701	0.8830	0.6195
	Deprived	0.0299	0.1170	0.3805

Table 5. Deprivation risk by area, 2005

Area	No deprivation	Moderate deprivation	Severe deprivation
Urban areas	56.01	38.40	5.59
Other intermediate areas	53.68	41.22	5.09
Scattered rural communities	52.01	43.14	4.85
Arable crops and permanent pastures smallholdings	58.24	39.23	2.53
Arable crops and permanent pastures large holdings	46.84	47.00	6.16
Mountain areas	57.85	39.81	2.34
Total	55.21	39.49	5.30

Table 6a. Structural latent class models for deprivation, 2005

Model	L^2	df	Prob	E	$\Delta\%L^2$	BIC
Full homogeneity	4130	482	1.7×10^{-570}	0.1410	0.0000	-945
Unrestricted	6436.73	2892	4.4×10^{-270}	0.1248	0.5585	-24015.15
Structural homogeneity	8038.03	3027	9.6×10^{-332}	0.1399	0.9463	-23835.35
Partial homogeneity	7071.51	2982	4.1×10^{-460}	0.1344	0.7122	-24328.03

Table 6b. Structural latent class models for deprivation, 2012

Model	L^2	df	Prob	E	$\Delta\%L^2$	BIC
Full homogeneity	2910	482	3.1×10^{-342}	0.1270	0.0000	-2112
Unrestricted	4809.86	2892	1.6×10^{-99}	0.1036	0.6525	-25327.86
Structural homogeneity	6401.13	3027	3.4×10^{-243}	0.1210	1.1997	-25143.42
Partial homogeneity	5362.36	2982	1.6×10^{-139}	0.1166	0.8427	-25713.24

Table 7. Latent profiles of deprivation, 2012

		No deprivation	Moderate deprivation	Severe deprivation
Latent class likelihood		0.5500	0.3475	0.1025
	Conditional likelihoods			
Payment in arrears	Non-deprived	0.9887	0.8632	0.4656
	Deprived	0.0113	0.1368	0.5344
Paid holidays	Non-deprived	0.8714	0.8482	0.0166
	Deprived	0.0113	0.1368	0.9834
Keeping adequate heating	Non-deprived	0.9913	0.8765	.5737
	Deprived	0.0087	0.1235	0.4263
Unforeseen expenses	Non-deprived	0.9360	0.1805	0.0140
	Deprived	0.0640	0.8195	0.9860
Eating meat or fish every other day	Non-deprived	0.9998	0.9728	0.8440
	Deprived	0.0002	0.0272	0.1560
Having a computer	Non-deprived	0.9909	0.9253	0.6592
	Deprived	0.0091	0.0747	0.3408
Owning a car	Non-deprived	0.9890	0.9490	0.6725
	Deprived	0.0110	0.0510	0.3275
Housing cost overburden	Non-deprived	0.9439	0.8391	0.5042
	Deprived	0.0561	0.1609	0.4958
Overcrowded household	Non-deprived	0.9793	0.9325	0.7746
	Deprived	0.0207	0.0675	0.2254

Table 8. Deprivation risk by area, 2012

Area	No deprivation	Moderate deprivation	Severe deprivation
Urban areas	55.47	33.99	10.53
Other intermediate areas	52.62	37.39	9.98
Scattered rural communities	61.69	32.66	5.65
Arable crops and permanent pastures smallholdings	58.44	34.42	7.14
Arable crops and permanent pastures large holdings	47.45	40.47	12.10
Mountain areas	61.72	29.77	8.51
Total	0.5500	0.3475	0.1025

Table 9. Decomposition of differences in deprivation 2005-2012

Area	Difference in deprivation	Changes in patterns	Changes in probabilities
Urban areas	0.0494	0.0097	0.0397
Other intermediate areas	0.0489	0.0100	0.0389
Scattered rural communities	0.0080	-0.0141	0.0222
Arable crops and permanent pastures smallholdings	0.0461	0.0149	0.0311
Arable crops and permanent pastures large holdings	0.0593	0.0158	0.0434
Mountain areas	0.0616	0.0336	0.0280
Total	0.0495	0.0108	0.0387

Figure 1. Relationship between variables in multi-group latent class models