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Poverty and social exclusion: two sides of the same coin or dynamically interrelated processes?

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Two Sides of the Same Coin or Dynamically Interrelated Processes?

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Abstract :

There is growing interest in the analysis and measurement of social exclusion, to complement the static and dynamic literature on income poverty. On theoretical grounds, social exclusion and income poverty are seen as different processes, but with closely interrelated dynamics. However, our empirical understanding of the way these two processes dynamically interact at the individual level is still very limited. To shed some light on the issue, we use a dynamic bivariate probit model, controlling for unobserved heterogeneity and Wooldridge (2005)-type initial conditions. Both first and second order Markov dynamics are examined. We estimate the model using the Italian sample of the ECHP, waves 1-8, and find a sizable extent of state dependence in both poverty and social exclusion. Moreover, there are dynamic cross-effects, implying that poverty and social exclusion are mutually reinforcing. Social policies aimed at eradicating poverty and avoiding individuals' social and economic marginalization should take these interaction effects explicitly into account.

Keywords: poverty dynamics, social exclusion, state dependence, dynamic bivariate probit model with random effects.

JEL-codes: I32, C33, C35, C61

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1. Introduction

In recent years a growing interest in the measurement and analysis of social exclusion has emerged, to complement the static and dynamic literature on income poverty. The deep economic and social transformations in Western countries, as well as decades of theoretical and empirical research, have contributed to a wider appreciation that human deprivations cannot only be related to a lack of financial resources. The increase in job precariousness and in labour market segmentation, the intensification of migration flows, the weakening of family ties and growing individualism, a rising violation of human rights and a decline in social and political participation, all show the inadequacy of the standard measures of poverty to describe the new reality and call for different and broader concepts of deprivation, encompassing economic dimensions but also social and political aspects of the individuals' life.

Social exclusion has been defined 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). Atkinson (1999) suggested three key elements in order to identify socially excluded individuals: *relativity, agency and dynamics*. Social exclusion involves the 'exclusion' of people from a particular 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 s/he lives in. Moreover, exclusion implies a voluntary act (agency) and depends on how situations and circumstances develop (dynamic process). Another essential characteristic of social exclusion is its *multidimensional* nature. In fact, the European Commission (1992 and 1993) suggests that "The concept of social exclusion is a dynamic one, referring both to processes and consequent situations... it also states out the multidimensional nature of the mechanisms whereby individuals and groups are excluded from taking part in social exchanges, from the component practices and rights of social integration and identity... it even goes beyond participation in working life: it is felt and shown in the fields of housing, education, health and access to services". The identification of the relevant aspects of social exclusion is still being debated, even if we have recently observed considerable advances in its measurement (Bossert, D'Ambrosio and Peragine, 2005; D'ambrosio and Chakravarty, 2006), in the empirical identification of the socially excluded (Whelan *et al*., 2002; Tsakloglou and Papadopoulos, 2002a and 2002b), or in the study of the dynamics of social exclusion (Poggi, 2007a and 2007b; Poggi and Ramos 2007).

In most, if not all, theoretical discourses on the subject, social exclusion and poverty are seen as different processes, leading to different states, with different implications and arising from a non-complete overlapping set of factors (e.g., Burchardt, 2000). The distinction is made with even greater emphasis if poverty is simply defined in terms of income insufficiency. For example, Atkinson (1998) points out that the process leading to exclusion from the labour market (exclusion from a desirable status: active participation in the society) may arise, under certain circumstances, from the operation of a social security system which induces people to reject labour market participation. However, exclusion from the labour market does not necessarily imply poverty, for example when the system provides generous social security benefits or if those out of employment can resort to their family's resources to maintain their standard of living. For another example, immigrants may be excluded from vote and local/neighbour organizations but they could have an income above the poverty line; conversely, they may have low incomes but be well integrated in their local communities and have developed a series of 'coping strategies' and informal networks aimed at maintaining an acceptable standard of living and participation status, despite their low income.

At the same time, while distinct, it is generally held that the two processes are characterized by an interrelated dynamics. Unfortunately, our empirical understanding (and empirical literature) on the way these two processes dynamically interact at the individual level is very limited. The aim of this paper is to contribute in filling this gap. In order to do so, we construct indicators for both poverty and social exclusion at the individual level and examine the dynamics of both, separately and jointly. We do not propose any new approach to the measurement of income poverty or social exclusion. We define poverty in terms of low income and look at the individual's longitudinal experiences of poverty, closely following the definitions adopted in a large body of the literature (e.g., Addabbo, 2000; Jenkins, 2000; Biewen, 2006; Cantò-Sanchez, 2002; Devicienti, 2002). The literature on social exclusion is comparatively smaller and there is even less consensus on how the concept is to be operationalized in an empirical analysis. In this paper we define social exclusion following the recent work of Poggi (2007a). While some of our definitional choices may not command universal support, referring to existing approaches has the advantage that we can focus on our main objective in this paper: shedding some light on the way the past history of the two processes affect each other at the individual level and in a dynamic context. While a few papers have separately studied the dynamics of low income (e.g., Cappellari and Jenkin, 2004) and social exclusion (Poggi, 2007a), and some have analyzed the interrelated dynamics of some dimensions of social exclusion (e.g., Stewart, 2005, on low-pay and employment), we are unaware of any econometric attempt of characterizing the joint dynamics of overall indicators of income poverty and social exclusion.

In order to do so, we use a dynamic bivariate probit model, incorporating unobserved heterogeneity and initial conditions, similar to the model of Alessie et al. (2004). Instead of their treatment of the initial conditions, however, we propose to extend the approach of Wooldridge (2005) to our bivariate case. Not only is the resulting estimator simpler to implement – which implies non-negligible savings in computing time in large datasets like our own; our approach does also more readily extend to higher order dynamics.

Our empirical analysis focuses on Italy, using data from waves 1-8 of the European Community Household Survey (1994-2001). Unlike other OECD countries, this is a country whose dynamics of both poverty and social exclusion has been to date little explored. Additionally, it constitutes an interesting case study. For, while its economy ranks among the largest in Europe, it is plagued by a long-standing territorial dualism, one of the lowest labour market participation among OECD countries and high segmentation of the labour force (above all, women, the young and the old). On the other, it features an overly generous, albeit largely inefficient, social security system (Ferrera, 2005) and a solid family-based social fabric. In these circumstances one would not expect that income poverty and social exclusion are simply "two sides of the same coin".

Our findings lend support to the view that poverty and social exclusion are rather distinct processes. In fact, the degree of dynamic overlap between the two is found to be weaker than generally assumed. This is in line with the findings of Whelan et al. (2004) who conclude that income and what they call "life-style deprivation" are tapping rather different dimensions of deprivation. The results of our econometric model show the existence of sizable 'true' state dependence in both poverty and social exclusion, after controlling for unobserved heterogeneity. Both processes are shaped by a rather persistent dynamics; in fact a second order dynamics was found to provide a better fit of the data. Moreover, the dynamics of poverty and social exclusion are found to be interrelated, with positive spillover effects that make the two processes mutually reinforcing. We argue that social policies aimed at eradicating poverty and avoiding individuals' social and economic marginalization should take these dynamic cross-effects effects explicitly into account.

The rest of the paper is structured as follows. Section 2 provides details of the data used, sample selection and the way the poverty and social exclusion indicators are constructed. Section 3 shows preliminary empirical evidence on the dynamics of poverty and social exclusion in Italy during the nineties. Section 4 illustrates our econometric methodology, whose results are presented in section 5. Section 6 contains our concluding remarks.

2. Data and indicators

Data and sample selection

To study the longitudinal experiences of poverty and social exclusion in Italy, we use the European Community Household Panel (ECHP), 1994-2001, arguably the only household panel survey covering a relatively long time period in this country and containing a wealth of information relevant for our aims. The ECHP is a multi-country comparative household panel survey conducted annually by following the same sample of households and persons in the Member States of the European Union. The advantage of the ECHP is that it permits us to analyze economic and social household conditions from a dynamic point of view. However, a significant disadvantage is the omission of the homeless population that would be expected to be socially excluded. To minimize sample selection and attrition problems our statistical analysis uses cross-sectional or the longitudinal weights available in the ECHP, as appropriate. However, as discussed in section 4, we do not use weights in any of our econometric models, which would otherwise result in a loss of efficiency.

Our analysis focuses on the adult population, excluding both children (individual aged 16 or less) and the elderly (aged 60 or more). In the case of children the restriction comes directly from the data: individuals in the ECHP are interviewed only when they reach age 16, making unavailable some of the indicators that we use below for the definition of social exclusion. The omission of the elderly rest on a more theoretical argument, as we believe that a different definition of social exclusion is likely to be relevant for this age group compared to the adult population. For example, the fact that individuals are "not able to work due to own illness, injury and incapacitation" – one of the indicator that we use below for identifying the adults at risk of social exclusion (Table 1) – is not an issue if the individuals do not belong to the active population. In the rest of the paper, therefore, all the analyses refer to the sample of individuals aged 16-60.[1]

Indicators of poverty and social exclusion

An individual is defined as poor if his/her household equivalent income is less than a chosen poverty line. The latter is defined as 60% of contemporaneous median income. Note that, even if this may be seen as arbitrary, its use has become common practice in Europe and, therefore, it allows comparisons with other studies on poverty dynamics. The income variable considered is 'equivalent household income', obtained after adding up income from all sources from any household member, and then dividing the result by the number of equivalent adults (using the OCED-modified equivalence scale). The unit of the analysis is the individual. Assuming an equal sharing of an household's resources, each person within the household is attributed the same value of the equivalent household income. These choices are not uncontroversial but are made in a large body of the empirical literature studying the dynamics of low-income (for a review, see Jenkins, 2000).

As we said, social exclusion may be defined as a process that fully or partially excludes individuals or groups from social, economic and cultural networks in the society they live in (Lee and Murie, 1999). Social exclusion can also been seen as a part of Sen's capability approach, and it can be defined as a process leading to a state of functioning deprivations (Sen, 2000). In particular, in order to operazionalize the concept, we use the working definition proposed by Poggi (2007a): "An individual is defined as socially excluded in a specific point in time if he/she is deprived of two or more relevant functionings". As a matter of fact, the definition of the relevant dimensions (functionings) is an open issue. Following the guidance offered by the recent literature (Brandolini and D'Alessio, 1998; Poggi, 2007a), and taking into account the actual information available in the ECHP, we select six relevant dimensions to capture all the principal aspects of social exclusion (see Table 1). The selected dimensions are " basic needs fulfilment", "reaching a certain quality of life", "having an adequate house", "being healthy and able to work", "living in a safe and clean environment" and "the ability to have social relationships". The first three dimensions describe the economic

[1] We chose the age 60 threshold, rather than 64 as commonly in LFS, in light of the low average age of retirement, at about 58 during the nineties, one of the lowest in Europe. Results were only marginally affected by the use of the higher threshold.

features of social exclusion, and the remaining dimensions emphasize the social dimension of exclusion. In addition, the sixth dimension gives also some information about the political dimension of social exclusion.

Table 1. Social exclusion dimensions

Basic needs fulfilment (BASIC)
Not eating meat or the like every second day
Being unable to buy new, rather than second hand clothes
Being unable to pay bills, rent, etc.
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 an indoor flushing toilet
Not having hot running water
Not having enough space
Not having enough light
Not having an adequate heating facility
Not having damp walls, floors, foundation...
Not having a leaky roof
Not having rot in the window frames, floors
Ability to have social relationships (SOCIAL)
Frequency of talk to the neighbours
Frequency of meeting people
Member of any club (sport club, neighbourhood group, party, etc.)
Being healthy and able to work (HEALTH)
Being hampered in daily activities by any physical or mental health problem
Not search for a job because own illness, injury and incapacitation
Living in a safe and clean environment (LIVING)
Noise from neighbours or outside
Pollution, crime or other environmental problems caused by traffic or industry
Vandalism or crime in the area

As in the case of poverty, social exclusion is measured at the individual level. 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'[2]. Instead, a score equal to zero means that the individual is deprived of that item. All the values between zero and one mean an intermediate situation.

[2] For example, s/he can afford a durable good or has an indoor flushing toilet or does not have pollution in the area where s/he lives.

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. 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 represent intermediate situations.

Inclusion or exclusion in each of the six 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 the threshold below which the individual is counted as deprived has some degree of arbitrariness. In the absence of exogenous rules, we fixed the threshold for a functioning at 60% of the median of the functioning distribution. This choice is the same as for income poverty. Every individual whose functioning score in any given year is below the functioning threshold is defined as deprived in that functioning in that year. Therefore, an individual can be deprived in one or more functionings. Moreover, we implicitly assume that anyone who is able to achieve a valuable functioning would do so. Finally, we combined the information about each functioning deprivations in a summary indicator of social exclusion. As in Poggi (2007a), our working definition of social exclusion assumes that deprivation in two functionings is sufficient for social exclusion. Therefore, an individual is counted as socially excluded at time t if he/she is deprived in at least two dimensions.

3. Poverty and social exclusion in Italy: preliminary empirical evidence

Table 2 shows the proportion of the Italian adult population who experience deprivation in any of the selected dimensions, from 1994 to 2001. The incidence of deprivation is particularly high in the following dimensions: “living in a safe and clean environment” and “ability to have social relationships”. Therefore, the importance of the non-income dimensions immediately emerges. The table also reports the proportion of the population who experience social exclusion, poverty, and both, according to our definitions. On average over the period 1994-2001, we find that about 8% of the sample is socially excluded and about 20% is poor. Over time, there is a declining trend in both poverty and social exclusion in the sample, which is consistent with the general economic growth, the rise in employment rates and steady decline in unemployment rates observed throughout the period.

Interestingly, only 3.5% of the sample is both poor and socially excluded. Of those who are poor in any given year, only about 16% are found in social exclusion in the same year (but the percentage is only 6% for those who are not poor). Conversely, for those who are socially excluded in a given year, about 41% also have their income below the poverty line (compared to only 18% for those who are not socially excluded). These findings are in line with those of the previous literature (e.g., Perry, 2002; Whelan et al., 2004) that, using a number of statistical and visual inspection techniques, point out the lack of overlap in the proportion of individuals defined as poor and deprived / socially excluded at a given point in time, for many different countries. Accordingly, we are tempted to conclude against the view that poverty and social exclusion are simply alternative ways of measuring the same, underlying, state of deprivation.

Another way to investigate if poverty and social exclusion are simply alternative ways of measuring the same underlying concept is by using a non-linear Wald proportionality test on the coefficients of two probit models, one for poverty, the other for social exclusion. Put simply, the idea is that, if poverty and social exclusion are two different proxies of a common latent variable, then one might expect that the coefficients of the poverty model are simply a scaled version of the coefficients of the social exclusion model. In other words, if β_k^{poor} represent the coefficients of covariate k in the poverty model, and β_k^{se} the corresponding coefficient in the social exclusion model, the null hypothesis of coefficient proportionality is stated as:

$$H_0: \quad \frac{\beta_1^{poor}}{\beta_1^{se}} = \ldots = \frac{\beta_k^{poor}}{\beta_k^{se}} = \ldots = \frac{\beta_K^{poor}}{\beta_K^{se}}$$

where the same K covariates are used in both equations. The test is carried out as a non linear Wald test.[3] We run the two (static) probit models using various specifications including a broad set of controls (sex, age, education, cohabitation status, number of household dependent members, number of household working members, area of residence and year dummies). In all cases we were able to reject the null hypothesis at the 1% level of statistical significance[4], which strengthen our confidence against the "two sides of the same

[3] Note that the non-linear Wald test is not invariant with respect to representation. In fact, an alternative representation of the null hypothesis is as follow: $H_0: \beta_1^1 \beta_2^1 = \ldots = \beta_1^k \beta_2^k = \ldots = \beta_1^K \beta_2^K$. If both representations lead to similar test statistics and p-values, one is able to accept or reject the hypothesis of proportionality of the coefficient of the two equations.

[4] The results of the tests are available upon request from the authors.

coin" hypothesis and in favor of the view that poverty and social exclusion are better interpreted as distinct, albeit related, processes.

All previous results refer to the cross-sectional incidence of poverty and social exclusion. To assess an individual's longitudinal experience of deprivation and, in particular, how the current state is related to past occurrences of poverty and social exclusion we now turn to the panel dimension of the data. Table 3 reports the proportion of the sample that experiences social exclusion / poverty for a certain number of years. As typically found in the literature, the fraction of the sample who is in deprivation in at least one year within the time period under investigation is much higher than the cross-sectional deprivation rate. In fact, about 48% is touched by income poverty in at lest one year, and 33% in the case of social exclusion (against a cross-sectional rate of 20% and 8%, respectively). Less than 1% of the sample experience social exclusion over the entire period of study, but about 4% of the sample is persistently poor in all eight waves. In other words, the deprivation states are characterized by a fair amount of turnover, so that it is not always the same individuals who are found below the deprivation thresholds. Devicienti and Gualtieri, 2006, provide compelling evidence of this phenomenon with respect of various definitions of poverty.

Nonetheless, people who have already suffered some form of deprivation in the past appear to be more likely of suffering further deprivation in the future. As shown in Table 4, the conditional probability of being poor in year t given that the individual was not poor in t-1 is 8%, but it dramatically increases to 65% for those who were poor in t-1. Similarly, the probability of being socially excluded in t is 3.5% for those who were not excluded in t-1, but is 42% for those who were already classified as socially excluded. The table also shows that lagged poverty (social exclusion) is positively associated to social exclusion (poverty) in the current year, hinting at the possibility that dynamic spillover effects exist between the two processes. In fact, the probability of being currently poor is 3% among those who were not socially excluded in the previous year, and rises at 45% for those who were. Similarly, the probability of being socially excluded in t is equal to 4% for those whose income in t-1 was above the poverty line, and 14% for those classified as income poor in t-1. How can we explain the correlation that we observe in the data between an individual's current and past poverty and current and past social exclusion? And how can we explain the cross-correlation found between current and past occurrences of the two forms of deprivation for the same individual? Clearly, these correlations may simply reflect the effect of individual observed and unobserved heterogeneity.

Alternatively, an individual's past experience in one form of deprivation may have a causal effect on current deprivation of the same type, or also of the other type. Our understanding of the causes leading to deprivation persistence at the individual level is likely to be enhanced if we were able to disentangle between these alternative explanations. This is the aim of the econometric model introduced in the next section.

4. An econometric model for the interrelated dynamics of poverty and social exclusion

To study the interrelated dynamics of poverty and social exclusion, in this section we introduce a dynamic random-effect bivariate probit model for the joint probability of experiencing the two states. The model allows for correlated unobserved heterogeneity and accounts for the initial conditions of the two processes. The presentation of the model follows that of Alessie et al. (2004) for the most part[5]; however, our treatment of the initial conditions is different and, we argue, more convenient for our purposes, as will be explained below.

For an individual *i*, the risk of being in poverty at time *t* is expressed in terms of a latent variable y^*_{1it}, as specified as in equation (1), while the risk of being socially excluded in *t* is expressed by the latent variable y^*_{2it}, specified in equation (2).

$$y^*_{1it} = x'_{it}\beta_1 + y_{1i,t-1}\gamma_{11} + y_{2i,t-1}\gamma_{12} + c_{1i} + u_{1it} \tag{1}$$

$$y^*_{2it} = x'_{it}\beta_2 + y_{1i,t-1}\gamma_{21} + y_{2i,t-1}\gamma_{22} + c_{2i} + u_{2it} \tag{2}$$

$$y_{jit} = 1\left[y^*_{jit} > 0\right], \qquad j = 1,2; \quad t = 2, \ldots, \mathrm{T} \tag{3}$$

The dependent variables are the dummy indicators y_{1it} (equal to one if the individual is at risk of poverty in *t*, and zero otherwise) and y_{2it} (equal to one if *i* is at risk of social exclusion in *t*, and zero otherwise). In the model represented by (1)-(3), x_{it} is a vector of independent variables, assumed to be strictly exogenous, and $\beta=(\beta_1, \beta_2)$ is the corresponding vector of parameters to be estimated. The errors

[5] See Heitmueller and Michaud (2006) and Miranda (2007) for applications of the model of Alessie et al. (2004) in different contexts.

terms u_{1it} and u_{2it} are assumed to be independent over time and to follow a bivariate normal distribution, with zero means, unit variances and cross-equation covariance ρ. The model also includes individual random effects, c_{1i} and c_{2i}, assumed to be bivariate normal with variances σ_{c1}^2 and σ_{c2}^2 and covariance $\sigma_{c1}\,\sigma_{c2}\,\rho_c$. We also assume that ($c_{1i}$, c_{2i}), (u_{1it}, u_{2it}; t=1,…,T) and (x_{it}; t=1,…,T) are independent (implying that x_{it} is strictly exogenous).

This dynamic random-effects model is well suited to tackle the issue of "true state dependence", that is to say to establish the causal impact of past poverty on current poverty and of past social exclusion on current social exclusion, once the confounding impact due to unobserved heterogeneity is accounted for. As is well known, both phenomena (unobserved heterogeneity and true state dependence) can explain why, say, being poor in *t*-1 is correlated with being poor in *t;* however, the policy implications are different in the two cases. For example, if the persistence of poverty (social exclusion) is, at least partly, due to true state dependence, then it is possible to reduce the risk of experiencing poverty (social exclusion) in the future by pulling the individual out of poverty (social exclusion) at time *t*. Thus, short-term policies may have long-lasting effects because they help breaking the "vicious circle" leading to deprivation. On the contrary, if the persistence of poverty (social exclusion) is merely due to adverse unobserved heterogeneity, any such policy intervention is bound to be ineffective in the long run and can have, at best, only temporary effects. To disentangle between unobserved heterogeneity and true state dependence, the lagged dependent variable, $y_{1i,t-1}$, is included in the poverty equation (1) and the lagged dependent variable $y_{2i,t-1}$ is included in the social exclusion equation (2). The dynamics of the model is here assumed to be first-order for simplicity; however, later in the paper, we will also allow for second order dynamics.

Reflecting our interest in uncovering the presence of dynamic spillover effects from poverty to social exclusion, and from social exclusion to poverty, the model also includes cross-effect lagged variables: lagged social exclusion $y_{2i,t-1}$ is included in the poverty equation and lagged poverty $y_{1i,t-1}$ is included in the social exclusion equation. This way it may be possible to understand whether the correlation observed in the data between, say, $y_{1,t-1}$ and y_{2t} is due to correlated unobserved heterogeneity (i.e., $\rho_c \neq 0$) or rather to state dependence across poverty and social exclusion (i.e., the spillover effects γ_{12} and γ_{21} are non-zero). The distinction is crucial for understanding the dynamics of the two forms of deprivation and for the design of policy. For example, if true spillover effects exist, and are positive, policies aimed at pulling individuals out of one type of deprivation may also contribute in breaking the cycle leading to deprivation of the other type.

The model in (1)-(3) embeds a few simpler models as special cases. If $\gamma_{12} = \gamma_{21} = 0$, equations (1) and (2) can be estimated separately, obtaining consistent estimates of the remaining parameters. This special case corresponds to the standard univariate random-effect dynamic probit model (see Heckman, 1981a; Stewart, 2005, provides further discussion). If $\gamma_{12} \neq 0$, but the error terms and the random effects of the two equations are independent (respectively, $\rho = 0$ and $\rho_c = 0$), then equation (1) can be estimated as a univariate model treating $y_{1i,t-1}$ as weakly exogenous. A similar reasoning applies to equation (2) in the independence case. In all other cases, consistent estimates of the parameters require the joint estimation of model (1)-(3).

Estimating the model: the Alessie et. al (2004) estimator

In dynamic panel data models with unobserved heterogeneity, the treatment of the initial observations is an important theoretical and practical problem, particularly so in short panels. The simplest approach assumes that the pre-sample history, or initial conditions, are exogenous and can be ignored (e.g. Heckman, 1981a). This restriction is valid only if the process begins at the start of the observed sample period, or if the disturbances that generate the process are serially independent, which is not the case in the presence of unobserved heterogeneity. In fact, if heterogeneity is a determining factor in the initial sample conditions, then this approach will overstate the amount of state dependence in the process.

For the initial period *t*=1, model (1)-(3) would require the observation of y_{1i0} and y_{2i0}; however, data at times 0, -1, -2, … are not available. In the univariate case, Heckman (1981b) suggests to replace the equation for *t*=1 by a static equation with different regression coefficients and arbitrary combinations of the random effects. This can be seen as a linearized approximation to the reduced form for the latent variable in the initial period. Alessie et al. (2004) propose to generalize Heckman's approach to the bivariate model represented by (1)-(3) and introduce two static equations for *t*=1, as follows:

$$y_{1i1}^{*} = x_{i1}^{'}\kappa_1 + \lambda_{11}c_{1i} + \lambda_{12}c_{2i} + \varepsilon_{1i1} \tag{4}$$

$$y_{2i1}^{*} = x_{i1}^{'}\kappa_2 + \lambda_{21}c_{1i} + \lambda_{22}c_{2i} + \varepsilon_{2i1} \quad (5)$$

where the error terms ε_{1i1} and ε_{1i2} are standard normal with correlation coefficient ρ_{ε}.[6]

Estimation of the model composed by equations (1)-(5) can be carried out by maximum likelihood methods. The likelihood contribution of an individual observed in *T* waves (*t*=1,…, *T*) is of the form:

$$L^{A} = \prod_{i=1}^{N} \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} h_i(c_1, c_2) g_i(c_1, c_2, \Sigma_c) dc_1 dc_2 \quad (6)$$

where *g* is the joint density of (c_1, c_2), with covariance matrix Σ_c, and h_i is the joint probability of the observed binary sequence for individual *i* :

$$\begin{aligned} h_i(c_1, c_2) = {} & \Phi_2\left(\tilde{y}_{1i1}\mu_{1i1}, \tilde{y}_{2i1}\mu_{2i1}, \tilde{y}_{1i1}\tilde{y}_{2i1}\rho_e \mid x_{it}\right) \times \\ & \times \prod_{t=2}^{T} \Phi_2\left(\tilde{y}_{1it}\mu_{1it}, \tilde{y}_{2it}\mu_{2it}, \tilde{y}_{1it}\tilde{y}_{2it}\rho \mid y_{1,t-1}, y_{2,t-1} \ldots, x_{it}\right) \end{aligned} \quad (7)$$

$\Phi_2(\cdot,\cdot,\rho)$ is the bivariate cumulative density function of a bivariate normal distribution with zero means, unit variances and covariance ρ, and $\tilde{y}_{jit} = 2y_{jit} - 1$, for *j*=1,2. For *t*=1, μ_{1i1} and μ_{2i1} are defined as:

$$\begin{aligned} \mu_{1i1} &= x_{i1}^{'}\kappa_1 + \lambda_{11}c_{1i} + \lambda_{12}c_{2i} \\ \mu_{2i1} &= x_{i1}^{'}\kappa_2 + \lambda_{21}c_{1i} + \lambda_{22}c_{2i} \end{aligned} \quad (8)$$

and for *t*=2,…, T, μ_{1it} and μ_{2it} are defined as:

$$\begin{aligned} \mu_{1it} &= x_{it}^{'}\beta_1 + y_{1i,t-1}\gamma_{11} + y_{2i,t-1}\gamma_{12} + c_{1i} \\ \mu_{2it} &= x_{it}^{'}\beta_2 + y_{1i,t-1}\gamma_{21} + y_{2i,t-1}\gamma_{22} + c_{2i} \end{aligned} . \quad (9)$$

The likelihood contribution in (6) is the expected value of the likelihood contribution conditional on the random effects (c_1, c_2). As discussed by Alessie et al. (2004), standard approaches of numerically integrating out the random effects are feasible but difficult in the present setting. Instead, they proceed by approximating the expectation in (6) by simulation methods. We do the same, as explained in Appendix 1.

[6] Heckman recommends the inclusion of exogenous s instruments in the initial condition equations, whenever available. This is done in a few studies, for example Stewart (2005) and Cappellari and Jenkins (2004) use information on the respondent's parental background when the respondent was 14 as exogenous instruments. However, this pre-sample information is not available in the ECHP. Note that Alessie et al. (2004) too do not include exogenous instruments in their initial condition equations.

An alternative Wooldridge-type estimator

The approach followed by Alessie et. al. (2004) provides a flexible characterization of the sample initial conditions in terms of the observable covariates and unobserved individual effects, and represents a straightforward generalization of the univariate Heckman estimator. In this paper, we will follow a different route for the treatment of the initial conditions, extending to the bivariate case the simple approach proposed by Wooldridge (2005) for univariate dynamic random effects probit models. We do so for two main reasons: (i) our treatment extends more readily to a model with higher order dynamics, which is found to be crucial in our empirical application; (ii) our treatment is simpler, resulting in substantial savings in computer time. This second issue may not be very important in samples of moderate size, but becomes very much relevant in cases, like our own, where there are almost 40,000 observations.

Rather than attempting to obtain the joint distribution of all outcomes of the endogenous variables, as in the previous estimator, Wooldridge (2005) proposes a Conditional Maximum Likelihood (CML) estimator that considers the distribution conditional on the initial values and the observed history of strictly exogenous explanatory variables. In other words, instead of modelling the density of ($y_{i1},..., y_{iT}$) given x_i, Wooldridge suggests modelling the density of ($y_{i2},..., y_{iT}$) conditional on (y_{i1}, x_i). The estimator can be viewed as simply using a different approximation which has computational advantages. While Heckman specifies a model for y_{i1} given x_i and c_i, Wooldridge specifies one for c_i given y_{i1} and x_i. For the univariate case, he assumes:

$$c_i = a_0 + a_1 y_{i1} + \bar{x}_i' a_2 + \alpha_i \qquad (10)$$

where a_0, a_1, and a_2 are parameters to be estimated, $\bar{x}_i$ contains longitudinal averages of x_{it},[7] and α_i has zero mean normal distribution and variance σ_α^2. Substituting (10) into a univariate dynamic probit model with random effects (say, equation (1) above, with γ_{12}=0 and $\rho = \rho_a = 0$), gives Wooldridge's final equation, which can be estimated with a standard random effects probit software (see, Stewart, 2005, for further discussion).

[7] Note that time-constant variables (e.g., gender) may be included in either (10) or in (1)-(2). It is not possible to separately identify the effect of time-constant variables on unobserved heterogeneity and on the latent variables.

To generalize this approach in the context of our bivariate probit model, we specify the individual specific effects c_{i1} and c_{i2} given the poverty initial condition, y_{1i1}, the social exclusion initial condition, y_{2i1}, and the time-constant explanatory variables $\bar{x}_i$, as follows:

$$c_{1i} = a_{10} + a_{11} y_{1i1} + a_{12} y_{2i1} + \bar{x}_i' a_{13} + \alpha_{1i} \tag{11}$$

$$c_{2i} = a_{20} + a_{21} y_{1i1} + a_{22} y_{2i1} + \bar{x}_i' a_{23} + \alpha_{2i} \tag{12}$$

where a_{j0}, a_{j1}, a_{j2} and a_{j3} (j=1,2) are parameters to be estimated, (α_{1i}, α_{2i}) are normally distributed with covariance matrix Σ_α:

$$\Sigma_\alpha = \begin{pmatrix} \sigma^2_{\alpha 1} & \sigma^2_{\alpha 1}\sigma^2_{\alpha 2}\rho_\alpha \\ . & \sigma^2_{\alpha 2} \end{pmatrix}. \tag{13}$$

Then after inserting in model (1)-(2) we obtain:

$$\begin{aligned} y^*_{1it} &= x_{it}'\beta_1 + y_{1i,t-1}\gamma_{11} + y_{2i,t-1}\gamma_{12} + a_{10} + a_{11} y_{1i1} + a_{12} y_{2i1} + \bar{x}_i' a_{13} + \alpha_{1i} + u_{1it} \\ y^*_{2it} &= x_{it}'\beta_2 + y_{1i,t-1}\gamma_{21} + y_{2i,t-1}\gamma_{22} + a_{20} + a_{21} y_{1i1} + a_{22} y_{2i1} + \bar{x}_i' a_{23} + \alpha_{2i} + u_{2it} \end{aligned} \tag{14}$$

Consistent estimates of the model's parameters can be obtained by Conditional Maximum Simulated Likelihood methods. The contribution of individual i to the likelihood may be written as follow:

$$L^W = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\prod_{t=1}^{T}\Phi_2\left(\tilde{y}_{1it}\mu_{1it}, \tilde{y}_{2it}\mu_{2it}, \tilde{y}_{1it}\tilde{y}_{2it}\rho \mid y_{1,t-1}, y_{2,t-1} \ldots x_{it}, \bar{x}_i\right) g\left(\alpha_1, \alpha_2, \Sigma_\alpha\right) d\alpha_{1i} d\alpha_{2i} \tag{15}$$

where μ_{1it} and μ_{2it} are the right-hand sides of equations in (14) excluding the error terms u_{1it} and u_{2it}.

A first advantage of our Wooldridge-type estimator over the Alessie et al. (2004) estimators is immediately clear. In fact, it can be easily shown that the number of parameters to be estimated is always smaller in the first estimator than in the second (and the gap grows in models where most exogenous variables are time-invariant). When savings in computing time is an issue, as it is in large samples like our own, it becomes important for applied researchers to be able to resort to simpler estimation approaches.

A second advantage of our estimator is that it can be easily used for estimating models with a higher order dynamics. In section 5, in fact, we will specify our model with second order dynamics but will still be able to use our estimator. As we have specified a model for $(\alpha_{1i}, \alpha_{2i})$ given the initial observations of the dependent variables (and the observed history of strictly exogenous explanatory variables), it is always possible to simply add $y_{ji,t-2}$ (j=1,2) in (14) and use the same estimator as developed above. In the Alessie et al. (2004) estimator, on the other hand, one would have to include additional static equations for the initial condition at time t=2, thereby considerably increasing the demands on the econometric model.

A final comment is in order concerning the requirement that models incorporating the initial condition solution proposed by Wooldridge (2005) be estimated on a balanced panel. Accordingly one may be worried that the estimator could potentially exacerbate attrition and sample selection present in the data. In fact, this is not the case, since Wooldridge's method has some advantages in facing selection and attrition problems. In particular, as explained in Wooldridge (2005; pp.44), it allows selection and attrition to depend on the initial conditions and, therefore, it allows attrition to differ across initial levels of deprivation. In particular, individuals with different initial statuses are allowed to have different missing data probabilities. Thus, we consider selection and attrition without explicitly modelling them as a function of the initial conditions. As a result, the analysis is less complicated and it compensates for the potential loss of information from using a balanced panel. Moreover, in the conditional MLE we can ignore any stratification that is a function of the initial level of deprivation and of the time-constant explanatory variables: thus, using sampling weights would lead to an efficiency loss.

5. Estimation Results

In this section, we discuss the results of the dynamic models for poverty and social exclusion discussed in the previous section. We start with simple univariate models, i.e. we estimate dynamic random-effects probit models separately for poverty and social exclusion. These represent special cases of the bivariate model presented in section 4: we can therefore test the restrictions imposed by the univariate models. We then compare the estimates obtained with the two different treatments of the initial conditions in the dynamic bivariate model. Next, we test the assumption that the dynamics are first order against the second order alternative. Finally, we discuss in details our preferred specification and show the implications of the model's estimates in terms of true state dependence and dynamic spillover effects.

Some of the explanatory variables included in the vector x_{it} refer to individual-level characteristics (see Table A1 for descriptive statistics): gender, age (linear), dummies for low and medium education (high education is the reference category), marital status (=1 if living as a couple). Household-level characteristics are also included in x_{it}: the number of economically active members of the household, and the number of dependent household members (children and non-active adults). These variables are allowed to be time varying. An unrestricted set of year dummies is also included in all specifications to capture the macroeconomic environment. Structural differences in local conditions (e.g., labour markets tightness, differences in regional prices) are summarized by a set of regional dummies, included in all specifications. In both equations, the same explanatory variables are used. While in principle a wider set of influences may be considered, we have maintained our reduced-form specifications relatively parsimonious because (i) we are already controlling for (correlated) unobserved heterogeneity, (ii) the estimation of our model is already computationally demanding. More importantly, the variables included in x_{it} do not constitute the main focus of the analysis: this lies instead in the interrelated dynamics of poverty and social exclusion, which is reflected in the estimates of the lagged indicators for both dependent variables. Indeed, as we show below with reference to the potentially endogenous variables of x_{it}, the inclusion/exclusion of observed heterogeneity controls does not significantly alter the main parameters of interest.

Univariate random-effects dynamics models for poverty and social exclusion

We start by estimating the poverty and the social exclusion equations separately. In this case we are implicitly assuming that (i) the cross-lagged variables effects are equal to zero; and/or (ii) the correlation of the errors and the correlation of random effects across the two equations are equal to zero. We estimate the two equations with both the Heckman and the Wooldridge estimators using the same specification: results are reported in Table 5 for the poverty equation and in Table 6 for the social exclusion equation. The corresponding pooled probit models (without random effects and no initial condition) are also reported in the Tables for comparison. Note that the initial conditions *a la* Wooldridge imply that the start-of-period status of poverty and social exclusion be included in the model. As shown by (11) and (12), longitudinally-averaged versions of the time-varying variables contained in x_{it} are also included in these models. The estimates of these additional variables, and in general of the variables referring to the initial conditions in each estimator, are reported in Appendix 2.

As noted in section 4, the Wooldridge estimator requires a balanced panel sample. For comparison, the same balanced sample is used for all other estimators in the paper. We have already pointed out that this restriction is not particularly problematic with the Wooldridge-type estimators. To provide further evidence on the issue, we compared the estimates of pooled univariate probit models of poverty and social exclusion with and without the balanced sample restriction. We repeated the same comparison with pooled bivariate models of the two equations. In each case, we found that the restriction to a balanced sample had only a negligible impact on the coefficients of the own-lags and cross-lags of the dependent variables.[8]

According to the results of Table 5, the Heckman and the Wooldridge estimators deliver very similar estimates of the coefficient of the lagged dependent variable, equal to 0.74 and 0.78, respectively. Both are also highly statistically significant. As remarked by Wooldridge (2005), the similarity between the two estimators is to be expected. On the other hand, the same coefficient is overestimated in the pooled probit models: the scaled[9] coefficient of lagged poverty is estimated at 0.55 with the Heckman estimator and at 0.64 with the Wooldridge's, compared with the pooled probit estimate of 1.5. This should not be surprising, as the pooled probit model does not control for the process' initial conditions, nor does it allow for unobserved heterogeneity. Similar conclusions can be drawn for the social exclusion equation in Table 6: the scaled coefficients estimated on lagged social exclusion is 0.40 for the Heckman estimator and 0.57 for the Wooldridge's, compared with an estimate of 1.4 for the pooled probit.

The results of Table 5 and 6 also show that there are positive and statistically significant dynamic spillover effects among the two equations. The coefficient of lagged social exclusion is estimated at 0.28 in the poverty equation if the Heckman estimator is used; the estimate obtained with the Wooldridge estimator is not too different, at 0.22. In the social exclusion equation, lagged poverty has a statistically significant coefficient of 0.29 with the Heckman estimator and 0.21 with Wooldridge's. One immediate consequence of

[8] The estimates of these and further robustness checks are available from the authors upon request.

[9] Note that the dynamic random effects probit models and the pooled probit model involve different normalizations (see Arulampalam, 1999) and, therefore, the estimated coefficients of the former need to be rescaled to be compared with the estimated coefficients of the latter. In our case the coefficients of the random effects models need to be multiplied by an estimate of $\left(1-\sigma_{\alpha}^{2}\right)^{-1/2}$.

the non-zero coefficients of the cross-lagged variables is that the two equations can be estimated separately, as done here, only if the error correlation and the random effects correlation are equal to zero ($\rho = \rho_a = 0$). To test the latter hypothesis, we now estimate the dynamic bivariate probit model with random effects of section 4.

Bivariate dynamic random-effects models for poverty and social exclusion

Table 7 reports the estimates of the dynamic bivariate probit model for poverty and social exclusion, which relaxes the assumption of independence in the errors and the random effects of the two equations. Columns 5 and 6 show the estimated coefficients and standard errors of the Alessie et al (2004) estimator, with initial conditions *a la* Heckman, as described by our equations (1)-(5). Columns 3 and 4 report instead the estimated coefficients and standard errors of the dynamic bivariate probit model with random effects and initial condition *a la* Wooldridge, as summarized by equation (14). For comparison, columns 1 and 2 report the estimated coefficients and standard errors of a pooled dynamic bivariate probit model.

We first note that in both the Alessie et al. (2004) model and our Wooldridge-type estimator we are able to reject the hypothesis of independence in the errors and the random effects of the two equations, indicating that the joint estimation of the model equations is necessary. In fact, ρ is statistically significant and equal to 0.05 in both estimators. As for the random effects correlation, ρ_α, this too is statistically significant, with an estimated coefficient of 0.27 in the first estimator and 0.32 in the second.

The estimates of the pooled bivariate probit model do not control for individual unobserved heterogeneity and assumes that the initial conditions are exogenous. One would then expect that this estimator overestimate the importance of state dependence, as the coefficient of the lagged dependent variable absorbs part of the effect that is instead due to (uncontrolled) unobserved heterogeneity. A quick glance at Table 7 confirms that this is indeed the case. We also note that the estimates of the lagged dependent variables and of the cross-lagged dependent variables are slightly lower in the bivariate random–effect models than in the corresponding univariate models. Thus, ignoring the cross-correlations in the error terms seems to slightly overestimate such parameters.

The results in Table 7 from both the dynamic random effects probit model estimators (i.e. our Wooldridge-type estimator and the Alessie et. al. estimator) show a strong degree of agreement, as already found with the univariate models. Given the advantages of the Wooldridge estimator pointed out in section 4, this is the estimator that we use in the rest of the paper. Two other specifications are considered in Table 8. First, we exclude the potentially endogenous variables in x_{it} and check that the estimates of the key variables of interest, the lagged dependent variables, were not overly affected by their inclusion (Specification 2). Second, we estimate a model with second order dynamics (Specification 3).

As a simple robustness check, Specification 2 excludes three time-varying variables that may be regarded as potentially endogenous (Biewen, 2007): the number of working members in the household, marital status and the number of dependent household members. The dynamics is assumed to be first-order. The results are compared with the ones obtained by Specification 1a, also reported in Table 8 for convenience. Both specifications point out that there is considerable unobserved heterogeneity that cannot be explained by the covariates: the standard deviations of the random effects are statistically significant and are estimated at 0.8 and 0.9 for poverty and social exclusion, respectively. In both specifications, we also observe true state dependence and positive cross-effects of lagged deprivation: in particular, the coefficients of lagged values of poverty and social exclusion are 0.1 and 0.7 in the poverty equation, and 0.6 and 0.09 in the social exclusion equation. Both specifications also highlight a statistically significant positive correlation between initial conditions (p(1) and se(1)) and the unobserved heterogeneity. Since the implication of the two specifications are very similar, we may conclude that the estimates of the key parameters are not affected by the excluded time-varying variables. Therefore, the richer specification 1a is preferred to specification 2.[10]

Second order dynamics

Specification 3 assumes that the dynamics is second-order. The idea is to test the sensitivity of the assumption of first-order dynamics imposed to the previous models: we do this by comparing specifications 1a and specification 3. Indeed, the raw conditional probabilities reported at the bottom of Table 4 show that an individual's current deprivation is related not only to the deprivation s/he experienced in the previous year (lag 1) but also to the deprivation status experienced two years earlier (lag 2). To what extent is this high persistency in the status of poverty and social exclusion due to unobserved heterogeneity (uncontrolled for in

[10] More generally, our econometric experimentation showed that estimates of true state dependence and the dynamic spillover effects are very much robust to the inclusion/exclusion of other controls in x_{it}.

Table 4) or is rather signalling that a first-order assumption is not an adequate representation of the dynamics of the processes under scrutiny? To investigate this issue we therefore augment our core random-effect bivariate model with initial conditions *a la* Wooldridge to include lag 2 of both poverty and social exclusion (Specification 3). As it happens, it turns out that the second order dynamics terms are all positive and statistically significant. Thus, the first-order Markov assumption is unwarranted and specification 3 is our preferred one. We therefore discuss the results of this specification more in depth.

For poverty, the lag-2 coefficient is estimated at 0.55, approximately half the size of the lag-1 coefficient, which is now estimated at 1.03 (higher than the 0.71 estimate reported in specification 1a). Also, the lag-2 cross effect is sizeable, estimated at 0.15 in the poverty equation. For social exclusion, own lag-2 estimate is even higher, at 0.71, and the lag-2 cross-effect is estimated at 0.12.

The standard deviations of the random effects are statistically significant and are estimated at 0.38 and 0.34 for poverty and social exclusion, respectively. Note that these standard deviations are less than half the size of the estimates obtained assuming first order dynamics. Unobserved heterogeneity then still plays a role in explaining the observed persistence in poverty and social exclusion, but it accounts for only a third of the unsystematic variation in the model. Much of the two processes' observed persistence, therefore, seems to be related to a 'true scarring impact', which (i) makes individuals experiencing poverty or social exclusion more likely to experience them again in the future, (ii) has 'long memory, in the sense that the risks are worse for those individuals who have spent more than one year in the state, and (iii) is cross-reinforcing as past (lag 1 and 2) experience of one type of deprivation significantly increases the chances of future deprivation of the other type.

Once the dynamics of the model is allowed to be second order, the correlation between the two random terms is negative but imprecisely estimated, resulting in a statistically insignificant coefficient. Therefore, we do not have sufficient evidence to suggest that people whose persistent unobserved personal, household and community characteristics make them more vulnerable to poverty tend to be the same people whose unobserved characteristics make them more vulnerable to social exclusion, compared to the rest of the population.

It may be noted that the correlation of the (contemporaneous) error terms in the two equations is statistically significant, with a point estimate of 0.11. A positive correlation suggests that the myriad of idiosyncratic shocks that, at any given time period, drive people into poverty and into social exclusion have common elements. This finding implies that the raw correlation found in the data between being in poverty and in social exclusion at any given time is also due to the correlation in the processes' idiosyncratic shocks. Therefore, even after allowing for a rich dynamics and unobserved heterogeneity, the two processes are simultaneously determined, and are more efficiently estimated jointly.

Finally, we briefly discuss the estimates of the controls included in the vector x_{it}. According to the results in specification 3, individuals with low education have a higher risk of being in poverty than those with medium education, and even more so than those with high education. The same is true with respect to social exclusion. Age, entered linearly for simplicity, has a negative and statistically significant effect on income poverty, reflecting the increased command on economic resources as the individual ages. However, the same coefficient is not statistically different from zero in the case of social exclusion. We are unable to detect clear differences on the deprivation risks faced by males and females: the dummy for female is generally found to be statistically insignificant in our models. The number of economically active members in the household decreases the probability of being in poverty and the probabilities of being socially excluded. Conversely, the risk of poverty increases with the number of children and other dependent adults in the household; however, the effect is not statistically different from zero in the case of social exclusion. Persons living as a couple (married or unmarried) are less likely to be socially excluded, while there is no statistical significant effect in the case of poverty. Reflecting the country's long-standing territorial dualism and the marked differences in the regional unemployment rates, southern regions consistently display higher risks of income poverty than both northern and central regions. However, regional disparities in income poverty do not always translate in similar disparities in social exclusion, as can be seen by comparing the two sets of regional dummies.

More in general, our reading of the results concerning the observed heterogeneity is that, while the effect of many of the controls included in the model goes in the expected direction, poverty and social exclusion are not always explained by the same set of factors, reinforcing the view expressed above that the two processes are genuinely distinct, albeit dynamically interrelated.

Predicted probabilities

For both equations, the lagged dependent variables concerning poverty and social exclusion are significantly positive. To evaluate the relevance of the dynamics in the model, we estimate the predicted probabilities of being in poverty, and for being in social exclusion, for various lagged statuses of deprivation (Table 9). As suggested by Wooldridge (2005), predicted probabilities are first computed at individual characteristics, keeping lagged dependent variables at specified values, and then averaged in the sample. The estimated parameters corresponding to each variable in $X_{it}=(x_{it},\ y_{1i,t-1},\ y_{2i,t-1},\ y_{1jit-2},\ y_{2jit-2})$ are multiplied by $\left(1+\hat{\sigma}_j^2\right)^{-1/2}$, for j=1,2, so as take into account the estimated distribution of unobserved heterogeneity, and the corresponding linear predictions are inserted into the cumulative standard normal distribution function, separately for each equation.

According to our preferred specification, the probability of being poor in t is about 0.12 for those who were neither poor nor socially excluded in t-1. However, the same probability is almost three times larger, at 0.35, if the individual was poor the year before, albeit not socially excluded. For those both poor and socially excluded in t-1, the chances of being poor in t raise further, at about 0.44. Similarly, the probability of being socially exclude in t is about 0.03 for those who were neither poor nor socially excluded in t-1. This probability is about five times higher, at 0.17, if the individual was socially excluded the year before, albeit not poor. For those both poor and socially excluded in t-1, the chances of being excluded in t increase further, at about 0.23. The results discussed so far are in line with the findings of the previous literature reporting positive state dependence in social exclusion (e.g., Poggi, 2007a) and income poverty (e.g., Cappellari and Jenkins, 2004). However, while those studies focus on the dynamics of a single process separately, either poverty or social exclusion, and assume first-order dynamics, our random-effect dynamic bivariate model also gives insights into the relation between the two types of deprivation and tests the appropriateness of the first-order assumption. In fact, we observe that the probability of being poor and the probability of being socially excluded in t are respectively about 0.092 and 0.024 for those were neither poor nor socially excluded in the two previous years (Table 10). These probabilities are instead much larger for those who were both poor and socially excluded in the two years before, and are equal, respectively, to 0.633 and 0.486, providing further evidence of the empirical relevance of the second order dynamics.[11]

6. Conclusions

This paper has studied the dynamics of poverty and social exclusion at the individual level, using the Italian sample of the European Community Household Panel, waves 1-8. On theoretical grounds, social exclusion is presented as a process with distinctive features than income poverty, albeit it is recognised that the two dimensions of deprivation share common traits and should be characterized by interrelated dynamics. Indeed, the empirical literature exploring the way the two processes interact over an individual's life course is scant, but generally provides indications that, at the individual level, they overlap less than commonly held. The statistical evidence presented in this paper has indeed provided elements that confirm this view: poverty and social exclusion do not simply constitute alternative ways of representing the same underlying concept of deprivation. Instead, the low correlation they display over time for the same individual is against a "two sides of the same coin" conjecture.

To further explore their dynamic interrelation, the paper has used a dynamic bivariate probit model with random effects, that controls for unobserved heterogeneity and initial conditions. For the latter, we show how the approach of Wooldridge (2005) can be easily extended to our bivariate dynamic model, resulting in an estimator that more readily accommodates second order dynamics and is computationally more convenient than the one originally proposed by Alessie et al. (2004).

We find a sizable extent of 'true' state dependence in both poverty and social exclusion, that is to say, past deprivation raises the chances of future deprivation once (observed and unobserved) heterogeneity is controlled for. Moreover, there are dynamic spillover effects, implying that poverty and social exclusion are mutually reinforcing. The results also suggest that the two processes are shaped by a rather persistent dynamics, and that a first-order Markov assumption, often used in empirical works on deprivation dynamics, is unwarranted. Instead, both second-lag of poverty and social exclusion significantly affect the chances of future deprivation of both types. Unobserved heterogeneity is also found to be empirically relevant,

[11] Note that experiencing poverty and/or social exclusion in the past, even if not the year before, is nonetheless harmful: in Table 10 the probability of being poor (socially excluded) in t is about 0.2 (0.1) for those who experienced either poverty and social exclusion in t-2 but not in t-1.

accounting for at least a third of the unsystematic variation in the model and making necessary the use of estimators that explicitly control for it. Moreover, poverty and social exclusion feature contemporaneous correlation, implying that the two processes are best estimated jointly.

Our results suggest that social policies aimed at eradicating poverty and avoiding individuals' social marginalization should take these dynamic interaction effects explicitly into account. Clearly, reliance on a single set of measures, for example those aimed at raising households' incomes above a chosen cut off, are unlikely to be successful in preventing material deprivation and outright social exclusion. Properly devised measures call instead for differentiated interventions for various groups of vulnerable individuals, carefully distinguishing between those whose primary matter of policy concern lies in their income insufficiency from those who appear vulnerable in light of a wider range of insufficiencies and impediments to a full participation in the social, economic and cultural life of the community in which they live. However, our results suggest that policies directed at one specific type of deprivation may also be effective in breaking the cycle leading to deprivation of the other form. As the identification of the various groups of vulnerable individuals is often difficult in practice, the existence of these spillover effects may be good news for the policy markers committed to combat all forms of human suffering.

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Tables:

Table 2. Proportion of deprived, excluded and poor individuals

Year	Basic	Quality	Housing	Social	Healthy	Living	Income Poverty (poor)	Social Exclusion (se)	Both poor and se	No. Obs.
1994	7.36%	2.11%	4.43%	17.65%	1.60%	20.79%	22.34%	9.18%	3.65%	14,157
1995	7.68%	2.54%	3.62%	16.22%	1.41%	20.66%	21.70%	10.48%	4.53%	14,112
1996	7.27%	1.51%	2.94%	11.24%	1.35%	24.04%	21.67%	8.76%	4.12%	13,982
1997	6.31%	1.36%	2.12%	11.28%	1.36%	23.61%	20.04%	8.40%	3.84%	12,954
1998	5.07%	1.19%	3.12%	11.76%	1.37%	18.16%	18.13%	7.09%	3.20%	12,387
1999	5.17%	1.10%	2.95%	10.74%	1.23%	18.45%	18.54%	6.67%	3.26%	11,882
2000	4.38%	0.81%	2.77%	9.53%	1.27%	18.01%	17.59%	5.80%	2.69%	11,184
2001	5.78%	0.66%	2.98%	9.32%	1.23%	15.88%	18.44%	5.83%	2.35%	10,195
1994-01	6.22%	1.46%	3.14%	12.46%	1.36%	20.17%	19.97%	7.93%	3.52%	100,853

Note: Unbalanced sample.

Table 3. Number of years in poverty and social exclusion (Proportion of individuals)

No. of years	poverty	se
0	52.00	76.65
1	13.05	12.16
2	7.19	4.58
3	6.31	2.44
4	4.28	1.35
5	4.17	0.95
6	3.83	0.67
7	5.01	0.70
8	4.17	0.50

Note: Balanced panel of 5,860 individuals, for a total of 41,020 person-year observations.

Table 4. Probability of deprivation in current year, conditional on past deprivation

Prob(poor t | poor t-1)	65.26
Prob (poor t | non poor t-1)	8.07
Prob (se t | se t-1)	42.5
Prob (se t | not se t-1)	3.49
Prob (poor t | se t-1)	44.98
Prob (poor t | not se t-1)	18.16
Prob (se t | poor t-1)	14.42
Prob (se t | not poor t-1)	4.37
Prob (poor t | poor t-2)	59.74
Prob (se t | se t-2)	36.71

Note: Raw probabilities in the unbalanced panel.

Table 5. Estimates of the probit model for the probability of being poor

Poverty	pooled probit model			Init. Cond: Heckman			Init. Cond: Wooldridge		
	Coef.		Robust Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
se(t-1)	0.3387	**	0.0311	0.2784	**	0.0408	0.2153	**	0.0409
poor(t-1)	1.5025	**	0.0185	0.7407	**	0.0270	0.7806	**	0.0254
se (1)							0.3319	**	0.0528
poor (1)							0.9191	**	0.0347
Female	0.0340		0.0173	0.0504		0.0338	0.0456		0.0288
Age	-0.0030	**	0.0010	-0.0056	**	0.0019	-0.0047	**	0.0018
medium education	0.3594	**	0.0479	0.6170	**	0.0922	0.4617	**	0.0757
low education	0.6885	**	0.0469	1.2526	**	0.0909	0.8956	**	0.0745
Lombardia	-0.0904		0.0530	-0.1469		0.0978	-0.0894		0.0824
North-east	-0.0669		0.0511	-0.1111		0.0907	-0.1212		0.0801
Emilia Romagna	-0.1755	*	0.0732	-0.3803	**	0.1271	-0.1784		0.1113
Centre	0.0239		0.0492	0.0631		0.0904	-0.0040		0.0778
Lazio	0.2975	**	0.0558	0.5159	**	0.1049	0.3596	**	0.0902
Abruzzo-molise	0.2683	**	0.0509	0.5101	**	0.0947	0.2810	**	0.0820
Campania	0.5402	**	0.0450	0.9495	**	0.0833	0.6546	**	0.0727
Sud	0.5752	**	0.0438	1.0721	**	0.0811	0.6867	**	0.0708
Sicilia	0.6555	**	0.0455	1.1959	**	0.0845	0.8042	**	0.0741
Sardegna	0.5408	**	0.0476	0.9779	**	0.0886	0.6587	**	0.0777
active members	-0.0381	**	0.0096	-0.0590	**	0.0148	-0.1273	**	0.0213
marital status	-0.0988	**	0.0232	-0.1752	**	0.0379	-0.2489	**	0.0618
depend. members	0.1250	**	0.0080	0.1645	**	0.0130	0.0639	**	0.0197
year dummies	yes			yes			yes		
longit average variables	no			no			yes		
constant	-2.2590	**	0.0762	-2.9333	**	0.1388	-2.8477	**	0.1234
σ_α				0.9201	**	0.0129	0.7064	**	0.0150
log-likelihood	-13342.7			-15400.7			-12572.5		
no. observations	41020			46880			41020		

Notes: robust standard errors are displayed, to account for individual repeated observations in the panel. (**) statistically significant at 1% level; (*) statistically significant at 5% level. Estimates of the initial conditions are reported in Appendix: Table A2.

Table 6. Estimates of the probit model for the probability of being socially excluded

Social Exclusion	pooled probit model			Init. Cond: Heckman			Init. Cond: Wooldridge		
	Coef.		Robust Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
se(t-1)	1.4452	**	0.0383	0.5468	**	0.0424	0.6982	**	0.0377
poor(t-1)	0.3109	**	0.0269	0.2881	**	0.0367	0.2127	**	0.0373
se(1)	---		---	---		---	0.8713	**	0.0538
poor(1)	---		---	---		---	0.2008	**	0.0437
female	-0.0416		0.0267	-0.0671		0.0418	-0.0560		0.0347
age	0.0006		0.0016	-0.0015		0.0024	-0.0013		0.0021
medium education	0.1012		0.0655	0.1637		0.0994	0.1092		0.0816
low education	0.3053	**	0.0639	0.5330	**	0.0976	0.3587	**	0.0799
Lombardia	-0.0078		0.0687	-0.0570		0.1086	-0.0361		0.0901
North-east	-0.1400	*	0.0700	-0.2649	*	0.1134	-0.2020	*	0.0926
Emilia Romagna	-0.0361		0.0778	-0.0482		0.1416	0.0229		0.1135
Centre	-0.1759	*	0.0764	-0.3773	**	0.1165	-0.2498	**	0.0935
Lazio	0.1827	**	0.0696	0.4089	**	0.1227	0.2650	**	0.1005
Abruzzo-molise	-0.2959	**	0.0788	-0.4779	**	0.1316	-0.3584	**	0.1088
Campania	0.1027		0.0620	0.2147	*	0.1013	0.1109		0.0844
Sud	0.3671	**	0.0561	0.6436	**	0.0959	0.4486	**	0.0796
Sicilia	0.2370	**	0.0620	0.4006	**	0.1000	0.2527	**	0.0848
Sardegna	0.0992		0.0666	0.1974		0.1070	0.1178		0.0911
active members	-0.0225		0.0147	-0.0165		0.0193	-0.0176		0.0282
marital status	-0.0570		0.0343	-0.0823		0.0490	-0.2046	*	0.0849
depend. members	-0.0107		0.0126	-0.0242		0.0164	-0.0622	*	0.0263
dear dummies	yes			yes			yes		
longit average variables	no			no			yes		
constant	-1.9046	**	0.1045	-2.4226	**	0.1602	-2.2196	**	0.1381
σ_{α}				0.9542	**	0.0166	0.6994	**	0.0167
log-likelihood	-7178.23			-8228.38			-6780.48		
no. observations	41020			46880			41020		

Notes: robust standard errors are displayed, to account for individual repeated observations in the panel. (**) statistically significant at 1% level; (*) statistically significant at 5% level. Estimates of the initial conditions are reported in Appendix: Table A2.

Table 7: Bivariate probit model: assessment of the initial condition

	Bivariate Pooled Model						Specification 1a: Wooldridge estimator						Specification 1b: Heckman initial cond.					
	Poverty			Social exclusion			Poverty			Social exclusion			Poverty			Social exclusion		
	coeff.		s.err.	coeff.		s.err.	coeff.		s.err.	coeff.		s.err.	coeff.		s.err.	coeff.		s.err.
se(t-1)	0.340	**	0.032	1.445	**	0.038	0.107	*	0.047	0.576	**	0.043	0.120	**	0.041	0.572	**	0.042
poor(t-1)	1.503	**	0.024	0.314	**	0.027	0.707	**	0.028	0.092	*	0.045	0.722	**	0.026	0.108	*	0.046
se(1)							0.402	**	0.058	1.017	**	0.068						
poor(1)							1.006	**	0.041	0.304	**	0.052						
female	0.034		0.020	-0.042		0.027	0.056		0.032	-0.029		0.040	0.069	*	0.034	-0.061		0.041
age	-0.003	*	0.001	0.001		0.002	-0.005	*	0.002	0.000		0.002	-0.006	**	0.002	-0.001		0.002
medium education	0.359	**	0.060	0.100		0.066	0.505	**	0.083	0.144		0.096	0.641	**	0.086	0.191	*	0.097
low education	0.688	**	0.058	0.303	**	0.064	0.978	**	0.082	0.434	**	0.095	1.288	**	0.088	0.577	**	0.095
Lombardia	-0.090		0.060	-0.009		0.069	-0.090		0.090	-0.052		0.106	-0.101		0.097	0.008		0.110
North-east	-0.067		0.061	-0.139	*	0.070	-0.126		0.088	-0.216	*	0.108	-0.105		0.094	-0.260	*	0.118
Emilia Romagna	-0.173	*	0.086	-0.037		0.078	-0.201		0.122	0.029		0.133	-0.325	*	0.135	-0.059		0.154
Centre	0.023		0.057	-0.176	*	0.076	0.021		0.086	-0.239	*	0.108	0.075		0.095	-0.292	*	0.115
Lazio	0.296	**	0.063	0.182	**	0.070	0.370	**	0.098	0.297	*	0.119	0.566	**	0.110	0.435	**	0.134
Abruzzo-molise	0.267	**	0.058	-0.300	**	0.079	0.300	**	0.090	-0.416	**	0.130	0.483	**	0.099	-0.442	**	0.145
Campania	0.539	**	0.052	0.099		0.062	0.692	**	0.081	0.149		0.099	0.986	**	0.087	0.275	**	0.108
Sud	0.572	**	0.050	0.363	**	0.056	0.729	**	0.079	0.507	**	0.095	1.108	**	0.086	0.687	**	0.105
Sicilia	0.655	**	0.053	0.233	**	0.062	0.845	**	0.082	0.308	**	0.100	1.238	**	0.088	0.473	**	0.107
Sardegna	0.540	**	0.055	0.096		0.067	0.699	**	0.087	0.155		0.108	1.047	**	0.091	0.265	*	0.115
active members	-0.038	**	0.011	-0.023		0.015	-0.128	**	0.022	-0.014		0.029	-0.057	**	0.013	-0.027		0.017
marital status	-0.098	**	0.026	-0.057		0.034	-0.261	**	0.063	-0.216	*	0.088	-0.191	**	0.035	-0.111	*	0.046
depend. members	0.125	**	0.009	-0.010		0.013	0.069	**	0.020	-0.061	*	0.027	0.171	**	0.012	-0.028		0.015
constant	-2.258	**	0.091	-1.901	**	0.104	-2.992	**	0.137	-2.422	**	0.164	-2.988	**	0.133	-2.465	**	0.161
year dummies	Yes			Yes			Yes			Yes			Yes			Yes		
longit. averaged variables x_{it}	No			No			Yes			Yes			No			No		
ρ	0.122	**	0.017				0.053	*	0.026				0.056	*	0.026			
$\sigma_{\alpha 1}$							0.824	**	0.024				0.960	**	0.027			
$\sigma_{\alpha 2}$							0.910	**	0.036				1.018	**	0.038			
ρ_{α}							0.267	**	0.045				0.323	**	0.033			
log-likelihood	-20497						-19299[§]						-23592					
no. observations	41020						41020						46880					

Notes: robust standard errors are displayed, to account for individual repeated observations in the panel. (**) statistically significant at 1% level; (*) statistically significant at 5% level; estimates of the initial conditions are reported in Table A2. [§] The log-likelihood of the bivariate probit at t=1 is equal to -4256.

Table 8: Estimates of the Dynamic random effect bivariate probit model (Wooldridge estimator)

	Specification 1a						Specification 2						Specification 3					
	Poverty			Social exclusion			poverty			Social exclusion			poverty			Social exclusion		
	coeff.		s.err.	coeff.		s.err.	coeff.		s.err.	coeff.		s.err.	coeff.		s.err.	coeff.		s.err.
se(t-1)	0.107	*	0.047	0.576	**	0.043	0.102	*	0.048	0.580	**	0.043	0.296	**	0.051	1.035	**	0.049
poor(t-1)	0.707	**	0.028	0.092	*	0.045	0.719	**	0.028	0.085		0.045	1.027	**	0.034	0.258	**	0.049
se(t-2)													0.145	**	0.047	0.712	**	0.046
poor(t-2)													0.552	**	0.031	0.120	**	0.045
se(1)	0.402	**	0.058	1.017	**	0.068	0.401	**	0.059	1.016	**	0.068	0.179	**	0.047	0.362	**	0.055
poor(1)	1.006	**	0.041	0.304	**	0.052	1.036	**	0.041	0.307	**	0.052	0.466	**	0.040	0.068		0.044
female	0.056		0.032	-0.029		0.04	0.057		0.032	-0.029		0.040	0.033		0.023	-0.052		0.029
age	-0.005	*	0.002	-0.000		0.002	-0.008	**	0.002	-0.002		0.002	-0.004	**	0.001	-0.001		0.002
medium education	0.505	**	0.083	0.144		0.096	0.551	**	0.085	0.150		0.096	0.359	**	0.064	0.080		0.072
low education	0.978	**	0.082	0.434	**	0.095	1.035	**	0.084	0.430	**	0.095	0.660	**	0.065	0.236	**	0.071
Lombardia	-0.090		0.090	-0.052		0.106	-0.129		0.090	-0.045		0.104	-0.113		0.067	-0.223	**	0.081
North-east	-0.126		0.088	-0.216	*	0.108	-0.096		0.087	-0.215	*	0.107	-0.15		0.095	-0.052		0.099
Emilia Romagna	-0.201		0.122	0.029		0.133	-0.314	*	0.122	0.020		0.132	-0.006		0.065	-0.212	**	0.081
Centre	0.021		0.086	-0.239	*	0.108	0.055		0.085	-0.227	*	0.107	0.308	**	0.074	0.013		0.088
Lazio	0.370	**	0.098	0.297	*	0.119	0.399	**	0.099	0.282	*	0.118	0.224	**	0.068	-0.269	**	0.093
Abruzzo-molise	0.300	**	0.090	-0.416	**	0.13	0.352	**	0.090	-0.414	**	0.128	0.484	**	0.061	-0.038		0.072
Campania	0.692	**	0.081	0.149		0.099	0.778	**	0.080	0.151		0.098	0.485	**	0.060	0.223	**	0.068
Sud	0.729	**	0.079	0.507	**	0.095	0.83	**	0.078	0.513	**	0.094	0.623	**	0.063	0.159	*	0.071
Sicilia	0.845	**	0.082	0.308	**	0.1	0.948	**	0.082	0.328	**	0.099	0.476	**	0.065	0.093		0.076
Sardegna	0.699	**	0.087	0.155		0.108	0.802	**	0.086	0.160		0.106	-0.152	**	0.023	-0.007		0.030
active members	-0.128	**	0.022	-0.014		0.029							-0.153	*	0.067	-0.227	*	0.092
marital status	-0.261	**	0.063	-0.216	*	0.088							0.038		0.022	-0.066	*	0.029
depend. Members	0.069	**	0.020	-0.061	*	0.027							0.099	**	0.028	-0.024		0.037
constant	-2.992	**	0.137	-2.422	**	0.164	-2.719	**	0.124	-2.555	**	0.148	-2.402	**	0.107	-2.114	**	0.121
year dummies	yes			yes			yes			yes			yes			yes		
longit. averaged x_{it}	yes			yes			yes			yes			yes			yes		
ρ	0.053	*	0.026				0.045		0.026				0.111	**	0.029			
$\sigma_{\alpha 1}$	0.824	**	0.024				0.844	**	0.024				0.375	**	0.039			
$\sigma_{\alpha 2}$	0.910	**	0.036				0.908	**	0.036				0.341	**	0.051			
ρ_{α}	0.267	**	0.045				0.281	**	0.045				-0.317		0.207			
log-likelihood	-19299						-19474						-15836					
no. observations	41020						41020						35160					

Notes: robust standard errors are displayed, to account for individual repeated observations in the panel. (**) statistically significant at 1% level; (*) statistically significant at 5% level;

Table 9: Conditional Probability of deprivation status in t, conditional on deprivation status in t-1

		Probability of status in t							
Probability of status in t-1		Pooled bivariate probit model		Specification 1a		Specification 2		Specification 3	
Poor	Socially excluded	Poor	Socially excluded	Poor	Socially excluded	Poor	Socially excluded	Poor	Socially excluded
0	0	0.089	0.032	0.154	0.049	0.153	0.049	0.123	0.032
1	0	0.509	0.061	0.280	0.056	0.283	0.056	0.351	0.051
0	1	0.150	0.326	0.170	0.103	0.168	0.104	0.174	0.169
1	1	0.630	0.442	0.303	0.114	0.305	0.115	0.439	0.232

Table 10: Conditional Probability of deprivation status in t, conditional on deprivation status in t-1 and t-2

				Probability of status in t	
Probability of status in t-1		**Probability of status in t-2**		Specification 3	
Poor	Socially excluded	Poor	Socially excluded	Poor	Socially excluded
0	0	0	0	0.092	0.024
1	1	0	0	0.405	0.212
0	0	1	1	0.225	0.111
1	1	1	1	0.633	0.486

Appendix 1:

Estimation of the bivariate dynamic random-effects probit models

The likelihood contribution for a given individual written in (7) and (15) represents the expected value of the likelihood contribution conditional on the random effects:

$$L = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} h(\alpha_1, \alpha_2) g(\alpha_1, \alpha_2, \Sigma_\alpha) d\alpha_1 d\alpha_2 \tag{A1}$$

where g is the bivariate normal density of the random effects α_1 and α_2. Following Alessie et al. (2004), simulated maximum likelihood estimators approximate such expectations with the simulated average:

$$L \approx \frac{1}{r}\sum_{R=1}^{r} h\left(\alpha_1^r, \alpha_2^r\right) \tag{A2}$$

where the random effects (α_1, α_2) are replaced by independent random draws (α^r_1, α^r_2). The latter are constructed as follows: for each of the N individuals, we first independently draw $\tilde{\alpha}_1^r$ and $\tilde{\alpha}_2^r$, r=1,…,R, from the standard normal distribution, for a total of 2RN draws. In all our estimation we have used Halton draws (see, Train, 2003) and R=60. These draws remain fixed during the estimation process.

At each step of the estimation process, the draws ($\tilde{\alpha}_1^r, \tilde{\alpha}_2^r$) are transformed into draws from a bivariate normal distribution with zero means and the given parameters of the covariance matrix Σ_α using a Cholesky decomposition of Σ_α, which implies that:

$$\begin{aligned} \alpha_1^r &= \sigma_{\alpha 1}\tilde{\alpha}_1^r \\ \alpha_2^r &= \sigma_{\alpha 2}\rho_\alpha \tilde{\alpha}_1^r + \sigma_{\alpha 2}\sqrt{1-\rho_\alpha^2}\,\tilde{\alpha}_2^r \end{aligned} \tag{A3}$$

As $R/\sqrt{N} \to \infty$, the resulting estimator will be asymptotically equivalent to Maximum likelihood. We have written our programs in both STATA (that uses a modified Raphson-Newton algorithm for maximization) and OX (which instead uses the BFGS algorithm). Our Wooldridge-type estimator could be estimated with both programs, obtaining the same results. The Alessie et al. model could be estimated only with the BFGS method, and required approximately twice the computing time of the Wooldridge-type estimator. Both sets of programs are available form the authors upon request.

Appendix 2. Tables

Table A1. Descriptive statistics

Sample composition (averaged over the period of study)	%
Female	50.13
Education	
High	7.87
Medium	39.09
Low	53.04
Living in couple	77.19
Area	
North–west	10.20
Lombardia	15.00
North-east	10.93
Emilia Romagna	5.71
Centre	9.95
Lazio	9.51
Abruzzo-molise	3.00
Campania	10.39
Sud	12.34
Sicilia	9.63
Sardegna	3.34
Years	
1994	14.04
1995	14.02
1996	13.72
1997	12.80
1998	12.31
1999	11.79
2000	11.14
2001	10.17
mean age	37.66
mean household dependent members	1.91
mean household working members	1.88

Table A2. Estimates of the initial conditions.

	univariate model			univariate model			bivariate model: Specification 2b					
	Estimates Init. Cond. Heckman Poverty			Estimates Init. Cond. Heckman Social Exclusion			Estimates Init. Cond. Heckman Poverty			Estimates Init. Cond. Heckman Social Exclusion		
	Coef.		Std.Err.	Coef.		Std.Err.	Coef.		Std.Err.	Coef.		Std.Err.
Female	0.0390		0.0496	-0.0359		0.0602	0.055		0.050	-0.036		0.061
Age	-0.0012		0.0032	0.0058		0.0038	-0.001		0.003	0.006		0.004
Medium education	0.5414	**	0.1270	0.2425		0.1473	0.551	**	0.127	0.243		0.149
Low education	1.1129	**	0.1252	0.5413	**	0.1441	1.122	**	0.127	0.537	**	0.147
Lombardia	-0.1310		0.1497	0.0536		0.1487	-0.093		0.151	0.079		0.151
North-east	0.2186		0.1378	-0.2062		0.1561	0.227		0.141	-0.212		0.160
Emilia Romagna	-0.4784	*	0.2117	-0.2861		0.2117	-0.436	*	0.213	-0.299		0.213
Centre	0.4369	**	0.1348	-0.5433	**	0.1723	0.453	**	0.135	-0.493	**	0.170
Lazio	0.5524	**	0.1601	0.3936	*	0.1671	0.581	**	0.166	0.401	**	0.167
Abruzzo-molise	0.8334	**	0.1430	-0.5137	**	0.1948	0.815	**	0.145	-0.517	**	0.200
Campania	0.9363	**	0.1298	0.2363		0.1411	0.953	**	0.132	0.247		0.144
Sud	1.1935	**	0.1262	0.4280	**	0.1334	1.201	**	0.129	0.418	**	0.135
Sicilia	1.2813	**	0.1312	0.2074		0.1436	1.299	**	0.134	0.201		0.150
Sardegna	1.0579	**	0.1379	0.0571		0.1565	1.104	**	0.140	0.073		0.161
Active members	-0.0649	*	0.0259	0.0027		0.0315	-0.067	*	0.026	-0.010		0.031
Marital status	-0.2331	**	0.0689	-0.2257	**	0.0814	-0.246	**	0.073	-0.241	**	0.080
Depend. members	0.1238	**	0.0216	-0.0001		0.0265	0.123	**	0.022	-0.016		0.028
constant	-2.4547	**	0.2051	-2.2683	**	0.2349	-2.470	**	0.202	-2.224	**	0.241
ρ_e										-0.040		0.0544
λ_{11}	0.8968	**	0.0470	---		---				1.369	**	0.216
λ_{12}	---		---	---		---				0.009		0.041
λ_{21}	---		---	---		---				0.103	**	0.052
λ_{22}	---		---	0.6988	**	0.0550				0.782	**	0.103

Note: (**) statistically significant at 1% level; (*) statistically significant at 5% level

Table A3: Estimates not reported in the previous Tables

Univariate models (Tables 5-6)	Without initial condition			Init. Cond: Heckman			Init. Cond: Wooldridge		
	Coef.		Robust SE	Coef.		Std.Err.	Coef.		Std.Err.
Social Exclusion									
wave3	-0.1710	**	0.0410	-0.1967	**	0.0457	-0.1871	**	0.0440
wave4	-0.0979	**	0.0358	-0.1456	**	0.0454	-0.1322	**	0.0437
wave5	-0.2659	**	0.0401	-0.3583	**	0.0482	-0.3321	**	0.0465
wave6	-0.2531	**	0.0377	-0.3916	**	0.0494	-0.3565	**	0.0476
wave7	-0.3081	**	0.0392	-0.4587	**	0.0505	-0.4187	**	0.0487
wave8	-0.2861	**	0.0402	-0.4496	**	0.0506	-0.4101	**	0.0490
Longitudinally averaged variables:									
Active members							-0.0323		0.0370
Marital status							0.1706		0.0995
Depend. members							0.0616		0.0325
Poverty									
wave3	0.0776	*	0.0311	0.0642		0.0351	0.0606		0.0346
wave4	0.0052		0.0314	-0.0184		0.0356	-0.0245		0.0351
wave5	-0.0484		0.0319	-0.1066	**	0.0363	-0.1164	**	0.0359
wave6	0.0103		0.0320	-0.0591		0.0365	-0.0726	*	0.0361
wave7	-0.0331		0.0323	-0.1003	**	0.0367	-0.1171	**	0.0365
wave8	-0.0137		0.0322	-0.0888	*	0.0368	-0.1114	**	0.0366
Longitudinally averaged variables:									
Active members							0.0952	**	0.0288
Marital status							0.1241		0.0765
Depend. members							0.1384	**	0.0253

Note: (**) statistically significant at 1% level; (*) statistically significant at 5% level

Table A4: Estimates not reported in the previous Tables

	Specification 1a						Specification 1b					
Tables 8 and 9	poverty			Social exclusion			poverty			Social exclusion		
	coeff.		Std.Err.	coeff.		Std.Err.	coeff.		Std.Err.	coeff.		Std.Err.
Act. Memb. (longit. mean)	0.089	**	0.031	-0.055		0.04	---		---	---		---
Marit. Stat. (longit. mean)	0.124		0.08	0.151		0.106	---		---	---		---
Dependent (longit. mean)	0.145	**	0.027	0.058		0.035	---		---	---		---
Year 1996	0.059		0.035	-0.204	**	0.046	0.065		0.034	-0.205	**	0.047
Year 1997	-0.031		0.036	-0.149	**	0.045	-0.019		0.036	-0.148	**	0.049
Year 1998	-0.127	**	0.037	-0.363	**	0.048	-0.106	**	0.037	-0.364	**	0.048
Year 1999	-0.086	*	0.037	-0.399	**	0.05	-0.062	*	0.038	-0.399	**	0.053
Year 2000	-0.132	**	0.037	-0.463	**	0.051	-0.105	**	0.037	-0.463	**	0.052
Year 2001	-0.127	**	0.037	-0.456	**	0.051	-0.094	**	0.037	-0.454	**	0.052
	Specification 2						Specification 3					
	poverty			Social exclusion			poverty			Social exclusion		
	coeff.		Std.Err.	coeff.		Std.Err.	coeff.		Std.Err.	coeff.		Std.Err.
Act. Memb. (longit. mean)	---		---	---		---	0.109		0.078	0.179		0.104
Marit. Stat. (longit. mean)	---		---	---		---	0.107	**	0.025	0.061		0.033
Dependent (longit. mean)	---		---	---		---	-2.402	**	0.107	-2.114	**	0.121
Year 1996	0.053		0.035	-0.205	**	0.046	-0.066	*	0.034	0.045		0.043
Year 1997	-0.049		0.035	-0.148	**	0.045	-0.158	**	0.035	-0.128	**	0.046
Year 1998	-0.149	**	0.036	-0.362	**	0.048	-0.098	**	0.035	-0.149	**	0.048
Year 1999	-0.111	**	0.036	-0.398	**	0.049	-0.132	**	0.036	-0.168	**	0.049
Year 2000	-0.155	**	0.036	-0.463	**	0.05	-0.134	**	0.036	-0.16	**	0.049
Year 2001	-0.163	**	0.036	-0.453	**	0.05	-0.083		0.069	-0.06		0.077

Note: (**) statistically significant at 1% level; (*) statistically significant at 5% level