Persistence of social exclusion in Italy:

a multidimensional approach

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Abstract

The aim of this paper is to analyse the multidimensional nature of social exclusion and its dynamics. We identify eight dimensions necessary to define an individual as socially excluded (basic needs, quality of life, housing, health, social relationships, environment conditions, income, work activities) and we analyse the contribution of each dimension to the social exclusion dynamics. In particular, we wish to understand if an individual experiencing social exclusion today is much more likely to experience it again. In fact, there are two distinct processes that may generate 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.

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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 to become 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). In a previous study, we analyse the causes leading the social exclusion dynamics in Spain. But, as far as we know, there are not any other studies focused on the causes of the social exclusion dynamic process that leads the individual to be defined as socially excluded.

Questions regarding the causes of social exclusion persistence ought 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 excluded in a certain dimension, it is important to document the efficacy of such policies and, therefore, we need to verify if the individual is permanently, or only temporally, helped out of social exclusion.

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

Persistence of social exclusion may arise from individual heterogeneity. That is, individuals could be heterogeneous with respect to characteristics that are relevant for the chance of experiencing social exclusion. 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.

Social exclusion can also be due to a process called true state of dependence. That is, 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 her 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 at forcing the individual out of social exclusion at time *t* is not really effective. In fact, forcing the individual out of social exclusion today does not affect her adverse characteristics, and therefore does not reduce her chance of experiencing social exclusion spells in subsequent periods.

This paper contributes to the literature on social exclusion in the following ways. First, it provides an analysis of social exclusion persistence identifying the causes of exclusion in Italy: true state of dependence, unobserved heterogeneity and/or observed heterogeneity. Previous studies on social exclusion identify the population members at high risk of social exclusion and present tabulations about the duration of social exclusion. However, they do not analyse, as we do, the processes that can lead to social exclusion persistence. Thus, following the methodology proposed in a previous study (Poggi, 2003), 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. Therefore, we perform a multidimensional analysis of social exclusion in Italy using an aggregate measure of social exclusion and studying every dimension separately.

In the next section, we shortly review the main literature about income (and earnings) 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 Italy. In section 5, we review the dynamic model presented in Poggi (2003): we use such model to analyse the persistency of social exclusion in Italy. In section 6, the empirical results are given. 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 analyse its dynamics.

Burchardt (2000) looks across different dimensions of social exclusion at a single point in time, and traces the course individuals follow over time. She finds 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, Burchardt, 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. [1]

Tsakloglou and Papadopoulos (2001) identify 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 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.

[1] British Household Panel Survey

Nolan, Whelan, Layte and Maitre had produced a certain number of articles about poverty, mobility and persistence of deprivation [2]: they mainly analyse 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. In a previous paper, we contribute to the literature analysing the causes leading to social exclusion in Spain: the analysis is performed by extending dynamic methods, normally used to explore income and poverty dynamics, to understand social exclusion (Poggi, 2003).

Jenkins (2000) describes 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 terms 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 that experiences 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 latter 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 in Italy (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), Capellari and Jenkins

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

(2002) focus 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 earnings (e.g. Stewart-Swaffield 1999). Trivellato et al. (2002) also test for true state of dependence, in presence of unobserved heterogeneity, using Italian panel data. We propose an alternative solution to the problem of modelling 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 (Sen, 2000). 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 she 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 seven waves (1994-00) 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 it permits to analyse economic and social household conditions from a dynamic point of view. Instead, the main disadvantage is the omission of the homeless populations that could be expected to be socially excluded. As with any data source, we can face sample selection problems: some eligible individuals do not yield an interview. In order to try to correct for the bias that may arise from initial non-response, the obtained sample is weighted to reflect population characteristics such as age, sex, type of dwelling, etc, as closely as possible (cross-sectional weights). A further problem of non-response specific to panel data arises because respondents at the first wave may fail to give an interview at subsequent waves, so that the remaining sample may be no longer representative. This process is known as attrition. A second set of weights, using more detailed information about individual characteristics available from the most recent interviews can be used to counter possible attrition bias (longitudinal weights). Therefore, the analyses reported in this paper are weighted using the cross-sectional or longitudinal weights available in the ECHP as appropriate. Note that longitudinal weights are not use in the estimates since from an econometric point of view is more efficient not to use sampling weights, as we see later.

The above working definition implies the following methodological problems in the construction of a summary measure of social exclusion. First, the choice of the relevant functionings (dimensions) and the items representing them. Second, the identification of deprived individuals. Third, the aggregation of the relevant functionings 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 needs fulfilment", "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 analyse the political dimension of social exclusion.

Each of these dimensions represents a functioning considered important in its own right. This is not to 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 analyse social exclusion, even if they are not constitutive causes of exclusion. Finally, we highlight that the educational qualification ought to 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.[3]

Figure 1 summarizes the operationalization of the eight dimensions of social exclusion: it shows the items from the ECHP selected to correspond to each dimension. 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'[4]. Instead, a score equal to zero means that the individual is deprived in that item. All the values between zero and one mean an intermediate situation. We aggregate the items corresponding to every functioning by summing up their scores and dividing the result by the number of items. Equal weights are given to all items.[5] 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 between different items belonging to the same dimension, and between different dimensions and we find low degrees of association. Most coefficients are, in absolute value, below 0.2; just a little stronger is the correlation between economic dimensions ("basic needs fulfilment", "having an adequate income", "to reach a certain quality of life" and "having an adequate house"). Except for the correlated "basic needs" and "quality of life", the contemporary

[3] About 70% of the sample has less than the second stage of education, so we doubt that education can be considered as a 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.
[4] For example, she can afford a durable or she has an indoor flushing toilet or she does not have pollution in the area she lives.
[5] See Brandolini and D'Alessio (1999) for more details about the use of equal weights and alternative weighting structures.

presence of two deprivations is rare, suggesting that the indicators tend to capture complementary aspects. In particular, social and economic dimensions seem to capture different aspects of social exclusion.

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 combine the information about each dimension deprivations in a summary measure of social exclusion. For each individual, the score of 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 in that dimension *g*. Therefore, an individual can be deprived in one ore more dimensions. Moreover, we implicitly assume that anyone able to achieve a valuable functioning would do so. Note that in a previous study (Poggi, 2003) we address the issues about the arbitrariness in the choice of the thresholds testing the robustness of the cut-points chosen. We conclude that the results about the state of dependence are robust to cut-points ranging between 40% and 60%[6].

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 1 shows the proportion of the population aged 16+ who fell below the threshold in each dimension through the panel. In 1994, we find that about 51% 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’ (about 21%), ‘having an adequate income” (18%), and ‘being healthy’ (13%).

[6] The analysis was performed using Spanish data from the ECHP

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 20% of people results deprived in at least two dimensions in 1994, about 6% in at least three dimensions and only less than 2% of the individuals results deprived in more than three dimensions (Table 2). As observed by Burchardt et al. (2002) studying the U.K., there is no evidence of a concentration of individuals who are excluded in all 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 0.5), and the association is only slightly lower in the subsequent years (Table 3). Table 4 shows how deprivation evolves over time in every dimension. The deprivation rate observed in 2000 results lower than the one registered in 1994 in every dimension. Table 4 also shows the evolution of social exclusion during the period of study: it slightly increases in 1995 and, then, decreases over time.

Table 4 shows the pattern of exclusion of the individuals that are excluded for one wave or more during the panel. As time progresses, an increasing proportion of the sample has some experience of exclusion, and, correspondingly, a decreasing proportion has never experienced exclusion during the panel. About 80% of the sample experienced social exclusion in at least one dimension and at least in one wave during the panel, but about 15% of the sample is excluded in at least one dimension in all the waves. The proportion of the sample that experiences some exclusion, but is not excluded throughout, is an indication of the degree of mobility. 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 15% 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 27% of the population is excluded in one or more dimensions during only one year, and about 9% of the population experiences spells 4 year long. Only 3% of the sample experiences spells 6 year longs, but 15% of the population is socially excluded during all period of study. Moreover, we observe that about 12% of the sample experiences multiple spells; in particular, about half of the individuals that exit from exclusion after one year, experience social exclusion again.

5. The Model

In this section, we review the econometric model used in Poggi (2003) in order to obtain more information about the persistence of social exclusion. As we 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 persistence 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=9921) is large and the number of periods, T, is fixed (T=0,…,6).

From an econometric point of view, analysing 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 it 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 effects approach and the fixed effects approach.

In the random effects approach, one parameterises 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 parameterised 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 assumptions 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 effects 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 effects 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, could be used for estimating the impact of a specific policy, we concentrate our attention to 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 test whether there is dynamics. This approach has also some computing advantages, if we consider a dynamic logit model (as appropriate in our case), standard random effects software can be used to estimate the parameters and the average effects. [7]

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: we assess the value of one if exclusion occurs and the value of zero if it does not. To analyse 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=1,2,3,4,5,6 the conditional probability that exclusion occurs is

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

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 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

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

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 estimated 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

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

[7] For futher details see Wooldridge (2002).

When we integrate this with respect to the normal distribution in (2), we obtain the density of (y_{it} , .., y $_{iT}$ $|$ y_{io} , c_i ;ρ). 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.

In the model, the value of ρ determines if the exclusion sequence {y_{it}} features true state of dependence. In other words, it determines 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 the individual specific effect and the initial conditions. Finally, the estimate of σ^2_a gives us information about the size of the dispersion accounted by unobserved heterogeneity.

Finally, note that the method proposed by Wooldridge (2002) requires a balanced panel. Therefore, we may face not only attrition problems (as already underlined) but also selection problems. Wooldridge's 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 levels of exclusion. 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 a result, the analysis is less complicated and it compensates the potential lost of information from 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 estimate the true state of dependence and the unobserved heterogeneity in every dimension

Estimates of social exclusion persistence

Using the dynamic logit model in section 5, we present in Table 7 the conditional maximum likelihood estimates (and the asymptotic standard errors) for the following three cases. First, we consider as the only explanatory variable the lag of social exclusion (Model A). Second, in order to explicitly control for some observed heterogeneity we include some time-constant variables (Models B). Third, we use dummies representing initial deprivations as initial conditions (Model C)

In Model A, after controlling for the unobserved effect, the coefficient on the lagged social exclusion is 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 (1.8) is larger than the coefficient on the lag (1.0). Moreover, the estimate of the conditional standard error of c_i (σ_a) is equal to 1.7 and it is statistically different from zero: this means that there is much unobserved heterogeneity.

In Model B, we include some time-constant variables: since in Model A we observe much unobserved heterogeneity, we wish to explicitly control for the heterogeneity that we can observe. 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 area of residence (North, Centre, South, Islands), the cohabitation status at the initial period (with or without children in the household).[8]. 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 high correlation between the initial condition and the unobserved heterogeneity, as in model A. However, model A 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 living in South Italy and in the Islands seems to increases the chance to be excluded. Moreover, the coefficients of the year dummies (wave2, .., wave6) suggest that social exclusion dec reased during the study period.

In Model C, we use eight dummies representing single dimension deprivations at the initial period as initial conditions. 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

[8] The variables "cohabitation without children" and "cohabitation and children" 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.

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, living in South Italy and in the Islands increases it and social exclusion still decreases over time. All the estimates of all initial deprivations result statistically significant and have positive sign. Thus, initial deprivations in single dimensions increase the probability to experience social exclusion in the future.

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 that may be ascribed to past exclusion. Note that these finding are of policy relevance: policies focused on getting people out of social exclusion and policies focused on keeping individuals out of social exclusion once out are both relevant policies.

Importance of the dynamics and impact of observed heterogeneity

In order to determine the importance of the dynamics in the model, and not just to test whether there are dynamics, we estimate average partial effects. We determine the magnitude of partial effects to analyse 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

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

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:

$$N^{-1}\sum_{i=1}^{N}\phi\left(\hat{\rho}_a\ y_{t-1} + \hat{a}_{0a} + \hat{a}_{1a}\ y_{i0} + z_i\,\hat{a}_{2a}\right)$$

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.

Using this estimator, we estimate the probability of being excluded in 2000 given that the individual is or is not excluded in 1999. The difference is an estimate of the state of dependence of being socially excluded. The probability to experience social exclusion in 2000 given that the individual is excluded in 1999 is 0.44, while it decreases to 0.21 if the individual is not excluded in 1999. Thus, the estimate of the state dependence of social exclusion is about 0.23 (Table 8). Note that the estimated probability of being excluded in 2000 given that the individual was excluded in 1994 is about 0.56, while the probability of experiencing exclusion is only about 0.09 if she was not excluded at the initial period. The impact of initial exclusion on the dynamics is about 0.47.

For a high educated individual that was excluded in 2000, the estimated probability of experiencing social exclusion in 1999 is 0.26. The probability to be socially excluded in 2000, having been excluded in 1999, is much higher if the individual does not have a high level of education: about 0.45. Moreover, for an individual with a high level of education, that was not excluded in 1999, the probability to experience social exclusion is very close to zero (0.07) but it is equal to 0.22 if the individual does not have a high level of education. Finally, we note that for a individual living in South Italy the probability to be excluded in 2000 is about 0.57 if he was excluded in 1999, and it is about 0.34 if she does not live there (see Table 8).

Table 9 reports the estimated density probabilities of being excluded in 2000 given that the individual was deprived in a certain dimension at the initial period. We observe that initial deprivations in the functionings "being healthy", "living in a safe and clean environment", "being able to perform a paid or unpaid work activity", and "having an adequate income", imply high probabilities to be socially excluded (about 0.3). Note that in these functionings we register the highest deprivation rates in 2000.

Estimates of persistence by single dimension

The above results suggest that public policies addressing social exclusion should focus on reducing deprivations in certain dimensions in order to decrease the individual probability to experience social exclusion. Thus, we need to analyse dimension by dimension to understand the kind of policy to use. In order words, we need to determine the causes (true state of dependence and/or unobserved heterogeneity) that may generate persistence of a certain deprivation. To do so, we estimate the probability to experience a certain deprivation using as explanatory variable the lag of the deprivation.

The initial condition is represented by the deprivation at the initial period. Results are reported in Table 10.

In every dimension, after controlling for the unobserved effect, the coefficient on the lagged social exclusion is 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. Moreover, in all dimension we observe much unobserved heterogeneity. Note that our results about persistence of income deprivations (poverty) can be discussed on the basis of the existing literature. In particular, we find that both true state of dependence and unobserved heterogeneity lead to persistence of poverty. Cappellari and Jenkins (2002) arrive to the same conclusion using UK data and a different methodology. Instead, Trivellato, Giraldo and Rettore (2002), using data from the Italian survey on household income and wealth and proposing a new methodology, conclude that there is no evidence of true state of dependence[9]. Future research should focus on comparing these different methodologies from an econometric point of view, and explain the eventual different results.

Conclusions

The aim of this paper was to study the dynamics of social exclusion in Italy from 1994 to 2000. 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).

Using descriptive techniques, we show that about 15% of the population is counted as excluded in at least one dimension in all years from 1994 to 2000 in Italy 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

[9] Note that the way to deal with attrition represents a difference in the approach of these authors. Cappellari and Jenkins (2002) model attrition explicity, but the model obtained is quite complex. Our model cosider attrition problems implicity and define initial conditions. Trivellato, Giraldo and Rettore (2002) do not consider attrition in their model since testing for attrition they conclude that attrition does not affect the dynamics.

of the sample that experiences some exclusion, but is 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 excluded is much bigger than the one counted as poor: therefore, social exclusion highlights a problem that involves more people than income poverty.

Looking to the persistence of social exclusion over time, we do find evidence of individual heterogeneity and true state of dependence, even after controlling for observed individual differences. Observed individual characteristics and individual initial conditions appear also strictly related to the probability to experience social exclusion.

Our analysis contributes to understand a little bit better the extent of social exclusion in Italy, and can be used to improve policies to reduce social exclusion. In fact, policies can be focused on getting people out of social exclusion or on keeping individuals out of social exclusion once out. Our results highlight the necessity of both kinds of policies. Moreover, our analysis underlines as certain areas (e.g. education, health, etc.) are more relevant than others to prevent people from falling into social exclusion.

In our view, this paper represents a first step in order to better understand the causes leading to social exclusion. Further research could focus on the use of the framework presented in this paper to monitor existing policies and to calculating the effects of alternative policies on social exclusion. In fact, prediction seems to be the logical direction in which research should go.

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Figure 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)
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 1. Headcount ratio - Weighted sample (cross sectional weights)

	1994	1995	1996	1997	1998	1999	2000
Basic	5.06	5.92	4.83	4.51	3.65	3.77	3.41
Quality	1.90	2.42	1.49	1.28	1.06	0.96	0.79
Housing	2.32	2.03	1.47	1.11	1.57	1.39	1.23
Social	11.14	11.27	5.91	5.65	6.49	6.68	5.51
Healthy	13.01	13.36	12.16	11.93	12.15	11.78	11.58
Living	21.18	21.15	24.44	24.42	18.41	18.72	18.63
Work	7.74	7.82	7.18	7.35	7.14	6.98	6.30
Income	18.23	18.04	17.33	15.69	14.94	14.19	13.56
SE	51.45	52.13	50.32	49.70	45.47	44.50	43.37

Table 2. Proportion of individuals excluded in at least j dimensions (in 1994)

	%
J=1	51.45
J=2	19.58
J=3	6.08
J=4	1.83
J=5	0.40
J=6	0.06
J=7	0.01
J=8	0.00

Table 3. Correlation across waves

	se_0	se_1	se_2	se_3	se_4	se_5	se_6
se_0	1.0000						
se_1	0.4664	1.0000					
se_2	0.4020	0.4704	1.0000				
se_3	0.3676	0.4305	0.4842	1.0000			
se_4	0.3409	0.3943	0.4385	0.4944	1.0000		
se_5	0.3282	0.3617	0.3925	0.4662	0.5661	1.0000	
se_6	0.3198	0.3461	0.3800	0.4507	0.5061	0.5882	1.0000

Table 4. Persistence (no-weighted sample):

	Basic	quality	housing	social	healthy	Living	work	income	SE
Never Excluded	84.5	95.04	93.44	75.29	73.36	53.91	83.47	63.05	19.76
Excluded 1 wave	8.85	3.01	4.42	14.45	8.74	13.51	6.25	13.15	15.13
Excluded 2 waves	2.96	0.96	1.14	5.16	4.62	8.98	3.33	5.84	12.49
Excluded 3 waves	1.25	0.53	0.28	2.51	3.35	5.70	2.09	4.98	10.57
Excluded 4 waves	1.01	0.12	0.22	1.04	2.65	5.52	1.60	3.78	9.57
Excluded 5 waves	0.53	0.14	0.27	0.63	1.89	4.41	1.29	2.99	8.44
Excluded 6 waves	0.72	0.15	0.14	0.44	2.32	4.45	0.97	3.64	9.44
Excluded 7 waves	0.19	0.06	0.08	0.47	3.07	3.51	1	2.57	14.59

Table 5. Persistence – subsequent years – and multiple spells

Individuals excluded in one or more consecutive years (%)		Individuals experiencing the following number of spells (%)			
		one	Two	three	four
only 1 year	23.66	15.13	6.44	1.91	0.18
2 years	15.42	13.10	2.32		
3 years	9.88	8.49	1.39		
4 years	8.70	8.70			
5 years	4.83	4.83			
6 years	3.16	3.16			
7 years	14.59	14.59			

Table 6. Characteristics of the sample at the initial period

	% tot
Sex	
Female	52.07
Male	47.93
Age	
16-24	16.80
25-44	35.24
45-64	47.96
65+	18.56
Couple without children	16.53
Couple with children	13.78
Education	
high level	5.98
Medium level	29.33
low level	57.19
Region	
north	37.91
centre	29.11
south	20.78
islands	11.49

Table 7. Social Exclusion – 6 waves balanced panel

Se	Model A		Model B		Model C Coef.	Std.
se_lag	1.0125**	.031611	0.9681**	.031726	1.0180**	.030581
se0	1.8119**	.047666	1.624**	.046590	----------	----------
h10	----------	----------	----------	----------	0.4933**	.089760
h20	----------	----------	----------	----------	0.8795**	.156049
h30	----------	----------	----------	----------	0.6525**	.142972
h40	----------	----------	----------	----------	0.5754**	.064394
h50	----------	----------	----------	----------	1.3608**	.065799
h60	----------	----------	----------	----------	1.2612**	.050047
h70	----------	----------	----------	----------	1.2243**	.079804
h80	----------	----------	----------	----------	0.9183**	.050514
edu_h0	----------	----------	-0.7676**	.086921	-0.7287**	.081722
edu_m0	----------	----------	-0.3930**	.046274	-0.3852**	.043431
sex0	----------	----------	-0.0993	.039223	-0.0905	.036361
age0	----------	----------	0.0034	.001312	0.0018	.001292
cc0	----------	----------	-0.1560*	.051668	-0.1244	.048363
cwc0	----------	----------	0.0048	.062872	-0.0298	.057627
north0	----------	----------	-0.1618*	.051044	-0.1807**	.047646
isole0	----------	----------	0.8539**	.060347	0.7951**	.056304
sud0	----------	----------	0.7141**	.054145	0.6030**	.050391
wave2	----------	----------	-0.1288*	.039991	-0.1040	.039038
wave3	----------	----------	-0.1241*	.040094	-0.1127*	.039141
wave4	----------	----------	-0.3931***	.040380	-0.3818**	.039441
wave5	----------	----------	-0.4012**	.040874	-0.3693**	.039868
wave6	----------	----------	-0.3685**	.041024	-0.3616**	.040031
Constant	-1.7073**	.030102	-1.5319**	.084922	-1.3235**	.080617
sigma_a	1.4475**	.029535	1.3988	.028686	1.3321	.027563
Log-Likelihhod	-27007.361		-26599.991		-28773.502	

Note: se_lag = social exclusion at time t-1; se0 = social exclusion at the initial period; edu_h0 = high level of education; edu_m0 = medium level of education; cwc0 = cohabitation without children; cc0 = cohabitation and children; north0. island0 and sud0 indicate the area of residence at the initial period; wave i = dummy variable of the wave i (the first wave is wave zero). All the variables are time constant variable at the initial period. unless differently specified.

Table 8a. Estimated probabilities

Estimated probability of being socially excluded in 2000 given that the individual is or is not excluded in 1999

.	excluded 1999	not excluded 1999	estimated dependence
probability	0.4405	0.2131	**0.2274**
.	excluded 1994	not excluded 1994	estimated dependence
probability	0.5644	0.0832	**0.4812**

Table 8b. Estimated probabilities

Probability of being excluded in 2000 if

.	excluded 1999	not excluded 1999
high education	0.2687	0.0669
otherwise	0.4410	0.2202

.	excluded 1999	not excluded 1999
South	0.5703	0.3381
otherwise	0.4017	0.1551

Table 9. Probability to be excluded in 2000 if the individual is initially deprived

Deprived in 1994 in:	Probability to be socially excluded in 2000:
Basic	0.0000
Quality	0.0005
Housing	0.0045
Social	0.0034
Health	0.3669
Living	0.2855
Work	0.3019
Income	0.2874

Table 10. Estimation by single dimension

	Basic		Quality		Housing		Social	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Lag	1.2972**	.0798377	1.6889**	.1619559	1.5061**	.1504012	1.0223**	.064336
initial value	2.2539**	.1503991	3.5671**	.2678201	3.5877**	.2214806	1.8825**	.0883783
_cons	-5.2019**	.086815	-6.6398**	.1824662	-6.2173**	.1509869	-4.2120**	.0559546
sigma_u	2.0659**	.0689067	1.8875**	.114722	1.7395**	.0997919	1.5046**	.0477084
Log-likelihood	-7986.7593		-2815.2157		-3315.6718		-10771.61	
	Health		Living		Work *		Income	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Lag	1.2856**	.0549518	1.0694**	.0406154	1.7465**	.0786522	1.2215**	.0424901
initial value	4.2446**	.1179943	2.6316**	.072008	3.6612**	.1499244	2.7713**	.0762706
_cons	-4.6153**	.065082	-3.3454**	.0409349	-5.0123**	.088547	-3.6413**	.0458256
sigma_u	2.1390**	.0531557	1.7807**	.038703	1.982**	.06586	1.8621**	.0414657
Log-likelihood		-12727.95	-19847.112		-8011.6661		-18377.984	

(*) we used 1994-1999 data