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Eirini Andriopoulou
Panos Tsakloglou

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Eirini Andriopoulou
Athens University of Economics and Business

Panos Tsakloglou
Athens University of Economics and Business and IZA

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

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The paper analyzes the effects of individual and household characteristics on current poverty status, while controlling for initial conditions, past poverty status and unobserved heterogeneity in 14 European Countries for the period 1994-2000, using the European Community Household Panel. The distinction between true state dependence and individual heterogeneity has very important policy implications, since if the former is the main cause of poverty it is of paramount importance to break the “vicious circle” of poverty using income-supporting social policies, whereas if it is the latter anti-poverty policies should focus primarily on education, training, development of personal skills and other labour market oriented policies. The empirical results are similar in qualitative but rather different in quantitative terms across EU countries. State dependence remains significant in all specifications, even after controlling for unobserved heterogeneity or when removing possible endogeneity bias.

JEL Classification: I32, I38

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Corresponding author:

Panos Tsakloglou
Athens University of Economics and Business
76 Patission Street
Athens 10434
Greece
E-mail: panos@aueb.gr

1. INTRODUCTION

In recent years, issues of state dependence feature prominently in poverty dynamics research. The main hypothesis tested in this research is whether past poverty experiences determine current poverty status. This may happen, for instance, because poverty spells might result in depreciation of human capital and employment skills, causing low-pay or unemployment spells and, finally, increasing the duration or the frequency of poverty spells (poverty reoccurrence). If the long run policy objective is to keep poverty rates low and state dependence is 'genuine', then it is important to bring individuals out of poverty using social benefits in the short run. Nevertheless, the state dependence usually observed in dynamic panel data models may also be attributed to sorting effects, in the sense that the individuals that escape poverty may possess particular observed (e.g. age, educational qualifications, etc) or unobserved characteristics (willingness to escape poverty, cleverness, social networks, life attitudes, etc) and, thus, differ in a systematic way from the individuals that remain poor. Consequently, when examining state dependence it is important to control for observed as well as unobserved heterogeneity. Further, a positive result in terms of state dependence may also be due to the fact that individuals with a higher tendency to remain permanently poor may be over-represented in the sample. Therefore, in the case of state dependence, controlling for the observed and unobserved determinants of initial poverty status (initial conditions) is also important.

In the current paper, we follow the methodology of Wooldridge (2005), which proposes a solution that handles simultaneously the problems of endogeneity of the initial conditions and unobserved heterogeneity. He suggests using a joint density distribution conditional on the strictly exogenous variables and the initial condition, instead of attempting to obtain the joint distribution of all outcomes of the endogenous variables. In this analysis, a multivariate random effects logit estimation has been employed for the analysis of poverty state dependence in 14 EU Member-States during the period 1994-2000 using the data of the European Community Household Panel (ECHP).

In the next two sections, the issues of unobserved heterogeneity and initial conditions are discussed drawing evidence from previous studies in poverty, employment and low-pay dynamics. The ECHP is briefly presented in section 4 along with household income and poverty definitions. Section 5, presents the model to be applied. The last two sections report the empirical results and the conclusions of our analysis, along with some policy implications.

2. TRUE STATE DEPENDENCE VERSUS UNOBSERVED HETEROGENEITY

True state dependence means that the experience of poverty in one year *per se* raises the risk of being poor in the next year (Heckman 1981a). However, since individuals with "favourable" characteristics are likely to leave poverty earlier, the state or duration dependence observed in data may not be genuine. Therefore it is important along with the effect of time to control also for observed as well as unobserved heterogeneity.[1]

In recent years, researchers focus on the distinction between true state dependence and individual heterogeneity. This distinction has very important policy implications. For instance, if true state dependence is indeed significant compared to individual heterogeneity, then it is important to break the "vicious circle" of poverty and try, even at high cost, to bring individuals out of poverty using income-support policies such as social benefits. On the contrary, if individual heterogeneity defines the duration of poverty, anti-poverty policies should focus on other schemes such as education, development of personal skills and capacities or other labour market and social policies.

Most studies find that poverty state dependence remains significant even when controlling for unobserved heterogeneity. Canto (1996) examines the duration dependence for poverty entries and exits in Spain using a non-parametric specification for the hazard rate. She controls for unobserved heterogeneity indirectly by testing the homogeneity of the hazard rate between groups that are likely to have different spell lengths. She finds significant duration dependence both for poverty re-entries and exits. Cappellari and Jenkins (2004) using data from the BHPS for the 1990s conclude that there is substantial state dependence in poverty, separately from the persistence caused by heterogeneity. Poggi (2007) studies social exclusion dynamics in Spain and also finds that both individual heterogeneity and true state dependence are related to the probability of experiencing social exclusion. Biewen (2006) reports that even after controlling for observed and unobserved individual characteristics, there is negative state dependence in poverty exit and re-entry behaviour. He also calculates that 6% of the German population has unobserved characteristics that lead to low poverty exit and high re-entry rates, thus making these individuals possible candidates for chronic poverty. According to Ayllón (2008), in Spain more than 50% of aggregate state dependence in poverty status is due to past poverty experiences. Finally, when focusing on youth poverty, while separating genuine state dependence in the poverty status from observed and unobserved characteristics, Aylon (2009) concludes that there is a substantial proportion of genuine state dependence in the poverty status.

On the other hand, Giraldo et al. (2002) stress that there are two sources of unobserved heterogeneity related to the study of poverty: first, the ability of household members to obtain income in a specific period and, second, the way in which this ability evolves over time. When allowing for time-variant unobserved heterogeneity, the authors

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[1] State and duration dependence are often used in the literature are synonyms. However, state dependence determines how the probability to be poor in the current period depends on whether the individual was poor in the previous period, while duration dependence indicates how the probability to be poor in the current period depends on the duration spent in the poverty spell. This means that when duration dependence is examined, more than one lagged values of the dependent variable are used in the regression, or when poverty exits or re-entries are examined (instead of poverty status *per se*), more than one period dummies are included in the hazard function. This paper focuses on state dependence rather than duration dependence. Further, since the paper focuses on the effect on time on poverty status *per se*, the literature of poverty entries and exits is not presented explicitly (see, for example, Jenkins (1995; 2000), Stevens (1999), Antolin *et al*. (1999), Muffels (2000), Oxley *et al.* (2000), OECD (2001), Jenkins *et al.* (2001), Canto (2002, 2003), Devicienti (2002; 2010), Finnie and Sweetman (2003), Fouarge and Layte (2005) and Callens and Croux (2009)). A literature review covering these papers as well as an analysis of poverty transitions in Europe using discrete-time proprotional hazard rate models with the ECHP data is presented in Andriopoulou (2009: ch. VI, VII) and Andriopoulou and Tsakloglou (2011).

do not find any sign of true state dependence in their analysis of persistent poverty in Italy. This finding reinforces the theory of incentives of the poor which may vary not only among individuals but also with time. As underlined by Aassve et al. (2006), there is also another issue on whether it is poverty experience or low income experience that really affects individuals with regards to the duration dependence. Poverty spells are not like unemployment spells, during which the individual is completely aware of the situation and, hence, his choices and preferences might be affected by his position. Studies that focus on low pay instead of poverty (Stewart and Swaffield 1999; Cappellari 2004; Stewart 2007)[2] show that the probability of being low paid depends strongly on low pay in the previous year. In the same line, Finnie and Gray (2002), when examining individual mobility across earning quintiles, conclude that the probability of having an upward or downward transition depends negatively on the time that an individual has spent in a given quintile and this negative duration dependence remains significant when controlling for unobserved heterogeneity. Likewise, Weber (2002) verifies that there is significant state dependence for women at the lower part of the distribution in Austria.

It should be noted that Cockx and Dejemeppe (2005) assert that the observed negative duration dependence in the exit rate very often turns out to be spurious, at least in unemployment studies. Nevertheless, Caliendo and Uhlendorff (2008) analyze the mobility between self-employment, wage employment and non-employment and find strong true state dependence in all three states. With regards to the labour force participation, Hyslop (1999) shows that participation decisions for women are characterized by significant state dependence, unobserved heterogeneity and feedback effects from fertility to participation decisions and vice versa.

3. THE INITIAL CONDITIONS PROBLEM

The initial conditions problem, developed by Heckman (1981b), in terms of transitions analysis, can be summarised to the fact that those who are poor in the first year of the survey may be a non-random sample of the population. Specifically, a positive result in terms of state dependence may be due to the fact that individuals with a higher tendency to remain permanently poor may be over-represented in the sample (Cappellari and Jenkins 2004; 2008). Therefore, in the case of state dependence, controlling for the observed and unobserved determinants of initial poverty status is important.

In practice, the problem arises because the start of the observation period does not concise with the start of the stochastic process that has generated the poverty or non-poverty experiences. Arulampalam *et al*. (2000) emphasize that even if the model controls for unobserved heterogeneity, in order to disentangle the effect of state dependence from unobserved heterogeneity, the initial conditions need to be modelled instead of assumed as exogenously given, because the initial conditions may be correlated with the unobservables.

The problem of initial conditions has been tackled more extensively in the literature of unemployment dynamics. Arulampalam *et al.* (2000) examine unemployment dynamics for men using the BHPS and introduce the econometric issues

[2] Stewart (2007) focuses more on how past low-pay employment affects the probability of being unemployed in the future using a similar methodology as when state dependence is examined.

concerning dynamic panel data models: unobserved heterogeneity (based on Chamberlain 1984), state dependence (based on Heckman 1981a, 1981c) and the initial conditions problem (based on Heckman 1981b). Even when controlling for initial conditions and unobserved heterogeneity, they find that there is strong state dependence especially for older unemployed individuals that may be attributed to depreciation of human capital, signalling (in the sense that past unemployment spells signal the capacities or productivity of individuals to potential employers) and to the fact that unemployed individuals may accept low quality jobs and this may lead to enterprise closure and future unemployment spells. Arulampalam (2002) extents this work further in various directions, using different definitions of unemployment.

Cappellari and Jenkins (2004) use a first-order Markov model in order to study poverty transitions[3]. The great virtue of this model, which is a complement to hazard and covariance structure models, is that it allows controlling for initial conditions effects. In addition, these models control for potential non-random sample retention (for individuals that do no attrite and for whom income is observed for at least two consecutive periods). Ayllón (2008) examines poverty transitions in Spain using the model proposed by Cappellari and Jenkins (2004). She finds that unobserved heterogeneity affecting poverty status in the base year as well as sample attrition, are exogenous to unobservables related to poverty transitions (although her results are sensitive to the selection of the poverty line). Models that control for initial conditions are also used in studies of earnings mobility (Stewart and Swaffield 1999; Cappellari 2004; Cappellari and Jenkins 2008).

The methodology that we use in this paper in order to control for initial conditions is based on Wooldridge (2005), which proposes a solution to handle the problem of endogeneity of the initial conditions, while controlling for unobserved. He suggests using a joint density distribution conditional on the strictly exogenous variables and the initial condition, instead of attempting to obtain the joint distribution of all outcomes of the endogenous variables (Hsiao 1986). For the binary response models of probit and logit form, the main advantage of this method is that it can be applied easily using standard random effects software. Yet, the explanatory variables included in the model must be strictly exogenous and at most one lag[4] of the dependent variable can be used in the estimation. Another restriction of the model is that it can be applied only to balanced panel data. This reduction from unbalanced to balanced panel data can always result in discarding useful information. An application of this methodology to social exclusion can be found in Poggi (2007).

4. THE EUROPEAN COMMUNITY HOUSEHOLD PANEL AND DEFINITIONS

The empirical research of the paper is based on the data of the European Community Household Panel (ECHP). The ECHP is a harmonized cross-national longitudinal survey, focusing on income and living conditions of households and individuals in the European Union. Due to its multidimensional nature, the ECHP provides information at micro-level across countries and across time on: income,

[3] Schluter (1997) also uses a Markov model with exogenous variables in order to study the German income mobility, with some extensions to poverty dynamics.

[4] D' Addio and Honore (2002) claim that the probability of exiting poverty may depend not only on the poverty status of the last period, but on the poverty status in the two most recent periods and they model second order state dependence, while controlling time–varying explanatory variables.

employment, health, education, housing, migration, social transfers and social participation, as well as demographics. In other words, as Eurostat describes it, ECHP offers data on EU social dynamics (Eurostat 2003). The duration of the survey is eight years; thus, the ECHP consists of eight waves, one for each year, from 1994 to 2001. The ECHP covers all the 15 Member-States of the EU in that period, but not all countries have participated in all waves. In addition some Member-States, such as the UK and Germany, used data from existing panel surveys and converted them to ECHP format. In the current paper, we use all eight waves of the ECHP for 14 EU Member-States[5].

Most of the income components in the ECHP have an annual time frame of the calendar year preceding the interview. In all the ECHP countries, apart from the UK, the calendar year coincides with the tax year, which is the reference period for income components. Although, in this way income comparability is ensured, other variables like the household composition variables, the economic activity status etc. refer to the time of interview and might not relate well to income measured over a period up to twelve months in the past (Eurostat 2001). This is particularly undesirable for poverty dynamic analysis that tries to identify changes in income components and also uses the lagged poverty status as an explanatory variable. Therefore, for the needs of the dynamic analysis that follows, we have reconstructed the household income, transferring all the income components one year back.[6]

Following the practice of Eurostat, the poverty line used in the paper is set at 60% of the national median equivalised household income per capita, as it has been calculated using the modified OECD scale which assigns 1 to the first adult, 0.5 to the remaing adults and 0.3 to children.

5. THE MODEL AND ECONOMETRIC DETAILS OF THE ANALYSIS

The main difference of the model used in this paper from a typical hazard model examining state dependence is that the dependent variable is the poverty status *per se* (whether someone is poor or non-poor) and not a variable signalling the poverty entry or exit. Moreover, state dependence is not captured with time dummies, but with the lagged value of the dependent variable. According to Wooldridge (2005, p. 42), only one lag of the dependent variable can be used when controlling for initial conditions. Nevertheless, this means that we cannot measure duration dependence, how much the chances of exiting poverty fall the longer one is in poverty.[7] Initial conditions are captured by introducing in the regression the value of the dependent variable in the first period. In this way, the assumption of exogeneity of all the explanatory variables is a strong assumption and, therefore, is tested at the end of the analysis.

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[5] For Sweden only cross-sectional data are available and, therefore, Sweden has been excluded from the analysis. Moreover, the panels of Austria, Finland and Luxembourg are shorter than those of the other countries.

[6] It should be underlined that we do not simply lag one wave back the total net household income, but we take into account the different composition that each household might had in the previous have. The methodology developed for the reconstruction of household income follows the logic of Eurostat's (2003a) construction of household income variable and is similar to the one applied by Debels and Vandecasteele (2008).The algorithm for the reconstruction of household income is available from the authors on request.

[7] This effect can only be captured when modelling poverty exit with hazard functions using time dummies so as to capture the increasing effect of state dependence year by year.

More specifically for a random individual in the population and t=1, 2, … T, the conditional probability that poverty occurs is:

$P(y_{it}=1 \mid y_{i,t-1},...,y_{i0},z_i,c_i)=\Phi(z_{it}\gamma+\rho y_{i,t-1}+c_i)$ (1)

Where y_{it} is the dependent variable or the poverty state of the individual i at period t (when $y_{it}=1$ the individual is poor in period t and when $y_{it}=0$ the individual is non-poor), $\Phi(x)$ is the logistic function $\Phi(x)=\frac{\exp(x)}{1+\exp(x)}=\Lambda(x)$, which is between zero and one for all real numbers x, γ and ρ are the parameters to be estimated, z_i and z_{it} are the vectors of time constant and time-varying explanatory variables and c_i is the unobserved effect. ρ is the coefficient of the lag value of the explanatory variable and the indicator of state dependence. If $\rho>0$ being poor (non-poor) at $t-1$ increases the chances of being poor (non-poor) at t.

There are three main assumptions related to equation (1). First, the dynamics are first order, once z_{it} and c_i are also conditioned on. Second, the unobserved effect is additive inside the st.andard normal cumulative distribution function $\Phi(x)$. Third, all time-constant and time-varying variables are strictly exogenous (Wooldridge 2005, p. 41).[8]

By assuming that the unobserved effect follows a normal distribution given the initial poverty condition y_{i0} and the time-constant explanatory variables z_i:

$c_i \mid y_{i0},z_i \approx Normal(a_0+a_1 y_{i0}+a_2 z_i,\sigma_\alpha^2)$ (2)

the parameters of equation (1) can be consistently estimated. a_1 offers information about the relationship between the unobserved effect and initial poverty status, while σ_α^2 indicates the dispersion accounted by unobserved heterogeneity. According to (Wooldridge 2005, p. 46), the density functions resulting from equations (1) and (2)

$f(y_{it},\ ...,y_{iT} \mid \mathrm{y}_{i0},z_i,c_i;\ \gamma,\rho)=\Pi_t\{\Phi(z_{it}\gamma+\rho y_{it-1}+c_i)^{yt}\cdot[1-\Phi(z_{it}\gamma+\rho y_{it-1}+c_i)]^{1-yt}\}$

can be specified in such a way that standard random effects software can be used for the estimation.[9]

The above estimation can be applied only to balanced panels. Therefore, there is a loss of information by dropping individuals that are not present in all seven waves,[10] while selection and attrition problems might also be present. Nevertheless, the loss of information is compensated by the fact that Wooldridge's methodology allows selection and attrition to depend on initial conditions. Specifically, individuals with different initial poverty status are allowed to have different missing data probabilities. In this way, attrition is controlled for without being explicitly modelled as a function of initial conditions (Wooldridge 2005; Poggi 2007). Moreover, since we control for initial conditions, we do not restrict the sample to an inflow sample and we also include in our

[8] For a framework for estimating dynamic, unobserved effects panel data models with possible feedback to future explanatory variables, see Wooldridge (2000).

[9] For the use of fixed effects when controlling for initial conditions in a different methodological framework see Hahn (1999). For a full discussion of the advantages of random effects versus fixed effects see Honore and Kyriazidou (2000) and Honore (2002).

[10] Six for Austria and Luxembourg and five for Finland.

analysis all the left-censored cases that we would have to exclude if a typical hazard analysis was used.

As in most poverty studies, since the equivalised household income per capita is used for the calculation of poverty status, it is indirectly assumed that the household members pool their income sources. Therefore, only personal characteristics of the household head are considered as regressors and not the personal characteristics of the household members (e.g. only the age of the household head is taken into account and not the age of each household member). Consequently, members of the same household have the same poverty determinants and, thus, the same poverty status. Since the panel includes repeated observations from the same individual and from the same family, the problem of possible violation of the homoskedasticity assumption is present. As a result, we use the “robust” or ”sandwich” estimators for the standard errors, which allow observations to be dependent within cluster, although they must be independent between clusters. The results reported in the following tables have been calculated without the use of weights and are reported in terms of marginal effects.[11]

6. EMPIRICAL RESULTS: ANALYSIS OF STATE DEPENDENCE CONTROLLING FOR INITIAL CONDITIONS

We develop four specifications using the dynamic logit model presented in the previous section. The first specification includes only the initial conditions dummy and the lagged value of the poverty status. In the second specification, variables controlling for the household and household head characteristics are included in the regression analysis, as well as wave dummies aiming to control for business cycles effects. In the third specification, a number of variables that may cause endogeneity bias are removed from the analysis, while in the fourth specification, the role of household type dummies is examined in detail. In order to facilitate comparisons across countries, the probability of the baseline group is reported on the top of each table.

Table 1 reports the results for the first specification. Both the marginal effects for the lagged poverty status and initial status are positive and significant at the 0.1% level in all 14 Member-States, implying that being poor in the initial or previous year increases the hazard of being poor in the current year. In most countries the initial conditions variable gives much higher marginal effects than the lag poverty status with the exception of Finland, the Netherlands and the UK, where the differences are small or go to the opposite direction, meaning that poverty reoccurrence is also an important issue. Specifically, the marginal effects for the initial conditions variable ranges from 11.3 to 38.6 in Greece, while in terms of absolute probability (the sum of the marginal effect and the baseline probability) ranges from 13.1 in the Netherlands to 43.7 in Greece. As suggested by the standard deviation of the heterogeneity variance, σ_{α},, unobserved heterogeneity is large. Also, the likelihood ratio test for rho[12] suggests that unobserved heterogeneity is statistically significant in all countries.

[11] In the tables of the paper, the marginal effects are multiplied by 100 (thus, reported as percentage changes from the baseline).

[12] rho is the ratio of the heterogeneity variance to one plus the heterogeneity variance $rho = \frac{(sigma\_u)^2}{1+(sigma\_u)^2}$ and, in a way, indicates how much of the model variance is due to unobserved heterogeneity.

In the second specification (Table 2), we include variables capturing certain characteristics of the household and the household head so as to control for the observed heterogeneity across individuals. Moreover, we add wave dummies in order to control for possible business cycle effects, especially for the time-varying variables such as the employment dummies. The baseline group consists of individuals that were not poor in the initial and previous year and live in a household with a male household head, aged 30-64, who has completed secondary education, is employed full-time and is a citizen of the country under examination. There are no dependent children[13] in the household, none of the household members is unemployed and none of the household members has severe disability or chronic disease. The probability of being poor while belonging to the baseline group is around 1% to 2% in all countries with the exception of the Netherlands (3.7%). The fact that there are no large differences in the baseline probability across countries, means that the choice of the baseline group is successful in facilitating comparisons across countries.

As expected, the effect of past poverty experiences declines in almost all countries in comparison to the first specification, when the household and the household head variables are added in the regression. The absolute decrease in the marginal effects corresponding to the effect of initial conditions is larger than the decrease in the marginal effects of lagged poverty status. This is expected since the socioeconomic variables that are included in the regression may also, in a way, determine whether someone is poor in the first place.

Living in a household with a head aged less than 30 or more than 64 increases the hazard of being poor in all countries. The effect is very strong for young headed households in Finland (5.5), the Netherlands (5.5.) and Denmark (4.6) as compared to the baseline group. Households headed by elderly individuals have a higher risk to be in poverty in 8 out of 14 countries and the highest marginal effect appears in Denmark (1.7) and Greece (1.2). Netherlands and France are the only countries where the chance to be in poverty decreases significantly for individuals living in households with heads aged above 64, as compared to the baseline group. The vulnerability of female-headed households to poverty is not evident in all countries. In Finland (0.8), France (0.4) and Germany (0.3) and Italy (0.2) the marginal effect is significantly positive, but only marginally above zero. On the contrary, in Portugal, living in a female-headed household ceteris paribus leads to a small but statistically significant decline in the probability of being poor (0.2).

The level of education of the household head also plays an important role in determining the chances of being in poverty at a particular point in time. Living in a household with a household head who has completed higher education sharply decreases the chances of being poor, while household heads with primary education increase the odds of being in poverty vis-a-vis the control group in all countries apart from the Netherlands. As expected, unemployment and inactivity of the household head also increase the probability of poverty. The effect of unemployment is particularly strong in Ireland (11.4), the Netherlands (10.9), Belgium (9.7) and the UK (6.0) and that of inactivity in the Netherlands (7.4), Denmark (5.9), Ireland (5.1), Finland (4.1) and the UK (4.1). The effect of citizenship of the household head is mixed across EU Member-

[13] The ECHP defines as “dependent children” the individuals who are aged less than 16 or 16-24 who live in the parental household and are economically inactive.

States with a tendency to increase the probability of being poor both for the EU and the non-EU citizenship whenever the effect is significant. The highest risk of being poor while living in a household with an immigrant household head is observed in Finland; especially when the household head has a non-EU citizenship. The Netherlands and Belgium are the only countries where living in a household headed by an immigrant (with an EU-citizenship in the first case and a non-EU citizenship in the second) seems to decrease the chances of being poor. Nevertheless, these results should be interpreted with caution, since it is likely that immigrants are under-represented in the samples of most countries.[14]

In all countries, the presence of dependent children in the household increases the chances of being poor with the exception of Denmark, where the effect is not significant.[15] The effect is particularly strong in the Netherlands, where the probability to be in poverty when living in a household with dependent children increases by 5.2 percentage points as compared to the baseline group. The corresponding figures are also relatively large in Spain (2.0) and Italy (1.8). Having an unemployed (other than the household head) or a disabled member in the household also increases the chances of being in poverty in the Member-States where the underlying odds ratio is significant. The effect is particularly strong in households with unemployed members in Italy and the Netherlands and in households disabled members in Ireland.

In total, the second specification (Table 2) fits the data much better than the first specification (Table 1), since both the Akaike Information Criterion and the (AIK) Baysenian Information Criterion (BIC) decrease. Yet, as suggested by σ_α unobserved heterogeneity remains large and significant at the 0.1% level in all countries.[16]

According to Wooldridge (2005, p. 41), when applying the methodology described in section 5, for the estimators to be efficient, all time-constant and time-varying variables must be strictly exogenous. The strict exogeneity assumption means that since we control for the past poverty status and unobserved heterogeneity, current poverty status must be unrelated to the value of the regressors in past or future period. In other words, violation of the exogeneity assumption exists if there are feedback effects from poverty status to future values of the covariates included as regressors in the logit model. Individual characteristics such as age, gender and nationality cannot depend on past poverty status. This is also likely to apply for education, for the limited period of observation used here. Nevertheless, the existence of past poverty spells might theoretically affect the employment status, fertility decisions (existence of dependent children in the household), employment and health status of household members. When

[14] It should be noted that in the way that ECHP sample persons were selected, immigrants could only appear in the panel, if they were selected at the first wave or if they move in to a sample household in the next waves. Therefore, it can be alleged that ECHP does not measure properly population resulting from immigration inflows.

[15] This is in accordance with the results of Andriopoulou and Tsakloglou (2011), which show that, unlike the rest of the EU, ceteris paribus, in Denmark and Finland the chances of exiting poverty increase when dependent children are present into the household; an effect that can be attributed to the importance of family benefits in these countries.

[16] We have also run all specifications using a standard logit regression without controlling for unobserved heterogeneity. It is interesting to note that although the odds ratio for the household and household head characteristics are slightly higher when unobserved heterogeneity is not controlled for, the odds for the state dependence are substantially higher while the odds for the initial conditions considerably lower. The results are available from the authors on request.

examining feedback effects, Biewen (2004) finds that there is evidence that experiencing poverty has a negative effect on future employment behaviour and household cohesion. Specifically, he finds that poverty experiences may be associated with processes of demoralization, depreciation of human capital and incentive problems, increasing the probability that individuals who become poor will remain so for an extended period of time. At the same time, he identifies that low income strains marriages and cohabitative relationships.

In the literature, there is not any commonly accepted test for testing the exogeneity assumption. In Table 3, the variables that may cause endogeneity were removed from the model. In total, six variables were excluded that are related to the employment status of the household head and the existence of dependent children, unemployed or disabled household members. Both the Akaike Information Criterion (Akaike 1973) and the Baysenian Information Criterion (Schwarz 1978) decrease, suggesting that the the explanatory power of the model deteriorated. Moreover, unobserved heterogeneity increases, implying that the variables that were removed from the specification did account significantly for the observed heterogeneity across individuals that explain differences in the probability of being poor. Despite the fact that a large number of variables were removed from the specification, when comparing the results of Table 2 and Table 3, in most cases we do not observe substantial differences in the estimates of the variables that are common in both specifications. Yet, in some cases the differences are large; for example, in the cases of young headed households in Denmark and Finland, elderly households in Denmark and immigrant-headed households in Spain (with EU citizenship) and immigrant-headed with non-EU citizenhip in France, Finland and Luxembourg. This indicates that the increase in the marginal effect absorbed by the remaining variables is not distributed proportionally in all cases and that there might be some issues of endogeneity for specific countries that cannot be easily examined at this context of analysis (for an approach examining feedback effects see Biewen 2009).

Table 4 focuses on the role of household type on poverty. Various household type classifications have been tested in the regressions and the one finally chosen includes ten different household types: single adult aged less than 30; single adult aged from 30 to 64; single adult aged more than 64; couple only, where both members are aged less than 65; couple only with at least one household member aged more than 64; other type of household without dependent children (e.g. a couple with working children living together, two brothers living together, three students living together, etc.); lone parent with at least one dependent child; couple with one or two dependent children; couple with more than two dependent children; other type of household with at least one dependent child (e.g. a couple with two dependent children and one grant-parent living together, two grandparents with a dependent grandchild, etc.). When the household type dummies are used, the age dummies for the household head and the dummy indicating whether there are dependent children in the household are removed from the specification as they partly capture the same effect in an aggregate way. The baseline household is a couple without children and none of the household members is over 64 years old. The rest of the baseline group characteristics remain unchanged.

In Table 4, the probability of being poor when belonging to the baseline group ranges from 0.7 in Luxembourg to 3.5 in Ireland and it is slightly higher for 10 out of 14 countries and lower for 4 countries as compared to the corresponding estimates of Table

2. Both the marginal effects for the initial and the lagged poverty status are high and significant suggesting that past poverty experience is a significant determinant of current poverty status irrespectively of the "amount" of observed and unobserved heterogeneity that we control for.

Compared to the baseline household type, almost all other household types have higher probability to be in poverty with few exceptions. For instance single adults aged more than 64 in Spain and the Netherlands and the residual category "other household type without dependent children" in Ireland, Spain, Greece, Portugal and Italy are less likely to be in poverty than the baseline group. With regards to the Mediterranean countries and Ireland, it should be noted that in this residual category belongs the family type with two parents and adult children that work but still live in their parents household, which is very common in these Member-States. More than 20% of the population lives in such households in the Mediterranean countries, while the corresponding figure is around 10% in countries like the Netherlands, Finland and Denmark.

Living alone and being less than 30 years old sharply increases the risk of being poor in most countries. In Portugal the effect is negative (-0.8), while in Spain, Greece, Ireland and Luxembourg the effect is not statistically significant. On the contrary, in the Northern countries such as the Netherlands (28.9), Finland (16.1), Denmark (10.4) and the UK (9.8), the increase in the probability to be poor, when living alone and being less than 30 years old, is particularly high. Being a single adult aged 30 to 65 years old increases the chances of being poor as compared to the baseline group only in 7 out of 14 countries and only in Ireland the marginal effect is greater than 2.0 percentage points. Also in Ireland, single adults aged more than 64 have significantly higher chances to be in poverty (9.4), while the relevant marginal effect ranges from 1.0 to 1.9 in the remaining countries where the effect is positive and significant. Netherlands is the only country where the effect is negative at the 5% level of significance. A couple with at least one member aged more than 64 has higher probability to be in poverty as compared to the baseline group in Greece (2.4), Austria (1.9), Denmark (1.9), Spain (1.1), Belgium (0.9), Portugal (0.8) and the UK (0.7); and statistically significantly lower probability but small in magnitude in Germany (-0.3) and France (-0.3). As already mentioned the residual type of household without dependent children gives negative marginal effects in a substantial number of countries and only in the Netherlands (4.4) and Denmark (1.7), the chances to be under the poverty line are higher when living in such a household.

In accordance with the previous results, all household types with dependent children have higher chances to be in poverty than the baseline group. The higher risk is found in lone-parent families and families with more than two children. In particular, lone-parent families have a substantially higher risk to be in poverty as compared to the baseline group in the Netherlands (18.3), the UK (8.4), Germany (4.6) and France (3.9), while families with more than two children have much higher probability to be under the poverty threshold in the Netherlands (11.6), Spain (6.1), Luxembourg (5.1), the UK (4.7) and Italy (4.4). It should be mentioned, though, that the share of the population belonging to this household type differs a lot across countries, varying from 5.4% in Greece to 20.3% in Ireland.

The estimates for the variables that are common in the second and the fourth specification are similar in magnitude and significance. Both the AIC and the BIC decline, as well as the measures of unobserved heterogeneity suggest that this, more detailed, specification explains in a better way the probability to be in poverty in all countries examined.

For each value of the predictor in period j there is a postulated value of the logit hazard. In Table 5, the impact of past poverty experience (initial and in the previous year) on the conditional probability of being in poverty is estimated using the first specification with and without controls for unobserved heterogeneity. Table 6 reports estimates of the impact of state dependence on the conditional probability of being in poverty now averaged over the other covariates using the fourth specification. The estimated probabilities reveal that when we do not control for unobserved heterogeneity the effect of poverty in the previous year is much stronger than the effect of the initial poverty status. When unobserved heterogeneity is controlled for, the result is reversed.

The probabilities in both parts of Table 5 correspond to four combinations of past poverty status. In the first line, the probability that an individual experiences poverty is estimated, when he/she is non-poor in both the initial and the previous year. When unobserved heterogeneity is taken into account, the probability to be in poverty in period t, while being non-poor in the initial year and in t-1 declines by half in most Member-States. If the individual experienced poverty in the past, either in the previous or initial year, the probability to be below the poverty line in t increases as compared to the initial combination (non-poor in the initial period, non-poor in t-1). When we do not control for unobserved heterogeneity, the effect of experiencing poverty in the previous but not in the initial year (line two) is much stronger than the effect of experiencing poverty in the initial year only (line three). The estimated probabilities are higher than 40% in all Member-States for the second combination (non-poor in the initial year, poor in the previous year,), while for the third combination (poor in the initial year, non-poor in the previous year), the probabilities range from 9.1% in the Netherlands to 23.2% in Greece. Yet, this result is reversed in almost all countries, in Part B of Table 5, where unobserved heterogeneity is controlled for (the exceptions being Finland and the Netherlands). The estimated probabilities for the second combination range from 9.9% in Belgium to 36.4% in Finland, while for the third combination the estimated probabilities increase and range from 10.7% in Germany to 43.7% in Greece. Finally, the individuals that experienced poverty in both the initial and the previous year have the highest probabilities to be in poverty in t with or without controlling for unobserved heterogeneity. In the first case, the estimated probabilities range from 64.6% in the Netherlands to 81.4% in Portugal and in the second case from 53.1% in the Netherlands to 80.3% in Portugal.

Table 6 estimates the corresponding probabilities using the fourth specification and, thus, a more "favourable" (with regards to poverty status) baseline group. In general, all estimated probabilities are lower than in the previous table. More specifically, Part A of Table 6 (without controls for unobserved heterogeneity) reveals that the probability of being poor in t while being non-poor in both the initial year of the survey and the previous year ranges from 1.1% in Luxembourg to 4.8% in Ireland. When the individual is non-poor in the initial year, but poor in the previous year (combination 2), the probability of being poor in t increases sharply and ranges from 11.6% in Denmark to 31.1% in the Netherlands. In all countries, the estimated probabilities reported in the third line of the panel, when the individual appears to be poor in the initial year but non-poor in the previous year are substantially lower that the probabilities reported in the second line (they range between 3.6% and 10.6%). Finally, when both the initial and lagged poverty values are set to 1, the estimated probability of being poor ranges from 24.2% in Denmark to 63.0% in Ireland. In line with the results of the first specification that are reported in Table 5, when observed heterogeneity is controlled for (Part B of Table 6), the estimated probabilities as well as the differences across Member-States decline. The probability of being poor in t, while being non-poor in the initial year of the survey and in the year t-1 is everywhere very low and ranges between 0.3% and 2.8%. In other words, individual unobserved characteristics "absorb" part of the differences in predicted probabilities across Member-States. The probability of being poor in t, while being non-poor in the initial year, but poor in the previous year is now much lower than in Panel A (ranging from 1.5% in Luxembourg to 12.2% in Ireland) and lower than the corresponding probabilities of being poor in the initial year and non-poor in the previous year (with the exceptions of Ireland and the UK). Finally, the probabilities of being poor in t, while being poor both in the initial year and in the year t-1 are on average fifteen percentage points than the probabilities without controlling for unobserved heterogeneity. The lowest value is reported in Luxembourg (18.2%) the highest in the Netherlands (45.0%).

The general conclusion to be drawn from these two tables is that, ceteris paribus, the probability of being in poverty now is higher for individuals that have experienced poverty in the past both with or without unobserved heterogeneity. When unobserved heterogeneity is added in the regression, the estimated probabilities decline and the effect of being poor only in the initial year (not the previous year) is higher than the effect of being poor only in the previous year (not the initial year).

7. CONCLUSIONS

The aim of this paper was to study the dynamics of poverty and in particular whether past poverty experience affects current poverty status. Our main conclusion is that state dependence remains significant in all specifications, even when controlling for observed, unobserved heterogeneity and initial conditions. Consequently, social benefits are likely to play an important role if breaking the "vicious circle" of poverty is among the long-run policy objectives of the policy-makers.

We also find that the coefficient of initial poverty status is significant in all specifications and when we control for unobserved heterogeneity the magnitude of the coefficient is higher than the magnitude of the coefficient of lagged poverty status. This indicates that an early intervention is necessary. As Finnie (2000) underlines, given the state dependence and the intergenerational effect that poverty often has, an early intervention offers the maximum of benefits to the poor households and society, because there are greater chances for an early than a late intervention to have long-lasting effects.

Irrespective of the magnitude of state dependence, unobserved heterogeneity remains also important in all specifications and its magnitude (as captured by sigma_a) does not decrease substantially as the specification of the model improves. Moreover, the results for the observed characteristics indicate that individual heterogeneity also affects current poverty status. Consequently, anti-poverty policies should include schemes such as education, development of personal skills and capacities or other labour market and social policies. It is also important to note that having an income over or under the poverty line and, thus, being characterised as "poor" or "non-poor" is not directly observable by the individuals concerned (contrary to the unemployment situation) and may not affect the behaviour and choices of persons and families as strong as it would be necessary for escaping from poverty. Providing appropriate incentives for the poor people to work harder, take advantage of opportunities and exploit life-chances might also be necessary.

To conclude, the empirical results of this paper indicate that both state dependence and individual heterogeneity (observed or unobserved) play an important role in keeping individuals into poverty. Consequently, there is no single path into or out of poverty, suggesting that multiple policies can be considered to help people getting out of poverty. Given that the education and development of personal skills is a long-run process, which is also related to household income levels, the importance of the intervention of state in the short-run for breaking the “vicious cycle” should not be underestimated.

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Table 1: Logit analysis of state dependence – Specification 1: with only initial and lag value of the dependent variable (controlling for unobserved heterogeneity)

Depvar=poverty exit	**Country**													
	A	**B**	**D**	**DK**	**E**	**EL**	**F**	**FIN**	**I**	**IRL**	**L**	**NL**	**P**	**UK**
Baseline probability	2.9	2.3	2.0	3.1	5.3	5.1	3.0	4.0	3.6	4.7	1.6	2.3	4.1	3.6
poor_lag	10.8***	7.6***	8.7***	12.9***	10.5***	12.4***	11.5***	32.4***	9.0***	18.3***	10.4***	12.9***	22.9***	16.7***
poor_0	27.5***	25.5***	15.5***	16.2***	30.1***	38.6***	30.0***	11.3***	32.0***	25.6***	23.2***	10.8***	28.0***	17.6***
Number of obs	*26,850*	*27,888*	*63,186*	*20,700*	*63,300*	*50,862*	*60,036*	*22,268*	*71,874*	*28,626*	*21,535*	*39,318*	*58,776*	*53,076*
Wald chi2	*3,129****	*2,533****	*5,429****	*1,547****	*6,121****	*5,907****	*6,861****	*2,748****	*7,274****	*3,175****	*2,575****	*3,013****	*11,509****	*6,200****
Log likelihood	*-7,219*	*-6,668*	*-13,970*	*-4,871*	*-22,854*	*-18,637*	*-16,379*	*-5,064*	*-23,593*	*-9,316*	*-4,170*	*-7,860*	*-19,735*	*-15,934*
AIC	*14,446*	*13,344*	*27,948*	*9,749*	*45,716*	*37,282*	*32,766*	*10,137*	*47,195*	*18,639*	*8,347*	*15,729*	*39,478*	*31,875*
BIC	*14,479*	*13,377*	*27,984*	*9,781*	*45,752*	*37,317*	*32,802*	*10,169*	*47,232*	*18,672*	*8,379*	*15,763*	*39,514*	*31,911*
sigma_u	*1.19****	*1.21****	*1.19****	*0.94****	*1.21****	*1.40****	*1.21****	*0.59****	*1.47****	*1.18****	*1.16****	*0.93****	*1.17****	*1.15****
rho	*0.30****	*0.31****	*0.30****	*0.21****	*0.31****	*0.37****	*0.31****	*0.09****	*0.40****	*0.30****	*0.29****	*0.21****	*0.29****	*0.29****

Notes:

1. Source: ECHP UDB 1994-2000 (Dec 2003 - 2nd issue)
2. Marginal effects are reported
3. *p<0.05, **<0.01, ***p<0.001
4. A constant term has been included in the regression
5. d.c. - variable dropped due to collinearity
6. s.n.o - variable dropped due to small number of observations, variable predicts failure or non-failure perfectly
7. Baseline probability: non-poor initially and non-poor in the previous year

Table 2: Logit analysis of state dependence - Specification 2: with initial and lag value of the dependent variable, other explanatory variables and wave dummies (controlling for unobserved heterogeneity)

Depvar=poverty exit	Country													
	A	B	D	DK	E	EL	F	FIN	I	IRL	L	NL	P	UK
Baseline probability	1.5	1.8	1.2	1.8	2.1	2.0	1.2	1.6	1.3	2.1	0.7	3.7	0.8	1.9
poor_lag	5.4***	4.9***	4.5***	4.6***	4.2***	5.8***	4.2***	7.8***	3.5***	7.9***	3.6***	16.2***	5.4***	8.9***
poor_0	15.9***	12.2***	7.4***	6.1***	10.3***	11.8***	9.0***	10.1***	8.6***	9.9***	5.0***	13.1***	5.9***	6.2***
Household head														
Aged <30	0.9***	0.4	1.5***	4.6***	0.9***	1.4***	1.5***	5.5***	0.6**	1.3**	0.1	5.5***	0.1	2.9***
Aged >64	0.7***	0.8***	-0.2	1.7***	0.0	1.2***	-0.4***	-0.3	0.2*	0.8***	-0.1	-0.8*	0.6***	0.3**
Female	-0.1	0.3	0.3***	0.2	0.3	-0.2	0.4***	0.8***	0.2**	0.0	0.1	0.7**	-0.2***	0.1
Higher education	-0.6**	-1.0***	-0.6***	-0.8***	-1.4***	-1.3***	-0.6***	-0.8***	-0.6***	-1.6***	-0.5***	-2.7***	-0.6***	-0.8***
Primary education	1.3***	1.6***	0.8***	0.8***	2.8***	3.9***	1.0***	0.9***	2.0***	1.0***	0.6***	-2.8***	1.9***	0.1
Unemployed	1.8***	9.7***	4.4***	2.5***	3.7***	3.3***	3.2***	3.7***	2.6***	11.4***	1.8***	10.9***	1.2***	6.0***
Inactive	1.1***	2.2***	1.7***	5.9***	1.0***	0.6***	2.5***	4.1***	0.3***	5.1***	0.4***	7.4***	0.4***	4.1***
Other EU citizenship	-1.2	1.0**	0.0	0.6	2.3	d.c.	0.5**	3.3**	s.n.o.	3.5***	0.6***	-3.4*	-0.5	-0.2
Non-EU citizenship	-0.3	-1.1**	0.6**	-0.4	0.2	0.5	2.3***	7.7**	2.9*	0.1	2.9***	0.7	s.n.o.	0.4
Household														
Having at least one dep. child	0.6***	0.5**	0.6***	0.0	2.0***	1.1***	1.3***	0.4**	1.8***	0.7***	1.0***	5.2***	0.3***	1.6***
At least one unemp. (exc.head)	0.7***	0.3	1.0***	0.6	0.7***	0.1	0.7***	0.8***	1.5***	0.5**	0.5***	1.4***	0.3***	1.1***
At least one disabled member	0.9***	0.1	0.2*	0.1	0.4***	0.7***	0.3***	-0.2	0.1	2.3***	d.c.	0.7*	0.1	0.5***
Wave dummies														
w2		-0.5***	-0.3***	-0.8***	-0.7***	-0.2	-0.2**		-0.3***	-0.4**		-0.4	0.1*	-0.2*
w3	-0.1	-0.6***	-0.4***	-0.6***	-0.5***	0.0	-0.3***		-0.3***	-0.8***	-0.2**	-0.7*	0.3***	-0.2
w4	0.0	-0.5***	-0.4***	-0.3	-0.7***	-0.5***	-0.2***	-0.6***	-0.3***	-0.7***	-0.1*	-0.9***	0.1***	0.2
w5	-0.4***	-0.7***	-0.4***	-0.2	-0.5***	-0.1	-0.1*	-0.2	-0.3***	-0.1	-0.2***	0.2	0.0	-0.1
w6	-0.1	-0.5***	-0.4***	-0.1	-0.5***	-0.1	0.0	-0.1	-0.3***	0.1	-0.1*	-0.6*	0.1*	0.1
Number of obs	*26,850*	*27,888*	*63,186*	*20,700*	*63,300*	*50,862*	*60,036*	*22,268*	*71,874*	*28,626*	*21,535*	*39,318*	*58,776*	*53,076*
Wald chi2	*2,914****	*2,734****	*5,590****	*2,045****	*6,618****	*6,709****	*6,843****	*2,511****	*8,730****	*3,746****	*2,395****	*3,127****	*10,595****	*6,732****
Log likelihood	*-7,012*	*-6,222*	*-13,138*	*-4,314*	*-21,930*	*-17,998*	*-15,536*	*-4,552*	*-22,799*	*-8,579*	*-3,902*	*-7,414*	*-19,255*	*-15,060*
AIC	*14,063*	*12,486*	*26,317*	*8,670*	*43,901*	*36,035*	*31,115*	*9,141*	*45,641*	*17,200*	*7,843*	*14,869*	*38,553*	*30,162*
BIC	*14,227*	*12,659*	*26,507*	*8,837*	*44,091*	*36,212*	*31,304*	*9,293*	*45,834*	*17,374*	*7,994*	*15,049*	*38,742*	*30,349*
sigma_u	*1.37****	*1.29****	*1.35****	*0.99****	*1.26****	*1.30****	*1.35****	*0.99****	*1.32****	*1.18****	*1.31****	*1.06****	*1.28****	*1.19****
rho	*0.36****	*0.34****	*0.36****	*0.23****	*0.33****	*0.34****	*0.36****	*0.23****	*0.34****	*0.30****	*0.34****	*0.25****	*0.33****	*0.30****

Notes: see Table 1
7. Baseline probability: non-poor initially and non-poor in the previous year;
hh head: male, aged [30,64], having completed secondary education, being employed full-time and being a citizen of the country under examination;
hh: without dependent children, none of the household members is unemployed, none of the household members has severe disability or chronic disease
8. For Austria and Luxembourg four year dummies have been used and for Finland three, since these countries jointed the panel one and two years later respectively

Table 3: Logit analysis of state dependence - Specification 3: with initial and lag value of the dependent variable, other explanatory variables and wave dummies (controlling for unobserved heterogeneity, excluding variables that may cause endogeneity)

Depvar=poverty exit	Country													
	A	**B**	**D**	**DK**	**E**	**EL**	**F**	**FIN**	**I**	**IRL**	**L**	**NL**	**P**	**UK**
Baseline probability	2.4	2.6	2.2	2.0	3.8	3.2	2.5	2.4	2.8	3.3	1.2	7.8	2.4	3.0
poor_lag	8.3***	7.6***	8.7***	4.3***	7.5***	9.0***	8.9***	11.4***	7.9***	13.4***	6.6***	30.2***	14.6***	13.8***
poor_0	22.7***	20.1***	14.7***	9.3***	19.4***	17.4***	19.9***	14.0***	19.0***	16.7***	10.6***	25.4***	15.6***	12.9***
Household head														
Aged <30	1.0***	0.3	1.9***	7.0***	0.9*	1.9***	2.3***	9.5***	0.2	1.7**	0.0	5.5***	0.3	4.2***
Aged >64	1.6***	1.7***	0.0	8.5***	-0.5***	1.7***	-0.2	1.5***	-0.6***	3.2***	-0.3*	-1.4*	1.8***	1.9***
Female	0.1	1.3***	0.9***	0.6***	0.2	-0.3	1.2***	1.5***	0.0	1.1***	0.1	4.7**	-0.3*	1.3***
Higher education	-1.0***	-1.5***	-1.2***	-1.0***	-2.4***	-2.1***	-1.3***	-1.4***	-1.3***	-2.6***	-0.8***	-5.8***	-1.8***	-1.4***
Primary education	2.3***	2.6***	1.4***	1.3***	5.4***	5.6***	2.6***	1.7***	4.0***	2.5***	1.2***	-5.8**	5.5***	0.5**
Other EU citizenship	-1.8	2.0***	0.0	0.3	6.7**	d.c.	1.1**	5.1**	s.n.o.	5.2***	1.2***	-7.0*	-1.6	-0.6
Non-EU citizenship	-0.3	-1.1	1.6***	-0.5	0.4	0.9	6.8***	10.1**	5.8*	2.2	6.0***	6.3	s.n.o.	1.4
Wave dummies														
w2		-0.7***	-0.5***	-0.9***	-0.8***	-0.3	-0.3**		-0.3*	0.1		0.9	0.3*	0.0
w3	-0.2	-0.8***	-0.7***	-0.7***	-0.5**	0.0	-0.5***		-0.5***	-0.7***	-0.2	-0.4	0.8***	-0.1
w4	0.1	-0.7***	-0.7***	-0.3	-1.1***	-0.8***	-0.3*	-0.8***	-0.5***	-0.7**	-0.1	-1.2*	0.5***	0.4*
w5	-0.5**	-0.9***	-0.6***	-0.2	-0.7***	-0.2	-0.2	-0.3	-0.5***	0.1	-0.3**	1.0	0.1	-0.1
w6	-0.2	-0.7***	-0.7***	-0.2	-1.1***	-0.2	0.1	-0.1	-0.4***	0.3	-0.2	-0.9	0.3*	0.1
Number of obs	*26,850*	*27,888*	*63,186*	*20,700*	*63,300*	*50,862*	*60,036*	*22,268*	*71,874*	*28,626*	*21,535*	*39,318*	*58,776*	*53,076*
Wald chi2	*2,869****	*2,497****	*5,127****	*1,645****	*6,067****	*6,613****	*6,506****	*2,404****	*7,995****	*3,249****	*2,351****	*2,809****	*10,603****	*8,846****
Log likelihood	*-7,069*	*-6,388*	*-13,556*	*-4,441*	*-22,301*	*-18,125*	*-15,895*	*-4,688*	*-23,309*	*-9,011*	*-3,972*	*-7,693*	*-19,386*	*-15,573*
AIC	*14,169*	*12,808*	*27,144*	*8,913*	*44,634*	*36,280*	*31,822*	*9,403*	*46,649*	*18,054*	*7,973*	*15,418*	*38,804*	*31,178*
BIC	*14,292*	*12,939*	*27,289*	*9,040*	*44,779*	*36,413*	*31,966*	*9,515*	*46,796*	*18,186*	*8,093*	*15,555*	*38,947*	*31,320*
sigma_u	*1.37****	*1.36****	*1.38****	*1.24****	*1.30****	*1.30****	*1.36****	*1.00****	*1.37****	*1.24****	*1.34****	*1.09****	*1.27****	*1.28****
rho	*0.36****	*0.36****	*0.37****	*0.32****	*0.34****	*0.34****	*0.36****	*0.23****	*0.36****	*0.32****	*0.35****	*0.26****	*0.33****	*0.33****

Notes: 1-6 and 8 see Table 2

7. Baseline probability: non-poor initially and non-poor in the previous year;

hh head: male, aged [30,64], having completed secondary education and being a citizen of the country under examination;

Table 4: Logit analysis of state dependence - Specification 4:with initial and lag value of the dependent variable, other explanatory variables, household type dummies and wave dummies (controlling for unobserved heterogeneity)

Depvar=poor	**Country**													
	A	**B**	**D**	**DK**	**E**	**EL**	**F**	**FIN**	**I**	**IRL**	**L**	**NL**	**P**	**UK**
Baseline probability	1.3	2.0	1.3	1.5	3.0	2.4	1.3	1.4	1.4	3.5	0.7	2.8	0.9	2.2
poor_lag	4.5***	5.2***	4.1***	3.8***	5.8***	6.6***	4.4***	6.4***	3.5***	11.6***	4.9***	11.4***	5.4***	10.8***
poor_0	12.8***	12.8***	7.1***	4.7***	13.5***	13.1***	9.6***	7.9***	8.5***	10.9***	4.0***	9.0***	6.7***	5.2***
Household head														
Female	-0.1	0.4	0.1	0.2	1.3***	-0.1	0.0	0.6***	0.1	-0.4	0.2*	0.2	-0.2***	-0.3**
Higher education	-0.6***	-1.1***	-0.7***	-0.7***	-2.0***	-1.4***	-0.6***	-0.8***	-0.6***	-2.7***	-0.5***	-2.1***	-0.7***	-1.0***
Primary education	1.2***	1.8***	0.7***	0.6***	4.5***	4.3***	1.0***	0.6***	2.1***	2.2***	0.9***	-2.2***	2.7***	0.0
Unemployed	1.6***	9.9***	4.8***	2.4***	5.6***	3.8***	3.6***	3.3***	2.7***	17.5***	1.8***	9.0***	1.5***	6.9***
Inactive	0.9***	2.7***	2.1***	5.6***	1.3***	0.7***	2.4***	3.9***	0.4***	8.8***	0.6***	6.3***	0.6***	4.1***
Other EU citizenship	-1.1*	1.1**	0.0	0.6	3.8*	d.c.	0.4*	2.2*	s.n.o.	4.7***	0.7***	-2.6*	-0.6	-0.3
Non-EU citizenship	-0.3	-1.2**	0.8***	0.1	-0.4	0.7	2.2***	11.7***	3.1*	1.0	2.4***	1.1	s.n.o.	0.3
Household														
Single adult <30	4.6***	2.1*	6.7***	10.4***	0.6	2.3	5.4***	16.1***	4.9***	2.7	0.2	28.9***	-0.8*	9.8***
Single adult [30,64]	0.7*	-0.1	1.0***	0.3	-0.1	0.8	0.2	1.7***	1.2***	6.0***	0.1	0.6	0.8***	1.4***
Single adult 65+	1.8***	-0.3	0.0	1.5***	-1.0**	1.3**	0.0	1.0**	1.0***	9.4***	-0.3	-0.9*	1.0***	1.9***
Couple only, at least one aged 65+	1.9***	0.9**	-0.3*	1.9***	1.1***	2.4***	-0.3**	-0.5**	0.3	0.3	0.1	-0.1	0.8***	0.7**
Other hh without dep children	0.0	-0.2	-0.3***	1.7***	-1.8***	-0.5**	-0.1	0.1	-0.3*	-2.3***	-0.1	4.4***	-0.4***	0.1
Lone parent,at least one dep child	3.0***	0.9*	4.6***	1.7***	0.1	0.5	3.9***	1.1**	1.6***	0.0	0.6*	18.3***	0.4**	8.4***
Couple with 1/2 dep children	0.8***	0.2	0.4***	-0.3	1.4***	0.4	0.7***	0.3	1.6***	-0.1	1.0***	4.1***	0.1	1.3***
Couple with 3+ dep children	2.9***	0.6	2.3***	1.5***	6.1***	2.6***	2.7***	2.4***	4.4***	2.8***	5.1***	11.6***	2.3***	4.7***
Other type of hh, at least one dep child	0.6**	0.4	-0.1	2.1***	-0.4	1.1***	1.2***	1.6***	1.2***	-1.7***	0.5**	10.0***	-0.2***	0.8***
At least one unemp. (exc.head)	0.8***	0.3	1.4***	0.6*	1.9***	0.3**	0.9***	1.0***	2.0***	2.5***	0.6***	1.2***	0.6***	1.8***
At least one disabled member	0.9***	0.1	0.3**	0.0	1.0***	0.9***	0.3***	-0.1	0.2*	4.5***	d.c.	0.4	0.2***	0.6***
Wave dummies														
w2		-0.5***	-0.2***	-0.6***	-1.0***	-0.2	-0.2**		-0.3***	-0.9***		0.0	0.1	-0.2*
w3	-0.1	-0.7***	-0.4***	-0.5***	-0.7***	0.0	-0.3***		-0.3***	-1.5***	-0.2**	-0.3	0.2***	-0.2
w4	0.0	-0.6***	-0.4***	-0.2***	-1.1***	-0.6***	-0.2***	-0.5***	-0.3***	-1.2***	-0.2*	-0.6**	0.1**	0.2
w5	-0.3***	-0.7***	-0.4***	-0.1	-0.7***	-0.1	-0.2*	-0.2	-0.3***	-0.3	-0.2***	0.2	0.0	-0.1
w6	-0.1	-0.5***	-0.4***	-0.1	-0.7***	-0.1	0.0	-0.1	-0.3***	0.2	-0.1	-0.4	0.1*	0.2
Number of obs	*26,850*	*27,888*	*63,186*	*20,700*	*63,300*	*50,862*	*60,036*	*22,268*	*71,874*	*28,626*	*21,535*	*39,318*	*58,776*	*53,076*
Wald chi2	*2,973****	*2,743****	*5,823****	*2,086****	*7,183****	*6,784****	*6,918****	*2,603****	*8,917****	*4,404****	*2,739****	*3,341****	*10,518****	*7,708****
Log likelihood	*-6,946*	*-6,213*	*-12,929*	*-4,259*	*-21,601*	*-17,928*	*-15,447*	*-4,444*	*-22,676*	*-8,282*	*-3,850*	*-7,219*	*-18,894*	*-14,917*
AIC	*13,944*	*12,481*	*25,912*	*8,571*	*43,256*	*35,908*	*30,947*	*8,939*	*45,405*	*16,619*	*7,750*	*14,492*	*37,842*	*29,889*
BIC	*14,157*	*12,703*	*26,156*	*8,785*	*43,500*	*36,138*	*31,190*	*9,139*	*45,653*	*16,842*	*7,949*	*14,724*	*38,085*	*30,128*
sigma_u	*1.36****	*1.29****	*1.32****	*0.96****	*1.20****	*1.29****	*1.34****	*0.95****	*1.30****	*0.95****	*1.02****	*1.04****	*1.31****	*0.99****
rho	*0.36****	*0.34****	*0.35****	*0.22****	*0.31****	*0.34****	*0.35****	*0.22****	*0.34****	*0.22****	*0.24****	*0.25****	*0.34****	*0.23****

Notes: 1-6 see table VII.3

7. Baseline probability: non-poor initially and non-poor in the previous year;
hh head: male, having completed secondary education, being employed full-time and being a citizen of the country under examination;
hh: couple both aged less than 65, none of the household members is unemployed, none of the household members has severe disability or chronic disease

Table 5: Prediction probabilities for being poor at t given initial and lag poverty values from Specification 1

A. Without controlling for unobserved heterogeneity

		Probability of being poor at t													
Initial poverty status	***Poverty status at t-1***	**A**	**B**	**D**	**DK**	**E**	**EL**	**F**	**FIN**	**I**	**IRL**	**L**	**NL**	**P**	**UK**
Non-poor	*Non-poor*	5.3	4.6	4.0	4.8	8.4	8.6	5.5	4.6	7.0	7.5	3.4	3.7	6.6	6.0
Non-poor	*Poor*	46.3	42.0	42.1	40.6	45.6	53.2	48.7	47.7	47.9	55.4	46.6	40.9	58.8	51.8
Poor	*Non-Poor*	16.6	15.8	11.3	13.5	21.8	23.2	17.8	12.4	19.5	17.3	12.4	9.1	17.9	13.5
Poor	*Poor*	75.3	73.8	68.8	68.1	71.8	78.4	77.9	72.6	74.8	76.4	78.0	64.6	81.4	72.3

B. Controlling for unobserved heterogeneity

		Probability of being poor at t													
Initial poverty status	***Poverty status at t-1***	**A**	**B**	**D**	**DK**	**E**	**EL**	**F**	**FIN**	**I**	**IRL**	**L**	**NL**	**P**	**UK**
Non-poor	*Non-poor*	2.9	2.3	2.0	3.1	5.3	5.1	3.0	4.0	3.6	4.7	1.6	2.3	4.1	3.6
Non-poor	*Poor*	13.7	9.9	10.7	16.0	15.8	17.5	14.5	36.4	12.4	23.0	12.1	15.2	27.0	20.3
Poor	*Non-Poor*	30.4	27.8	10.7	19.3	35.4	43.7	33.1	15.3	35.5	30.4	24.8	13.1	32.1	21.3
Poor	*Poor*	69.7	64.0	55.7	58.6	64.8	75.4	73.0	71.3	67.8	72.4	73.3	53.1	80.3	64.7

Table 6: Prediction probabilities for being poor at t given initial and lag poverty values from Specification 4

A. Without controlling for unobserved heterogeneity

		Probability of being poor at t													
Initial poverty status	***Poverty status at t-1***	**A**	**B**	**D**	**DK**	**E**	**EL**	**F**	**FIN**	**I**	**IRL**	**L**	**NL**	**P**	**UK**
Non-poor	*Non-poor*	2.8	2.9	2.1	1.9	4.1	4.3	2.5	1.9	2.4	4.8	1.1	3.6	2.0	3.2
Non-poor	*Poor*	26.9	23.0	19.8	11.7	22.8	30.3	24.5	17.4	18.5	30.0	14.5	31.3	25.5	28.4
Poor	*Non-Poor*	8.9	8.0	5.3	4.5	10.0	10.6	7.1	5.9	6.4	12.6	3.1	9.1	5.4	6.0
Poor	*Poor*	55.6	46.7	39.0	24.2	43.7	53.5	48.8	40.4	38.4	63.0	33.4	61.8	49.2	43.4

B. Controlling for unobserved heterogeneity

		Probability of being poor at t													
Initial poverty status	***Poverty status at t-1***	**A**	**B**	**D**	**DK**	**E**	**EL**	**F**	**FIN**	**I**	**IRL**	**L**	**NL**	**P**	**UK**
Non-poor	*Non-poor*	0.8	1.3	0.8	1.1	2.3	2.0	0.9	1.0	1.0	2.8	0.3	2.0	0.8	1.9
Non-poor	*Poor*	2.6	4.3	2.9	3.6	6.5	7.0	3.5	4.1	3.2	12.2	1.5	7.3	5.2	10.2
Poor	*Non-Poor*	14.3	11.9	6.5	4.8	13.6	15.1	10.0	9.3	8.4	11.0	4.2	15.0	8.7	7.6
Poor	*Poor*	36.2	31.1	20.9	14.8	32.1	39.8	31.0	31.2	23.5	38.0	18.2	45.0	39.2	32.6