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Abstract

The aim of this paper is to analyze the causes leading to social exclusion dynamics. In particular, we wish to understand why any individual experiencing social exclusion today is much more likely to experience it again. In fact, there are two distinct processes that may generate a persistence of social exclusion: heterogeneity (individuals are heterogeneous with respect to some observed and/or unobserved adverse characteristics that are relevant for the chance of experiencing social exclusion and persistence over time) and true state of dependence (experiencing social exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods). Distinguishing between the two processes is crucial since the policy implications are very different.

Keywords: Social Exclusion, Dynamics, Persistence, Heterogeneity, Discrete panel data model.

JEL – code: I30, C23, C25

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1. Introduction

Social policy debates have often focused on social exclusion in recent years in Europe and elsewhere. Social exclusion can be seen as a process that, fully or partially, excludes individuals or groups from social, economic and cultural networks and has been linked to the idea of citizenship (Lee-Murie, 1999). Therefore, social exclusion is a multidimensional process leading to a state of exclusion. Atkinson (1998) suggested three key elements in order to identify socially excluded individuals: *relativy, agency and dynamics*. Social exclusion involves the 'exclusion' of people from a particularly society, so to judge if a person is excluded or not, we have to observe the person relative to the context of the rest of the society she lives in. Moreover, exclusion implies a voluntary act (agency) and depends on how a situation and circumstances develop (dynamic process).

In order to promote social cohesion and inclusion (as explicitly required by the Lisbon Summit), the EU states have to identify not only the individuals most likely to be excluded but also who is most likely to remain excluded and who is most likely of becoming excluded. There is a growing literature that focuses on the definition of an appropriate measure of social exclusion and on the identification of who is socially excluded today (e.g. D'Ambrosio – Chakravarty 2002, Tsaklogou-Papadopoulos 2001, Nolan-Whelan-Maitre-Layte 2000). Other studies analysed the degree of exclusion by number of dimensions and by duration (e.g. Burchardt 2000, Burchardt et al. 2002). But, there are no studies focused on the causes of the dynamic process that leads the individual to be defined as socially excluded, as far as we know.

Questions regarding the causes of social exclusion persistence have to be central in the debate on the extent of social exclusion and public policies to address it. In fact, if social exclusion persists for many years, policymakers and others have good reasons for concern over the causes of such long-term exclusion. In addition, since government programs frequently provide assistance to those are excluded in a certain area, it is important to document the efficacy of such policy and, therefore, we need to verify if the individual is permanent, or only temporally, forced out of social exclusion.

The aim of this paper is to analyze the causes behind the dynamic process that we call social exclusion. In particular, we wish to understand if any individual experiencing social exclusion today is much more likely to experience it again. Moreover, we wish to understand better the process that may generate a persistence of social exclusion.

Persistence of social exclusion can depend from individual heterogeneity. In fact, individuals could be heterogeneous with respect to characteristics that are relevant for the chance of experiencing social exclusion and persistent over time. In this case, an individual experiencing social exclusion in any point of time because of adverse characteristics will also be likely to experience social exclusion in any other period because of the same adverse characteristics. These adverse characteristics can be observed (e.g. sex, level of education, household status) or unobservable. In the latter case, we speak about unobserved heterogeneity as a cause that may generate persistence of social exclusion.

We can also observe social exclusion persistent due to a process called true state of dependence. It means that experiencing social exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods (Heckman, 1978).

Distinguishing between the two processes is crucial since the policy implications are very different. If persistence of social exclusion is (at least partly) due to a true state of dependence, then it makes sense to force the individual out of social exclusion at time *t* in order to reduce his chance of experiencing exclusion in the future. Thus, it is logical to intervene on the dimensions that (at least partly) generated the true state of dependence in order to break the “vicious circle”. But if persistence of social exclusion is due only to unobserved heterogeneity any short-time policy aimed to force the individual out of social exclusion at time *t* is not really effective. In fact, forcing individuals out of social exclusion today does not affect their adverse characteristics, and therefore does not reduce their chance of experiencing social exclusion spells in subsequent periods.

This paper contributes to the literature on social exclusion in the following three ways. First, it provides an analysis of social exclusion persistence identifying the causes of exclusion: true state of dependence, unobserved heterogeneity and/or observed heterogeneity. Previous studies on social exclusion identified the population members at high risk of social exclusion and presented tabulations about the duration of social exclusion. However, they do not analyze, as we do, the processes that can lead to social exclusion persistence. Thus, we provide estimates of the extent to which the experience of social exclusion today increases the risk of being socially excluded in the future (true state of dependence), while controlling for differences in observed and unobserved characteristics between individuals (heterogeneity). Second, we consider eight dimensions as components of social exclusion. Previous studies on income, and earnings, suggested analyzing true dependence controlling for observed and unobserved heterogeneity. These studies focused only on one dimension: income or earnings. Instead, we perform a multidimensional analysis using an aggregate measure of social exclusion and studying every dimension separately. Third, we apply an econometric technique that has never been applied to neither social exclusion nor income, as far as we know. This technique, proposed by Wooldridge 2002, estimates consistently a logit model with both lagged dependent and exogenous variable to distinguish between to different sources of dynamics, true state dependence and heterogeneity.

In the next section, we shortly review the main literature about income (and earning) dynamics as well as studies about social exclusion dynamics. In section 3, we operationalize the definition of social exclusion and we define our binary measure of social exclusion. In section 4, we analyse how social exclusion evolves over time in Spain. In section 5, we present the dynamic model that we use to analyze the persistency of social exclusion. In section 6, the empirical results are given. In section 7, we discuss the robustness of our analysis performing sensitivity analysis in order to consider eventually problems on the definition of social exclusion. The last section concludes.

2. Literature review

Nowadays, a lot of studies focus on social exclusion mainly suggesting an appropriate definition of social exclusion and/or proposing an adequate social exclusion measure. However, only few of them pay attention to analyze its dynamics.

Burchardt (2000) looked across different dimensions of social exclusion at a single point in time, and traced the course individuals follow over time. She found that exclusion on a particular dimension (consumption, production, political engagement or social interaction) increases the exclusion on the same dimension in the following year. In a more recent study, Burchandt and Le Grand and Piachaud (2002) extended the analysis of Burchardt (2000) proposing a multidimensional dynamic measure of social exclusion to monitor the effectiveness of government policies. The empirical analysis in both studies is made using British data from the BHPS. [2]

Tsakloglou and Papadopoulos (2001) identified the population members at high risk of social exclusion in Europe. Following the idea that social exclusion is a dynamic process leading to deprivation, they construct static indicators of deprivation in particular fields (income, living conditions, necessity of

[2] British Household Panel Survey

life and social relations). Then, they aggregate this information in order to obtain a static indicator of cumulative disadvantage. So, individuals classified as being at high risk of cumulative disadvantage at least twice during the period of three years, are classified as being at high risk of social exclusion.

Nolan, Whelan, Layte and Maitre had produced a certain number of articles about poverty mobility and persistence of deprivation [3]: they mainly analyze persistence using tabulation of the duration of deprivation and poverty. The empirical analysis is a comparative study across European countries done using the European Community Household Panel (ECHP).

The general message that comes from the literature surveyed above is that approaches to the analysis of social exclusion dynamics mainly focus on the duration of social exclusion and on the identification of individuals at high risk of exclusion, without taking into account movements into and out of social exclusion and the causes leading to exclusion. Therefore, the main contribute of our study is to analyse the causes leading to social exclusion. The analysis is performed extending dynamic methods, normally used to explore income and poverty dynamics, to understand social exclusion.

Jenkins (2000) described four main types of dynamic models that have been applied in income and poverty dynamics literature to data. The first type of models describes different patterns of poverty dynamics in term of the fixed characteristics of the individual, and it identifies who experiences certain types of poverty transition (e.g. Gardiner and Hill, 1999). The second approach examines the chances of exit from, or entry into, poverty as function of observed characteristics of the individuals underlining who experience these events. In other words, it emphasizes which individual types are more likely to exit from, or entry in, poverty (e.g. Huff Stevens, 1999). The third approach seeks to explain the path of individual income in terms of observed characteristics and other non-observed processes in order to try to discover regularities in the process driving poverty dynamics. The final approach is to model the economic processes that underlie poverty transitions as function of observed and unobserved characteristics of the individual in order to identify the main characteristics, or events, that cause poverty dynamics (e.g. Burgess and Propper, 1998).

These approaches are reviewed is some detail in Jenkins (2000), so here we focus on the final method which we have adopted. The aim of this paper, as explained in the introductory section, is to analyse the causes leading to social exclusion persistence (unobserved heterogeneity and true state of persistence). Therefore, we need to model social exclusion allowing for a complex lag and error structure to capture dynamics. Recent papers, as Stevens (1999), Devicienti (2000) and Capellari – Jenkins (2002), focused on the question of unobserved heterogeneity and true state of dependence in poverty dynamics, and on the related issues of endogeneity of initial conditions and panel attrition. Related models have been also applied to transitions into and out of low earning (e.g. Stewart-Swaffield 1999). Trivellano et al. (2002) also tested for true state of dependence, in presence of unobserved heterogeneity, using Italian panel data. We propose an alternative answer to the problem of modeling unobserved heterogeneity and true state of dependence, as we explain in depth in section 4.

3. Definitions and data

We have defined social exclusion as a process that fully or partially excludes individuals or groups from social, economic and cultural networks in the society they live in. Social exclusion can also been seen as a part of the Sen's capability, and it can be defined as a process leading to a state of functioning deprivations.[4] Therefore, the "process" of social exclusion produces a "state" of exclusion that can be interpreted as a combination of some relevant deprivations. Thus, we use the following working definition of social exclusion:

"An individual is defined as socially excluded in a specific point in time if she is deprived of one or more relevant functionings".

This definition refers to the "state" of social exclusion, and it implies that an individual is defined as socially excluded at time t if he is deprived in at least one dimension, where every dimension represents one functioning.

To construct an indicator of the individual state of social exclusion based one the above working definition, we used the first six waves (1994-99) of the European Community Household Panel (ECHP). The ECHP is a multi-country comparative household panel survey conducted annually by following the same sample of households and persons in Member States of European Union. The advantage of the ECHP is that permits to analyze economic and social household conditions from a dynamic point of view.

[3] Social exclusion can be seen as a process leading to a state of deprivations (Sen, 2000)

Instead, the main disadvantage is the omission of the homeless populations that could be expected to be socially excluded.

Our working definition implies the following methodological problems in the construction of a summary measure of social exclusion. First, how to select the relevant functionings (dimensions) and the items representing them. Second, how to point out which individuals are deprived in every dimension. Third, how to aggregate the relevant functonings in a summary measure of social exclusion. These issues are discussed below.

Functionings selection

The issue of which are the relevant functionings to identify an individual as excluded, or how to select them, is subject to ongoing discussion since a complete list cannot be unequivocally compiled. However, some guidance is offered by Sen and by the "Scandinavian approach to welfare" as proposed by Brandolini-D'Alessio (1998). Following such guidance, we select eight relevant functionings (dimensions) to capture all the principal aspects of social exclusion.

The selected dimensions are "the basic need fulfillment", "having an adequate income", "to reach a certain quality of life", "to have an adequate house", "the ability to have social relationships", "being healthy", "living in a safe and clean environment", and "being able to perform a paid, or unpaid, work activity (social status)". The first four functionings describe the economic features of social exclusion, and the remaining four functionings emphasize the social dimension of exclusion. Unfortunately, our data does not permit us to analyze the political dimension of social exclusion.

Each of these dimensions represents a functioning considered important in its own rights. This is not deny that there are intersections between functionings, but rather to emphasize that the achievement of every functioning is regarded as necessary for social inclusion. Conversely, impossibility to achieve any one functioning is sufficient for social exclusion. Note that while some functioning deprivations can be themselves causes of exclusion, other functioning deprivations are only instrumentally causes of exclusion (Sen, 2000). In this second case, deprivations may not be impoverishing in themselves but they can lead to impoverishment of life through their causal consequences. Therefore, the environment conditions and ill health become important dimensions to analyze social exclusion, even if they are not

[4] Sen (2000)

constitutive causes of exclusion. Finally, we highlight that the educational qualification should also be included among the social exclusion dimensions since it is instrumentally cause of exclusion, but we have to omit it due to problems with the data.[5]

Table 1 summarizes the operationalization of the eight dimensions of social exclusion into items available in ECHP. For each selected item, we assigned to each individual a score ranging from zero to one. A score of one means that the individual can afford the item, has the item or does not have 'the problem'[6]. Instead, a score equal to zero means that the individual is deprived in that item. All the values among zero and one mean an intermediate situation. We aggregate the items corresponding to every functioning summing up their scores and dividing the result by the number of items. Equal weights are given to all items.[7] Thus, for each functioning, an individual receives a score between zero and one. A score of one means that the functioning has been fully achieved, a score of zero means that the functioning has not been achieved, and intermediate values represents intermediate situations.

Finally, we estimate the correlation existing between different items belonging to the same dimension, and between different dimensions: we found low degrees of association.

Summary measure of social exclusion

Inclusion or exclusion on each of the eight dimensions we selected is clearly a matter of degree. A functioning can be achieved at different levels at a point in time, and any choice about a threshold (below which the individual is counted as deprived) has some degree of arbitrariness. However, for convenience, we choose a deprivation threshold (cut-point) for each dimension at a point in time, and we combined the information about each dimension deprivations in a summary measure of social exclusion. For each individual, the score on such measure is one if the individual is socially excluded and zero otherwise.

In absence of endogenous rules, we fix the threshold in each dimension equal to the 50% of the functioning distribution mean. Every individual below the cut-point in dimension g is defined as deprived

[5] About 70% of the sample have less than the second stage of education, so we doubt that education can be consider as normal activity of the individual in the society she lives in. In fact, we consider "normal activity" every activity that is performed by at least the 50% of the population.
[6] For example, he can afford a durable or he has an indoor flushing toilet or he does not have pollution in the area he lives.
[7] See Brandolini and D'Alessio (1999) for more the details about the use of equal weights and alternative weighting structures.

in dimension *g*. Therefore, an individual can be deprived in one ore more dimensions. Moreover, we implicitly assume that anyone was able to achieve a valuable functioning would do so. Note that issues about the arbitrariness in the choice of the thresholds are addressed in Section 7, where a sensitivity analysis is performed.

Finally, as we have already stressed, our working definition of social exclusion implies that any deprivation in one functioning is sufficient for social exclusion. Therefore, an individual is counted as socially excluded at time *t* if she is deprived in at least one dimension.

3. Evidence of Social Exclusion and its persistence

Table 2 shows the proportion of the population aged 16+ who fell below the threshold in each dimension through the panel. In the 1993, we found that about 54.5% of the sample is socially excluded at least in one dimension. High deprivation rates are observed in the following dimensions: “living in a safe and clean environment”, “having an adequate income”, “being healthy”, and “being able to perform a work activity”. All of them, except “having an adequate income”, describe non-economic aspects of social exclusion. However, the proportion of the population counted as excluded is sensitive to the particular threshold chosen in every dimension: the higher the threshold, the more people result deprived in a certain dimension and, therefore, the more people appear socially excluded. So possibly of more interest than the level of social exclusion is the relationship between dimensions at a point in time and the pattern of exclusion over time.

Looking across dimensions of exclusion at a single point in time, we notice that less than 18% of people results deprived in at least two dimensions in 1993, less than 4% in a least three dimensions and only less than 1.05% of the individuals results deprived in more than three dimensions. As observed by Burchardt et al. (2002) studying U.K., there is no evidence of a concentration of individuals who are excluded in all the dimensions.

Connection over time in social exclusion is quite strong: social exclusion in one year is strongly associated with social exclusion in the following year (the correlation is about 0.4), and the association is only slightly lower in the subsequent years. Figure 1 shows how deprivation evolves over time in every dimension: it clearly decreases only in the dimensions “reaching a certain quality of life” and “living in a safe and clean environment”, even if the deprivation rates in 1999 result lower than the ones in 1994 for all the dimensions. Figure 2 shows the evolution of social exclusion during the panel: it decreases over time resulting about 10% lower at the end of the panel (see also Table 2).

Table 3 shows the pattern of exclusion of the individuals that are excluded for one wave or more during the panel. As time progress, an increasing proportion of the sample has some experience of exclusion, and, correspondingly, a decreasing proportion have never experienced exclusion during the panel. About 81% of the sample experienced social exclusion in at least one dimension and at least in one wave during the panel, but about 13% of the sample is excluded in at least one dimension in all the waves. The proportion of the sample who experiences some exclusion, but is not excluded throughout, is an indication of the degree of mobility into and out social exclusion. So, we observe a high degree of mobility in the sample through the panel. Note that we also observe a strong persistence in social exclusion since about 13% of the population is counted as excluded in all waves during the panel.

Focusing our attention on the duration and the frequency of the exclusion spells, we note that about 25% of the population is excluded in one or more dimensions in only one year, and 10.33% of the sample excluded in only one wave experiences multiple spells (see Table 4). About 13% of the entire sample experiences multiple spells during the panel. But, only about 25% of the population experiences exclusion spells longer than 3 years.

Finally, looking to the sample structure of the excluded in the panel, we can note that about 27% of the excluded individuals are females and only about 21% of excluded are males. We also observe that about 14.30% of the excluded population is aged between 16 and 35, about 14.73% is aged between 36 and 56, and about 17% is aged 65+. Moreover, about 10% of the excluded individuals have a high or medium level of education: the 37.41% of the individuals counted as excluded does not have the second level of education (see Table 5).

5. The Model

In this section, we use an econometric model in order to obtain more information about the persistence of social exclusion. As I have mentioned above, there are two processes that can generate persistence: unobserved heterogeneity and true state of dependence. In the first process, individuals could be heterogeneous with respect to characteristics that are relevant for the chance of experiencing social exclusion and persistent over time. In this case, an individual experiencing social exclusion at any point in time because of (unobserved) adverse characteristics will also be likely to experience social exclusion in any other period because of the same adverse characteristics. In the second process, experiencing social exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods. Remember that, for each individual, the score on the social exclusion indicator is equal to one if the individual is excluded, and zero otherwise. The number of individuals aged 16+ with complete observations during the panel (N=8914) is large and the number of periods, T, is fixed (T=0,…,5).

From an econometric point of view, analyzing the persistence of a discrete choice variable, and in particular the presence of true state of dependence and unobserved heterogeneity, leads to some methodological problems connected with the consistent estimation of a non-linear model. Thus, the choice of the initial conditions or alternatively of a semi-parametric structure is crucial for the correct estimation (Honore 1993).

In general non-linear panel data models have received little attention because it is not possible to difference out individual specific effects as is the practice for linear models. Thus, if the individual specific effects are not run out, the estimation will not be consistent. There are essentially two approaches to deal with this problem: the random effect approach and the fixed effect approach.

In the random effect approach, one parameterizes the distribution of the individual specific effects conditional to the exogenous explanatory variables. The estimation of the model can be done by a pseudo-maximum likelihood method that ignores the panel structure of the model. Under suitable regularity conditions, this will lead to a consistent and asymptotically normal estimator. The model results to be fully parameterized and the initial conditions have to be also specified. A simple solution to the initial conditions problem, in dynamic non-linear panel data models with unobserved heterogeneity, is given by Wooldrigde (2002). He proposed finding the individual specific effect distribution conditional on the initial value (and the observed history of strictly exogenous explanatory variables). He treats the general problem of estimating average partial effects, and shows that simple estimators exist for important special cases.

In the fixed effects approach, one attempts to estimate the parameters making only minimal assumption on the individual specific effects. If there are at least four time periods, and the exogenous explanatory variables are not included, Chamberlain (1985) has shown that the parameters of a dynamic logit model can be estimated by considering the distribution of the data conditional on a sufficient statistic for the individual specific effect (conditional likelihood estimation). Honore and Kyriazidou (2000) generalized this to the case where the logit model was also allowed to contain exogenous explanatory variables.

The choice between random effects and fixed effects model is fully discussed in Honore (2002). He argues that "estimating a random effects panel data model results in a fully specified model in which one can estimate all the quantities of interest, whereas fixed effect panel data models typically result in the estimation of some finite dimensional parameter from which one cannot calculate all functions of the distribution of the data. Moreover, random effects models will usually lead to more efficient estimators of the parameters of the model if the distributional assumptions are satisfied. On the other hand, violation of the distributional assumption in a random effects model will typically lead to inconsistent estimation of the parameters. The fixed effects model imposes fewer such assumptions. Based on this, it seems that if the main aim of an empirical exercise is to judge the relative importance of a number of variables, or to statistically test whether certain variables are needed, and if efficiency is not too much of an issue, then fixed effect approach is preferable because it will be less sensitive to distributional assumptions. On the other hand, if one wants to use the model for prediction or for calculating the effect of various 'what-if is', then a random effects model would be preferable".

Since we wish to use a model that, in a future, can be used for calculating the impact of a specific policy, we concentrate our attention on random effects models. In particular, we follow the approach proposed by Wooldridge (2002) to estimate consistently the parameters. Moreover, we estimate the average partial effects in order to determine the importance of the dynamics in the model, and not only to testing whether there is dynamics. This approach has also some computing advantages, if we consider a dynamic logit model (as appropriate in our case), a standard random effects software can be used to estimate the parameters and the average effects.

Dynamic Logit Model

In the previous section, we constructed an individual indicator of the state of exclusion. It indicates the presence or the absence of an exclusion state: the value of 1 if exclusion occurs and 0 if it does not. To analyze how this static indicator evolves over time, we use a dynamic panel data logit model.

For a random draw i from the population, and t=1,2,3,4,5, the conditional probability that exclusion occurs is

$$P(y_{it} = 1 \mid y_{it-1}, \ldots, y_{io}, c_i) = \phi(\rho y_{it-1} + c_i). \quad (1)$$

where the functional form of ϕ is a logistic distribution, the dependent variable y_{it} is the exclusion state of individual i at time t, ρ is a parameter to be estimate and c_i is the individual specific effect.

The assumptions implied by this equation are the following: first, the dynamics are first order, once c_i is also conditioned on; second, the unobserved effect is additive inside the distribution function, ϕ. As suggested by Wooldridge (2000), the parameters in (1) can be consistently estimated by specifying a density for c_i given the exclusion initial condition y_{i0}. Therefore, we assume that

$$c_i \mid y_{i0} \sim \text{Normal}\,(a_0 + a_1 y_{i0} + \mathbf{z}_i \mathbf{a}_2, \sigma^2_a) \quad (2)$$

where $\mathbf{z}_i$ is the row vector of all time constant explanatory variables, a_0, a_1 and $\mathbf{a}_2$ are parameters to be estimate and σ^2_a is the conditional standard deviation of c_i. Note that the vector $\mathbf{z}_i$ appears in (2), and not in equation (1), because otherwise we could not identify the coefficients on time constant covariates.

Given (1) and (2), we can write the conditional density for the conditional distribution as

$$f(y_{it}, \ldots, y_{iT} \mid y_{io}, c_i; \rho) = \Pi_t \{\phi(\rho y_{it-1} + c_i)^{yt} \,.\, [1-\phi(\rho y_{it-1} + c_i)]^{1-yt}\}$$

When we integrate this with respect to the normal distribution in (2), we obtain the density of $(y_{it}, \ldots, y_{iT} \mid y_{io}, c_i; \rho)$.[8] Then, we maximize the density obtained (likelihood) in order to estimate the parameters ρ, a_0, a_1, $\mathbf{a}_2$, σ^2_a. The estimation is consistent only under the assumption that the model is correctly specified.

[8] Wooldridge (2002) show that the integrated density can be specified in such way that the standard random effect logit software can be used for estimation. In particular, if the software used is STATA, the command for estimation is "xtlogit" using as explanatory variables, at time period t, $x_{it} = (1, y_{it-1}, y_{i0}, z_i)$.

In the model, the value of ρ determines if the exclusion sequence $\{y_{it}\}$ features true state of dependence. In other words, it determine if experiencing exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods. In particular, if $\rho>0$, then experiencing exclusion at time t-1, $y_{it-1}=1$, increases the chance to experience exclusion at time t ($y_{it}=1$). Moreover, the estimate of a_1 is of interest in its own right, since it tells us the direction of the relationship between c_i and y_{i0}. Finally, the estimate of σ^2_a gives us information about the unobserved heterogeneity.

Finally, we underline that the method proposed by Wooldridge (2002) need a balanced panel. Therefore, selection can be an issue: the estimation may be subject to bias if the non-response is endogenously determined. Selection problems also arise as consequence of attrition: in Spanish data between the 1st and 2nd wave attrition is around 10%, and it is less than 5% between the subsequent waves. We have a 11488 individuals per year in the 4-waves balanced panel and only 8914 individuals per year in the 6-waves balanced panel. Wooldridge method derives the density conditional on (y_{i0} , z_i) and it has some advantages in facing selection and attrition problems. In particular, it allows selection and attrition to depend on the initial conditions and, therefore, it allows attrition to differ across initial level of y.In particular, individuals with different initial status are allowed to having different missing data probabilities. Thus, we consider selection and attrition without explicitly model them as a function of initial conditions. As results, the analysis is less complicated and it compensated the potential lost of information using a balanced panel. Similar comments apply to stratified sampling: any stratification that is function of (y_{i0} , z_i) can be ignored in the conditional MLE analysis since it is more efficient not to use any sampling weights (Wooldridge, 2002).

6. Empirical results

We discuss the results in three stages. First, we present the estimates of the true state of dependence and the heterogeneity. Second, we analyse the importance of the dynamics in the model. Third, we discuss the estimated impact of each dimension on social exclusion.

Estimates of persistence

Using the dynamic logit model in section 5, we present in Table 6 the conditional maximum likelihood estimates (and the asymptotic standard errors) in the following two cases. First, we consider as only explanatory variable the lag of social exclusion (model 1). Second, we explicitly control for some observed heterogeneity (model 2 and model 3).

In model 1, after controlling for the unobserved effect, the coefficient on the lagged social exclusion is very statistically significant. The initial value of social exclusion is also very important, and it implies that there is substantial correlation between the initial condition and the unobserved heterogeneity. In fact, the coefficient on initial social exclusion (1.7) is much larger than the coefficient on the lag (0.4). Moreover, the estimate of the conditional standard error of c_i (σ_a) is equal to 1.3 and it is statistically different from zero: this means that there is much unobserved heterogeneity.

In model 2, we include some time-constant variables (Model 2 in Table 6). The time-constant covariates are sex (equal to one if male), the level of education (high or medium), the year dummies (to capture an eventual trend), the age at time zero, the cohabitation status at the initial period (with or without children in the household),[9] the presence of one or more individuals in the household in the initial period and being a lone parent at time zero. Interestingly, even after time constant variables are included, there is much unobserved heterogeneity that cannot be explained by the covariates: the estimated σ_a is still equal to 1.3. We also observe true state of dependence and high correlation between the initial condition and the unobserved heterogeneity, as in model 1. However, model 2 has a better fit. Among the time constant variables included, the level of education (high and medium) seems to reduce significantly the probability to experience social exclusion while being lone parent seems to increases the chance to be excluded. Moreover, the coefficients of the years dummies (wave2,..,wave5) suggest that social exclusion decreases over time.

In model 3, we included also region dummies[10] to take into account geographical differences (see Table 10 and 11). The European Household Panel divides Spain in seven regions: North - West, North – East, Comunidad the Madrid, Centre, East, South, and Canarias. Among these regions, we observe the lowest social exclusion rate in the North East (about 33%) and the highest rate in Canarias (about 61%). Consistently, we found that an individual living in South Spain and, especially, in Canarias has higher probabilities to experience social exclusion than one living in Comunidad of Madrid. Instead,

[9] The variables cwc0 (cohabitation without children), cc0 (cohabitation and children), old0 (old individual in the household) and single0 (lone parent) could be also designed as time variant variable; however, it would not add much to the analysis but it would make the model much more complicated.

an individual living in the North West, in the East and, specially, in the North East has lower probabilities to be socially excluded than one living in the Madrid area. Finally, note that even after region dummies are included, the estimate of the true state of dependence and the estimate of unobserved heterogeneity are still very statistically significant.

One general lesson from the estimation of the previous models is that there is great individual heterogeneity (observed and unobserved) in the possibility to experience social exclusion. A second general lesson from the results discussed above is that there is a non-trivial part of social exclusion persistence may be ascribed to past exclusion. These results are similar to the ones reported by Cappellari and Jenkins (2002) for the UK in the 1990s. Note that these finding are of policy relevance since they suggest both policies focused on getting people out of social exclusion and policies focused on keeping individuals out of social exclusion once out are relevant.

Importance of the dynamics and impact of observed heterogeneity

In order to determine the importance of any dynamics in the model, and not just testing whether there are dynamics, we estimate average partial effects. So, we determine the magnitudes of partial effects to analyze the importance of any state of dependence. In the same way, we can investigate the impact of any observed heterogeneity on the probability to experience social exclusion. The average partial effects on the response probability are based on

$$E\,[\,\phi\,(\,\rho\, y_{t-1} + c_i\,)]$$

where the expectation is with respect to the distribution of c_i. A consistent estimator of the previous expected value was proposed by Wooldridge 2002, and it is the following:

$$N^{-1}\sum_{i=1}^{N}\phi\left(\hat{\rho}_a\, y_{t-1} + \hat{a}_{a0} + \hat{a}_{a1}\, y_{i0} + z_i\,\hat{a}_{a2}\right)$$

where the a subscript denotes multiplication by

$$\left(1+\hat{\sigma}_a^{2}\right)^{-1/2}$$

and the parameters are estimated using the conditional MLEs.

[10] Region dummies: es1=North-West, es2=North-East, es3=Comunidad de Madrid, es4=centre, es5=East,

Using this estimator, we estimate the probability of being excluded in 1999 given that the individual is or is not excluded in 1998. The difference is an estimate of the state of dependence of being socially excluded. Thus, we observed that the probability to experience social exclusion in 1999 given that the individual is excluded in 1998 is 0.42, and it decreases to 0.29 if the individual is not excluded in 1998: the estimate of the state dependence of social exclusion is about 0.1269 (Table 6).

For a high educated individual, that was excluded in 1998, the estimated probability of experience social exclusion in 1999 is 0.166. The probability to be socially excluded in 1999, being excluded in 1998, is much higher if the individual does not have a high level of education: about 0.4486. Moreover, for an individual with a high level of education, that was not excluded in 1998, the probability to experience social exclusion is very close to zero (0.06) but it is equal to 0.31 if the individual does not have a high level of education. Finally, we note that for a single parent the probability to be excluded in 1999 is about 0.7 if he was excluded in 1998, and it is about 0.57 if he was not (Table 6).

The general lessons from analyzing the probabilities of experience social exclusion is that individuals excluded at certain point in time have higher probability to experience social exclusion in the future than individuals non-excluded. This probability appears related to differences in observed individual characteristics. Therefore, governments should direct policies to force out people from exclusion taking into account which characteristics increase the probability to remain excluded.

Impact of each dimension on social exclusion

In Table 7, we consider the impact of each dimension on social exclusion. The main idea is to decompose the social exclusion initial value in its 8 components (the dimensions initial conditions) in order to understand which component affects more the probability to experience social exclusion. We still observe true state of dependence, high correlation between initial conditions and unobserved heterogeneity, and much unobserved heterogeneity. Education still reduces the probability to experience exclusion, being single parent increases it and social exclusion still decreases over time. The estimates of all initial deprivations, with exception of initial housing deprivation, result statistically significant. To better see the implications of the estimates, we examine the probabilities of experience social exclusion in 1999 that the estimates imply for different initial deprivations. The various estimated probabilities are

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es6=South and es6=Canarias

summarized in Table 9. The following initial deprivations imply the highest probabilities to be socially excluded (>0.53): not being able to reach a certain quality of life, not being healthy, not being able to perform work activities or/and being poor. In Table 8, we analyse the relation between estimate state of dependence and initial deprivations. The main result is that all the initial deprivations (except initial housing deprivation) appear related to social exclusion persistence over time. In particular, the above mentioned initial deprivations affect more the estimate probability to experience social exclusion in 1999 if the individual is socially excluded in 1998. Therefore, we can extrapolate the following lesson: public policies direct to reduce social exclusion should focus on reduce single dimension deprivations in order to decrease the individual probability to experience social exclusion.

7. Sensitivity analysis

In this section, we report on the robustness of our results to variation in some hypothesis underlying the model presented in the previous sections. First, we consider what happens when we used alternative definitions of social exclusion. Second, we test the robustness of the cut-points chosen.

We consider the following alternative definitions of social exclusion. First, we omit the functioning "having an adequate income" in the construction of the social exclusion variable. Second, we use the following working definition: "an individual is defined as socially excluded at time *t* if he is deprived in at least *two* relevant functionings". Using the first alternative definition, the headcount ratios and the persistence rates are lower than the ones presented in the previous section, but the dynamics has the same behavior. Using the second alternative definition, the probability to be excluded in 1999, being excluded in 1998, is much lower than the one observed in section 5 as well as the estimated state dependence (but still statistically different from zero). Thus, in both cases we still observe true state of dependence and much unobserved heterogeneity (see Table 12).

Finally, we highlight that the definition of the dimension cut-points that was utilized so far was inspired by definitions used in Britain's official income statistics. However, its choice is arbitrary in essence (Atkinson, 1987).This motivated us to re-estimate the model using alternative definitions of the cut-points: 40% of the mean distribution and 60% of the mean distribution. The comparisons of the results suggest the higher are the cut-points the higher are the persistence and deprivation rates in every dimension. Therefore, the level of social exclusion is sensitive to the chosen cut-points. Instead, the estimated state of dependence remains result statistically equivalent for all considered cut-points. Thus, we can conclude that our results about the state of dependence are robust to cut-points ranging between 40% and 60% (see Table 12).

Conclusions

The aim of this paper was to study the dynamics of social exclusion in Spain from 1994 to 1999. The main idea is the following: there are two opposite explanations for the often observed empirical regularity according to which individuals who have experienced social exclusion in the past are more likely to experience that event in the future. One explanation is that as a consequence of experiencing exclusion future choices are altered (true state of dependence). A second explanation is that individuals may differ in certain characteristics, observed and/or unobserved, that influence their probability of experiencing exclusion (heterogeneity).

We shown the existence of social exclusion persistence: an individual experiencing social exclusion today is much more likely to experience it again in the future. We observe that about 13% of the population is counted as excluded in at least one dimension in all years from 1994 to 1999 in Spain and about 81% of the sample experienced social exclusion in at least one dimension and in at least one wave during the panel. The high proportion of the sample who experience some exclusion, but are not excluded throughout, suggests a great degree of mobility into and out of social exclusion. Moreover, note that the proportion of the sample counted as socially exclusion is much bigger than one counted as poor: therefore, social exclusion highlights a problem that involves more people than income poverty.

Of more interest than the levels of exclusion at a point in time and over time, we found the analysis of the dynamics and of the causes leading to exclusion. We found evidence of individual heterogeneity and true state of dependence, even after controlling for observed individual differences. Moreover, we observe that the probability to experience social exclusion appear related to observed individual characteristics. For instance, having a high or medium level of education and not being lone parent reduce the probability to experience social exclusion. We also note geographical differences in the probability to experience social exclusion. Therefore, we estimate the probability to experience exclusion conditional to the probability to be excluded in the previous period and conditional to individual characteristics. We found a strong relationship between the social exclusion dependence and some individual characteristics. In particular, we explore the relationship between initial deprivations and social exclusion persistence. Initial deprivations in all the dimension (except in housing conditions) increase the probability to be socially excluded. We also highlighted which initial deprivation imply a higher probability to experience social exclusion at certain time if the individual is excluded in the previous period.

Finally, we reported on the rubustness of our results to variation in some hypothesis underlying our model. In particular, we considered what happen when we use alternative definitions of social exclusion and when we use different cut-points.

Note that our analysis contributes to understand a little bit better the extent of social exclusion in Spain, and suggests how to improve policies to reduce social exclusion. In fact, the main lesson from our analysis is that public policies should focus on both getting people out of social exclusion and keeping individuals out of social exclusion once out. In particular, policies focusing on reducing deprivation in a certain area (e.g. education, health, etc.) are very relevant to prevent people from falling into social exclusion. Observed individual characteristics have also to be considered in order to focus on population groups at high risk of exclusion.

References

- Atkinson A.B., “On the poverty measurement”, *Econometrica*, 55, pp. 749-64
- Baltagi, “Econometric analysis of Panal Data”, *John Wiley & Sons Ltd*, 1995
- Bane and Ellwood, “Slipping into and out of poverty: the dinamics of spells”, *The Journal of Human Resources*, 12, 1986
- Bond S., “Dynamic Panel Data Models: a guide to micro data methods and pratice”, *cemmap working paper CWP09/02*, 2002
- Brandolini and D’Alessio, 1999
- Burchardt and LeGrande and Piachaud, “Social Exclusion in Britain 1991-1995”, *Social Policy and Administration*, 33 (3), 227-244, 1999
- Burchardt, “Social Exclusion: concept and evidence”, In “*Bradline Europe: the measurement of poverty*”, edit by D.Gordon and P.Townsend, 2000
- Cappellari and Jenkins, “Who stays poor? Who becomes poor? Evidence from the British household panel survey”, *the Economic Journal*, 112, March, 2002
- Cappellari and Jenkins, “Modelling low income transitions”, IZA, *Discussion Paper No. 504*, May 2002 (or ISER, Working Papers, No. 2002-8)
- Chamberlain G., “Heterogeneity, omitted variable bias, and duration dependence”, in *Longitudinal analysis of Labor Markets Data*, ed. by Heckman and Singer, 1985
- D’Ambrosio and Chakravarty, “The measurement of social exclusion”, Conferences on Conflict and Polarization, December 2002
- D’Ambrosio and Tsakloglou and Papadopoulos, “Social Exclusion in EU Member-States: a comparison of two alternative approaches”, Working Paper, June 2002
- Ducan G., “Years of poverty years of pleanty”, Institute for social Reseach, 1984
- Foster and Tarcalli and Till, “eeu_draft”, IARIW papers, 15 June 2002
- Honore Bo E., “Orthogonality conditions for Tobit models with fixed effects and lagged dependent variables”, *Journal of Econometrics*, 59, 1993
- Honore Bo E., “Non-linear Models with Panel Data”, *cemmap working paper*, CWP13/02, 2002
- Honore and Arellano, “Panel data models: some recent developments”, *CEMFI working paper No. 0016*, November 2000

- Honore and Hu, “Estimation of cross sectional and panel censored regression models with endogeneity”, working paper, July 2002, www.princeton.edu/honore/papers
- Honore and Kyriazidou, “Panel data discrete choice models with lagged dependent variables”, working paper, May 1998, www.princeton.edu/honore/papers
- Hsiao C., “ Analysis of Panel Data”, 1986
- Honore and Kyriazidou, “Estimation of Tobit-type models with individuals specific effects”, 1998, www.princeton.edu/honore/papers
- Kyriazidou E., “Estimation of dynamic panel data sample selection models”, wp, department of economics, University of Chicago, 1999
- Jenkins, S.P. “Modeling household income dynamics”, *Journal of Population Economics*, No. 13, pp. 529-567, 2000
- Martinez and Ruiz and Huerta, “Income, multiple deprivation and poverty: an empirical analysis using Spanish data”, Conference of the international association for research in income and wealth, Cracow, Poland
- Michaud p., “Dynamic binary chioce models: true vs. spurious state-dependence”, Tilburg University wp 2002
- Nolan and Whelan, "Resource, Deprivation and Poverty", Clarendon Press, Oxf
- Nolan and Whelan and Maitre and Layte, “Persistent income Poverty and Deprivation in the European Union”, ISER, EPAG, wp 17, 2001
- Nolan and Whelan and Maitre and Layte, “Explaing levels of Deprivation in European Union”, ISER, EPAG, wp 12, 2001
- Nolan and Whelan and Maitre and Layte, “Poverty dynamics: an analysis of the 1994-95 waves of the European Community Household Panel”, ISER, EPAG, wp 10, 2000
- Nolan and Whelan and Maitre and Layte, “Income deprivation and economic stream: an analysis of the European Community Household Panel”, ISER, EPAG, wp 5, 1999
- Sen A., "Commodities and Capabilities", Amsterdam: North-Holland Press 1985
- Sen A., "Social Exclusion: concept, application and scrutiny", Social *Development Papers*, No.1, ADB, June 2000

- Stevens A. H., “Climbing out of poverty, falling back in”, *The Journal of Human resources*, XXIV,1999
- Steward and Swaffield, “Low pay dynamics and transition probabilities”, *Economica*, Vol 66, No 261, 1999
- Tsakloglou and Papadopoulos, “Poverty, material deprivation and multi-dinensional disadvantage during four life stage: Evidence from ECHP”, chapter 2, 2001
- Trivellano and Giraldo and Rettore, “The percistence of poverty: true state dependence or unobserved heterogeneity? Some evidence from the Italian survey on household income and wealth”, paper prepared for the 27th General Conference of the IARIW, 2002
- Whelan and Layte and Maitre, “Persistent Deprivation in the European Union”, EPAG wp23, ISER, 2001
- Whelan and Layte, “Moving in and out of Poverty: the impact of welfare regimes on the poverty dynamics in the European Union”, ISER, EPAG, wp 23, 2002
- Wooldridge J. M., “Simple solution to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity”, *cemmap working paper CWP18/02*, 2002

Table 1. Functionings

Basic needs fulfillment (BASIC)
Not eating meat or like every second day
Being unable to buy new, rather than second hand clothes
Being unable to pay bills, rents, etc.
Having an adequate income
Income
To reach a certain quality of life (QUALITY)
Car or van
Color TV
Video recorder
Telephone
Paying for a week's annual holiday
Having friends or family for a drink/meal at least once a month
Having an adequate house (HOUSING)
Not having indoor flushing toilet
Not having hot running water
Not having enough space
Not having enough light
Not having adequate heating facility
Not having damp walls, floors, foundation...
Not having leaky roof
Not having rot in windows frame, floors
Ability to have social relationships (SOCIAL)
Frequency of talk to the neighbors
Frequency of meeting people
Being healthy (HEALTH)
Health of the person in general
Living in a safe and clean environment (LIVING)
Noise from neighbors or outside
Pollution, crime or other environment problems caused by traffic or industry
Vandalism or crime in the area
Being able to perform a paid or unpaid work activity (WORK)
Being unemployed

Note: Each item represent a good affordable, a good holds or the absence of a problem for at least the 50% of the sample.

Table 2. Headcount ratio - Weighted sample (cross sectional weights)

HEADCOUNT RATIO

	1994	1995	1996	1997	1998	1999
Basic	2.38	1.54	1.52	1.15	1.06	1.75
Quality	5.27	4.52	3.66	3.16	2.36	2.02
Housing	1.52	0.90	1.40	0.77	0.55	1.02
Social	2.83	2.03	2.36	2.21	2.25	2.55
Healthy	14.08	12.12	11.23	10.91	11.06	9.65
Living	23.60	21.54	18.51	17.42	15.64	13.70
Work	9.47	10.76	11.47	10.32	8.94	7.46
Income1	18.36	17.70	16.67	18.85	18.28	17.97
SE	54.54	51.70	48.79	47.91	46.00	43.96

Table 3. Persistence (no-weighted sample):

	Basic	quality	housing	social	healthy	Living	work	income	se
never excluded	93.49	88.84	96.66	92.35	71.35	57.11	78.33	60.98	18.46
Excluded 1 wave	5.06	6.10	2.45	6.04	10.61	16.57	9.11	12.61	15.23
Excluded 2 waves	0.88	2.15	0.40	1.04	5.36	9.54	5.26	7.79	13.75
Excluded 3 waves	0.40	1.11	0.24	0.39	4.17	7.05	3.37	6.16	13.63
Excluded 4 waves	0.13	1.05	0.15	0.10	3.37	4.72	2.25	5.36	13.09
Excluded 5 waves	0.03	0.65	0.08	0.06	3.05	3.49	1.09	3.69	12.82
Excluded 6 waves	0	0.09	0.03	0.02	2.09	1.53	0.59	3.41	13.02

Table 4. Persistence – subsequent years – and multiple spells

Individuals excluded in j consecutive years in:	one ore more	% of individuals experiencing the following # of spells:		
	%	One	two	three
only 1year	25.56	15.23	8.02	2.31
2 years	17.61	15.22	2.39	---
3 years	12.81	12.81	---	---
4 years	7.71	7.71	---	---
5 years	4.83	4.83	---	---
6 years	13.02	13.02	---	---

Table 5. Characteristics of the sample

	% tot	% of the tot population that is socially excluded
Sex		
Female	53.15	27.07
Male	46.85	21.46
Age		
16-25	15.02	7.10
26-35	16.59	7.20
36-45	18.79	7.73
46-55	15.53	7.03
56-65	16.93	8.37
65+	17.14	8.26
Lone parent	0.37	0.27
Couple without children	15.20	7.73
Couple with children	19.34	8.18
Education		
high level	12.82	4.39
medium level	16.57	6.73
low level	70.61	37.41
At least one person aged		
65+ in the household	19.14	9.34

Figure 1. Dynamic in every dimension

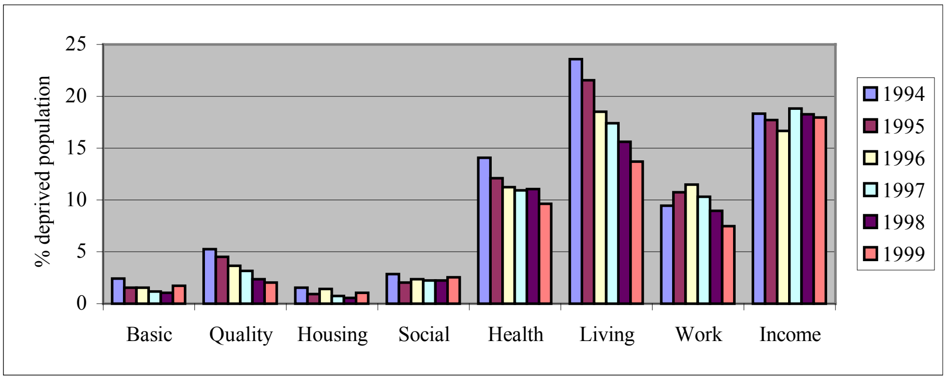

Figure 2. Social Exclusion Dynamics

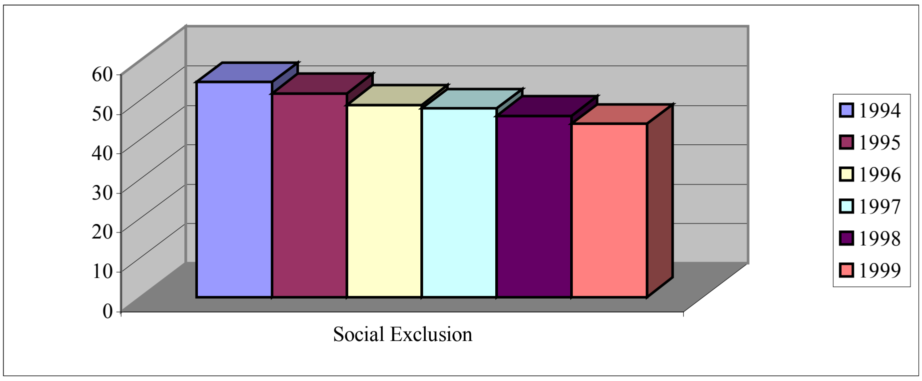

Table 6. Social Exclusion – 6 waves balanced panel

se	Model 1 Coef	Model 1 Std. Err	Model 2 Coef.	Model 2 Std. Err.
se_lag	0.4834**	0.0343	0.4586**	.0352046
se0	1.7092**	0.0462	1.6577**	.0470765
edu_h0			-0.9499**	.0634124
edu_m0			-0.4703**	.0579092
sex			-0.0996*	.0391625
age0			-0.0036**	.0013668
old0			-0.0554	.1148726
cc0			-0.0319	.0522191
cwc0			0.1249	.1177814
single0			1.0904**	.3212533
wave2			-0.0772*	.039314
wave3			-0.1047**	.0394217
wave4			-0.2423**	.0393452
wave5			-0.3662**	.0393187
_cons	-1.3943**	0.0294	-0.7954**	.0823838
sigma_a	1.3139**	0.0296	1.3098**	.0302728
Log likelihood	-24397.886		-23202.452	

Estimated probability of being socially excluded in 1999 given that the individual is or is not excluded in 1998.

.	excluded 1998	not excluded 1998	estimated
dependence probability	0.4185	0.2916	0.1269

Probability of being excluded in 1999 if …

.	excluded 1998	not excluded 1998
high education	0.1660	0.0615
otherwise	0.4486	0.3193

.	excluded 1998	not excluded 1998
single parent	0.7011	0.5754
otherwise	0.4174	0.2904

Table 7. Estimation specifying the effect of each dimension on the probability to be excluded

se	Coef.	Std. Err.
se_lag	0.4805**	.0347857
basic0	0.4281**	.1362487
quality0	1.0924**	.0919919
housing0	0.1924	.1608001
social0	0.7570**	.1547137
health0	1.2322**	.0621426
living0	1.0743**	.048633
work0	1.1472**	.074938
income0	1.2816**	.0529865
edu_h0	-0.8089**	.0613832
edu_m0	-0.3650**	.055713
sex	-0.0958*	.0377421
age0	-0.0034*	.001376
old0	-0.0506	.1112991
cc0	-0.0124	.0500585
cwc0	0.1408	.1137412
single0	0.8975**	.3131783
wave2	-0.0770*	.0390712
wave3	-0.0958*	.0391705
wave4	-0.2384**	.0391193
wave5	-0.3615**	.0391023
_cons	-0.7733**	.080938
sigma_a	1.2341**	.0296985
Log likelihood	= -23287.742	

Table8

Estimated probability of being socially excluded in 1999 given that the individual is or is not excluded in 1998.

.	excluded 1998	not excluded 1998	estimated dependence
probability	0.2733	0.1426	0.1307

Probability of being excluded in 1999 if ...

.	excluded 1998	not excluded 1998	estimate dependence
excluded in basic	0.3681	0.2067	0,1614
not excluded in basic	0.2712	0.1404	

.	excluded 1998	not excluded 1998	estimate dependence
excluded in quality	0.5307	0.3326	0,1981
not excluded in quality	0.2584	0.1275	

.	excluded 1998	not excluded 1998	estimate dependence
excluded in housing	0.3143	0.2727	0,0416
not excluded in housing	0.1696	0.1421	

.	excluded 1998	not excluded 1998	estimate dependence
excluded in social	0.4497	0.2695	0,1802
not excluded in social	0.2708	0.1408	

.	excluded 1998	not excluded 1998	estimate dependence
excluded in health	0.5419	0.3351	0,2068
not excluded in health	0.2289	0.1080	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in living	0.4753	0.2847	0,1906
not excluded in living	0.2215	0.1086	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in work	0.5353	0.3373	0,1980
not excluded in work	0.2518	0.1254	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in income	0.5713	0.3261	0,2452
not excluded in income	0.2518	0.0914	

Table 9

Deprived in 1994 in:	Probability to be socially excluded in 1999:
Basic	0.36.81
Quality	0.5307
Housing	0.3143
Social	0.4497
Health	0.5419
Living	0.4753
Work	0.5353
Income	0.5380

Table 10. Regional differences – headcount ratios

Exclusion	North-West	North-East	Com. Madrid	Centre	East	South	Canarias
SE	46.24%	33.36%	43.36%	48.27%	41.40%	54.84%	61.13%
Basic	0,72%	0,48%	0,48%	1,21%	0,66%	1,70%	7,25%
Quality	3,78%	0,96%	1,04%	5,00%	1,74%	4,74%	6,71%
Housing	1,34%	0,51%	0,63%	1,26%	0,16%	0,45%	1,08%
Social	1,42%	1,05%	2,32%	1,33%	1,97%	1,73%	3,35%
Health	15,79%	9,89%	6,75%	13,36%	10,97%	13,93%	15,53%
Living	14,09%	12,59%	26,77%	8,75%	20,46%	15,95%	23,89%
Work	7,34%	6,17%	7,35%	7,55%	6,68%	12,54%	7,83%
Income	17.02%	9.31%	8.37%	26.07%	9.83%	27.12%	28.32%

Table 11. Regional differences – 6 waves balanced panel

se	Model 3 Coef.	Std. Err.
se_lag	0.4575**	.0351711
se0	1.5787**	.0465527
edu_h	-0.9008**	.0630247
edu_m	-0.4376**	.0575788
sex	-0.0982*	.0387147
age	-0.0028*	.0013544
old	-0.0258	.1135326
cc	-0.0559	.0518272
cwc	0.0767	.1163954
single0	1.0042**	.3177836
wave2	-0.0775*	.0393159
wave3	-0.1059**	.0394199
wave4	-0.2431**	.0393487
wave5	-0.3668**	.0393242
es1	-0.1997*	.0795023
es2	-0.6077**	.0793418
es4	-0.0396	.0780843
es5	-0.3387**	.0747151
es6	0.1592*	.0767638
es7	0.3789**	.1033336
_cons	-0.6437**	.1002111
sigma_a	1.2819**	.0299696
Log likelihood	= -23101.352	

Table 12. Sensitivity analysis

Alternative definitions

Estimated probability of being socially excluded in 1999 given that the individual is or is not excluded in 1998.

.	excluded 1998	not excluded 1998	estimated dependence
SE without income dimension	0.2382	0.1328	0.1054
SE (in at least 2 dimensions)	0.2382	0.1328	0.1054

Cut-Points

% SE	1994	1995	1996	1997	1998	1999
Cut-points: 40% of the mean	36.97	35.52	33.62	33.42	30.42	28.60
Cut-points: 60% of the mean	48.86	45.94	43.14	41.11	37.11	34.43
% individuals excluded in all waves (persistence)						
Cut-points: 40% of the mean						7.46
Cut-points: 60% of the mean						14.19

Estimated prob. of being socially excluded in 1999 given that the individual is or is not excluded in 1998

.	excluded 1998	not excluded 1998	estimated dependence
cut-points: 40% of the mean	0.2087	0.0941	0.1146
cut-points: 60% of the mean	0.5530	0.4096	0.1434

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